Bank of Finland Research Discussion Papers
10 • 2024

Gonçalo Faria – Fabio Verona

Unlocking predictive potential: the frequency-domain approach to equity premium forecasting

Bank of Finland
Research

Bank of Finland Research Discussion Papers
Editor-in-Chief Esa Jokivuolle

Bank of Finland Research Discussion Papers 10/2024
31 October 2024

Gonçalo Faria – Fabio Verona:
Unlocking predictive potential: the frequency-domain approach to equity premium forecasting

ISSN 1456-6184, online

Bank of Finland
Research Unit

PO Box 160
FIN-00101 Helsinki

Phone: +358 9 1831

Email: research@bof.fi
Website: www.suomenpankki.fi/en/research/research-unit/

Unlocking predictive potential: the frequency-domain approach to equity premium forecasting*

Gonçalo Faria† Fabio Verona‡

Abstract

This paper explores the out-of-sample forecasting performance of 25 equity premium predictors over a sample period from 1973 to 2023. While conventional time-series methods reveal that only one predictor demonstrates significant out-of-sample predictive power, frequency-domain analysis uncovers additional predictive information hidden in the time series. Nearly half of the predictors exhibit statistically and economically meaningful predictive performance when decomposed into frequency components. The findings suggest that frequency-domain techniques can extract valuable insights that are often missed by traditional methods, enhancing the accuracy of equity premium forecasts.

Keywords: equity premium, predictability, frequency domain

JEL classification: C58, G11, G17

* The views expressed here are those of the authors and do not necessarily reflect those of the Bank of Finland. Faria gratefully acknowledges financial support by FCT - Fundação para a Ciência e Tecnologia, I.P., by project reference UIDB/00731/2020 and DOI identifier 10.54499/UIDB/00731/2020 (https://doi.org/10.54499/UIDB/00731/2020). Research at *Cef.up* has been financed by Portuguese public funds through FCT, I.P., in the framework of the project with reference UIDB/04105/2020.

† Universidade Católica Portuguesa, Católica Porto Business School, Research Centre in Management and Economics, Portugal and *RGEA* of University of Vigo, Spain (gfaria@ucp.pt).

‡ Bank of Finland – Monetary Policy and Research Department, and University of Porto – *Cef.up* (fabio.verona@bof.fi).

1 Introduction

Since Goyal and Welch (2008), there has been a surge of research on forecasting the equity premium, with numerous new predictors and methodologies emerging. This literature has been dominated by traditional time-series analysis. While frequency-domain techniques have been around for a long time, their application to finance and economics is relatively recent. Works like Chaudhuri and Lo (2016) on spectral portfolio theory, Dew-Becker and Giglio (2016) on asset pricing in the frequency domain, and Crouzet, Dew-Becker and Nathanson (2020) on multi-frequency trade models illustrate this growing relevance.

Moreover, studies by Faria and Verona (2018) and Bandi, Perron, Tamoni and Tebaldi (2019) show that equity returns and predictors are linear aggregates of components operating over different frequencies, and predictability is frequency-specific. Frequency-domain analysis offers a way to uncover hidden information in the original time series.

Goyal, Welch, and Zafirov (2024) reassessed the empirical performance of 46 well-known equity premium predictors with updated data until December 2021. They found that only a small fraction of the predictors exhibited strong out-of-sample (OOS) performance. In this paper, we reexamine these predictors by focusing on the information embedded in the original time series. The key question we explore is whether valuable predictive information is hidden in the equity premium predictors' time series. Building on Faria and Verona's (2020) work, which showed that the lowest frequency component of the term spread is a reliable equity premium predictor, we evaluate a broader set of predictors and their frequency components over a longer period ending in 2023.

Our findings reveal that, while only one of the original predictors analyzed demonstrates OOS predictive power, nearly half of the predictors' frequency components show statistically and economically significant predictive value. A substantial portion of the standard predictors of equity risk premium in the literature holds significant OOS predictive power, which is obscured in their original time series and can be revealed through frequency decomposition. We evaluate the robustness of these findings with different benchmark models and across different business cycle phases. Our results confirm that highly valuable information can be extracted using frequency-domain techniques, even when the original predictors perform poorly.

This paper is organized as follows: Section 2 details the data and methodology, section 3 discusses empirical results, and section 4 concludes.

2 Data and methodology

We use monthly data from January 1973 (1973M01) to December 2023 (2023M12). The equity risk premium (*ERP*) for month t is defined as the difference between the return on the S&P500 index in month t and the one-month T-bill known at the beginning of month t. The predictors we use include the following 25 variables from Goyal et al. (2024): log dividend-price ratio (DP), log dividend yield (DY), log earnings-price ratio (EP), dividend-payout ratio (DE), excess stock return volatility (RVOL), book-to-market ratio (BM), net equity expansion (NTIS), treasury bill rate (TBL), long-term bond yield (LTY), long-term bond return (LTR), term spread (TMS), default yield spread (DFY), default return spread (DFR), lagged inflation rate (INFL), average correlation of stock returns (AVGCOR), distance to 52-week maximum price of the Dow-Jones index (DTOAT), distance to historical maximum price of the Dow-Jones index (DTOY), log of the number of zero returns (LZRT), ratio of new orders to shipments of durable goods (NDRBL), cross-sectional standard deviation on the set of 100 size and book-to-market portfolios (RDSP), cross-section based tail-risk (TAIL), price of west-Texas intermediate crude oil (WTEXAS), dividend-price ratio net of the 10-year government bond yield (YGAP), cross-sectional skewness (SKVW), and short interest index (SII).[1]

[1] From the 46 equity premium predictors analysed by Goyal et al. (2024), with updated time series available at https://sites.google.com/view/agoyal145, we select the 24 predictors that are defined in monthly frequency and have data for the full sample period (1973M021 to 2023M12). We are thankful to Matthew Ringgenberg for providing us an updated time-series of the SII variable.

2.1 Frequency-decomposition of the predictors

To extract the frequency components from the original variables, we employ the maximal overlap discrete wavelet transform (MODWT) and band-pass the original time series with the Haar filter, which is commonly used in macroeconomic and finance applications (see e.g. Faria and Verona, 2018, 2021, Bandi et al., 2019, Kilponen and Verona, 2022, Martins and Verona, 2023, 2024, Canova, 2024, and Stein, 2024). Each predictor X_t is decomposed as:

$$X_t = \sum_{j=1}^{J} X_t^{D_j} + X_t^{S_J} \ , \tag{1}$$

where $X_t^{D_j}$ are the wavelet detail coefficient at scale j, and $X_t^{S_J}$ is the wavelet smooth coefficient. These coefficients are given by

$$X_t^{D_j} = \frac{1}{2^j}\left[\sum_{i=0}^{2^{(j-1)}-1} X_{t-i} - \sum_{i=2^{(j-1)}}^{2^j-1} X_{t-i}\right] \tag{2}$$

and

$$X_t^{S_J} = \frac{1}{2^J}\sum_{i=0}^{2^J-1} X_{t-i} \ . \tag{3}$$

The decomposition allows us to break the original time series into different components that fluctuate at distinct frequencies. Given the length of the data series, we consider seven frequency components. The first component (D_1) captures oscillations between 2 and 4 months, the second component (D_2) captures oscillations between 4 and 8 months, while components D_3 to D_6 capture oscillations with a period of 8-16, 16-32, 32-64, and 64-128 months, respectively. Finally, component S_6 captures oscillations with a period longer than 128 months (10.6 years). Importantly, the sum of these time series frequency components gives exactly the time series of the original variable.[2]

To demonstrate the dynamics embedded – and often obscured – within the original time series, figure 1 presents the time series of one of the predictors (the short interest index) alongside its seven frequency

[2] In the MODWT, each wavelet filter at frequency j approximates an ideal high-pass filter with passband $f \in \left[1/2^{j+1}, 1/2^j\right]$, while the smooth component is associated with frequencies $f \in \left[0, 1/2^{j+1}\right]$. The level j wavelet components are therefore associated to fluctuations with periodicity $\left[2^j, 2^{j+1}\right]$ (months, in this case). As regards the choice of J, the number of observations dictates the maximum number of frequency bands that can be used. In particular, if t_0 is the number of observations in the in-sample period, then J has to satisfy the constraint $J \leq \log_2 t_0$.

components. These frequency components exhibit distinct time series characteristics and behavior, suggesting that only certain components carry valuable predictive information, making them potentially strong predictors.

