ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Master Thesis programme Financial Economics

Impact of the US Business Cycles on Asset Classes Performance: Practical Evidence and Econometric Modelling

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Date final version: 05.08.2022

Abstract

This paper investigates the relationship between business cycles and their effect on equity, government bonds, and commodities in the US. In line with theory and previous research, we show that the economic state can be predicted relatively well. Moreover, the model we construct outperforms Chicago Fed National Activity Index in predictive power and is based on just a few publicly available time series. Current work also sheds light on the relation between financial markets and expectations of economic conditions. Our results suggest that information about the economic state signals consequent commodity premiums but is useless for stocks and bonds prediction. Finally, we investigate the ability of macro and financial factors to forecast the performance of these asset classes. Although the future level of stock and commodities return is still hard to estimate, this study provides evidence that some indicators can consistently predict Treasuries return, including a new one.

Keywords: business cycles, economic state, stocks, bonds, commodities.

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1 Introduction

The asset pricing problem appears to be the most deeply investigated field of the finance industry throughout its history. At the same time, it is the most unclear research area, which still involves many active discussions both from the theoretical and practical sides. Financial markets are closely connected with the economy, being a part of it, while the state of the economy changes over time, forming business cycles. This means that investors must manage the portfolio under the expectations of the future economic environment. Although the National Bureau of Economic Research (NBER) documents economic peaks and recessions, they do it ex-post, so this information cannot be used for asset allocation decisions. In this paper, we create a model that indicates the leading state of the economy. We use three different methodologies to find the best model, including Lasso, which has recently become quite popular for solving prediction and variable selection problems. We also examine whether it is possible to improve predictive power over the Chicago Fed National Activity Index (CFNAI), one of the most used indexes for measuring the health of the US economy.

Looking at the theory, one notices that various asset classes, such as stocks, bonds, and commodity futures, are inextricably linked to macroeconomic conditions. For example, according to the dividend discount model (Gordon & Shapiro, 1956), the share price can be calculated based on the net present value of all paid in future dividends (Equation 1). Alternatively, it also can be found with Equation 2, using the expected dividend amount discounted by the difference in the firm’s rate of profit and long-term growth rate. Regardless of the method, one should make reasonable assumptions about each term. They can all be influenced by the state of the economy, its changes, and even expectations of these changes. For example, the expected dividend relates to the company’s recent profit and short-term cash demand, a shortage of which was experienced during Covid lockdowns. The rate of profit reflects a long-term firm’s ability to generate cash flows, depending on numerous factors, such as the need for a product, sector-specific risks, etc.

$$P_0 = \sum_{t=1}^{\infty} \frac{D_t}{(1+k)^t} \tag{1}$$

where P_0 is a current stock price, D_t denotes dividends at time *t*, and *k* is a firm’s rate of profit.

$$P_0 = \frac{D_1}{k-g} \tag{2}$$

where D_1 is an expected dividend, and g is a long-term growth rate.

The same concept holds for bonds. The clean bond price can be derived with Equation 3 as a discounted sum of the coupons C_t and par value PV_T received by investors until maturity (Fabozzi, 2021). Nevertheless, all coupons and principal are, in general, known in advance, the bond pricing does not become less complicated since the discount rate is unknown and may vary over the period. The most widely used approach is to use the government bonds yield curve to derive the discount rate, which can also be affected by the economic conditions. Treasury prices could be affected by the quantitively easing programs, announcements to support the liquidity of the financial markets, or even by the worsened expectations of market participants.

$$P_B = \sum_{t=1}^{T} \frac{C_t}{(1+r)^t} + \frac{PV_T}{(1+r)^T} \tag{3}$$

Moreover, if one wants to calculate yield to maturity (YTM), it can only be derived from Equation 3 by replacing discount rate r with YTM. However, investors will get this yield only if they reinvest all coupons at the same rate. This reinvestment risk is a large part of fixed income securities and is closely related to the risk-free level and, consequently, to the economy's health, especially in recent history when the US Federal Reserve System (FED) targets inflation with the interest rate.

As for commodities, this market became a widely used separate investment segment with the development of derivatives instead of its original concept of a place for manufacturers, miners, and farmers to hedge their operational risks. However, hedgers still make most of the transaction turnover and reckon their decisions based on expectations of the future state of the economy and the need for their products. The calculation of future theoretical value F_t (Equation 4) involves information from financial markets and macro data, namely spot price S_t and risk-free rate *r*. Hence, in theory, the connection between commodity markets and business cycles also exists.

$$F_t = S_t e^{(r+u-y)(T-t)} \tag{4}$$

As we have just shown with the theory example, there is reason to assume that the prices and, therefore, the returns of financial assets may depend on future expectations of economic activity. Based on historical data and our economy forecasting model, we analyse whether the information about the US economic growth expectations can be used to predict the consequent performance of the S&P500 index, 12 industry portfolios, 10-year Treasury bonds, and the Thomson Reuters CRB commodities index.

Important to note the existence of evidence that returns of different assets relate not only to internal factors, e.g., size for stocks and credit ratings for bonds but also to external indicators. In addition, there is a possibility that our created model is good at predicting the future state of the economy but misses those factors that are important for explaining the returns of the assets. Considering the above, another meaningful question is whether commonly used economic indicators and some additional variables can be used to predict stocks, bonds, and commodities returns. In the last part of our research, we investigate which factors help to model the returns on these assets. To the best of our knowledge, no prior studies have examined mentioned asset classes in a single research and considered discussed questions simultaneously.

The remainder part of the paper is constructed as follows. The next section provides detailed information on the main research questions and hypotheses to test. Section 3 reviews the literature and discusses key nowadays opinions. We discuss datasets and variables in Section 4, as well as the methodology of the various regression models. Section 5 is dedicated to the empirical results of the analysis. The main implications of the results, confirmations, and rejection of the hypothesis are discussed in Section 6, and Section 7 concludes.

2 Research questions

The current and future state of the economy is inevitably linked to financial markets, given the expectations that market participants form. Therefore, we consider both aspects in this paper – the condition of the US economy, financial markets, and the relationship between them.

The main objectives and research questions are presented below and discussed further in detail.

1. How accurately can the US business cycles be predicted by means of macro and financial variables? Is it possible to improve upon the Chicago FED index?
2. Can one use the acquired information about the US economic state in the next period to forecast the performance of various financial markets such as stocks, bonds, and commodities?

3. Evaluate the performance of these asset classes in terms of variables used, or not necessarily used, for business cycles forecast. Are the results obtained with the new data consistent with the existing studies, and are there any new significant explanatory factors?

One may argue that the main asset pricing issue is to find factors that directly relate to the financial market's prediction; therefore, one may skip the first two questions to work on the third question directly. And this is a reasonable comment. However, the purpose of this work is, among searching for predictive factors, to determine whether the relationship between business cycles in the US economy and financial markets indeed exists and whether this information can be used to predict different asset returns.

2.1 Business cycles prediction

The main objective of this part is to create an econometric model to describe the future pattern of the US economy with a set of time series, which may include either macro or financial variables or both. Although some financial institutions already have such models and use them to support asset allocation decisions or directly in trading, most of these models are not available to everyone. An example of an available index is Chicago Fed National Activity Index (CFNAI).

Therefore, this work is also valuable for testing the hypothesis about the possibility of creating a similar or better model based on publicly available data. We select CFNAI as a benchmark and for comparison of the prediction accuracy since this index is the most often used to evaluate the overall economic activity. The Data and Methodology section presents detailed information about the variables used.

2.2 Using business cycles information to forecast financial markets

The second question involves studying the consistency of the model obtained at the previous stage for predicting the returns of equity, fixed income, and commodity markets in the US. This part tests the hypothesis about the relationship between financial markets and the economy and the ability to predict future asset movements using information about business cycles. While many papers discuss the existence of cycles, no one, according to our knowledge, pays enough attention to testing the relationship with financial markets and especially the ability to predict them.

2.3 Financial markets prediction with macro and other factors

Of course, the result of the second research question may be that there is no predictive power. It would be possible to conclude the study on this point, rejecting the main hypothesis. However, it may be that those variables that can predict the state of the economy and those that can predict the movements of financial markets are different. Hence, regardless of the outcome of the second question, this paper analyses whether the selected macro and financial factors can predict the returns of stocks, bonds, and commodities and if these data are the same as used for US economic state prediction.

3 Literature review

Many research papers are written about business cycles themselves and the relation of economic factors to financial markets since the Great Depression. Most of them argue that, indeed, some economy-related variables can be used for future return prediction. Some studies also analyse an ability to forecast the economic state, but very few try to connect these two aspects. Besides, bonds, especially commodity markets, are always the least studied compared to equity markets. The analysis we perform in this study aims to improve these two gaps.

Blitz and van Vliet (2009) use four forward-looking economic indicators and study the stages of the business cycles. They find that premiums of the different assets are subject to various cyclical patterns. More interestingly, they find evidence that financial markets are ahead of business cycles by about one stage in their sample. Another paper by Ma and Zhang (2016) supports the assumption that the financial cycle has an important impact on the business cycle and vice-versa but does not find the leading power. In addition, they find that financial cycle variations are predominantly explained by the shock to itself (i.e., the financial cycle shock), while the impact of the other shocks seems to be very limited. Lustig and Verdelhan's (2012) research suggests that market participants realise the state of the economy before NBER and OECD announcements by using Media and Internet searches. We find a lack of investigation of the relationship between business cycles and financial markets as a drawback and address it as a separate question in our study. We create a model competitive with CFNAI and research if this relationship exists.

One of the most influential papers by Chen et al. (1986) models equity returns as a function of macro variables and finds that industrial production, inflation, Fama-French DEF, and TERM spreads are significant stock pricing factors in their sample, while oil prices have no overall effect. They also note that outcomes depend on the subperiod. In the later paper, Chen (1991) extends the analysis and research on whether economic state variables are related to the macroeconomy consistent with previous forecasts of asset returns. He finds that market dividend yield, default premium, short-term interest rate, term structure, and lagged industrial production growth rate forecast the deviation of future economic growth measured as GNP. Baker and Wurgler (2006) construct a composite investor sentiment index based on six proxy characteristics and find that it comoves with economic cycles. However, they also conclude that found effect is hard to value and arbitrage. In recent research (Baker & Wurgler, 2012), they perform a similar analysis, decomposing the sentiment index into global and local terms. They find that global sentiment is a statistically and economically significant contrarian predictor of market returns. Later, Sibley et al. (2016) decompose this index furthermore and show that about 63% of the variations in the sentiment can be attributed to the 13 economic variables, where Treasury-bill rate and liquidity risk factors are the most powerful. Goyal et al. (2021) examine 26 papers published after Goyal and Welch (2008) and more than 40 macro and other variables to examine the equity premium prediction. Authors find it disappointing that almost all factors fail to consistently forecast stock returns and conclude that it is still extremely hard to construct a robust investment strategy based on one or several variables to outperform the market. Each of these studies supports a link between stock returns and economic conditions. However, no one directly investigates this relationship and tests the hypothesis that information about the future economic state can be important for asset pricing. We do this with our model for business cycle prediction. Besides, our research confirms the relevance of some separate indicators for stock returns forecast with more recent data and finds new factors, although all of them are inconsistent and do not provide stable results.

The first effect of business conditions on expected stock *and* bond returns was analysed by Fama and French (1989) and shows that common factors can explain the variation of both, e.g., dividend yield can also forecast bond returns. In contrast, DEF and TERM spreads track stock returns. Keim and Stambaugh (1986) also find that expected premiums on common US stocks and government bonds appear to change in a manner partially described by proxy variables, including yield spread and others. Ferson and Harvey (1991) support findings that expected risk premium rises during economic downturns and reaches its highest before the business cycle lows. The general view that the stock market risk premium is most important for capturing variation of stock portfolios, while the interest rate risks premium captures the bond returns' predictability, is also supported by this paper. In the consequent research, Ferson and

Harvey (1999) also find that lagged economy-wide predictor variables help to reveal patterns in the cross-section of the expected stock returns that the Fama and French 3-factor model do not capture. However, Ferson and Harvey note that it is hardly likely to find the individual coefficient that drives the result. Chan and Wu (1993) investigate the relation of different bond returns to the business cycles and conclude that, on average, fixed income securities' monthly returns are higher when the economy is contracting than when it is expanding. Baltussen et al. (2021) find the robust and persistent bond returns predictability over the 70 years for both in-sample and out-of-sample tests. However, they do not provide a clear answer on the main predictability driver, concluding that it seems neither to be solely related to market nor macroeconomic risks. Since equities are more popular among investors and fewer papers are focused on studying bonds, the fixed-income market is, in theory, more prone to inefficiencies. In addition, existing studies analyse a much smaller number of factors related to bond premiums, which, in our opinion, is a significant drawback. Our work improves these gaps by analysing bonds on an equal base with stocks and using more explanatory factors. We also find new statistically significant and consistent predictor indicators that might remain helpful in explaining future bond premiums.

Finally, regarding the commodity market, Gorton and Rouwenhorst (2006) find that commodity futures return has a negative relation with the stock and bond returns since commodity prices move differently during the business cycles. On the other hand, Tang and Xiong (2012) find that non-energy commodities became more correlated and more affected by spill volatility from other markets after the increasing popularity of index-investing in commodity markets and their financialisation. Due to its specificity and short history, the commodities are studied even less than fixed-income securities. We research the commodity markets in the same manner we do it for other asset classes because, in our opinion, studying the link between the economic state and financial markets should also include commodities.

4 Data and methodology

4.1 Measuring the business cycles

Several approaches were used over time to measure the state of the economy and, consequently, business cycle variation. The most widely used are growth rates of GDP or GNI (as in Chen, 1991), consumption growth (as in Ma & Zhang, 2016) or the composite index of several economic indicators (as in Blitz & van Vliet, 2009). An example of such a composite indicator is the widely used Chicago Fed National Activity Index (CFNAI), constructed based on the first principal components of 85 economic activity factors. It represents the US economic growth, is 72% correlated with quarterly changes in real GDP, and is also used to track persistent inflation increases.

We use the real GDP (RGDP) as the main measure in this paper. Being adjusted for inflation, it captures output in constant prices, which allows correct comparisons between different periods. Besides, the use of GDP is preferable, compared to consumption and separate index, because having its values, we can make reasonable recession forecasts, defined as two consecutive quarters of negative GDP and announced ex-post by the National Bureau of Economic Research (NBER). It also allows us to compare the performance of our model with the CFNAI. Real US gross domestic product time series is obtained from FRED and available with a quarterly frequency starting from 1947. We use the decimal logarithm to calculate the RGDP growth rate.

4.2 Selecting economic and financial factors

We create a list of independent variables used for further prediction mostly based on the completed literature review but also add some new indicators, which may be important in our opinion. It consists of 41 original time series of economic state factors and financial factors with different frequency and availability periods. Some of these time series were used to construct multiple variables, so the final number of factors increased to 45. Detailed information about each variable is in Appendix A.

Since data on variables are available in different historical periods, we divide them into groups to consider three separate subperiods. The most important and economically interesting are 1948-2022 as the post-World War II period and the close to the foundation of the Bretton Woods system; 1974-2022 as the period of the end of the Bretton Woods system in its original form, the end of fixed exchange rates, and the beginning of the derivatives widespread; 2004-2022 as the newest sample with the largest number of variables, which allows to test the previous finding on the recent data and investigate the importance of newly added factors.

