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A MULTIFACTOR SECTOR MODEL FOR THE STOCK MARKET. EVIDENCE FROM SPAIN*

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ABSTRACT

A factor model which relates the macroeconomy and the stock market evolution is presented. This relation is shown to be different among activity sectors. These differences are detected and quantified in an empirical application to the Madrid Stock Market. Forecasting experiments show that it is possible to improve the predictive ability of widely used models by means of the sensible use of the information provided by macroeconomic variables.

RESUMEN

Se presenta un modelo de factores para relacionar la evolución de la Bolsa con el entorno macroeconómico. El objetivo es señalar que dicha relación no es uniforme en todos los valores cotizados , sino que varía entre los distintos sectores de actividad. En una aplicación empírica a la Bolsa de Madrid se detectan y cuantifican dichas diferencias. Mediante ejercicios de predicción se constata que es posible incrementar sensiblemente la capacidad predictiva de los modelos habituales utilizando de modo apropiado la información contenida en las variables macroeconómicas.

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1. Introduction

Investors deal every day with possible changes affecting their consuming and investing positions in a dynamic and stochastic framework [Fama (1970)]. As they try to hedge against these changes, equilibrium prices of the assets negotiated in the market react to any state variable that seems to be influential on their opportunity set. Aggregate production, prices, interest rates and other macroeconomic variables turn out to be relevant to explain how expectations (and hence stock prices) evolve, provided that investors check the corresponding figures to make their decisions. More formal expositions of the connection between the stock market quotations and economic variables can be found in Fama (1981), Pearce and Roley (1985) or Balvers, Cosimano and McDonald (1990).

In empirical terms, these theoretical considerations have been strongly supported by a number of papers finding testable relationships between macroeconomic variables and the stock market: Fama (1981), Pearce and Roley (1985), Chen, Roll and Ross (1986), Fama (1990), Schwert (1990), Chen (1991) for U.S. economy, Schmitz (1996) for Canada and Asprem (1989), Wasserfallen (1989) and Peiró (1994) for several european countries. We do not know of any similar study for Spain.

The so-called Multifactor Models and Industry Index Models[1] can help us to understand the afore-mentioned evidence. Multifactor models explain that there are variables other than the stock market ones, driving stock market returns. For instance, inflation, interest rates, the growth pattern or other economic forces can be cited. Industry Index Models relate the return of an asset, belonging to a specific industry, to the market return and a variety of industry-specific factors. In this paper the main ideas of both classes of models are combined into the following questions: Do economic forces affect all assets in the same way or does this relation differ among stocks belonging to different industries? Are there economic variables that are influential in some industries and are irrelevant for others? If those differences do exist, how relevant are they in order to explain and forecast the stock market behavior? A Multifactor Sector Model to answer these questions is formulated and tested with data from the Spanish economy.

Both Multifactor and Industry Index Models are proposed in the financial literature to explain individual asset returns, but applied studies report the influence of macroeconomic variables on the stock market in general. Now, we suggest a way to couple the most salient features of theoretical individual models with aggregated ones, that may be taken as reduced forms of the former. For this purpose, we use an intermediate level of aggregation according to the different existing industries.

Under the efficience hypothesis, investors react to any piece of news, including information about the future. Therefore, stock returns will be dependent not only on actual changes of macroeconomic variables, but also on expected changes. Accordingly, in the same fashion as Asprem (1989), Schwert (1990), Chen (1991) and Peiró (1994) future macroeconomic figures are included as explicative variables of stock returns, taken for granted that expectations are rational and hence unbiased. Another way to add the role of expectations is to construct (nonobservable) expected and unexpected components, in which case some mechanism to make up the expectations must be used, as in Fama (1981), Pearce and Roley (1985), Chen, Roll and Ross (1986), Wasserfallen (1988) and Fama (1990).

In Section 2 a Multifactor Sector Model relating the return of different industries with macroeconomic variables and the general stock market is presented. This model gives way to a reduced form that claims a relationship between economic variables and the general stock market. After the variables description in Section 3, the empirical relevance of the industry

[1]Vid. Elton and Gruber (1988) or Campbell, Lo and McKinlay (1997) for a summary of these models.

separation is tested in Section 4 by estimating several factor models for the Madrid Stock Market General Index and also for the particular industry indexes. Interest rates, inflation, production, consumption, public deficit, exchange rates, the evolution of some international stock markets and the impact of elections are taken into account as explicative variables. Some regularities among sectors are observed, such as the relevant influence of the interest rates, inflation and the market index. But some interesting differences among industries as regards its sensitivity to different macroeconomic variables are also found. In Section 5 we evaluate the predictive ability of the estimated models. CAPM and univariate forecasting are beaten thanks to the information provided by macroeconomic variables. The forecasting of the General Index return is also improved by the aggregation of sectoral predictions. In Section 6 the main consequences of this paper are summarized.

