PHBS WORKING PAPER SERIES

Forecasting Stock Returns: The Role of New Global Market Integration Indices

Cindy S.H. Wang
Peking University

Cheng Hsiao
University of Southern California

Gary C.K. Wen
National Tsing Hua University

March 2023

Working Paper 20230301

Abstract

This research examines the usefulness of new proposed equity premium predictors through their superior out-of-sample forecasting gains relative to the historical average return method and currently well-known spillover indices (Diebold and Yilmaz, 2009) and the global market portfolio return (Fama and French, 1998) for international equity markets. Predictors are based on various trading strategies and finance theories. Answers to several important arguments in current literature are also justified as follows, (i) the forecasting accuracy could be improved remarkably once one or more of new predictors are incorporated into predictive models, even the out-of-sample forecast period covers several unexpected global events; (ii) predictive models with new predictors outperform simple statistical time series and panel models; (iii) a reliable world factor to predict the U.S. equity premium is necessary; (iv) the new predictors possess the characteristics of exogenous regressors and overlapping observations in the prediction; (v) our predictive procedure incorporates issues of model uncertainty and parameter uncertainty. and (vi) new indices perform more accurately during expansions than recessions, which is in marked contrast to the current literature.

Keywords: CD_{AR} test, Forecast combination, Lasso, Panel predictive model, Three-pass regression filter (3PRF), Complete subset regression.
JEL Classification: G11, G12, G14

Peking University HSBC Business School
University Town, Nanshan District
Shenzhen 518055, China

Forecasting Stock Returns: The Role of New Global Market Integration Indices

Cindy S.H. Wang [1] **Cheng Hsiao** [2] **Gary C.K. Wen** [3]

Jan 30, 2023

Abstract

This research examines the usefulness of new proposed equity premium predictors through their superior out-of-sample forecasting gains relative to the historical average return method and currently well-known spillover indices (Diebold and Yilmaz, 2009) and the global market portfolio return (Fama and French, 1998) for international equity markets. Predictors are based on various trading strategies and finance theories. Answers to several important arguments in current literature are also justified as follows, (i) the forecasting accuracy could be improved remarkably once one or more of new predictors are incorporated into predictive models, even the out-of-sample forecast period covers several unexpected global events; (ii) predictive models with new predictors outperform simple statistical time series and panel models; (iii) a reliable world factor to predict the U.S. equity premium is necessary; (iv) the new predictors possess the characteristics of exogenous regressors and overlapping observations in the prediction; (v) our predictive procedure incorporates issues of model uncertainty and parameter uncertainty. and (vi) new indices perform more accurately during expansions than recessions, which is in marked contrast to the current literature.

KEYWORDS: CD_{AR} test, forecast combination, lasso, panel predictive model, three-pass regression filter (3PRF), complete subset regression.

1. Introduction

The traditional data based approaches to generate a predictive model are widely discussed in the current literature. For examples, using a pattern recognition algorithm to search for relevant observed predictive covariates or adopting model averaging to tackle model uncertainty. However, among these studies. relatively few of them utilize economic or financial theories. In this paper, we explore if combining trading strategies, economic or financial theories with the traditional data-based approach may yield more accurate and robust predictive models. In addition, we also shed light on the feasibility of incorporating the global predictors based on trading strategies into the equity return predictive model and answer several arguments arisen in current literature.

One of the most studied and yet still not fully understood issues in financial literature is whether the equity premium is predictable based on publicly available information(e.g. Fama(1970)), and various

[1] HSBC Business School, Peking University, China.
[1] Corresponding author, e-mail: cindywang9177@gmail.com; cindywang@phbs.pku.edu.cn.
[2] Department of Economics, University of Southern California, U.S.A. Email: chsiao@usc.edu.
[3] Department of Quantitative Finance, National Tsing Hua University, Taiwan, R.O.C.
Email: s123321678@yahoo.com.tw
We are very grateful for the very helpful comments and suggestions of Professor Tong Yu, and Hui Guo from University of Cincinnati, Neil Ericsson from Federal Reserve Board and Allan Timmermann from UCSD and participants at the 24th Dynamic Econometric Conference, 2022 SETA Econometrics Theory and Application Conference, 2022 Cross Country Perspectives in Finance Conference (CCPF), and the 42nd International Symposium on Forecasting.

measures of the financial and economics variables including valuation ratios, risk premiums, various interest rates, etc. More than 20 years of research have shown that prediction models based on these variables could yield worse out-of-sample forecasts than simple time series prediction models (historical average returns method, HA). For examples, using a number of observed variables, Bossaerts and Hillion (1999) fails to deliver substantial evidence in favor of the out-of-sample forecasting ability of a predictive regression on equity markets of industrialized countries from 1990-1995. Goyal and Welch (2003) show that the dividend-price ratio is not a robust predictor for the out-of-sample forecast of the equity premium. A recent comprehensive study by Welch and Goyal (2008) brought this issue to the center stage again with their bearish view on equity premium predictability. They show that the long list of predictors such as dividend price ratio, earning-price ratio, and an assortment of financial ratios in the literature largely lack predictive power toward equity premiums when compared to the historical average return method. Nelson (1972) also reveals the prediction accuracy of the U.S. economy by the simple ARIMA time series model in a comparison with an econometrics model (FMP). To be more specific, the wisdom of whether any econometrics models with well-suited predictors outperform simple time series models in helping forecast stock returns or economics activities is controversiASal. In what follows, we attempt to search for a useful out-of-sample forecasting procedure, which not only beats the historical average return method, but also generates more accurate forecasts against those by other predictive approaches.

Two focuses are emphasized in this study. First, in order to predict global stock returns, we propose a proper global equity return predictor from the perspective of the growth rate of international market integration, namely, the $\triangle CD_{AR}$ predictor. This focus is in accordance with Fama and French (1998) and Griffin (2002), that there should be one set of risk factors that explain expected returns in all countries under the null hypothesis of market integration. The $\triangle CD_{AR,t}$ predictor is defined as

$$\triangle CD_{AR,t} = \frac{CD_{AR,t} - CD_{AR,t-1}}{CD_{AR,t-1}}, \tag{1}$$

where $CD_{AR,t}$ is the AR-filtered cross-sectional correlation measure suggested by Wang *et al.* (2021). They first use an autoregressive model (AR) to filter each time series, then compute the cross-sectional correlations using the filtered series. The reasons for using (1) are two folds: (i) $CD_{AR,t}$ is an optimal diagnostic statistic measuring the strength of market integration or systemic risk, because it relies on the AR-filtered version of the conventional CD test, which avoids the spurious correlation issue, and (ii) when data are noisy and volatile, the apparent spurious phenomenon of the predictive regressor caused by highly persistent variables could be tackled (Campbell and Thompson, 2008).

Second, in the last two decades, economists have devoted substantial attention to the role of the global factor in predicting asset returns, because the choice of a global factor can substantially affect expected return estimates (e.g., Fama and French, 1998; Liew and Vassalou, 2000; Zhu, 2015). We here place interest in investigating whether the $\triangle CD_{AR}$ predictor could help to explain the time series variation in global or U.S. equity returns. To address the impact of the $\triangle CD_{AR}$ predictor in the prediction of U.S.equity returns explicitly, several existing forecasting methods are considered. These predictive models include the simple time series predictive models commonly used in forecasting studies (e.g., Welch and Goyal, 2008; Kostakis *et al.*, 2015; Dai and Kang, 2021), a pooled panel framework (Hjalmarsson, 2010), a pool autoreregressive approximation (PAR)-forecasting method (Wang *et al.*, 2022). a simple average forecast combination (Hsiao and Wan, 2014), conditional forecast combination strategies (Aiolfi and Timmermann, 2006), multivariate regressions including the ridge regression, Lasso, Elastic net and the complete subset regression (Elliott *et al.*, 2013), and the three-pass regression filter (Kelly and Pruitt, 2015) as well as observed predictors from the long list of variables considered by Welch and Goyal (2008) and several commonly used macroeconomics variables, documented in many studies (e.g., Rapach *et al.*, 2010; Zhang *et al.*. 2019).

The $\triangle CD_{AR}$ predictor possesses several desirable and appealing features. First, the $\triangle CD_{AR}$ predictor is easy to implement and available for any data frequencies. What we need to do is to simply use the autoregressive model (AR) to filter each return or volatility of international financial assets at different data frequencies and construct the predictor by the fitted residuals. Return and volatility data at different data frequencies are obtainable from public resources, unlike most finance, accounting and economics variables considered in forecasting studies that only allow for a monthly, quarterly, or annually basis. Moreover, this predictor is an aggregation of interactions among all units of a mixed panel. That is to say, this indicator displays a time series containing cross-sectional information. In addition, this predictor is dynamics, based on a rolling window AR method, i.e., filtering each series of a mixed panel by an AR model with the samples in a given window. When the window is rolling as with the time, the estimated parameters change. This implies the information contained in each observation of CD_{AR}-family predictors is consecutive and connected. More specifically, this predictor possesses the characteristics of exogenous regressors and overlapping observations in predictive models and our predictive procedure also incorporates issues of model uncertainty and parameter uncertainty, being consistent with what suggested in Rapach *et al.* (2014). Thus, it could be a well-suited predictor to be used to generate forecasts that lead to better economic decisions or utility in real time.

Second, in a predictive power comparison with the historical average return method and two global factors, the spillover index by Diebold and Yilmaz (2009), and the global market portfolio return of Fama and French (1998), $\triangle CD_{AR}$-family predictors constructed by returns and volatilities of international financial assets generate more accurate out-of sample forecasts of international equity returns. Basically, exiting studies did not document the out-of sample forecasting ability of two existing global factors. One possible explanation for this finding is that the CD_{AR} index captures the time-varying behaviors of international capital movements among major financial assets in a precise way relative to the spillover index as indicated by Wang *et al.* (2021). Their empirical results show that the occurrence of each global event or shock usually lags behind the local peak of the CD_{AR} indicator. More specifically, this CD_{AR}-family predictors could signal the changing pattern of market information triggered by international capital movements, being earlier than the real-time occurrence for each global event or shock. Additionally, the selection burden of the portfolio weights for constructing the global market portfolio return by Fama and French (1998) could be neglected when building up the CD_{AR}-family predictors. Thus, the out-of sample predictive ability of the $\triangle CD_{AR}$ predictor performs convincingly even when the forecasting period covers several unexpected common events, such as, the recent Sino-U.S. trade war, and Covid-19 pandemic crisis. Moreover, the promising predictive ability of the CD_{AR}-family predictors is robust to daily and monthly frequencies and the global or U.S stock return forecasting.

Third, parallel to increasing literature that has confirmed the great out-of-sample prediction ability of the three-pass regression filter (3PRF) method (see Kelly and Pruitt, 2015; Huang, *et al.*, 2015; Dai and Kang, 2021), the more encouraging predictive outcome occurs in this research when we adopt the 3PRF predictive model with a list of variables in Welch and Goyal (2008) and one of the $\triangle CD_{AR}$-family predictors. It implies that the marginal impact of the $\triangle CD_{AR}$ predictor on the improvement of prediction accuracy for U.S. stock returns is remarkable. In practice, no matter which predictive method is adopted, as long as one of the $\triangle CD_{AR}$-family predictors or a $\triangle CD_{AR}$ related-combination is incorporated into the pool of selected variables, the resulting forecasts will outperform those generated by the original pool without the $\triangle CD_{AR}$ predictor or a $\triangle CD_{AR}$ related-combination. That could imply that the worse out-of sample forecasts of U.S. stock returns by Welch and Goyal (2008) might be due to ignoring a suitable world factor, since the increasing degree of the international market integration (e.g., Caramazza *et al.*, 2004; Tong and Wei, 2011) and capitals in the U.S. stock market may move internationally. That is to say, the $\triangle CD_{AR}$index is informative and meaningful, which captures the time-varying patterns of international capital movements and interactions triggering impending global events in real time. As a consequence, our empirical findings which appear to suggest expanding the set of possible predictions based on financial theories may overcome the observation of Welch and Goyal (2008), that is "the profession has yet to find some variable that has meaningful and robust empirical equity premium forecasting power." More importantly, we provide the strong support the fact that a global risk factor may be necessary in return forecasting.

Finally, the $\triangle CD_{AR}$ predictor also justifies the argument of Pollet and Wilson (2010), that (i) higher aggregate risk can be revealed by higher correlation between stocks; and (ii) the average correlation between stock returns has forecasting power in the return prediction. More importantly, all encouraging outcomes from the CD_{AR}-family predictors confirm the feasibility of the econometrics model in stock returns prediction when compared to the simple time series model. This evidence is in marked contrast to findings in current studies (e.g., Nelsen, 1972; Welch and Goyal, 2008).

The remainder of this paper proceeds as follows. Section 2 presents the widely used predictive regression and forecast evaluation measures. Section 3 suggests a new family of global market integration indices and shows their promising prediction power at different data frequencies. Section 4 displays various predictive approaches and predictive variables. Section 5 provides an empirical comparison of various predictive models and predictors. We examines the forecasting performance of new predictors for recession and expansion periods. Concluding remarks are in section 7.

2. Out of sample Return Forecasting

This section describes the traditional predictive regression model to forecast stock market returns and the criteria we used to evaluate the out-of-sample forecasts.

2.1. Predictive regression model

We start with a standard predictive regression model for the equity premium, which regresses:

$$r_{t+1} = \alpha + \beta x_t + u_{t+1}, \tag{2}$$

where r_{t+1} is the return on a stock market index in excess of the risk-free interest rate, x_t is a predictor whose predictive ability is of interest, and u_{t+1} is a disturbance term.

In order to reduce forecast estimation by parameter instability when there exist structural breaks between predictors and the dependence variable, we generate out-of sample forecasts of stock market returns using rolling forecast window scheme. Two commonly rolling window sizes are of concern . One is based on the suggestion of Hansen and Timmermann (2015) to use half of the full sample for in-sample estimation (=$T/2$ observations), and the remaining for out-of-sample evaluation. The rolling forecast window scheme is designed as follows: given a simulated sample of size $T = 2\widetilde{T}$, where $\widetilde{T}$ is the rolling window size, we estimate the model using the first $\widetilde{T}$ observations, and generate the forecasts of $R_{\widetilde{T}+1}$. Next, we add one observation to the estimation sample to generate the forecasts of $R_{\widetilde{T}+2}$ and drop the first observation at the same time to maintain the fixed window size $\widetilde{T}$. We continue like this until observation $T-1$, which enables us to forecast y_T. The other one is in line with fund managers' practical consideration in portfolio adjustments. For example, $\widetilde{T} = 60$ is commonly used in empirical applications when data are at monthly frequency (e.g., Solnik and Roulet,1998; Hjalmarsson, 2010). Thus, the initial out-of-sample forecast of the equity premium based on the predictor x_t is given by:

$$\widehat{r}_{\widetilde{t}+1} = \widehat{\alpha}_{\widetilde{t}} + \widehat{\beta}_{\widetilde{t}} x_{\widetilde{t}},$$

where $\widehat{\alpha}_{\widetilde{t}}$ and $\widehat{\beta}_{\widetilde{t}}$ are the ordinary least square (OLS) estimates of α and β, respectively. Basically, this out-of-sample forecasting exercise simulates the situation of a forecaster in real time. Welch and Goyal (2008) and Campbell and Thompson (2008) suggest using the historical average of the equity premium

$$r_t = \sum_{j=1}^{t-1} \frac{r_j}{t-1}, \tag{3}$$

serving as a natural benchmark forecasting model corresponding to a constant expected equity premium. Generally speaking, the sample average forecast does not exploit all of the information inherent in a fully specified probabilistic model of excess stock returns. However, if x contains information useful for predicting the equity premium, the $\widehat{r}_{\tilde{t}}$ should outperform $r_{\tilde{t}}$.

2.2. Evaluation measures

Two measures for a comparison of the equity premium forecasts are considered. One is the R^2_{OS} prediction evaluation measure suggested by Campbell and Thompson (2008) and implemented by Rapach *et al.* (2010) to examine the $\widehat{R}_t$ and $\bar{r}_t$ forecasts.

$$R^2_{OS} = 1 - \frac{\sum_{k=q_0+1}^{q}(R_{m+k} - \widehat{R}_{m+k})^2}{\sum_{k=q_0+1}^{q}(R_{m+k} - \bar{r}_{m+k})^2}, \tag{4}$$

where $q_0 + 1, ..., q$ are the out-of-sample period, and $\widehat{R}_{m+k}$ is either an individual forecast based on the predictive regression model or a combined forecast (see Rapach *et al.*, 2010); $\bar{r}_{m+k} = \sum_{j=1}^{m+k-2} r_j$ is the historical average serving as a natural benchmark forecasting model corresponding to a constant expected equity premium. Intuitively, if $X_{i,t}$ contains information useful for predicting the equity premium, then $\widehat{R}_{m+k}$ should perform better than r_{m+k}. Therefore, when $R^2_{OS} > 0$, the $\widehat{R}_{m+k}$ forecast outperforms the historical average forecast according to the (MSPE) metric as it brings a reduction in MSPE for the predictive regression. Campbell and Thomspon (2008) argue that even very small positive R^2_{OS}, values, such as 0.5% for monthly data and 1% for quarterly data, can signal an economically meaningful degree of return predictability in terms of increased annual portfolio returns for a mean-variance investor. This indeed provides a simple assessment of predictability in practice.

The other measurement is the MSPE-adj test by Clark and West (2007). They treat the predictive model as the unrestricted model and the historical average model as the restricted model (please refer to Clark and West (2007)), and then do the test as follows:

$$MSPE - adj = \frac{\sqrt{P}\bar{f}}{\sqrt{\hat{V}}'} \tag{5}$$

where $\bar{f} = P^{-1}\sum_t \hat{f}_{t+k}$, and $\hat{f}_{t+k} = (\hat{u}^r_{t+k})^2 - [(\hat{u}^{ur}_{t+k})^2 - (\hat{y}^r_{0,t+k} - \hat{y}^{ur}_{0,t+k})^2]$, $P = q - q_0$ is the number of out-of-sample observations, $\hat{u}^{ur}_{t+k}$ and $\hat{u}^r_{t+k}$ are the estimated residuals of the competing predictive and historical average benchmark models correspondingly, and $\hat{V}$ is the sample variance of $(\hat{f}_{t+k} - \bar{f})$. The Clark-West test is an approximately normal test for equal predictive accuracy in nested models.

The null hypothesis specifies equal MSPEs, $H_0 : MSPE^{ur} = MSPE^r$ while the alternative is that the unrestricted model has a smaller MSPE than the restricted model, i.e. $H_1 : MSPE^{ur} < MSPE^r$. The asymptotic distribution for the statistic is simply the standard normal distribution. If the test statistic is statistically significantly positive, the null hypothesis is rejected meaning that $\widehat{R}_{m+k}$ forecast outperforms the historical average forecast. If the test statistic is a value not significantly positive or negative, it implies there is no substantial difference between $\widehat{R}_{m+k}$ and $\bar{r}_{m+k}$.

3. Global Market Indices

Several studies in the literature have identified the crucial role of global factors in deriving time variations in financial and macroeconomics variables. Fama and French (1998) extend a three-factor model of Fama and French (1993) to a global context and show that a two-factor model with a world market and world book-to-market equity factor explains international stock returns better than the world capital asset pricing model. Thus, this section follows the implication from the international asset pricing theory applied in Fama and French (1998) and Griffin (2002), illustrating under the null hypothesis of market integration, that there should be one set of risk factors that explain expected returns in all countries.

In practice, there is still no consensus about the construction of common variables among global financial markets. Part of this difficulty is attributed to the existence of the unobserved components, which are random variables drawn from the population along with the observed explained and explanatory variables as opposed to parameters to be estimated. These unobserved effects could be explained by the latent common factors contemporaneously affecting all market returns and varying with time. By doing so, we then propose a global market integration index as an equity premium predictor and further examine its predictive ability in the out-of-sample forecasts of international equity markets.

