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Abstract

This study aims to verify whether there are any macroeconomic variables that have significant power in predicting the dynamics of financial markets. In particular, the paper wants to identify an econometric model that can guide the strategies of operators in building their investment portfolios. The analysis considers the US market during a period of rapid economic change and high volatility of stock prices. The authors evidence that a number of variables have systematically influenced the evolution of the stock market during the period under review. These variables are the macroeconomic indicators that relate to the sentiment of consumers and companies, the term structure, the premium for the risk of default, the rate of growth of the monetary base, the oil price and sea freight rates.

Keywords: macroeconomic news, stock market, regression with distributed delays.
JEL Classification: G10, G11, G17, N20.

Introduction

The relationship between macroeconomic variables and the dynamics of the financial markets has traditionally been considered crucial by investors, who have to observe the economic context prior to making their own portfolio choices. In fact, all of the decisions taken by rational investors contain an implicit and/or explicit evaluation of the present and future economic conditions.

Although neoclassical financial theory has identified within the systematic risk the risk component that is inherent in any type of financial instrument, it has failed to indicate which macroeconomic variables are able to produce a persistent impact on the stock exchange trend. The necessity of investigating this relationship arises more deeply from the need of investors to make projections about their investment strategies in order to increase the payoffs from their stock portfolios.

The aim of this study is therefore to determine, through the analysis of a panel of data related to the US market over a seven-year period, an econometric model that is able to anticipate the trend of the stock market, based on certain macroeconomic variables.

In an attempt to define a conceptual reference frame, the next section provides a review of the current literature on this topic. Then, in section 2 we carry out an illustration of the methodology used to identify the macroeconomic variables that may have a significant impact on stock performance. In section 3, we conduct different statistical analyses and interpret the empirical findings in the light of previous research. Finally, after having verified the robustness of the model, we perform an investment strategy by creating an out-of-sample portfolio based on our model's assumptions.

1. Literature review

The possibility that macroeconomic indicators affect asset prices has been the focus of a considerable number of studies during the last 30 years. Prior research has produced numerous theoretical models, but none appears entirely satisfactory.

A first effort in this direction was made by Ross (1976), who affirmed that the price of financial activities is influenced by a series of risk factors that define the macroeconomic context, for example, the oil price, the interest rate trend, inflation and GDP. Subsequently, Fama and Schwert (1977) found that real stock returns are negatively correlated to the expected and unexpected inflation components. They also indicated that industrial production and the growth of GDP provide a good capacity for forecasting the future yields of certain financial activities. Cutler, Poterba and Summers (1989) affirmed that a sudden and unexpected increase in the industrial production growth rate would trigger a significant upward movement of stock prices. Further, the findings of a study carried out by DeFina (1991) highlighted how an unexpected increase in the inflation rate produces adverse effects on firms' earnings. This relationship is explained by two factors: first, by the nature of commercial contracts concluded by firms[1]; and second, by the presence in the tax legislation of a series of elements that amplify inflation effects, enhance fiscal pressure and reduce firms' profits[2].

[1] Quite often, firms conclude nominal contracts with their customers and suppliers. A typical example of a nominal contract is that between a manufacturing firm and its wholesalers, which fixes *ex ante* the amount payable by the latter for the future purchase of each completed lot.

[2] As an example, depreciation of tangible assets reduces earnings before taxes. However, an unexpected fluctuation in the inflation rate reduces the real depreciation value, increasing the real tax value. FIFO methodology for the evaluation of inventories may lead, during inflation periods, to an increase in profits and, therefore, a higher taxation value.

Other studies have concentrated on the ability of the monetary policy to influence the course of financial markets. Homa and Jaffee (1971) indicated that growth in the monetary base had preceded good performance in terms of quarterly earnings results for the period of 1954-1961. Kaul (1987) found that the negative correlation between the real stock returns and inflation in the post-war period may have been the result of a non-cyclic monetary policy. Hardouvelis (1987) examined the reaction of the financial markets to news items relating to fifteen different macroeconomic variables. The results showed that news items about monetary policies had significantly influenced stock prices during the period of 1979-1982. Asprem (1989) conducted an analysis of the relationship between market indices and macro data in ten European countries. His results highlighted the fact that a negative correlation emerges between the rate of increase in the monetary base and the stock market.

An additional variable that has been considered fundamental in influencing the future trend of the stock market is the oil price. However, the literature has not provided conclusive results on this topic. Kling (1985) asserted that an increase in the oil price is accompanied by a downward movement in the financial markets. Chen, Rol and Ross (1986), on the other hand, showed that variations in the oil price have no significant effects on stock prices. Huang, Masulis and Stoll (1996), however, using daily data from 1979 to 1990, found no significant evidence of a relationship.

A number of empirical studies have indicated that the term structure possesses a predictive capacity regarding the future trend of stock prices. Campbell (1987) noticed that the existing spread between short-term government bonds has significant predictive power for future stock returns. Such evidence was later confirmed by Fama and French (1989), who extended the validity of the model to the spreads among mid-term and long-term government bonds. Chen, Rol and Ross (1986) showed that a variation in the slope of the term structure produces significant effects on share prices. Keim and Stambaugh (1986) underlined a positive correlation between shifts in the term structure and fluctuations in US stock prices.