2.2 Out-of-sample (OOS) forecasts

The OOS forecasts of the *ERP* are generated using a sequence of expanding windows. We use an initial sample (1973:M01 to 1989:M12) to make our first one-step-ahead OOS forecast. The sample is then increased by one observation and a new one-step-ahead OOS forecast is produced. The full OOS period runs from 1990M01 to 2023M12, that is, we produce 408 one-step-ahead monthly OOS forecasts.

In the forecasting exercise, we use a two-sided version of the Haar filter (see Stein, 2024), so we recompute the frequency components of the original predictors at each iteration of the OOS forecasting process using data from the start of the sample through the month of forecast formation. This step ensures that our method does not have a look-ahead bias, as the forecasts are made with current and past information only.[3] Likewise, when using a two-sided filter some assumptions as regards how to deal with boundary observations has to be made. The literature suggests several types of boundary treatment rules to deal with boundary effects (e.g. periodic rule, reflection rule, zero padding rule, and polynomial extension). Here, we use a reflection rule, whereby the original time series are reflected symmetrically at the boundaries before filtering the time series.

2.2.1 Predictive regression model

Let X be a predictor. The predictive regression model for the equity premium is

$$ERP_{t+1} = \alpha + \beta X_t + \varepsilon_{t+1} \ , \tag{4}$$

[3] The SII is also computed recursively at each step of the OOS period. See Rapach, Ringgenberg and Zhou (2016) for details.

and the one-step-ahead OOS forecast of the *ERP*, denoted $\widehat{ERP}_{t+1}$, is given by:

$$\widehat{ERP}_{t+1} = \hat{\alpha}_t + \hat{\beta}_t X_t \ , \tag{5}$$

where $\hat{\alpha}$ and $\hat{\beta}$ are the Ordinary Least Squares (OLS) estimates of parameter α and β, respectively.

As predictors, we consider one original predictor at a time (model denoted *TD*), or one frequency component of one original predictor at a time.

2.2.2 Performance measurement

The OOS forecasting performance of each predictor is evaluated using the Campbell and Thompson (2008) R^2_{OS} statistic, which measures the proportional reduction in the mean squared forecast error (MSFE) for the predictive model relative to a benchmark and is given by:

$$R^2_{OS} = 100\left[1 - \frac{\sum_{t=t_0}^{T-1}\left(r_{t:t+1} - \widehat{ERP}_{t+1}\right)^2}{\sum_{t=t_0}^{T-1}\left(r_{t:t+1} - \widehat{ERP}_{t+1}^{benchmark}\right)^2}\right], \tag{6}$$

where $\widehat{ERP}_{t+1}^{benchmark}$ is the forecast from the historical mean (HM) model, which is the standard benchmark model in the literature (see e.g. Goyal and Welch, 2008). Following e.g. Rapach et al. (2016), we evaluate the statistical significance of the R^2_{OS} using the Clark and West (2007) statistic. This statistic tests the null hypothesis that the MSFE of the HM model is less than or equal to the MSFE of the predictive model against the alternative hypothesis that the MSFE of the HM model is greater than the predictive model ($H_0 : R^2_{os} \leq 0$ against $H_A : R^2_{os} > 0$).

Additionally, to analyze the economic value of the different predictors from an asset allocation perspective, we consider a mean-variance investor allocating his wealth between equities and risk-free bills. At the end of month t, the investor optimally allocates:

$$w_t = \frac{1}{\gamma}\frac{\hat{R}_{t+h}}{\hat{\sigma}^2_{t+h}} \qquad (7)$$

of the portfolio to equity for the period from t to t+h. In (7), γ is the investor's relative risk aversion coefficient, $\hat{R}_{t+h}$ is the OOS forecast of stock return at time t for the period t+h, and $\hat{\sigma}^2_{t+h}$ is the OOS forecast of the variance of the stock return. Following Rapach et al. (2016), we assume a relative risk aversion coefficient of three, use a ten-year moving window of past excess returns to estimate the variance of the excess return, and constrain the weights w_t to a range between -0.5 and 1.5.

The average utility (or certainty equivalent return, CER) of an investor that uses the portfolio rule (7) is given by $CER = \overline{RP} - 0.5\gamma\sigma^2_{RP}$, where $\overline{RP}$ and σ^2_{RP} are the sample mean and variance of the portfolio return, respectively. We report the annualized utility gain from using the predictive models associated with different predictors, which is computed as the difference between the CER for an investor that uses the predictive model to forecast excess returns and the CER for an investor who uses the HM benchmark for forecasting. To test if the CER gains are statistically greater than zero, we follow Bianchi, Buchner and Tamoni (2021) and use the Diebold and Mariano (1995) test.

3 Results

Table 1 reports the R^2_{OS} statistic for each individual predictor, using both its original time series (*TD* model) and its frequency components (D_1 to S_6). The analysis yields three main findings. First, out of all the original predictors, only the short interest index (SII) demonstrates out-of-sample predictive power for the equity premium, with a positive R^2_{OS}. This result indicates that, using the updated sample period ending in 2023, the performance of the traditional predictors is generally worse than previously reported by Goyal et al. (2024).

Second, when the predictors are decomposed into their frequency components, a significant improvement in predictive power is observed. Specifically, eleven predictors (EP, RVOL, BM, LTR, TMS, INFL, NDRBL, TAIL, WTEXAS, YGAP, SII) exhibit statistically significant out-of-sample predictive performance at specific frequencies. For instance, the fifth frequency component of the SII, which captures oscillations between 32 and 64 months, achieves an R^2_{OS} of 1.67 %, statistically significant at the 1 % level.

Third, the predictive power of the frequency components is dependent on the specific predictor being analyzed. While some predictors reveal strong predictive capabilities in lower frequencies, others show improvements at higher frequencies. Nevertheless, it becomes evident that the frequency-domain approach extracts valuable information from all frequencies of the predictors that is otherwise concealed in their original time series.

Table 1 illustrates that the best-performing predictors are the sixth and first frequency components of WTEXAS ($WTEXAS^{S_6}$ and $WTEXAS^{D_1}$), and the fourth and fifth components of SII (SII^{D_4} and SII^{D_5}). For those four predictors, in figure 2, the time-series plots of the cumulative squared prediction error differences between the benchmark historical mean forecast and the forecasts based on both the original predictors and their frequency components provide further insights. For the WTEXAS predictor, the results show that the frequency-domain forecasts (depicted by the blue lines) provide more stable and consistent out-of-sample gains compared to the forecasts using the original time series (black lines). Notably, a structural break is observed around the global financial crisis, after which the original time-series forecasts significantly underperform. The results for SII show that both the original time series and the selected frequency components outperform the benchmark after the global financial crisis. This highlights the relevance of frequency-domain methods in capturing important predictive signals during different phases of the economic cycle.

