Macroeconomic attention and stock market return predictability

Feng Ma[a], Xinjie Lu[a]*, Jia Liu[b], Dengshi Huang[a]

[a] *School of Economics and Management, Southwest Jiaotong University, Chengdu, China*

[b] *Business School, University of Portsmouth, England, UK*

*** Corresponding author**

E-mail addresses: mafeng2016@swjtu.edu.cn (F.Ma); luxinjie@my.swjtu.edu.cn (X.Lu); jia.liu@port.ac.uk (J.Liu); dengshi.huang@126.com (D.Huang)

Acknowledgments:

The authors are very grateful to the editor and anonymous referees for insightful comments that have significantly improved the paper. All errors remain our own.

This work is supported by the Natural Science Foundation of China [72071162; 71971191; 72073109].

Macroeconomic attention and stock market return predictability

Abstract

Our investigation evaluates the novel macroeconomic attention indices (MAI) of Fisher et al. (2021) in terms of their ability to predict stock market returns based on dimension reduction methods and shrinkage methods. Our results demonstrate that macroeconomic attention indices can predict stock market returns with a significant degree of accuracy. In addition, the components of MAI indices based on partial least squares (PLS) and the least absolute shrinkage and selection operator (LASSO) methods have a greater capacity to improve the accuracy of the prediction of stock market returns than the components of the traditional macroeconomic variables. Moreover, we find that shrinkage methods can generate performances superior to those of the other models for forecasting stock market returns. We further demonstrate that macroeconomic attention indices embody superior predictive ability during the COVID-19 pandemic and over longer periods of time. Our study sheds new light on stock market returns' prediction from the perspective of macroeconomic fundamentals.

Keywords: Macroeconomic attention indices; Macroeconomic variables; Stock market return predictability; Shrinkage methods; selection operator (LASSO) methods; COVID-19 pandemic

1. Introduction

Catastrophic events during the last two decades, from the financial crisis of 2008 to the COVID-19 pandemic, have dealt a series of macroeconomic shocks to the global economy, exacerbated by the uncertainty of recovery and unpredictable stock market returns (Chundakkadan et al., 2021; Edmans et al., 2021; Izzeldin et al., 2021; Jiang et al., 2021; Leippold et al., 2021). As a consequence, investors' confidence has been undermined, limiting the ability of corporate enterprises to secure the provision of the long-term capital required to fund sustainable development and growth. Investors view the volatility of markets with apprehension, unable to make rational investment decisions because of the fluctuations of erratically performing shares (Ologunde et al., 2006; Ma et al., 2021; Nasir et al., 2021; Raghutla and Chittedi, 2021). Therefore, policymakers, market participants, and investors are in urgent need of a means of deriving accurate forecasts of stock market returns (Fama and French, 1988; Goyal and Welch, 2003; Campbell and Vuolteenaho, 2004; Cochrane, 2010; Leippold et al., 2021), which is the vital focus of this investigation. Employing macroeconomic attention indices (MAI), we predict stock market returns based on dimension reduction and shrinkage methods.

Extant research demonstrates that stock market performance is highly correlated with economic fundamentals, and a model based on this relationship is essential for predicting future trajectories and trends (Morck et al., 2000; Rapach et al., 2005; Ahn et al., 2019; Gopinathan and Durai, 2019; Karanasos et al., 2021). According to Engle et al. (2013), macroeconomic factors such as the growth of industrial production, interest rates, inflation, and unemployment often determine stock market movements. Numerous studies demonstrate that stock market returns can be systematically impacted by the behaviors of macroeconomic variables (Fama and French, 1988; Goyal and Welch, 2003; Rapach et al., 2005; Ang and Bekaert, 2007; Cochrane, 2011). Utilizing a study of 12 industrialized countries, Rapach et al. (2005) investigate the ability of macroeconomic variables to predict share returns, concluding that interest rates are the best indicators in an international context. Liu and Kemp (2019) examine the forecasting accuracy of macroeconomic variables for predicting excess returns of the U.S. oil and gas industry stock index, finding that macroeconomic variables can provide valuable information for determining the future performance of the stock market, and that macroeconomic fundamentals have concentrated effects during a bear market period.

Despite recent advancements in utilizing macroeconomic variables for the prediction of stock returns, several limitations remain. First, although an extensive set of macroeconomic variables have been identified and tested, empirical studies show their forecasting capability to be limited (Goyal and Welch, 2008). For example, classical research establishes that some fundamental predictors can have better in-sample performances, but it is difficult for them to better the historical average forecast during the out-of-sample process, indicating the need for constructing more powerful predictors. Second, when incorporating a greater number of variables or predictors, the stability and power of the predictive model are difficult to maintain (Çakmaklı and van Dijk, 2016), providing a compelling motivation for this study. These unresolved issues emphasize the difficulties of accurately predicting stock market returns.

In response to the first concern, Fisher et al. (2021) significantly augment the existing literature by constructing 8 macroeconomic attention indices based on news articles published in the New York Times and Wall Street Journal, providing new measures of market attention to specific macroeconomic fundamentals that are empirically confirmed to be efficient predictors for announcement risk premia. In addition, they provide valid evidence confirming that different measures of market attention correspond to different types of macroeconomic news.

With respect to the second problem, some researchers apply dimension reduction methods, including principal component analysis (PCA), scaled principal component analysis (SPCA), and partial least squares (PLS) models to predict stock returns. Further, shrinkage methods, such as the least absolute shrinkage and selection operator (LASSO) of Tibshirani (1996), and the elastic net (ENET) of Zou and Hastie (2005), can deal with a scenario that involves greater numbers of variables or predictors while maintaining the stability of the predictive model. According to Tibshirani (1996) and Li and Tsiakas

(2017), shrinkage methods have an ability to select more useful and important predictors while setting other predictors to zero. In addition, shrinkage methods have better forecasting accuracy because of the bias-variance balance (Zhang et al., 2019). Given the foregoing discussion, in this study, we adopt the novel macroeconomic attention indices of Fisher et al. (2021) to predict stock market returns and assess how well they can be predicted by shrinkage methods.

We derive several important findings. First, we establish that the predictive performances of all macroeconomic attention indices for stock market returns are superior to the performances of all traditional macroeconomic variables. Second, the performances of macroeconomic attention indices perform relatively better during periods of economic growth rather than in recessions, while traditional macroeconomic variables exhibit relatively better performances during recessions. Third, based on the dimension reduction model and shrinkage methods, we determine that the components of MAI indices are more informative for improving the forecasting accuracy of stock market returns than traditional macroeconomic variables, and all other predictors besides. Importantly, the shrinkage methods (LASSO and ENET) display better performances than the other models for forecasting stock market returns. In addition, further discussions indicate that the MAI indices have more robust predictive power than the macroeconomic variables, even during the devastating period of the COVID-19 pandemic, and also over longer horizons.

Our study contributes threefold to the existing literature. First, based on the novel macroeconomic attention indices, we investigate whether the newly constructed macroeconomic attention indices of Fisher et al. (2021) can predict stock market returns. In addition, based on the 14 traditional macroeconomic variables of Goyal and Welch (2008), comparing the predictability of macroeconomic attention indices and macroeconomic variables, we dmonstrate that individual macroeconomic attention indices have a more powerful capability than individual macroeconomic variables for predicting stock market returns.

Second, based on a large set of predictors, we evaluate dimension reduction methods such as the principal component analysis model, scaled principal component analysis model, and partial least squares model in their prediction of stock returns. Our results determine that these dimension reduction methods can further improve the forecasting accuracy of stock market returns. Importantly, we further apply some shrinkage methods, such as the least absolute shrinkage and selection operator and the elastic net methods, which have been confirmed to have better performances than the other models for forecasting stock market returns. Additionally, we find that the components of macroeconomic attention indices are more powerful predictors of stock returns than the components of macroeconomic variables.

Third, we further evaluate the performance of the predictors' forecasting capability for stock market returns during the COVID-19 pandemic, our results confirming that the MAI indices have perform better than the macroeconomic variables even during this devastating period. Additionally, we evaluate the portfolio performances of investors with different risk aversion coefficients. Further, we assess the macroeconomic attention indices' forecasting performances over longer horizons, finding that macroeconomic attention indices maintain satisfactory performances over lengthier periods. The totality of our results emphasize that the novel MAI indices are indeed an efficient predictor for stock market returns.

Our study is close to that of Neely et al. (2014), who compare the predictability of 14 macroeconomic variables and 14 technical indicators for stock market returns, finding that macroeconomic variables produce worse forecasts than technical indicators. However, our study is differs from theirs in the following repects. First, we compare the predictability of macroeconomic attention indices and macroeconomic variables for stock market returns, while they compare the predictability of technical predictors and macroeconomic variables. Second, we consider not only the principal component analysis model, but also the scaled principal component analysis model, partial least squares model, and shrinkage methods, such as the least absolute shrinkage and selection operator and the elastic net methods, demonstrating their robustness. Third, we further consider the portfolio performances of investors with different risk aversion coefficients. Our study is also related to that of Fisher et al. (2021), who apply macroeconomic attention indices to predict announcement risk premia. The differences between our study and theirs are as follows. First, we add the commonly used traditional macroeconomic variables to compare the predictive performances of macroeconomic attention indices and the traditional macroeconomic variables. Second, we further evaluate the macroeconomic attention indices' forecasting performances over longer horizons, and we find that macroeconomic attention indices maintain satisfactory performances over lengthier periods.

The remainder of the paper is organized as follows. Section 2 presents the predictive models. Section 3 reports descriptive statistics, and Section 4 discusses the empirical results. Section 5 presents further discussions, and finally, Section 6 concludes.

2. Predictive models

2.1 Linear regression models

We apply univariate regression to investigate each predictor's ability to forecast stock market returns, as specified below:

$$r_{t+1} = \alpha + \beta_q \cdot x_{q,t} + \epsilon_{t+1}, \tag{1}$$

where α and β_q are OLS estimates from regression, r_{t+1} is the monthly stock market excess return; $x_{q,t}$ is one of the predictors, which are macroeconomic attention indices or traditional macroeconomic variables; and ϵ_{t+1} is the error term. The least square method is used to estimate the model parameters, and the *t* values are adjusted by the method of Newey and West (1987). In this study, we apply the recursive window method to forecast excess stock returns.