3.1. Basic Approach

Many leading indicators for the capital flow and spillover behaviors of international financial assets have been widely discussed in the literature empirically, such as the spillover (S) index by Diebold and Yilmaz (2009). Traditionally, the first step to understand transmission of shocks across border is through the measurement of correlation between the markets. The Pearson correlation coefficients (PSCCC) is a commonly used measure of interaction between two markets. However, many financial variables such as returns and volatility of financial assets, exhibit a pattern similar to the long memory process ($I(d), d \neq 0, d \in (-0.5, 0.5)$)(e.g. Bailie, 1996; Lobato and Savin,1998; Bollerslev and Wright(2000); Maynard *et al.*, 2013). In addition, Andersen *et al.* (2001) and Andersen *et al.* (2003) report that the average long memory parameters for a set of realized volatilities of equity and foreign exchange rate returns approximately 0.35 and 0.4, respectively. It is thus not surprising to examine the correlations between any two return series as one of them is a stationary $I(0)$ process and the other one is a long memory series. Wang *et al.* (2021) show that when one of pair variables is the stationary $I(0)$ process and the other is the $I(d)$ process or when both variables are , the limiting distribution of the PSCCC does not follow the standard normal distribution as $T \to \infty$. This finding further leads the non-N(0,1) distribution of CD test for the cross-sectional correlation in panels when panels are mixed, which simultaneously allows for the existence of $I(0)$ and $I(d)$ processes and resemble reality.

Instead of using the classical Pearson correlation coefficient to measure the correlation between $y_{t,i}$ and $y_{t,j}$ series, Wang *et al.* (2021) suggest to first empirically fit each $y_{t,i}$ and $y_{t,j}$ series with the AR(k) approximation as follows:

$$\widehat{\phi}_i(L)y_{t,i} = \widehat{e}_{t,i,k} \quad \text{and} \quad \widehat{\phi}_j(L)y_{t,j} = \widehat{e}_{t,j,k}, \tag{6}$$

where $\widehat{e}_{t,i,k}$ and $\widehat{e}_{t,j,k}$ are AR-filtered residuals. In addition, $\widehat{e}_{t,i,k}$ and $\widehat{e}_{t,j,k}$ asymptotically mimic $e_{t,i}$ and $e_{t,j}$, correspondingly. We then use $\widehat{e}_{t,i,k}$ and $\widehat{e}_{t,j,k}$ to measure the correlation between $y_{t,i}$ and $y_{t,j}$ (or $e_{t,i}$ and $e_{t,j}$):

$$\widehat{\rho}_{AR,ij} = \frac{T^{-1}\sum_{t=1}^{T}\widehat{e}_{t,i,k}\widehat{e}_{t,j,k}}{\sqrt{T^{-1}\sum_{t=1}^{T}\widehat{e}_{t,i,k}^2}\sqrt{T^{-1}\sum_{t=1}^{T}\widehat{e}_{t,j,k}^2}}, \tag{7}$$

where the lag length k of AR(k) to approximate the $I(0)$ and $I(d), d \in (0, 0.5)$ processes increases with the growth rate of $k = o(T^{1/3})$ and $k = o((T/logT)^{0.5-d})$, respectively. They further show the following lemma under the null hypothesis of cross-sectional independence between $y_{t,i}$ and $y_{t,j}$(or $e_{t,i}$ and $e_{t,j}$), i.e., $H_0 : E(y_{t,i}y_{t,j}) = E(e_{t,i}e_{t,j}) = 0, i \neq j$.

Lemma 1. *Consider a mixed panel $y_{t.i}, i = 1, 2, \cdots, N$, which simultaneously allows for the existence of $I(0)$ and $I(d), d \in (0, 0.5)$ processes (at least one element of this panel satisfies an $I(d), d \in (0, 0.5)$ process); then as $(k_1, k_2, k_3, T) \to \infty$, under the null hypothesis of no cross-sectional independence, when $(N, T) \to \infty$ and $\frac{N}{T} \to c$, we have:*

$$CD_{AR} = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\widehat{\rho}_{ij,AR}\right) \xrightarrow{d} N(0,1),$$

where (i) $\widehat{\rho}_{AR,ij}$ is the AR-filtered version of Pearson correlation coefficient with $k_1 = o(T^{1/3})$ for an $I(0)$ process, $k_2 = o((T/logT)^{0.5-d_i})$ for an $I(d_i) \in (0, 0.5)$ process, and $k_3 = o((T/logT)^{0.5-d_j})$ for an $I(d_j) \in (0, 0.5)$ process; (ii) k_1, k_2, and k_3 are lag lengths for the AR approximation of the I(0), $I(d_i)$, and $I(d_j)$ processes, respectively; and (iii) $(d_i^2 + d_i) + (d_j^2 + d_j) - 1 < 0$.

The residual at time t of an AR model is treated as the shock or innovation at time t. Thus, the observed $y_{t,i}$ may be considered as the weighted sum of current and past shocks. Under the market integration hypothesis, the correlation between the shocks in two markets may increase if a shock that created a crisis in one market spreads to other markets. If two time series are correlated, then prewhitening individual series by separate AR filters alone will not be remove the correlations between two prewhitened series. In other words, the larger the cross-correlations, the larger is the absolute value of the CD_{AR} test statistics. More specifically, the co-movements of returns or volatilities in two or more financial assets could be due to a number of common shocks. This implies when a market expects a crisis is evolving, it could trigger nervous cross-market flows of bank lending or investment flows. We suggest ro use the CD_{AR} test statistic to represent the strength of the common shock or event that brings all markets together. Accordingly, Wang *et al.* (2021) propose an early warning indicator based on the CD_{AR} statistics to track the pattern of the market integration or systemic risk in order to know the timing of incoming global events and shocks, since the desirable features possessed by this CD_{AR} test are able to discover the increase in cross-sectional correlations.

The construction of the CD_{AR}-type market integration index is quite flexible and easy to implement. It allows for accommodating returns and volatilities of any financial assets at various frequencies. The intensity of market integration behavior may of course vary over time, and the nature of any time-variation is of potentially great interest. Without loss of generality, we suggest a rolling window CD_{AR}-type indicator. Such an indicator has two distinct manifestations: (i) it is dynamic and (ii) it displays a time series of cross-section framework. The dynamics of the CD_{AR}-type index based on volatilities and returns of financial assets is a rolling window AR method, i.e., filtering each series of a mixed panel by an AR model with the samples in a given window. When the window is rolling with the time, the estimates change to reflect the changes in the underlying parameters characterize the time series process. The rolling window CD_{AR}-type test statistics thus illustrates the information contained in each observation of CD_{AR}-family predictors is consecutive and connected. To be more specific, this predictor possesses the characteristics of exogenous regressors and overlapping observations in predictive models and our predictive procedure also incorporates issues of model uncertainty and parameter uncertainty, being consistent with what suggested in Rapach *et al.* (2014). Moreover, this indicator is an aggregation of interactions among all units of a mixed panel. That is to say, this indicator displays a time series containing cross-sectional information. The related strategies to construct the CD_{AR}-family indices are listed later.

3.2. Variable specification: construction of CD_{AR}-family indices

The surge in international asset trade since the early 1990s has renewed interest in the international portfolio choice. The analysis of Diebold and Yilmaz (2009, 2012) and Kopyl and Lee (2016) shows that the capital flows in and out among international equities and hedging assets. For example while looking at sovereign bonds, a negative co-movement between bonds and equities holds during business cycle contractions (e.g., Baele *et al.*, 2009; Dicle and Levendis, 2016). Ranaldo and Soderlind (2010) find that the Japanese Yen and Swiss franc exhibit safe haven properties. Furthermore, inspired by the 2008 global financial crisis, which appears to have started in credit markets but spilled over into equities, it is of particular interest to use our framework to measure the market integration among different assets. That implies that the international capital flows among different assets could play an important role resulting that leads to the market fluctuation. Moreover, a number of new equity markets have emerged in Europe, Latin America, Asia, and Africa in recent years, which provides a new menu of opportunities for investors, in that the addition of emerging market assets significantly enhances portfolio opportunities (see Harvey, 1995). With the international diversification rationale behind a portfolio setting, we consequently set our data pool consisting of excess returns and volatilities of seven advanced economies (U.K., U.S., Germany, Canada, Australia, France and Japan), seven emerging markets (Thailand, India, Malaysia, Taiwan, Brazil, Russia, and China), and six commonly used hedging assets (US dollar, 10-year Treasury bond, Japanese Yen, Swiss Franc, 30-year Treasury bond, and gold). Daily data covers the period from January, 2000 to March, 2021, while the periods for both monthly and quarterly range from January 1992 to March 2021. Those data periods cover several global events and crises, especially including the 2007-2008 subprime crisis, the recent Sino-U.S. trade war, and COVID-19 pandemic crisis.

We next define and construct $\triangle CD_{AR}$-family predictors, according to the following strategies, categorized by three groups.

Group A: Market interactions among equities of advanced economies only

(S1). $\triangle CD_{AR,R,t}$ represents the growth rate of the $CD_{R,t}$ test statistics constructed by equity returns of the above seven advanced economies at time t.

(S2). $\triangle CD_{AR,RV,t}$ represents the growth rate of the $CD_{RV,t}$ test statistics constructed by equity volatilities of the above seven advanced economies at time t.

(S3). $\triangle CD_{AR,RRV,t-1}$ represents the growth rate of the $CD_{RRV,t}$ test statistics constructed by equity returns and volatilities of the above seven advanced economies at time t and $t-1$, respectively. The intuition behind $\triangle CD_{AR,RRV,t}$ is inspired by the risk-return trade-off in finance studies, i.e., $R_t = \alpha_t + \beta_t RV_{t-1} + u_t$, where R_t and RV_{t-1} represent the return at time t and volatility at time $t-1$, correspondingly.

(S4). $\triangle CD_{AR,RRV,t-2}$ represents the growth rate of the $CD_{RRV,t}$ test statistics constructed by equity returns and volatilities of the above seven advanced economies at time t and $t-2$, respectively. The intuition behind $\triangle CD_{AR,RRV,t-2}$ is inspired by the risk-return trade-off in finance studies, i.e., $R_t = \alpha_t + \beta_t RV_{t-2} + u_t$, where R_t and RV_{t-2} represent the return at time t and volatility at time $t-2$, correspondingly.

Group B: Market Interactions among equities of advanced market and hedging assets

(S5). $\triangle CD_{AR,R,H,t}$ represents the growth rate of the $CD_{AR,R,H,t}$ test statistics constructed by equity returns of the above seven advanced economies and hedging assets at time t.

(S6). $\triangle CD_{AR,RV,H,t}$ represents the growth rate of the $CD_{AR,RV,H,t}$ test statistics constructed by equity volatilities of the above seven advanced economies and hedging assets at time t.

(S7). $\triangle CD_{AR,RR,H,t-1}$ represents the growth rate of the $CD_{AR,RR,H,t}$ test statistics constructed by equity returns of the above seven advanced economies at time t and returns of six hedging assets at $t-1$.

(S8). $\triangle CD_{AR,RR,H,t-2}$ represents the growth rate of the $CD_{AR,RR,H,t}$ test statistics constructed by equity returns of the above seven advanced economies at time t and returns of six hedging assets at $t-2$.

(S9). $\triangle CD_{AR,RVRV,H,t-1}$ represents the growth rate of the $CD_{AR,RVRV,H,t}$ test statistics constructed by equity volatilities of the above seven advanced economies at time t and volatilities of six hedging assets at $t-1$.

(S10). $\triangle CD_{AR,RVRV,H,t-2}$ represents the growth rate of the $CD_{AR,RRV,H,t}$ test statistics constructed by equity volatilities of the above seven advanced economies at time t and volatilities of six hedging assets at $t-2$.

(S11). $\triangle CD^*_{AR,RR,H,t-1}$ represents the growth rate of the $CD^*_{AR,RR,H,t}$ test statistics constructed by equity returns of the above seven advanced economies at time $t-1$ and returns of six hedging assets at t.

(S12). $\triangle CD^*_{AR,RR,H,t-2}$ represents the growth rate of the $CD^*_{AR,RR,H,t}$ test statistics constructed by equity returns of the above seven advanced economies at time $t-2$ and returns of six hedging assets at t.

(S13). $\triangle CD^*_{AR,RVRV,H,t-1}$ represents the growth rate of the $CD^*_{AR,RVRV,H,t}$ test statistics constructed by equity volatilities of the above seven advanced economies at time $t-1$ and volatilities of six hedging assets at t.

(S14). $\triangle CD^*_{AR,RVRV,H,t-2}$ represents the growth rate of the $CD^*_{AR,RRV,H,t}$ test statistics constructed by equity volatilities of the above seven advanced economies at time $t-2$ and volatilities of six hedging assets at t.

Group C: Market Interactions among equities of advanced and emerging economies

(S15). $\triangle CD_{AR,R,E,t}$ represents the growth rate of the $CD_{AR,R,E,t}$ test statistics constructed by equity returns of the above seven advanced economies and seven emerging economies at time t.

(S16). $\triangle CD_{AR,RV,E,t}$ represents the growth rate of the $CD_{AR,RV,E,t}$ test statistics constructed by equity volatilities of the above seven advanced economies and seven emerging economies at time t.

(S17). $\triangle CD_{AR,RR,E,t-1}$ represents the growth rate of the $CD_{AR,RR,E,t}$ test statistics constructed by equity returns of the above seven advanced economies at time t and of seven emerging markets at $t-1$.

(S18). $\triangle CD_{AR,RR,E,t-2}$ represents the growth rate of the $CD_{AR,RR,E,t}$ test statistics constructed by equity returns of the above seven advanced economies at time t and of seven emerging markets at $t-2$.

(S19). $\triangle CD_{AR,RVRV,E,t-1}$ represents the growth rate of the $CD_{AR,RVRV,E,t}$ test statistics constructed by equity returns of the above seven advanced economies at time t and of seven emerging economies at $t-1$.

(S20). $\triangle CD_{AR,RVRV,E,t-2}$ represents the growth rate of the $CD_{AR,RVRV,E,t}$ test statistics constructed by equity returns of the above seven advanced economies at time t and of seven emerging economies at $t-2$.

(S21). $\triangle CD^*_{AR,RR,E,t-1}$ represents the growth rate of the $CD^*_{AR,RR,E,t}$ test statistics constructed by equity returns of the above seven advanced economies at time $t-1$ and of seven emerging markets at t.

(S22). $\triangle CD^*_{AR,RR,E,t-2}$ represents the growth rate of the $CD^*_{AR,RR,E,t}$ test statistics constructed by equity returns of the above seven advanced economies at time $t-2$ and of seven emerging markets at t.

(S23). $\triangle CD^*_{AR,RVRV,E,t-1}$ represents the growth rate of the $CD^*_{AR,RVRV,E,t}$ test statistics constructed by equity returns of the above seven advanced economies at time $t-1$ and of seven emerging economies at t.

(S24). $\triangle CD^*_{AR,RVRV,E,t-2}$ represents the growth rate of the $CD^*_{AR,RVRV,E,t}$ test statistics constructed by equity returns of the above seven advanced economies at time $t-2$ and of seven emerging economies at t.

We then compare the performance of the CD_{AR}-type index with the well-known spillover index of Diebold and Yilmaz (2009) in the out-of-sample forecasting. The construction of the spillover index is based on the vector autoregressive (VAR) model, and its resulting variance composition are further allows for the aggregation of spillover effects across markets, which distills a wealth of information into a single spillover measure. Our strategies to build up the spillover index throughout this paper are based on S1-S2, S5-S6 and S15-S16.

The volatility proxy at daily frequency considered here follows Engle *et al.* (2012) in the following form,

$$\sigma^2_{RV,i,t} = \sqrt{\frac{\pi}{8}}(logP^{high}_{i,t} - logP^{low}_{i,t}).$$

Moreover, to calculate monthly volatility, we use the average sum of square of daily stock returns:

$$\sigma^2_{RV,i,t} = 22 \times \frac{1}{M_{lt}} \sum_{k=1}^{M_{lt}} \gamma^2_{lkt}, \tag{8}$$

where γ_{lkt}^2 is the kth daily stock return of country i in month t, M_{it} is the number of trading days in month t in country i, and the approximate number of trading days in one month is 22.

3.3. Empirical analysis: OLS, pooled OLS (POLS) and PAR-forecasting

Developing an all-encompassing model for the out-of-sample forecasts of international stock returns is not an easy task in international finance. While recently some studies have examined the international market linkage using panel data analysis, only a few have explicitly modeled the interactions among global stock markets. In particular, the exact nature and influence of predictor are still to be determined. Thus, except for the univariate predictive regression with the ordinary least square (OLS) estimation commonly considered in literature as equation (2), we follow Hjalmarsson (2010) to address the out-of-sample forecasts of international equity returns by the pooled panel regression with N cross-sectional units and T time periods.

Let $R_{i,t}$ denote the equity premium for i at time t, the standard panel regression model takes the form

$$R_{i,t} = \alpha_i + \beta_i X_{i,t-1} + u_{i,t} \tag{9}$$

$$u_{i,t} = \lambda_i f_t + \epsilon_{i,t}, \quad i = 1, 2, \ldots, N, \quad \text{and} \quad t = 1, 2, \ldots, T,$$

where $X_{i,t}$ denote the vectors of predictors for $R_{i,t}$, and the error term takes a factor structure with f_t denoting the common time effects that vary over t and λ_i denoting the individual specific effects that vary over i but stay constant over time(e.g., Bai *et al.*(2019)). We assume the idiosyncrvatic component $\varepsilon_{i,t}$ is i.i.d over i and t.

For regression model (9), if $X_{i,t}$ are independent of $\lambda_i' f_t$, then a conventional fixed effects estimator (see Hsiao, 2014) can yield consistent estimator of β_i(Coakley *et al.*, 2006; Sarafidis and Wansbeek, 2012). The model (9) is also considered in Hjalmarsson (2010). He suggests that the pooled estimator of β_i in equations (8) (see Theorem 1 of Hjalmarsson (2010)) can produce more precise estimates than that of individual β_i by the time-series regression when the regressors are nearly persistent and endogenous.

A favorable addition from pooling the data is that the endogeneity problems peculiar to an aggregate time-series in small samples (e.g., Stambaugh, 1999) can be minimized by exploiting heterogeneous cross-sectional information (see Hjalmarsson, 2010). Furthermore, even when the assumption of parameter homogeneity does not hold in the panel, the pooled estimator can be viewed as the average relation of the true relation between the stock return and financial ratios or variables in a global panel, which proves to be useful in interpreting empirical results, and provides a new perspective on issues by current studies that use time series data alone. Hence, we consider equation (9) with or without the addition of the ΔCD_{AR}-family predictors.

Under this framework, we treat the $\triangle CD_{AR}$ predictor as the common factor(f_t) in (8) and consider (i) the stock variance, or (ii) book-to market ratio as the regressor $X_{t,i}$. In view of the estimation procedure of Hjalmarsson (2010), we address the pooled OLS estimator of β_i for equations (8) with or without the ΔCD_{AR}-family predictors. To be more specific, our interest is centered on the pooled OLS estimate (POLS) of slope coefficients β_i (i.e., $\widehat{\beta}_i = \widehat{\beta}_{POLS}$) for each country, because the Stambaugh bias arising from persistent and endogenous regressors can be removed by using pooling the data.

In a comparison, two panel-forecasting frameworks are of concern. We first consider the predictability of the PAR(k) approximation-forecasting (pool autoregressive approximation) proposed by Wang *et al.* (2022), which is inspired by Han *et al.* (2015) that discuss the use of the modified BIC for selecting an order k of a panel autoregressive model (PAR(k)). A simple panel autoregressive (PAR(k)) process by Han *et al.* (2015) in brevity

$$y_{t,i} = \sum_{s=1}^{k} \rho_s y_{t-s,i} + \epsilon_{t,i}, \quad \epsilon_{t,i} \sim iidN(0, \sigma^2), i = 1, 2, \cdots, N; t = 1, \cdots, T, \tag{10}$$

where $\widehat{\rho}(k) = (\sum_{i=1}^{N}\sum_{t=k+1}^{T} X_{k,ti}X'_{k,ti})^{-1}(\sum_{i=1}^{N}\sum_{t=k+1}^{T} X_{k,ti}y'_{k,ti})$ with corresponding error variance estimator $\widehat{\sigma}_k^2 = \frac{1}{n(T-k)}\sum_{i=1}^{N}\sum_{t=k+1}^{T}\widehat{\epsilon}_{k,ti}^2$, $\widehat{\epsilon}_{k,ti} = y_{t,i} - X'_{k,ti}\widehat{\beta}_k$, $X_{k,ti} = (y_{t-1,i},\cdots,y_{i,t-k})'$ and $\rho(k) = (\rho_1,\cdots,\rho_k)'$. Wang *et al.* (2022) extend the above PAR(k) process to develop a PAR-approximation forecasting method for a mixed panel. Without the loss of generality, we further address the following dynamic panel-forecasting predictive procedure, parallelled to the univariate AR(1) predictive model considered in Dai and Kang (2021),

$$y_{t,i} = \rho_0 + \rho_1 y_{t-1,i} + \rho_2 X_{t-1} + \epsilon_{t,i}, \quad \epsilon_{t,i} \sim iidN(0,\sigma^2), i = 1,2,\cdots,N; t = 1,\cdots,T, \tag{11}$$

where (i)$\widehat{\rho}_0$, $\widehat{\rho}_1$ and $\widehat{\rho}_2$ are obtained from the pooled-OLS estimation; (ii) X_{t-1} stands for one of ΔCD_{AR}-family predictors.