More recent literature has provided further contributions with regard to the long-term link between macroeconomic data and the financial markets. Rapach (2001) studied the effects of the *shocks* produced by the money supply and by the aggregate demand and supply on stock returns, identifying contradictory results. Drawing on studies previously conducted by Lee (1992), Flannery and Protopapadakis (2002) developed an analysis of the way in which the daily stock quotations respond to macroeconomic news. Guidolin and Ono (2006) undertook an empirical analysis based on monthly data for the period of 1924-2004 and demonstrated that, in the long term, there is a substantially stable relationship between different financial markets (stock, bonds and money market) and the main macroeconomic aggregates.

In the last few years, there have also been contributions aiming to affirm the opposite relationship, suggesting that financial market performance is helpful in forecasting the future trends of certain macroeconomic indicators. In this regard, James, Koreisha and Partch (1985) evidenced that stock returns enable the forecasting of future fluctuations in expected inflation and the nominal interest rate. Further, by evaluating the findings of previous researchers, Lee (1992) explained how stock returns are good indicators of future real economic growth, which is measured by industrial production. However, in contrast to the above arguments, a study carried out by Canova and De Nicolò (2000) has found that US stock returns do not have any significant forecasting power on future trends in inflation and real economic growth.

There has been little attempt to study the ability of macroeconomic variables to affect the price fluctuations of financial instruments. The international literature has also produced only a few studies focusing on the ability of these variables to predict the volatility of financial markets. Ederington and Lee (1993) examined the effect of 22 reports related to US macroeconomic data on fluctuations in futures on treasury bills and exchange rates during a three-year period. The study showed how fluctuations in futures prices (in particular, those on government bonds) reach a high level of volatility in the first fifteen minutes following the dissemination of news related to five macroeconomics variables: the unemployment rate, the consumption price index, the trade balance, GDP and retail sales.

We contribute to the existing literature by using special regression techniques to highlight the significant dependence between the main macroeconomic variables and future trends in the US stock index (S&P500).

2. Sample selection and methodology

The data used in this paper were collected on a monthly basis[1] from January 2002 to December 2009. The high frequency and lengthy time span enables the inclusion in the analysis the impact of

[1] Data source: *Datastream.*

some extraordinary historical events on the capital markets, including the recent crises triggered by subprime loans. Additionally, the use of sufficiently numerous historical series guarantees significant outcomes from the econometric analysis, thus mitigating the distortion effects of potentially exceptional events when only short periods are considered.

Basically, stock prices are conditional on two factors: future expected dividends and the discount rate[1]. We assume in advance that only those macroeconomic variables that influence the aforementioned factors on a regular basis can be revealed as potential anticipatory indicators of the future trend in stock prices.

In order to establish the existence of a potential correlation between the macro indicators and the trend in stock prices, we apply a time-series regression model with distributed delays[2]. This has been widely proposed in the literature for studying the current and future causal dynamic effects of a change in an independent variable (X_t) on the dependent (Y_t) (Pierce, 1975; Stock and Watson, 2003). Practically, Y_t can be estimated as a linear combination of the current and r lagged values[3] of the variable X, namely:

$$Y_t = \alpha + \sum_{i=0}^{r} \beta_i X_{(t-i)} + \mu_t, \quad (1)$$

where α is the constant; β_i are the regression coefficients or dynamic multipliers; μ_t is the error term.

Equation (1) allows the determination of the potential dependence and respective intensity among the variables that are the subject of our study. The estimation of the regression coefficients with distributed delays is conducted through the traditional technique of ordinary least squares (OLS).

Prior to proceeding with an empirical verification, a preliminary statistical analysis is carried out on the time series in order to ascertain whether the hypothesis of stationarity holds for it. For this purpose, the original time series are tested using the unit root Phillips-Perron test[4]. In order to avoid the eventual existence of unit roots in the original time series (that is, their non-stationarity), we calculate the first difference or the first differences of the logarithms[5].

3. Empirical results

In this section we ascertain whether there is any causal effect between the lagged variations of several macroeconomic variables and current changes in the S&P500 index. The analysis was divided into two parts. In the first part, the predictive ability of each individual macroeconomic variable was tested. Subsequently, two prediction models were proposed, into which we inserted only those regressors that had been shown to be most significant in the short term.

3.1. An overview of the macroeconomic variables used as regressors. The analysis mentioned above was performed using several US macroeconomic indicators. Such indicators, which are summarized in Table 1, contain important information on growth and inflation. The analysis of these variables synthesizes the dynamics of the economic cycle. As has been observed previously in the literature, analysts' reports and investors' preferences are widely conditioned and driven by these macroeconomic data. The Federal Reserve itself conducts extremely scrupulous control and analysis of the configuration of these data, so that it can optimize its policy in relation to interest rates.

In particular, six of these variables refer to interest rates and raw material prices: the term spread (difference between the 10-year or 30-year Treasury Bond yield and the 3-month Treasury Bill yield), the Fed Funds rate, the risk premium (difference between the 30-year Treasury Bond yield and the yield of low-creditworthiness corporate bonds), the default premium (difference between the yields of high-rated and low-rated corporate bonds), the oil price and the trend in the Baltic Dry Index. The results of a study conducted by Estrella and Hardouvelis (1991) revealed how the slope of the term structure has often preceded future stages of expansion or recession in the real economy, to the extent that the term spread has been included in the Federal Reserve's Conference Board's Index of Leading Indicators.