In addition to the statistical measures presented so far, table 2 presents the economic value of the frequency components from an asset allocation perspective. Using a mean-variance investor framework, we compute the certainty equivalent return (CER) gains. Four original predictors (TBL, LTY, SKVW, and SII) deliver positive and statistically significant CER gains, despite some of them having negative

R^2_{OS}.[4] In contrast, eleven predictors, including DP, DY, EP, BM, TMS, INFL, NDRBL, TAIL, WTEXAS, YGAP, and SII, show statistically significant CER gains when their frequency components are used. Notably, the maximum CER gain achieved through the frequency components is 458 basis points (SII^{D_5}), which is higher than the maximum CER gain achieved with the original predictors (368 basis points with SII).

We also compute the R^2_{OS} and CER gains for each frequency component relative to its original predictor, rather than the historical mean benchmark. Tables 3 and 4 summarize these results, showing that the frequency components consistently outperform their original time-series counterparts. At least one frequency component from seventeen predictors achieves a statistically significant R^2_{OS}, and eight predictors deliver positive and significant CER gains.

Finally, following Rapach, Strauss and Zhou (2010), we examine the predictive performance of the predictors across different phases of the business cycle by separating the sample into periods of bad, normal, and good growth based on U.S. industrial production growth rates. The results, presented in tables 5 to 10, demonstrate that frequency-domain methods provide robust predictive power across all phases of the business cycle. The predictors $WTEXAS^{S_6}$ and $WTEXAS^{D_1}$ continue to rank among the top performers during bad- and normal-growth phases, while SII^{D_5} is among the top performers during both bad- and good-growth phases. This consistency across different phases supports the hypothesis that frequency-domain forecasts offer more stable out-of-sample gains over time.

In sum, a substantial number of equity premium predictors exhibit hidden predictive value in their frequency components. These components not only offer statistically significant predictive power but also provide economically meaningful gains, confirming the efficacy of frequency decomposition in enhancing the predictive performance of equity premium predictors.

[4] This is consistent with previous findings that forecast error-based measures, such as R^2_{OS}, are not necessarily correlated with economic gains, as documented by Leitch and Tanner (1991) and Kelly, Malamud and Zhou (2024).

4 Conclusion

Goyal et al. (2024) found that only a small fraction of well-known equity premium predictors performed reasonably well in out-of-sample (OOS) forecasts. Using a similar set of predictors, we extended the analysis to the period ending in December 2023. Our findings show that only one predictor from the original time series, the short interest index (SII), demonstrates significant predictive power for the equity premium. This aligns with previous findings, reinforcing the idea that many traditional predictors perform poorly in OOS forecasts when assessed through conventional time-domain analysis.

Motivated by these results, we explored whether there is valuable predictive information hidden within the time series of these equity premium predictors, which may not be evident when looking solely at their original time series. Our main finding is that a significant portion of the standard equity risk premium predictors in the literature have strong OOS predictive power when their frequency components are considered. By decomposing the time series into frequency bands using wavelet techniques, we uncovered hidden predictive signals. Nearly half of the predictors showed frequency components with statistically and economically significant predictive power, even when the original time series performed poorly. These results hold up under various benchmark models and across different phases of the business cycle.

This study highlights the potential of frequency-domain techniques for extracting valuable information from predictors that are otherwise noisy or ineffective in their original form. The evidence suggests that relying solely on traditional time-domain models may lead to underestimating the predictive capabilities of certain variables. Our findings demonstrate the importance of considering the entire frequency spectrum when assessing the predictive power of equity premium predictors.

In conclusion, frequency decomposition provides a robust framework for uncovering hidden predictive signals within the time series of widely-used equity premium predictors. This approach offers both statistical and economic gains, underscoring its efficacy for future empirical work in financial forecasting.

References

Bandi, Federico, Bernard Perron, Andrea Tamoni, and Claudio Tebaldi, "The Scale of Predictability," *Journal of Econometrics*, 2019, *208* (1), 120–140.

Bianchi, Daniele, Matthias Buchner, and Andrea Tamoni, "Bond Risk Premiums with Machine Learning," *Review of Financial Studies*, 2021, *34* (2), 1046–1089.

Campbell, John Y. and Samuel B. Thompson, "Predicting Excess Stock Returns Out of Sample: Can Anything Beat the Historical Average?," *Review of Financial Studies*, 2008, *21* (4), 1509–1531.

Canova, Fabio, "FAQ: How do I estimate the output gap?," *Economic Journal*, 2024, *forthcoming.*

Chaudhuri, S. and Andrew Lo, "Spectral Portfolio Theory," 2016. mimeo.

Clark, Todd E. and K.D. West, "Approximately normal tests for equal predictive accuracy in nested models," *Journal of Econometrics*, 2007, *138* (1), 291 – 311.

Crouzet, Nicolas, Ian Dew-Becker, and Charles G Nathanson, "On the Effects of Restricting Short-Term Investment," *Review of Financial Studies*, 2020, *33* (1), 1–43.

Dew-Becker, Ian and Stefano Giglio, "Asset Pricing in the Frequency Domain: Theory and Empirics," *Review of Financial Studies*, 2016, *29* (8), 2029–2068.

Diebold, F.X. and R.S. Mariano, "Comparing Predictive Accuracy," *Journal of Business & Economic Statistics*, 1995, *13* (3), 253–263.

Faria, Gonçalo and Fabio Verona, "Forecasting stock market returns by summing the frequency-decomposed parts," *Journal of Empirical Finance*, 2018, *45*, 228–242.

_ and _ , "The yield curve and the stock market: Mind the long run," *Journal of Financial Markets*, 2020, *50* (C).

— **and** — , "Out-of-sample time-frequency predictability of the equity risk premium," *Quantitative Finance*, 2021, *21* (12), 2119–2135.

Goyal, A. and I. Welch, "A Comprehensive Look at The Empirical Performance of Equity Premium Prediction," *Review of Financial Studies*, 2008, *21* (4), 1455–1508.

— , — , , and A. Zafirov, "A Comprehensive 2022 Look at the Empirical Performance of Equity Premium Prediction," *Review of Financial Studies*, 2024, *37* (11), 3490–3557.

Kelly, Bryan, Semyon Malamud, and Kangying Zhou, "The Virtue of Complexity in Return Prediction," *Journal of Finance*, 2024, *79* (1), 459–503.

Kilponen, Juha and Fabio Verona, "Investment dynamics and forecast: Mind the frequency," *Finance Research Letters*, 2022, *49* (C).

Leitch, Gordon and J. Ernest Tanner, "Economic Forecast Evaluation: Profits Versus the Conventional Error Measures," *American Economic Review*, 1991, *81* (3), 580–590.

Martins, Manuel M. F. and Fabio Verona, "Inflation dynamics in the frequency domain," *Economics Letters*, 2023, *231*, 111304.

— **and** — , "Forecasting inflation with the new Keynesian Phillips curve: frequencies matter," *Oxford Bulletin of Economics and Statistics*, 2024, *86* (4), 811–832.

Rapach, David E., Jack K. Strauss, and Guofu Zhou, "Out-of-Sample Equity Premium Prediction: Combination Forecasts and Links to the Real Economy," *Review of Financial Studies*, 2010, *23* (2), 821–862.

— , Matthew C. Ringgenberg, and Guofu Zhou, "Short interest and aggregate stock returns," *Journal of Financial Economics*, 2016, *121* (1), 46 – 65.

Stein, Tobias, "Forecasting the equity premium with frequency-decomposed technical indicators," *International Journal of Forecasting*, 2024, *40* (1), 6–28.