We begin the empirical analysis by investigating the predictive ability for each of the ΔCD_{AR}-family predictors and comparing its performance against that of the spillover index and of the PAR-forecasting. Two data frequencies are included. All $\Delta CD_{AR,t}$ -family predictors are constructed in a rolling estimation window scheme with a fixed window size W containing the market information during period from $t - W$ up to t.

3.3.1 Daily prediction

Tables 1.1-1.2 indicates the predictive power of $\triangle CD_{AR}$-family predictors relative to the historical average return method (HA) for both OLS and pooled OLS estimations, respectively. We investigate the predictive power of $\triangle CD_{AR}$-family predictors relative to the historical average return method using daily data from January, 2019 to March, 2021, covering the period of recent Sino-U.S. trade war and COVID-19 pandemic crisis. Rolling window forecasts here are obtained using the rolling estimation windows with window size $T = 63$, which satisfies fund managers' practical consideration in portfolio adjustments. To save the space, we only reports strategies S1-S3, S5-S6, S15-S17, S21, and S24. The rest are available upon request.

The values of R^2_{OS}s generated by OLS and POLS for most reported strategies perform positively and the MSPE-adj test [1] results reveal the convincing forecasting powers of the $\triangle CD_{AR}$-family indices, covering the recent Sino-U.S. trade war and COVID-19 pandemic crisis. All R^2_{OS} values throughout this paper expressed in percentage terms. In particular, relative to the historical average return method, the corresponding highest forecast gains yielded by these $\triangle CD_{AR}$-family predictors with OLS and POLS estimations are 3.75% and 6.3%, respectively. These results appear to meet the consideration of Campbell and Thompson (2008).

For justifying the robust forecasting power of the $\triangle CD_{AR}$-family predictors, their predictive ability of the other sample period from January, 2000 to March, 2021 is also explored. Tables 2.1-2.2 show the forecasting behaviors of the OLS and POLS frameworks, correspondingly. For most strategies, both MSPE-adj tests based on OLS and POLS estimation significantly reject the null hypothesis where there is no difference between forecasts by HA and the $\triangle CD_{AR}$-predictors, More importantly, R^2_{OS} values of most strategies generated by the $\triangle CD_{AR}$-family predictors with the pooled panel framework behave quite good. Many of them display positive values.

The predictive ability of the spillover index based on six strategies for two sample periods is reported in Table 3. All R^2_{OS} values by OLS and POLS estimations are negative, In addition, most resulting MSPE-adj tests does not reject the hull hypothesis.

In this regard, we note that the CD_{AR}-family predictors could help to explain the fluctuation of international stock markets. While most macroeconomics and financial variables at daily frequency are absent, however, returns and volatilities of financial assets are easy to obtain publicly. All the above results confirm the applicability of the CD_{AR}-family predictors for daily return forecasting .

[1] The critical values for the MSPE-adj test are 1.645 and 1.28 at the 5% and 10% significant levels.

3.3.2. Monthly prediction

A. OLS and Pooled OLS estimation

We examine the out-of-sample forecasting performance of the $\triangle CD_{AR}$-family predictors for the international equity premium ranging from Jan, 1992 to March, 2021[2]. The rolling window size for monthly data is fixed at 60, which is the same as the analysis of Campell and Thomspon (2008) and Hjalmarsson (2010). Strategies S1-S3, S5-S6, S15-S21 are of concern. We also consider two competing global factors, the spillover index by Diebold and Yilmaz (2009) and the global market portfolio return by Fama and French (1998). The out-of sample forecasting performance of both factors has not been discussed yet thus far.

Tables 4.1-4.2 reveals the encouraging out-of-sample forecasts of global returns produced by $\triangle CD_{AR}$-family predictors using both univariate (OLS) and pooled panel predictive (POLS) frameworks. The values of R^2_{OS}s for most strategies are positive, and the resulting MSPE-adj tests indicate the rejection of the null hypothesis for both estimation frameworks. When compared to the historical average return method, the highest forecast gains yielded by the selected $\triangle CD_{AR}$-family predictors could reach around 8%, although traditionally 0.5% for monthly data is enough to signal an economically meaningful degree of return predictability. Table 4.3 shows that the influence of the spillover index constructed by the strategy S1, S2, S5, S6, S15 or S16 on the equity premium prediction is not significant. The values of R^2_{OS} generated by the six spillover indices with the OLS estimation are around -0.01% and 0.01%, or much smaller than those by $\triangle CD_{AR}$-family predictors under the same six strategies. The R^2_{OS} values are negative when out-of-sample forecasts are produced by the POLS estimation with six spillover indices.

To deepen the CD_{AR}-family predictors in playing a role of the global factor, we further follow the analysis of Fama and French (1998) and then compare their global market portfolio return's and CD_{AR}-family predictors's predictability in global equity returns. Two trading strategies to form the CD_{AR} predictors in this comparison are $S1$ and $S17$, since the structure of the global market portfolio return is mainly based on financial asset returns. All outcomes are reported in Table 4.4, which displays that the CD_{AR} predictor based on the strategies $S1$ and $S17$ produce better out-of sample forecasts than those by the global market portfolio return in most cases, especially for equity returns of the U.K., Japan, France and Australia. For examples, the top two largest R^2_{OS} values at 8.13% and 7.62% are generated by using POLS and OLS estimations with the CD_{AR} predictor upon the strategy $S17$ and $S1$for the Japanese and Australia equity premium forecasting correspondingly. This evidence strengthens the feasibility of $\triangle CD_{AR}$-family predictors in the out-of-sample prediction of the monthly international equity premium and their roles in playing global factors.

We then investigate whether or not other financial variables could improve the forecast accuracy under the pooled OLS framework based on the analysis of Hjalmarsson (2010). The book-to-market ratio or stock variance here is the variable considered as the regressor X_{t-1} of equation (8). Tables 4.5-4.6 present there exists worse forecasting behaviors when the book-to market or stock variance of each country is included. The results appear to suggest the inferior predictive ability of these two variables in the international stock return forecasting and further provide strong evidence of the $\triangle CD_{AR}$-family predictors on the return forecasting.

B. PAR-forecasting method

Forecasts generated by two PAR-forecasting frameworks (equations (10) and (11)) are displayed in Tables 5.1-5.2, respectively. The lag k selected by the modified BIC criterion for equation (10) is 2. We further consider lag $k = 3$ to examine the robustness of results by lag $k = 2$. Many R^2_{OS}s produced by the equation (10) are smaller than those by equation (11), especially for the cases of Japan, France, Germany and Australia, where all R^2_{OS} values are positive and significant no matter which trading strategy is of

[2] Since our CD_{AR}-family indicators consider emerging markets, however, stock price data for some of them are absent before Jan,1992.

concern. This situation reveals a simple panel autoregressive model performs inferior to a predictive model considering one of the CD_{AR}-family predictors.

3.3.3. Quarterly prediction

Without loss of generality, we also put interest in the out-of sample forecasts by quarterly CD_{AR}-family predictors over the sample period from January, 1992 to March, 2021. From the analysis of Hansen and Timmermann (2015), the rolling window size is fixed at $T/2$, where T represents the number of observations. We display the forecasting performances generated by strategies S1-S3, S5-S8, S15-S17, S19-S22 and S24.

Not surprisingly, Tables 6.1-6.2 present in terms of out-of-sample quarterly stock return forecasting that the CD_{AR}-family predictors have superior performance as well, while the R^2_{OS} values generated by six spillover indices with the OLS estimation are much smaller. The highest forecast gain by the CD_{AR} family predictors is around 10%. A competing index is the Diebold and Yilmaz (2009) spillover index that is constructed from a multivariate vector autoregressive model. Table 6.3 indicates using the spillover indices with the POLS estimation yields inferior out-of-sample forecasts.

In summary, we utilize the growth rate of the CD_{AR}-family indices to generate forecasts of the global equity returns directly and compare their performance with those of historical average return methods at daily, monthly, and quarterly frequencies. Overall results show that these indices exhibit statistically and economically significant out-of-sample predictive power for the global equity returns. In addition, a panel forecasting model with one of $_{AR}$-family predictors outperforms a simple panel autoregressive model.

3.4. Explanation of empirical results

The better predictive power of the ΔCD_{AR}-type predictor over the spillover index (S) is due to the differences in constructing the indices. The spillover indices are built from a VAR model. Although theoretically, a multivariate process can capture the outcome better than a univariate process. In practice, neither the model nor the parameters of a multivariate process are unknown. They have to be constructed and estimated from finite sample observations (e.g., Box and Tiao, 1977). The shortage of degrees of freedom and multicollinearity , etc, often lead to imprecise inference and less accurate predictions than predictions based on modeling univariate process (e.g., Andersen, *et al*, 1974). Furthermore, a multivariate time series model can be transformed into a univariate process (e.g., Zellner and Palm, 1974; Wallis, 1977), and the empirical identification and estimation of a univariate process (say an AR or a MA process) is simple to implement. Moreover, if two series are correlated or uncorrelated, their prewhitened processes still remains correlated or uncorrelated [3]. Moreover, the statistical distribution of the CD_{AR} statistics follows a standard normal distribution (see Wang *et al.*, 2021), and the ΔCD_{AR}-family predictors display the identical and independent distribution. Based on above merits of the ΔCD_{AR}-family predictors, When these predictors are considered in a predictive regression, the statistical inference of this predictive regression still satisfies the classical regression assumptions, which could lower the possibility of yielding misleading estimates of slope coefficients.

Second, Table B in Appendix presents behaviors of the AR-and VAR-filtered residuals with the AIC model selection criterion when considering the simulation design in Table A. We use the Ljung-Box test to examine whether or not both filtered residuals satisfy identical and independent distribution (I.I.D). Simulation results indicate the rate of rejecting I.I.D for the VAR-filtered residuals is higher than that for the AR-filtered residuals. Furthermore, the lag length of the VAR approximation of a mixed panel is quite important. Even a lag length k is chosen by the AIC criterion, this k cannot enable each VAR-filtered residual series to follow the I.I.D distribution. Nevertheless, each lag length k of the AR approximation selected by the AIC criterion for each series of a mixed panel could garantee each AR-filtered residual series to satisfy the I.I.D distribution. That implies the spurious correlation induced by the VAR-filtered residuals could

[3] Please refer to the explanation on page. 755 of Wang *et al.*, 2021.

occur with high possibility. Table C reports the averge selected lags for the AR-and VAR-filtering procedure and indicate the instability of lag selection for the VAR-filtering one. It shows that this CD_{AR}-type index is more informative, noise-reducing and flexible compared to the spillover index based on the VAR framework, because it is not affected by the number of N units. As a consequence, ΔCD_{AR}-family predictors generate significantly better out-of sample forecasts.

Finally, compared to the the global market return consisting of a great of firm returns from different countries, our ΔCD_{AR}-family predictors are easy to construct, since return and volatility data of international asset markets are simple to yield from public resources. In addition, the number of financial assets considered in constructing the new proposed predictors are not many, such as trading strategy S1, which includes seven main national stock indices only. Most importantly, our predictors could avoid the issue of how to select the optimal weight in forming portfolio, because the inefficiently selected weight could lead to biased out-of-sample forecasts.

4. Out-of-sample Forecasts of U.S Equity Premium

We further demonstrate the usefulness of incorporating our family of CD_{AR}-type market indices into the traditional predictive models for forecasting U.S. equity premium. We report the data and model considered in this section and empirical results in section 5.

4.1 Data and variables

Motivated by an influential work by Goyal and Welch (2008) that demonstrates a list of U.S. country-specific variables failed at the out-of-sample prediction, we investigate whether global predictors, i.e., $\triangle CD_{AR}$-family predictors, help to explain the time-series variation in the U.S. stock returns by using popularly used predictive methods. This focus parallels the emphasis on the question of whether a world market factor (or a global risk factor) can substantially affect expected return estimates, being consistent with the arguments in Fama and French (1998), Liew and Vassalou (2000) and Griffin (2002).

The primary goal of this analysis is not just to better understand empirical facts, but also to properly account for relevant variables. In the last two decades, academics and practitioners have devoted remarkable attention to predicting the equity premium. To date, two groups of factors are identified as predictors of the equity premium in current literature, which are respectively financial ratio variables and macroeconomics factors. We list our considered predictors in our study as follows:

(Vi) 14 variables from Welch and Goyal (2008): dividend-ratio (d/p), default yield spread (dfy), net equity expansion (ntis), treasury-bill rate (tbl), long term yield (lty), earing price ratio (e/p), book-to-market ratio (b/m), term spread (tms), long term return (ltr), default return spread (dfr), inflation (infl), dividend payout ratio (d/e), dividend yield (d/y), and stock variance (svar).

(Vii) 6 economic state (ES) variables: the growth rate of money supply (MS, M_2 money stock), the growth rate of industrial production index (IPI), the growth rate of non-farm payroll (NFP), the growth rate of economic policy uncertainty (EPU), the growth rate of unemployment rate (UEM), and the growth rate of foreign domestic investment (FDI).

(Viii) The CD_{AR}-family predictors constructed by 24 strategies.

Data concerned in (Vi)-(Viii) are on a monthly basis ranging from January, 1992 to March 2021 as well.

4.2 Prediction models considered for the equity premium

4.2.1 Forecast combination

Over the last few decades, model averaging or forecast combination has gained attention in reducing the model uncertainty and instability (e.g. Bates and Granger, 1969; Stock and Watson, 2004; Aiolfi and Timmermann, 2006 ; Hansen, 2007; Rapach *et al.*, 2010; Hsiao and Wan, 2014). The combination of forecasts may be superior to each of the constituents, when models do not draw on a common information pool, the forecasts are of an essentially different type and nature, or when models are differentially susceptible to structural breaks (e.g., Clements and Hendry, 1998; Timmermann, 2006). That implies the forecast combinations could offer diversification gains, which make it encouraging to combine individual forecasts rather than relying on forecasts from a single model. Particularly, due to diversification gains, even when the best model could be identified at each point in time, combination may still be a convincing strategy, although its success will depend on the combination weights.

A well-known puzzle of forecast combination existing in forecasting literature is that a simple equally weighted average often dominate more refined combination schemes aimed at estimating the theoretically optimal combination weights in empirical applications (see Timmermann, 2006; Hsiao and Wan, 2014), other than the conditional forecast combination strategies (see Aiolfi and Timmermann, 2006). In other words, simple averaging of all predictive could be a robust way to generate prediction in finite sample. As a consequence, we examine the predictive ability of the $\triangle CD_{AR}$-family predictor with the simple average forecast combination and conditional forecast combination strategies (CFCS). Following the analysis of Aiolfi and Timmermann (2006), we consider the combination of forecasts from pre-selected quartiles (hereafter, PSQ) with two conditional combination strategies (or combination weights), i.e., previous best (PB), equal-weighted (EW). See more details in Aiolfi and Timmermann (2006).

Although the simple average method can generate good forecasts, some or all predictive models could be biased as noted by Hsiao and Wan (2014). We thus adopt a mean corrected simple averaging (MCSA) suggested by Hsiao and Wan (2014).

4.2.2 The three-pass regression filter (3PRF)

The three-pass regression filter (3PRF) by Kelly and Pruitt (2015) is an approach to forecasting time series using many predictor variables. The 3PRF consolidates the cross-section according to covariance with the forecast target, being in contrast to principal component regression (PCR), which combines the the cross section according to covariance within the predictors. The advantage of the 3PRF is to reduce the dimension of predictive information, since the number of predictors N may be large and number near or more than available time series observations T, which makes OLS problematic.

In order to make forecasts of a target variable, the 3PRF uses proxies. These proxies are variables, driven by target-relevant factors in particular, which are always available from the target and predictor themselves, but may alternatively be supplied to the econometrician on the basis of economic theory. Furthermore, the target could be a linear function of a subset of the latent factors plus some unpredictable noise. On the other hand, the optimal forecast therefore comes from a regression on the true underlying relevant factors. The procedures of the 3PRF are listed in Tables 1 and 2 of Kelly and Pruitt (2015). All detailed discussions are listed in Kelly and Pruitt (2015) as well.

4.2.3 Ridge regressions

Ridge regression obtains parameters from a linear regression model subject to a penalty term

$$\widehat{\beta}_{\lambda} = argmin_{\beta}\left(\sum_{t=1}^{T-1}(R_{t+1} - x_t'\beta)x^2 + \lambda\sum_{j=1}^{K}\beta_j^2\right).$$

Ridge regression shrinks the coefficients of correlated predictors toward each others. On the analysis of Inoue and Killian (2008) and Gargano and Timmermann (2014), a range of values of λ, $\lambda \in \{0.5, 5, 10, 20, 50, 100, 150, 200, 1000\}$ are considered in this study. The only parameter that has to be chosen under the ridge approach is λ, regulating the amount of shrinkage imposed on the regression coefficients.

When $\lambda \to \infty$, $\widehat{r}_{t+1|t} \to \frac{1}{T}\sum_{j=1}^{T} r_j$, the ridge forecast simply converges to the sample mean. For a given value of λ, the ridge forecasts are calculated as

$$\widehat{r}_{t+1|t}^{RIDGE} = x_t' \widehat{\beta}_{\lambda}.$$

4.2.4 LASSO

Retaining the features of both model selection and ridge regression, least absolute shrinkage and selection operator (LASSO) by Tibshirani (1996) shrinks some coefficients and set others to zero. If some of the powerful predictors are highly correlated, LASSO is indifferent to very correlated predictors and tends to pick one and throw away the rest. In other words, as a continuous shrinkage method, the LASSO usually provides the improvement on the predictive accuracy due to the bias-variance tradeoff (see Tibshirani, 1996; Li and Tsiakas, 2017; Zhang *et al.*, 2019).

Statistically, lasso forecasts of equity returns are given as

$$\widehat{r}_{t+1}^{LASSO} = \widehat{\beta}_0 + \sum_{i=1}^{N} \widehat{\beta}_i x_{i,t},$$

where

$$\widehat{\beta}_{\lambda} = argmin_{\beta} \left(\frac{1}{2(t-1)} \sum_{t=1}^{T-1} (r_{t+1} - \widehat{\beta}_0 - \sum_{i=1}^{N} \widehat{\beta}_i x_{i,t})^2 + \lambda \sum_{j=1}^{N} \|\beta_j\| \right).$$

Our LASSO implementing procedure is related to Li and Tsiakas (2017) and Zhang *et al,* (2019). $\widehat{\beta}_{\lambda}$ is the shrinkage estimator of regression coefficients in the lasso, which are estimated by the data available up to month t, and λ is the nonnegative regularization parameter serving as the penalty function of β. The estimation algorithm for determining the LASSO shrinkage factors are listed in Zhang *et al.* (2019). A grid of value $\lambda \in \{0.003, 0.007, 0.01, 0.02, 0.03, 0.05\}$ is considered.

4.2.5 Elastic net

Various flexible generalizations of the LASSO are proposed recently, for examples, adaptive Lasso of Zou (2006) or Elastic Net of Zou and Hastie (2005) and Zou and Zhang (2009). Among them, the Elastic Net has been studied in economic literature and plays a role as the useful compromise between ridge and Lasso (see Korobilis, 2013; Elliott et al., 2013; Zhang et al., 2019). since it could avoid the extreme solutions.