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[1] These factors produce a contradictory effect on the stock price. The prospects of a growing economy in the future trigger an increase in the expected profits, but they also cause an increase in the interest rates applied to such future profits. Likewise, the prospect of a future decline in the economy triggers a fall in expected profits and a corresponding reduction of the price discount rate. In order to know which of the two effects prevails, it is essential to observe the state of health of the real economy. During downturns in the economic cycle, the effects of positive economic reports have a stronger influence on expected profits than on interest rates. The opposite occurs during periods of expansion, when the impact on interest rates is generally predominant.

[2] We presume that the macroeconomic variables are exogenous factors with respect to the formation of stock prices in the financial markets.

[3] Specifically, for each variable, delays from zero to 12 months have been inserted in the regression.

[4] Phillips and Perron's test statistics can be viewed as Dickey-Fuller statistics that have been made robust to serial correlation by using the Newey-West (1987) heteroskedasticity and autocorrelation consistent covariance matrix estimator. For brevity, we do not present the full results here.

[5] The use of logarithms can be justified by the fact that many economic series are characterized by exponential growth and/or by the fact that, for many economic series, the standard deviation is approximately proportional to the level. In the latter case, the standard deviation of the logarithm is approximately constant. The variation of the logarithm of a variable calculated in hundreds, or the first log difference Y_t, is equal to:

$$d\log(Y_t) = \log\left(\frac{Y_t}{Y_{t-1}}\right) \times 100.$$

Table 1. Descriptive statistcs of main variables

Symbol	Variable	Source	Units	Mean	SD	P5	Median	P95
Dependent variable								
S&P500	Standard & Poors 500 Index	Standard & Poor's	b.p.	-0.0196	5.1221	-9.07	0.62	7.18
Independent variables								
BDI	Baltic Dry index	Baltic Exchange	b.p.	1.5479	24.2662	-29.40	3.02	35.06
CC	Consumers' confidence	The Conference Board	Number	-0.5918	11.0810	-16.31	-0.50	14.30
CPMI	Chicago PMI	National Association of Purchasing Managers	Number	0.3487	8.2620	-11.58	0.52	11.65
CUR	Capacity utilization rate	Federal Reserve	%	-0.0156	0.6033	-1.09	0.07	0.79
DP	Default premium	USA Corporate bond yield Moody's BAA – USA Corporate bond yield Moody's AAA	%	0.0032	0.1902	-0.34	0.01	0.28
FFR	Fed Funds rate	Federal Reserve	%	-0.0177	0.1977	-0.37	0.00	0.22
HBP	Building permits	Bureau of the Census	($/000)	-0.9407	5.5100	-8.09	-0.90	7.07
IP	Industrial production	Federal Reserve	Number	0.0245	0.7986	-1.62	0.10	1.11
ISM	ISM index	Institute for Supply Management	Number	0.2002	4.1531	-5.54	0.00	7.27
M2	M2 aggregate	The Conference Board	$/Billions	0.4726	0.3747	-0.15	0.45	1.11
MCSI	Michigan consumer sentiment index	University of Michigan	Number	-0.2113	6.0207	-9.98	-1.05	10.96
NOR	Industrial orders	Bureau of the Census	$/Millions	0.2417	2.2014	-4.48	0.75	2.94
OP	Oil price (Brent)	ICE	$/Barrels	1.4530	10.9328	-15.30	2.73	16.16
RP	Risk premium	USA Corporate bond yield Moody's BAA −T-Bond 30Y yield	%	-0.0066	0.2643	-0.55	-0.01	0.33
TS10	Term structure 10Y	T-Bond 10Y (30Y) yield − T-Bill 3M yield	%	0.0026	0.3702	-0.51	-0.47	0.58
TS30	Term structure 30Y	T-Bond 30Y yield − T-Bill 3M yield	%	0.0072	0.3505	-0.50	-0.07	0.64
UCL	Unemployment claims	Department of labor	($/000)	0.0221	6.3630	-9.10	-0.40	10.57

The Fed Funds rate has been included in the analysis as a representative indicator of monetary policy. Even the past risk premium has proved to be a valid indicator in predetermining the evolution of the stock market (Friedman and Kuttner, 1992), as has the default premium (Fama and French, 1989; Gertler and Lown, 2000). An increase in either of these spreads is generally linked to a drop in stock prices. Finally, fluctuations in the oil price and in the price of sea freight rates for raw materials are typically considered revealing indicators about the world economy. In Table 2 (see the Appendix), we present the correlation coefficients between the S&P500 and the main variables under different lags.

The remaining macroeconomic variables used here measure different aspects of the real economy, including the sentiment of consumers and the purchasing managers of manufacturing firms, trends in the real estate and industrial sectors, the total money supply in the economic system, and the conditions of the labor market.

3.2. Macroeconomic variables and stock market performance. This section presents the findings of the empirical analysis based on the results shown in Tables 3-5. The results in Table 3 (see the Appendix) show that, at different periods, certain macroeconomic indicators have anticipated the S&P500 index. Among these, the Baltic Dry index, which summarizes the variation in the sea freight rates of so-called "dry goods" during 2009, has seen an increasing trend that has preceded the market index trend by some months.