2. A Multifactor Sector Model

In contrast to the CAPM, which claims that the only reason justifying the correlation between different stocks is each of them correlation with the market (Vid. Sharpe (1964) and Lintner (1970)), Multifactor Models and Industry Index Models consider other different sources too. King (1966) showed first some evidence in this regard. The general framework of Multifactor Models is

$$R_j = a_j + b_{j1} I_1 + b_{j2} I_2 + \dots + b_{jL} I_L + c_j$$

where the return R_j of asset j depends on a set of factors $I_1, I_2, \dots, I_L$, among which some macroeconomic variables can be considered. a_j represents how much of the dependent variable is not explained by the explicit regressors on average, and c_j is a random element. b_{jk} parameters measure the response of asset j return with respect to factor k.

Industry Index Models show the j-th asset return depending on the market and a set of industry-specific variables or factors. The general form is

$$R_j = a_j + b_{jm} I_m + b_{j1} I_1 + b_{j2} I_2 + \dots + b_{jL} I_L + c_j$$

where I_m represents the Market General Index and $I_1, I_2, \dots, I_L$ a set of industry specific factors.

According to both Multifactor and Industry Index models, the return of all those assets belonging to a certain industry i may depend on three groups of factors:

- The market return.
- Factors buffeting all the industries.
- Factors affecting a particular industry (or subset of industries).

The return of any portfolio made with assets belonging to the industry i would depend on the same mentioned factors. We can group all the assets in the stock market into k different sectors or industries and then build a representative portfolio for each sector. Portfolio i return can be expressed as

$$R_i = a_i + \alpha_i R_m + b_i F_i + c_i F + \varepsilon_i \qquad (i = 1, \dots, k)$$

being R_m the general stock market return, F_i a vector of the industry i specific factors, F a vector involving the common factors for all industries and ε_i a white noise random variable. F and F_i may contain very heterogenous variables, but we focus on macroeconomic variables and self

lagged returns. Both F and F_i can contain contemporaneous, lagged and/or forwarded variables with respect to R_i, according to how the influence pattern can be described.[2]

In the CAPM, Multifactor and Industry Index Models, there is a definite unidirectional causality from the market to the individual returns, for the reverse effect (from one single asset to the market) can be considered as neglegible. But if we take a relatively small number of sectors including all available assets, we can not judiciously accept that each sector influence on the market is neglegible, given that the latter is a weighted combination of all sectoral indexes[3]. Therefore we have the following model of k equations to represent the k industry returns and one further equation to define the general stock market return as an average of the former.

$$\begin{array}{ll} (1) & R_1 = a_1 + \alpha_1 R_m + b_1 F_1 + c_1 F + \varepsilon_1 \\ (2) & R_2 = a_2 + \alpha_2 R_m + b_2 F_2 + c_2 F + \varepsilon_2 \\ & \dots \\ (k) & R_k = a_k + \alpha_k R_m + b_k F_k + c_k F + \varepsilon_k \\ (k+1) & R_m = \gamma_1 R_1 + \gamma_2 R_2 + \dots + \gamma_k R_k + \omega \end{array} \qquad (A)$$

γ_i being the average weight of industry i in the market, and ω a white noise random variable. Had the share of each industry in the stock market been constant, (k+1)-th equation would be an identity. We need to add ω to make sense of the varying weights of industries[4].

Now, if we substitute equations (1), (2),...,(k) into equation (k+1) and rearrange, we get a reduced form for R_m as a function of all the factors.

$$R_m = a + b_m F + b_{m1} F_1 + b_{m2} F_2 + \dots + b_{mk} F_k + \xi \qquad (B)$$

where

$$a = \frac{\gamma_1 a_1 + \gamma_2 a_2 + \dots + \gamma_k a_k}{1 - \gamma_1 \alpha_1 - \gamma_2 \alpha_2 - \dots - \gamma_k \alpha_k}$$

$$b_m = \frac{\gamma_1 c_1 + \gamma_2 c_2 + \dots + \gamma_k c_k}{1 - \gamma_1 \alpha_1 - \gamma_2 \alpha_2 - \dots - \gamma_k \alpha_k}$$

$$b_{mi} = \frac{\gamma_i b_i}{1 - \gamma_1 \alpha_1 - \gamma_2 \alpha_2 - \dots - \gamma_k \alpha_k} \qquad i = 1, 2, \dots k$$

$$\xi = \frac{\omega + \gamma_1 \varepsilon_1 + \gamma_2 \varepsilon_2 + \dots + \gamma_k \varepsilon_k}{1 - \gamma_1 \alpha_1 - \gamma_2 \alpha_2 - \dots - \gamma_k \alpha_k}$$

[2] The most usual factors used in the literature to sudy returns evolution can be summarized as: i) "Fundamentals" or firm specific features, ii) technical factors, usually associated with past returns, iii) macroeconomic factors, iv) statistical factors, generally derived from main components technique (vid. Connor and Korajzyck (1988)), v) General Stock Market Index. We focus on in ii), iii) and v).

[3] In the Madrid Stock Market, the General Index is built using a wide set of relevant assets. For instance in 1993, if we neglect foreign asset shares, the firms taken into account amounted to 84,4% of the stock market capitalization.