The Elastic Net forecasts are calculated as

$$\widehat{r}_{t+1}^{NET} = \widehat{\beta}_0 + \sum_{i=1}^{N} \widehat{\beta}_i x_{i,t},$$

where

$$\widehat{\beta}_{\lambda} = argmin_{\beta} \left(\frac{1}{2(t-1)} \sum_{t=1}^{T-1} (r_{t+1} - \widehat{\beta}_0 - \sum_{i=1}^{N} \widehat{\beta}_i x_{i,t})^2 + \lambda \sum_{j=1}^{K} ((1-\alpha)\beta_i^2 + \alpha|\beta_j|) \right).$$

is a positive constant strictly between 0 and 1. In particular, the elastic net reduces to the lasso as $\alpha = 1$ and to the ridge regression when α shrinks toward to 0. Similarly, the elastic net picks one variable from a data pool and ignore the rest of correlated predictors. We also use the estimation algorithm steps provided in Zhang *et al.* (2019). We set α =0.3, 0.5 and 0.9 for the elastic net in our empirical analysis, while a grid of value $\lambda \in \{0.003, 0.007, 0.01, 0.02, 0.03, 0.05\}$ is of concern.

4.2.6 Subset regression approach

The subset regression approach introduced by Elliott *et al.* (2013), which outperforms other multivariate approaches empirically such as the ridge, LASSO, and Elastic net regressions has been documented by Elliott *et al.*(2013) and Gargano and Timmermann (2014). In fact, these multivariate regressions could produce good out-of-sample forecasts, because the effects of estimation errors on the forecasts could be adjusted.

The subset regression approach considers equally-weighted combinations of forecasts constructed by all possible models and contains a particular subset of the predictor variables. Suppose that there are K different variables included in the set of potential predictor variables. Each subset has a specified number of regressors $k \leq K$. Two steps are considered to implement this approach including (i) we estimate regressions based on a particular subset of the predictors; (ii) we then average the results across all $k \leq K$ dimensional subset of the regressors. The details of this approach are reported in Elliott *et al.* (2013).

5. Empirical analysis and discussion

5.1. Welch and Goyal (2008) Data, macroeconomics variables and spillover indices

To address the robustness analysis on the predictive power of the $\triangle CD_{AR}$-family predictors, we consider to use an extended monthly dataset of Welch and Goyal (2008) up to March, 2021. We follow the analysis of Welch and Goyal (2008) to consider 14 financial and macroeconomics predictors (d/p, e/p, b/m, svar, infl, tbl, lty, dfy, ntis, Itr, d/y, dfr, d/e, tms)[4] and the continuously compounded returns on S&P 500 index, including dividends minus the prevailing short-term interest rate.

Table 7 demonstrates the out-of-sample forecasts of excess returns by 20 variables in total (14 variables from Welch and Goyal (2008) and 6 economics state variables) for the period covering from January, 1992 to March, 2021. Apparently, except for b/m, d/e and uem variables, the rest 17 predictors produce negative R^2_{OS}s as well as accept the null hypothesis where there exist no better predictive power of these variables than the historical average return method.

5.2. Simple average forecast combination

We investigate forecasting results by a simple average forecast combination concerning the aforementioned 14 variables of Welch and Goyal (2008), 6 economic stat variables, 6 spillover indices and $\triangle CD_{AR}$-family predictors (strategies S1-S24). Combination strategies to explore the predictive ability of the $\triangle CD_{AR}$-family predictors are considered as follows.

(Sa) FM(WG) denotes the forecast combination scheme combining all 14 variables of Welch and Goyal (2008).

(Sb) FM(All1) denotes the forecast combination scheme combining all 24 strategies in Groups A-C and all 14 variables of Welch and Goyal (2008).

(Sc) FM(All2) denotes the forecast combination scheme combining 4 strategies of Group A and all 14 variables of Welch and Goyal (2008).

(Sd) FM(All3) denotes the forecast combination scheme combining 10 strategies of Groups B and all 14 variables of Welch and Goyal (2008).

(Se) FM(All4) denotes the forecast combination scheme combining 10 strategies of Groups C and all 14 variables of Welch and Goyal (2008).

(Sf) FM(All5) denotes the forecast combination scheme combining all 24 strategies in Groups A-C.

(Sg) FM(GA) denotes the forecast combination scheme combining 4 strategies of Group A.

(Sh) FM(GB) denotes the forecast combination scheme combining 10 strategies of Group B.

(Si) FM(GC) denotes the forecast combination scheme combining 10 strategies of Group C.

[4] Definitions of the 14 predictors are given in Welch and Goyal (2008). They are the dividend-ratio (d/p), default yield spread (dfy), net equity expansion (ntis), treasury-bill rate (tbl), long term yield (lty), earing price ratio (e/p), book-to-market ratio (b/m), term spread (tms), long term return (ltr), default return spread (dfr), inflation (infl), dividend payout ratio (d/e), dividend yield (d/y), stock variance (svar).

(Sj) FM(R) denotes the forecast combination scheme combining 11 strategies of return interactions (strategy S1 of Group A; strategies S5, S7-S8 and S11-S12 of Group B; strategies S15, S17-S18 and S21-S22 of Group C).

(Sk) FM(Vol) denotes the forecast combination scheme combining 11 strategies of volatility interactions (strategy S2 of Group A; strategies S6, S9-S10 and S13-S14 of Group B; strategies S16, S19-S20 and S23-S24 of C).

(Sl) FM(All6) denotes the forecast combination scheme combining 11 strategies of the combination FM(R) and all 14 variables of Welch and Goyal (2008).

(Sm) FM(All7) denotes the forecast combination scheme combining 11 strategies of the combination FM(Vol) and all 14 variables of Welch and Goyal (2008).

(Sn) FM(SI) denotes the forecast combination scheme combining 6 spillover indices constructed by strategies S1-S2, S5-S6 and S15-S16.

(So) FM(MV) denotes the forecast combination scheme combining 5 macroeconomics variables considered in (Vii).

(Sp) FM(All8) denotes the forecast combination scheme combining all 14 variables of Welch and Goyal (2008), all cases in Group A-C, six strategies of the combination FM(SI) and five macroeconomic variables of the combination FM(MV).

Table 8 presents results by the equally-weighted forecast combination method (EWFG) (or simple average method (SA)) for strategies (Sa)-(Sp). When we consider the simple average method using all 14 variables in Welch and Goyal (2008) (FM(WG) combination) or 5 macroeconomics variables (FM(MV) combination), even the values of R^2_{OS} of both strategies are positive positive (0.49% and 0.09%), and the MSPE-adj test does not reject the null hypothesis for both of them, which implies combining forecasts by these 14 variables or 5 macroeconomics variables is insignificantly different from those by the historical average return method. However, when simply combining individual forecasts generated by combinations FM(All5), FM(GA), FM(GB), FM(GC), FM(R) or FM(Vol), each R^2_{OS} is positive and larger than those by combinations FM(WG) or FM(MV). The MSPE-adj test shows the significant predictive power of these combinations. More importantly, for combinations FM(All1)-FM(All4) and FM(All6)-FM(All7), where the combination includes $\triangle CD_{AR}$-family predictors and 14 variables of Welch and Goyal (2008), the values of R^2_{OS}s generated by these combinations see significant improvement when compared to that by FM(WG) combination and the resulting MSPE-adj test also performs significantly. In particular, the R^2_{OS} produced by the combination FM(All8) reaches 1.46%, a remarkable improvement on that by FM(WG), FM(MV) or FM(SI), where the combination FM(SI) even generates a negative value of R^2_{OS}. These findings demonstrate the substantially marginal impact of the CD_{AR}-family predictors on the S&P equity premium.

In comparison with results by the simple average method, the MCSA method produces more accurate forecasts for most strategies. For examples, the R^2_{OS} and MSPE-adj testing results by the MCSA methods considering combinations FM(GA), FM(GB), FM(GC), FM(All5), FM(R) or FM(Vol) perform much better and more significantly. Similarly, MCSA forecasts from combinations FM(All1)-FM(All4) and FM(All6)-FM(All7) have better R^2_{OS} and MSPE-adj performances as compared to a negative R^2_{OS} by the combination FM(WG). In addition, the R^2_{OS} value by MCSA forecasts with the combination FM(All8) is 0.67%, which is even better than those by the combinations FM(MV) and FM(GW) at -2.12% and -0.74%, respectively.

In brief, all findings in Table 8 illustrate a fact that the forecast accuracy will improve as we incorporate $\triangle CD_{AR}$-family indices into forecast strategies. In other words, the $\triangle CD_{AR}$-family indices indeed explains the fluctuation of the equity returns.

5.3. Conditional forecast combination strategies

We display results from the pre-selected quartile combinations using two combination weights in Table 9. Table 8 reveals no matter which combination weight is used, the most forecasting outcomes resulting from combination strategies FM(All5)-FM(All8), FM(GA)-FM(GC), FM(R), and FM(Vol) remarkably outperform those by combination strategies FM(WG) and FM(MV). Among them, the value of R^2_{OS} generated by the PSQ-PB approach with combination strategy FM(Vol) is the largest at 2.3%. Moreover, the resulting MSPE-adj tests reject the null hypothesis significantly. It thus appears that the CD_{AR}-family predictors could improve the forecast accuracy of U.S. stock returns.

5.4. The three-pass regression filter

We present the predictive performances of the S&P equity premium by the three-pass regression filter (3PRF) method with various forecasting strategies in Table 10. The forecasting strategies are organized as follows.

(Sa') 3PRF(WG) denotes the 3PRF approach considering 14 variables in Welch and Goyal (2008).

(Sb') 3PRF(WG+S) denotes the 3PRF approach considering 14 variables in Welch and Goyal (2008) and one of the strategies S1-S24 of Groups A-C.

(Sc') 3PRF(WG+SI) denotes the 3PRF approach considering 14 variables in Welch and Goyal (2008) and one of six spillover indices constructed by strategies S1-S2, S5-S6, and S15-S16.

Table 10 apparently reveals most ΔCD_{AR}-type predictors could improve the forecast accuracy quite well, especially for strategies 3PRF(WG+S1), 3PRF(WG+S2), 3PRF(WG+S5), 3PRF(WG+S6), 3PRF(WG+S7), 3PRF(WG+S8), 3PRF(WG+S10), 3PRF(WG+S11), 3PRF(WG+S12), 3PRF(WG+S15), 3PRF(WG+S16), 3PRF(WG+S19), 3PRF(WG+S20), 3PRF(WG+S21) and 3PRF(WG+S24), because the aforementioned strategies can generate higher values of R^2_{OS} and MPSE-adj test statistics, when compared to those by the strategy 3PRF(WG), i.e., $R^2_{OS} = 13.84$ and MSPE-adj test statistics = 3.70. In addition, values of R^2_{OS}s by all strategies considered in Sc' (3PRF(WG+SI1), 3PRF(WG+SI2), 3PRF(WG+SI5), 3PRF(WG+SI6), 3PRF(WG+SI15), and 3PRF(WG+SI6)) are not superior to those by combination strategies mentioned earlier. Among the above strategies, relative to the historical average return method, the largest forecast gain could be 13.84 % where the strategy 3PRF(WG+S19) is of concern.

5.5. The ridge regression

Table 11 reports results from the ridge regression. Not surprisingly, all values of R^2_{OS} are positive for combinations FM(GA), FM(GB), FM(GC), FM(R), FM(SI) and FM(Vol) and their corresponding MPSE-adj tests reveal significance, no matter what λ is. On the contrary, the R^2_{OS} measures for combinations FM(WG) and FM(MV) behave quite poorly, being huge negative values. This situation subsequently leads to the negativeness of R^2_{OS} for FM(All2)-FM(All4), FM(All6)-FM(All8). However, relative to the R^2_{OS} performance by the combination FMWG) the R^2_{OS} results of these strategies improve substantially. This finding further shows the usefulness of ΔCD_{AR}-type predictors under the ridge regression framework.

5.6. LASSO and Elastic net

Tables 12 and 13.1-13.3 reveal the forecasting performances by LASSO and Elastic net approaches, respectively. From Table 11, we note that for strategies FM(GA)-FM(GC), FM(R) and FM(Vol), the computed R^2_{OS}s perform positive when $\lambda \geq 0.007$, while those by FM(WG), FM(MV) and FM(SI) are positive only as $\lambda \geq 0.3$. Furthermore, combining information from 14 variables and more of the CD_{AR}-family predictors produces superior equity premium as $\lambda \geq 0.03$.

The out-of sample forecasts by the Elastic net methods with different αs of concern are available upon request, however, we only present the its forecasting outcomes at $\alpha = 0.3$, 0.5, 0.9 here. Table 12 evidently illustrates for most combination strategies that at the same level of λ, when α increases, R^2_{OS} values become larger. Similar to the forecasting performance by the LASSO method, the Elastic net approach with combination strategies, such as FM(GA)-FM(GC), FM(R) and FM(Vol), could produce convincing forecasts to those by combination strategies FM(WG), FM(SI) and FM(MV). Moreover, when incorporating one of the

CD_{AR}-family predictors into Welch and Goyal's predictive variable set, the forecasting results outperforms those by the FM(WG) combination strategy.

5.7. Complete subset regression

The out-of-sample forecasts by the complete subset regression with combination strategies FM(WG), FM(All1)-FM(All4) and FM(SI)are indicated in Table 14. Results are consistent with those in Elliott *et al.* (2013) in which the R^2_{OS} declines with the rise of k. We only report the results as $k = \{1, cdots, 14\}$. The results for other values of ks are reliable on request. Similarly, as long as the CD_{AR}-family predictors are combined with the set of 14 Welch and Goyal (2008) 's variables, the improvement on forecast accuracy are reasonably significant. When $k = 2$, the R^2_{OS}s generated by the strategies FM(All1)-FM(All4) are more encouraging than that by the strategy FM(WG). Particularly, the value of R^2_{OS} of the FM(A112) is 1.86%, which performs best over other strategies. In such doing, the substantial forecasting performances of $\triangle CD_{AR}$-family predictors are verified.

5.8. Short summary

We summarize all the above results as follows: First, a reliable predictor is necessary. Results presented in this section provide strong evidence on showing that the $\triangle CD_{AR}$-family predictor exhibit statistically and economically significant out-of sample forecasts for the monthly U.S. equity premium, as compared to the list of finance and macroeconomics variables in Welch and Goyal (2008) or spillover indices by Diebold and Yilmaz (2009, 2012, 2014). It also demonstrates that a suitable world factor cannot be ignored when doing the out-of-sample forecasts of U.S. equity returns. For examples, under the forecast combination, LASSO , or Elastic net predictive framework, it appears that out of sample forecasts by the combinations FM(GA)-FM(GC), FM(R) or FM(Vol) are more precise than those by FM(WG), FM(SI) and FM(MV) at the same level of λ or α. Such a consequence supports the claim of Welch and Goyal (2008) that it is crucial to have some meaningful and information predictor in doing the out-of-sample prediction of U.S. equity returns. The same phenomenon is also clarified by the rest considered methods. In this regard, this research successfully models the prediction of U.S. equity returns based on new predictors which have not been thoroughly investigated in the past.

Second, in terms of the R^2_{OS} measure, the 3PRF combing with one of several combinations of strategy (Sb') performs quite well. Among them, the largest one is 13.84 for the combination 3PTF(WG+S19), surpassing all other results in this study. Thus, a predictive procedure containing the 3PTF approach and combination Sb', especially the strategy (WG+S19) could be a suitable tool in terms of doing the out-of sample forecasts of U.S. stock returns. Nevertheless, a list of variables in Welch and Goyal (2008) is only at the monthly or quarterly frequency. The $\triangle CD_{AR}$-family predictor could bridge the gap. The $\triangle CD_{AR}$-family predictor is flexible relative to most finance, accounting and economics variables that are only available at the monthly, quarterly and annually frequencies, because it could be constructed by returns and volatilities of financial assets at high or low frequencies and these data resources are not difficult to obtain. In other words, the $\triangle CD_{AR}$-family predictors are useful for daily return forecasting. When speaking of forecasting daily equity returns, a conventional univariate predictive regression or a pooled panel predictive framework with one of the $\triangle CD_{AR}$-family predictors could be a viable candidate without any doubts.

5.9. Discussion

In view of all empirical results, several merits of the $\triangle CD_{AR}$-family predictors are worth pointing out here. First, during the years in our sample of 1992 to 2021, many challenges occurred, which are described as continuous evolutions, crises, and bursts. Examples include globalization, the rise of mutual and hedge funds, the development of electronic technology, 2007-2008 subprime crisis, European debt crisis, and the recent Sino-U.S. trade war and COVID-19 pandemic crisis. When compared to the historical average return method, most $\triangle CD_{AR}$-family predictors perform encouragingly over all considered predictive models in predicting the out-of-sample stock returns. The convincing advantage of $\triangle CD_{AR}$-family predictors is that in real time, the $\triangle CD_{AR}$-family predictors could capture the pattern of the growth rate of global capital flows or market interactions, since they are in a dynamic or time-varying framework in order to further interpret the fluctuations and interactions among equity and hedging asset markets. To be more specific, the time series of each $\triangle CD_{AR}$-family predictor is constructed in the rolling window scheme, that implies consecutive observations of this time series could contain more connected market information and ignore the model instability issue. In particular, not only does the CD_{AR}-type index detect the upward and downward trends of the market integration precisely, but it also characterizes the timing and nature of global events or financial crises. Hence, the $\triangle CD_{AR}$-family predictors are informative, meaningful, and powerful and consistent with the claim of Welch and Goyal (2008). This scenario further demonstrates that average stock returns could be predicted through publicly available information or data resources, such as the correlations among returns or volatilities of international financial assets, supporting the assertion of Fama (1970). More importantly, the $\triangle CD_{AR}$-family predictors are easy to implement and generate appealing results of forecasts in comparison to the historical average return method and simple time series and panel predictive models.

Second, the largest R^2_{OS} value appears when the 3PRF predictive model is employed with a list of variables in Welch and Goyal (2008) and one of the $\triangle CD_{AR}$-family predictors (the combination 3PTF(WG+S19)) to do the out-of sample prediction of the U.S. equity premium. In practice, the values of R^2_{OS}s calculated by most strategies of Sb' (3PRF(WG+S)) are promising. On the analysis of the 3PRF predictive framework, we note that the main idea of this method is to utilize the covariance structure between the predictors and target variable (i.e., stock return). By doing this, relative to the R^2_{OS} by the strategy Sa'(3PRF(WG)), the increase in R^2_{OS} value by one of the $\triangle CD_{AR}$-family predictors provides further evidence on the desirable predictive ability of the CD_{AR}-family predictors for the out-of sample forecasts of stock returns. That implies that global factors, the $\triangle CD_{AR}$-family predictors, are necessary to the out-of-sample prediction of the U.S. equity premium. For most CD_{AR}-family predictors, as long as one of them is incorporated into any aforementioned predictive models, the resulting out-of-sample forecasts become more accurate than those without considering the CD_{AR}-family predictors. In line with our findings, combining information from both the CD_{AR}-family predictors and macroeconomics and financial ratio variables produces superior equity premium. Moreover, the marginal impacts of the $\triangle CD_{AR}$-family predictors on U.S. equity premium are remarkable. This finding illustrates that U.S. financial or macroeconomics variables alone are obviously not rich enough to capture movement in international markets simply, because the capitals in the U.S. stock market may move internationally. Apparently, having a reliable world predictor helps to explain the variation in U.S. stock returns. Our study provides evidence on the improvement of U.S. stock return forecasting by world factors, consistent with the assertion of Fama and French (1998) and Liew and Vassalou (2000).

Finally, several issues discussed in the current literature could be answered through using the $\triangle CD_{AR}$-family predictors. First, combining the previous two points, the fact that a predictor based on financial theorems could increase predictability of aggregate stock returns is noted. This fact is also in marked contrast to findings in Nelson (1972) and Welch and Goyal (2008), i.e., a simple econometric model with reliable and meaningful predictors could outperform a simple time series model. In other words, there exists a need for predictors based on economics or finance theories in addition to the historical average returns. Second, empirical results show that using $\triangle CD_{AR}$-family predictors may avoid the practices proposed in Campbell and Thompson (2008) and Pettenuzzo *et al.* (2014), where they impose restrictions on return forecasting models[5].

[5] Campell and Thompson (2008) impose the restrictions on the signs of coefficients in return forecasting models and truncate equity premium forecasts at zero. Pettenuzzo *et al,* (2014) further modify the posterior distribution of the parameters of the predictive return regression by imposing two economics constraints on time series forecasts of the equity premium, including non-negative equity premia and bounds on the conditional Sharpe ratio.