As the RGDP data is only available on a quarterly basis, we convert factors' time series from daily and monthly frequency to quarterly data with an exponential weighted function, giving priority to the most recent days/months. This approach allows us to use the latest observations with the highest weights and, at the same time, capture movements during the quarter, which can be especially important for high-frequency variables. Furthermore, we perform an augmented Dickey-Fuller test for each time series to account for stationarity. Before doing that, we calculate decimal logarithm changes, similarly to RGDP, for all factors, except a few already stationary series, e.g., Unemployment Rate (UR), the difference between the yields of US 10-Year Treasury bonds and US 3-Months bills. Only a few time series remain non-stationary after that, so we calculate the first difference for them and repeat the test, which finally confirms that the process is stationary and resolves this problem.

We estimate correlations as the final part of the factors' time series analysis. The outcome is that only 11 and 5 out of 45 variables have a correlation that exceeds 0.8 and 0.9, respectively. Figure 1 shows a correlation heatmap for all 45 factors sorted in order of data availability. We exclude 5 time series with a correlation greater than 0.9 from the list of explanatory factors.

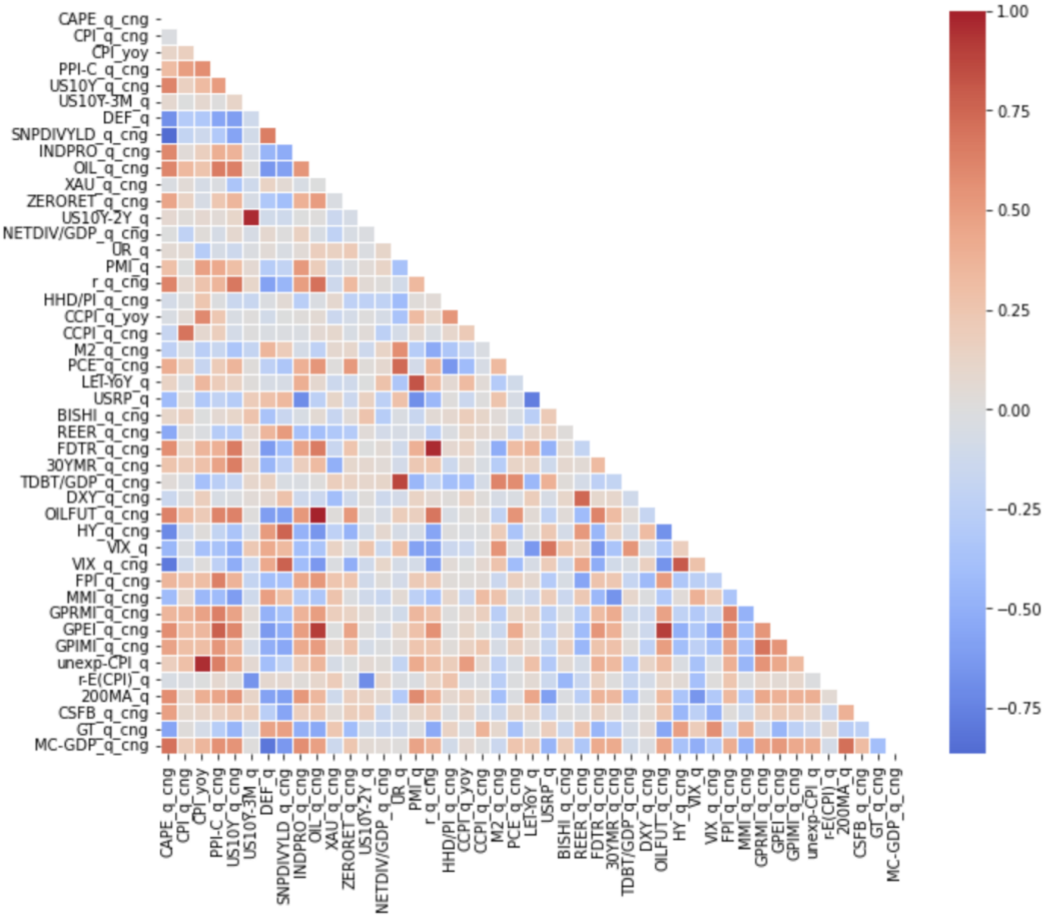
- US federal funds effective rate (FDTR) obtained from Bloomberg as it is highly correlated (0.96) with the discount rate for the United States (r_q_cng) obtained from FRED and has a larger history.
- The spread between US 10Y and 2Y Treasuries, as it is 0.96 correlated with US 10Y bonds and 3M bills spread, which is available from 1926.
- The global price of the energy index (GPEI_q_cng) is highly correlated (0.91) with oil and oil futures prices.
- Oil futures prices, which are 0.99 correlated with Oil prices and have a marginal difference in prices adjusted for the risk-free rate.
- CPI forecast error (CPI_err_q), measured as expected inflation from the previous period minus observed inflation, which is highly correlated (0.95) with CPI year-to-year changes.

This results in the following number of factors in each of mentioned subperiods.

- 1948-2022 subperiod – 15 variables;
- 1974-2022 subperiod – 28 variables;
- 2004-2022 subperiod – 40 variables.

Figure 1

Correlation matrix of 45 economic and financial factors



Note. The *q* subscript, used alone, denotes the quarterly value of the indicator itself. The *q* subscript, combined with the *cng* subscript, denotes quarterly logarithm change. The *yoy* subscript denotes the quarterly observations of Year-to-Year change.

This paper analyses several asset classes: stocks, bonds, and commodities. The list of all specific time series is presented in Table 1. We do not separately test the performance of the Dow Jones corporate bonds and S&P GSCI commodity indexes but use them as additional independent variables in some models to account for the spill-over effect between markets. Government bonds, in our opinion, are of greater interest than corporate issues, which are almost 60% correlated with the Treasury return series. The exclusion of the GSCI index is supported by the fact that it is rebalanced annually and has a large (e.g., about 33% in 2022 and more than 61% in 2020) energy component, so monthly rebalanced CRB is more diversified and preferred for commodity analysis.

We use data from the CRSP database on US stocks from January 1926 to December 2021 to form 12 industry equally weighted portfolios based on the company's SIC codes and calculate their returns in excess to market. Industries classifications are those that Fama and French proposed, are obtained from Kenneth R. French data library, and are presented in Table 1 without SIC codes for the shortage.

To further estimate the potential forecast effect of RGDP on cyclical and counter-cyclical industries, we calculate the historical betas for each industry portfolio using regressions with a rolling window of 3 years. Even though there is no general approach to determining cyclical and defensive sectors, several studies have used market betas. For example, Novy-Marx (2016) provides evidence of the rise in popularity and effectiveness of defensive strategies favour low-beta and underweight cyclical firms. We use a threshold of 1 to define the industry type and present betas' values in Table 2.

According to the results, only three industries, namely Consumer Nondurables, Utilities, and Finance, are counter-cyclical in our sample of 1926-2022. The same industry distribution holds if we use a 5- and even 1- or 10-year window with the marginal changes in betas, so these results are not presented.

Table 1

The list of asset classes used in the analysis, their availability, frequency, and source

Assets	Period	Frequency	Source
S&P500 Index	1926–2022	Monthly	CRSP Database
US 10-Year Treasury-Bonds	1786–2022	Monthly	Global Financial Data
Thomson Reuters Commodity CRB Index	1914–2022	Monthly	Global Financial Data
Dow Jones Corporate Bond Price Index	1915–2022	Monthly	Global Financial Data
S&P GSCI Commodity Aggregate Index	1970–2022	Monthly	Global Financial Data
12 US Industry Portfolios			
Consumer Nondurables	1926–2022	Monthly	Personal Calculations
Consumer Durables	1926–2022	Monthly	Personal Calculations
Manufacturing	1926–2022	Monthly	Personal Calculations
Energy	1926–2022	Monthly	Personal Calculations
Chemicals	1926–2022	Monthly	Personal Calculations
Chemicals	1926–2022	Monthly	Personal Calculations
Telecom	1926–2022	Monthly	Personal Calculations
Utilities	1926–2022	Monthly	Personal Calculations
Shops	1926–2022	Monthly	Personal Calculations
Healthcare	1926–2022	Monthly	Personal Calculations
Finance	1926–2022	Monthly	Personal Calculations
Other	1926–2022	Monthly	Personal Calculations

Table 2

The average and median market betas of 12 US Industry portfolios

Industry	Average market beta	Median market beta
Consumer Nondurables	0.95	0.96
Consumer Durables	1.20	1.15
Manufacturing	1.15	1.09
Energy	1.09	1.04
Chemicals	1.12	1.12
Business Equipment	1.49	1.35
Telecom	1.35	1.29
Utilities	0.59	0.59
Shops	1.08	1.04
Healthcare	1.26	1.22
Finance	0.73	0.73
Other	1.16	1.19

4.3 Regression analysis methods

4.3.1 Real GDP prediction

We use several methods to find the best model to fit real GDP data. First, we perform Ordinary List Squares (OLS) regression for all three history subperiods, using the actual RGDP growth rate and the one-quarter lag for all economic and financial factors.

$$RGDP_t = \alpha + \boldsymbol{\beta} * \boldsymbol{F}_{t-1}^{N} + \varepsilon_t \qquad (5)$$

where $RGDP_t$ is a log change of real GDP in quarter t, $\boldsymbol{F}_{t-1}^{N}$ is an $N \times 1$ vector of factor variables known in quarter $t-1$, $\boldsymbol{\beta}$ is a $1 \times N$ vector of factors coefficients, α is a constant term, and ε_t is the error term.

Since we do not find OLS regression results consistent over different periods, we try to apply Principal Component Analysis (PCA) to reduce the dimensionality of the dataset, given the low correlation between most factors. We select the level of about 80% explained variance to choose the number of principal components. Figure 2 presents scree plots of eigenvalues.

- 1948-2022 subperiod: 8 components explain 80.26% variance of 15 factors;
- 1973-2022 subperiod: 11 components explain 79.94% variance of 28 factors;
- 2004-2022 subperiod: 10 components explain 80.47% variance of 40 factors.

After PCA analysis, we repeat the OLS regression as follows.

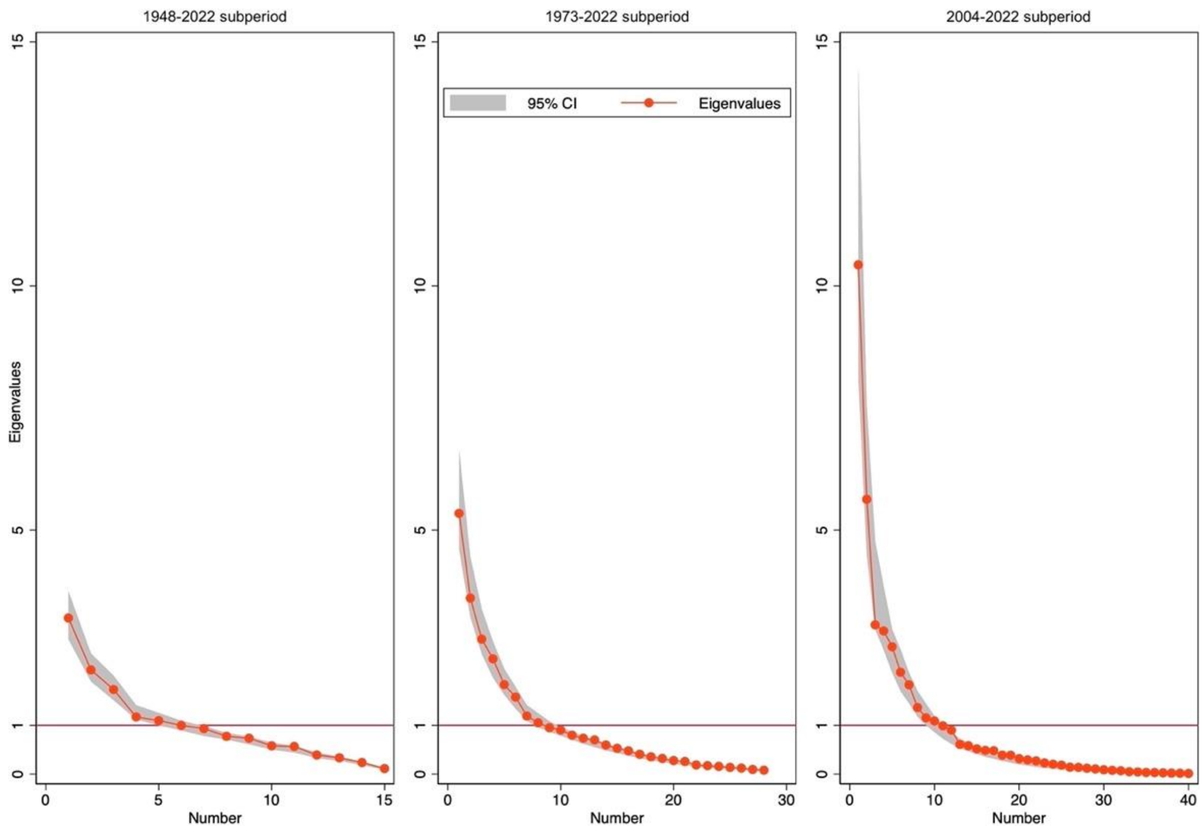
$$RGDP_t = \alpha + \boldsymbol{\beta} * \boldsymbol{PC}_{t-1}^{N} + \varepsilon_t \qquad (6)$$

where $\boldsymbol{PC}_{t-1}^{N}$ is an $N \times 1$ vector of principal components of variables known at time $t-1$, and N is the specific number of components for each testing period.

Finally, we incorporate the Lasso estimator into our model, which has appealing properties for prediction purposes, as shown by Feng et al. (2020) in comparison to numerous other methods in their influential *Taming the Factor Zoo: A Test of New Factors* paper. Lasso was originally designed by Tibshirani (1996) and is commonly used for creating prediction models. What is more important for us, it works the most efficiently in the samples with a large number of predicting variables compared to the number of observations and in a case when it is uncertain which variables (covariates) belong to the model. Hence, Lasso helps to avoid the dataset dimension issue which OLS faces in the 2004-2022 period, having only 72 observations and 40 independent variables. At the same time, it solves the problem of the lack of confidence about whether the variable is a true factor.

Figure 2

Scree plots of eigenvalues after PCA for each analysis period



If one rewrites Equation 5 to include the whole data set in the following way,

$$\boldsymbol{RGDP} = \beta_1 * \boldsymbol{f}_1 + \beta_2 * \boldsymbol{f}_2 + \cdots + \beta_k * \boldsymbol{f}_k + \boldsymbol{\varepsilon}$$

Lasso will minimise to obtain the solution

$$\frac{1}{2T}(\boldsymbol{RGDP}-\boldsymbol{F\beta}')'(\boldsymbol{RGDP}-\boldsymbol{F\beta}')+\lambda\sum_{i=1}^{k}|\beta_i|$$

where T is the number of observations, the first term is the in-sample prediction error, and $\lambda\sum_{i=1}^{k}|\beta_i|$ is a penalty term, which Lasso uses to omit variables.

When $\lambda=0$, there are no omitted variables, and the model has a maximum complexity. Lasso minimises the above term for given values of λ and chooses one of those solutions as the best model based on the estimate of the out-of-sample prediction error. Consequently, this solution has the highest out-of-sample R-squared measure.

We use two methods to select λ: cross-validation (CV) and adaptive, both of which minimise an estimate of the out-of-sample prediction error, which is the most important in our analysis, while one could also minimise the Bayesian or Akaike information criterion (BIC or AIC). The only difference between these methods is that adaptive Lasso performs several runs of CV Lasso, removing variables with zero coefficients on each step and penalising small coefficients to drive them to zero.

The main Lasso advantage is that it prevents data from overfitting, which is highly important in our research when a two-step analysis is performed (for real GDP prediction and then for asset classes performance forecast based on the RGDP fitted values). As we show in the later sections, Lasso performs better than OLS and 'PCA plus OLS' models, but it also has some drawbacks.