In fact, as we can observe from the *t*-tests, the most significant lag is the one-month lag. Additionally, the estimated dynamic multipliers show that an increase in the Baltic Dry index leads to an almost immediate increase in the stock markets. Moreover, the fact that the cumulative multiplier increases up to the eighth month demonstrates that an increase in sea freight rates produces a persistent and significant impact on the level of stock prices. The reported results show that oil quotations and stock market returns develop a mutually positive relationship within the short term. However, in the medium term, a positive variation in crude oil prices is accompanied by a negative variation in the S&P500 index. A delay of five months provides results that are particularly significant (Table 4 see in the Appendix).

Another indicator that anticipates the future movements of the stock index is the consumers' confidence index (*CC*). During the recent financial crisis, this indicator started a downward trend, anticipating the stock markets by a few months, and reaching minimum levels by February 2009, which was exactly one month before the stock market reached its lowest value. The statistical analysis shows positive and significant regression coefficients for the first two lags of the indicator. The analysis of the dynamic multipliers is particularly interesting; it shows that an increase in consumers' confidence leads to an immediate increase in stock prices. Similar findings are obtained for the Michigan Consumer Sentiment Index (*MCSI*). In the past, this indicator has anticipated downward trends in the stock index by about nine months.

With regard to the Chicago Purchasing Managers' Index (*PMI*) trend analysis, we can observe that it has been able to anticipate by one month the fall in the S&P500 index from the peaks reached in October 2007. From the statistical analysis, we can also observe the high significance of the first two lags.

We notice equally relevant results from the trend analysis of the production index of the Institute for Supply Management (*ISM*), which indicates that several particularly low values of this indicator have anticipated the positive performance of the stock markets in the following months. The most significant coefficients are related to lags of three to five months.

Turning to unemployment figures, the analysis highlights that this indicator began an upward trend a few months before the stock index reached its highest quotation in December 2008. The statistical analysis indicates negative regression coefficients that are significant for the first three lags of the variable. Additionally, the analysis of the dynamic multipliers signals that an increase in requests for unemployment benefit is accompanied by an immediate decrease in stock prices. Looking at the cumulative dynamic multipliers, we can observe that deterioration in labor market conditions produces a persistent negative impact on the level of stock prices for a period of about four months.

From the perspective of monetary policy, it is interesting to note that the federal funds rate has reached its maximum/minimum levels one month in advance of the stock index. Likewise, the cumulative dynamic multipliers relevant to the M2 aggregate indicate that the positive impact of a Fed initiative on the stock markets ends five or six months after the injection of new liquidity into the system.

Finally, it is worth mentioning the good forecasting capacity of the spreads between corporate bond yields for different risk ratings, and those between government bonds of different durations. We can see that the spread grew rapidly in the least favourable stages of the economic cycle, reaching its maximum by December 2008, and then falling during 2009 when the prospects for the economy started to improve. These results show that the first five spread lags are highly significant in predicting the future evolution of the S&P500 index. Similar findings are obtained for the risk premium variable.

The spread between government bond yields with different expiry dates, in the course of the last ten years, has proven to be a good predictor of future upward and downward movements in the S&P500 index. The statistical analysis indicates a negative relation between past variations in the spread and the current stock price, demonstrating the capacity of the spread to anticipate future trends in the stock market.

3.3. Short-term prediction models. The proposed prediction models have been constructed in an effort to offer a useful tool for investors who determine their portfolio strategies on the basis of an asset allocation policy mainly oriented towards short-term market opportunities. The following prediction models have been evaluated using lags in those macroeconomic variables revealed to be quite significant over a short period:

$$S\&P500_t = \alpha + \beta BDI_{t-1} + \gamma TS10_{t-1} + \\ + \delta DP_{t-2} + \varepsilon_t, \quad (2)$$

$$S\&P500_t = \alpha + \beta BDI_{t-1} + \theta CC_{t-1} + \vartheta M2_{t-1} + \\ + \gamma TS10_{t-1} + \delta DP_{t-2} + \varepsilon_t. \quad (3)$$

Model (2) only includes variables linked to the interest rate and the prices of raw materials. Model (3), on the other hand, also includes variables that refer to certain real aspects of the economy and, in particular, to the sentiment of consumers and money aggregate variations.

The empirical results are presented in Table 5. Both models present significant regression coefficients at the 1% level, their adj. R^2 are 0.389 and 0.572, respectively, and they satisfy all specification tests[1]. The standard errors are given in parentheses, below are the estimates of the coefficients.

Table 5. Time series regression for models (2) and (3)

Variable	Model (2)	Model (3)
BDI_{t-1}	0.092*** (5.21)	0.105*** (6.87)
CC_{t-1}		0.211*** (5.93)
$M2_{t-1}$		3.514** (3.26)
$TS10_{t-1}$	-4.235*** (-3.66)	-4.262*** (-4.35)
DP_{t-3}	-11.149*** (-4.93)	-10.054*** (-4.96)
Adj. R^2	0.368	0.547
F	18.852***	23.204***

Notes: For every macroeconomic variable, we present regression coefficients, with *t*-test results in parentheses; the regression adj. R^2 and the F-statistic are listed below. ***, ** and * indicate significance levels of 1%, 5% and 10%, respectively. Intercept is not reported.