Third, the promising out-of-sample forecasts by the $\triangle CD_{AR}$-family predictors are due to two reasons at least. One is that it avoids the apparent spurious phenomenon of the predictability caused by highly persistent variables (e.g., Campbell and Yogo, 2006; Campbell and Thompson, 2008; Kostakia *et al.*, 2014)[6], because these predictors are resulted from the growth rate of the AR-filtered version of CD test which could reduce the degree of persistence of the data and spurious correlations. The other one is that the estimated bias resulted from the correlation between the regressor and its resulting error terms of the predictive regression as considered by Stambaugh (1999) no longer presents, since the computed correlations between $\triangle CD_{AR}$-family predictors and their resulting error terms of the predictive regressions are quite low, i.e., 0.02 at most. [6] In brief, our $\triangle CD_{AR}$-family predictors do not display nearly persistence and strongly endogenous.

6. Forecasting Performance in Recessions and Expansions

A massive amount of literature (e.g., Rapach *et al.*, 2010; Henkel *et al.* 2011, Neely *et al,*, 2014; Gargano and Timmermann, 2014; Wang *et al.*, 2018; Dai and Kang, 2021) have shown that the predictability of stock returns is stronger during slow growth or recessionary states of the economy. Following the analysis of Gargano and Timmermann (2014), to identify recessions, an indicator variable proposed by Stock and Watson (2010), lining up well with the NBER recessions determined ex-post, is considered to explore the predictability of the CD_{AR}-family predictors in different economy states. This indicator variable is based on the unemployment rate recession gap, given as

$$\widehat{U}_t = \begin{cases} 1, & \text{if} \quad \mathrm{U}_t^* = U_t - \frac{1}{36}\sum_{s=1}^{36} U_{t-s} > 0.5, \\ 0, & \text{otherwise.} \end{cases}$$

where U_t is the (vintage) monthly unemployment ratio.

Likewise, we use the same evaluation measure as the equation (10) on page 840 of Gargano and Timmermann (2014). Relative to the historical average return method (HA, the constant benchmark), the positive and significant value of the slope coefficient illustrate the univariate predictive model could generate more accurate forecasts during recessions than during expansions.

Tables 14 and 15 display the ratios of the mean squared forecast errors (MSFEs) of univariate and 3PRF prediction models for monthly returns in recessions versus expansions ($\frac{MSFE_{Rec}}{MSFE_{exp}}$), respectively All results are undertaken for the monthly data, because the recession indicator is less well-defined at the quarterly and annual horizons. Several interesting facts emerges, including: (1) all values in Tables 14-15 perform above 1. It illustrates the predictive accuracy of the ΔCD_{AR}-family predictors tends to be strongly better during expansions than recessions. This finding is in marked contrast to the result in the current literature (see Gargano and Timmermann, 2014; Neely *et al.*, 2014), which demonstrates the commodity and stock returns are most predictable during recessions; (2) The notations "*", "**" , and "***" denote as the statistical significance at the 10%, 5%, and 1%, correspondingly, based on the evaluation criterion of Gargano and Timmermann, (2014), i.e., the equation (10) on page 840 of Gargano and Timmermann, (2014). This criterion examines that relative to the historical average return benchmark (HA), statistical significance measures whether the average squared forecast error of a competing predictive model is significantly lower in recessions. Results provide evidence on the fact that even during recessions, the forecasts by ΔCD_{AR}-family predictors outperform those by the HA method; and (3) the considered ΔCD_{AR}-family predictors serve as world factors, since they are constructed by the cross-sectional correlations among international markets. Nevertheless, by the " wake-up" hypothesis (see Bekaert *et al.*, 2014), we note that markets

[6] We examine the time series properties of the $\triangle CD_{AR}$-family predictors by the KPSS test. Evidence indicates all $\triangle CD_{AR}$-family predictors perform I(0) processes. Relevant results are available on request.

[6] Results are available and on request as well.

tend to focus more on country-specific characteristics during the crisis. The wake-up call hypothesis is one primarily proposed contagion channels by Goldstein (1998), which addresses international investors will reassess creditworthiness of borrowers and country specific fundamentals. This implies that the world factors can only have little impact on domestic equity returns during recessions. Moreover, the CD_{AR}-type indicator possesses a market integration index and the characteristics of an early warning indicator to an incoming global event, which indicates a significantly increasing pattern until a local peak where a global event or crisis arrives with high possibility (see Wang *et al*, 2021). To be more specific, as illustrated in Wang *et al.*(2021), the CD_{AR}-type indicators increase after a crisis until the next crisis comes. Clearly, it could explicitly capture the market behaviors during expansion. For aforementioned three reasons, the stock return predictability produced by the ΔCD_{AR}-family predictors is closely linked to the economic cycle and accesses stronger predictive accuracy during expansions. This stylized fact supports the practical value of using ΔCD_{AR}-family predictors in practitioners' tool box.

7. Concluding remark

Based on the idea of Fama and French (1998) and Griffin (2002) that under the market integration assumption, there should be one set of risk factors which explain expected returns for all countries, we suggest a family of market integration indices to summarize the strength of correlations among different participants of different markets. These indices are based on economics and finance theories as predictors that have not been thoroughly investigated in the past. Our empirical findings confirm the usefulness of the new predictor since (i) compared to two-well known global market indices by Diebold and Yilmaz (2009) and Fama and French (1998) this index provides an alternative in the out-of-sample forecasts of global equity returns. In line with our empirical findings, combing information from both the $\triangle CD_{AR}$-family predictors and macroeconomics or financial ratio variables could also produce superior equity premium forecasts; (ii) predictive models with one of $\triangle CD_{AR}$-family predictor could outperform the simple univariate time series and panel autoregressive models; (iii) incorporating this predictor into the pool of 14 variables by Welch and Goyal (2008) with the three pass regression filter (3PRF) predictive model has thus far outperformed other commonly considered econometrics models; (iv) incorporating various trading strategies and finance theories into an econometrics model could beat simple time series models, which is in marked contrast to results of Nelson (1972) and Welch and Goyal (2008); (v) the predictive power of this predictor varies substantially across economic states and performs better during economic expansions, which is in marked contrast to the findings of current literature.

Table 1.1 Forecast Evaluation (OLS) at Daily Frequency

		US	UK	FRA	GER	JAP	CAN	AUS
1/3/2019-3/31/2021								
S1	R^2_{OS}	0.60	0.72	1.25	2.26	2.07	0.90	0.36
	$MSPE-adj$	1.03	1.12	1.28	1.67	2.04	0.88	1.08
S2	R^2_{OS}		−1.09	−0.73	−0.88	3.49	−1.9	−2.41
	$MSPE-adj$	−0.13	0.23	0.36	0.4	1.92	−0.53	−0.4
S3	R^2_{OS}	−0.91	3.45	3.52	3.74	3.76	1.06	1.61
	$MSPE-adj$	1.14	1.93	2.03	2.18	2.53	1.21	1.53
S5	R^2_{OS}	−1.97	−0.48	0.25	0.36	−1.74	−0.28	−1.56
	$MSPE-adj$	0.55	0.33	0.68	0.68	0.47	0.46	0.02
S6	R^2_{OS}	−3.08	−2.1	−1.34	−1.03	−0.41	−3.31	−2.39
	$MSPE-adj$	−0.12	0.04	0.3	0.31	0.6	−0.62	−0.36
S15	R^2_{OS}	0.80	0.55	0.40	1.08	1.32	0.42	−0.46
	$MSPE-adj$	0.17	1.02	1.15	1.47	1.95	0.68	0.95
S16	R^2_{OS}	0.09	0.81	0.92	−1.18	−1.10	0.39	0.97
	$MSPE-adj$	1.07	1.06	1.21	0.45	−0.46	1.41	1.27
S17	R^2_{OS}	0.47	2.50	2.00	2.55	1.32	−0.81	
	$MSPE-adj$	0.56	0.85	0.86	0.83	1.2	0.5	0.28
S21	R^2_{OS}	0.50	1.74	1.29	2.04	0.77	0.18	0.54
	$MSPE-adj$	1.24	1.44	1.46	1.78	1.32	0.71	1.00
S24	R^2_{OS}	−0.69	−2.32	−2.50	0.12	1.58	1.38	0.89
	$MSPE-adj$	1.14	0.90	−0.45	1.28	1.38	1.30	1.29

Table 1.2 Forecast Evaluation (POLS) at daily Frequency ($R^2_{OS}(\%)$)

		US	UK	FRA	GER	JAP	CAN	AUS
1/3/2019-3/31/2021								
S1	R^2_{OS}	1.39	2.12	2.13	2.62	1.87	1.41	1.45
	$MSPE-adj$	0.31	0.44	0.54	0.58	0.37	0.27	−0.32
S2	R^2_{OS}	0.07	0.12	0.28	0.43	0.79	0.80	0.77
	$MSPE-adj$	1.40	1.31	1.29	1.25	1.21	1.26	1.36
S3	R^2_{OS}	−0.18	3.68	3.19	2.94	6.32	1.55	3.22
	$MSPE-adj$	0.24	1.21	1.31	1.31	2.33	0.54	0.94
S5	R^2_{OS}	2.80	1.77	1.76	1.50	1.34	2.04	0.87
	$MSPE-adj$	1.66	1.46	1.46	1.35	1.51	1.46	1.30
S6	R^2_{OS}	0.02	−1.23	1.85	−1.59	0.36	0.98	0.91
	$MSPE-adj$	1.21	−0.35	1.42	−0.59	1.25	1.29	1.33
S15	R^2_{OS}	1.24	0.64	0.50	0.86	−0.16	1.25	2.45
	$MSPE-adj$	1.42	1.16	1.12	1.29	1.03	1.21	1.78
S16	R^2_{OS}	2.93	2.81	2.93	2.49	−0.54	2.69	0.01
	$MSPE-adj$	1.69	1.87	1.92	1.80	0.90	1.64	0.87
S17	R^2_{OS}	2.00	3.88	3.40	3.52	1.41	1.67	1.18
	$MSPE-adj$	2.24	2.53	2.28	2.44	1.88	1.70	1.72
S21	R^2_{OS}	0.65	1.15	0.97	1.23	1.34	1.08	1.80
	$MSPE-adj$	1.17	1.18	1.18	1.32	1.50	1.02	1.49
S24	R^2_{OS}	−2.97	0.75	0.99	1.60	6.10	−3.57	−1.65
	$MSPE-adj$	−0.88	1.29	1.29	1.30	3.09	0.64	−0.7

Table 2.1 Forecast Evaluation (OLS) at Daily Frequency ($R^2_{OS}(\%)$)

		US	UK	FRA	GER	JAP	CAN	AUS
1/3/2000-3/31/2021								
S1	R^2_{OS}	−0.70	0.31	−0.16	0.16	1.55	−0.52	1.07
	$MSPE-adj$	2.20	2.73	3.48	3.72	2.51	2.49	2.59
S2	R^2_{OS}	0.53	0.07	−0.53	−0.10	−1.41	−0.10	−1.34
	$MSPE-adj$	2.51	3.70	3.05	3.66	3.43	2.78	2.58
S3	R^2_{OS}	−0.05	0.40	0.12	0.13	0.24	0.08	−0.24
	$MSPE-adj$	2.88	4.29	4.27	3.98	4.25	2.79	3.72
S5	R^2_{OS}	−0.47	0.74	0.64	−1.02	0.62	−0.53	−0.77
	$MSPE-adj$	3.12	2.11	2.69	2.85	3.97	2.47	2.41
S6	R^2_{OS}	−0.43	−0.18	0.07	−1.46	−1.59	−0.85	−1.63
	$MSPE-adj$	2.66	3.62	3.03	3.23	2.95	2.46	1.98
S15	R^2_{OS}	0.49	0.11	0.16	0.18	−1.13	0.01	−0.92
	$MSPE-adj$	3.47	3.09	3.47	3.55	2.26	2.79	2.02
S16	R^2_{OS}	−0.43	1.55	1.33	−0.91	−0.45	−1.32	2.04
	$MSPE-adj$	2.51	3.55	3.82	3.76	2.23	2.84	1.92
S17	R^2_{OS}	0.06	−0.06	−0.17	−0.35	−0.91	0.02	−0.81
	$MSPE-adj$	3.52	3.22	3.36	3.35	3.21	3.11	3.03
S18	R^2_{OS}	1.23	0.52	0.24	0.39	−0.88	1.41	−0.79
	$MSPE-adj$	4.20	4.02	3.56	4.04	3.40	4.23	2.65
S21	R^2_{OS}	−0.14	0.85	0.55	0.19	−0.77	−0.77	−0.69
	$MSPE-adj$	2.60	2.24	3.24	3.32	3.56	1.70	2.97
S24	R^2_{OS}	−0.14	1.76	1.99	1.36	2.04	−0.10	1.07
	$MSPE-adj$	0.62	1.50	1.52	1.51	2.37	1.36	2.06

Table 2.2 Forecast Evaluation (POLS) at Daily Frequency (R^2_{OS}(%))

		US	UK	FRA	GER	JAP	CAN	AUS
1/3/2000-3/31/2021								
S1	R^2_{OS}	0.43	0.43	0.69	0.79	0.43	0.16	−0.19
	$MSPE-adj$	3.10	3.32	3.88	4.05	3.67	2.82	3.13
S2	R^2_{OS}	0.52	0.63	0.87	0.94	0.53	−0.10	−0.31
	$MSPE-adj$	3.55	3.83	4.18	4.35	3.74	2.94	3.06
S3	R^2_{OS}	0.15	1.02	1.24	1.31	1.05	0.25	0.62
	$MSPE-adj$	2.71	4.22	4.64	4.92	4.64	2.89	4.27
S5	R^2_{OS}	−0.01	−0.05	0.62	0.47	0.55	−0.45	−0.74
	$MSPE-adj$	2.64	2.77	3.38	3.73	4.19	2.41	2.67
S6	R^2_{OS}	0.75	0.32	0.34	0.45	0.44	0.16	−0.52
	$MSPE-adj$	3.80	3.45	3.53	3.77	3.78	2.98	2.74
S15	R^2_{OS}	1.00	0.39	0.70	0.82	0.28	0.39	−0.57
	$MSPE-adj$	3.81	3.18	3.80	4.09	3.24	2.97	2.10
S16	R^2_{OS}	−0.08	0.03	0.55	0.76	0.85	0.84	−0.19
	$MSPE-adj$	3.26	4.05	4.77	4.93	1.81	2.82	1.62
S17	R^2_{OS}	0.97	0.69	0.81	0.67	0.58	0.72	0.34
	$MSPE-adj$	4.04	3.74	4.14	4.08	3.85	3.54	3.85
S18	R^2_{OS}	1.76	1.30	1.32	1.54	0.47	1.00	−0.08
	$MSPE-adj$	4.33	4.50	4.42	4.90	3.72	3.98	2.31
S21	R^2_{OS}	0.15	−0.01	1.63	0.76	1.01	0.06	1.01
	$MSPE-adj$	2.90	2.77	3.91	4.10	4.59	2.30	3.52
S24	R^2_{OS}	2.02	1.63	1.76	1.44	1.43	0.09	−0.95
	$MSPE-adj$	1.72	1.75	2.48	3.26	4.54	1.29	1.04

Table 3. Forecast Evaluation (OLS and POLS) of Spillover indices at Daily Frequency ($R^2_{OS}(\%)$)

		US	UK	FRA	GER	JAP	CAN	AUS
4/3/2000-3/31/2021								
OLS								
SPI1	R^2_{OS}	-0.05	-0.03	-0.03	-0.02	-0.02	-0.05	-0.02
	$MSPE-adj$	-0.83	-0.62	-0.56	-0.46	-0.43	-0.59	-0.22
SPI2	R^2_{OS}	-0.04	-0.04	-0.03	-0.02	-0.01	-0.04	-0.01
	$MSPE-adj$	-0.76	-0.77	-0.63	-0.28	-0.11	-0.49	-0.17
SPI5	R^2_{OS}	-0.02	-0.02	-0.02	-0.01	-0.01	-0.02	-0.01
	$MSPE-adj$	-0.83	-0.73	-0.76	-0.61	-0.61	-0.57	-0.33
SPI6	R^2_{OS}	-0.02	-0.02	-0.02	-0.01	-0.01	-0.02	-0.01
	$MSPE-adj$	-0.71	-0.83	-0.79	-0.44	-0.32	-0.53	-0.37
SPI15	R^2_{OS}	-0.04	-0.04	-0.03	-0.02	-0.03	-0.04	-0.02
	$MSPE-adj$	-1.03	-1.07	-1.06	-0.83	-0.78	-0.71	-0.48
SPI16	R^2_{OS}	-0.03	-0.04	-0.03	-0.02	-0.02	-0.03	-0.02
	$MSPE-adj$	-0.82	-1.01	-1.09	-0.55	-0.52	-0.52	-0.44
POLS								
SPI1	R^2_{OS}	-1300	-1418	-9560	-9058	-9296	-1611	-1935
	$MSPE-adj$	1.19	1.09	1.17	1.32	1.77	1.48	1.04
SPI2	R^2_{OS}	-4095	-4460	-3005	-2844	-2905	-5093	-6086
	$MSPE-adj$	0.47	0.74	0.85	1.21	1.46	0.25	0.85
SPI5	R^2_{OS}	-5700	-6208	-4187	-3969	-4072	-7065	-8472
	$MSPE-adj$	-0.38	-0.32	-0.24	-0.3	0.44	-0.56	-0.53
SPI6	R^2_{OS}	-1314	-1429	-9636	-9121	-9357	-1632	-1952
	$MSPE-adj$	0.16	0.72	0.96	1.26	1.21	-0.21	0.71
SPI15	R^2_{OS}	-2480	-2700	-1820	-1723	-1771	-3071	-3687
	$MSPE-adj$	1.06	0.97	1.02	1.94	2.06	1.15	1.07
SPI16	R^2_{OS}	-1204	-1312	-8841	-8371	-8599	-1496	-1791
	$MSPE-adj$	0.48	0.72	0.9	1.05	1.23	0.23	0.54

Table 4.1. Forecast Evaluation (OLS) at Monthly Frequency ($R^2_{OS}(\%)$)

		US	UK	FRA	GER	JAP	CAN	AUS
M1/1993-M3/2021								
S1	R^2_{OS}	0.60	3.94	4.68	3.38	5.44	0.96	7.62
	$MSPE-adj$	1.78	2.82	3.01	2.67	3.41	1.36	3.02
S2	R^2_{OS}	2.10	5.07	4.16	2.96	1.41	0.33	2.93
	$MSPE-adj$	2.14	3.15	2.97	2.34	2.46	1.78	2.76
S3	R^2_{OS}	1.57	2.82	2.44	0.54	2.54	0.69	0.98
	$MSPE-adj$	2.43	3.75	3.53	2.66	2.71	1.59	2.15
S5	R^2_{OS}	-5.66	0.28	1.26	2.00	1.09	-1.65	-0.80
	$MSPE-adj$	1.05	1.49	2.21	2.50	2.83	1.46	1.93
S6	R^2_{OS}	4.04	6.54	5.41	2.82	3.37	0.51	2.44
	$MSPE-adj$	2.35	2.80	2.43	2.56	2.59	1.66	2.05
S15	R^2_{OS}	-4.22	3.84	4.65	3.62	2.14	0.83	6.33
	$MSPE-adj$	1.12	2.63	3.36	2.80	2.94	2.01	3.45
S16	R^2_{OS}	0.17	3.83	3.81	2.70	2.59	0.62	3.61
	$MSPE-adj$	1.62	2.94	3.08	2.49	2.63	1.89	3.04
S17	R^2_{OS}	2.74	3.36	4.56	3.23	6.38	3.57	6.20
	$MSPE-adj$	2.17	2.41	2.67	2.23	2.91	2.09	2.26
S18	R^2_{OS}	0.92	2.37	2.54	2.34	2.78	-0.18	2.29
	$MSPE-adj$	1.93	2.52	2.54	2.56	2.94	1.40	2.24
S19	R^2_{OS}	0.81	2.77	3.89	3.37	3.60	3.28	2.72
	$MSPE-adj$	1.49	2.76	3.05	2.40	2.85	2.04	1.97
S20	R^2_{OS}	-0.62	2.92	2.87	2.59	1.39	1.30	0.89
	$MSPE-adj$	1.26	2.38	2.51	1.81	2.16	1.85	1.41
S21	R^2_{OS}	-2.20	3.59	2.61	2.57	3.21	1.85	0.17
	$MSPE-adj$	1.05	3.23	2.32	2.39	3.40	1.73	1.32

Table 4.2 Forecast Evaluation (POLS) at Monthly Frequency ($R^2_{OS}(\%)$)