Once we run these four methods over three subperiods, 12 models appear to select from. We choose one based on the out-of-sample prediction power, test it on the accuracy of predicting the NBER-based recession dates, and compare the results with the CFNAI index. The best model is further used to test the relationship with financial markets.

4.3.2 Stocks, bonds, and commodities return prediction

Next, we use the selected from the previous stage model to analyse its ability to forecast the performance of the S&P500 index, 12 industry portfolios, 10-year Treasury bonds and the CRB commodity index.

Since the obtained prediction of real GDP is based on the quarterly frequency, while financial data is monthly, we interpolate RGDP signals with an equal value for all three months in the quarter. In this part, only the OLS regression is used due to the relatively small number of independent variables. We perform two regressions (Equation 7) with RGDP fit alone and

(Equation 8) including the lag returns of all asset classes from Table 1 to account for potential spill-over effects between financial markets.

$$R_{i,t} = \alpha + \beta \cdot \widehat{RGDP}_t + \varepsilon_{i,t} \tag{7}$$

where $R_{i,t}$ is a logarithm return of i-th asset class: the S&P500 Index, equally weighted industry portfolios, cyclical and defensive sectors portfolios, US 10-years Treasury-bonds, and CRB commodity index, and $\widehat{RGDP}_t$ is a fitted (predicted) value of a real GDP.

$$R_{i,t} = \alpha + \beta \cdot \widehat{RGDP}_t + \beta \cdot R_{j,t-1} + \varepsilon_{i,t}\,; \quad \text{for } i \neq j \tag{8}$$

where $R_{i,t}$ is a logarithm return of i-th asset class at month t, and $R_{j,t-1}$is a logarithm return of assets from Table 1 observed one month before, except industry portfolios. For Treasury bond returns calculation, we use the approximation methodology proposed by Swinkels (2019), and other time series returns are used directly.

Our final test involves analysing whether some common factors can drive the business cycles and assets' performance. To investigate this, we perform OLS regression for stocks, bonds, and commodities returns on the lagged economic and financial variables similarly to the model specified in Equation 5 and add the lagged return of the same asset as a regressor to consider potential time-series momentum effects.

$$R_{i,t} = \alpha + \beta \cdot R_{i,t-1} + \boldsymbol{\beta} * \boldsymbol{F}^{N}_{i,t-1} + \varepsilon_{i,t}$$

Lasso performs great for variables selection problems as well as for prediction, but we do not use it to analyse financial assets. Since financial data is monthly, the number of observations increases three times while the number of the selected factors becomes smaller relative to the sample. Besides, assets' returns are more volatile and generally less correlated with factors' time series than RGDP. Due to these aspects, Lasso fails to find the optimal λ coefficient and cannot select variables that correlate well with the outcome in several training samples and, at the same time, predict the outcome in the testing sample well. Therefore, it omits all factors and estimates a constant term as the better predictor. The reason for this may be either non-linear dependency between asset returns and a list of selected factors, or one has to choose smaller λ manually to offset the loss from greater linear coefficients. However, the last option will likely lead to overfitting, so we do not exploit it.

The described methodology allows for critical asses all the defined research questions. We do not claim that the chosen methodologies are the only possible and correct ones, nor that the set of variables is exhaustive. However, the described methods make it possible to improve economic state prediction upon CFNAI and obtain results that, to some extent, throw light on the relationship between business cycles and financial markets. Empirical results and findings are discussed in the subsequent section.

5 Empirical results

Using a defined economic and financial factors list, we begin the research by creating the best model to predict US real GDP in the next quarter. We later compare it with CFNAI forecasting performance and analyse the relationship with the future variation of asset classes.

5.1 Predicting real GDP

The results for the first three models, obtained with OLS regressions for subperiods starting in Q2 1948, Q4 1973, and Q1 2004 and finishing in the first quarter of the 2022 year, are presented in Table 3. Each model has at least a few factors that, according to the t-test, are statistically significant predictors of future RGDP growth. This first notice provides evidence that economic growth can be predicted in advance based on currently available and observable data. However, only one factor – the industrial production index – is significant in all subperiods. Moreover, all 12 new variables added after 2004 (e.g., VIX, ‘recession’ word screening, fear barometer) have no statistical power. On the other hand, 4 out of 8 factors from the 1973 model (an INDPRO, HHD/PI, PCE, and short-term interest rate) remain significant in 2004-2022. Overall, we find that only these four factors among 40 indicators are consistently significant. All the above suggests that the factors influencing economic patterns may change over time and lose forecasting ability.

Explanatory power measured by adjusted R-squared increases from approximately 0.52 for the longest subperiod to 0.70 in 1973-2022 and then to 0.84 in 2004-2022. Although the last model may impress at first glance, we are not confident about its accuracy because the 2004-2022 period includes 72 observations which are less than twice greater than the number of regressors. This may lead to an overfitting problem, and the coefficients may rather represent a noise than the actual relationship of the sample.

In short, our first conclusion is that business cycles, measured with real GDP, can be predicted. Predictive strength varies with the number of included factors but does not necessarily depend on it and seems specific to the analysis period. The significance of financial factors such as short-term rate movements and changes in 10-year Treasury yields signals that the fixed-income market is a 'smart money' market and can also forecast the economy.

As the above approach does not provide consistent results, we move to OLS regression based on the obtained 8-11 principal components, depending on the period. It provides a lower adjusted R_sq of about 0.38 for the longest sample, 0.60 for 1973-2022 years and 0.79 in the most recent period (Table 4). The more important result is that four components are significant in all models and the other two, available only for the second and third models, are significant in both. A closer look at each component suggests that the highest weights in these six components have the same factors that had the greatest statistically predictive power in our previous test. These results seem more reliable than OLS due to the observed consistent pattern through different samples. Important to note that CFNAI, despite being a significant predictor of the future economic state, provides only 0.12 adjusted R_sq measure. It is constructed based just on the first principal component, and its 3-month average value has a 72% correlation with real RGDP, while the correlation of real GDP predicted with our PCA models and observed GDP growth is about 78%. The vast difference in the prediction results can be explained by a different number of components and the included factors: while our indicators are broader and consist of various macro and financial data, CFNAI uses 85 specific and highly correlated datasets.

While PCA helps reduce the dataset dimension and fit the data in the best way, it still uses variables that might not have explanatory power. To test which factors particularly can forecast the economic state, we move to analysis with the linear Lasso methodology. Since Lasso is designed to maximise the out-of-sample R-squared, we compare all models by this measure. To obtain out-of-sample R_sq for OLS and ‘OLS plus PCA’ models, we conduct the previous analysis again, using odd years as a training sample and even years as a testing sample to account for potential changes in economic patterns throughout the years.

Table 3

Linear regression results for the relationship between RGDP growth and lagged economic and financial factors

	Real GDP growth rate		
	1948-2022	1973-2022	2004-2022
Shiller CAPE	0.0956**	0.0279	-0.0002
US Consumer Price Index (YoY)	-0.0000	-0.0014	-0.0038*
US Consumer Price Index (Quarterly Changes)	0.1092	-0.1307	0.0235
Producer Price Index by Commodity: All Commodities	-0.1838*	-0.0300	0.1529
US 10-year Treasury Bond Yield	0.0324**	-0.0088	0.0103
US 10-year T-bonds and 3-months T-bill Yield Spread	0.0007	0.0010*	-0.0008
Fama and French Default (DEF) Spread	-0.0002	0.0001	-0.0036
S&P500 Dividend Yield	0.0070	-0.0194	0.0829
The Industrial Production Index in the US	0.8119***	0.6170***	0.6038*
Global Oil Spot Prices	0.0180*	-0.0069	-0.0034
Global Gold Spot Prices	-0.0003	-0.0041	0.0211
Percentage of US Stocks with Zero Returns Over the Past Year	0.0038	0.0088*	0.0056
US Corporate Net Dividends as % of GDP	0.0020	0.0005	0.0197
Unemployment Rate in the US	0.0037***	0.0004	0.0007
Manufacturing Purchasing Managers Index (PMI) in the US	0.0002	-0.0000	0.0002
Household Debt to Personal Income Ratio		0.0767**	0.1725*
Core-CPI Index (YoY)		0.0002	0.0018
Core-CPI Index (Quarterly Changes)		0.4278*	-0.0161
Money Growth Rate (M2) in the US		0.6570***	0.2392
US Personal Consumption Expenditure: Core Price Index		0.4305***	0.6029**
Leading Economic Indicators (YoY Changes)		0.0000	-0.0003
Smoothed US Recession Probabilities		-0.0000	-0.0001
BIS Residential Property Price Index in the US		-0.0036	-0.2356
Real Effective Exchange Rate		-0.0804	-0.2320
US MBA 30-year Mortgage Rate		-0.0145	-0.0477
Total US Debt to GDP Ratio		-0.0100	-0.0697
Dollar Index		-0.0023	0.0266
Nominal US Short-term Interest Rate		0.0464***	0.0563***
Low-graded US Corporate Bonds Yield			0.0338
CBOE Volatility Index (Last Quarter Value)			0.0006
CBOE Volatility Index (Quarterly Changes)			-0.0144
The FAO Food Price Index			-0.0722
US Mortgage Market Index			-0.0044
Global Price of Agr. Raw Material Index			-0.0542
Global Price of Industrial Materials Index			0.0389
Short-term Rate – CPI 5-year Forecast			-0.0014
Percent of the US Stocks Traded Above 200-day Average			0.0001
Credit Suise Fear Barometr			0.0132
US 1-month T-bill Rate			-0.0041
‘Recession’ Word Screening in Google			0.0008
Constant	-0.0034	0.0033	-0.0149
R_sq	.5456	.7444	.9302
R_sq_adj	.5212	.7008	.8401
N_obs	295	193	72

Note. *p < .05. **p < .01. ***p < .001. t-statistics are not precented for the shortage.

Table 4

Linear regression results for the relationship between RGDP growth, principal components of the lagged economic and financial factors, and CFNAI

	Real GDP growth rate			
	1948-2022	1973-2022	2004-2022	1967-2022
pc1	0.0029***	0.0019***	0.0028***	
	(9.66)	(8.10)	(10.59)	
pc2	0.0030***	0.0038***	0.0031***	
	(8.24)	(13.69)	(8.75)	
pc3	-0.0009**	-0.0006*	-0.0024***	
	(-2.30)	(-1.77)	(-4.93)	
pc4	-0.0006	0.0009**	-0.0012**	
	(-1.28)	(2.50)	(-2.50)	
pc5	-0.0000	0.0005	-0.0006	
	(-0.04)	(1.40)	(-1.18)	
pc6	0.0005	0.0013***	0.0022***	
	(0.95)	(3.17)	(3.65)	
pc7	0.0022***	-0.0006	0.0014**	
	(4.01)	(-1.18)	(2.18)	
pc8	-0.0013**	-0.0011**	0.0022***	
	(-2.12)	(-2.10)	(3.08)	
pc9		-0.0010*	-0.0024***	
		(-1.86)	(-2.98)	
pc10		0.0018***	0.0031***	
		(3.25)	(3.76)	
pc11		0.0000		
		(0.08)		
Lagged CFNAI				0.0071***
				(5.49)
Constant	0.0076***	0.0064***	0.0046***	0.0067***
	(14.18)	(12.11)	(5.40)	(9.34)
R_sq	.3989	.6191	.8165	.1219
R_sq_adj	.3821	.5959	.7864	.1178
N_obs	295	193	72	219

Note. PCs denote principal components of the economic and financial factors (listed in Table A1) available in the analysis period. *p < .05. **p < .01. ***p < .001. t-statistics in parentheses.

The comparison of postestimation characteristics for each model is presented in Table 5. The results suggest that the adaptive Lasso methodology works the best for our analysis. For each subperiod adaptive Lasso provides the highest out-of-sample R_sq, while CV Lasso underperforms the OLS model just once and never if compared to the 'OLS plus PCA' models. In terms of selected factors, Lasso models use 2 to 19 variables and are quite consistent with other methods. The list of selected factors for each model in Table 6 shows that industrial production, short-term interest rate, and personal consumption expenditures are still the most meaningful RGDP predictors. Interestingly, the 2004-2022 CV Lasso model, for the first time, determines ‘recession’ word screening in Google as another variable that can forecast business cycles, supporting the findings of Lustig and Verdean (2012); however, it is not significant.

We select the 1973-2022 adaptive model as a reference for subsequent analysis stages against the fact that the 2004-2022 adaptive Lasso has the greatest (0.81) out-of-sample R_sq of all models. This decision is supported by the fact that the period since 2004 is too short and, although, including the 2008 credit crisis and several other shocks, it is, in our opinion, insufficiently representative to be used for testing the impact of business cycles on financial markets. Figure 3 shows the prediction accuracy of adaptive Lasso models for all three subperiods. Overall, these models predict RGDP that comoves with observed series quite well. However, the accuracy depends on the period, being almost the same line with actual data during, e.g., years from 2002 to 2007, and having sometimes poor performance, e.g., during the 1990s.

To summarise the results of the three methods, we provide evidence that real GDP, as a measure of an economic state, can be predicted relatively well with different models and even with a relatively low number of variables. The OLS regression estimates the future economic state with in-sample R-squared measure from 0.52 to 0.84, depending on the period. It provides numerous significant factors, but only a few are consistent over time: short-term interest rate, industrial production, personal consumption expenditures, and household debt to income ratio. The second methodology, which involves PCA, produces lower R_sq but more persistent results. However, the linear Lasso models perform even better than the ‘OLS plus PCA’ approach in our dataset and with the list of explanatory factors we use, resulting in R_sq from 0.47 to 0.89. If one compares these models by out-of-sample R_sq, adaptive Lasso models outperform all the others. Hence, we believe that the adaptive Lasso model should be used for further assets analysis, as its results will depend on the RGDP accuracy prediction. And we select the 1973 model to cover more business cycles.

Table 5

Postestimation characteristics of linear Lasso regression results for the relationship between RGDP growth and the lagged economic and financial factors in comparison to OLS and PCA models

	Lasso models postestimation characteristics					
	1948-2022		1973-2022		2004-2022	
	CV	Adaptive	CV	Adaptive	CV	Adaptive
In-sample R2	.5324	.4721	.7407	.7392	.8569	.8926
Out-of-sample R2	.3958	.4295	.4585	.5194	.3932	.8113
MSE	.0000632	.0000668	.0000341	.0000347	.0000252	.0000255
Mean prediction error	.0000632	.0000714	.0000721	.0000639	.0001441	.0000448
No. of selected vars.	6	2	19	13	11	9
λ	.0009538	.0000367	.0001283	.0000170	.0010799	.0000260
	OLS models postestimation characteristics					
In-sample R2	.5212		.7008		.8401	
Out-of-sample R2	.3800		.5046		-	
	PCA models postestimation characteristics					
In-sample R2	.3989		.6191		.8165	
Out-of-sample R2	.3104		.3774		.2903	

Note. Out-of-sample analysis for OLS and PCA models is based on odd/even years. The exception is the 2004-2022 subperiod for the OLS model, where it is impossible to conduct a statistical test due to the small number of variables.