2.2 Dimensionality reduction models

2.2.1 Principal component analysis (PCA) model

We consider different principal components from macroeconomic attention indices, macroeconomic variables and all the variables evaluated. Based on the principal component analysis method, the excess stock returns are thus the following:

$$r_{t+1} = \alpha_0 + \sum_{p=1}^{P} \delta_p F_{p,t}^{\mathrm{PCA\_}j} + \epsilon_{t+1}, for\ j = \mathrm{MAI, ECON, or\ ALL} \quad (2)$$

where $F_{p,t}^{\mathrm{PCA\_}j}$ is the p-th principal component extracted from the 8 macroeconomic attention indices (j = MAI), the 14 macroeconomic variables (j = ECON), or the 8 macroeconomic attention indices and 14 macroeconomic variables together (j = ALL). Following Neely et al. (2014), P is chosen based on the adjusted R^2. We choose the first principal components of the PCA method to predict stock returns.

2.2.2 Scaled principal component analysis (SPCA) model

Based on the PCA method, Huang et al. (2022) propose scaled principal component analysis (SPCA), which can scale each variable according to its effect on the target: stock market volatility in this context. It can be obtained as follows. We take the scaled principal component obtained from macroeconomic attention indices as an example. First, the predictability of each macroeconomic attention index for excess return can be evaluated from the following regression:

$$r_{t+1} = \alpha_i + \beta_i \mathrm{MAI}_{i,t} + \epsilon_{i,t+1}. \quad (3)$$

Based on the regression, we obtain the scaled coefficient, β_i, and the panels of scaled macroeconomic attention indices ($\beta_1 \mathrm{MAI}_{1,t}, \dots, \beta_I \mathrm{MAI}_{I,t}$).

Second, the target-specific diffusion indices can be extracted based on the PCA and scaled macroeconomic attention predictors $\beta_1 X_{1,t}, \dots, \beta_I X_{I,t}$), which are:

$$\beta_i \mathrm{MAI}_{i,t} = \lambda_i' F_t^{\mathrm{SPCA}} + e_{i,t} \quad (4)$$

where β_i reflects the prediction ability of the i-th predictor to the target, $F_t^{\mathrm{SPCA\_MAI}}$ denotes the diffusion indices extracted by SPCA, which is M-dimensional ($M \ll I$), and $e_{i,t}$ is the error term. Notably, the values of M are chosen based on the cumulative variance contribution rate.

Following Neely et al. (2014), we choose the first principal components of the SPCA method to predict return, as specified below:

$$r_{t+1} = \alpha_0 + \sum_{p=1}^{P} \delta_p F_{p,t}^{\text{SPCA\_}j} + \epsilon_{t+1}, for\ j = \text{MAI, ECON, or ALL} \tag{5}$$

where $F_{p,t}^{\text{SPCA\_}j}$ is the p-th principal component of the SPCA method extracted from the 8 macroeconomic attention indices (j = MAI), the 14 macroeconomic variables (j = ECON), or the 8 macroeconomic attention indices and 14 macroeconomic variables taken together (j = ALL).

2.2.3 Partial least squares (PLS) model

We take the partial least squares component obtained from macroeconomic attention indices as an example. The PLS_MAI factors can be extracted as follows. First, we run a time-series regression of the i-th predictor $\text{MAI}_{i,t-1}$ and stock excess returns, which is:

$$\text{MAI}_{i,t-1} = \alpha_{i,0} + \beta_i r_{i,t} + e_{i,t-1} \tag{6}$$

Second, we run cross-sectional regressions of the i-th predictor $\text{MAI}_{i,t}$ on the corresponding coefficient $\hat{\beta}_i$ for each month t,

$$\text{MAI}_{i,t} = \varphi_{i,0} + F_t^{\text{PLS\_MAI}} \hat{\beta}_i + \mu_{i,t-1} \tag{7}$$

where $F_t^{\text{PLS\_MAI}}$, is the PLS diffusion index.

Thus, the return prediction is obtained by:

$$r_{t+1} = \alpha_0 + \sum_{p=1}^{P} \delta_p F_{p,t}^{\text{PLS\_}j} + \epsilon_{t+1}, for\ j = \text{MAI, ECON, or ALL} \tag{8}$$

where $F_{p,t}^{\text{PLS\_}j}$ is the p-th principal component of the PLS method extracted from the 8 macroeconomic attention indices (j = MAI), the 14 macroeconomic variables (j = ECON), or the 8 macroeconomic attention indices and 14 macroeconomic variables taken together (j = ALL).

2.3 Shrinkage methods

2.3.1 Least absolute shrinkage and selection operator (LASSO) model

Shrinkage methods are increasingly commonly applied to economic and financial prediction processes because of their ability to deal with a large set of predictors (Li and Tsiakas, 2017; Zhang et al., 2019). The least absolute shrinkage and selection operator (LASSO) of Tibshirani (1996) is a popular shrinkage method that considers L_1 penalty functions:

$$r_{\text{LASSO},t+1} = \alpha_{0,\text{LASSO}} + \textstyle\sum_{q=1}^{Q} \hat{\beta}_{q,\text{LASSO}} x_{q,t} \tag{9}$$

where Q is the number of individual predictors in month t and $\hat{\beta}_{q,\text{LASSO}}$ is the coefficient of each individual predictor based on the LASSO model. The optimal coefficient ($\widehat{\beta_{\text{LASSO}}}$) estimate is calculated based on the maximum likelihood estimation method and it can be：

$$\widehat{\beta_{\text{LASSO}}} = \underset{\beta}{\operatorname{argmin}}\Big(\frac{1}{2(t-1)}\sum_{l=1}^{t-1}\left(r_{\text{LASSO},t+1} - \alpha_{0,\text{LASSO}} - \sum_{q=1}^{Q} \hat{\beta}_{q,\text{LASSO}} x_{q,t}\right)^2$$

$$+\lambda \textstyle\sum_{q=1}^{Q} \left|\beta_q\right|\Big) \tag{10}$$

where λ is the non-negative regularization parameter for the L_1 penalty function and α is a positive constant ($\alpha \in [0,1]$).

2.3.2 Elastic net (ENET) model

The elastic net (ENET) of Zou and Hastie (2005) is a commonly used shrinkage method and considers both L_1 and L_2 penalty functions, which can be:

$$r_{\text{ENET},t+1} = \alpha_{0,\text{ENET}} + \textstyle\sum_{q=1}^{Q} \hat{\beta}_{q,\text{ENET}} x_{q,t} \tag{11}$$

where Q is the number of predictors and $\hat{\beta}_{q,ENET}$ is the shrinkage estimator of regression coefficients. The optimal coefficient ($\widehat{\beta_{\text{ENET}}}$) is:

$$\widehat{\beta_{\text{ENET}}} = \underset{\beta}{\text{argmin}}(\frac{1}{2(t-1)}\sum_{l=1}^{t-1}\left(r_{\text{ENET},t+1} - \alpha_{0,\text{ENET}} - \sum_{q=1}^{Q}\hat{\beta}_{q,\text{ENET}}x_{q,t}\right)^2$$

$$+\lambda \sum_{q=1}^{Q}((1-\alpha)\beta_i^2 + \alpha|\beta_q|) \quad (12)$$

where λ is the non-negative regularization parameter for the L_1 and L_2 penalty functions, and α is a positive constant ($\alpha \in [0,1]$)[1].

2.4 Combination forecast method

According to Rapach et al. (2010) and Zhang et al. (2019), when forecasting stock market performance, utilizing a combination approach produces results that outperform the historical average of single predicators. Given the complexity of diverse economic influences, individual predictors are limited in modelling the impact of frequently changing market conditions. Thus, to enhance the predictability of individual predictors, we adopt a combination forecast method, which can be defined as the weighted averages of *N* individual forecasts:

$$\hat{r}_{c,t} = \sum_{k=1}^{N} \omega_{k,t-1}\,\hat{r}_{k,t} \quad (13)$$

where $\hat{r}_{c,t}$ is the prediction from the combination method; $\hat{r}_{k,t}$ is the prediction from the individual models above mentioned; and $\omega_{k,t-1}$ is the combined weight of the *k*-th individual forecast formed at *t*.

3. Data description

According to Durham (2007) and Miao et al. (2014), Standard & Poor's 500 index has a broader content and is efficient in representing an overall economy; thus, we obtain the excess stock returns based on Standard & Poor's 500 index. Importantly, based on the work of Fisher et al. (2021), which construct macroeconomic attention indices (MAI) to measure attention to different macroeconomic risks, such as employment and monetary policy risk.

[1] For more details about the estimation, refer to Zhang et al. (2019).

The construction of the MAI indices is based on the New York Times (NYT) and Wall Street Journal (WSJ), starting in June 1980 for the NYT and January 1984 for the WSJ, and ending in December 2020, from which we derive a total of 487 observations. Thus, the data series range from June 1980 to December 2020. Eight individual categories of macroeconomic news are considered: unemployment, monetary policy, output growth, inflation, the housing market, credit ratings, oil, and the U.S. dollar. Correspondingly, the 8 macroeconomic attention indices are constructed based on these 8 categories of macroeconomic news, which are labeled as the UNEMP_ni, MONE_ni, GDP_ni, INFL_ni. HM_ni, CR_ni, OIL_ni, USD_ni, respectively. In addition, we consider the effects of the 14 popular macroeconomic variables of Goyal and Welch (2008) on Standard & Poor's 500 index's excess returns, which can be obtained from Amit Goyal's website[2].

Table 1 presents the data's descriptive statistics. For the macroeconomic attention indices, the minimums of all the macroeconomic attention indices are greater than zero, while the macroeconomic variables are sometimes positive and sometimes negative. We also conclude from the Jarque-Bera (JB) statistical test that there is no suggestion of Gaussian distributions at the 1% significance level in all the data series, except with the NTIS variable. We also conclude from the Ljung-Box test that, except for the LTR and DFR variables, all the data series have serial auto-correlations up to the 20th order at the 1% significance level.

Insert Table 1 about here

To provide a visual inspection of the predictive performances of the variables, we draw Figure 1 and Figure 2, which reflect the predictive performances of macroeconomic attention indices and macroeconomic variables, respectively. More specifically, the color sample on the right side shows a specific value. We can look for values based on the color sample. If the value is larger, that means this variable has better predictability during the sample period. From Figure 1, we find that UNEMP_ni and GDP_ni have relatively more

[2] More details about the 14 macroeconomic variables can refer to Goyal and Welch (2008).

powerful predictive performances than the other MAI indices. From Figure 2, we find that none of the macroeconomic variables is efficient in predicting stock returns during the sample period. Comparing Figure 1 and Figure 2, we find that MAI indices indeed display better forecasting performances than the macroeconomic variables.