		US	UK	FRA	GER	JAP	CAN	AUS
M1/1993-M3/2021								
S1	R^2_{OS}	0.30	3.71	5.35	4.44	6.88	1.94	7.02
	$MSPE-adj$	1.64	2.80	3.19	2.77	3.60	1.63	3.15
S2	R^2_{OS}	0.88	4.52	4.86	4.31	2.41	2.06	3.49
	$MSPE-adj$	1.97	2.86	3.30	2.73	2.57	2.04	2.69
S3	R^2_{OS}	0.26	4.08	4.12	3.86	3.71	−3.17	−0.46
	$MSPE-adj$	2.55	3.92	3.68	3.26	3.00	1.83	2.11
S5	R^2_{OS}	−0.09	−0.05	0.88	1.55	2.55	0.45	0.02
	$MSPE-adj$	0.84	1.07	2.48	2.48	3.06	1.55	2.22
S6	R^2_{OS}	4.16	6.79	5.62	4.02	4.76	3.09	2.99
	$MSPE-adj$	2.28	2.76	2.69	2.35	2.32	1.68	2.08
S15	R^2_{OS}	−0.03	1.90	4.64	4.08	3.89	1.03	5.26
	$MSPE-adj$	1.18	2.29	3.61	3.13	3.74	1.99	2.91
S16	R^2_{OS}	0.09	3.13	4.54	3.47	4.28	2.14	3.95
	$MSPE-adj$	1.65	2.66	3.45	2.73	3.51	2.07	2.91
S17	R^2_{OS}	2.63	2.89	5.76	5.27	8.10	5.04	4.80
	$MSPE-adj$	2.09	2.28	2.75	2.65	3.17	1.99	2.35
S18	R^2_{OS}	0.16	1.92	3.45	3.63	4.42	0.35	2.28
	$MSPE-adj$	1.81	2.44	2.98	2.72	3.34	1.52	2.27
S19	R^2_{OS}	0.33	3.08	4.65	4.52	3.44	3.35	3.67
	$MSPE-adj$	1.71	2.61	3.38	2.99	2.89	2.09	2.24
S20	R^2_{OS}	−1.79	2.09	2.67	2.76	2.48	1.49	0.19
	$MSPE-adj$	1.20	2.05	2.33	1.98	2.56	1.58	1.29
S21	R^2_{OS}	−2.70	3.18	3.37	3.21	4.02	0.68	0.20
	$MSPE-adj$	0.92	3.15	2.48	2.35	3.63	1.47	1.18

Table 4.3 Forecast Evaluation (OLS and POLS) of Spillover indices at Monthly Frequency ($R^2_{OS}(\%)$)

		US	UK	FRA	GER	JAP	CAN	AUS
M1/1993-M3/2021								
S1	R^2_{OS}	0.14	0.05	0.03	0.04	0.04	0.12	0.12
	$MSPE-adj$	1.75	0.72	0.49	0.4	0.6	1.55	1.60
S2	R^2_{OS}	-0.05	-0.05	-0.06	-0.07	-0.05	-0.08	-0.06
	$MSPE-adj$	-0.83	-1.13	-1.12	-1.38	-0.97	-1.68	-1.23
S5	R^2_{OS}	0.08	0.04	0.02	0.03	0.02	0.05	0.06
	$MSPE-adj$	1.54	0.77	0.33	0.42	0.43	0.96	1.16
S6	R^2_{OS}	0.01	-0.01	-0.03	-0.02	-0.01	-0.04	0.01
	$MSPE-adj$	0.02	-0.73	-1.46	-0.77	-0.25	-1.67	-0.13
S15	R^2_{OS}	0.05	0.01	0.03	0.02	0.01	0.08	0.06
	$MSPE-adj$	1.26	0.21	0.6	0.23	0.3	1.65	1.37
S16	R^2_{OS}	-0.06	-0.03	-0.07	-0.06	-0.06	-0.06	-0.01
	$MSPE-adj$	-1.49	-0.9	-1.78	-1.49	-1.81	-1.71	-0.3
POLS								
S1	R^2_{OS}	-16457	-17502	-11365	-8776	-8674	-18179	-16117
	$MSPE-adj$	0.8	0.79	1.05	1.29	0.74	-0.02	0.57
S2	R^2_{OS}	-20676	-21948	-14123	-11080	-10688	-22920	-20239
	$MSPE-adj$	0.06	-0.21	0.85	0.4	1.03	-0.1	0.87
S5	R^2_{OS}	-57739	-61342	-39741	-30920	-30289	-63635	-56569
	$MSPE-adj$	0.93	0.68	1.40	1.43	1.16	0.29	0.67
S6	R^2_{OS}	-21824	-23045	-14975	-11760	-11439	-24121	-21363
	$MSPE-adj$	-1.46	-1.59	-1.22	-1.48	-1.48	-2.04	-0.98
S15	R^2_{OS}	-13135	-14010	-9088	-7020	-6921	-14534	-12885
	$MSPE-adj$	0.66	0.8	1.15	1.16	0.86	0.13	0.66
S16	R^2_{OS}	-15665	-16577	-10852	-8460	-8266	-17426	-15434
	$MSPE-adj$	-0.46	-0.75	-0.95	-1.24	-0.67	-1.72	-0.61

Table 4.4 Forecast Evaluation (OLS and FOLS) on global equity returns at Monthly Frequency

OLS		*US*	*UK*	*France*	*German*	*Japan*	*Canada*	*Australia*
M1/1993-M3/2021								
Rm-Rf	R^2_{OS}	0.62	2.42	4.39	5.54	4.41	4.51	3.27
	$MSPE-adj$	1.82	2.27	3.02	3.24	3.47	2.25	2.14
S1	R^2_{OS}	0.60	3.94	4.68	3.38	5.44	0.96	7.62
	$MSPE-adj$	1.78	2.82	3.01	2.67	3.41	1.36	3.02
S17	R^2_{OS}	2.74	3.36	4.56	3.23	6.38	3.57	6.21
	$MSPE-adj$	2.17	2.41	2.67	2.23	2.91	2.09	2.26
POLS		*US*	*UK*	*France*	*German*	*Japan*	*Canada*	*Australia*
M1/1993-M3/2021								
Rm-Rf	R^2_{OS}	1.90	1.05	4.75	5.77	5.51	5.28	2.38
	$MSPE-adj$	2.08	2.13	3.18	3.31	3.61	2.37	2.00
S1	R^2_{OS}	0.41	3.76	5.67	5.81	7.13	1.48	7.02
	$MSPE-adj$	1.73	2.99	3.41	2.95	3.72	1.69	3.31
S17	R^2_{OS}	2.56	2.92	5.73	5.27	8.13	5.07	4.95
	$MSPE-adj$	2.14	2.33	2.80	2.68	3.29	2.05	2.42

Notes: Rm-Rf represents the global market portfolio return by Fama and French (1998). ($R^2_{OS}(\%)$)

Table 4.5 Forecast Evaluation (POLS) including B/M ratio at Monthly Frequency When B/M Ratio is Considered as a Regressor

		US	UK	FRA	GER	JAP	CAN	AUS
M1/1991-M3/2021								
S1	R^2_{OS}	-1.33	-5.54	-9.58	-2.84	-3.97	-5.46	0.85
	$MSPE-adj$	1.99	1.62	1.35	1.66	1.88	1.45	2.36
S2	R^2_{OS}	2.01	-3.96	-10.54	-2.3	-7.8	-4.38	-2.53
	$MSPE-adj$	2.40	1.82	1.44	1.85	1.41	1.95	2.06
S3	R^2_{OS}	-0.77	-8.75	-16.21	-5.54	-9.68	-14.46	-8.92
	$MSPE-adj$	2.71	2.16	1.70	1.97	1.84	1.28	1.84
S5	R^2_{OS}	-7.67	-17.7	-19.5	-9.76	-11.57	-14.88	-10.2
	$MSPE-adj$	1.30	0.81	1.07	1.15	1.44	1.05	1.62
S6	R^2_{OS}	8.05	2.7	-4.45	1.53	-1.58	1.24	2.02
	$MSPE-adj$	3.15	2.48	1.77	2.27	2.00	2.23	2.42
S15	R^2_{OS}	-4.11	-9.23	-13.05	-4.82	-8.85	-8.73	-2.34
	$MSPE-adj$	1.54	1.37	1.34	1.52	1.46	1.27	1.99
S16	R^2_{OS}	-0.82	-7.67	-11.69	-4.53	-7.42	-6.02	-3.31
	$MSPE-adj$	2.00	1.53	1.41	1.58	1.52	1.74	2.13
S17	R^2_{OS}	3.75	-4.31	-7.32	0.01	-0.67	0.67	-0.01
	$MSPE-adj$	2.52	1.65	1.45	1.97	2.19	2.00	1.95
S18	R^2_{OS}	-1.02	-12.1	-18.99	-7.67	-9.57	-11.06	-7.82
	$MSPE-adj$	2.06	1.17	1.1	1.31	1.64	1.11	1.53
S19	R^2_{OS}	1.63	-7.71	-13.11	-3.04	-7.54	-5.54	-3.16
	$MSPE-adj$	2.25	1.31	1.29	1.66	1.57	1.50	1.78
S20	R^2_{OS}	-4.59	-19.07	-28.92	-13.14	-17.91	-16.65	-14.93
	$MSPE-adj$	1.87	1.15	1.01	1.23	$1.40*$	0.95	1.25
S21	R^2_{OS}	-4.8	-12.54	-20.94	-9.37	-11.58	-14.32	-11.68
	$MSPE-adj$	1.40	1.40	1.06	1.14	1.62	0.77	1.03

Table 4.6 Forecast Evaluation (POLS) at Monthly Frequency ($R^2_{OS}(\%)$) When Stock Variance is Considered as a Regressor

		US	UK	FRA	GER	JAP	CAN	AUS
M1/1992-M3/2021								
S1	R^2_{OS}	−21.8	−9.25	−2.8	−0.32	−0.45	−20.1	−8.24
	$MSPE-adj$	1.49	2.32	2.56	2.87	2.81	1.26	2.42
S2	R^2_{OS}	−15.72	−6.29	−2.52	0.8	−3.77	−15.52	−9.47
	$MSPE-adj$	2.01	2.57	2.41	2.84	1.91	1.67	2.03
S3	R^2_{OS}	−20.76	−14.87	−7.45	−2.02	−4.1	−33.48	−22.37
	$MSPE-adj$	2.74	2.94	2.73	3.06	2.62	1.40	2.02
S5	R^2_{OS}	−21.83	−16.45	−8.61	−3.01	−5	−26.01	−17.94
	$MSPE-adj$	1.51	1.55	1.87	2.38	2.10	1.1	1.75
S6	R^2_{OS}	−15.32	−5.82	−2.11	−0.19	−2.34	−16.09	−11.43
	$MSPE-adj$	2.27	2.69	2.35	2.54	1.99	1.55	1.80
S15	R^2_{OS}	−20.97	−10.21	−3.73	−0.49	−3.06	−20.02	−9.83
	$MSPE-adj$	1.40	2.06	2.36	2.72	2.36	1.18	2.05
S16	R^2_{OS}	−21.57	−11.69	−5.09	−2.26	−4.45	−20.49	−13.55
	$MSPE-adj$	1.51∗	1.97	2.03	2.36	1.85	1.27	1.69
S17	R^2_{OS}	−13.31	−7.02	−0.42	2.09	3.1	−13.18	−7.66
	$MSPE-adj$	1.92	2.04	2.45	2.91	2.91	1.55	1.96
S18	R^2_{OS}	−12.09	−8.84	−3.63	1.06	−0.72	−19.68	−11.99
	$MSPE-adj$	2.09	1.91	2.10	2.72	2.45	1.01	1.90
S19	R^2_{OS}	−14.72	−8.59	−3.75	0.34	−3.18	−16.79	−11.53
	$MSPE-adj$	1.79	1.84	1.91	2.43	1.76	1.28	1.67
S20	R^2_{OS}	−17.15	−12.62	−7.22	−1.82	−4.03	−22.7	−16.96
	$MSPE-adj$	1.95	2.01	1.89	2.41	2.01	1.11	1.56
S21	R^2_{OS}	−19.57	−12.44	−6.95	−1.96	−2.83	−22.98	−17.51
	$MSPE-adj$	1.68	2.36	2.03	2.38	2.51	1.21	1.50

Table 5.1. Forecast Evaluation (Equation (10)) at Monthly Frequency ($R^2_{OS}(\%)$)

		US	UK	FRA	GER	JAP	CAN	AUS
M1/1993-M3/2021								
PAR(2)	R^2_{OS}	−3.23	−2.38	2.75	3.00	2.18	0.36	1.02
	$MSPE-adj$	1.02	0.81	2.46	2.50	2.58	1.34	1.62
PAR(3)	R^2_{OS}	−3.75	−4.03	3.32	3.32	1.25	1.20	0.79
	$MSPE-adj$	1.13	0.66	2.44	2.61	2.48	1.23	1.73

Table 5.2 Forecast Evaluation (Equation (11)) at Monthly Frequency ($R^2_{OS}(\%)$)

		US	UK	FRA	GER	JAP	CAN	AUS
M1/1993-M3/2021								
S1	R^2_{OS}	-0.17	1.93	5.5	4.49	6.76	1.46	7.06
	$MSPE-adj$	1.90	2.61	3.61	3.06	3.59	1.74	3.28
S2	R^2_{OS}	1.59	1.87	4.57	3.66	2.06	2.51	3.97
	$MSPE-adj$	2.05	2.18	3.09	2.64	2.48	1.98	2.55
S3	R^2_{OS}	-0.05	0.82	4.47	3.75	3.13	2.18	0.29
	$MSPE-adj$	2.71	2.98	3.78	3.32	3.01	2.12	2.47
S5	R^2_{OS}	-2.31	-3.29	2.09	2.48	2.57	0.23	1.14
	$MSPE-adj$	1.38	0.9	2.60	2.47	2.86	1.56	1.92
S6	R^2_{OS}	4.41	4.29	5.38	3.63	3.86	3.05	3.12
	$MSPE-adj$	2.47	2.44	2.87	2.48	2.32	1.74	2.21
S15	R^2_{OS}	-1.77	0.22	5.65	4.71	4.03	1.77	5.91
	$MSPE-adj$	1.64	2.13	4.00	3.38	3.52	2.17	3.28
S16	R^2_{OS}	0.26	0.28	3.94	2.78	3.26	2.22	4.44
	$MSPE-adj$	1.74	1.79	2.94	2.49	2.98	1.95	2.71
S17	R^2_{OS}	3.59	1.03	5.67	5.19	8.38	5.26	5.11
	$MSPE-adj$	2.39	1.86	3.08	2.92	3.29	2.04	2.62
S18	R^2_{OS}	0.91	-0.05	4.5	3.99	2.79	3.22	3.89
	$MSPE-adj$	1.72	1.43	2.83	2.64	2.79	1.86	2.12
S19	R^2_{OS}	0.02	-1.33	3.52	3.26	3.57	-0.23	2.12
	$MSPE-adj$	1.75	1.42	2.88	2.68	3.12	1.45	2.17
S20	R^2_{OS}	-0.91	-1.94	2.76	2.18	2.52	2.31	0.99
	$MSPE-adj$	1.69	1.15	2.28	2.18	2.70	1.74	1.71
S21	R^2_{OS}	-1.39	0.19	3.86	3.00	5.83	3.14	0.86
	$MSPE-adj$	1.49	1.71	2.81	2.49	3.12	1.79	1.70

Table 6.1 Forecast Evaluation (OLS) at Quarterly Frequency

		US	UK	FRA	GER	JAP	CAN	AUS
Q1/1992-Q1/2021								
S1	R^2_{OS}	0.75	2.2	3.25	1.24	3.29	1.3	1.73
	$MSPE-adj$	0.67	1.31	1.78	0.98	1.34	0.95	1.01
S2	R^2_{OS}	0.48	9.66	7.18	5.45	-0.12	4.24	4.93
	$MSPE-adj$	0.99	2.74	2.53	1.90	0.39	1.55	1.58
S3	R^2_{OS}	0.34	1.13	1.37	-0.05	6.23	-4.08	-0.27
	$MSPE-adj$	0.73	0.85	0.95	0.67	1.58$*$	0.14	0.76
S5	R^2_{OS}	0.61	1.04	0.54	2.11	1.66	0.05	1.18
	$MSPE-adj$	1.29	1.55	1.24	1.48	1.89	0.98	1.31
S6	R^2_{OS}	0.25	7.49	6.85	4.36	0.56	3.79	4.31
	$MSPE-adj$	1.01	2.80	2.88	1.71	1.03	1.39	1.50
S7	R^2_{OS}	1.56	6.14	8.02	6.97	6.7	4.85	8.65
	$MSPE-adj$	1.36	2.16	2.94	2.05	2.12	1.60	2.35
S8	R^2_{OS}	0.95	10.82	11.52	9.32	1.07	6.92	7.62
	$MSPE-adj$	0.94	3.19	3.19	2.29	0.95	1.80	2.09
S15	R^2_{OS}	-0.78	4.51	2.89	2.67	1.29	1.23	2.95
	$MSPE-adj$	0.34	1.64	0.93	1.04	0.73	0.67	1.08
S16	R^2_{OS}	-1.93	1.86	2.42	-3.8	-0.41	2.86	3.07
	$MSPE-adj$	0.66	1.24	1.60$*$	0.14	0.30	1.28$*$	1.31
S17	R^2_{OS}	-0.33	4.36	3.69	4.3	2.12	2.62	5.16
	$MSPE-adj$	1.15	1.78	1.03	1.99	1.51	0.83	2.06
S19	R^2_{OS}	-0.91	2.12	2.53	3.57	0.29	0.94	3.76
	$MSPE-adj$	1.15	1.65	1.54	2.36	1.37	1.23	2.16
S20	R^2_{OS}	-0.37	7.43	5.63	2.57	1.37	4.98	6.16
	$MSPE-adj$	0.77	2.65	2.53	1.46	0.72	1.51	1.90
S21	R^2_{OS}	-0.61	6.87	8.47	7.76	2.06	4.56	4.5
	$MSPE-adj$	0.91	2.65	2.87	2.16	1.32	1.30	1.52
S22	R^2_{OS}	-0.06	5.55	5.65	1.75	1.65	4.80	4.89
	$MSPE-adj$	0.98	2.63	2.61	1.51	1.30	2.33	2.51
S24	R^2_{OS}	0.01	6.77	7.76	5.23	2.21	4.6	5.81
	$MSPE-adj$	0.93	2.78	2.79	1.90	1.36	1.55	1.81

Table 6.2 Forecast Evaluation (POLS) at Quarterly Frequency

		US	UK	FRA	GER	JAP	CAN	AUS
Q1/1992-Q1/2021								
S1	R^2_{OS}	0.33	0.74	3.75	1.46	2.51	2.37	1.51
	$MSPE-adj$	1.31	1.22	1.91	1.13	1.28	1.34	1.99
S2	R^2_{OS}	1.15	8.62	7.37	5.3	0.9	4.76	5.17
	$MSPE-adj$	1.09	2.72	2.81	1.82	0.91	1.60	1.65
S3	R^2_{OS}	1.61	1.65	3.52	0.21	3.11	2.19	0.22
	$MSPE-adj$	1.43	1.22	1.50	0.76	1.27	1.40	1.26
S5	R^2_{OS}	0.98	2.09	3.55	0.45	2.55	0.16	1.27
	$MSPE-adj$	1.42	1.28	1.62	0.72	1.47	1.21	1.36
S6	R^2_{OS}	1.15	4.96	5.81	3.75	1.8	4.34	5.01
	$MSPE-adj$	1.77	2.29	2.68	1.48	1.03	1.53	1.78
S7	R^2_{OS}	1.72	8.38	8.52	6.67	5.81	6.27	9.09
	$MSPE-adj$	1.43	2.38	2.92	1.99	2.07	1.95	2.46
S9	R^2_{OS}	1.83	9.84	10.01	7.35	3.34	6.81	7.44
	$MSPE-adj$	1.26	3.14	3.21	2.42	1.53	1.77	2.08
S15	R^2_{OS}	0.64	2.41	4.25	2.42	1.27	2.34	2.55
	$MSPE-adj$	1.17	1.27	1.97	1.04	1.29	1.85	1.31
S16	R^2_{OS}	1.57	1.92	3.67	0.89	-0.37	2.94	1.93
	$MSPE-adj$	1.60	1.31	1.93	1.41	0.25	1.33	1.24
S17	R^2_{OS}	-0.28	3.99	5.08	3.97	2.11	3.53	5.17
	$MSPE-adj$	1.14	2.24	1.98	1.89	1.34	1.86	2.01
S19	R^2_{OS}	-0.22	1.65	4.24	2.52	0.58	1.56	2.77
	$MSPE-adj$	1.10	1.30	2.29	1.81	1.29	1.38	1.82
S20	R^2_{OS}	0.05	5.52	6.11	3.74	1.86	5.15	6.07
	$MSPE-adj$	0.89	2.56	2.90	1.52	1.35	1.62	1.98
S21	R^2_{OS}	0.59	6.43	7.47	5.67	2.78	5.48	5.95
	$MSPE-adj$	1.05	2.58	2.91	1.81	1.54	1.56	1.78
S22	R^2_{OS}	0.09	6.13	6.15	3.89	2.35	4.66	4.99
	$MSPE-adj$	1.22	2.58	2.91	1.81	1.54	1.56	1.78
S24	R^2_{OS}	0.28	6.85	7.64	5.16	2.22	4.75	6.02
	$MSPE-adj$	1.00	2.70	2.86	1.84	1.44	1.62	1.92