Table 6

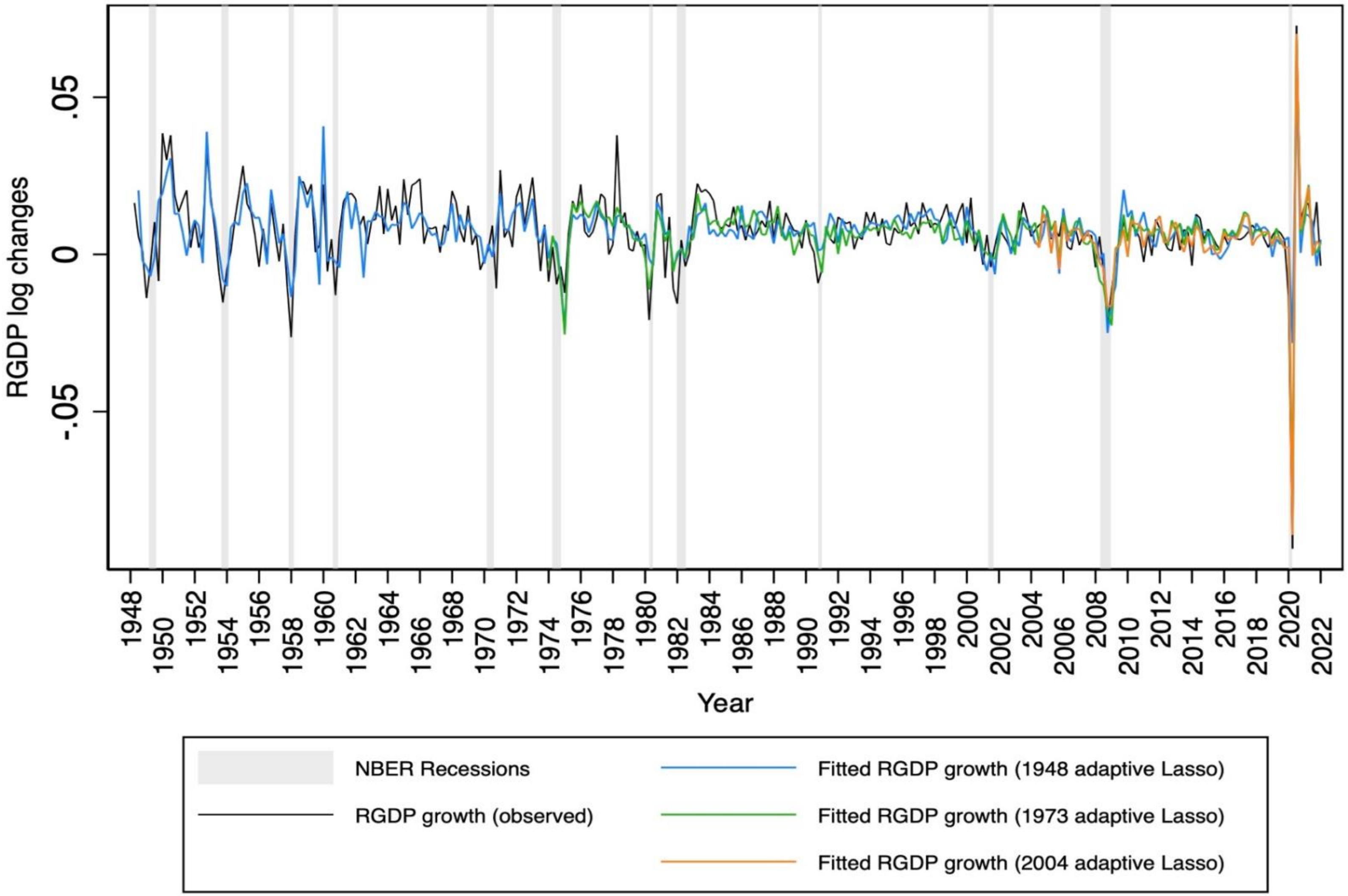
Economic and financial factors selected by linear Lasso regression models for real GDP growth prediction

Economic Variables	1948-2022 Lasso model		1973-2022 Lasso model		2004-2022 Lasso model	
	CV	Adaptive	CV	Adaptive	CV	Adaptive
Nominal US Short-term Interest Rate			0.0227**	0.0432***	0.0590***	0.0587***
The Industrial Production Index in the US	0.8828***	0.8690***	0.2471*	0.5807***	0.5773***	0.5603***
US Personal Consumption Expenditure: Core Price Index			0.1617	0.3982***	0.2270**	0.2241***
Money Growth Rate (M2) in the US			0.8123***	0.6506***	0.9856***	1.0118***
US Consumer Price Index (YoY)			-0.0006	-0.0017***	-0.0018**	-0.0018**
Shiller CAPE	0.0959***	0.1176***	0.1624***	0.0426**		
Household Debt to Personal Income Ratio			0.0239	0.0672**		
US 10-year T-bonds and 3-months T-bill Yield Spread			0.0005	0.0009**		
Percentage of US Stocks with Zero Returns Over the Past Year	0.0038		0.0021	0.0073*	0.0118*	0.0113*
Smoothed US Recession Probabilities			-0.0000	-0.0000		
Core-CPI Index			0.5471**	0.3046**		
Real Effective Exchange Rate			-0.0890	-0.0669	-0.1175	-0.1024
US MBA 30-year Mortgage Rate			-0.0015	-0.0315	-0.0609*	-0.0493*
Producer Price Index by Commodity: All Commodities			-0.0416			
S&P500 Dividend Yield			0.0989**			
Global Oil Spot Prices	0.0093		0.0073			
Unemployment Rate in the US	0.0033***		-0.0025			
US 10-year Treasury Bond Yield	0.0310**		-0.0100			
US Consumer Price Index (Quarterly Changes)			-0.0174			
Low-graded US Corporate Bonds Yield					0.0188	
CBOE Volatility Index (Last Quarter Value)					-0.0099	-0.0056
‘Recession’ Word Screening in Google					-0.0008	

Note. *p < .05. **p < .01. ***p < .001. t-statistics are not presented for the shortage.

Figure 3

RGDP growth prediction accuracy with adaptive Lasso models in each subperiod



Another test of prediction accuracy

In addition to interpreting out-of-sample R_sq as a measure of predictive accuracy, we want to test how precisely fitted RGDP values could determine NBER-based US recession dates. Given that a recession is defined as two successive negative GDP values, the accuracy of the prediction should be relatively high. We perform probit regressions for three adaptive Lasso models in all subperiods and present results in Table 7.

All three models provide highly significant results, confirming our hypothesis. The 1973-2022 model has the highest explanatory power, based on the Pseudo R_sq measure, supporting our selection to use it in the following research question.

Table 7

Probit regression results for NBER-based US quarterly recession dates prediction with fitted RGDP with adaptive Lasso models

	NBER-based US quarterly recession dates		
	1948-2022	1973-2022	2004-2022
RGDP_hat	-183.49***	-356.80***	-321.61**
	(-7.93)	(-5.02)	(-2.52)
Constant	-0.29**	0.0637	-0.71**
	(-2.04)	(-0.25)	(-2.11)
Pseudo R_sq	.4895	.6382	0.5931
AIC	129.10	57.84	24.44
BIC	13.65	64.36	28.99
N_obs	295	193	72

Note. RGDP_hat is a fitted values of the real GDP growth rate with the '1973 adaptive Lasso' model.
$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$. t-statistics in parentheses.

As shown in Table 8, Panel 1, the overall rate of correct classification is the highest for the 1973 model and is estimated at 93.78%, with 64.00% of the ex-post recession dates correctly classified (sensitivity) and 98.28% of the non-recessions correctly classified (specificity). It gives only 9 'type 1' and 3 'type 2' errors out of 193 observations. These results come from the good fit of RGDP prediction in the previous step. It is important to note that the difference in accuracy is marginal, as other models classify correctly 92.54% and 93.06% of observations, meaning they all can determine recession dates well.

It might be interesting to study each model's results for the most recent Q1 2022 GDP observation. To test that, we run Lasso regression, excluding the last observations, especially Q1 2022 RGDP value and Q4 2021 factors data, and perform ex-ante prediction for one quarter ahead period to obtain the Q1 2022 real GDP growth rate that was announced recently. We find that the 1973-2022 adaptive Lasso model is the only one that indeed provides a negative number, -0.0044 specifically, and is quite close to reality, while the 1948 and 2004 models' outputs are 0.0326 and 0.0124, respectively. This test does not have any statistical power but gives an idea of what the result one would have received if used this model to predict GDP growth in the next quarter.

Table 8

Probit regression summary statistics for NBER-based US quarterly and monthly recession dates prediction with fitted RGDP

Panel 1		NBER-based US quarterly recession dates		
		1948 Lasso model	1973 Lasso model	2004 Lasso model
Sensitivity	Pr(+| D)	62.79%	64.00%	50.00%
Specificity	Pr(-|~D)	97.62%	98.21%	98.44%
Correctly classified		92.54%	93.78%	93.06%
Panel 2		NBER-based US monthly recession dates		
		1973 Lasso	CFNAI	
Sensitivity	Pr(+| D)	60.76%	43.04%	
Specificity	Pr(-|~D)	97.60%	98.80%	
Correctly classified		92.57%	91.19%	

Note. True D defined as recession date. Classified + if predicted Pr(D) >= .5

'1973 adaptive Lasso' model vs CFNAI

Another important test is how our model performs compared to the CFNAI index, which is constructed based on 85 monthly indicators of national economic activity, some of which are not available with Erasmus data centre subscription. In contrast, our model consists of 13 time series, mostly free available. To interpolate obtained earlier fitted real GDP values to a monthly frequency, we use the predicted one-quarter signal for all following three months. Figure 4 shows RGDP fitted with the '1973 adaptive Lasso' model and CFNAI, the correlation between which is 0.61 from January 1974 to March 2022. The graph shows that the data from our model is smoothed relative to CFNAI since signals do not change within a quarter, unlike the Chicago index. Nevertheless, this does not prevent our model from being better in terms of out-of-sample RGDP and ex-post recession dates prediction.

Both our model and CFNAI are highly significant monthly recession dates predictors and are consistent in sign, as shown in Table 9. CFNAI has higher power in terms of Pseudo

R_sq (0.31) and lower Akaike and Bayesian information criterion due to the monthly availability but can correctly classify only 43.04% of recession dates and has a 91.19% overall rate while Lasso achieves 92.57% accuracy and correctly classify 60.76% of true recessions, as shown in Table 8, Panel 2.

We conclude that our adaptive Lasso model, which estimates real GDP growth based on 13 factors available since 1973, outperforms the CFNAI index in terms of predictive power measures as R-squared. Besides, it is a statistically significant predictor of recession dates and can classify them more correctly than CFNAI. Another advantage of our model is that it uses only 13 variables, mostly publicly available compared to 85 specific and mostly unavailable indicators in the index by Chicago FED.

Table 9

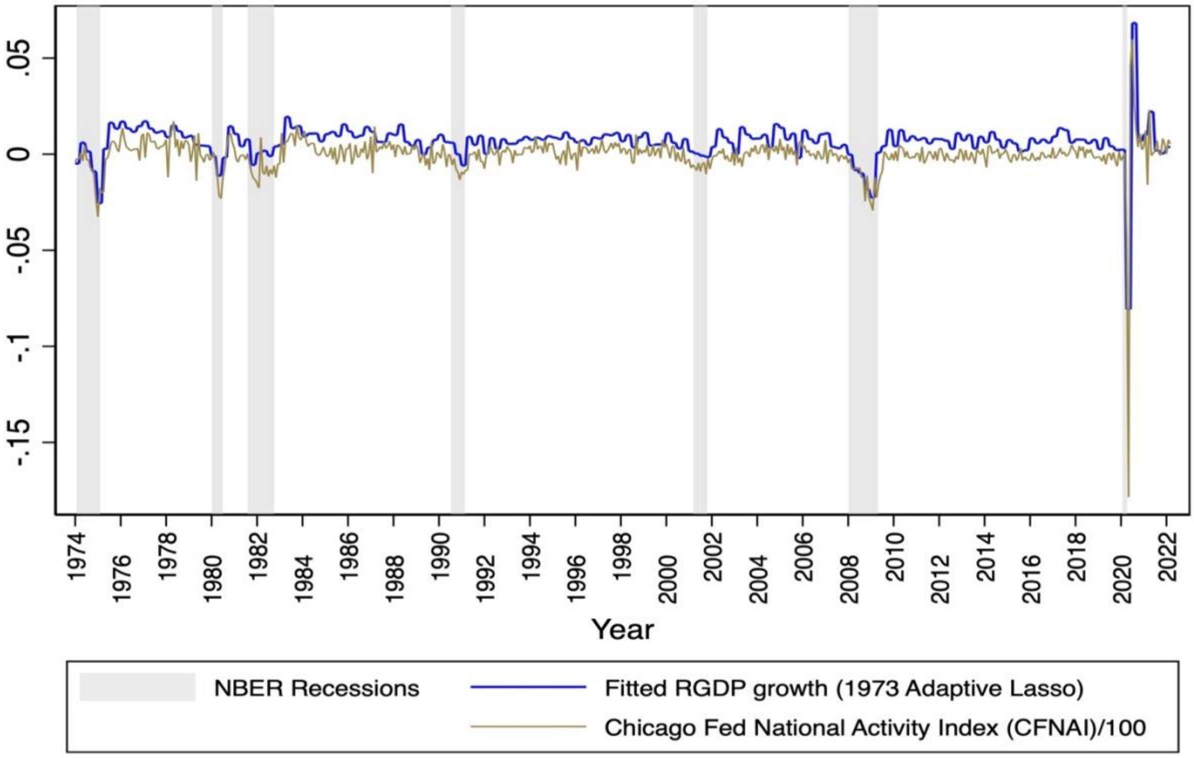
Probit regression results for NBER-based US monthly recession dates prediction with fitted RGDP and CFNAI

	NBER-based US monthly recession dates	
RGDP_hat	-63.06***	
	(-9.46)	
CFNAI		-1.46***
		(-27.01)
Constant	-0.86***	-1.37***
	(-11.31)	(-17.05)
Pseudo R_sq	.2105	.3064
AIC	368.30	324.05
BIC	377.00	332.77
N_obs	579	579

Note. RGDP_hat is a fitted values of the real GDP growth rate with the ‘1973 adaptive Lasso’ model.
*p < .05. **p < .01. ***p < .001. t-statistics in parentheses.