Insert Figure 1 and Figure 2 about here

4. Empirical results and discussions

4.1 In-sample estimation

The predictive regression estimates using the ordinary least squares (OLS) method are presented in Table 2. For the macroeconomic attention indices, we find that the HM_ni and INFL_ni indices can negatively affect the stock returns at the 10% significance level. UNEMP_ni can positively affect the stock returns at the 5% significance level. For the macroeconomic variables, we find that only DFR can positively affect stock returns at the 10% significance level. Regarding the performances of dimension reduction methods, we find that SPCA_MAI and PLS_MAI can positively affect the stock returns at the 5% and 1% levels, respectively. In addition, PLS_ECON can positively affect stock returns at the 5% level. We also find that SPCA_ALL and PLS_ALL can positively affect the stock returns at the 5% level. The coefficient of SPCA_MAI is 0.676, which is the largest among the predictions, showing that the MAI component based on the scaled principal component analysis model is able to affect the stock market volatility.

4.2 Out-of-sample analysis

4.2.1 Statistical evaluation

Following Campbell and Thompson (2008) and Wang et al. (2019), we apply the recursive window method to obtain the predictive values. The data range is from June 1980 to December 2020. The initial window (*M*) is 240 months (20 years), and the out-of-sample interval of the recursive window method is from June 2000 to December 2020.

According to Campbell and Thompson (2008), Neely et al. (2014), Huang et al. (2015), and Lin et al. (2018), the out-of-sample $R^2(R^2_{\text{oos}})$ method is efficient in capturing the predictive distinctions among the forecasting models. Thus, after obtaining all the predictions, we evaluate the models' performances by applying this method, which is:

$$R^2 = 1 - \frac{\text{MSPE}_{\text{model}}}{\text{MSPE}_{\text{bench}}} = 1 - \frac{\sum_{t=M+1}^{T}(\hat{r}_t - r_t)^2}{\sum_{t=M+1}^{T}(r_t - \overline{r_t})^2} \tag{14}$$

where $\text{MSPE}_{\text{model}}$ and $\text{MSPE}_{\text{bench}}$ are the prediction errors of a predicting model and benchmark model, respectively. The benchmark model is the historical average forecast. $\hat{r}_t$, r_t, and $\overline{r_t}$ are the prediction of the model, the actual excess stock return and the historical average of return, respectively. Following Clark and West (2007), the MSPE metric is applied to evaluate the significant differences among the forecasting models.

The stock market's performance is closely related to changing business conditions (Neely et al., 2014; Zhang et al., 2019). In line with the National Bureau of Economic Research (NBER), business conditions can comprise periods of business recession or periods of expansion[3]. We investigate the predictive models' performances during different business conditions. According to Neely et al. (2014), R^2_{OOS} can be:

$$R^2_{\text{c}} = 1 - \frac{\sum_{f=1}^{F} I^c(\text{r}_t - \text{r}_t^j)^2}{\sum_{f=1}^{F} I^c(\text{r}_t - \text{r}_t^0)^2}, \text{for} \quad c = \text{EXP}, \text{REC} \tag{15}$$

where I^{EXP} and I^{REC} are indicators in a unified value when the month is classified as an expansion (recession) period; otherwise, they are set to zero.

4.2.2 Out-of-sample forecasting

The out-of-sample results are presented in Table 2. Several important findings are obtained. Panel A of Table 2 reports the out-of-sample results for predictive regression forecasts based on individual macroeconomic attention indices and macroeconomic variables. Regarding the performances of macroeconomic attention indices, we find that the values of R^2 for 3 macroeconomic attention indices are larger than zero, which are CR_ni, UNEMP_ni and USD_ni. Importantly, the value of R^2 of UNEMP_ni is 2.138, which is the highest R^2 value among the macroeconomic attention indices and significant at the 1% level, showing that the macroeconomic attention risk from

[3] For more details, please refer to https://www.nber.org/research/business-cycle-dating.

unemployment can significantly predict stock market returns. For the forecasting performances of macroeconomic variables, we find only that the R^2 value of DY is positive, but it is not significant, showing that the traditional macroeconomic variables have relatively worse performances than the macroeconomic attention indices for predicting stock market returns. Importantly, we find that the performances of macroeconomic attention indices are relatively better during expansions than during recessions, while traditional macroeconomic variables have relatively better performances during recessions.

Panel B of Table 2 reports the out-of-sample results for the dimension reduction and shrinkage methods forecasts based on macroeconomic attention indices and macroeconomic variables. We find that the R^2 values of PLS_MAI, LASSO_MAI and ENET_MAI are 2.760, 4.239 and 4.240, respectively, which are all significant at the 5% significance level, showing that the components of MAI indices can significantly improve the forecasting accuracy for predicting stock market returns. Importantly, the shrinkage methods (LASSO and ENET) can obtain relatively better performances than other models. In addition, the components of the MAI indices have relatively better performances during the economic expansions than during recessions. For the dimension reduction and shrinkage methods based on the information of traditional macroeconomic variables, the R^2 values are all negative, showing that traditional macroeconomic variables fail to predict stock market returns. Additionally, the components of traditional macroeconomic variables have worse performances than the historical average during both expansions and recessions.

Panel C of Table 2 reports the out-of-sample results for the dimension reduction, combination and shrinkage methods forecasts based on the 8 macroeconomic attention indices and 14 macroeconomic variables together. We find that the R^2 values for the dimension reduction model and shrinkage methods based on all predictors taken together are all negative, while the R^2 value for the combination model is positive but not significant. In addition, the components of all the predictors together exhibit worse performances than the historical average, during both expansions and recessions.

In summary, macroeconomic attention indices have relatively better performances than traditional macroeconomic variables. Based on the dimension reduction model and shrinkage methods, we find that the components of MAI indices are more informative for improving the forecasting accuracy and for predicting stock market returns than traditional macroeconomic variables and all the other predictors together. Importantly, the shrinkage methods (LASSO and ENET) can obtain better performances than the other models for forecasting stock market returns.

We contend that MAI indices display better predictive performances for the following reasons. First, MAI indices are closely tied to economic fundamentals, and a change in macroeconomic fundamentals can always be seen as an underlying systematic risk factor affecting future stock returns based on the framework of arbitrage pricing theory (APT) of Ross (1976). In addition, based on the discounted cash flow or present value model (PVM), macroeconomic fundamentals affect the future expected cash flows or the discount rate and then affect stock prices (Humpe and Macmillan, 2009). Importantly, MAI indices are not only related to macroeconomic fundamentals but can also reflect endogenous investor attention to related macroeconomic news. Based on the theories of endogenous attention, endogenous attention increases with economic uncertainty (Bansal and Shaliastovich, 2011; Kacperczyk et al., 2016). MAI indices can capture investors' endogenous attention to different macroeconomic risks (Fisher et al., 2021); thus, they have more valuable content for predicting stock market returns than traditional macroeconomic variables.

Insert Table 2 about here

4.3 Portfolio performances

It might be argued that investors are more concerned about the models' predictive ability from an economic perspective. Following Campbell and Thompson (2008) and Neely et al. (2014), we assess the economic value of stock return predictability of all the forecasting models. More specifically, we focus on the Sharpe ratio (SR) gains and certainty-equivalent return (CER) gains for a mean-variance investor. Suppose an investor optimally allocates his assets between stocks and risk-free bills, based on stock return forecasts. The optimal weight of stocks is as follows:

$$w_t = \frac{1}{\gamma} \frac{\hat{r}_{t+1}}{\hat{\sigma}^2_{t+1}} \tag{16}$$

where $\hat{r}_{t+1}$ represents the forecasts of the stock return; $\hat{\sigma}^2_{t+1}$ represents the forecast of the variance, and γ denotes the investor's risk aversion coefficient (e.g., Rapach et al., 2010; Wang et al., 2019). Following Campbell and Thompson (2008), we also define w_t as a value between 0 and 1.5 and apply a five-year moving window to obtain the variance.

The portfolio return is modelled as follows:

$$R_{p,t+1} = w_t r_{t+1} + R_{f,t} \tag{17}$$

where $R_{f,t+1}$ is the risk-free rate. According to Wang et al. (2019), the SR gain and CER gain can reflect the portfolio performance. The SR gains of predictability are the differences between the given portfolio's SR and the benchmark portfolio's SR. We multiply the SR gain by $\sqrt{12}$ to obtain the annual value.

Further, the CER of the portfolio (REFs) is specified below:

$$\mathrm{CER} = \hat{\mu}_p - 0.5\gamma\hat{\sigma}^2_p \tag{18}$$

where $\hat{\mu}_p$ is the sample mean and $\hat{\sigma}^2_p$ is the sample variance. The CER gains are the differences between the given portfolio's CER and the benchmark portfolio's CER. Then, we multiply the CER gain by 1200 to obtain the annual percentage.

The portfolio performances of all the models based on different investor risk aversion coefficients ($\gamma = 2, 3, 4$) are contained in Tables 3, 4 and 5. As a norm, a risk aversion coefficient of 3 means that the portfolio is suitable for risk-neutral investors; and the coefficients of 2 and 4 mean that the portfolio is suitable for risk-seeking and risk-averse investors, respectively. We take the portfolio performances of all the models based on γ=2 as an example. Based on the individual macroeconomic attention indices, the CER gains for 5 of the 8 macroeconomic attention indices are positive, and the largest CER gain is 4.178. Based on the individual macroeconomic variables, we find that the CER gains for 6 of the 14 macroeconomic attention indices are positive, and the largest CER gain is 3.096. Comparing the performances of the individual macroeconomic attention indices and macroeconomic variables, we find that the macroeconomic attention indices can have better portfolio performances than the macroeconomic variables.

Using the dimension reduction and shrinkage methods, forecasts are obtained based on macroeconomic attention indices and macroeconomic variables. For MAI indices, we find that the CER gains for SPCA_MAI, PLS_MAI, LASSO_MAI, ENET_MAI are 1.403, 3.543, 3.281, and 3.288, respectively, which are much higher than the gains based on the traditional macroeconomic variables or all the predictors.

Regarding the models' SR gains, we find that the SR gains of the individual macroeconomic attention indices are relatively higher than those of the traditional macroeconomic variables. In addition, the SR gains of the dimension reduction and shrinkage methods based on macroeconomic attention indices show that the macroeconomic attention indices have relatively better performances than the traditional macroeconomic variables and all the predictors. Tables 4 and 5 present the results based on investor risk aversion coefficients of 3 and 4 ($\gamma = 3, 4$), demonstrating similar results to those of Table 3.

Insert Tables 3, 4, and 5 about here

4.4 Robustness checks

4.4.1 Alternative macroeconomic attention indices based on the Wall Street Journal

In the previous sections, we have conducted the analysis based on macroeconomic attention indices obtained from the New York Times. To check the robustness of the macroeconomic attention indices' predictive ability for stock market returns, we apply macroeconomic attention indices obtained from the Wall Street Journal, which are from January 1984 to December 2020. The results are presented in Table 6.