[4] In the sample between February 1986 and December 1996, average weigths in the Madrid Stock Market General Index were: *Banking*, 34.7%; *Electricity*, 17.7%; *Food, Drinks and Tobacco* 6.4%; *Building and Construction*, 8.1%; *Investment*, 4%; *Mining and metal*, 4.1%; *Chemical and Textiles*, 8%; *Communications*, 12.7% and *Others*, 5.7%

Papers relating the evolution of stock market with macroeconomic variables (like Fama and Swhert (1977), Chen, Roll and Ross (1986), Fama (1981), Asprem (1989) and others) are consistent with an econometric specificacion of type (B), which is appropriate for measuring aggregate effects of macroeconomic variables on the stock market. We propose to estimate an (A) type specification, to isolate the particular impact of macro environment on each particular industry. As a matter of fact, when going from specificacion (A) to (B), some of the following situations may happen:

- A variable can have opposite sign effects on two different sectors. Both effects can mutually cancel, resulting in an inexistent or neglegible aggregate effect on the market.

- The sum of slight, but always same sign, effects of a variable on several sectors could result in a significant effect of that variable on the market.

- The effect of a variable on a highly weighted sector, could dominate the sign of the aggregated effect of that variable on the market, even if that variable did not affect, or affected the opposite sign, several less weighted sectors.

The Madrid Stock Market data, classified by sectors, allows to estimate a type (A) model.

3. Description of variables [5]

3.1. Stock returns

Endogenous variables are the Madrid Stock Market monthly returns of the *General Index* (GI henceforth) and the following sectoral indexes: *Banks*; *Electricity; Food, Drinks and Tobacco*; *Building and Construction*; *Investment*; *Mining and Metal*; *Chemicals and Textiles*; *Communications* and *Others*. Monthly data ranging from February 1986 to May 1997 are available[6]. In order to perform out of sample forecasting exercises, we only use the sample up to December 1996. After we checked the distorting influence of the 1987 Crash on the statistical properties of the stock returns, we performed intervention analysis by means of impulse dummy variables in October-November 1987. Appendix 1 shows the parameter values associated with these impulse variables.

Table 1 shows some statistical properties of each sector return in the sample: average annualized return, annualized volatility, sensitivity to GI *-beta* according to CAPM model- and R^2 of the CAPM regression. It turns out that these properties greatly differ among sectors, so the disaggregated study seems to be justified. In Table 1 we observe, for instance, that volatilities range from 24.7% on *Electricity* to 38.3% on *Mining and Metal*, and average returns from a negative return of -0.1% on *Others* to the *Electricity*'s 4.7%. As regards betas, we can see that *Bulding and Construction, Mining and Metal,* and *Chemicals and Textiles* clearly appear as offensive sectors, with a beta value greater than one, while *Electricity* is the only clearly defensive sector and the others vary statistically one to one with GI[7].

Insert Table 1

[5] We take all the data from the Spanish Ministry of Economics and Finance data base "Síntesis mensual de Indicadores Económicos: Series" ("Monthly Synthesis of Economic Indicators: Time Series").

[6] Data correspond to the last day of the month and are corrected of paid dividends and capital increases.

[7] For a more accurate description of the sectoral returns and their temporal evolution in the sample, see the monthly review *Bolsa de Madrid*, published by the Madrid Stock Market.

3.2. Explicative variables

We have chosen a number of macroeconomic variables that seem to be natural factors to explain the stock returns evolution. The standpoint to select these factors is a consequence of the reasons described in Section 1: all variables that might alter the market participants' consumption and investment possibilities set, might be taken into account. We allow for every variable to affect returns contemporaneously, lagged and forwarded, out of phase one, two or three months. Forwarded variables are interpreted as expectations. For econometric purposes, we perform the necessary transformations to make the series stationary, according to statistic and graphic tests. Appendix 2 shows the definition of the variables involved, as well as the transformations carried out.

Interest rates

As reported by many theoretical and empirical works, there is a close relationship between interest rates and stock prices. An increase in interest rates reduces the expected present value of any asset income flows, and so its market price. In addition, interest rates can be regarded as a measure of the opportunity cost of stock market investment, and also as a major determinant of the level of real investment and economic growth prospectives. The following variables regarding interest rates are included: DINTER, for the monthly change in the intervention interest rate, DINT1 and DINT2, for the slope of the term structure in the short and long run respectively, and DIFTA for the difference between Spanish and German interest rates.

Money and Inflation

Both real and expected evolution of money and inflation are clearly relevant for stock prices because of its role in determining the real value of any investment return and providing information about the credibility of the monetary policy. We have considered monthly consumer index inflation (DP), the difference between Spanish and German inflation rates (DIFPA) and the interannual rate of change of the M4 monetary aggregate (DM4).

Production and Consumption

The real and expected growth of production and consumption are essential for evaluating the overall economic performance. Because of the lack of monthly data for the Gross Domestic Product and Total Consumption, we have used the Industrial Production Index (DIPI). and imports (DIMPORT) as proxies.