Figure 4

Comparison of fitted RGDP and CFNAI, Jan 1974 – Mar 2022

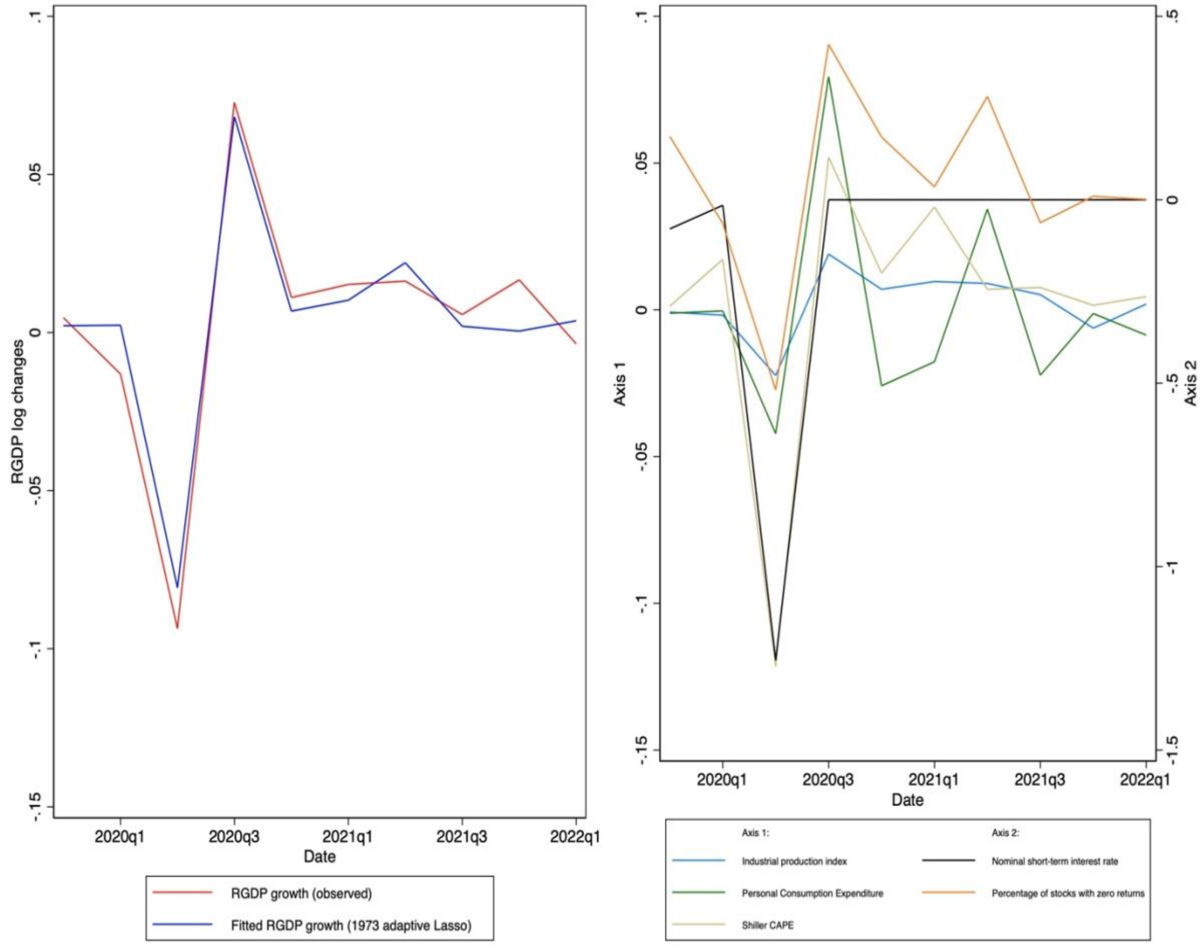


A deep look at the Covid-crisis

Based on Figure 3, one may suppose that our model was even able to predict the Covid-crisis. However, this is not quite true. A more detailed look at the left part of Figure 5 makes it clear that the crisis that began in the first quarter of 2020, specifically in February, was not predicted. This is not surprising since it was not connected with the previous state of the economy and, therefore, could not be reflected in macro and financial factors. While the actual RGDP drop was about 1.31% in the first quarter, the Lasso model estimated a 0.23% growth. However, an estimated -8.07% drop in the second quarter is very close to reality, as the observed collapse was -9.36%. The comparable accuracy holds for the third quarter (6.82% vs observed 7.28% surge). The right part of Figure 5 shows the main drivers of such predictability, which comes from rapid changes in these factors during two quarters: industrial production, personal consumption expenditures, short-term rate, Shiller CAPE, and percentage of stocks with zero return.

Figure 5

A detailed look at RGDP prediction accuracy and its main drivers during the Covid-crisis



5.2 Forecasting asset classes performance with RGDP

We proceed with the '1973 adaptive Lasso' model to the next research question to test whether movements in the economy can forecast asset classes' performance. This part of the work includes the analysis of the S&P500 index, 12 Fama-French US industry portfolios, 10-year Treasury bonds and the Thomson Reuters commodity CRB index.

5.2.1 The S&P500 index

Forecasting with real GDP

Unlike individual factors, we find no evidence that information about the future state of the economy can be used to predict the movements of the S&P500 index. Table 10 presents the results of regressions with RGDP used alone and in combination with the 10-year Treasures, Dow Jones corporate bonds index, CRB and GSCITOT commodities indexes to account for potential spill-over effects between markets. The last four columns represent robustness checks for the same regressions in different subsamples, divided randomly into equal halves and for odd/even years. Fitted values of RGDP are never significant regardless of the sample period. The same holds for CFNAI, 1-month lagged returns of fixed income instruments, and aggregated commodity indexes.

We conclude, at this stage, that future stock market levels are hardly predictable with such vast indicators as the real GDP growth rate or other financial instruments. Important to note that it does not mean that expectations about future economic growth have nothing with equity markets at all. It might be the case that market participants use expectations to adjust their portfolios to them so that the information about the consequent economic state is already priced in the market. The monthly variation of RGDP and S&P500 are presented in Figure 6.

Figure 6

Variation of S&P500 index return and fitted RGDP growth, Jan 1974 – Mar 2022

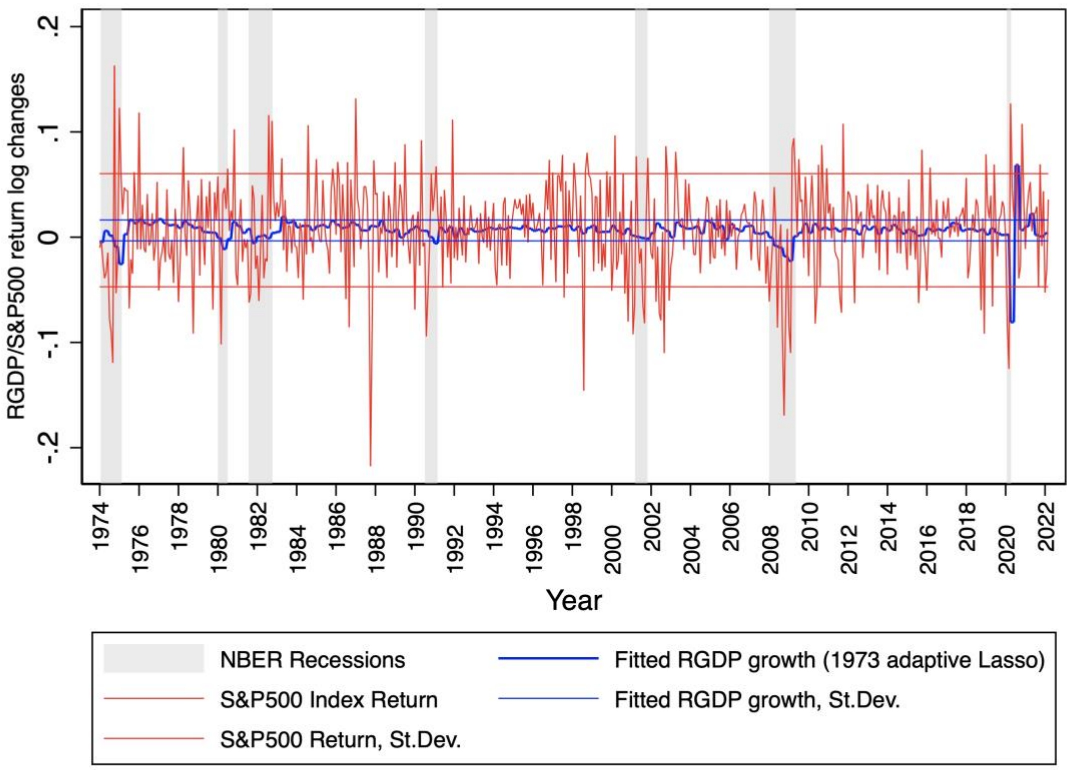


Table 10

Linear regression results for the relationship between the S&P550 index return and fitted RGDP, CFNAI, and lagged returns of fixed-income and commodity indexes

	S&P500 index monthly return							
					Robustness checks for in\out samples			
	1973-2022	1973-2022	1973-2022	1973-2022	Odd years	Even years	Random sample 1	Random sample 2
RGDP_hat	-0.0139		-0.0326		-0.0141	-0.1551	-0.2830	0.5024
	(-0.08)		(-0.17)		(-0.06)	(-0.41)	(-1.10)	(1.61)
Lagged CFNAI		-0.0003		-0.0005				
		(-0.19)		(-0.26)				
Lagged US10Y_ret			0.0578	0.1225	0.2016	-0.0339	0.2717	-0.2655*
			(0.50)	(1.14)	(1.18)	(-0.22)	(1.65)	(-1.67)
Lagged DJCBIND_ret			0.2036	0.1553	0.2366	0.0272	0.0786	0.4210**
			(1.40)	(1.13)	(1.15)	(0.13)	(0.37)	(2.16)
Lagged CRB_ret			-0.0468	-0.0370	0.0444	-0.1722**	0.0099	-0.1142
			(-0.87)	(-0.74)	(0.59)	(-2.26)	(0.12)	(-1.63)
Lagged GSCITOT_ret			0.0349	0.0452	0.0190	0.0680	0.0802*	-0.0098
			(1.11)	(1.48)	(0.43)	(1.54)	(1.72)	(-0.24)
Constant	0.0077***	0.0069***	0.0074***	0.0063***	0.0021	0.0130***	0.0071**	0.0060*
	(3.54)	(4.07)	(3.20)	(3.36)	(0.62)	(3.71)	(2.11)	(1.86)
r2	9.88e-06	0.0001	0.0134	0.0166	0.0355	0.0265	0.0347	0.0298
r2_a	-0.0017	-0.0015	.0048	0.0087	0.0186	0.0092	0.0181	0.0122
N	579	660	576	625	291	288	297	282

Note. RGDP_hat is a fitted values of the real GDP growth rate with the '1973 adaptive Lasso' model. US10Y_ret, DJCBIND_ret, GSCITOT_ret, CRB_ret are returns of 10-year Treasury bonds, Dow Jones corporate bond index, Goldman Sachs commodity total return index and Tomson Reuters commodity CRB index return, respectively. *p < .05. **p < .01. ***p < .001. t-statistics in parentheses.

Forecasting with economic factors

As was discussed in the research question section, regardless of the ability of RGDP to predict various asset classes' returns, it is also essential for us to assess which economic and financial factors can help forecast the performance of those assets. This analysis is also relevant because the model we use to predict real GDP can omit factors that might appear important to explain the variation of financial assets. We analyse the factors from Table A1 for correlation between each other again (since now factors are used with monthly frequency) and remove the following time series.

- Short-term interest rate minus CPI, as it is highly correlated (0.96) with the US 1-month Treasury bill yield.
- Oil futures, being a 0.99 correlated with oil spot prices.

In addition, for the S&P500 regression individually, we exclude the S&P500 dividend yield from the list of independent variables due to the -0.90 correlation. These changes lead to the following total number of factors per sample.

- 1926-2022 subperiod: 12 variables;
- 1948-2022 subperiod: 16 variables;
- 1973-2022 subperiod: 28 variables;
- 2004-2022 subperiod: 42 variables.

The OLS regression results for the previously used three subperiods and the overall 1926-2022 history period are presented in Table 11. The first and most interesting finding is that there is no predictive power in any of the economic and financial factors for the 1926-2022 period, while the short-term momentum effect is statistically significant only in this sample. Another important result is that no variables are significant in all four or even three (except the 1926-2022) tested periods. This supports the claim of Goyal et al. (2021) that indicators seem not to offer the desired stable, forward-looking performance. On the other hand, each model brings new significant factors with the newly available data, and the sign of those is consistent over periods. In line with that, the 2004-2022 model has the highest R_sq of about 18.47%.

Since discussing each factor separately in this paper is impossible, we mention the most important ones to note and compare with the existing literature. Consistent with previous papers, all models include some economic factors in addition to variables observed in financial markets, e.g., PMI, unemployment rate, personal consumption expenditures, etc. We also find supportive arguments for the forecasting power of known predictors, such as lagged industrial production and the percentage of stocks with zero return, though they provide significant results in a few samples. Interestingly, some market indicators explicitly used in the recent periods and available only in the 2004-2022 period, such as VIX (both the last month's value and monthly changes) and fear barometer, are significant. This pattern is difficult to interpret. One could argue its connection with underreaction (Hong & Stein, 1999), confirming it with the recent study of Cheng (2020), who provides evidence of underreaction to VIX signals at the beginning of the Covid-crisis. However, some factors remain priced, e.g., the number of stocks above 200MA. Moreover, there is an opposite view of an overreaction (Howe, 1986). Same contradictory patterns appear among economic factors: leading economic indicators, constructed by Conference Board, seem to be predictive in both subperiods when available, while PMI is in two out of three, and US recession probabilities are never significant.

We conclude that economic factors may not directly relate to equity markets. However, they may indirectly influence market performance at specific periods, while the predictive power of financial factors is highly dependent on the period used too. In other words, most factors lose their power and, despite the significance of some of them, one should carefully use them because of discussed concerns and very low estimates of adjusted R-squared measures. We do not perform a multi-stage robustness test to draw conclusions about the predictive ability of each factor, as Goyal et al. (2021) did, since the main goal of our work is different, and we cannot cover all the criteria they used in this paper. In the meantime, we are in solidarity with their concern about the possibility of finding a reliable predictor of the equity premium on a forward-looking basis, as our results provide huge inconsistency in significance over time. However, we propose to pay special attention to a few significant factors in the 2004-2022 period, at least at the 5% level, such as PCE, INDPRO, CPI, VIX, and others, and leave their further investigation to separate research. As discussed in the methodology section, we do not provide Lasso model results, as it does not work well in this case (as well as for Treasuries and commodities) and omits all the selected variables.

Table 11

Linear regression results for the relationship between the S&P550 index return and the list of the lagged economic and financial factors, and time-series momentum

	S&P500 index monthly return			
	1926-2022	1948-2022	1973-2022	2004-2022
Lagged S&P550 index return	0.0888**	0.0071	-0.0367	0.0539
Lagged Shiller CAPE	-0.0174	-0.0108	0.0017	-0.2124
Lagged US Consumer Price Index (YoY)	-0.0001	-0.0015**	-0.0015	-0.0079**
Lagged US Consumer Price Index (Monthly Changes)	-0.5662	-0.2685	0.6516	-0.8874
Lagged Fama and French Default (DEF) Spread	0.0021	-0.0040	0.0007	-0.0023
Lagged Industrial Production Index in the US	0.0494	0.1977	0.4730	1.4265***
Lagged Global Oil Spot Prices	-0.0335	-0.0347*	-0.0272	0.0162
Lagged Producer Price Index by Commodity	0.2611	0.3014	0.1629	0.8198
Lagged US 10-year T-bonds and 3-months T-bill Yield Spread	-0.0002	-0.0016	-0.0032	-0.0063
Lagged US 10-year Treasury Bond Yield	-0.0333	-0.0481**	-0.0307	-0.0248
Lagged Global Gold Spot Prices	-0.0283	-0.0371	-0.0590	-0.1414**
Lagged Percentage of US Stocks with Zero Returns	-0.0032	0.0098**	0.0181**	0.0126
Lagged Manufacturing Purchasing Managers Index (PMI)		-0.0007**	-0.0017***	-0.0009
Lagged Unemployment Rate in the US		0.0037***	0.0028	0.0007
Lagged US Corporate Net Dividends as % of GDP		0.0024	-0.0217	0.0183
Lagged Household Debt to Personal Income Ratio		-0.0361	-0.2143	-0.0762
Lagged US MBA 30-year Mortgage Rate			0.0362	0.0985
Lagged Core-CPI Index (YoY)			-0.0004	-0.0210
Lagged Core-CPI Index (Monthly Changes)			-1.9706**	1.0537
Lagged Dollar Index			-0.0515	0.1231
Leading Economic Indicators (YoY Changes)			0.0010*	0.0028**
Lagged Money Growth Rate (M2) in the US			-0.0535	0.7802
Lagged US Personal Consumption Expenditure: Core Price Index			-0.2583	-1.2583***
Lagged Real Effective Exchange Rate			-0.2566	-0.0039
Lagged US Recession Probabilities			-0.0001	0.0003
Lagged Nominal US Short-term Interest Rate			-0.0169	0.0009
Lagged BIS Residential Property Price Index in the US			0.4781	0.2276
Lagged Total US Debt to GDP Ratio			-0.0473	-0.3823**
Lagged Percent of the US Stocks Traded Above 200-day Average				-0.0004
Lagged Expected CPI – real CPI				-0.0031
Lagged Credit Suisse Fear Barometer				-0.0452*
Lagged The FAO Food Price Index				0.0568
Lagged Global Price of Industrial Materials Index				0.1022
Lagged Global Price of Agr. Raw Material Index				0.0613
Lagged Global Price of Energy Index				0.0295
Lagged Low-graded US Corporate Bonds Yield				-0.0329
Lagged US Mortgage Market Index				0.0240
Lagged CBOE Volatility Index (Last Month Value)				0.0019*
Lagged CBOE Volatility Index (Monthly Changes)				-0.0585**
Lagged Total US Market Capitalization to GDP ratio				0.2352**
Lagged Recession' Word Screening in Google				0.0037
Constant	0.0050	0.0326*	0.0861***	0.0583
R_sq	.0143	.0466	.0794	.3454
R_sq_adj	.0039	.02798	.0324	.1847
N_obs	1149	835	577	214

Note. *p < .05. **p < .01. ***p < .001. t-statistics are not presented for shortage.