Regarding the performances of the macroeconomic attention indices from the Wall Street Journal, we find that the values of R^2 for 5 of the 8 macroeconomic attention indices are larger than zero, including CR_wi, HM_wi, INFL_wi, UNEMP_wi, USD_wi. For the forecasting performances of the traditional macroeconomic variables, we find that the values of R^2 for 3 (DP, DY, BM) of the 14 macroeconomic variables are larger than zero, showing that the macroeconomic attention indices can significantly predict stock market returns better than the traditional macroeconomic variables.

From Panel B of Table 6, for the dimension reduction and shrinkage methods based on MAI indices, we find the R^2 values of PCA_MAI, LASSO_MAI and ENET_MAI are 0.114, 2.922 and 2.915, respectively, while the R^2 values of the dimension reduction and shrinkage methods based on the traditional macroeconomic variables are all negative, showing that the components of MAI indices can significantly improve the forecasting accuracy for predicting stock market returns compared to the traditional macroeconomic variables.

Panel C of Table 6 reports the results for the dimension reduction, combination and shrinkage methods forecasts based on the 8 macroeconomic attention indices and 14 macroeconomic variables combined. We find that the R^2 values for the dimension reduction model and shrinkage methods based on all predictors taken together are all negative, while the R^2 value for the combination model is positive but not significant. All these results demonstrate that the MAI indices have better performances than the macroeconomic variables, which is consistent with our out-of-sample results.

Insert Table 6 about here

4.4.2 Alternative forecasting windows

Predictions are sensitive to forecasting windows (Liang et al., 2021; Lu et al., 2021; Wang et al., 2022). In this section, we assess the robustness of the variables in alternative forecasting windows. More specifically, the initial window (*M*) is 120 and 180 months (10 and 15 years). The results are presented in Table 7 and Table 8.

We take the forecasting performances of all the models based on the initial window of 120 months (10 years) as an example. Regarding the performances of the macroeconomic attention indices, we find that the values of R^2 for 3 (CR_ni, INFL_ni and UNEMP_ni) of the 8 macroeconomic attention indices are larger than zero, but only the R^2 value of UNEMP_ni is significant. For the forecasting performances of the traditional macroeconomic variables, we find that the values of R^2 for all the macroeconomic variables are negative, showing that the macroeconomic attention indices can significantly predict stock market returns better than the traditional macroeconomic variables.

From Panel B of Table 7, for the dimension reduction and shrinkage methods based on MAI indices, we find the R^2 values of PLS_MAI, LASSO_MAI and ENET_MAI are 1.163, 3.03, 3.028, respectively, which are all significant and positive, while the R^2 values of the dimension reduction and shrinkage methods based on the traditional macroeconomic variables are all negative, demonstrating that the components of the MAI indices can significantly improve the accuracy of forecasting stock market returns compared to the traditional macroeconomic variables.

Panel C of Table 7 reports the results for the dimension reduction, combination and shrinkage methods forecasts based on the 8 macroeconomic attention indices and 14 macroeconomic variables together. We find that the R^2 values for the dimension reduction model and shrinkage methods based on all predictors taken together are all negative, and the R^2 value for the combination model is also negative.

Insert Table 7 about here

Similar results can be found in Table 8, which reports the results of the prediction with an initial window of 180 months (15 years). All these results show that the MAI indices have better performances than the macroeconomic variables, which is consistent with our out-of-sample results.

Insert Table 8 about here

5. Further analysis

5.1 Have the predictive abilities of the shrinkage methods changed during the COVID-19 pandemic?

The COVID-19 pandemic has abruptly curtailed the development of the global economy, arguably creating an economic crisis unparalleled since the Great Depression of the 1920s, causing financial markets to contract acutely and menacing business survival worldwide (Baek and Lee, 2021; Ftiti et al., 2021; Liu et al., 2022). In this section, we further discuss the macroeconomic variables' predictive ability for excess stock returns during the COVID-19 pandemic. Given the lockdown of Wuhan city imposed at the beginning of January 2020[4], we choose the COVID-19 pandemic sample from January 2020. The results are presented in Table 9.

Regarding the performances of the macroeconomic attention indices, we find that the values of R^2 for 4 (GDP_ni, INFL_ni, OIL_ni, UNEMP_ni) of the 8 macroeconomic attention indices are larger than zero. In respect of the forecasting performances of the traditional macroeconomic variables, we find that the values of R^2 for 3 (DE, TBL, LTY) of the 14 macroeconomic variables are positive. Overall, these results demonstrate that the macroeconomic attention indices can significantly predict stock market returns better than traditional macroeconomic variables during the COVID-19 pandemic.

From Panel B of Table 9, for the dimension reduction and shrinkage methods based on the MAI indices, we find that the R^2 values of SPCA_MAI, PLS_MAI, LASSO_MAI and ENET_MAI are significantly positive, while the R^2 values of the dimension reduction and shrinkage methods based on the traditional macroeconomic variables are all negative except for PLS_ECON, but that the R^2 value of PLS_ECON is not significantly positive. These results show that the components of the MAI indices can significantly improve the forecasting accuracy for predicting stock market returns compared to traditional macroeconomic variables.

---

[4] The World Health Organization announced the outbreak of the COVID-19 pandemic on March 11, 2020. The results are also robust when we choose the COVID-19 pandemic sample from March 2020.

Panel C of Table 9 reports the results for the dimension reduction, combination and shrinkage methods forecasts based on the 8 macroeconomic attention indices and 14 macroeconomic variables together. We find that the R^2 values for the dimension reduction model and shrinkage methods based on all predictors taken together are all negative except for the PLS_ALL and combination models, and the R^2 values of the PLS_ALL and combination models are not significantly positive. All these results indicate that the MAI indices have better performances than the macroeconomic variables, even during the destructive period of the COVID-19 pandemic.

Insert Table 9 about here

5.2 Multi-period forecasting

Thus far, our examination of the predictive ability of macroeconomic attention indices focuses on one-month-ahead forecasts. It can be questioned whether the macroeconomic attention indices and macroeconomic variables have longer-term predictive powers. In this section, we will examine the variables' predictive ability over longer periods, i.e., three-month-ahead and six-month-horizons. The results are presented in Table 10 and Table 11, respectively.

We take the predictive performances of all the models based on the three-month-ahead forecast as an example. Regarding the performances of the macroeconomic attention indices, we find that the values of R^2 for 4 (GDP_ni, OIL_ni, UNEMP_ni and USD_ni) of the 8 macroeconomic attention indices are larger than zero. More specifically, the values of R^2 for GDP_ni and UNEMP_ni are 8.827 and 5.507, respectively, which are significant at the 1% significance level. For the forecasting performances of the traditional macroeconomic variables, we find that the values of R^2 for 3 (LTR, DFR and INFL) of the 14 macroeconomic variables are positive, but they are significant. Comparing the performances of the macroeconomic attention indices and traditional macroeconomic variables, we find that macroeconomic attention indices can more significantly predict stock market returns than the traditional macroeconomic variables.

From Panel B of Table 10, for the dimension reduction and shrinkage methods based on the MAI indices, we find that the R^2 values of PLS_MAI, LASSO_MAI and ENET_MAI are 7.207, 9.099, and 9.051, respectively, which are positive at the 1% significance level. For the R^2 values of the dimension reduction and shrinkage methods based on the traditional macroeconomic variables, the R^2 values of LASSO_ECON and ENET_ECON are 0.564 and 0.604, respectively, which are all significant at the 1% level. These results show that the components of the MAI indices can significantly improve the accuracy for predicting stock market returns compared to the traditional macroeconomic variables.

Panel C of Table 10 reports the results for the dimension reduction, combination and shrinkage methods forecasts based on the 8 macroeconomic attention indices and 14 macroeconomic variables together. We find that the R^2 values for the dimension reduction model and shrinkage methods based on all predictors taken together are all negative except for LASSO_ALL and ENET_ALL, and that the R^2 values of LASSO_ALL and ENET_ALL are significant at the 5% significance level. Similar results can also be found in Table 11. All these results show that the MAI indices have better performance than the macroeconomic variables for predicting stock excess returns over the longer term.

Insert Table 10 and Table 11 about here

6. Conclusion

In this paper, we apply the novel macroeconomic attention indices of Fisher et al. (2021) to predict stock market returns based on dimension reduction methods and shrinkage methods. A few interesting findings emerge. We determine that macroeconomic attention indices can more significantly predict stock market returns than traditional economic variables. Second, the components of MAI indices are more informative in the improvement of accuracy for predicting stock market returns. We also evaluate the macroeconomic attention indices' forecasting performances over longer periods and find that the macroeconomic attention indices produce a satisfactory performance.

In addition, the performances of macroeconomic attention indices are relatively more accurate during economic expansions than during recessions, while traditional macroeconomic variables exhibit relatively better performances during recessions. Importantly, the shrinkage methods can obtain better performances than the other models for forecasting stock market returns. Our further investigation confirms the predictive performance of the predictors for stock market returns during the COVID-19 pandemic, and the results demonstrate that the MAI indices display better performances than the macroeconomic variables, even during this devastating period.

Our paper provides new evidence for stock market prediction by applying novel macroeconomic attention indices and shrinkage models. Obtaining more accurate predictions of stock price returns not only provides and effective means of managing risk and investment decisions, but also allows policymakers to design better policies for managing crises in a world that is increasingly subject to unforeseeable macroeconomic shocks. Increasing globalization means that all advanced, and many developing, economies are interconnected, such that an economic crisis in one part of the world can have unavoidable consequences in many others. The ability to predict stock returns with confidence can be invaluable in the aftermath of such catastrophes, recovery from which depends upon the willingness of investors worldwide to provide the funds essential for economic regeneration. Such predictive models can never predict the onset of such unforeseeable calamities; but, once they are upon us, they can enable the world to escape their consequences with greater celerity by giving investors, market participants, and policymakers the tools they require to navigate safe courses out of the recessions they produce.

References

Ahn, K., Lee, D., Sohn, S., & Yang, B. (2019). Stock market uncertainty and economic fundamentals: an entropy-based approach. *Quantitative Finance*, *19*(7), 1151-1163.

Ang, A., & Bekaert, G. (2007). Stock return predictability: Is it there?. *The Review of Financial Studies*, *20*(3), 651-707.

Baek, S., & Lee, K. Y. (2021). The risk transmission of COVID-19 in the US stock market. *Applied Economics*, *53*(17), 1976-1990.