Table 6.3 Forecast Evaluation (OLS and POLS) of Spillover indices at Quarterly Frequency ($R^2_{OS}(\%)$)

		US	UK	FRA	GER	JAP	CAN	AUS
Q1/1992-Q1/2021								
S1	R^2_{OS}	0.41	0.05	−0.03	0.15	0.1	−0.08	−0.13
	$MSPE-adj$	1.32*	0.36	−0.21	0.86	0.4	−0.22	−0.56
S2	R^2_{OS}	0.37	−0.22	−0.33	0.1	0.11	−0.35	−0.23
	$MSPE-adj$	0.72	−0.65	−1	0.32	0.38	−0.48	−0.5
S5	R^2_{OS}	0.03	−0.03	−0.11	0.01	0.01	−0.1	−0.12
	$MSPE-adj$	0.16	−0.39	−1.22	0.09	0.1	−0.55	−0.84
S6	R^2_{OS}	0.04	−0.1	−0.22	0.02	0.1	−0.16	−0.14
	$MSPE-adj$	0.15	−0.54	−1.23	0.14	0.62	−0.46	−0.64
S15	R^2_{OS}	0.07	−0.05	−0.16	0	0.01	−0.16	−0.21
	$MSPE-adj$	0.26	−0.4	−1.27	0.05	0.07	−0.47	−0.98
S16	R^2_{OS}	0.21	−0.12	−0.24	0.01	0.08	−0.22	−0.2
	$MSPE-adj$	0.63	−0.66	−1.35	0.07	0.34	−0.51	−0.79
POLS								
S1	R^2_{OS}	−293	−361	−187	−174	−141	−336	−302
	$MSPE-adj$	0.76	0.22	1.04	0.69	0.92	0.23	0.63
S2	R^2_{OS}	−141	−233	−131	−102	−105	−200	−195
	$MSPE-adj$	0.26	−0.72	−0.18	−0.16	0.04	−0.66	−0.56
S5	R^2_{OS}	−886	−946	−546	−496	−460	−876	−822
	$MSPE-adj$	0.16	−0.03	0.6	0.47	0.29	0.12	0.41
S6	R^2_{OS}	−446	−522	−329	−275	−301	−456	−464
	$MSPE-adj$	−0.95	−1.27	−1.2	−0.86	−1.52	−0.9	−1.11
S15	R^2_{OS}	−527	−695	−382	−328	−304	−622	−591
	$MSPE-adj$	0.52	−0.38	0.64	0.35	0.67	−0.24	−0.05
S16	R^2_{OS}	−794	−1011	−580	−512	−481	−888	−867
	$MSPE-adj$	−0.14	−0.83	−0.1	−0.5	−0.22	−0.52	−0.48

Table 7. Forecast Evaluations by variables in Welch and Goyal (2008) and Macroeconomics Variables at Monthly Frequnecy.

		$infl$	$svar$	tbl	b/m	$ntis$	Ity	Itr
01/1992-03/2021								
OLS	$R^2_{OS}(\%)$	−0.11	−18.71	−4.20	0.50	−0.75	−0.22	−2.79
	$MSPE-adj$	−2.20	−6.50	−2.06	0.24	−3.51	−0.93	−3.08
		dfy	d/p	e/p	d/e	tms	dfr	d/y
OLS	$R^2_{OS}(\%)$	−3.15	−5.26	−1.92	0.00	−0.45	−0.10	−0.90
	$MSPE-adj$	−2.03	−6.67	−1.74	−0.12	−0.24	−0.17	−0.91
		NFP	IPI	MS	UEM	EPU	FDI	
OLS	$R^2_{OS}(\%)$	−0.24	−0.19	−0.58	0.49	−9.10	−0.12	
	$MSPE-adj$	−0.15	−0.15	−0.62	0.52	−4.97	−0.17	

Table 8. Simple Avergae Forecast Combination (SA) and Mean Corrected Simple Avergae Forecast Combination (MCSA) at Monthly Frequency

SA	Sa	Sb	Sc	Sd	Se	Sf	Sg	Sh	
R^2_{OS}	0.49	1.06	1.14	1.30	1.24	1.41	1.10	1.22	
MSPE-adj	0.91	1.21	1.54	1.71	1.83	1.97	1.2.19	2.15	
	Si	Sj	Sk	Sl	Sm	Sn	So	Sp	
R^2_{OS}	1.03	0.72	1.42	1.14	1.30	0.11	0.09	1.46	
MSPE-adj	2.01	1.87	2.21	1.54	1.83	1.83	1.83	0.01	1.96
MCSA	Sa	Sb	Sc	Sd	Se	Sf	Sg	Sh	
R^2_{OS}	−0.74	0.87	1.30	0.95	0.94	1.68	2.56	2.42	
MSPE-adj	1.37	0.82	1.83	2.38	2.45	2.90	3.17	3.26	
	Si	Sj	Sk	Sl	Sm	Sn	So	Sp	
R^2_{OS}	2.45	2.02	2.73	0.39	0.94	−2.13	−2.12	0.67	
MSPE-adj	3.24	2.87	3.48	2.00	2.45	0.89	−2.05	2.34	

Table 9. Pre-selected Quartile Forecast Combinations at Monthly Frequency

Weight		Sa	Sb	Sc	Sd	Se	Sf	Sg	Sh
PB	R^2_{OS}	0.16	0.46	0.68	−0.86	−1.65	1.58	0.23	0.39
	$MSPE-adj$	0.92	1.33	1.27	0.57	0.54	2.37	1.88	1.89
		Si	Sj	Sk	Sl	Sm	Sn	So	Sp
	R^2_{OS}	0.07	−7.79	2.29	−1.49	−5.32	0.07	−0.11	0.29
	$MSPE-adj$	1.89	0.64	2.48	0.77	0.16	0.01	−0.33	1.51
Weight		Sa	Sb	Sc	Sd	Se	Sf	Sg	Sh
EW	R^2_{OS}	−0.34	0.52	0.48	0.85	0.13	0.81	0.71	1.60
	$MSPE-adj$	0.34	1.31	1.24	1.64	0.99	1.73	2.01	2.30
		Si	Sj	Sk	Sl	Sm	Sn	So	Sp
	R^2_{OS}	0.66	−0.13	1.52	−1.26	−0.18	0.10	0.08	2.24
	$MSPE-adj$	1.92	1.73	2.25	0.45	0.92	0.02	0.03	2.23

Table 10. Forecasts by Three-Pass Regression Filter at Monthly Frequency

	WG	$WG+S1$	$WG+S2$	$WG+S5$	$WG+S6$	$WG+S7$	$WG+S8$
R^2_{OS}	13.84	13.92	14.89	13.95	14.11	14.97	14.69
MSPE-adj	3.70	3.74	3.84	3.75	3.76	3.78	3.65
	$WG+S10$	$WG+S11$	$WG+S15$	$WG+S16$	$WG+S19$	$WG+S20$	$WG+S21$
R^2_{OS}	14.91	13.96	15.68	14.10	16.40	14.74	14.65
MSPE-adj	3.82	3.71	3.81	3.87	3.83	3.68	3.76
	$WG+S24$	$WG+SI1$	$WG+SI2$	$WG+SI3$	$WG+SI4$	$WG+SI5$	$WG+SI6$
R^2_{OS}	14.47	13.29	13.01	13.34	14.35	12.85	13.08
MSPE-adj	3.72	3.73	3.68	3.73	3.72	3.70	3.68

Table 11. Forecats by Ridge at Monthly Frequency ($R^2_{OS}(\%)$)

λ		Sa	Sb	Sc	Sd	Se	Sf	Sg	Sh
0.5	R^2_{OS}	−1303	−1118	−1113	−1015	−1017	−807	0.42	0.09
	$MSPE-adj$	−1.63	−0.70	−1.45	−1.17	−1.40	−0.61	1.83	1.71
5	R^2_{OS}	−275	−270	−231	−207	−221	−145	0.41	0.15
	$MSPE-adj$	−0.94	−0.31	−0.76	−0.61	−0.71	−0.03	1.83	1.73
10	R^2_{OS}	−144	−155	−121	−111	−120	−79.81	0.40	0.19
	$MSPE-adj$	−0.62	−0.13	−0.46	−0.38	−0.41	0.15	1.82	1.74
20	R^2_{OS}	−73.54	−87.65	−63.34	−59.26	−64.08	−44.72	0.39	0.23
	$MSPE-adj$	−0.30	0.02	−0.16	−0.14	−0.14	0.27	1.82	1.75
50	R^2_{OS}	−30.54	−41.76	−27.40	−26.30	−28.24	−21.64	0.36	0.27
	$MSPE-adj$	0.10	0.18	0.19	0.18	0.17	0.41	1.81	1.76
100	R^2_{OS}	−15.87	−24.06	−14.73	−14.35	−15.21	−12.62	0.32	0.27
	$MSPE-adj$	0.40	0.32	0.46	0.45	0.42	0.57	1.79	1.77
150	R^2_{OS}	−10.83	−17.38	−10.22	−10.03	−10.54	−9.12	0.30	0.27
	$MSPE-adj$	0.58	0.42	0.63	0.62	0.59	0.70	1.78	1.76
200	R^2_{OS}	−8.24	−13.74	−7.86	−7.74	−8.09	−7.18	0.29	0.26
	$MSPE-adj$	0.71	0.51	0.75	0.74	0.72	0.80	1.78	1.76
1000	R^2_{OS}	−1.62	−3.24	−1.59	−1.58	−1.61	−1.54	0.23	0.23
	$MSPE-adj$	1.37	1.14	1.38	1.37	1.37	1.38	1.76	1.75

λ		Si	Sj	Sk	Sl	Sm	Sn	So	Sp
0.5	R^2_{OS}	0.54	0.04	0.34	−1157	−924	1.26	−773	−977
	$MSPE-adj$	1.84	1.68	1.77	−1.43	−1.40	1.81	−1.63	1.61
5	R^2_{OS}	0.49	0.15	0.35	−228	−202	0.74	−455	−420
	$MSPE-adj$	1.83	1.72	1.78	−0.77	−0.68	1.73	−1.68	0.13
10	R^2_{OS}	0.46	0.21	0.36	−120	−112	0.51	−486	−333
	$MSPE-adj$	1.82	1.74	1.78	−0.45	−0.41	1.71	−1.73	−0.51
20	R^2_{OS}	0.43	0.26	0.36	−62.71	−60.86	0.39	−290	−209
	$MSPE-adj$	1.81	1.76	1.78	−0.14	−0.15	1.72	−1.80	−1.09
50	R^2_{OS}	0.37	0.29	0.35	−27.24	−27.25	0.49	−181	−180
	$MSPE-adj$	1.80	1.77	1.78	0.20	0.16	1.80	−1.90	−1.64
100	R^2_{OS}	0.33	0.29	0.32	−14.70	−14.84	0.69	−162	−165
	$MSPE-adj$	1.78	1.77	1.78	0.46	0.42	1.89	−1.94	−1.90
150	R^2_{OS}	0.30	0.28	0.30	−10.23	−10.34	0.79	−143	−135
	$MSPE-adj$	1.78	1.77	1.77	0.62	0.59	1.92	−1.95	−2.00
200	R^2_{OS}	0.28	0.27	0.29	−7.88	−7.96	0.82	−97	−126
	$MSPE-adj$	1.77	1.77	1.77	0.74	0.72	1.94	−1.95	−2.06
1000	R^2_{OS}	0.23	0.23	0.24	−1.59	−1.60	0.60	−62	−81
	$MSPE-adj$	1.76	1.76	1.76	1.37	1.37	1.86	−1.90	−2.09

Table 12. Forecats by Lasso at Monthly Frequency ($R^2_{OS}(\%)$)

λ		Sa	Sb	Sc	Sd	Se	Sf	Sg	Sh
0.003	R^2_{OS}	−22431	−13663	−17737	−17512	−17852	−12675	−1.05	−5.30
	$MSPE-adj$	−0.21	0.34	0.25	0.18	0.11	0.42	2.33	1.42
0.007	R^2_{OS}	−2497	−1992	−1871	−2304	−2260	−1789	0.34	1.19
	$MSPE-adj$	0.12	0.33	0.40	0.32	0.17	0.24	2.30	2.17
0.01	R^2_{OS}	−622	−553	−473	−627	−615	−490	0.97	2.18
	$MSPE-adj$	0.43	0.040	0.48	0.50	0.34	0.38	2.20	2.45
0.02	R^2_{OS}	−3.61	−3.01	−3.55	−2.81	−3.75	−2.81	0.26	1.01
	$MSPE-adj$	0.32	0.44	0.32	0.53	0.27	0.53	1.76	2.08
0.03	R^2_{OS}	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
	$MSPE-adj$	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75
0.05	R^2_{OS}	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
	$MSPE-adj$	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75

λ		Si	Sj	Sk	Sl	Sm	Sn	So	Sp
0.003	R^2_{OS}	−6.37	−8.09	−1.98	−16974	−18273	−1.8008	−6111	−18559
	$MSPE-adj$	1.11	0.95	2.15	0.06	0.23	1.16	−1.60	0.26
0.007	R^2_{OS}	0.75	−0.94	2.00	−2305	−2289	−2701	−2587	−3150
	$MSPE-adj$	1.38	1.52	2.15	0.06	0.34	1.53	−1.48	0.43
0.01	R^2_{OS}	0.79	0.52	2.18	−617	−265	−1001	−1096	−981
	$MSPE-adj$	1.46	1.53	2.38	0.42	0.46	0.01	−1.31	0.40
0.02	R^2_{OS}	0.11	0.20	1.01	−3.66	−2.81	−27.07	−0.35	−15.07
	$MSPE-adj$	1.69	1.74	2.08	0.30	0.53	0.01	1.59	−0.21
0.03	R^2_{OS}	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
	$MSPE-adj$	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75
0.05	R^2_{OS}	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
	$MSPE-adj$	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75

Table 13.1 Forecats by Elastic Net($\alpha = 0.3$) at Monthly Frequency
All R^2_{OS}s are prsented by (%)

λ		Sa	Sb	Sc	Sd	Se	Sf	Sg	Sh
0.003	R^2_{OS}	-61925	-100986	-122649	-118661	-115199	-97650	-4.94	-15.33
	$MSPE$	-0.57	0.39	-0.20	-0.15	-0.35	0.40	$2.03**$	0.89
0.007	R^2_{OS}	-25687	-27397	-37031	-37205	-36162	-26563	-2.16	-8.40
	$MSPE$	-0.27	0.71	0.23	0.11	0.09	0.71	$2.24**$	1.23
0.01	R^2_{OS}	-11387	-12533	-16965	-16648	-17142	-12167	-0.98	-5.17
	$MSPE$	-0.18	0.43	0.26	0.20	0.11	0.43	$2.33***$	$1.43*$
0.02	R^2_{OS}	-3595	-2561	-2775	-3081	-3173	-2503	0.41	0.72
	$MSPE$	0.05	0.10	0.29	0.23	-0.01	0.10	$2.39***$	$2.10**$
0.03	R^2_{OS}	-981	-797	-751	-989	-962	-771	0.93	1.83
	$MSPE$	0.49	0.49	0.57	0.54	0.47	0.50	$2.26**$	$2.33***$
0.05	R^2_{OS}	-13.27	-13.77	-13.09	-11.67	-13.89	-12.23	0.58	1.93
	$MSPE$	0.59	0.63	0.62	0.79	0.54	0.71	$1.90**$	$2.43***$

λ		Si	Sj	Sk	Sl	Sm	Sn	So	Sp
0.003	R^2_{OS}	-15.65	-24.82	-11.74	-116914	-116273	-35315	-11895	-262243
	$MSPE$	1.27	0.47	0.98	-0.23	-0.19	0.52	-1.31	0.28
0.007	R^2_{OS}	-8.72	-12.57	-4.47	-35166	-37795	-30135	-7563	-63565
	$MSPE$	1.16	0.82	$1.32*$	0.20	0.12	0.56	-1.47	0.13
0.01	R^2_{OS}	-6.22	-7.92	-1.90	-16289	-17431	-26104	-5962	-28677
	$MSPE$	1.12	0.98	$1.47*$	0.23	0.24	0.53	-1.61	-0.29
0.02	R^2_{OS}	-2.05	-1.31	1.69	-3228	-3134	-11635	-3134	-5340
	$MSPE$	$1.40*$	$1.48*$	2.01	-0.11	0.22	0.30	-1.51	-1.49
0.03	R^2_{OS}	0.22	-0.10	2.01	-968	-980	-3361	-1419	-1546
	$MSPE$	1.45	$1.53*$	$2.30**$	0.52	0.49	-0.05	-1.40	-1.33
0.05	R^2_{OS}	0.94	0.58	1.85	-14.06	-11.74	-43.49	-106	-27.48
	$MSPE$	1.56	1.62	2.40	0.54	0.78	-0.92	-1.00	-0.11

Table 13.2 Forecats by Elastic Net($\alpha = 0.5$) at Monthly Frequency (R^2_{OS}(%))

λ		Sa	Sb	Sc	Sd	Se	Sf	Sg	Sh
0.003	R^2_{OS}	−28562	−51299	−65584	−66204	−63659	−50409	−3.27	−11.34
	$MSPE$	−0.41	0.55	−0.01	−0.15	−0.06	0.56	2.16	1.08
0.007	R^2_{OS}	−14337	−8384	−11221	−11061	−11820	−8246	−0.50	−3.72
	$MSPE$	−0.05	0.26	0.30	0.22	0.00	0.26	2.38	1.55
0.01	R^2_{OS}	−5387	−3640	−4214	−4362	−4675	−3601	0.23	0.29
	$MSPE$	0.06	0.17	0.32	0.20	−0.02	0.17	2.41	1.95
0.02	R^2_{OS}	−606	−491	−467	−615	−604	−484	0.97	2.17
	$MSPE$	0.42	0.38	0.47	0.49	0.35	0.37	2.20	2.45
0.03	R^2_{OS}	−16.02	−14.03	−14.61	−13.60	−16.09	−13.62	0.59	1.95
	$MSPE$	0.48	0.64	0.56	0.71	0.47	0.65	1.90	2.44
0.05	R^2_{OS}	0.21	0.43	0.21	0.43	0.21	0.43	0.21	0.43
	$MSPE$	1.75	1.84	1.75	1.84	1.75	1.84	1.75	1.84
λ		Si	Sj	Sk	Sl	Sm	Sn	So	Sp
0.003	R^2_{OS}	−11.67	−17.56	−7.32	−63568	−66130	−32840	−9482	−124274
	$MSPE$	1.22	0.69	1.18	0.04	−0.10	0.57	−1.42	0.17
0.007	R^2_{OS}	−5.17	−6.22	−0.85	−11315	−11673	−23820	−5447	−18740
	$MSPE$	1.18	1.06	1.56∗	0.09	0.20	0.53	−1.63	−0.55
0.01	R^2_{OS}	−2.69	−2.49	1.22	−4677	−4540	−16194	−3998	−7868
	$MSPE$	1.39	1.35	1.86	−0.02	0.14	0.46	−1.55	−1.05
0.02	R^2_{OS}	−0.78	−0.49	2.17	−608	−613	−2001	−1068	−921
	$MSPE$	1.46	1.54	2.38	0.41	0.44	0.05	−1.30	−1.26
0.03	R^2_{OS}	0.16	0.10	1.89	−15.60	−13.67	−44.99	−110	−27.69
	$MSPE$	1.56	1.62	2.41	0.48	0.70	−0.93	−1.01	−0.12
0.05	R^2_{OS}	0.21	0.21	0.43	0.21	0.43	0.21	0.21	0.43
	$MSPE$	1.75	1.75	1.84	1.75	1.84	1.75	1.75	1.84