[1] The purpose of the specification tests is to verify the hypothesis that the residuals are normally distributed, with means equal to zero and constant variance (homoskedasticity), and that they are not self-correlated. If such conditions were not met, it would be necessary to intervene in the time series, to stabilize the variance or avoid autocorrelation. To this end, the Jarque-Bera test is conducted first of all; it is used to ascertain normality. We proceed by testing the homoskedasticity of the residuals by applying the Breusch-Pagan test and the absence of autocorrelation using the Breusch-Godfrey test.

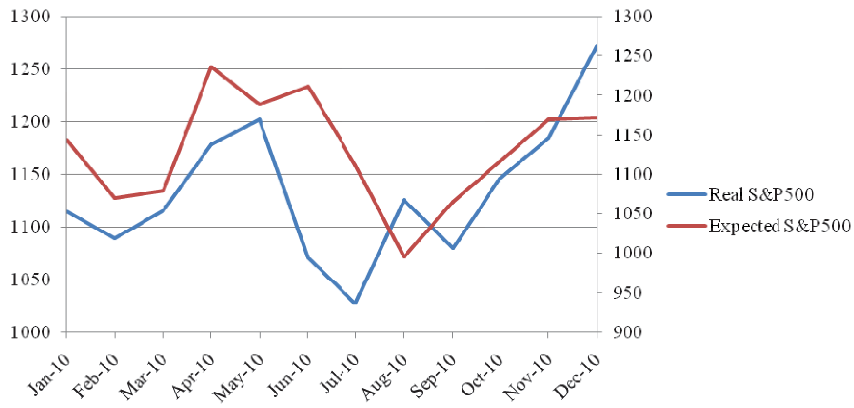
4. Robustness checks

We tested the robustness of our models by checking their performance using out-of-sample data analysis. A number of statistical methods can be used to implement prediction models in "real time". In this case, we applied the out-of-sample pseudo-forecast method.

We chose a date near the end of the sample, estimated the forecast model up to that date, and then used the model to make a forecast on the remaining sample data, that is, the data beyond the date we had chosen. Employed in this way, the model offers a series of pseudo-forecasts and, therefore, a series of pseudo-residuals. The reason why we refer to these as out-of-sample *pseudo*-forecasts is that they are not real out-of-sample forecasts. The latter would occur only in real time, or rather, without knowledge of the future values of a time series. This method allows us to make forecasts in order to evaluate the adequacy of the applied model.

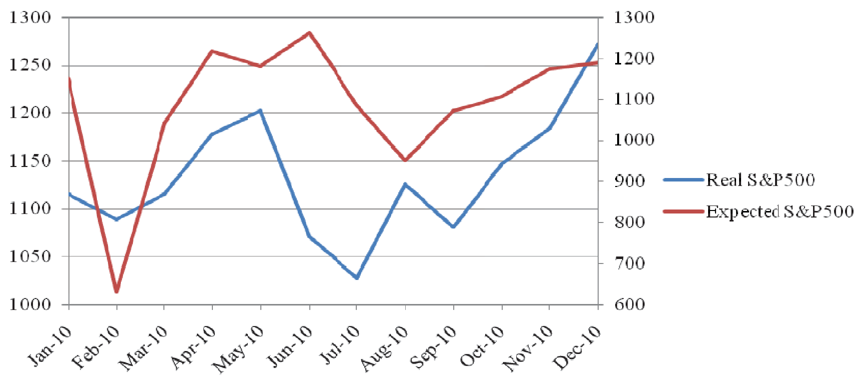
The use of the method illustrated above also enabled us to estimate the *RMSFE*[1]. This last indicator can be used both to measure the uncertainty of aforecast method and to build forecast intervals or, more precisely, intervals that are predicted to have a certain probability of containing the future value of a variable.

The out-of-sample pseudo-forecasts of the 2010 S&P500 index, calculated by applying the forecast models presented in equations (2) and (3), are shown in Figures 1 and 2, along with the real index values. In both cases, the forecasts approximately follow the effective trend of the S&P500 index. However, the former are on average higher than the observed values[2]. In other words, the predictions anticipate the stock index variations. Such forecast distortions suggest that both proposed models are unstable and the instability has led to index variation forecasts that are systematically higher than the observed values. For this reason, before making real-time applications of the above models, it would be useful to attempt to identify the source of the distortion and create a modified version of the models.



Source: Datastream.

Fig. 1. S&P500 and out-of-sample pseudo-forecasts calculated using model (2), year 2010



Source: Datastream.

Fig. 2. S&P500 and out-of-sample pseudo-forecasts calculated using model (3), year 2010

[1] The *root mean squared forecast error* is a measure of the forecast error or, more precisely, of the error typically obtained from using a forecast model. RMSFE is equal to the square root of the mean squared forecast:

$$RMSFE = \sqrt{E\left[(Y_{t+1} - \hat{Y}_{t+1})^2\right]}$$

[2] The mean forecast errors are equal to 3.86 for the model represented in equation (2) and 45.20 b.p. for the model represented in equation (3). The pseudo out-of-sample forecasts' RMSFEs are both higher than those estimated in the sample.

Conclusions

The aim of this paper was to prove empirically the capacity of certain macroeconomic variables, and their past variations, to predict the trend in the S&P500 index. Within the limits of our experiment, the analysis developed herein has shown a satisfactory ability to establish the main macroeconomic indicators with significant predictive power over the dynamics of the stock index.