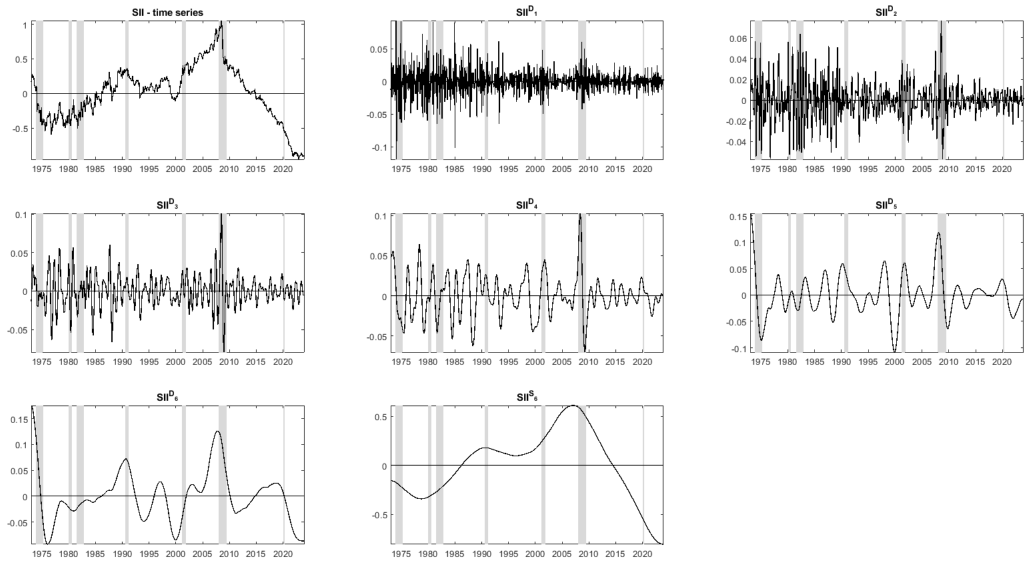

Figure 1: SII time series with frequency decomposition

This figure plots the time series of the short interest index (*SII*, upper left graph) and the seven frequency components into which the time series is decomposed using a Haar filter (SII^{D_1},..., SII^{D_6}, and SII^{S_6}, remaining graphs).

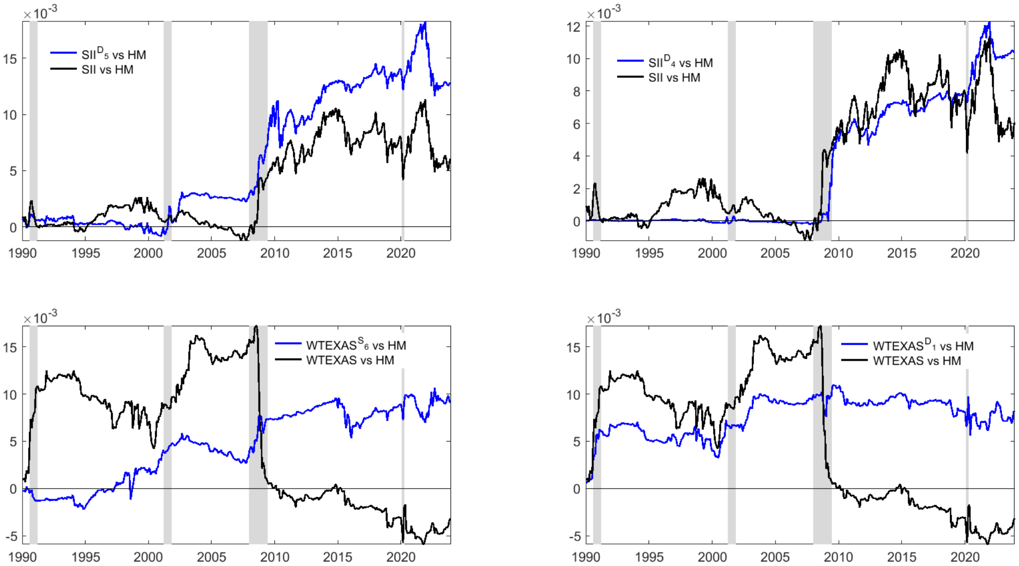

Figure 2: Cumulative differences in squared forecast errors

Cumulative differences in squared forecast errors, equity premium out-of-sample forecasts based on individual predictors. Black (blue) line delineates the cumulative difference in squared forecast errors for the historical average forecast relative to the predictive regression forecast using the original time-series of individual predictors (selected frequency component). The out-of-sample period is from 1990:M01 to 2023:M12.

	TD	D_1	D_2	D_3	D_4	D_5	D_6	S_6
DP	-1.55	-26.1	-20.9	-4.64	-0.96	-0.59	-0.56	-0.67
DY	-1.69	-0.06	-50.9	-22.8	-4.26	-1.02	-0.59	-0.67
EP	-0.88	-27.2	-10.8	0.44**	0.29	-0.31	-1.61	-0.63
DE	-1.54	-10.4	-30.6	-6.68	-0.72	-0.99	-1.61	0.26
RVOL	-0.08	-0.24	-3.67	-4.22	-2.21	0.30*	-0.41	-1.15
BM	-0.43	-5.03	-4.09	-1.00	-0.01	0.40**	0.15	-0.43
NTIS	-2.19	-0.01	-1.15	-2.67	-2.36	-2.04	-1.37	-1.09
TBL	-0.13	-0.01	0.05	-1.32	-3.81	-1.38	-0.13	-0.28
LTY	-0.10	-0.66	-0.11	-0.70	-0.09	-0.05	-0.01	-0.68
LTR	-0.42	-0.32	-2.36	-2.31	-2.01	-0.97	-0.15	0.51*
TMS	-0.97	-0.11	-0.20	-1.29	-2.49	-1.47	-0.54	1.00***
DFY	-2.14	-1.03	-5.20	-12.2	-6.62	-1.46	-0.82	-0.74
DFR	-2.25	0.06	-2.01	-11.3	-11.5	-2.44	-0.76	-1.90
INFL	-0.54	0.69*	0.68*	-0.90	-0.80	0.80**	0.44*	0.12
AVGCOR	-0.41	-5.16	-11.5	-2.75	-0.45	-0.70	-0.31	-1.94
DTOAT	-0.03	-16.5	-8.84	-0.14	0.03	-0.25	-1.55	-2.73
DTOY	-0.21	-13.9	-5.64	-0.19	-0.88	-2.44	-3.86	-3.94
LZRT	-0.95	-0.52	-1.04	-3.46	-3.92	-2.04	-1.52	-0.91
NDRBL	-1.57	-0.28	-0.28	-7.89	-5.23	-1.48	-0.29	0.06*
RDSP	-0.92	-0.21	-0.58	-1.15	-0.56	-0.94	-1.31	-0.78
TAIL	-0.36	0.61*	-0.54	-2.67	-0.89	-0.69	0.28	1.03**
WTEXAS	-0.41	1.05**	0.25	-2.06	-0.84	-0.97	-0.10	1.19**
YGAP	-0.89	-27.7	-12.4	0.55**	0.35	-0.32	-1.63	-0.64
SKVW	-0.68	-2.55	-0.42	-0.57	-3.83	-3.03	-0.42	-1.84
SII	0.79***	0.01	-1.81	-0.14	1.36***	1.67***	0.38**	0.46*

Table 1: R^2_{OS} vs HM

R^2_{OS} (in percentage) for the equity premium forecasts from the model as given by equation (6), considering the historical mean (HM) as the benchmark for forecasting. Column (TD) reports the results when using the original time-series of each predictor. Remaining columns report the results when using frequencies D_1 to S_6, respectively, from each predictor. The out-of-sample period is from 1990:M01 to 2023:M12. ***, **, and * denote statistically significant coefficients at the 1 %, 5 %, and 10 % level, respectively. Statistical significance is based on the p-value for the Clark and West (2007) out-of-sample MSFE-adjusted statistic.