Imports, Exports and Exchange Rates

One of the most important sectors in Spanish economy is the foreign sector. We included exports (DEXPORTS) and import prices (DPIM) to portray its influence on the stock market. The pts/$ exchange rate (DUS) is also included as determinant for the degree of national products competitiveness and the price of foreing currencies assets as alternative investments.

Public Deficit

State financial liabilities increase total credit demand, affecting interest rates and stock prices. In addition, a relatively high Public Deficit figure may cast some doubts on fiscal policy and then affect expectations on future returns. This is specially true nowadays if Maastrich Agreements are taken into account, for this is one of the criteria posed for convergence. (DEFICIT)

International stock markets

It is apparent that some foreign stock markets remarkably affect the Spanish ones[8]. On the one hand, foreign investment represents another choice as opposed to domestic investment;

[8] Peña (1991) studied the relationships between different European stock markets using a VAR methodology.

on the other hand, the trend of stock markets is constantly buffeted by external forces and so its data contain information that it is not ready at stake in domestic macrovariables. This issue is particularly relevant in a small and open economy as the Spanish one is. New York and Frankfurt stock markets are obviously two basic references for Spanish investors. In this regard, we have used two variables, namely, DDJ (rate of return of Dow Jones Index) and DFRAN (rate of return of Commerzbank Index). Both were treated, taking into account the October 1997 crisis, in exactly the same fashion as Madrid Stock Market was (see Appendix 1).

Elections

As a matter of course, investors decisions are dependent on their more or less accurate expectations about the future prevailing government, and the actual results once it is known. Theoretically, the effect of elections on the stock market can be either positive or negative. To grasp this effect on average, we define the dummy variable VOTO, which is assumed to be one at the time of national, regional, local or European elections and zero at any other month.

4. Estimated Models

Table 2A presents estimated type (A) factor models, as presented in Section 2, for each Madrid Stock Market sector. Table 2B exhibits an estimated model for IG (which is used as a measure of R_m), according to specification (B) in Section 2. Among all the explicative variables described in Section 3, each equation comprise only those affecting the rate of return of a certain industry. For the sake of concreteness, we have roughly considered as influential those variables for which we rejected the individual non-significance hypothesis at a 5% significance level. In this way, we choose clearly influential variables, and leave out those which are doubtly or weakly influential.

As for the econometric procedure, it is worth noting that if we consider F, $F_1, F_2, \ldots, F_k$ as exogenous variables[9], Ordinary Least Squares (OLS) estimation of model (B) will be consistent. However, OLS estimation of equations (1), (2), ..., (k) of the (A) model is inconsistent because of a simultaneity problem. Equation (k+1) makes R_m to be contemporaneously correlated with errors $\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_k$. In order to obtain consistent estimates of (1), (2), ..., (k), we use the Two Stage Least Squares (TSLS) procedure. To estimate equation i (i = 1, 2, ..., k):

- In the first stage, an instrument variable for R_m is made up by means of an OLS regression, with IG as endogenous variable and with the regressors DDJ, DDJ(1), DINT2, DP(3), DP(-1), DIFPA(-3), IG(-2)[10] plus all the exogenous variables included in equation i. So we obtain a variable which is contemporaneously uncorrelated with ε_i and has a high contemporaneous correlation with IG at the same time.

- In the second stage, the i-th equation is estimated through the Instrument Variables procedure.

[9] We take this – rather common- assumption for granted. It is obvious that we can hardly justify that the relationship between stock market and macroeconomic variables goes only one direction. However, as we simply want to model equity returns as functions of macrovariables we will take the stock market as endogenous, relative to other markets.

[10] These variables alone are enough to build an instrument variable whose correlation with IG is 0.64 (which will be indeed improved once new variables are considered). We considered these variables because they exhibit the biggest predictive power on IG (see Section 5).

- Hereroskedasticity-Consistent Standard Errors are computed according to the White (1980) method.

Why the disaggregation by sectors is relevant seems fairly clear by checking Table 2A equations, showing a number of regularities, but also important differences as regards explaining factors affecting each sector return and the sign and timing of the effects. Now, we show a general view that should be read in the light of the arguments above.

The inclusion of macroeconomic variables and international stock markets in the rate of return regressions allows us to improve the CAPM models[11] explicative power in terms of R^2, with gains ranging from 0.06 (in the cases of *Banks*, *Building & Construction* and *Chemicals & Textiles*) to 0.3 (in the case of *Investment*). GI is in all the cases the most robust variable and the best one in terms of explanatory ability. R^2 ranges from 0.20 to 0.50 if GI is excluded.