The implementation of appropriate strategies aimed at benefitting from these relationships could be useful for investors wishing to efficiently reallocate their investment portfolios. In particular, this paper could be useful for those investment managers who adopt a top-down approach in building their portfolios, where macroeconomic variables are relevant in determining the amount of capital to be invested in various sectors of the financial market.

In implementing these models there should be a careful evaluation of their "learning" level. In fact, the performance of the models will gradually improve overtime as they "learn" from the data they process. Additionally, many further robustness checks should be performed by testing the models on different timeseries of historical data and real-time data simulations.

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Appendix

Table 2. Pairwise correlations between S&P500 index and current and lagged values of independent variables

Lags	BDI	CC	CPMI	FFR	HBP	IP	ISM	M2	MCSI	NOR	OP	UCL	DP	RP	TS10	TS30
0	0.248*	0.416*	0.322*	0.284*	0.41*	0.146	0.478*	-0.421	0.296*	0.28*	0.188	-0.241*	-0.385*	-0.478*	0.074	0.009
1	0.394*	0.421*	0.275*	0.307*	0.038	0.058	0.221*	-0.088	0.318*	0.233*	0.071	-0.171	-0.222*	-0.258*	-0.262*	-0.242*
2	0.179	0.084	0.129	0.206*	0.119	0.219*	0.221*	-0.269*	-0.010	0.247*	0.262*	0.071	-0.034	-0.111	0.077	0.109
3	0.196	-0.144	-0.238*	0.124	0.253*	0.258*	0.3*	-0.120	-0.172	0.158	0.106	-0.189	-0.335*	-0.327*	0.027	0.026
4	0.212*	-0.029	0.144	0.223*	0.196	-0.149	-0.036	0.114	0.152	0.998	0.047	-0.081	-0.314*	-0.358*	-0.27*	-0.242*
5	-0.006	0.258*	0.156	0.175	0.020	-0.117	0.125	-0.088	0.068	-0.140	-0.223*	0.051	0.089	-0.010	-0.064	-0.072
6	-0.158	-0.078	-0.146	-0.028	-0.233*	0.215*	-0.027	0.168	0.027	-0.054	-0.095	0.068	0.099	0.160	-0.049	-0.040
7	-0.154	-0.017	-0.205	0.056	0.140	-0.193	-0.085	0.237*	0.000	-0.058	-0.118	-0.101	-0.012	0.041	0.103	0.088
8	-0.028	0.093	0.021	0.139	0.005	-0.095	-0.123	0.010	0.131	-0.293*	-0.196	0.089	-0.027	-0.056	-0.100	-0.109
9	-0.126	0.281*	0.020	0.288*	-0.218*	-0.210	-0.110	-0.018	0.214*	-0.053	-0.199	0.122	0.116	0.126	-0.125	-0.166
10	0.061	-0.135	0.002	0.291*	0.145	0.064	-0.057	0.038	-0.010	0.005	0.087	0.019	0.032	-0.013	-0.051	-0.086
11	-0.080	-0.005	-0.077	0.096	-0.036	-0.141	-0.100	0.066	0.108	-0.126	-0.179	-0.134	-0.075	-0.138	-0.22*	-0.265*
12	-0.064	-0.021	-0.126	0.158	0.105	-0.105	-0.426	-0.093	0.029	-0.252*	-0.100	0.069	-0.046	0.041	-0.004	-0.053

Note: * Indicate significant values at the 5% level.

Table 3. Time-series regression with distributed delays. Dependent variable: S&P500 index