Bansal, R., & Shaliastovich, I. (2011). Learning and asset-price jumps. *The Review of Financial Studies*, *24*(8), 2738-2780.

Li, J., & Tsiakas, I. (2017). Equity premium prediction: The role of economic and statistical constraints. *Journal of financial markets*, *36*, 56-75.

Campbell, J. Y., & Thompson, S. B. (2008). Predicting excess stock returns out of sample: Can anything beat the historical average?. *The Review of Financial Studies*, *21*(4), 1509-1531.

Clark, T. E., & West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of econometrics*, *138*(1), 291-311.

Çakmaklı, C., & van Dijk, D. (2016). Getting the most out of macroeconomic information for predicting excess stock returns. *International Journal of Forecasting*, *32*(3), 650-668.

Chundakkadan, R., & Nedumparambil, E. (2021). In search of COVID-19 and stock market behavior. *Global Finance Journal*, 100639.

Cochrane, J. H. (2011). Presidential address: Discount rates. *The Journal of finance*, *66*(4), 1047-1108.

Durham, G. B. (2007). SV mixture models with application to S&P 500 index returns. *Journal of Financial Economics*, *85*(3), 822-856.

Edmans, A., Fernandez-Perez, A., Garel, A., & Indriawan, I. (2021). Music sentiment and stock returns around the world. *Journal of Financial Economics*, doi.org/10.1016/j.jfineco.2021.08.014.

Engle, R. F., Ghysels, E., & Sohn, B. (2013). Stock market volatility and macroeconomic fundamentals. *Review of Economics and Statistics*, *95*(3), 776-797.

Fama, E. F., & French, K. R. (1988). Dividend yields and expected stock returns. *Journal of financial economics*, *22*(1), 3-25.

Fisher, Adlai J. and Martineau, Charles and Sheng, Jinfei, Macroeconomic Attention and Announcement Risk Premia (January 11, 2022). Review of Financial Studies, Forthcoming. http://dx.doi.org/10.2139/ssrn.2703978

Ftiti, Z., Ameur, H. B., & Louhichi, W. (2021). Does non-fundamental news related to COVID-19 matter for stock returns? Evidence from Shanghai stock market. *Economic Modelling*, *99*, 105484.

Goyal, A., & Welch, I. (2003). Predicting the equity premium with dividend ratios. *Management Science*, *49*(5), 639-654.

Huang, D., Jiang, F., Li, K., Tong, G., & Zhou, G. (2022). Scaled PCA: A new approach to dimension reduction. *Management Science*, *68*(3), 1678-1695.

Huang, D., Jiang, F., Tu, J., & Zhou, G. (2015). Investor sentiment aligned: A powerful predictor of stock returns. *The Review of Financial Studies*, *28*(3), 791-837.

Humpe, A., & Macmillan, P. (2009). Can macroeconomic variables explain long-term stock market movements? A comparison of the US and Japan. *Applied financial economics*, *19*(2), 111-119.

Izzeldin, M., Muradoğlu, Y. G., Pappas, V., & Sivaprasad, S. (2021). The impact of Covid-19 on G7 stock markets volatility: Evidence from a ST-HAR model. *International Review of Financial Analysis*, *74*, 101671.

Jiang, Y., Wu, L., Tian, G., & Nie, H. (2021). Do cryptocurrencies hedge against EPU and the equity market volatility during COVID-19?–New evidence from quantile coherency analysis. *Journal of International Financial Markets, Institutions and Money*, *72*, 101324.

Kacperczyk, M., Van Nieuwerburgh, S., & Veldkamp, L. (2016). A rational theory of mutual funds' attention allocation. *Econometrica*, *84*(2), 571-626.

Karanasos, M., Yfanti, S., & Hunter, J. (2021). Emerging stock market volatility and economic fundamentals: the importance of US uncertainty spillovers, financial and health crises. *Annals of operations research*, 1-40.

Leippold, M., Wang, Q., & Zhou, W. (2021). Machine learning in the Chinese stock market. *Journal of Financial Economics*, doi.org/10.1016/j.jfineco.2021.08.017.

Liang, C., Ma, F., Wang, L., & Zeng, Q. (2021). The information content of uncertainty indices for natural gas futures volatility forecasting. *Journal of Forecasting*, *40*(7), 1310-1324.

Liu, J., & Kemp, A. (2019). Forecasting the sign of us oil and gas industry stock index excess returns employing macroeconomic variables. *Energy Economics*, *81*, 672-686.

Liu. J., Y. Shahab; H. Hoque (2022). Government response measures and public trust during the COVID-19 pandemic: Evidence from around the world. *British Journal of Management*. 33(2), 571-602.

Lu, X., Ma, F., Wang, J., & Zhu, B. (2021). Oil shocks and stock market volatility: New evidence. *Energy Economics*, *103*, 105567.

Lin, Q. (2018). Technical analysis and stock return predictability: An aligned approach. *Journal of Financial Markets,* 38, 103–123.

Miao, H., Ramchander, S., & Zumwalt, J. K. (2014). S&P 500 index-futures price jumps and macroeconomic news. *Journal of Futures Markets*, *34*(10), 980-1001.

Morck, R., Yeung, B., & Yu, W. (2000). The information content of stock markets: why do emerging markets have synchronous stock price movements?. *Journal of Financial Economics*, *58*(1-2), 215-260.

Nasir, M. A., Shahbaz, M., Mai, T. T., & Shubita, M. (2021). Development of Vietnamese stock market: Influence of domestic macroeconomic environment and regional markets. *International Journal of Finance & Economics*, *26*(1), 1435-1458.

Neely, C. J., Rapach, D. E., Tu, J., & Zhou, G. (2014). Forecasting the equity risk premium: The role of technical indicators. Management Science, 60, 1772–1791.

Newey, W. K., & West, K. D. (1987). Hypothesis testing with efficient method of moments estimation. *International Economic Review*, 777-787.

Ross, S. A. (1976). The Arbitrage Theory of Capital Asset Pricing. *Journal of Economic Theory*, 13, 341-360.

Raghutla, C., & Chittedi, K. R. (2021). Financial development, real sector and economic growth: evidence from emerging market economies. *International Journal of Finance & Economics*, *26*(4), 6156-6167.

Rapach, D. E., & Zhou, G. (2013). Forecasting stock returns. Elliott G, Timmermann A, eds. *Handbook of Economic Forecasting*, Vol. 2A. (Elsevier, Amsterdam), 328-383.

Rapach, D. E., Strauss, J. K., & Zhou, G. (2010). Out-of-sample equity premium prediction: Combination forecasts and links to the real economy. *The Review of Financial Studies*, *23*(2), 821-862.

Rapach, D. E., Wohar, M. E., & Rangvid, J. (2005). Macro variables and international stock return predictability. *International journal of forecasting*, *21*(1), 137-166.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, *58*(1), 267-288.

Wang, J., He, X., Ma, F., & Li, P. (2022). Uncertainty and oil volatility: Evidence from shrinkage method. *Resources Policy*, *75*, 102482.

Wang, Y., Pan, Z., Liu, L., & Wu, C. (2019). Oil price increases and the predictability of equity premium. *Journal of Banking & Finance*, *102*, 43-58.

Welch, I., & Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *The Review of Financial Studies*, *21*(4), 1455-1508.

Zhang, Y., Ma, F., Wang, Y., 2019. Forecasting crude oil prices with a large set of predictors: Can LASSO select powerful predictors? *Journal of Empirical Finance*, 54, 97-117.

Zou, H., & Hastie, T. (2005). Regularization and variable selection via the elastic net. Journal of the royal statistical society: series B (statistical methodology), 67(2), 301-320.

Table 1. Descriptive statistics

Variables	Mean	Max	Min	Median	Std.Dev	Jarque-Bera	Q(5)	Q(20)
CR_ni	0.185	1.895	0.000	0.148	0.158	23068.755***	502.997***	997.700***
GDP_ni	0.278	1.300	0.000	0.248	0.158	657.872***	479.899***	1324.754***
HM_ni	0.228	1.282	0.000	0.140	0.216	534.938***	1696.599***	5924.862***
INFL_ni	0.734	2.195	0.000	0.656	0.348	108.901***	981.215***	2433.063***
MONE_ni	0.910	2.316	0.121	0.906	0.366	35.637***	628.258***	1324.318***
OIL_ni	0.734	4.479	0.000	0.609	0.567	955.651***	1225.635***	2790.758***
UNEMP_ni	0.708	2.416	0.141	0.614	0.382	295.757***	1128.968***	2334.012***
USD_ni	0.059	0.421	0.000	0.025	0.088	913.205***	1656.412***	4387.492***
DP	-3.750	-2.753	-4.524	-3.874	0.394	22.968***	2296.526***	7905.669***
DY	-3.743	-2.751	-4.531	-3.863	0.395	22.006***	2297.327***	7948.002***
EP	-2.968	-2.021	-4.836	-2.958	0.430	234.374***	2024.340***	4263.846***
DE	-0.783	1.380	-1.244	-0.844	0.352	4446.011***	1901.509***	2607.690***
SVAR	0.003	0.073	0.000	0.001	0.006	168498.471***	114.454***	123.335***
BM	0.383	1.207	0.121	0.315	0.220	414.316***	2265.326***	7380.818***
NTIS	0.003	0.046	-0.058	0.006	0.020	6.296**	2076.057***	4196.491***
TBL	4.055	16.300	0.010	3.900	3.482	71.873***	2292.080***	6933.837***
LTY	6.236	14.820	0.620	5.760	3.172	30.028***	2310.946***	7856.939***
LTR	0.776	14.430	-11.240	0.800	3.147	56.396***	5.494	22.192
TMS	2.182	4.550	-3.650	2.270	1.394	31.136***	1828.878***	3265.025***
DFY	1.081	3.380	0.550	0.950	0.455	753.819***	1780.466***	3417.630***
DFR	0.012	7.370	-9.760	0.050	1.618	1349.883***	5.191	29.801*
INFL	0.240	1.253	-1.915	0.240	0.333	389.906***	139.729***	257.722***

Notes: Descriptive statistics of the data series are presented in this table. In line with Jarque and Bera (1987), we set the null hypothesis of a normal distribution for each variable. Ljung and Box (1978) propose the Ljung-Box statistic called Q(n); in our study, we check the 5^{th-} and 20^{th-}order serial correlation. Asterisks ***, ** and * denote rejections of the null hypothesis at the 1%, 5% and 10% levels, respectively.