Interest rates turn out to be relevant in the evolution of either most of the sectors and GI. Between the variables intended to capture the slope of temporal structure, DINT1, built to grasp the long term slope, does not appear significant in any case, in contrast with DINT2, that clearly turns out to be significant for six of the nine sectors, supporting the belief that short term interest rates really reckon the opportunity cost of stock market investing. Spanish Central Bank intervention rate (DINTER) turns out relevant in the *General Index* and in *Banks*, *Electricity*, *Others*, *Food, Drinks & Tobacco*, and *Chemicals & Textiles*, in these two latter sectors with a peculiar positive sign. DIFTA only appears relevant in two sectors, also with a positive sign, but this influence vanishes in GI. As an illustrative difference among sectors, note that *Investment*, known as a conservative sector, seems not to be influenced in any sense by interest rates whereas *Mining and Metal*, the highest risk sector, -according to its volatility and its beta value- is clearly sensitive to the intervention interest rate and the short term slope of the term structure. As for the impact on GI, DINT2 and DINTER seem relevant with negative sign (as expected).

Inflation seems to be relevant in most cases. Its lags turns out to affect negatively and its expectation positively. In fact, both effects are kept in the *General Index*. The only exception is *Others*, in which there are a three lagged value affecting positively and a three periods expectation with a negative sign. Then, the results about the American economy in Fama and Schwert (1977) and other papers finding negative relationships between stock returns and either expected or not expected inflation do not seem relevant as applied to the Madrid Stock Market. Nevertheless, the positive sign associated with forward inflation is in the line of the evidence shown for the UK by Firth(1979) and Asprem(1989). The difference between Spanish and German inflation, appears lagged in the *General Index* with a positive sign, although it is only relevant in *Communications*, with a negative sign, and *Investment*, with an ambiguous sign.

Production rarely shows any influence, but in the event of appearing, when lagged affects negatively the rates of return, and its expectation has a positive impact, as one may expect (see Chen (1991)). As an example, note that both in expansions and regressions, the Building sector works as a leading indicator of the overall production change. Consistently with this evidence, the stock market return of *Building & Construction* appears positively correlated with the two months expectation of Industrial Production. Consumption, measured by DIMPORT, always exhibits a positive effect, namely in the six sectors in which appears. These results are consistent with the role of consumption in the prospective possibilities of profits for firms. With regard to GI, it seems that relevant information is expectations of two and three periods ahead, though for a number of sectors one can point out lagged values of this variable.

[11] OLS estimation of models $R_j-R_f = \alpha_j + \beta_j (R_m-R_f) + \varepsilon_j$ is inconsistent because of simultaneity. We have performed Instrument Variables estimation using DDJ, DDJ(1), DINT2, DP(-1), DIFPA(-3) and GI(-2) as instruments. See footnote 10 for an explanation of this election.

Public Deficit expectation reveals a positive effect one and two months ahead in *Others* and three months ahead in *Chemicals & Textiles*, though these effects vanish in the GI.

DM4 represents a remarkable case, since although it appears in 8 sectors with different lags and future values, these effects counterbalance in such a way that they finally disappears in GI. A similar case, though not so severe, occurs with the pts/$ exchange rate (DUS) and import prices (DPIM): being relevant in four and six sectors respectively they are not included in the GI. Exactly the opposite occurs for exports, for they do not appear in any sector, but the aggregation of individually insignificant effects results in a significant influence of one period expectation in the *General Index*. There is also a noticeable effect of elections (VOTO), except in *Electricity*, either contemporaneous, lagged or forwarded. However, the sign varies from sector to sector.

Apparently, there exists a contradiction in the NY Stock Market being influential contemporaneously, one period lagged and one period ahead over the GI, while it does not appear in most sectors (the only exceptions are *Food, Drinks & Tobacco* and *Construction*). This fact is due to the inclusion of GI as a regressor for sectoral rates of return, portraying most of the effect of Dow Jones on each sector[12]. Frankfurt Stock Market influence is fairly lesser.

In a variety of cases (*Building, Mining & Metal* and the *General Index* itself) we find out the usefulness of including lagged values of the endogenous variable as regressors, in order to capture some of the inertia in the rates of return. It is also worth noting that for *Food, Drinks & Tobacco, Investment*, and *Chemicals & Textiles* order one MA terms were included to capture the residuals autocorrelation.

5. Predictive ability of macroeconomic variables

In this section we try to answer the following question: can the knowledge of macroecomic variables help to forecast the future evolution of the stock market to any degree?. Or alternativelly, do economic variables contain any earning information in order to forecast, which is not already included in the stock market return time series?

In order to evaluate the predictive ability of macroeconomic variables, we compare different models forecasts for 1, 2, 3, 4 and 5 months horizon using two criteria. First, the Root of the Mean Squared Error (RMSE) in percent terms, defined as:

$$RMSE_n = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(\frac{R^P_{T+j,1} - R_{T+j,1}}{R_{T+j,1}}\right)^2}$$

where

$$R_{t,h} = \nabla_h \ln(I_t) = \ln(I_t) - \ln(I_{t-h})$$

being

T	Forecast origin (last figure in the sample, in this case December 1996)
n	Forecast horizon (n=1,2,3,4,5)
$R_{t,h}$	Rate of return (at term h) between t-h and t
$R^P_{t,h}$	Forecast of $R_{t,h}$

[12] In fact, if we estimate the same models GI excluded, the rate of return of Dow Jones systematically becomes one of the most significant variables.