	TD	D_1	D_2	D_3	D_4	D_5	D_6	S_6
DP	-2.44	-2.42	-3.74	-2.96	-2.43	-1.37	-0.48	0.15**
DY	-2.31	-0.30	-4.77	-3.90	-4.39	-2.13	-0.57	0.09*
EP	-0.32	2.89	3.99*	3.11	1.92	0.97	0.40	0.16**
DE	-0.52	0.81	-2.53	-1.46	-0.27	0.20	0.54	1.56
RVOL	-1.46	-0.41	-2.38	-1.47	-1.67	-0.21	-0.68	0.44
BM	-0.64	-3.34	-4.59	-1.94	-0.47	0.73	0.53	0.40***
NTIS	-1.81	-0.05	-0.21	-1.00	-2.03	-2.28	-1.33	-1.80
TBL	0.83***	0.03	-0.28	-1.32	-2.14	-1.76	0.04	-0.12
LTY	0.29**	-0.70	-0.88	-0.61	0.00	-0.04	0.05	-0.84
LTR	-0.62	-0.28	-1.05	-1.78	0.26	-1.17	-0.47	1.01
TMS	-0.35	-0.19	-0.31	-1.84	-2.88	-1.72	-0.82	3.86**
DFY	-3.57	-0.94	-3.13	-4.46	-4.90	-1.95	-0.97	-1.09
DFR	0.86	1.27	-0.42	-2.54	-4.39	-0.18	0.77	-0.04
INFL	-0.57	1.37	1.11	-1.13	0.68	2.17	1.36	1.60***
AVGCOR	-0.23	-3.19	-3.55	-3.71	0.35	-0.86	0.29	-1.91
DTOAT	-1.31	-1.73	-3.39	-1.39	-0.27	0.33	0.06	-3.12
DTOY	-1.31	-1.68	-3.07	-1.13	-0.90	-0.92	0.82	-1.39
LZRT	-0.75	-1.39	1.13	0.08	-2.31	-0.55	-0.60	-1.33
NDRBL	-0.21	-0.47	-0.51	-4.98	-4.54	-2.63	-0.09	1.91***
RDSP	-0.63	-0.84	-1.03	-0.52	0.54	-0.28	0.72	0.03
TAIL	1.42	2.48*	0.28	-3.15	-1.59	-0.91	1.08	4.16***
WTEXAS	0.83	1.10	0.28	-2.09	-0.60	-0.91	0.72	3.33*
YGAP	-0.26	3.23*	4.03*	3.15	2.19	1.08	0.47	0.18**
SKVW	1.43*	-2.78	-1.05	-1.03	-4.18	-3.04	-0.43	-2.06
SII	3.68***	0.10	-2.46	0.67	2.05***	4.58***	4.18***	2.07**

Table 2: CER gains vs. HM

CER gains computed for a mean-variance investor with relative risk aversion $\gamma = 3$, considering the historical mean (HM) as the benchmark for forecasting. First column (TD) reports the results when using the original time-series of each predictor. Remaining columns report the results when using frequencies D_1 to S_6, respectively, from each predictor. The out-of-sample period is from 1990:M01 to 2023:M12. ***, **, and * denote statistically significant coefficients at the 1 %, 5 %, and 10 % level, respectively. Statistical significance is based on the Diebold and Mariano (1995) test.

	D_1	D_2	D_3	D_4	D_5	D_6	S_6
DP	-24.1	-19.1	-3.04	0.58*	0.95**	0.97**	0.87**
DY	1.60***	-48.3	-20.7	-2.52	0.66*	1.08**	1.01**
EP	-26.1	-9.84	1.31**	1.16**	0.57**	-0.72	0.26
DE	-8.71	-28.6	-5.07	0.80**	0.53*	-0.07	1.77*
RVOL	-0.16	-3.59	-4.14	-2.13	0.38*	-0.33	-1.07
BM	-4.58	-3.6 5	-0.58	0.42	0.82**	0.57**	0.00
NTIS	2.13***	1.02**	-0.47	-0.17	0.15	0.81*	1.08**
TBL	0.12	0.17	-1.20	-3.68	-1.25	0.00	-0.16
LTY	-0.56	0.00	-0.60	0.01	0.05	0.10	-0.58
LTR	0.09	-1.94	-1.89	-1.59	-0.55	0.27	0.92**
TMS	0.85**	0.77**	-0.31	-1.51	-0.50	0.42*	1.95***
DFY	1.08**	-2.99	-9.81	-4.39	0.67**	1.29**	1.37***
DFR	2.26*	0.24	-8.84	-9.07	-0.18	1.46*	0.34*
INFL	1.23**	1.22**	-0.35	-0.25	1.33**	0.98**	0.67**
AVGCOR	-4.74	-11.0	-2.33	0.04	-0.29	0.09	-1.53
DTOAT	-16.5	-8.81	-0.10	0.06	-0.21	-1.51	-2.69
DTOY	-13.6	-5.42	0.01	-0.67	-2.23	-3.65	-3.72
LZRT	0.42	-0.09	-2.49	-2.95	-1.08	-0.57	0.04
NDRBL	1.28**	1.28**	-6.21	-3.59	0.09*	1.26**	1.61**
RDSP	0.70	0.33	-0.23	0.35	-0.02	-0.38	0.13
TAIL	0.97**	-0.18	-2.30	-0.53	-0.33	0.64**	1.38**
WTEXAS	1.46**	0.65*	-1.65	-0.43	-0.55	0.31*	1.59**
YGAP	-26.6	-11.4	1.43**	1.23**	0.57**	-0.74	0.25
SKVW	-1.85	0.26	0.11	-3.12	-2.33	0.26	-1.15
SII	-0.79	-2.62	-0.94	0.57**	0.89**	-0.42	-0.33

Table 3: R^2_{OS} vs TD

R^2_{OS} (in percentage) for the equity premium forecasts from the model as given by equation (6), considering the time domain (TD) model as the benchmark for forecasting. Columns report the results when using frequencies D_1 to S_6, respectively, from each predictor. The out-of-sample period is from 1990:M01 to 2023:M12. ***, **, and * denote statistically significant coefficients at the 1 %, 5 %, and 10 % level, respectively. Statistical significance is based on the p-value for the Clark and West (2007) out-of-sample MSFE-adjusted statistic.

	D_1	D_2	D_3	D_4	D_5	D_6	S_6
DP	0.02	-1.30	-0.52	0.01	1.07	1.96*	2.59***
DY	2.01**	-2.46	-1.60	-2.08	0.17	1.73	2.39***
EP	3.21*	4.31**	3.44*	2.24	1.29*	0.73	0.48
DE	1.32	-2.02	-0.95	0.25	0.72	1.06	2.07
RVOL	1.05	-0.91	0.00	-0.21	1.25	0.78	1.90
BM	-2.70	-3.95	-1.30	0.17	1.37	1.17	1.04***
NTIS	1.76	1.60	0.81	-0.22	-0.47	0.47	0.01
TBL	-0.80	-1.11	-2.15	-2.97	-2.59	-0.79	-0.95
LTY	-0.99	-1.17	-0.90	-0.29	-0.33	-0.24	-1.13
LTR	0.35	-0.43	-1.16	0.88	-0.55	0.15	1.63
TMS	0.17	0.04	-1.49	-2.53	-1.36	-0.47	4.21***
DFY	2.63**	0.44	-0.89	-1.32	1.62**	2.60*	2.48**
DFR	0.41	-1.29	-3.40	-5.26	-1.04	-0.10	-0.90
INFL	1.94	1.68	-0.56	1.26	2.75	1.93	2.17***
AVGCOR	-2.96	-3.32	-3.48	0.58	-0.63	0.52	-1.68
DTOAT	-0.41	-2.08	-0.07	1.04	1.64	1.37	-1.81
DTOY	-0.37	-1.76	0.18	0.41	0.39	2.13	-0.08
LZRT	-0.64	1.88	0.83	-1.56	0.19	0.15	-0.59
NDRBL	-0.26	-0.30	-4.77	-4.33	-2.42	0.12	2.12
RDSP	-0.21	-0.40	0.11	1.18	0.35	1.35	0.66
TAIL	1.06	-1.14	-4.57	-3.01	-2.32	-0.34	2.74
WTEXAS	0.27	-0.55	-2.92	-1.43	-1.75	-0.11	2.50
YGAP	3.48*	4.29**	3.40*	2.45*	1.33*	0.73	0.44
SKVW	-4.22	-2.48	-2.47	-5.62	-4.48	-1.87	-3.49
SII	-3.58	-6.14	-3.01	-1.63	0.90	0.50	-1.61