Lags	BDI	CC	CPMI	CUR	FFR	HBP	IP	ISM	M2	MCSI	NOR	OP	UCL	DP	RP	TS10	TS30
0	0.040*	0.170***	0.225***	0.269	7.423*	0.342***	0.226	0.542***	-4.61**	0.205*	0.585*	0.096	-0.29**	-12.04***	-6.14***	-0.637	-1.224
	(1.69)	(4.05)	(4.04)	(0.31)	(2.01)	(4.13)	(0.35)	(4.14)	(-3.17)	(2.47)	2.45	(1.86)	(-3.22)	(-4.65)	(-3.63)	(-0.41)	(-0.78)
1	0.082***	0.157***	0.219***	0.279	5.352	0.042	0.149	0.144	-0.677	0.288***	0.050	-0.009	-0.266*	-8.148**	-4.985*	-3.014	-2.946
	(3.19)	(3.68)	(3.88)	(0.33)	(1.22)	(0.5)	(0.23)	(1.11)	(-0.45)	(3.47)	0.2	(-0.17)	(-2.43)	(-2.8)	(-2.37)	(-1.86)	(-1.85)
2	-0.009	0.127***	0.150***	2.511***	-3.140	0.013	1.813**	0.102	-2.789	0.123	0.587*	0.053	-0.044	9.352**	1.854	1.656	3.421*
	(-0.35)	(2.99)	(2.67)	(2.92)	(-0.76)	(0.15)	(2.77)	(0.77)	(-1.83)	(1.42)	2.42	(1.09)	(-0.47)	(3.19)	(0.86)	(1.03)	(2.2)
3	0.025	0.002	-0.069	3.174***	-3.804	0.240**	2.336***	0.209	0.937	-0.088	0.178	0.064	-0.217*	-12.98***	-2.985	1.276	2.771
	(0.99)	(0.04)	(-1.20)	(3.61)	(-0.93)	(2.71)	(3.47)	(1.55)	(0.6)	(-1.02)	0.71	(1.29)	(-2.33)	(-4.35)	(-1.38)	(0.8)	(1.77)
4	0.051**	-0.015	0.130**	-1.241	4.028	0.253**	-1.068	-0.082	-0.404	0.253**	0.361	0.026	-0.068	-9.881**	-7.74***	-2.421	-0.948
	(2.01)	(-0.35)	(2.27)	(-1.36)	(0.98)	(2.83)	(-1.53)	(-0.60)	(-0.24)	(2.9)	1.42	(0.54)	(-0.72)	(-3.26)	(-3.64)	(-1.58)	(-0.62)
5	-0.001	0.145***	0.126**	-1.207	7.704	-0.077	-0.989	0.269	-2.459	0.106	-0.396	-0.14**	0.060	11.806***	1.316	-1.460	-0.550
	(-0.04)	(3.41)	(2.11)	(-1.27)	(1.96)	(-0.86)	(-1.37)	(1.98)	(-1.35)	(1.23)	-1.55	(-3.02)	(0.62)	(3.79)	(0.58)	(-1.01)	(-0.37)
6	-0.016	-0.022	-0.074	1.436	-10.15*	-0.291**	1.080	0.057	1.189	0.087	-0.095	0.029	0.170	-1.466	5.171*	0.085	0.846
	(-0.66)	(-0.52)	(-1.22)	(1.43)	(-2.59)	(-3.22)	(1.41)	(0.42)	(0.66)	(1)	-0.37	(0.6)	(1.75)	(-0.46)	(2.23)	(0.06)	(0.59)
7	-0.028	0.039	-0.135**	-2.145**	-3.720	0.093	-1.650*	-0.033	4.326*	0.148	-0.253	-0.020	-0.032	-5.394	-1.336	1.225	1.688
	(-1.06)	(0.91)	(-2.17)	(-2.16)	(-0.95)	(1.04)	(-2.16)	(-0.24)	(2.42)	(1.7)	-1.01	(-0.41)	(-0.34)	(-1.77)	(-0.6)	(0.84)	(1.13)
8	0.062**	0.046	-0.029	-1.287	-1.056	0.004	-0.944	-0.027	-1.828	0.155	-0.466	-0.071	0.090	1.043	-7.755**	-1.333	-1.357
	(2.33)	(1.02)	(-0.47)	(-1.34)	(-0.26)	(0.04)	(-1.27)	(-0.2)	(-0.94)	(1.76)	-1.85	(-1.44)	(0.98)	(0.32)	(-2.98)	(-0.87)	(-0.87)
9	-0.048*	0.065	-0.035	-1.281	4.892	-0.211*	-1.007	0.022	-1.821	0.300**	0.133	-0.065	0.097	-1.022	8.496**	-1.334	-2.297
	(-1.72)	(1.29)	(-0.54)	(-1.39)	(1.19)	(-2.33)	(-1.42)	(0.16)	(-0.95)	(3.26)	0.53	(-1.33)	(1.11)	(-0.31)	(3.12)	(-0.84)	(-1.45)
10	0.019	-0.049	-0.035	1.736*	5.899	0.165	1.312	0.095	0.781	0.040	0.209	0.108*	0.000	-6.968*	-4.829	-1.883	-2.820
	(0.64)	(-1)	(-0.54)	(1.85)	(1.44)	(1.8)	(1.81)	(0.68)	(0.43)	(0.45)	0.86	(2.21)	(0)	(-2.2)	(-1.83)	(-1.17)	(-1.77)
11	-0.032	0.056	-0.051	-0.321	-6.192	-0.022	-0.334	0.025	3.049	0.234**	0.136	-0.130*	-0.121	-3.046	-8.875**	-3.74*	-5.33**
	(-1.05)	(1.09)	(-0.84)	(-0.34)	(-1.51)	(-0.25)	(-0.46)	(0.18)	(1.62)	(2.67)	0.56	(-2.46)	(-1.28)	(-0.92)	(-3.16)	(-2.3)	(-3.19)
12	0.010	0.000	-0.039	0.000	3.452	0.012	-0.078	0.089	-2.352	0.068	-0.56*	-0.023	-0.051	-1.393	6.126*	-0.786	-1.745
	(0.36)	(0)	(-0.64)	(0)	(0.99)	(0.14)	(-0.1)	(0.62)	(-1.3)	(0.78)	-2.33	(-0.41)	(-0.56)	(-0.48)	(2.59)	(-0.5)	(-1.04)
Adj. R^2	0.252	0.429	0.353	0.284	0.236	0.379	0.285	0.249	0.240	0.304	0.238	0.195	0.167	0.515	0.555	0.096	0.162
F	3.147	5.792	4.484	3.538	2.971	4.892	3.542	3.114	3.014	3.784	2.998	2.542	2.278	7.772	8.954	1.678	2.237

Notes: For every macroeconomic variable, we present regression coefficients with *t*-test in parentheses; the regression Adj. R^2 and the F-statistic are listed below. ***, ** and * indicate significance levels of 1%, 5% and 10%, respectively.