5.2.1 US industry portfolios

The correlation of industry portfolios' total returns with S&P500 varies from about 0.71 to 0.89. Since the market premium is more important for the asset pricing problem, we use the industry portfolios' returns in excess of the market for analysis.

The predictive power of RGDP is significant for Energy, Telecom, and 'Other' industries at a 5% confidence level and 1% – for Shops and Healthcare, but adjusted R_sq measures are extremely low, as shown in Table 12. The difference in predictability between industries corresponds to similar findings by Ferson and Harvey (1991).

The sign of all coefficients is negative with no difference between sectors, so one may assume that each industry separately underperforms the market when expectations of future economic growth are positive. This may seem strange given the existence of the paradigm of cyclical and counter-cyclical sectors. However, we find an explanation for this in the difference in the estimated constants in each model. If we fix the constants at zero level, five separate industries appear to beat the market at a time when the economy is going to perform well, namely Consumer Nondurables, Manufacturing, Chemicals, Business Equipment, and Utilities.

We also compare the above results with CFNAI forecasting ability by running similar regressions and find that CFNAI can predict only two industries' returns, namely Shops and Healthcare, with significance at 5% and 1% confidence levels, respectively (results are not presented), despite the fact it provides signals every month.

Cyclical vs counter-cyclical sectors

We perform linear regressions for cyclical and counter-cyclical industries using the equally weighted portfolios formed with the mean industry betas. Table 13 provides results for RGDP only and in combination with lagged returns of other financial assets.

We find that real GDP can only help predict cyclical industries, being consistent in sign and statistically significant as a separate predictor and when lagged fixed-income and commodity indexes are included. Conversely, RGDP is never significant in predicting counter-cyclical industries, except in one randomly created sample (Table 13, panel 2). Moreover, adjusted R_sq are more meaningful (up to 3.84%) over different samples but still very low, while they were even negative for some particular industries and portfolio of counter-cyclical sectors. For these tests, CFNAI again performs even worse and is significant only for one randomly selected subsample, so it cannot provide any predictive insights, and the results are not presented.

Table 12

Linear regression results for the relationship between the US equally weighted industry portfolios excess return and fitted RGDP

	EW_NoDur	EW_Durbl	EW_Manuf	EW_Enrgy	EW_Chems	EW_BusEq
RGDP_hat	-0.0502	-0.1254	-0.0725	-0.5796**	-0.0122	-0.3672
	(-0.40)	(-0.71)	(-0.52)	(-2.00)	(-0.09)	(-1.62)
Constant	0.0021	0.0024	0.0038**	0.0048	0.0036**	0.0082***
	(1.42)	(1.16)	(2.28)	(1.41)	(2.32)	(3.05)
R_sq	0.0003	0.0009	0.0005	0.0069	0.0000	0.0046
R_sq_adj	-0.0015	-0.0009	-0.0013	0.0052	-0.0017	0.0028
N	576	576	576	576	576	576
	EW_Telcm	EW_Utils	EW_Shops	EW_Hlth	EW_Money	EW_Other
RGDP_hat	-0.4322**	-0.0169	-0.4392***	-0.5468***	-0.0541	-0.3899**
	(-2.27)	(-0.12)	(-2.80)	(-2.75)	(-0.47)	(-2.51)
Constant	0.0073***	0.0011	0.0059***	0.0090***	0.0010	0.0046**
	(3.22)	(0.67)	(3.16)	(3.82)	(0.71)	(2.47)
R_sq	.0089	.0000	.0135	.0130	.0004	.0108
R_sq_adj	.0072	-.0017	.0118	.0112	-.0014	.0091
N_obs	576	576	576	576	576	576

Note. RGDP_hat is a fitted values of the real GDP growth rate with the '1973 adaptive Lasso' model. Equally weighted (EW) industry portfolios are classified based on the Kenneth R. French SIC codes distribution. *p < .05. **p < .01. ***p < .001. t-statistics in parentheses.

Table 13

Linear regression results for the relationship between the US equally weighted cyclical and counter-cyclical portfolios excess return, fitted RGDP, and lagged returns of fixed-income and commodity indexes

Panel 1	EW portfolio of cyclical industries					
			Robustness checks for in\out samples			
	1973-2022	1973-2022	Odd Years	Even Years	Random Sample 1	Random Sample 2
RGDP_hat	-0.3294**	-0.3982***	-0.6547**	-0.3672**	-0.2961	-0.7168***
	(-2.33)	(-2.68)	(-2.07)	(-2.21)	(-1.56)	(-2.79)
Lagged US10Y_ret		-0.0978	-0.0145	-0.1241	-0.1375	-0.0314
		(-1.11)	(-0.11)	(-1.03)	(-1.13)	(-0.24)
Lagged DJCBIND_ret		0.2305**	0.1861	0.1798	0.2636*	0.1619
		(2.07)	(1.07)	(1.24)	(1.68)	(1.00)
Lagged GSCITOT_ret		-0.0003	-0.0323	0.0177	0.0139	-0.0189
		(-0.01)	(-0.86)	(0.57)	(0.40)	(-0.56)
Lagged CRB_ret		0.0728*	-0.0254	0.1589***	0.0645	0.0927
		(1.77)	(-0.39)	(3.01)	(1.10)	(1.60)
Constant	0.0055***	0.0062***	0.0104***	0.0032	0.0045*	0.0094***
	(3.28)	(3.51)	(3.53)	(1.38)	(1.81)	(3.55)
R_sq	.0094	.0258	.0356	.0552	.0223	.0417
R_sq_adj	.0076	.0173	.0185	.0384	.0054	.0243
N_obs	576	576	288	288	288	288

Panel 2	EW portfolio of counter-cyclical industries					
			Robustness checks for in\out samples			
	1926-2022	1926-2022	Odd Years	Even Years	Random Sample 1	Random Sample 2
RGDP_hat	-0.0404	-0.0344	-0.2623	0.0138	0.1294	-0.5530***
	(-0.40)	(-0.32)	(-1.19)	(0.11)	(0.98)	(-2.91)
Lagged US10Y_ret		0.0381	0.1206	-0.0249	-0.0776	0.2224**
		(0.60)	(1.34)	(-0.27)	(-0.92)	(2.30)
Lagged DJCBIND_ret		0.0566	0.0359	0.0536	0.2024*	-0.1647
		(0.70)	(0.29)	(0.48)	(1.86)	(-1.38)
Lagged GSCITOT_ret		-0.0029	-0.0186	0.0055	0.0139	-0.0204
		(-0.16)	(-0.71)	(0.23)	(0.58)	(-0.82)
Lagged CRB_ret		0.0094	-0.0036	0.0248	0.0240	0.0004
		(0.31)	(-0.08)	(0.61)	(0.59)	(0.01)
Constant	0.0014	0.0011	0.0020	0.0013	0.0003	0.0042**
	(1.15)	(0.84)	(0.99)	(0.74)	(0.16)	(2.13)
R_sq	.0003	.0060	.0299	.0037	.0247	.0597
R_sq_adj	-.0015	-.0027	.0127	-.0140	.0078	.0426
N_obs	576	576	288	288	288	288

Note. RGDP_hat is a fitted values of the real GDP growth rate with the '1973 adaptive Lasso' model. US10Y_ret, DJCBIND_ret, GSCITOT_ret, CRB_ret are returns of 10-year Treasury bonds, Dow Jones corporate bond index, Goldman Sachs commodity total return index and Tomson Reuters commodity CRB index return respectively. *p < .05. **p < .01. ***p < .001. t-statistics in parentheses.

5.2.2 US 10-year Treasury bonds

Forecasting with real GDP

Similarly to the S&P500 index, the fitted values of real GDP do not provide statistically significant results, meaning that future economic growth cannot directly predict the variation of the 10-year Treasury excess returns (Table 14). Surprisingly, lagged CFNAI alone can do this with significance on a 10% level and marginal R_sq, but its forecasting power disappears once lagged returns of financial indexes are included. Figure 7 displays the variation of Treasuries and RGDP over the tested period.

Another notable finding is that all included 1-month lagged financial instruments provide significant results in the whole 1973-2022 sample. A negative S&P500 coefficient sign supports a theory of the relation between flows into equity and fixed income markets (Fama & French, 1993). However, results highly depend on the data sample. Both robustness checks provide substantial changes in both significance and explanatory power. This gives grounds to conclude that only the relationship between the stock market and Treasuries bonds return is persistent over time.

Figure 7

Variation of 10-year Treasury bonds excess return and fitted RGDP, Jan 1974 – Mar 2022

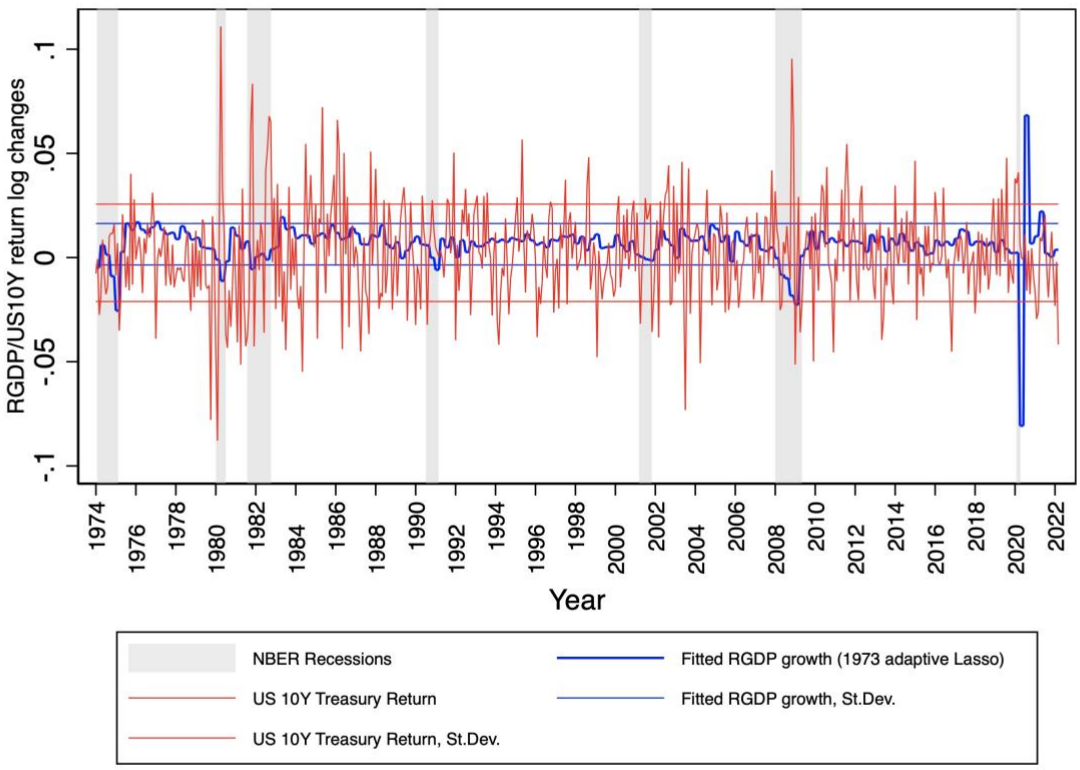


Table 14

Linear regression results for the relationship between the US 10-year Treasury bonds excess return, fitted RGDP, CFNAI and lagged returns of S&P500, fixed-income and commodity indexes

	US 10Y Treasury bonds monthly excess return							
					Robustness checks for in\out samples			
	1973-2022	1973-2022	1973-2022	1973-2022	Odd years	Even years	Random sample 1	Random sample 2
RGDP_hat	-0.0815		0.0546		0.0589	0.0714	0.1281	-0.0648
	(-0.83)		(0.54)		(0.27)	(0.64)	(1.02)	(-0.36)
Lagged CFNAI		-0.0016*		-0.0006				
		(1.78)		(-0.60)				
Lagged SP500_ret			-0.0936***	-0.0886***	-0.0627*	-0.1173***	-0.0650**	-0.1272***
			(-3.95)	(-3.98)	(-1.77)	(-3.80)	(-1.99)	(-3.66)
Lagged DJCBIND_ret			0.1010*	0.1055*	-0.0908	0.2734***	0.0917	0.1176
			(1.81)	(1.95)	(-1.06)	(3.82)	(1.20)	(1.43)
Lagged CRB_ret			-0.0643**	-0.0653**	0.0165	-0.1332***	-0.0880**	-0.0453
			(-2.33)	(-2.56)	(0.39)	(-3.78)	(-2.28)	(-1.13)
Lagged GSCITOT_ret			-0.0373**	-0.0318**	-0.0028	-0.0587***	-0.0519**	-0.0209
			(-2.27)	(-2.00)	(-0.11)	(-2.80)	(-2.23)	(-0.89)
Constant	0.0028**	0.0018**	0.0029**	0.0031***	0.0017	0.0041***	0.0034**	0.0030
	(2.42)	(1.98)	(2.55)	(3.31)	(0.85)	(2.84)	(2.14)	(1.64)
R_sq	0.0012	0.0048	0.0547	0.0541	0.0219	0.1660	0.0584	0.0642
R_sq_adj	-0.0006	0.0033	0.0463	0.0465	0.0041	0.1513	0.0420	0.0469
N_obs	579	661	569	626	281	288	293	276

Note. RGDP_hat is a fitted values of the real GDP growth rate with the '1973 adaptive Lasso' model. SP500_ret, DJCBIND_ret, GSCITOT_ret, CRB_ret are returns of the S&P500 index, Dow Jones corporate bond index, Goldman Sachs commodity total return index and Tomson Reuters commodity CRB index return, respectively *p < .05. **p < .01. ***p < .001. t-statistics in parentheses.

Forecasting with economic factors

Due to the data availability, we start the forecasting analysis with economic variables for Treasury bonds and later for the CRB index from 1963, so the number of factors in each model changes.

- 1963-2022 subperiod: 21 variables;
- 1973-2022 subperiod: 29 variables;
- 2004-2022 subperiod: 43 variables.

We do not discuss the results of each used factor individually, as this would take excessive time. Thus, we focus on the most important of them and on the most meaningful findings that are worth emphasising in our study.

Similarly to equity market regression, each model introduces new significant predictors, as shown in Table 15. However, default spread and market dividend yield are the only significant factors in all three periods. The US recession probabilities are available in two samples and significant in both. We observe time-series momentum again but now in two, 1948-2022 and 1973-2022 periods. Another interesting finding is that both S&P500 dividend yield and net dividend to GDP ratio may help to forecast 10-year US bonds, whereas they were useless in predicting equity market returns. Conversely, the Credit Suisse fear barometer and PMI provide statistically significant signals about future Treasury premiums, being also significant predictors for the S&P500 index in some samples. Regarding the R_sq measure, results are comparatively similar for the 2004-2022 model (about 14%) and higher for other subperiods compared to estimates obtained for stock market regressions.