The second criterion is the forecasting error in relative terms with respect to the rate of return at term n, written as:

$$e_n = \left|\frac{R^P_{T+n,n} - R_{T+n,n}}{R_{T+n,n}}\right|$$

$R_{T+n,n}$ is obtained as

$$R_{T+n,n} = \nabla_n \ln(I_{T+n}) = \ln(I_{T+n}) - \ln(I_T) = \sum_{j=1}^{n} \nabla \ln(I_{T+j}) = \sum_{j=1}^{n} R_{T+j,1}$$

and, accordingly,

$$R^P_{T+n,n} = \sum_{j=1}^{n} R^P_{T+j,1}$$

It is apparent that if n=1, then e_n= $RMSE_n$

The first criterion (RMSE) is fairly standard in Econometrics and can be regarded as a more proper measure of the model ability to give account of the actual evolution of the rates of return. The second, however, has a more suitable financial interpretation. Suppose we consider the problem of forecasting up to an horizon n>1, from the origin T. The first criterion takes into account the forecasting errors in T+1, T+2, ... T+n on the monthly rate of return; besides these errors are penalized cuadratically. The second criterion only considers the rate of return at term n, this is to say, the addition of monthly rates of return from T+1 to T+n, in such a way that intermediate forecasting errors, from above and below, compensate. Those people interested in investing at term n, would prefer the most accurate models according to the second criterion, while those concerned about the fitting from an econometric viewpoint, would prefer the best model as judged from the first one.

In Table 3A sectoral rates of return given by the different models are compared. More precisely, for each sector:

- Model 1 is the one selected in Section 4, and displayed in Table 2A, because of its explaining ability[13].
- Model 2 is a version of Model 1 without GI, then only macroeconomic variables and international stock markets are included.
- Model 3 is a reduced version of Model 1, selecting that subset of the explaining variables which showed the best forecasting ability. Depending on the case, GI is either included or not included. The rationale for this model is that, although a high number of variables foster the explaining ability, the need of obtaining forecasts for all of them also increases the forecasting errors.
- CAPM model.
- An autorregresive model of order 3 (AR(3))
- A Random Walk model, consistent with a markov Chain hypothesis, according to which all relevant information prior to period t, is already included in the rate of return of period t-1.

[13] In all the cases, future figures of macroeconomic variables and international stock exchange markets necessary to make predictions are substituted by its own univariate forecast from the origin (December 1996), by means of an AR(3). For GI we used the forecast provided by the model displayed in Table 2B, Pannel B.

For each forecasting horizon, the cell refered to the model that presented better predicting results, according to the corresponding criterion, is shadowed. Now, the following conclusions can be pointed out:

The inclusion of macroeconomic variables and international stock markets largely improve forecasts for sectoral indexes. In all the cases sets of variables able to improve forecasts of CAPM, AR(3) and Random Walk models can be found, providing evidence that causality in the sense of Granger applies to these variables. This fact supports the idea that Multifactor Models and Industry Index Models can be useful at forecasting the evolution of the rates of return. In fact, save very rare cases, some of the models including exogenous variables (models 1, 2, 3) always beats CAPM, AR(3) and Random Walk.

In particular, Model 3, that presents only a small set of the variables at work in Model 1, is the one that exhibits better results at forecasting. In regard to *Electricity, Building & Construction, Investment, Mining & Metal* and *Others*, GI is not included. In this sense it is worthwile noting that Model 2 forecasts, not including GI, are better than CAPM's in two sectors, considering jointly the two criteria. However, in general Model 1 and Model 2 do not differ very much in this respect.

The following cases can be pointed out as rather peculiar. *Electricity* only requires two macroeconomic variables (DINT2(-2) and DPIM(2)) to improve the forecast of all alternative models. *Construction & Building* does not admit any more parsimonious model that turns out to be better at forecasting. *Mining & Metal* is an example of conflict between both criteria: according to RMSE, Model 3 (not including GI) is the best at every horizon while, according to the second criterion, CAPM is clearly better off.

In Table 3B different models intended to predict the rate of return of Madrid Stock Market General Index are compared.

- Models 1, 2 and 3 employ different sets of macroeconomic and international markets variables and autorregresive components. In particular, Model 1 is the one chosen in Section 4, and displayed in Table 2B, because of its explaining ability, and Models 2 and 3 contain subsets of Model 1 regressors, in order to improve its forecasting results.
- AR(3) and Random Walk models are employed as references for comparison.
- The "Composite" model makes a GI forecast starting from sectoral indexes forescasts - which, in turn, are obtained from Model B for each sector (see Table 2A)- and computing a weighted sum using each sector relative weight in GI[14]

It turns out that *General Index* forecasting can also be improved through the additional information offered by international markets and macroeconomic variables.

From Model 1 to Model 3 the forecasting ability is considerably improved according to the first criterion, while the second remains roughly the same. Model 3 excludes real variables DIMPORT, DIPI and EXPORT, keeping the variables related to interest rates, inflation and New York Stock Market. This fact provides evidence to support that stok market investors main considerations are about the rate of return of alternative investments rather than the state of the whole economy .