Table 4. Dynamic effects of past variations in macroeconomic variables on current values of S&P500 index: estimates of dynamic multipliers (MD) and cumulative dynamic multipliers (MC)

Lags	BDI		CC		CPMI		CUR		FFR		HBP		IP		ISM		M2
	MD	MC	MD	MC	MD	MC	MD	MC	MD	MC	MD	MC	MD	MC	MD	MC	MD
0	0.04	0.04	0.17	0.17	0.23	0.23	0.27	0.27	7.42	7.42	0.34	0.34	0.23	0.23	0.54	0.54	-4.62
1	0.08	0.12	0.16	0.33	0.22	0.44	0.28	0.55	5.35	12.77	0.04	0.38	0.15	0.37	0.14	0.69	-0.68
2	-0.01	0.11	0.13	0.45	0.15	0.59	2.51	3.06	-3.14	9.63	0.01	0.40	1.81	2.19	0.10	0.79	-2.79
3	0.02	0.14	0.00	0.46	-0.07	0.53	3.17	6.23	-3.80	5.83	0.24	0.64	2.34	4.52	0.21	1.00	0.94
4	0.05	0.19	-0.02	0.44	0.13	0.66	-1.24	4.99	4.03	9.86	0.25	0.89	-1.07	3.46	-0.08	0.92	-0.40
5	0.00	0.19	0.14	0.59	0.13	0.78	-1.21	3.79	7.70	17.56	-0.08	0.81	-0.99	2.47	0.27	1.18	-2.46
6	-0.02	0.17	-0.02	0.56	-0.07	0.71	1.44	5.22	-10.16	7.41	-0.29	0.52	1.08	3.55	0.06	1.24	1.19
7	-0.03	0.14	0.04	0.60	-0.13	0.57	-2.15	3.08	-3.72	3.69	0.09	0.62	-1.65	1.90	-0.03	1.21	4.33
8	0.06	0.21	0.05	0.65	-0.03	0.54	-1.29	1.79	-1.06	2.63	0.00	0.62	-0.94	0.95	-0.03	1.18	-1.83
9	-0.05	0.16	0.06	0.71	-0.03	0.51	-1.28	0.51	4.89	7.52	-0.21	0.41	-1.01	-0.06	0.02	1.20	-1.82
10	0.02	0.18	-0.05	0.66	-0.03	0.48	1.74	2.24	5.90	13.42	0.17	0.57	1.31	1.26	0.10	1.30	0.78
11	-0.03	0.14	0.06	0.72	-0.05	0.42	-0.32	1.92	-6.19	7.23	-0.02	0.55	-0.33	0.92	0.03	1.32	3.05
12	0.01	0.15	0.00	0.72	-0.04	0.38	0.00	1.92	3.45	10.68	0.01	0.56	-0.08	0.84	0.09	1.41	-2.35

Lags	MCSI		NOR		OP		UCL		DP		RP		TS10		TS30	
	MD	MC	MD	MC	MD	MC	MD	MC	MD	MC	MD	MC	MD	MC	MD	MC
0	0.20	0.20	0.59	0.59	0.10	0.10	-0.30	-0.30	-12.04	-12.04	-6.41	-6.41	-0.64	-0.64	-1.22	-1.22
1	0.29	0.49	0.05	0.64	-0.01	0.09	-0.23	-0.52	-8.15	-20.19	-4.98	-11.39	-3.01	-3.65	-2.95	-4.17
2	0.12	0.62	0.59	1.22	0.05	0.14	-0.04	-0.57	9.35	-10.84	1.85	-9.54	1.66	-2.00	3.42	-0.75
3	-0.09	0.53	0.18	1.40	0.06	0.20	-0.22	-0.79	-12.98	-23.82	-2.98	-12.53	1.28	-0.72	2.77	2.02
4	0.25	0.78	0.36	1.76	0.03	0.23	-0.07	-0.85	-9.88	-33.70	-7.75	-20.27	-2.42	-3.14	-0.95	1.08
5	0.11	0.89	-0.40	1.37	-0.15	0.08	0.06	-0.79	11.81	-21.90	1.32	-18.96	-1.46	-4.60	-0.55	0.53
6	0.09	0.97	-0.09	1.27	0.03	0.11	0.17	-0.62	-1.47	-23.36	5.17	-13.79	0.08	-4.52	0.85	1.37
7	0.15	1.12	-0.25	1.02	-0.02	0.09	-0.03	-0.66	-5.39	-28.75	-1.34	-15.12	1.22	-3.29	1.69	3.06
8	0.15	1.28	-0.47	0.55	-0.07	0.02	0.09	-0.57	1.04	-27.71	-7.76	-22.88	-1.33	-4.63	-1.36	1.70
9	0.30	1.58	0.13	0.69	-0.06	-0.04	0.10	-0.47	-1.02	-28.73	8.50	-14.38	-1.33	-5.96	-2.30	-0.59
10	0.04	1.62	0.21	0.89	0.11	0.06	0.00	-0.47	-6.97	-35.70	-4.83	-19.21	-1.88	-7.84	-2.82	-3.41
11	0.23	1.85	0.14	1.03	-0.13	-0.06	-0.12	-0.59	-3.05	-38.75	-8.88	-28.09	-3.74	-11.59	-5.34	-8.75
12	0.07	1.92	-0.56	0.47	-0.02	-0.09	-0.05	-0.64	-1.39	-40.14	6.13	-21.96	-0.79	-12.37	-1.74	-10.50