We find that some equity market factors are consistent and significant bond return indicators. For example, as previously reported by Fama and French (1989), the dividend yield has a positive sign and is a predictor in all tested periods. Moreover, Shiller CAPE provides the opposite pattern but is significant in two longer samples, losing its power in the 2004-2022 period. As for the bond market factors, we confirm the findings of Fama and French (1989, 1993); Ferson and Harvey (1991) about default spread negative relation to future Treasury risk premiums, which is also significant in all three samples.

Overall, most of the factors, unfortunately, produce inconsistent results. However, the ability to predict the US government bonds return seems more feasible to us. Based on new data, we find supportive arguments on the default spread and dividend yield being bond premium predictors. In addition, recession probabilities are significant through both available periods and may remain reliable in future. All remaining factors do not reveal confidence, as they show inconsistent results among different periods or are significant only in one, the most recent period, but only at a 10% level.

Table 15

Linear regression results for the relationship between the 10-year Treasury bonds excess return, the list of the lagged economic and financial factors, and time-series momentum

	US 10Y Treasury bonds monthly excess return		
	1963-2022	1973-2022	2004-2022
Lagged 10-year Treasury bonds excess return	0.0795**	0.2357***	-0.0385
Lagged Shiller CAPE	-0.0623*	-0.0776**	-0.1078
Lagged Core-CPI Index (YoY)	0.0025	0.0007	0.0067
Lagged Core-CPI Index (Monthly Changes)	0.0608	-0.0457	0.6322
Lagged US Consumer Price Index (YoY)	-0.0000	-0.0006	0.0020
Lagged US Consumer Price Index (Monthly Changes)	-0.5452	-0.5274	-0.1511
Lagged Fama and French Default (DEF) Spread	-0.0037**	-0.0064***	-0.0106*
Lagged Industrial Production Index in the US	0.0686	0.2329	0.2453
Leading Economic Indicators (YoY Changes)	0.0002	0.0005*	-0.0004
Lagged Money Growth Rate (M2) in the US	-0.1506	-0.0848	-0.1158
Lagged Global Oil Spot Prices	-0.0038	-0.0058	0.0111
Lagged US Personal Consumption Expenditure: Core Price Index	-0.1580	-0.2506*	-0.1614
Lagged Manufacturing Purchasing Managers Index (PMI)	-0.0006**	-0.0006**	-0.0011
Lagged Producer Price Index by Commodity	-0.0338	-0.0979	-0.1012
Lagged S&P500 Dividend Yield	0.0559**	0.0483*	0.0878*
Lagged Unemployment Rate in the US	0.0003	-0.0000	0.0001
Lagged US 10-year T-bonds and 3-months T-bill Yield Spread	0.0030***	0.0018	0.0048*
Lagged Global Gold Spot Prices	-0.0317**	-0.0181	0.0089
Lagged Percentage of US Stocks with Zero Returns	-0.0001	-0.0042	-0.0012
Lagged US Corporate Net Dividends as % of GDP	-0.0326	-0.0483	-0.0924***
Lagged Household Debt to Personal Income Ratio	-0.0781	-0.0881	-0.1163
Lagged US MBA 30-year Mortgage Rate		0.0887**	0.0558
Lagged Dollar Index		0.0409	-0.0996
Lagged Real Effective Exchange Rate		-0.0996	-0.2713
Lagged US 10-year Treasury Bond Yield		0.0443	-0.0115
Lagged US Recession Probabilities		0.0001**	-0.0003**
Lagged BIS Residential Property Price Index in the US		0.0306	0.0414
Lagged Total US Debt to GDP Ratio		0.0770	0.0328
Lagged Percent of the US Stocks Traded Above 200-day Average			-0.0002
Lagged Expected CPI – real CPI			0.0018
Lagged The FAO Food Price Index			-0.0836
Lagged Global Price of Industrial Materials Index			0.0135
Lagged Global Price of Agr. Raw Material Index			-0.0575
Lagged Global Price of Energy Index			-0.0653*
Lagged Low-graded US Corporate Bonds Yield			0.0068
Lagged US Mortgage Market Index			0.0486
Lagged CBOE Volatility Index (Last Month Value)			-0.0155
Lagged CBOE Volatility Index (Monthly Changes)			0.0004
Lagged Total US Market Capitalization to GDP ratio			-0.0171
Lagged Credit Suisse Fear Barometer			0.0210*
Lagged Recession' Word Screening in Google			-0.0107*
Constant	0.0364***	0.0508***	0.0802*
R_sq	.0945	.1386	.3092
R_sq_adj	.0665	.0946	.1445
N_obs	702	577	214

Note. *p < .05. **p < .01. ***p < .001. t-statistics are not presented for the shortage.

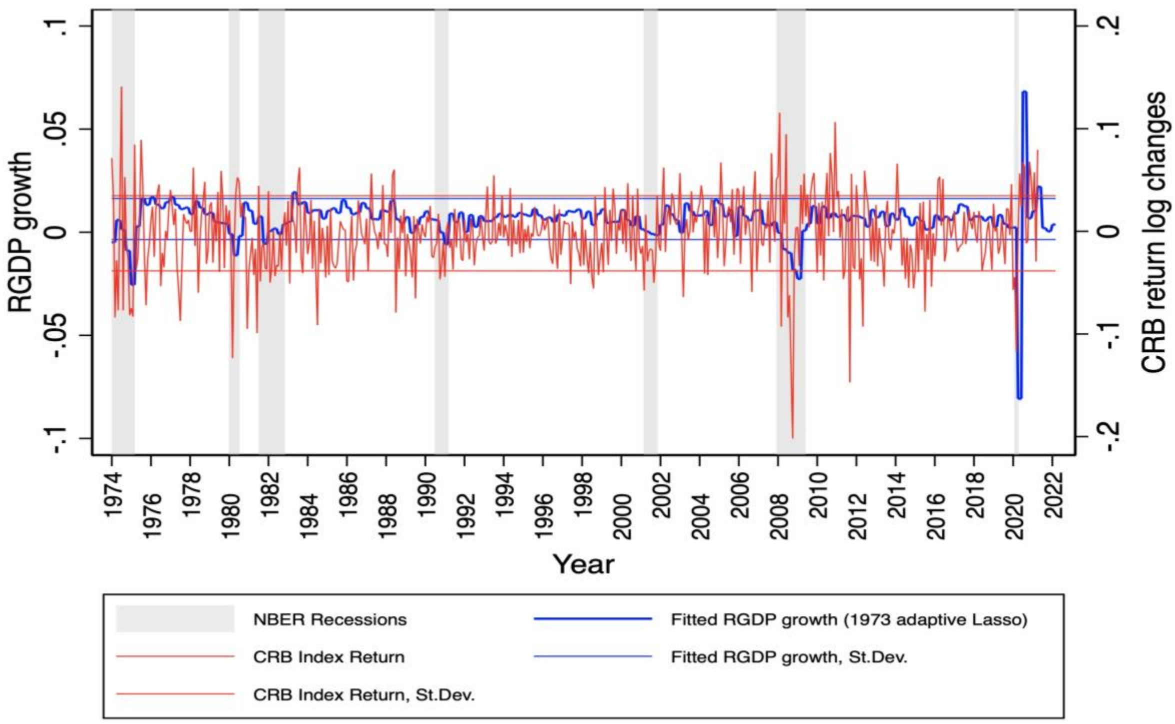
5.2.3 *Thomson Reuters commodity CRB index*

Forecasting with real GDP

For commodities, unlike other assets, we find for the first time a statistically significant effect of economic growth, as measured by real GDP, on future CRB index excess return (Table 16). The same holds for CFNAI, and even the coefficients are identical. This result may be explained by the hypothesis that expectations of positive GDP growth reflect the expectations of investors, households, and businesses in a favourable environment for future development, production, and construction. However, adjusted R_sq measures are still extremely low, and explanatory power seems to disappear after robustness checks in subsamples. The variation of the CRB index and RGDP is presented in Figure 8.

Figure 8

Variation of CRB index excess return and fitted RGDP growth, Jan 1974 – Mar 2022



We find the spill-over effect between financial markets more pronounced when explaining the future performance of the CRB index. The slopes of equity and fixed income lagged returns appear in line with Gorton and Rouwenhorst's (2006) findings. However, only the relation between the CRB excess return and 10-year Treasures is persistent among subsamples. Based on this, we conclude that the performance of commodities, in general, appears to be more connected to the stock and bond markets. However, our results do not seem reliable due to the high dependence on the analysis sample.

Table 16

Linear regression results for the relationship between the CRB index excess return, fitted RGDP, CFNAI and lagged returns of S&P500, fixed income and commodity indexes

	CRB index monthly excess return							
					Robustness checks for in\out samples			
	1973-2022	1973-2022	1973-2022	1973-2022	Odd years	Even years	Random sample 1	Random sample 2
RGDP_hat	0.3000*		0.2818*		0.1694	0.5955**	0.2173	0.4131
	(1.95)		(1.76)		(0.83)	(2.00)	(1.09)	(1.43)
Lagged CFNAI		0.0029**		0.0027*				
		(2.11)		(1.77)				
Lagged SP500_ret			-0.0721*	-0.0709*	-0.0631	-0.0882*	-0.0578	-0.0900
			(-1.86)	(-1.91)	(-1.09)	(-1.74)	(-1.11)	(-1.52)
Lagged US10Y_ret			-0.2849***	-0.2743***	-0.2572*	-0.3095**	-0.3406***	-0.2058
			(-2.95)	(-3.02)	(-1.70)	(-2.53)	(-2.67)	(-1.36)
Lagged DJCBIND_ret			0.4250***	0.4235***	0.5405***	0.2731	0.5452***	0.2571
			(3.26)	(3.39)	(2.78)	(1.56)	(3.11)	(1.28)
Lagged GSCITOT_ret			-0.0069	0.0070	-0.0002	-0.0154	-0.0143	0.0066
			(-0.27)	(0.27)	(-0.01)	(-0.44)	(-0.39)	(0.18)
Constant	-0.0039**	-0.0009	-0.0018	0.0011	-0.0015	-0.0033	-0.0021	-0.0016
	(-2.13)	(-0.64)	(-0.93)	(0.70)	(-0.51)	(-1.16)	(-0.81)	(-0.53)
R_sq	.0067	.0067	.0270	.0261	.0331	.0415	.0425	.0187
R_sq_adj	.0050	.0052	.0183	.0183	.0160	.0240	.0259	.0005
N_obs	568	661	568	626	288	280	293	275

Note. RGDP_hat is a fitted values of the real GDP growth rate with the '1973 adaptive Lasso' model. SP500_ret, US10Y_ret, DJCBIND_ret, GSCITOT_ret are returns of the S&P500 index, 10-year Treasury bonds, Dow Jones corporate bond index, and Goldman Sachs commodity total return index, respectively. *p < .05. **p < .01. ***p < .001. t-statistics in parentheses.

Forecasting with economic factors

Consistently for our research, it is challenging to find significant variables for all subperiods, and the results for the CRB index are not exceptional (Table 17). None of the factors are stable in all three periods or even in two for those variables that are available in two samples. Short-term momentum is also observed only in one period, namely 2004-2022. The explanatory power measured as adjusted R_sq is the highest for the 2004-2022 model (about 20%) compared to 14% for S&P500 and 18% for Treasury regressions for the same period.

We conclude that predicting the premium of the CRB index is not less complex than estimating the future returns of the stock and bond markets. Although some factors are significant in specific periods, none of them offers robust results. We also note that VIX can be investigated in more detail since it is a significant predictor in the most recent sample in the 5% level, and its power may remain down the line, given the idea of commodities financialisation after the increased popularity of index and ETF investing (Tang & Xiong 2012).

Table 17

Linear regression results for the relationship between the CRB index excess return, the list of the lagged economic and financial factors, and time-series momentum

	CRB index monthly excess return		
	1963-2022	1973-2022	2004-2022
Lagged CRB index excess return	-0.0014	0.0110	-0.2242*
Lagged Shiller CAPE	0.0379	0.0398	-0.2038
Lagged Core-CPI Index (YoY)	0.0001	0.0037	0.0147
Lagged Core-CPI Index (Monthly Changes)	0.2286	0.5078	0.4200
Lagged US Consumer Price Index (YoY)	-0.0013*	-0.0013	-0.0116***
Lagged US Consumer Price Index (Monthly Changes)	-0.5415	-0.5078	-2.1470
Lagged Fama and French Default (DEF) Spread	0.0008	-0.0005	-0.0217*
Lagged Industrial Production Index in the US	0.2905	0.2337	1.2352***
Leading Economic Indicators (YoY Changes)	-0.0009**	-0.0012**	0.0015
Lagged Money Growth Rate (M2) in the US	0.4765	0.2296	0.0208
Lagged Global Oil Spot Prices	0.0250	0.0190	-0.0021
Lagged US Personal Consumption Expenditure: Core Price Index	-0.0563	-0.0991	-1.1614***
Lagged Manufacturing Purchasing Managers Index (PMI)	0.0010***	0.0005	-0.0016
Lagged Producer Price Index by Commodity	0.3083	0.2926	0.6200
Lagged S&P500 Dividend Yield	0.0391	0.0550	0.0099
Lagged Unemployment Rate in the US	0.0014	0.0018	0.0032
Lagged US 10-year T-bonds and 3-months T-bill Yield Spread	-0.0000	0.0005	-0.0041
Lagged Global Gold Spot Prices	-0.0026	-0.0183	-0.0080
Lagged Percentage of US Stocks with Zero Returns	0.0037	0.0108*	0.0052
Lagged US Corporate Net Dividends as % of GDP	0.0892**	0.1039**	0.0678
Lagged Household Debt to Personal Income Ratio	0.0419	0.0593	0.0006
Lagged US MBA 30-year Mortgage Rate		-0.0046	0.1860
Lagged Dollar Index		0.0597	0.2035
Lagged Real Effective Exchange Rate		-0.1258	-0.0433
Lagged US 10-year Treasury Bond Yield		-0.0120	0.0436
Lagged US Recession Probabilities		-0.0001	0.0003
Lagged BIS Residential Property Price Index in the US		-0.0077	-0.6830
Lagged Total US Debt to GDP Ratio		0.0615	-0.1078
Lagged Percent of the US Stocks Traded Above 200-day Average			-0.0003
Lagged Expected CPI – real CPI			-0.0028
Lagged Credit Suisse Fear Barometer			0.0072
Lagged The FAO Food Price Index			0.3363*
Lagged Global Price of Industrial Materials Index			0.0259
Lagged Global Price of Agr. Raw Material Index			0.0875
Lagged Global Price of Energy Index			0.1217
Lagged Low-graded US Corporate Bonds Yield			0.0722
Lagged US Mortgage Market Index			-0.1062
Lagged CBOE Volatility Index (Last Month Value)			0.0547**
Lagged CBOE Volatility Index (Monthly Changes)			0.0020**
Lagged Total US Market Capitalization to GDP ratio			-0.0511*
Lagged 'Recession' Word Screening in Google			0.0055
Constant	-0.0592***	-0.0329	0.1302
R_sq	0.0604	0.0721	0.3610
R_sq_adj	0.0310	0.0239	0.2003
N_obs	693	568	205

Note. *p < .05. **p < .01. ***p < .001. t-statistics in parentheses.

6 Results discussion and implications

This paper examines three major topics to answer the research questions. At first, the ability to forecast business cycles based on macro and financial factors and whether it is possible to create a model that outperforms CFNAI in predictive accuracy. Secondly, the relationship between the expectations of the economic movements, measured as real GDP growth, and the risk premiums of the various financial assets, such as equities, government bonds, and commodities. Lastly, we analyse whether the separate variables can help predict the future returns of these financial markets. We draw several conclusions that confirm and reject our hypotheses based on the results obtained. Additionally, some findings support previous literature, and some appear new. We discuss all these findings below in detail, connecting them to each research question for clarity.