Table 13.3 Forecats by Elastic Net($\alpha = 0.9$) at Monthly Frequency
All R^2_{OS}s are prsented by (%)

λ		Sa	Sb	Sc	Sd	Se	Sf	Sg	Sh
0.003	R^2_{OS}	−19156	−16385	−22965	−22942	−22663	−16272	−1.38	−6.25
	$MSPE$	−0.26	0.56	0.25	0.18	0.13	0.55	2.30	1.36
0.007	R^2_{OS}	−3303	−2307	−2508	−2886	−2929	−2301	0.39	0.84
	$MSPE$	0.04	0.09	0.30	0.23	0.01	0.09	2.37	2.12
0.01	R^2_{OS}	−1025	−797	−774	−1028	−999	−795	0.91	1.84
	$MSPE$	0.46	0.48	0.56	0.53	0.45	0.48	2.27	2.33
0.02	R^2_{OS}	−4.70	−3.70	−4.53	−3.60	−5.07	−3.68	1.17	1.34
	$MSPE$	0.48	0.66	0.50	0.67	0.41	0.66	1.80	2.21
0.03	R^2_{OS}	0.21	0.25	0.21	0.25	0.21	0.25	0.21	0.25
	$MSPE$	1.75	1.76	1.75	1.76	1.75	1.76	1.75	1.76
0.05	R^2_{OS}	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
	$MSPE$	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75

λ		Si	Sj	Sk	Sl	Sm	Sn	So	Sp
0.003	R^2_{OS}	−7.18	−9.72	−2.71	−21664	−23605	−27694	−6541	−38096
	$MSPE$	1.09	0.90	1.42	0.22	0.24	0.54	−1.55	−0.15
0.007	R^2_{OS}	−1.04	−0.91	1.76	−2986	−2916	−10733	−3049	−4847
	$MSPE$	1.38	1.49	2.04	−0.11	0.25	0.27	−1.50	−1.62
0.01	R^2_{OS}	1.17	1.11	2.04	−1004	−1019	−3475	−1514	−1570
	$MSPE$	1.46	1.51	2.31	0.51	0.49	−0.05	−1.41	−1.34
0.02	R^2_{OS}	1.22	1.29	1.37	−4.82	−3.60	0.21	−14.24	−3.66
	$MSPE$	1.60	1.69	2.21	0.45	0.67	1.75	−0.08	0.53
0.03	R^2_{OS}	0.21	0.21	0.25	0.21	0.25	0.21	0.21	0.25
	$MSPE$	1.75	1.75	1.76	1.75	1.76	1.75	1.75	1.76
0.05	R^2_{OS}	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
	$MSPE$	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75

Table 14. Forecasts by Complete Subset Regression at Monthly Frequency

M1/1992-M3/2021								
		$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$
Sa	R^2_{OS}	0.00	0.70	−1.48	−4.53	−7.65	−11.92	−16.88
	$MSPE-adj$	−0.53	0.86	1.02	1.12	1.20	1.13	1.15
Sb	R^2_{OS}	0.00	1.69	2.10	1.95	1.46	0.40	−0.49
	$MSPE-adj$	−0.53	1.21	1.24	1.27	1.36*	1.36*	1.43
Sc	R^2_{OS}	0.00	1.86	1.18	−0.45	−2.48	−5.69	−9.29
	$MSPE-adj$	−0.53	1.06	1.19	1.29*	1.36*	1.35*	1.32
Sd	R^2_{OS}	0.00	1.42	1.13	−0.41	−2.02	−4.50	−6.67
	$MSPE-adj$	−0.53	0.96	1.03	1.05	1.09	1.11	1.13
Se	R^2_{OS}	0.00	1.49	1.24	−0.05	−1.68	−3.52	−5.34
	$MSPE-adj$	−0.53	0.97	1.06	1.12	1.20	1.22	1.27
Sn	R^2_{OS}	0.00	0.86	−1.25	−3.84	−7.34	−11.35	−15.90
	$MSPE-adj$	−0.53	0.85	0.91	0.97	0.95	0.82	0.76
		$k=8$	$k=9$	$k=10$	$k=11$	$k=12$	$k=13$	$k=14$
Sa	R^2_{OS}	−23.56	−31.10	−37.91	−47.95	−56.65	−66.27	−75.39
	$MSPE-adj$	1.07	1.00	0.99	0.92	0.90	0.86	0.82
Sb	R^2_{OS}	−2.11	−3.77	−5.90	−7.22	−10.11	−12.85	−15.03
	$MSPE-adj$	1.40	1.38	1.36	1.38	1.30	1.23	1.19
Sc	R^2_{OS}	−13.60	−18.83	−24.15	−30.26	−38.02	−45.44	−53.08
	$MSPE-adj$	1.28	1.17	1.14	1.03	0.97	0.91	0.90
Sd	R^2_{OS}	−12.41	−16.26	−18.86	−23.07	−28.24	−33.93	−49.24
	$MSPE-adj$	1.11	1.08	1.04	1.05	1.00	0.93	0.84
Se	R^2_{OS}	−7.71	−11.88	−14.48	−17.59	−21.69	−27.52	−32.50
	$MSPE-adj$	1.30	1.18	1.19	1.20	1.21	1.08	1.05
Sn	R^2_{OS}	−19.91	−25.62	−33.53	−39.80	−50.45	−56.84	−66.56
	$MSPE-adj$	0.73	0.64	0.55	0.56	0.47	0.47	0.48

Table 15.1 Relative Predictive Power Ratio (OLS) at Monthly Frequency During Recession

	US	UK	FRA	GER	JAP	CAN	AUS
M1/1993-M3/2021							
S1	2.45***	2.34***	2.00**	2.05**	2.06*	2.36***	1.37**
S2	2.60**	2.40**	2.00**	2.07*	2.04**	2.61**	1.48*
S3	2.74	2.44*	2.06	2.10	2.11	2.76	1.52
S5	2.37*	2.37*	2.03*	2.10*	2.06	2.45***	1.38**
S6	2.50**	2.32***	1.97**	1.96**	1.95**	2.58*	1.40**
S15	2.44**	2.47	2.11	2.13	2.10	2.62**	1.43*
S16	2.57**	2.41**	2.04**	2.10**	2.03*	2.59**	1.49
S17	2.73*	2.46*	2.18	2.22	1.98**	2.48**	1.40*
S18	2.88	2.50*	2.16	2.13	2.10	2.68*	1.48**
S19	2.76*	2.49**	2.09**	2.17	2.08**	2.79	1.46**
S20	2.76	2.53	2.16	2.24	2.05*	2.64**	1.49
S21	2.89	2.70	2.27	2.21	2.23	3.02	1.70

Table 15.2 Relative Predictive Power Ratio (POLS) at Monthly Frequency During Recession

	US	*UK*	*FRA*	*GER*	*JAP*	*CAN*	*AUS*
M1/1992-M3/2021							
S1	2.45***	2.29***	2.01**	2.05**	2.01**	2.33***	1.39**
S2	2.62**	2.36**	2.06**	2.10**	2.03**	2.60**	1.46*
S3	2.79	2.50	2.16	2.21	2.14	2.51**	1.47
S5	2.48*	2.29	2.00*	2.06*	2.11	2.38***	1.39**
S6	2.60**	2.34**	2.03**	2.10*	1.94**	2.45**	1.40*
S15	2.52*	2.38	2.08*	2.10*	2.10	2.57*	1.48
S16	2.59**	2.33**	2.08**	2.09**	2.08**	2.55**	1.46*
S17	2.68*	2.42	2.16	2.21	2.02**	2.37***	1.39**
S18	2.83	2.51	2.14*	2.17	2.14*	2.64*	1.49*
S19	2.72**	2.49**	2.11**	2.18*	2.13*	2.73*	1.47**
S20	2.77	2.54	2.15	2.22	2.11	2.62**	1.48*
S21	3.01	2.61	2.28	2.28	2.20	2.97	1.66

Table 15.3 Relative Predictive Power Ratio (TPRF) at Monthly Frequency During Recession M1/1992-M3/2021

WG	$WG+S1$	$WG+S2$	$WG+S3$	$WG+S4$	$WG+S5$	$WG+S6$	$WG+S7$
4.71***	4.27***	4.64***	4.41***	4.46***	4.59***	4.51***	4.54***
WG+S8	$WG+S9$	$WG+S10$	$WG+S11$	$WG+S13$	$WG+S14$	$WG+S15$	$WG+S16$
4.61 ***	4.61***	4.60***	4.47***	4.61***	4.37***	4.59***	4.57***
WG+S17	$WG+S18$	$WG+S19$	$WG+S20$	$WG+S21$	$WG+S22$	$WG+S23$	$WG+S24$
4.73***	4.44***	4.63***	4.51***	4.46***8	4.66***	4.60***	4.60***

REFERENCES

Acharya, V. (2009). A theory of systemic risk and design of prudential bank regulation. Jounral of Fiancial Stability 5: 224-255.

Aiolfi, M., Timmermann, A. 2006. Persistence in forecasting performance and conditional combination strategies. Journal of Econometrics 135: 3153.

Andersen, T. G., Bollerslev, T., Diebold, F. X., Labys, P. 2001. The distribution of realized exchange rate volatility. Journal of the American Statistical Association 96: 4255.

Andersen, T. G., Bollerslev, T., Diebold, F. X., Labys, P. 2003. Modeling and forecasting realized volatility. Econometrica 71: 579625.

Baig, T., I., Goldfajn. 1999. Financial Market Contagion in the Asian Crisis. IMF Staff Papers 46(2): 167-195, International Monetary Fund.

Baillie, R. T. 1996. Long Memory Processes and Fractional Integration in Econometrics. Journal of Econometrics 73: 5-59.

Baillie, R. T., Bollerslev, T. 2000. The Forward Premium Anomaly Is Not as Bad as You Think. Journal of International Money and Finance 19(4): 471-488.

Bates, J., Granger, C. 1969. The Combination of Forecasts. Journal of Operation Research, 20: 451-468.

Bekaert, G., Harvey, C. R., Ng, A. 2005. Market Integration and Contagion. The Journal of Business 78(1): 39-70.

Bekaert, G., Ehrmann, M., Fratzscher, M., Mehl, A. 2014. The global crisis and equity market contagion. The Journal of Finance (6): 2597-2649.

Berk, K. N. 1974. Consistent Autoregressive Spectral Estimates. The Annals of Statistics 2: 489-502.

Bollerslev, T. 1990. Modelling the Coherence in Short-run Nominal Exchange Rates: A Multivariate Generalized ARCH Model. The Review of Economics and Statistics 72(3): 498-505.

Bollerslev, T., Wright, J.H. 2000. Semiparametrics Estimation of Long-memory Volatility Dependencies: the Role of High-frequency Data. Journal of Econometrics 98: 81-106.

Bossaerts, P., Hillion, P. 1999. Implementing statistical criteria to select return forecasting models: What do we learn? Review of Financial Studies 12: 405428.

Bookstaber, R. 1997. Global Risk Management: Are We Missing the Point? Journal of Portfolio Management 23(3): 102107.

Calvo, S., Reinhart, C. 1996. "Capital Flows to Latin America: Is There Evidence of Contagion Effects?" In Guillermo A. Calvo and Morris Goldstein and Eduard Hochreiter (ed.), Private Capital Flows to Emerging Markets After the Mexican Crisis, pages 151-171. Peterson Institute Press.

Campbell, J.Y., & Yogo, M. 2006. Efficient tests of stock return predictability. Journal of Financial Economics 81, 27-60.

Caramazza, F., Ricci, L., Salgado, R. 2004. International Financial Contagion in Currency Crises. Journal of International Money and Finance 23(1): 51-70.

Dai, Z., Kang, J. 2021. Bond yield and crude oil prices predictability. Enery Economics 97: 1-13.

Diebold, F. X., Yilmaz, K. 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. The Economic Journal 119: 158171.

Diebold, F.X., Yilmaz, K. (2012). Better to give than to receive: predictive directional measurement of volatility spillovers. International Journal of Forecasting 28: 57-66.

Diebold, F.X., Yilmaz, K. (2014). On the network topology of variance decompositions: easuring the connectedness of financial firms.

Eun, C.S., Lee, J. 2010. Mean-variance convergence around the world. Jounral of Banking and Finance 34: 856-870.

Elliott, G., Gargano, A., Timmermann, A. 2013. Complete subset regresssions. Journal of Econometrics 177, 357-373.

Fama, E. F. 1970. Efficient capital markets: a review of theory and empirical work. The Journal of Finance 25: 383417.

Fama, E.F., French, K. R. 1998. Value versus growth: the international evidence. Journal of Finance, 53, 1975-1999.

Forbes, K., Rigobon, R. 2002. No Contagion, Only Interpendence: Measuring Stock Market Co-movements. The Journal of Finance 57(5): 2223-2261.

Griffin J.M. 2002. Are the Fama and French factors Global or Country Specific? 32 The Review of Finanical Studies 15(2): 783-803.

Goyal, A., Welch, I. 2003. Predicting the equity premium with dividend ratios. Management Science 49: 639654.

Goyal, A., Welch, I. 2008. A comprehensive look at the empirical performance of equity premium prediction." Review of Financial Studies 21: 1455-1508.

Gargano, A., Timmermann, A. 2014. Interbational Journal of Forecasting 30: 825-843.

Han, C., Phillips, P.C.B. and Sul, D. 2017. Lag length selection in panel autoregression. Econometric Reviews 36: 225-240.

Harvey, C.R. 1995. Predictable risk and returns in emerging markets. Review of Financial Studies 8, 773–816.

Hartmann, P., Straetmans, S., and de Vries, C.G. 2004. Asset Market Linkages in Crisis Periods. The Review of Economics and Statistics 86(1): 313-326.

Hjalmarsson, E. 2010. Predicting Global Stock Returns. Journal of Financial and Quantitative Analysis 45(1), 49-80.

Hsiao, C., Wan, S. K. 2014. Is there an optimal forecast combination? Journal of Econometrics 178: 294309.

Kostakis, A., Magdalinos, T., Stamatogiannis, M. P. 2015. Robust econometric inference for stock return predictability. The Review of Financial Studies 28: 15061553.

Kelly, B., Pruitt, S. 2015. The three-pass regresssion filter: A new appraoch to forecasting using many predictors. Jounral of Econometrics 186: 294-316.

Lee J. H. H., King, M. L. 1993. A Locally Most Mean Powerful Based Score Test for ARCH and GARCH Regression Disturbances. Journal of Business Economic Statistics 11(1): 17-27.

Lin, W.L., Engle, R.F., Ito, T. 1994. Do bulls and bears move across borders? International Transmission of Stock Returns and Volatility. Review of Financial Studies 7: 507-538.

Lo, A. W. 1991. Long-term memory in stock market prices. Econometrica 59: 12791313.

Lobato, I.N., Savin, N.E. 1998. Real and Spurious Long-memory Properties of Stock-market Data. Journal of Business and Economic Statistics 16: 261268.

Longin, F., Solnik, B. 2001. Extreme Correlation of International Equity Markets. Journal of Finance 56(2): 649676.

Liew J., Vassalou, M. 2000. Can book-to-market, size, and momentum be risk factors that predict economic growth ? Journal of Finanical Economics 57: 221-245.

Neely, C.J., Rapach, D.E., Tu, J., Zhou, G. 2014. Forecasting the equity risk premium: the role of technical indicators. Management Science 60(7): 1772-1791.

Nelson, C. The prediction performance of the FRB-MIT-PENN model of the U.S. economy. The Amerieican Economic Review 62(5): 902-917.

Patro. D. K., Qi, M. and Sun X. 2009. A Simple Indicator of Systemic Risk. Journal of Fiancial Stability 9:105-116.

Paye, B. S., & Timmermann, A. 2006. Instability of return prediction models. Journal of Empirical Finance, 13(3), 274-315.

Pesaran, H.M., Timmermann, A. 1995. Predictability of Stock Returns: Robustness and Economic Significance. Journal of Finance 4:1201-1228.

Pettenuzzo, D., Timmermann, A., & Valkanov, R. 2014. "Forecasting stock returns under economic constraints." *Journal of Financial Economics*, 114(3), 517-553.

Pollet, J. M., Wilson, M. 2010. Average correlation and stock market returns. Journal of Financial Economics 96: 364380.

Pukthuanthong, K., Roll, R. 2009. Global market integration: An Alternative Measure and Its Application. Journal of Financial Economics 94: 214232.

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: 821862.

Stambaugh, R. F. 1999. "Predictive regressions." *Journal of Financial Economics*, 54(3), 375-421.

Stock, J. H., Watson, M. W. 2002. Forecasting using principal components from a large number of predictors. Journal of the American Statistical Association 97: 11671179.

Stock, J. H., Watson, M. W. 2004. Combination forecasts of output growth in a seven-country data set. Journal of Forecasting 23: 405430.

Stock, J.H., Mertens, K., Lewis, D. 2021. Measuring real volatility using a weekly economic index. Harvard University.

Kostakis, A., Magdalinos, T. and Stamatogiannis, M. 2014. Robust econometrics inference for stock return predictability.

Tibshirani, R. 1996. Regression shrinkage and selection via the lasso. Journal of the Royal Statistical Society. Series B (Methodological) 58: 267288.

Tong, H., Wei, S.-J. 2011. The composition matters: Capital inflows and liquidity crunch during a global economic crisis. Review of Financial Studies 24: 20232052.

Wallis, K.F. (1977). Multiple time series analysis and the final form of econometric models. Econometrica 45(6): 1481-1497.

Wang, C.S.H., Hsiao, C., Yang, H.C. 2021. Market Integration, Systemic Risk and Diagnostic Tests in Large Mixed Panels. Econometirc Reviews 40: 450-495.

Zellner, A., Palm, F. 1974. Time series analysis and simultaneous equation econometric models. Journal of Econometrics 2: 17-54.

Zhu X. 2015. Out-of-sample bond risk premium predictions: A global common factor. Journal of International Monery and Finance 51: 155-173.

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.

APPENDIX

Table A. Experimental Designs of The ARMA-ARFIMA Mixed Pnael System

DGP		series	Model Setting	AR	d	MA
Case1	N=3	1	$ARFIMA(0,d,0)$	NA	0.4	NA
		2	$ARMA(1,1)$	0.7	NA	0.4
		3	$ARMA(1,1)$	0.6	NA	0.4
Case2	N=10	$1-4$	$ARFIMA(0,d,0)$	NA	0.4	NA
		$5-7$	$ARMA(1,1)$	$U(0.7.0.9)$	NA	0.6
		$8-10$	$ARMA(1,1)$	0.7		$U(0.4,0.1)$

Table B. I.I.D Rejection Rates (%)of AR-and VAR-filtered Residuals by Ljung-Box Test For Cases in Table A.

	$Series$	1	2	3	4	5	6	7	8	9	10
Case1											
T=100	AR	6.4	7.4	4.0							
	VAR	5.0	10	5.0							
T=200	AR	3.6	6.4	5.2							
	VAR	8.0	8.4	4.6							
Case2											
T=100	AR	3.8	2.6	6.2	4.8	7.2	7.0	6.4	4.8	7.2	6.2
	VAR	32.4	35.8	32.8	35.2	34.0	32.0	33.6	31.2	35.2	30.0
T=200	AR	4.0	3.6	2.8	3.4	6.4	6.2	4.6	5.8	5.4	5.2
	VAR	13.8	13.2	11.6	11.4	39.0	38.4	40.0	8.8	10.4	8.8

Table C. Average Selected Lag k of AR(k)-and VAR(k)-approximation For Cases in Table A.

	$Series$	1	2	3	4	5	6	7	8	9	10
Case1											
T=100	AR	2.01	2.16	1.49							
	VAR		2.182								
T=200	AR	2.87	2.75	1.85							
	VAR		2.37								
Case2											
T=100	AR	2.03	2.09	1.97	2.00	2.14	2.13	2.13	1.43	1.43	1.42
	VAR					8					
T=200	AR	2.89	2.89	2.84	2.96	2.76	2.71	2.76	1.84	1.84	1.94
	VAR					1.46					