Table 2. Predictive regression estimations and out-of-sample results

Macroeconomic attention indices					Macroeconomic variables				
Variables/Models	Slope coefficient	R^2(%)	R^2_{EXP}(%)	R^2_{REC}(%)	Variables/Models	Slope coefficient	R^2(%)	R^2_{EXP}(%)	R^2_{REC}(%)
Panel A: Predictive regressions									
CR_ni	-0.020(-1.583)	0.392	0.010	-0.009	DP	0.004(0.861)	-0.043	0.012	-0.007**
GDP_ni	0.020 (1.621)	-0.527	0.003	-0.022	DY	0.005(0.959)	0.003	0.017	-0.009***
HM_ni	-0.015(-1.668) *	-0.569	-0.041	0.065	EP	0.002(0.529)	-0.624	-0.001	-0.009
INFL_ni	-0.009(-1.654) *	-0.120	0.005	-0.013	DE	0.002(0.320)	-1.782	-0.039	-0.007
MONE_ni	0.000(-0.037)	-0.800	-0.013	0.002	SVAR	-0.369(-1.109)	-3.747	0.056	-0.085
OIL_ni	-0.003(-0.733)	-0.113	0.000	-0.003	BM	0.001(0.071)	-0.335	0.001	-0.006
UNEMP_ni	0.014(2.624) **	2.138***	0.031***	0.003	NTIS	-0.012(-0.126)	-1.305	-0.029	-0.005
USD_ni	-0.020(-0.881)	0.091	0.003	-0.004	TBL	-0.001(-1.539)	-1.219	-0.041	0.002
-	-	-	-	-	LTY	-0.001(-1.397)	-0.933	-0.032	0.002
-	-	-	-	-	LTR	0.001(1.076)	-0.164	-0.014	0.004
-	-	-	-	-	TMS	0.001(0.668)	-0.739	0.000	-0.011
-	-	-	-	-	DFY	-0.002(-0.414)	-0.485	-0.008	-0.003
-	-	-	-	-	DFR	0.002(1.827) *	-2.426	-0.003	-0.035
-	-	-	-	-	INFL	0.003(0.455)	-1.025	0.005	-0.018
Panel B: Dimension reduction and shrinkage methods									
PCA_MAI	0.000(0.303)	-0.538	-0.007	-0.003	PCA_ECON	0.000(-0.073)	-0.572	-0.009	0.001
SPCA_MAI	0.676(1.960) **	-1.041	-0.044	0.057	SPCA_ECON	0.405(0.937)	-10.840	-0.111	-0.102
PLS_MAI	0.025(3.505) ***	2.760***	0.029 **	0.025	PLS_ECON	0.009(2.143) **	-3.371*	0.012	-0.125
LASSO_MAI		4.239***	0.032**	0.063	LASSO_ECON		-3.664	-0.049	-0.013
ENET_MAI		4.240***	0.032**	0.063	ENET_ECON		-3.633	-0.049	-0.012
Panel C: Dimension reduction, combination model and shrinkage methods, all predictors taken together									
PCA_ALL	0.000(-0.187)	-0.460	-0.007	0.000	-	-	-	-	-

SPCA_ALL	0.640(1.986) **	-10.856	-0.118	-0.089	-	-	-	-	-
PLS_ALL	0.010(2.170) **	-3.499	0.014*	-0.132	-	-	-	-	-
LASSO_ALL	-	-3.241	-0.041	-0.015	-	-	-	-	-
ENET_ALL	-	-3.232	-0.041	-0.015	-	-	-	-	-
MF	-	0.032	-0.002	0.005	-	-	-	-	-

Notes: The table presents the predictive regression estimation and out-of-sample performance of the model evaluation. The slope coefficient is the regression estimation of each variable. LASSO_MAI, ENET_MAI, LASSO_ECON, ENET_ECON, LASSO_ALL, ENET_ALL and MF are models. MF is the mean combination prediction model. If R^2 is larger than zero, the corresponding model is superior to the benchmark model.

Table 3. Portfolio performances of the variables based on investor's risk aversion coefficients ($\gamma = 2$)

Macroeconomic attention indices			Macroeconomic variables		
Models	CER gains	SR gains	Models	CER gains	SR gains
Panel A: Predictive regressions					
HA	0.705	0.093	HA	0.705	0.093
CR_ni	-0.435	-0.028	DP	-0.323	-0.052
GDP_ni	4.178	0.274	DY	-0.036	-0.042
HM_ni	1.241	0.068	EP	3.360	0.239
INFL_ni	-0.005	0.034	DE	1.033	0.064
MONE_ni	-1.108	-0.098	SVAR	2.305	0.151
OIL_ni	-0.233	-0.011	BM	-0.458	-0.035
UNEMP_ni	3.352	0.225	NTIS	-0.846	-0.046
USD_ni	0.108	0.019	TBL	-0.979	0.012
-	-	-	LTY	-0.687	0.013
-	-	-	LTR	-0.359	-0.014
-	-	-	TMS	-2.114	-0.145
-	-	-	DFY	0.257	0.014
-	-	-	DFR	3.096	0.212
-	-	-	INFL	-2.769	-0.186
Panel B: Dimension reduction and shrinkage methods					
PCA_MAI	-0.930	-0.061	PCA_ECON	-0.907	-0.069
SPCA_MAI	1.403	0.091	SPCA_ECON	-0.241	-0.026
PLS_MAI	3.543	0.238	PLS_ECON	0.102	0.078
LASSO_MAI	3.281	0.221	LASSO_ECON	-0.121	-0.016
ENET_MAI	3.288	0.221	ENET_ECON	-0.113	-0.015
Panel C: Dimension reduction, combination model and shrinkage methods, all predictors taken together					

PCA_ALL	-0.751	-0.053		-	-	-
SPCA_ALL	-0.981	-0.087		-	-	-
PLS_ALL	0.825	0.112		-	-	-
LASSO_ALL	0.704	0.048		-	-	-
ENET_ALL	0.741	0.051		-	-	-
MF	1.315	0.084		-	-	-

Notes: This table provides the Sharpe ratio (SR) gains and the certainty equivalent return (CER) gains of all the given models in this paper based on investor's risk aversion coefficients ($\gamma = 2$). HA is the historical average prediction. The model columns mean regressions including the corresponding variable.

Table 4. Portfolio performances of the variables based on investor's risk aversion coefficients ($\gamma = 3$)

Macroeconomic attention indices			Macroeconomic variables		
Models	CER gains	SR gains	Models	CER gains	SR gains
Panel A: Predictive regressions					
HA	0.259	0.072	HA	0.259	0.072
CR_ni	-0.648	-0.024	DP	0.135	-0.061
GDP_ni	2.933	0.258	DY	0.411	-0.046
HM_ni	1.296	0.097	EP	2.589	0.211
INFL_ni	0.365	0.082	DE	0.657	0.047
MONE_ni	-0.614	-0.067	SVAR	1.687	0.134
OIL_ni	0.104	0.019	BM	-0.388	-0.044
UNEMP_ni	3.160	0.270	NTIS	-1.059	-0.074
USD_ni	-0.147	0.022	TBL	-1.783	0.005
-	-	-	LTY	-1.136	0.020
-	-	-	LTR	-0.046	0.021
-	-	-	TMS	-2.142	-0.187
-	-	-	DFY	0.250	0.020
-	-	-	DFR	1.855	0.153
-	-	-	INFL	-2.739	-0.210
Panel B: Dimension reduction and shrinkage methods					
PCA_MAI	-0.635	-0.052	PCA_ECON	-0.728	-0.076
SPCA_MAI	0.962	0.085	SPCA_ECON	-0.166	-0.018
PLS_MAI	3.927	0.335	PLS_ECON	-1.308	0.059
LASSO_MAI	3.036	0.269	LASSO_ECON	-0.315	-0.021
ENET_MAI	3.040	0.269	ENET_ECON	-0.253	-0.016
Panel C: Dimension reduction, combination model and shrinkage methods, all predictors taken together					

PCA_ALL	-0.610	-0.055	-	-	-
SPCA_ALL	-0.273	-0.033	-	-	-
PLS_ALL	-0.737	0.092	-	-	-
LASSO_ALL	0.762	0.083	-	-	-
ENET_ALL	0.768	0.083	-	-	-
MF	1.042	0.083	-	-	-

Notes: This table provides the Sharpe ratio (SR) gains and the certainty equivalent return (CER) gains of all the given models in this paper based on investor's risk aversion coefficients ($\gamma = 3$). The model columns mean regressions including the corresponding variable.

Table 5. Portfolio performances of the variables based on investor's risk aversion coefficients ($\gamma = 4$)

Macroeconomic attention indices			Macroeconomic variables		
Models	CER gains	SR gains	Models	CER gains	SR gains
Panel A: Predictive regressions					
HA	0.071	0.041	HA	0.071	0.041
CR_ni	-0.662	0.007	DP	0.603	-0.030
GDP_ni	2.170	0.260	DY	0.809	-0.015
HM_ni	0.973	0.103	EP	2.517	0.253
INFL_ni	0.534	0.131	DE	0.616	0.055
MONE_ni	-0.550	-0.055	SVAR	1.455	0.154
OIL_ni	-0.003	0.022	BM	-0.125	-0.030
UNEMP_ni	2.878	0.312	NTIS	-1.240	-0.090
USD_ni	-0.453	0.015	TBL	-1.725	0.032
-	-	-	LTY	-1.080	0.060
-	-	-	LTR	0.058	0.051
-	-	-	TMS	-1.418	-0.170
-	-	-	DFY	0.210	0.033
-	-	-	DFR	1.287	0.143
-	-	-	INFL	-1.944	-0.185
Panel B: Dimension reduction and shrinkage methods					
PCA_MAI	-0.622	-0.062	PCA_ECON	-0.428	-0.065
SPCA_MAI	0.926	0.100	SPCA_ECON	-0.074	0.011
PLS_MAI	3.905	0.418	PLS_ECON	-1.742	0.084
LASSO_MAI	2.482	0.313	LASSO_ECON	-0.137	0.006
ENET_MAI	2.485	0.313	ENET_ECON	-0.090	0.010
Panel C: Dimension reduction, combination model and shrinkage methods, all predictors taken together					

PCA_ALL	-0.425	-0.051	-	-	-
SPCA_ALL	0.392	0.042	-	-	-
PLS_ALL	-1.339	0.110	-	-	-
LASSO_ALL	0.790	0.118	-	-	-
ENET_ALL	0.801	0.118	-	-	-
MF	0.759	0.080	-	-	-

Notes: This table provides the Sharpe ratio (SR) gains and the certainty equivalent return (CER) gains of all the given models in this paper based on investor's risk aversion coefficients ($\gamma = 4$). The model columns mean regressions including the corresponding variable.