Table 4: CER gains vs. TD

CER gains computed for a mean-variance investor with relative risk aversion $\gamma = 3$, considering the time domain (TD) model as the benchmark for forecasting. Columns report the results when using frequencies D_1 to S_6, respectively, from each predictor. The out-of-sample period is from 1990:M01 to 2023:M12. ***, **, and * denote statistically significant coefficients at the 1 %, 5 %, and 10 % level, respectively. Statistical significance is based on the Diebold and Mariano (1995) test.

	TD	D_1	D_2	D_3	D_4	D_5	D_6	S_6
DP	-1.27	-30.7	-24.0	-3.17	-0.21	-0.34	-0.27	-1.11
DY	-1.39	0.33	-48.0	-20.1	-2.25	-0.24	-0.21	-1.14
EP	-1.70	-30.5	-7.64	5.26**	0.20	-0.85	-1.90	-0.88
DE	-1.93	-24.3	-47.5	-5.08	-0.27	-1.33	-2.12	1.37**
RVOL	0.06	0.13	-0.48	-1.22	-1.26	0.28	-0.73	-1.74
BM	-0.70	-4.17	-1.53	1.29*	0.98*	0.82**	0.18	-0.58
NTIS	-3.65	0.21	0.63	-4.76	-4.74	-4.57	-2.04	-1.00
TBL	0.02	-0.09	0.00	-3.08	-5.75	-1.12	-0.10	-0.40
LTY	-0.23	-1.23	0.07	0.28	-0.08	-0.39	-0.14	-0.85
LTR	0.10	-0.82	-2.00	-2.17	1.08*	-0.17	0.13	0.60
TMS	-0.23	-0.09	-0.20	-2.44	-3.32	-0.74	-0.26	1.71**
DFY	-1.80	-1.59	-8.06	-17.4	-4.52	-0.82	-1.14	-1.03
DFR	-11.7	-1.38	-7.65	-26.2	-15.8	-4.61	-2.24	-3.40
INFL	-0.57	0.67	2.21*	-1.26	-1.70	1.17*	0.44	0.13
AVGCOR	-0.74	-5.21	-11.1	-4.74	-0.84	-1.02	-0.14	-1.46
DTOAT	0.19	-21.5	-9.98	0.98	-0.10	-0.88	-2.40	-2.26
DTOY	-0.12	-15.7	-2.23	0.62	-1.25	-4.49	-4.10	-4.18
LZRT	-1.29	0.31	-2.39	-5.23	-2.86	-1.03	-1.05	-0.85
NDRBL	-1.05	-0.29	0.10	-9.01	-5.74	-1.47	0.37	0.57
RDSP	-0.75	0.37	-1.25	-1.22	0.18	-0.39	0.36	-1.68
TAIL	1.12	0.43	-0.60	-3.65	-0.91	-0.08	1.51*	1.72*
WTEXAS	1.28*	3.51**	1.65*	-3.28	-3.27	-1.70	0.71	2.01**
YGAP	-1.72	-30.7	-9.19	5.54**	0.24	-0.90	-1.93	-0.86
SKVW	-0.54	-0.81	0.46	-0.85	-2.44	-1.80	-0.77	-1.03
SII	1.12**	0.04	-2.01	-0.30	1.44**	2.35**	0.27	0.52

Table 5: R^2_{OS} vs HM: bad growth periods

R^2_{OS} (in percentage) for the equity premium forecasts from the model as given by equation (6), considering the historical mean (HM) as the benchmark for forecasting. Column (TD) reports the results when using the original time-series of each predictor. Remaining columns report the results when using frequencies D_1 to S_6, respectively, from each predictor. The out-of-sample period is from 1990:M01 to 2023:M12. Bad-growth regime is defined as the bottom third of US industrial production sorted values. ***, **, and * denote statistically significant coefficients at the 1 %, 5 %, and 10 % level, respectively. Statistical significance is based on the p-value for the Clark and West (2007) out-of-sample MSFE-adjusted statistic.

	TD	D_1	D_2	D_3	D_4	D_5	D_6	S_6
DP	-2.29	-1.39	-2.51	-2.81	-1.76	-0.90	0.22	-1.13
DY	-2.06	0.16	-4.42	-2.56	-1.98	-0.99	0.53	-1.28
EP	-1.14	7.34	9.12**	7.93**	1.82	1.35	-0.41	-0.53
DE	0.96	1.98	-4.42	-2.27	0.39	1.25	0.22	3.74*
RVOL	-1.75	0.02	-0.97	-0.55	-3.07	-0.92	-1.76	-0.41
BM	-1.45	-6.03	-5.05	0.43	1.93*	2.00*	0.63	-0.06
NTIS	-4.46	0.35	1.61	-2.06	-5.21	-7.25	-2.93	-1.92
TBL	0.66*	-0.18	-0.93	-3.41	-5.08	-2.79	-0.10	-0.76
LTY	-0.26	-2.34	-0.02	1.47	0.07	-1.40	-0.32	-1.53
LTR	-0.18	-1.59	-1.58	0.05	2.05	-0.04	0.57	0.91
TMS	-0.81	-0.33	-0.45	-4.90	-4.89	-1.66	-0.35	5.51
DFY	-2.70	-1.04	-5.12	-3.33	-2.47	-1.46	-1.17	-2.31
DFR	-3.14	0.09	-5.75	-4.49	-7.79	-3.46	-0.72	-3.32
INFL	-0.24	2.15	2.51	-0.88	-1.96	2.77	1.54	1.35**
AVGCOR	-0.91	-2.32	-3.55	-4.37	-0.74	-1.40	0.60	-0.95
DTOAT	-1.65	-3.87	-0.33	-0.33	-0.44	-0.26	-0.75	-4.29
DTOY	-1.24	-1.96	-0.34	0.01	-1.84	-4.46	1.27	-3.26
LZRT	-1.03	-1.47	0.79	-0.95	-3.39	-0.31	-0.53	-1.71
NDRBL	0.96	-0.91	-0.29	-4.86	-3.73	-3.15	1.11	2.64***
RDSP	-0.80	0.39	-2.56	-0.16	2.09	1.26	4.79	-0.42
TAIL	4.97	2.71	-0.37	-6.90	-1.85	0.07	4.53	5.33*
WTEXAS	2.99	3.54	1.56	-3.79	-4.98	-1.52	3.13	4.43
YGAP	-0.99	7.85*	9.35**	7.57**	2.17	1.42	-0.44	-0.42
SKVW	-0.23	-3.00	-1.04	-1.42	-2.19	-1.04	-1.18	-0.72
SII	4.21**	0.19	-4.18	1.54	2.57**	6.39***	2.81	2.59

Table 6: CER gains vs. HM: bad growth periods

CER gains computed for a mean-variance investor with relative risk aversion $\gamma = 3$, considering the historical mean (HM) as the benchmark for forecasting. First column (TD) reports the results when using the original time-series of each predictor. Remaining columns report the results when using frequencies D_1 to S_6, respectively, from each predictor. The out-of-sample period is from 1990:M01 to 2023:M12. Bad-growth regime is defined as the bottom third of US industrial production sorted values. ***, **, and * denote statistically significant coefficients at the 1 %, 5 %, and 10 % level, respectively. Statistical significance is based on the Diebold and Mariano (1995) test.