[14] As long as these weights are not constant, those prevalent in the last months of 1996 are used. In particular, we employed observations ranging from April 1996 to December 1996 of General Index and Sectorial Indexes. Nine linear equations of the form $R_m = \gamma_1 R_1 + ... + \gamma_9 R_9$ are built, where R_m is the General Index rate of return and R_i is the rate of return of sector i. This nine equations system is solved to obtain the weights $\gamma_1,...,\gamma_9$.

The forecast performed by means of the sectoral aggregation are clearly much better than the rest for all horizons according to the second criterion, which is the most relevant from a financial viewpoint. This observation is consistent with the fact that the *General Index*, as an aggregation of individual figures, ignores a good deal of information, that can be partially restated through the consideration of different sectoral stock market indexes.

6. Concluding remarks

The building of a general index to summarize the stock market evolution (as in the case of Madrid Stock Market General Index, Dow Jones Index in New York, Commerzbank Index in Frankfurt, Nikkei in Tokyo, etc) performs a fundamental part of the stock markets study. However, the aggregation of different values to carry out this task implies the loss of disaggregated information which can also be of great utility.

As an intermediate step between the high level of aggregation of a general index and an extremely detailed study of individual stocks, a study of the existing sectors or industries is often considered. In this paper, we show one of the potential applications of this approach.

Both in theoretical and empirical studies have often been pointed out the close correspondence between the macroeconomic environment and the stock market evolution. In this paper, this relationship is substantiated and enriched with a Multifactor Sector Model in order to study the influence of several economic forces on the evolution of different industries stock returns. This approach amounts to a combination of Multifactor and Industry Index Models.

The relevance of a sectoral analysis approach is tested by means of an empirical application with data of the Madrid Stock Market, where the differences between the response of different industries to the movements of macroeconomic variables are pointed out.

Predictive experiments show that macroecomic variables offer relevant information for the purpose of predicting the rates of return, in such a way that they allow us to improve the results of traditional univariate and CAPM models. When forecasting, the division by sectors is also earning, since the aggregation of sectoral predictions allows largely to improve the results of the aggregated forecasts of the General Index of Madrid Stock Market.

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APPENDIX 1: Intervention analysis

Regression $X_t = \left(\varpi_0 - \varpi_1 B\right) \xi_t + \nabla N_t$. Where B is the lag operator and ∇=1-B. ξ_t takes the value 1 in october 1987 and zero in the other months. Standard deviations in brackets.

X_t	ω_0	ω_1
General Index	-0.23 (0.05)	0.15 (0.05)
Banks	-0.25 (0.06)	0.10 (0.06)
Electricity	-0.09 (0.06)	0.08 (0.06)
Food, Drinks and Tobacco	-0.34 (0.06)	0.24 (0.06)
Construction	-0.31 (0.08)	0.31 (0.08)
Investment	-0.06 (0.06)	0.11 (0.06)
Mining and Metal	-0.27 (0.08)	0.32 (0.08)
Chemicals and Textiles	-0.20 (0.07)	0.19 (0.07)
Communications	-0.24 (0.05)	0.15 (0.05)
Others	-0.48 (0.07)	0.23 (0.07)
Dow Jones	-0.17 (0.03)	0.15 (0.03)
Commerzbank	-0.11 (0.05)	0.12 (0.05)

APPENDIX 2: Explicative variables

$$GI = \nabla \log(MSMGI)$$

$$DINTER = \nabla \log(1+r)$$

$$DINT1 = [\log(1+r^{1\ year}) - \log(1+r^{3\ month})]$$

$$DINT2 = [\log(1+r^{3\ month}) - \log(1+r^{1\ day})]$$

$$DIFTA = r_{Spain}^{3\ month} - r_{Germany}^{3\ month}$$

$$DP = \nabla \log(CPI)$$

$$DIFPA = [\nabla \log(CPI)]_{Spain} - [\nabla \log(CPI)]_{Germany}$$

$$DIPI = \nabla \log(IPI).$$

$$DIMPORT = \nabla \log(IMPORT)$$

$$DEFICIT$$

$$DM4 = \nabla \log(M4)$$

$$DUS = \nabla \log(PT/\$)$$

$$DEXPORT = \nabla \log(EXPORT)$$

$$DPIM = \nabla \log(PIM)$$

$$DDJ = \nabla \log(DOWJ)$$

$$DFRAN = \nabla \log(FRAN)$$

$$VOTO$$

$$R_f$$

being,

MSMGI	Madrid Stock Market General Index
r	Bank of Spain: rate on ten days period auctions (average).
r^t	MIBOR at term t.
r_{Spain}^{t}	MIBOR at term t.
$r_{Germany}^{t}$	FIBOR at term t.
CPI	Consumer Price Index (Seasonally Adjusted)
IPI	Industrial Production Index (Seasonally Adjusted)
IMPORT	Total imports (Seasonally Adjusted)
DEFICIT	Government Cash Deficit
M4	Monetary Aggregate.
PT/$	Peseta/US Dollar exchange rate
EXPORT	Total exports (Seasonally Adjusted)
PIM	Import Prices
DOWJ	Dow Jones Index
FRAN	Commerzbank Index
VOTO	Dummy variable taking value 1 in case of General, Autonomical, Local or European elections and 0 otherwise
R_f	Savings banks. Liabilities interest rates at a maturity between 1 and 2 years.