First question. "How accurately can the US business cycles be predicted by means of macro and financial variables? Is it possible to improve upon the Chicago FED index?"

As for the first question, we confirm the ability to predict the movements of economic growth one quarter ahead with high accuracy, supporting the results of Chen (1991), Blitz and van Vliet (2009), Ma and Zhang (2016). All three of our methodologies provide in-sample explanatory power measured with R_sq from 40% to 89% in different periods. The adaptive Lasso model, which includes 13 economic and financial factors, performs the best within the out-of-sample test with a 52% R-squared. It also outperforms the Chicago Fed National Activity index in terms of real GDP and recession dates prediction. Our model can correctly classify 93.78% of ex-post NBER announced recession periods, whereas CFNAI classification shows 91.19% accuracy. Another advantage of our model is that it uses only 13 time series, mostly publicly available, while CFNAI is constructed based on 85 series, most of which are unavailable to everyone.

Looking generally, we find the three most influential and significant economic state explanatory factors, and our findings are in line with the literature. Consistently with Chen (1991), industrial production and short-term interest rate forecast changes in the future RGDP growth. Similarly to Ferson and Harvey (1991), we observe the same patterns for personal consumption expenditures. Chen (1991) also shows that the current default premium indicates the economy's current health. Our findings do not contradict this statement, but we do not find any forecasting power in default spread at the same time.

Moreover, we find new indicators that provide statistically significant signals about consequent RGDP growth, namely the M2 measure and the spread between 10-year Treasury bonds and 3-month Treasury bills. The first factor, the money supply, may be influenced by FED, as they can use it to balance unemployment and inflation. In other words, the weekly published M2 information can form expectations about further changes in money supply and inflation trajectory. As both M2 and inflation targets are unlikely to be adjusted within a short time, these signals can remain persistent until the next quarter. The significance of the treasury spread can be explained by the fact that it forms the yield curve of government bonds, which itself and the change in the shape of which reflect investors' expectations regarding the future state of the economy.

Another empirically important conclusion related to the findings of the first question is that our model includes not only macro variables but also factors observed in financial markets directly, e.g., 10Y and 3M Treasuries spread, meaning that financial markets and the economy are interconnected. This does not necessarily mean that one can predict another, as we show later, but supports the idea of the connection between their movements.

Second question. "Can one use the acquired information about the US economic state in the next period to forecast the performance of various financial markets such as stocks, bonds, and commodities?"

Next, we use our economic state prediction model to analyse its ability to forecast stocks, bonds, and commodities returns and test the hypothesis about the relationship between business cycles and financial markets. The results suggest that expectations in the change in RGDP growth cannot provide statistically significant signals about the future performance of the S&P500 index or 10-year US government bonds. Since, to the best of our knowledge, previous papers have not studied similar questions in the same way, we cannot compare the results of this part directly. However, during our analysis, we find evidence that equity market returns can be a statistically significant and consistent predictor of future 10-year Treasury premiums.

We also find that excess returns of a few equally weighted industry portfolios, namely Energy, Telecom, Shops, Healthcare, and 'Other', can be attributed to the expected health of the economy, estimated with our model. It also tends to be true for the portfolio of cyclical sectors. Nevertheless, we express concerns about the reliability of the predictive power for these results due to extremely low estimates of the R_sq measure.

Additionally, we show evidence that the future risk premium of the Tomson Reuters CRB index can be predicted using the expectations about the economic state. Its variation can also be attributed to the 1-month lagged equity and fixed income markets' performance, which is in line with previous findings of Gorton and Rouwenhorst (2006).

To summarise the finding of this part, the traditional definition of the business cycle, estimated with GDP or alternative measures, does not seem directly related to financial markets. The expectations in its movements do not indicate future levels of the S&P500 or Treasury bonds but might be considered for forecasting the commodities returns.

Third question. "Evaluate the performance of these asset classes in terms of variables used, or not necessarily used, for business cycles forecast. Are the results obtained with the new data consistent with the existing studies, and are there any new significant explanatory factors?"

Finally, we test if separate macro and financial factors can help to forecast equity markets, Treasuries, and commodities. Since we cannot discuss the results for each factor separately, we explain the most important of them and new findings. We also encourage the reader to examine the rest of the results presented in Tables 11, 15, and 17 in detail.

Regarding equity markets, as well as Chen et al. (1986), we find that lagged industrial production growth rate and inflation are important determinants for future S&P500 index return. Besides, the percentage of stocks with zero return indicates the future positive market performance in line with Sibley et al. (2016). However, we do not find all these factors persistent over time, as they provide significant signals only in one or two out of four samples, losing the predictive ability. One contradiction is the oil spot prices, which can significantly forecast future S&P500 return in the 1948-2022 sample, while Chen et al. (1986) find that oil prices are not separately rewarded. Similarly, this indicator does not provide robust results over several periods, and we suppose this result is specific to our sample. We also show that some well-known and other relatively new but not widely studied factors, such as PMI or VIX and fear barometer, can explain future stock market levels in several samples. Although, they also do not seem stable for constructing a trading strategy.

As for the fixed income market, results are more encouraging, as we find three factors that provide statistically significant signals in all available periods. In line with Fama and French (1989), dividend yield, commonly used to forecast stock returns, also forecasts bond returns with a positive slope in all three of our periods. Default spread results are also consistent through analysis and with the findings of Fama and French (1989, 1993); Ferson and Harvey

(1991). In addition, we provide evidence of the US recession probabilities (as in Chauvet & Piger, 2008) being a persistent predictor of the 10-year Treasury bonds premium, which, as far as we know, was not previously used as bonds return indicator. Among all factors, we note a few more that provide significant results in specific periods but do not show consistency in other samples. These are Shiller CAPE, PMI, fear barometer, and 'recession' word screening in Google.

With respect to commodity markets, we do not have much literature to compare with. Our results show that both macro and financial factors can provide statistically significant signals about future CRB index levels. Examples of such indicators are personal consumption expenditures, CPI and PMI indexes, US corporate net dividends to GDP ratio, VIX and others. Nevertheless, none of the factors used show consistently significant results throughout our periods, meaning they are hardly reliable indicators.

Based on these results, we make the following conclusion about our third hypothesis. In general, macro and financial variables that can explain future levels of economic health and assets' returns are different. These factors may be the same in some cases, but only given the fundamental reasons these variables carry. For example, industrial production growth for RGDP and commodities or CPI changes for RGDP and Treasury bonds. Besides, in line with Goyal et al. (2021), we conclude that stock market variation is extremely hard to forecast to use this information for trading. Although some factors might be helpful, occasionally or not, under certain conditions, they are not persistent in providing stable, forward-looking signals. We draw a similar conclusion about the commodities market since we do not find a single indicator that would be significant in each analysis period. Treasuries seem more likely to be predicted, supporting Baltussen et al. (2021) findings, as our results bring at least three significant and consistent factors, two of which are already known, and one is new.

To summarise a broad vision of economic variation and its connection with financial markets, we suppose that the traditional concept of business cycles (Keynes, 1937; Schumpeter, 1939) is less and less connected with asset movements nowadays. When this concept was formed, there were not as many financial instruments, and the financial market was structurally different. Since that moment, macro-regulation has changed dramatically; such concepts as QE, Soft landing, and others have appeared. The current objective of economic regulation is related to unemployment constraint, inflation targeting, and controlling the households' earnings. While all these factors can indirectly affect financial markets, regulators do not intend to influence markets directly. These give reason to think about how business cycles should be determined in the current realities, what observable factors they should be associated with, and whether they can be used to forecast markets. At the same time, we note the importance of studying economic factors in assessing the future movements of financial markets, as our work shows several factors that can be useful for predicting them.

Limitations and suggestions for further research

Portfolio diversification requires the allocation of domestic and foreign assets to be weighted by the market capitalisation of each country (e.g., less than 40% for the US and less than 1% for the Netherlands). Because of this and the high interaction between countries' capital flows, one may argue that our findings cannot be used for asset allocation strategies. However, this study provides a theoretical framework only for the US market due to the availability of the data and the longer history of the market itself and leaves the global diversification benefits for further research.

Another concern one could think about is the methodology we use to construct a model for the prediction of business cycles' variation. Since we have chosen the real GDP as the dependent variable, our model works with quarterly data, which leads to a smoothing of the time series used to analyse financial assets, as we observed in comparison with CFNAI. Despite this, our model outperforms the Chicago FED index. Nevertheless, we believe that creating a composite monthly index makes sense for investigating possible improvements in predictive power.

Lastly, other models than Lasso and other macro and financial factors can be used. Since Lasso, as our results show, can be unreliable for determining true factors due to the theory behind it and since we do not pretend that the list of variables we have chosen is complete and do not lack omitted indicators.

7 Conclusion

In this paper, we explore the ability to predict business cycles in the US using various macro and financial market-observable factors and their relationship with financial market movements. In support of previous studies and existing economic index indicators, we create a set of models capable of forecasting the future movements of the economy, measured in terms of real GDP, with reasonable accuracy. One such model based on the Lasso methodology shows an out-of-sample R-squared measure of about 52% and is a statistically significant predictor of ex-post NBER-based recession dates with 93.78% selection accuracy, outperforming the Chicago Fed National Activity Index.

The presence of financial variables in our model suggests the relationship between financial markets and economic cycles. However, this relationship is limited and insufficient to predict the future movements of the stock market and Treasury bonds. We do not find the consistency of this model in explaining the future variation of the S&P500 index and 10-year Treasury bonds' excess returns. Still, it provides significant signals about the next month's risk premium of the Tomson Reuters CRB commodity index. The same evidence is observed for excess returns of an equally weighted portfolio of cyclical industries and four separate industry-based portfolios. The CFNAI appears to produce fewer substantial results for all these tests.

We find numerous supporting results about the ability of individual variables to predict the state of the economy and the performance of various assets. The most powerful indicators of future real GDP growth are industrial production, short-term interest rate (as in Chen, 1991) and personal consumption expenditures (as in Ferson & Harvey, 1991). At the same time, we find new significant factors such as money supply, Treasuries term spread, etc.

As for financial assets, our results also support evidence of some previously known indicators and show the existence of new significant factors within specific samples. Unfortunately, almost all of them do not seem persistent in providing reliable prediction power for stock and commodities markets throughout different periods. Thus, we stay concerned, similarly to Goyal et al. (2021), about the ability to find stable factors to outperform the equity market and conclude the same for commodities. We also, in general, agree with the literature on the ability to predict bond premiums; unlike stocks and commodities, we confirm the predictability of bonds (Baltussen et al., 2021) using the time series of the 10-year Treasury returns. In addition to well-known indicators such as default spread and dividend yield, we find a significant and consistent pattern in the US recession probabilities.

We believe that the results of our work shed light on some of the relationships between business cycles and financial markets and the ability of macro and financial variables to explain variations in economic growth and returns across different asset classes. We confirm some of the past studies with new data, provide new insights, and note the importance of continuing research in this field given the development of financial markets, the factors behind them and economic growth.

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Appendix A

Table A1

The list of the used economic and financial factors, period of availability, frequency, and sources

Abbreviation	Economic Variables	Period	Frequency	Source
CAPE	Shiller CAPE	1925-2022	Monthly	Robert Shiller website
CPI	US Consumer Price Index	1925-2022	Monthly	US Bureau of Labor Statistics
DEF	Fama and French Default (DEF) Spread	1925-2022	Monthly	Personal calculations (based on Global Financial Data)
INDPRO	The Industrial Production Index in the US	1925-2022	Monthly	Federal Reserve Economic Data (FRED)
OIL	Global Oil Spot Prices	1925-2022	Monthly	Global Financial Data
PPI-C	Producer Price Index by Commodity: All Commodities	1925-2022	Monthly	Federal Reserve Economic Data (FRED)
SNPDIVYLD	S&P500 Dividend Yield	1925-2022	Monthly	Global Financial Data
US10Y	US 10-year Treasury Bond Yield	1925-2022	Monthly	CRSP Database
US10Y-3M	US 10-year T-bonds and 3-months T-bill Yield Spread	1925-2022	Monthly	Personal Calculations (based on CRSP data)
XAU	Global Gold Spot Prices	1925-2022	Monthly	Global Financial Data
ZERORET	Percentage of US Stocks with Zero Returns	1926-2022	Monthly	Personal Calculations (based on CRSP data)
US10Y-2Y	US 10-year and 2-year Treasury-bonds Yield Spread	1941-2022	Monthly	Personal Calculations (based on CRSP data)
NETDIV/GDP	US Corporate Net Dividends as % of GDP	1947-2022	Quarterly	Global Financial Data
PMI	Manufacturing Purchasing Managers Index (PMI) in the US	1948-2022	Monthly	NASDAQ Data Center
UR	Unemployment Rate in the US	1948-2022	Monthly	US Bureau of Labor Statistics
r	Nominal US Short-term Interest Rate	1950-2022	Monthly	Federal Reserve Economic Data (FRED)
HHD/PI	Household Debt to Personal Income Ratio	1952-2022	Quarterly	Bloomberg
CCPI	Core-CPI Index	1957-2022	Monthly	US Bureau of Labor Statistics
M2	Money Growth Rate (M2) in the US	1959-2022	Monthly	Federal Reserve Economic Data (FRED)
PCE	US Personal Consumption Expenditure: Core Price Index	1959-2022	Monthly	Bloomberg

Abbreviation	Economic Variables	Period	Frequency	Source
LEI-YoY	Leading Economic Indicators (YoY Changes)	1960-2022	Monthly	Bloomberg
USRP	Smoothed US Recession Probabilities	1967-2022	Monthly	Federal Reserve Economic Data (FRED)
BISHI	BIS Residential Property Price Index in the US	1970-2021	Quarterly	BIS Website
REER	Real Effective Exchange Rate	1970-2022	Monthly	OECD Statistics
30YMR	US MBA 30-year Mortgage Rate	1971-2022	Weekly	Federal Reserve Economic Data (FRED)
FDTR	US Federal Funds Effective Rate	1971-2022	Monthly	Federal Reserve Economic Data (FRED)
TDBT/GDP	Total US Debt to GDP Ratio	1973-2021	Quarterly	Federal Reserve Economic Data (FRED)
DXY	Dollar Index	1973-2022	Monthly	Investing
OILFUT	Oil Futures Prices	1983-2022	Monthly	Global Financial Data
HY	Low-graded US Corporate Bonds Yield	1988-2022	Monthly	NASDAQ Data Center
FPI	The FAO Food Price Index	1990-2022	Monthly	Food and Agriculture Organization (FAO)
GPRMI	Global Price of Agr. Raw Material Index	1990-2022	Monthly	Federal Reserve Economic Data (FRED)
MMI	US Mortgage Market Index	1990-2022	Weekly	Investing
VIX	CBOE Volatility Index	1990-2022	Daily	Chicago Board Options Exchange
E(CPI)	5-year CPI Forecasts	1992-2022	Quarterly	Philadelphia FED. Survey of Professional Forecasters
GPEI	Global Price of Energy Index	1992-2022	Monthly	Federal Reserve Economic Data (FRED)
GPIMI	Global Price of Industrial Materials Index	1992-2022	Monthly	Federal Reserve Economic Data (FRED)
200MA	Percent of the US Stocks Traded Above 200-day Average	1994-2022	Monthly	Personal Calculations (based on CRSP data)
CSFB	Credit Suise Fear Barometr	1999-2022	Monthly	Bloomberg
GT	‘Recession’ Word Screening in Google	2004-2022	Monthly	Google Trends
MC/GDP	Total US Market Capitalization to GDP ratio	2004-2022	Monthly	Bloomberg