	TD	D_1	D_2	D_3	D_4	D_5	D_6	S_6
DP	-0.83	-16.2	-18.5	-5.89	-2.60	-1.17	0.35	1.11
DY	-0.98	-0.81	-47.3	-27.1	-8.43	-2.14	0.33	1.12
EP	0.63	-15.5	-19.6	-7.56	-3.23	-0.32	-1.09	0.37
DE	-1.57	-0.14	-12.7	-8.85	-4.40	-1.85	-0.84	-0.77
RVOL	-1.11	-0.14	-6.60	-10.5	-4.75	0.70	0.88*	0.11
BM	0.34	-2.90	-3.14	-1.67	-1.51	-0.23	0.43	0.33
NTIS	-0.98	-0.17	-2.75	0.48	1.14	0.83	-2.43	-1.94
TBL	-0.29	0.11	0.48	0.57	-1.48	-1.55	-0.01	-0.24
LTY	-0.52	-0.07	-0.92	-1.91	0.60	0.22	-0.08	-0.85
LTR	-0.61	-0.19	-3.26	-3.72	-4.42	-0.77	-0.24	0.47
TMS	-0.58	0.01	0.06	0.11	-1.72	-1.89	-0.42	1.20**
DFY	-2.73	0.24	-1.67	-6.56	-7.62	-2.58	-0.13	0.00
DFR	0.17	0.86	0.07	-6.75	-12.4	-1.80	0.12	-0.81
INFL	0.14	0.29	-1.42	-0.43	0.22	0.24	0.92	0.88
AVGCOR	-1.55	-2.75	-10.1	-3.54	-0.90	0.54	-0.02	-1.49
DTOAT	-0.49	-9.98	-10.6	-0.65	-0.16	0.14	-0.14	-3.02
DTOY	-0.48	-6.13	-6.99	-0.20	0.48	0.29	-3.85	-2.55
LZRT	0.58	-0.45	3.14**	-0.10	-3.31	-1.93	-1.26	0.17
NDRBL	-0.85	-0.35	-0.32	-5.21	-4.66	-1.75	-0.32	0.57
RDSP	-0.74	-0.45	0.41	-0.80	-0.77	-0.49	-0.99	1.38
TAIL	-0.85	0.52	1.60**	-0.60	-0.52	-0.52	0.78	-0.62
WTEXAS	3.23**	2.26**	0.55	-0.08	1.17	1.48*	0.68	2.63**
YGAP	0.65	-16.5	-21.9	-7.86	-3.19	-0.28	-1.15	0.37
SKVW	-0.32	-2.44	0.38	-0.21	-4.23	-3.04	-0.06	-3.34
SII	-2.75	-0.12	-0.59	-0.65	-0.64	-1.67	-3.25	-0.97

Table 7: R^2_{OS} vs HM: normal growth periods

R^2_{OS} (in percentage) for the equity premium forecasts from the model as given by equation (6), considering the historical mean (HM) as the benchmark for forecasting. Column (TD) reports the results when using the original time-series of each predictor. Remaining columns report the results when using frequencies D_1 to S_6, respectively, from each predictor. The out-of-sample period is from 1990:M01 to 2023:M12. Normal-growth regime is defined as the middle third of US industrial production sorted values. ***, **, and * denote statistically significant coefficients at the 1 %, 5 %, and 10 % level, respectively. Statistical significance is based on the p-value for the Clark and West (2007) out-of-sample MSFE-adjusted statistic.

	TD	D_1	D_2	D_3	D_4	D_5	D_6	S_6
DP	-1.18	1.91	-4.06	-1.57	-4.69	-2.39	1.38	0.41
DY	-1.22	-0.84	-3.08	-4.81	-7.94	-3.32	1.62	0.44
EP	0.98	4.14	-0.14	-4.13	-0.37	0.20	1.24	0.06
DE	-1.77	-0.57	-1.50	-1.04	-1.45	-2.04	0.63	-0.44
RVOL	-2.35	-0.66	-1.72	-2.90	0.56	1.99	0.07	2.36
BM	-0.15	1.38	-2.65	-1.55	-2.93	-0.32	1.28	-0.18
NTIS	-0.47	-0.44	-0.85	0.83	1.70	2.07	-2.75	-2.72
TBL	0.83*	0.18	1.25	1.72	1.15	-0.59	0.67	-0.38
LTY	0.06	-0.03	-1.98	0.92	2.01	1.12	0.05	-1.23
LTR	-0.04	-0.07	0.49	-4.55	-3.00	-1.99	0.14	1.17
TMS	1.54	0.20	0.19	0.73	-2.11	-1.38	-0.28	4.66**
DFY	-4.59	1.28	-0.43	-5.41	-7.42	-2.96	-0.14	-0.65
DFR	0.73	1.43	0.92	-2.23	-3.32	3.08	2.31	-0.98
INFL	-0.31	0.12	-0.33	-0.50	2.48	2.03	1.93	1.41
AVGCOR	-0.25	-2.21	-2.69	-3.32	-1.74	0.96	0.71	-2.67
DTOAT	-1.18	4.04	-3.34	0.19	-0.73	0.40	1.48	-2.21
DTOY	-1.77	4.02	-3.66	-0.42	0.86	3.53	0.59	0.33
LZRT	1.86	0.21	3.88	2.42	0.55	2.56	1.52	-1.42
NDRBL	-0.86	-0.20	-0.49	-2.63	-3.19	-1.46	-0.35	0.55
RDSP	-0.09	-1.37	0.43	-0.41	-0.55	0.04	0.69	2.24
TAIL	0.83	1.75	2.72	0.62	-0.81	-0.71	1.59	2.99
WTEXAS	4.80*	3.25	1.01	-0.17	4.31**	1.68	0.85	4.83
YGAP	1.11	4.42	-0.25	-4.03	-0.47	0.29	1.29	0.06
SKVW	2.88	-3.15	1.16	-0.27	-5.68	-4.03	0.31	-4.25
SII	1.26	-0.24	-0.22	-0.93	0.84*	1.74	2.97*	0.54

Table 8: CER gains vs. HM: normal growth periods

CER gains computed for a mean-variance investor with relative risk aversion $\gamma = 3$, considering the historical mean (HM) as the benchmark for forecasting. First column (TD) reports the results when using the original time-series of each predictor. Remaining columns report the results when using frequencies D_1 to S_6, respectively, from each predictor. The out-of-sample period is from 1990:M01 to 2023:M12. Normal-growth regime is defined as the middle third of US industrial production sorted values. ***, **, and * denote statistically significant coefficients at the 1 %, 5 %, and 10 % level, respectively. Statistical significance is based on the Diebold and Mariano (1995) test.