Table 6. Results of alternative macroeconomic attention indices based on Wall Street Journal

Macroeconomic attention indices				Macroeconomic variables			
Models	R^2(%)	MSPE-Adj.	p-value	Models	R^2(%)	MSPE-Adj.	p-value
Panel A: Predictive regressions							
CR_wi	1.669	1.623	0.052	DP	0.553	1.185	0.118
GDP_wi	-1.410	-0.804	0.789	DY	0.661	1.310	0.095
HM_wi	0.197	0.506	0.306	EP	-0.780	0.383	0.351
INFL_wi	1.131	1.953	0.025	DE	-2.175	-0.384	0.650
MONE_wi	-1.012	0.184	0.427	SVAR	-3.910	0.105	0.458
OIL_wi	-0.421	0.117	0.453	BM	0.174	0.698	0.243
UNEMP_wi	0.269	0.951	0.171	NTIS	-0.783	-0.881	0.811
USD_wi	0.385	1.114	0.133	TBL	-0.776	-0.705	0.760
-	-	-	-	LTY	-0.699	-0.997	0.841
-	-	-	-	LTR	-0.321	-0.270	0.606
-	-	-	-	TMS	-0.547	-1.258	0.896
-	-	-	-	DFY	-1.198	0.065	0.474
-	-	-	-	DFR	-2.584	-0.219	0.587
-	-	-	-	INFL	-1.000	-0.763	0.777
Panel B: Dimension reduction and shrinkage methods							
PCA_MAI	0.114	0.713	0.238	PCA_ECON	-0.448	-0.623	1.000
SPCA_MAI	-0.034	1.168	0.121	SPCA_ECON	-11.034	-0.934	0.825
PLS_MAI	-0.324	0.925	0.177	PLS_ECON	-3.288	-0.760	0.776
LASSO_MAI	2.922	1.830	0.034	LASSO_ECON	-7.303	-0.839	0.799
ENET_MAI	2.915	1.827	0.034	ENET_ECON	-7.269	-0.832	0.797
Panel C: Dimension reduction, combination model and shrinkage methods, all predictors taken together							
PCA_ALL	-1.705	-0.794	0.786		-	-	-

SPCA_ALL	-6.092	-0.294	0.616				-	-	-
PLS_ALL	-4.043	-0.089	0.536				-	-	-
LASSO_ALL	-5.162	-0.295	0.616				-	-	-
ENET_ALL	-5.731	-0.363	0.642				-	-	-
MF	0.226	0.427	0.335				-	-	-

Notes: The table presents the out-of-sample performance of model evaluation by R^2 and the MSPE-adjusted statistic. The model columns mean regressions including the corresponding variable. If R^2 is larger than zero, the corresponding model is superior to the benchmark model.

Table 7. Results of the variables' performances based on different forecasting windows (10 years in-sample)

Macroeconomic attention indices				Macroeconomic variables			
Models	R^2(%)	MSPE-Adj.	*p*-value	Models	R^2(%)	MSPE-Adj.	*p*-value
Panel A: Predictive regressions							
CR_ni	0.026	0.588	0.278	DP	-0.696	-0.565	0.714
GDP_ni	-0.946	0.167	0.434	DY	-0.747	-0.515	0.697
HM_ni	-0.573	0.415	0.339	EP	-0.827	-0.275	0.609
INFL_ni	0.142	1.019	0.154	DE	-1.766	-0.577	0.718
MONE_ni	-0.817	-1.331	0.908	SVAR	-3.087	0.012	0.495
OIL_ni	-0.297	-0.725	0.766	BM	-0.318	-0.872	0.808
UNEMP_ni	1.376	2.166	0.015	NTIS	-2.467	-1.288	0.901
USD_ni	-1.239	-1.496	0.933	TBL	-1.150	0.064	0.475
-	-	-	-	LTY	-0.696	0.147	0.442
-	-	-	-	LTR	-0.172	0.007	0.497
-	-	-	-	TMS	-1.122	-0.627	0.735
-	-	-	-	DFY	-0.599	-0.406	0.658
-	-	-	-	DFR	-2.271	-0.025	0.510
-	-	-	-	INFL	-0.626	-0.764	0.778
Panel B: Dimension reduction and shrinkage methods							
PCA_MAI	-0.557	-1.368	0.914	PCA_ECON	-0.585	-1.046	0.852
SPCA_MAI	-0.900	0.265	0.395	SPCA_ECON	-8.308	-1.182	0.881
PLS_MAI	1.163	2.160	0.015	PLS_ECON	-2.858	-0.326	0.628
LASSO_MAI	3.039	2.477	0.007	LASSO_ECON	-3.093	-0.950	0.829
ENET_MAI	3.028	2.474	0.007	ENET_ECON	-6.728	-0.794	0.787
Panel C: Dimension reduction, combination model and shrinkage methods, all predictors taken together							
PCA_ALL	-0.487	-0.660	0.745		-	-	-

SPCA_ALL	-8.241	-0.971	0.834	-	-	-
PLS_ALL	-2.969	-0.173	0.569	-	-	-
LASSO_ALL	-2.590	-0.752	0.774	-	-	-
ENET_ALL	-2.537	-0.730	0.767	-	-	-
MF	-0.127	-0.168	0.567	-	-	-

Notes: The table presents the out-of-sample performance of model evaluation by R^2 and the MSPE-adjusted statistic. The model columns mean regressions including the corresponding variable. If R^2 is larger than zero, the corresponding model is superior to the benchmark model.

Table 8. Results of the variables' performances based on different forecasting windows (15 years in-sample)

Macroeconomic attention indices				Macroeconomic variables			
Models	R^2(%)	MSPE-Adj.	p-value	Models	R^2(%)	MSPE-Adj.	p-value
Panel A: Predictive regressions							
CR_ni	0.161	0.635	0.263	DP	-0.657	-0.708	0.761
GDP_ni	-0.885	0.179	0.429	DY	-0.653	-0.654	0.743
HM_ni	-0.540	0.446	0.328	EP	-0.765	-0.199	0.579
INFL_ni	0.094	0.787	0.216	DE	-1.521	-0.419	0.662
MONE_ni	-0.869	-1.305	0.904	SVAR	-3.417	0.007	0.497
OIL_ni	-0.083	-0.090	0.536	BM	-0.271	-0.658	0.745
UNEMP_ni	1.571	2.204	0.014	NTIS	-1.516	-2.045	0.980
USD_ni	-1.385	-1.556	0.940	TBL	-0.557	0.018	0.493
-	-	-	-	LTY	-0.374	0.281	0.389
-	-	-	-	LTR	-0.238	-0.124	0.550
-	-	-	-	TMS	-1.070	-0.957	0.831
-	-	-	-	DFY	-0.588	-0.475	0.683
-	-	-	-	DFR	-2.168	0.024	0.490
-	-	-	-	INFL	-0.699	-0.839	0.799
Panel B: Dimension reduction and shrinkage methods							
PCA_MAI	-0.555	-1.213	0.887	PCA_ECON	-0.482	-0.748	0.773
SPCA_MAI	-0.905	0.276	0.391	SPCA_ECON	-8.597	-1.130	0.871
PLS_MAI	2.362	2.504	0.006	PLS_ECON	-2.302	-0.420	0.663
LASSO_MAI	3.314	2.461	0.007	LASSO_ECON	-3.099	-1.144	0.874
ENET_MAI	3.315	2.463	0.007	ENET_ECON	-3.057	-1.132	0.871
Panel C: Dimension reduction, combination model and shrinkage methods, all predictors taken together							
PCA_ALL	-0.420	-0.474	0.682		-	-	-

SPCA_ALL	-8.595	-0.933	0.825	-	-	-
PLS_ALL	-2.418	-0.236	0.593	-	-	-
LASSO_ALL	-2.624	-0.880	0.811	-	-	-
ENET_ALL	-2.616	-0.886	0.812	-	-	-
MF	-0.113	-0.118	0.547	-	-	-

Notes: The table presents the out-of-sample performance of model evaluation by R^2 and the MSPE-adjusted statistic. The model columns mean regressions including the corresponding variable. If R^2 is larger than zero, the corresponding model is superior to the benchmark model.

Table 9. Results of the variables' performances during the COVID-19 pandemic

Macroeconomic attention indices				Macroeconomic variables			
Models	R^2(%)	MSPE-Adj.	p-value	Models	R^2(%)	MSPE-Adj.	p-value
Panel A: Predictive regressions							
CR_ni	-0.012	-0.459	0.677	DP	-0.002	-0.174	0.569
GDP_ni	0.017	0.772	0.220	DY	-0.001	-0.099	0.539
HM_ni	0.000	0.048	0.481	EP	-0.009	-0.844	0.801
INFL_ni	0.019	0.944	0.172	DE	0.002	1.482	0.069
MONE_ni	-0.022	-1.316	0.906	SVAR	-0.462	-1.007	0.843
OIL_ni	0.002	0.414	0.340	BM	-0.001	-0.515	0.697
UNEMP_ni	0.111	2.246	0.012	NTIS	0.000	-0.389	0.651
USD_ni	-0.001	-0.191	0.576	TBL	0.016	0.821	0.206
-	-	-	-	LTY	0.011	0.473	0.318
-	-	-	-	LTR	-0.020	-0.725	0.766
-	-	-	-	TMS	-0.006	-0.257	0.601
-	-	-	-	DFY	-0.010	-2.844	0.998
-	-	-	-	DFR	-0.040	-0.189	0.575
-	-	-	-	INFL	-0.005	-0.774	0.780
Panel B: Dimension reduction and shrinkage methods							
PCA_MAI	0.000	-0.152	0.561	PCA_ECON	-0.002	-0.997	0.841
SPCA_MAI	0.049	1.716	0.043	SPCA_ECON	-0.506	-0.930	0.824
PLS_MAI	0.113	1.773	0.038	PLS_ECON	0.001	0.151	0.440
LASSO_MAI	0.080	1.361	0.087	LASSO_ECON	-0.246	-0.943	0.827
ENET_MAI	0.080	1.359	0.087	ENET_ECON	-0.246	-0.944	0.827
Panel C: Dimension reduction, combination model and shrinkage methods, all predictors taken together							
PCA_ALL	-0.001	-0.917	0.820		-	-	-

SPCA_ALL	-0.416	-0.834	0.798	-	-	-
PLS_ALL	0.001	0.152	0.440	-	-	-
LASSO_ALL	-0.193	-0.662	0.746	-	-	-
ENET_ALL	-0.194	-0.672	0.749	-	-	-
MF	-0.011	-0.521	0.699	-	-	-

Notes: The table presents the out-of-sample performance of model evaluation by R^2 and the MSPE-adjusted statistic. The model columns mean regressions including the corresponding variable. If R^2 is larger than zero, the corresponding model is superior to the benchmark model.