	TD	D_1	D_2	D_3	D_4	D_5	D_6	S_6
DP	-2.58	-29.5	-19.3	-5.30	-0.38	-0.35	-1.78	-1.77
DY	-2.73	0.15	-57.7	-22.1	-2.88	-0.94	-1.91	-1.73
EP	-1.27	-34.0	-6.66	1.87**	3.67**	0.37	-1.73	-1.24
DE	-1.02	-2.61	-26.2	-6.67	2.13*	0.22	-1.67	-0.15
RVOL	0.70	-0.80	-4.92	-2.15	-1.03	-0.04	-1.21	-1.58
BM	-0.80	-8.07	-8.14	-3.24	0.16	0.45	-0.15	-0.95
NTIS	-1.49	-0.13	-1.89	-2.99	-2.66	-1.54	0.46	-0.41
TBL	-0.15	-0.01	-0.29	-0.89	-3.57	-1.54	-0.28	-0.17
LTY	0.44	-0.50	0.42	-0.81	-0.75	0.11	0.22	-0.32
LTR	-0.89	0.17	-1.98	-1.18	-3.62	-2.14	-0.41	0.42
TMS	-2.26	-0.25	-0.43	-1.15	-2.18	-2.00	-1.01	-0.08
DFY	-2.01	-1.52	-4.91	-10.8	-8.30	-1.21	-1.07	-1.07
DFR	7.22*	1.11	3.09*	3.08	-5.48	-0.32	0.26	-1.05
INFL	-1.15	1.09	0.73	-0.88	-0.63	0.86	0.01	-0.58
AVGCOR	1.06	-7.34	-13.2	0.46	0.45	-1.44	-0.80	-2.96
DTOAT	0.11	-16.4	-5.79	-1.05	0.36*	0.17	-1.80	-3.04
DTOY	-0.07	-18.7	-8.62	-1.20	-1.68	-2.42	-3.59	-4.92
LZRT	-1.94	-1.62	-3.23	-4.38	-5.81	-3.41	-2.35	-1.99
NDRBL	-2.91	-0.20	-0.70	-8.97	-5.10	-1.24	-1.08	-1.06
RDSP	-1.29	-0.69	-0.68	-1.39	-1.29	-2.03	-3.67	-1.67
TAIL	-1.74	0.93*	-2.45	-3.36	-1.21	-1.61	-1.70	1.70**
WTEXAS	-5.89	-3.11	-1.78	-2.39	0.32	-2.31	-1.85	-1.18
YGAP	-1.28	-34.3	-7.40	2.15**	3.78**	0.38	-1.71	-1.29
SKVW	-1.19	-4.81	-2.26	-0.56	-5.18	-4.55	-0.33	-1.44
SII	3.67***	0.10	-2.69	0.53	3.11***	3.93***	3.87***	1.73**

Table 9: R^2_{OS} vs HM: good growth periods

R^2_{OS} (in percentage) for the equity premium forecasts from the model as given by equation (6), considering the historical mean (HM) as the benchmark for forecasting. Column (TD) reports the results when using the original time-series of each predictor. Remaining columns report the results when using frequencies D_1 to S_6, respectively, from each predictor. The out-of-sample period is from 1990:M01 to 2023:M12. Good-growth regime is defined as the top third of US industrial production sorted values. ***, **, and * denote statistically significant coefficients at the 1 %, 5 %, and 10 % level, respectively. Statistical significance is based on the p-value for the Clark and West (2007) out-of-sample MSFE-adjusted statistic.

	TD	D_1	D_2	D_3	D_4	D_5	D_6	S_6
DP	-3.85	-7.76	-4.66	-4.52	-0.81	-0.81	-3.06	1.16**
DY	-3.63	-0.21	-6.82	-4.33	-3.18	-2.08	-3.86	1.09**
EP	-0.81	-2.81	3.04	5.69	4.35	1.36	0.38	0.91**
DE	-0.73	1.02	-1.70	-1.08	0.25	1.42	0.76	1.40
RVOL	-0.28	-0.60	-4.45	-0.95	-2.52	-1.74	-0.36	-0.63
BM	-0.33	-5.37	-6.10	-4.70	-0.41	0.52	-0.32	1.41**
NTIS	-0.50	-0.06	-1.38	-1.78	-2.58	-1.65	1.70	-0.77
TBL	0.97*	0.08	-1.15	-2.28	-2.52	-1.91	-0.46	0.79
LTY	1.07**	0.29	-0.63	-4.22	-2.08	0.15	0.43*	0.24
LTR	-1.65	0.84	-2.07	-0.80	1.77	-1.49	-2.14	0.95
TMS	-1.80	-0.44	-0.68	-1.36	-1.65	-2.11	-1.83	1.40
DFY	-3.41	-3.08	-3.85	-4.64	-4.77	-1.42	-1.62	-0.32
DFR	5.09*	2.29	3.63	-0.88	-2.04	-0.12	0.72	4.23*
INFL	-1.19	1.84	1.16	-2.02	1.53	1.72	0.61	1.99**
AVGCOR	0.45	-5.06	-4.43	-3.46	3.56	-2.16	-0.45	-2.10
DTOAT	-1.12	-5.35	-6.51	-4.04	0.36	0.84	-0.56	-2.89
DTOY	-0.93	-7.10	-5.21	-3.01	-1.72	-1.80	0.61	-1.26
LZRT	-3.06	-2.93	-1.30	-1.24	-4.09	-3.90	-2.80	-0.87
NDRBL	-0.74	-0.31	-0.75	-7.47	-6.70	-3.28	-1.04	2.52***
RDSP	-1.00	-1.54	-0.96	-1.01	0.10	-2.14	-3.29	-1.76
TAIL	-1.55	2.99	-1.51	-3.17	-2.12	-2.08	-2.87	4.16**
WTEXAS	-5.29	-3.49	-1.75	-2.32	-1.10	-2.91	-1.83	0.72
YGAP	-0.89	-2.58	3.05	6.04	4.92	1.53	0.56	0.90*
SKVW	1.62	-2.20	-3.29	-1.41	-4.68	-4.06	-0.42	-1.19
SII	5.58***	0.35	-3.01	1.40*	2.74***	5.62***	6.77***	3.07*

Table 10: CER gains vs. HM: good growth periods

CER gains computed for a mean-variance investor with relative risk aversion $\gamma = 3$, considering the historical mean (HM) as the benchmark for forecasting. First column (TD) reports the results when using the original time-series of each predictor. Remaining columns report the results when using frequencies D_1 to S_6, respectively, from each predictor. The out-of-sample period is from 1990:M01 to 2023:M12. Good-growth regime is defined as the top third of US industrial production sorted values. ***, **, and * denote statistically significant coefficients at the 1 %, 5 %, and 10 % level, respectively. Statistical significance is based on the Diebold and Mariano (1995) test.

Bank of Finland Research Discussion Papers 2024

ISSN 1456-6184, online

1/2024	Gene Ambrocio – Iftekhar Hasan – Xiang Li **Global political ties and the global financial cycle**
2/2024	Michaela Elfsbacka-Schmöller – Nigel McClung **Price stability and debt sustainability under endogenous trend growth**
3/2024	Diego Moreno – Tuomas Takalo **Stress test precision and bank competition**
4/2024	Eleonora Granziera – Pirkka Jalasjoki – Maritta Paloviita **The bias of the ECB inflation projections: a state-dependent analysis**
5/2024	Maria Eskelinen – Christopher G. Gibbs – Nigel McClung **Resolving new Keynesian puzzles**
6/2024	Markus Haavio – Joni Heikkinen – Pirkka Jalasjoki – Juha Kilponen – Maritta Paloviita – Ilona Vänni **Reading between the lines - Uncovering asymmetry in the central bank loss function**
7/2024	Aleksi Paavola – Ville Voutilainen **Central bank collateral policy and credit pricing: evidence from Finland**
8/2024	Joni Heikkinen – Kari Heimonen **Media tone: the role of news and social media on heterogeneous inflation expectations**
9/2024	Dominik Hecker – Hun Jang – Margarita Rubio – Fabio Verona **Robust design of countercyclical capital buffer rules**
10/2024	Gonçalo Faria – Fabio Verona **Unlocking predictive potential: the frequency-domain approach to equity premium forecasting**