Table 10. Results of the variables' performances during different horizons (*H*=3)

Macroeconomic attention indices				Macroeconomic variables			
Models	R^2(%)	MSPE-Adj.	*p*-value	Models	R^2(%)	MSPE-Adj.	*p*-value
Panel A: Predictive regressions							
CR_ni	-2.465	-2.591	0.995	DP	-0.215	0.241	0.405
GDP_ni	8.827	4.453	0.000	DY	-0.320	0.111	0.456
HM_ni	-5.965	0.177	0.430	EP	-3.352	-1.081	0.860
INFL_ni	-2.068	-2.038	0.979	DE	-6.214	-2.149	0.984
MONE_ni	-1.421	-1.931	0.973	SVAR	-5.075	-1.999	0.977
OIL_ni	0.120	0.650	0.258	BM	-1.021	-2.906	0.998
UNEMP_ni	5.507	4.464	0.000	NTIS	-4.467	-3.616	1.000
USD_ni	0.558	1.443	0.074	TBL	-3.007	-1.473	0.930
-	-	-	-	LTY	-2.694	-2.059	0.980
-	-	-	-	LTR	0.578	1.115	0.132
-	-	-	-	TMS	-0.871	0.062	0.475
-	-	-	-	DFY	-4.195	-1.774	0.962
-	-	-	-	DFR	0.085	0.550	0.291
-	-	-	-	INFL	0.653	1.085	0.139
Panel B: Dimension reduction and shrinkage methods							
PCA_MAI	-0.308	-0.242	0.596	PCA_ECON	-1.620	-3.735	1.000
SPCA_MAI	-2.473	0.787	0.216	SPCA_ECON	-3.508	-3.153	0.999
PLS_MAI	7.207	4.062	0.000	PLS_ECON	-3.934	-0.692	0.755
LASSO_MAI	9.099	3.355	0.000	LASSO_ECON	0.564	2.690	0.004
ENET_MAI	9.051	3.362	0.000	ENET_ECON	0.604	2.767	0.003
Panel C: Dimension reduction, combination model and shrinkage methods, all predictors taken together							

PCA_ALL	-1.460	-2.839	0.998	-	-	-
SPCA_ALL	-9.607	-0.673	0.750	-	-	-
PLS_ALL	-3.593	-0.534	0.703	-	-	-
LASSO_ALL	1.878	1.778	0.038	-	-	-
ENET_ALL	1.975	1.918	0.028	-	-	-
MF	-0.075	-0.009	0.503	-	-	-

Notes: The table presents the out-of-sample performance of model evaluation by R^2 and the MSPE-adjusted statistic. The model columns mean regressions including the corresponding variable. If R^2 is larger than zero, the corresponding model is superior to the benchmark model.

Table 11. Results of the variables' performances during different horizons (*H*=6)

Macroeconomic attention indices				Macroeconomic variables			
Models	R^2(%)	MSPE-Adj.	*p*-value	Models	R^2(%)	MSPE-Adj.	*p*-value
Panel A: Predictive regressions							
CR_ni	-3.953	-2.886	0.998	DP	-2.290	-1.341	0.910
GDP_ni	1.105	3.933	0.000	DY	-2.719	-1.620	0.947
HM_ni	-20.628	-1.055	0.854	EP	-4.145	-1.821	0.966
INFL_ni	-3.959	-2.073	0.981	DE	-8.444	-4.724	1.000
MONE_ni	-2.206	-3.183	0.999	SVAR	-3.604	-1.816	0.965
OIL_ni	-0.788	-1.761	0.961	BM	-2.774	-4.560	1.000
UNEMP_ni	3.293	3.861	0.000	NTIS	-10.038	-4.944	1.000
USD_ni	2.417	2.962	0.002	TBL	-3.366	-1.068	0.857
-	-	-	-	LTY	-4.618	-3.131	0.999
-	-	-	-	LTR	-0.692	0.315	0.376
-	-	-	-	TMS	3.074	2.908	0.002
-	-	-	-	DFY	-3.741	-2.941	0.998
-	-	-	-	DFR	-1.085	-0.103	0.541
-	-	-	-	INFL	1.762	1.808	0.035
Panel B: Dimension reduction and shrinkage methods							
PCA_MAI	-1.308	-1.237	0.892	PCA_ECON	-3.449	-4.716	1.000
SPCA_MAI	-18.852	-0.505	0.693	SPCA_ECON	-6.979	-4.524	1.000
PLS_MAI	-5.800	0.923	0.178	PLS_ECON	-3.868	-0.118	0.547
LASSO_MAI	19.690	3.774	0.000	LASSO_ECON	1.266	4.632	0.000
ENET_MAI	19.687	3.774	0.000	ENET_ECON	1.275	4.651	0.000
Panel C: Dimension reduction, combination model and shrinkage methods, all predictors taken together							
PCA_ALL	-3.305	-3.910	1.000		-	-	-

SPCA_ALL	-26.578	-1.831	0.966	-	-	-
PLS_ALL	-4.502	-0.220	0.587	-	-	-
LASSO_ALL	4.102	2.324	0.010	-	-	-
ENET_ALL	4.107	2.366	0.009	-	-	-
MF	-1.018	-1.429	0.924	-	-	-

Notes: The table presents the out-of-sample performance of model evaluation by R^2 and the MSPE-adjusted statistic. The model columns mean regressions including the corresponding variable. If R^2 is larger than zero, the corresponding model is superior to the benchmark model.

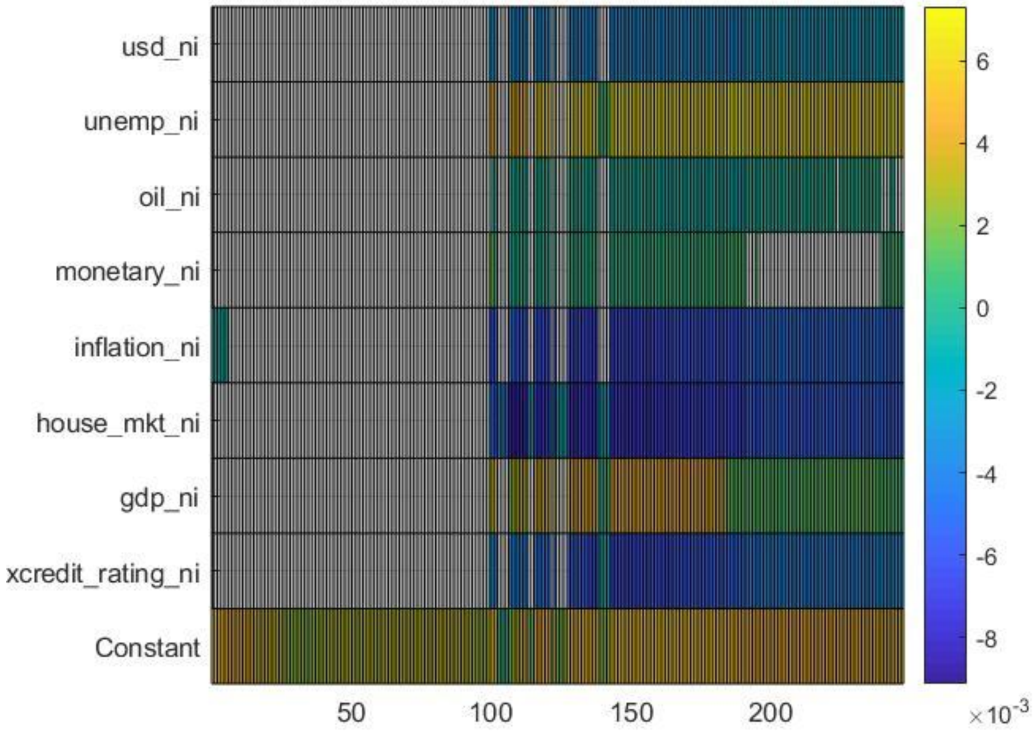

Figure 1 The performances of MAI indices based on the LASSO model.

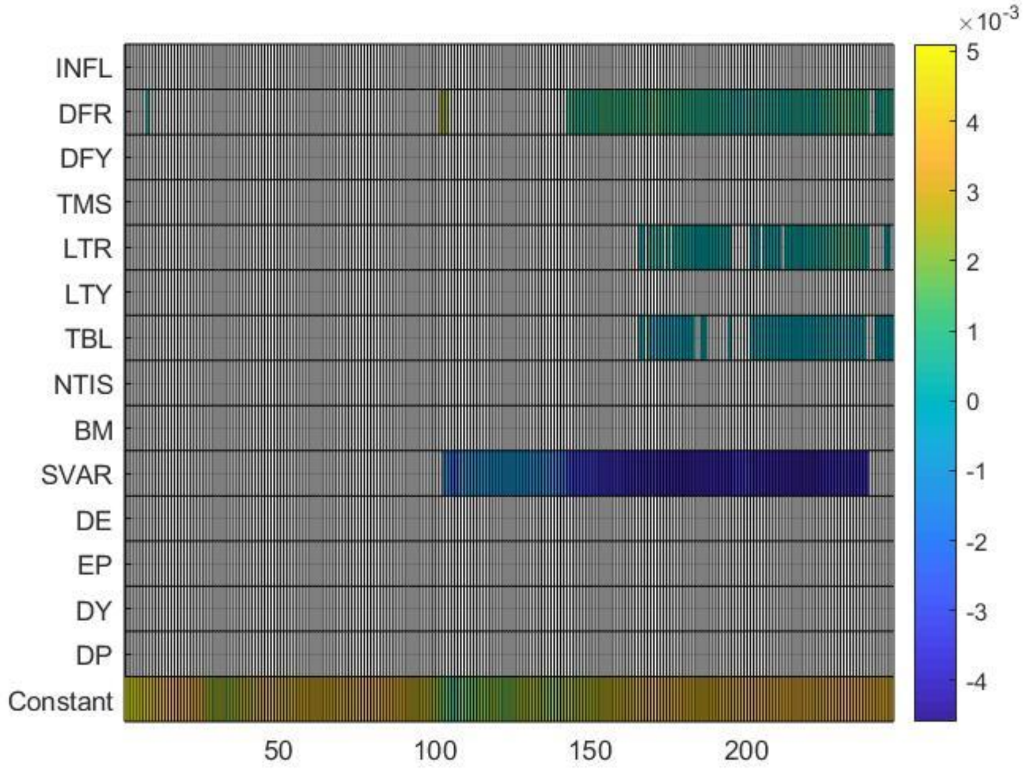

Figure 2 The performances of macroeconomic variables based on the LASSO model.