Table 1: Statistics for the Indexes Returns

	General Index	Banks	Electricity	Food, Drinks & Tobacco	Building & Construction
Mean (1)	3.70	3.63	4.69	2.07	3.72
Volatility (2)	23.83	25.58	24.72	29.99	35.82
Beta (3)		0.89 (0.08)	0.70 (0.15)	1.05 (0.10)	1.30 (0.10)
R^2 (3)		0.81	0.47	0.73	0.76
	Investment	**Mining & Metal**	**Chemicals & Textiles**	**Communications**	**Others**
Mean (1)	3.52	2.18	3.20	3.92	-0.11
Volatility (2)	26.60	38.33	31.37	24.80	35.85
Beta (3)	0.87 (0.15)	1.45 (0.17)	1.41 (0.11)	0.88 (0.12)	1.17 (0.15)
R^2 (3)	0.36	0.67	0.75	0.56	0.70

NOTES:

(1) **Mean:** annualized mean.

(2) **Volatility:** annualized standard deviation.

(3) **Beta:** coefficient from the regression: $R_j - R_f = \alpha_j + \beta_j (R_m - R_f) + \varepsilon_j$, being R_j each sector index return, R_f the riskless asset return and R_m the General Index return. Estimation method: Instrument Variables; see footnotes 10 and 11 in the text for more details. Standard deviation in parentheses. R^2 is that of this regression.

* **Sample:** February 1986 - December 1996

Table 2A. Panels A-C
Regressions for the Sectoral Indexes

PANEL A: Banks	Coefficient	t-Statistic	PANEL B: Electricity	Coefficient	t-Statistic	PANEL C: Food, Drinks & T.	Coefficient	t-Statistic
C	0.00	-0.64	C	0.02	1.54	C	0.00	0.42
GI	0.95	11.63	GI	0.79	7.95	GI	1.02	11.01
DM4(3)	1.31	2.25	DM4(3)	-3.10	-3.29	DM4(-1)	-2.48	-2.87
DM4(-2)	-1.79	-2.64	DM4(-1)	-4.06	-2.60	DDJ(-1)	0.32	4.31
DM4(-3)	1.99	2.85	DM4(-2)	4.52	2.68	DIFTA(-2)	2.17	4.51
DFRAN(3)	-0.08	-2.09	DIMPORT(-3)	0.06	1.82	DIMPORT(-1)	0.04	1.53
DFRAN(-2)	-0.09	-2.35	DINT2(-2)	3.58	4.61	DINTER(2)	1.38	1.97
DINT2(-1)	2.32	2.49	DINTER	-2.31	-3.10	DP(3)	3.11	1.91
DINT2(-2)	-2.14	-2.51	DINTER(3)	-2.91	-3.67	DPIM(1)	-0.28	-2.54
DINTER(-2)	-1.03	-1.96	DIPI(-2)	-0.66	-3.05	DUS(2)	-0.27	-2.15
DP(-1)	-2.13	-1.77	DPIM(2)	-0.39	-2.25	VOTO(-2)	-0.02	-1.86
DPIM(-3)	-0.27	-2.90				MA(1)	0.38	4.37
VOTO(-2)	0.01	2.07						
R^2	0.86		R^2	0.71		R^2	0.84	
S.E. of reg	0.02		S.E. of reg	0.04		S.E. of reg	0.03	
Durb. Watson	1.79		Durb. Watson	2.36		Durb. Watson	2.03	

NOTES:

* Sample 1986:02 - 1996:12; 125 observations after adjusting endpoints

* Estimation Method: Two Stages Least Squares. Instruments: DDJ, DDJ(1),DIFPA(-3), DINT2, DP(3), DP(-1) GI(-2)+all each case explicative variables

* t statistic computed fromWhite Heteroskedasticity-Consistent Standard Errors.

Table 2A. Panels D-F
Regressions for the Sectoral Indexes

PANEL D: Build. & Const.	Coefficient	t-Statistic	PANEL E: Investment	Coefficient	t-Statistic	PANEL F: Mining and M.	Coefficient	t-Statistic
C	-0.03	-3.12	C	0.00	-0.30	C	0.02	2.07
GI	1.31	13.66	GI	0.72	5.55	GI	1.20	8.44
B5(-1)	0.09	2.15	DM4(1)	4.04	3.06	DFRAN(1)	0.23	2.82
DM4(2)	2.36	2.36	DM4(-2)	-1.93	-2.13	DIMPORT(-2)	0.23	3.93
DDJ(2)	0.20	2.65	DFRAN(1)	-0.18	-2.21	DINT2(-2)	-4.97	-3.88
DIMPORT	0.07	1.68	DIFPA	3.39	2.46	DINTER	2.73	3.32
DINT2	4.45	3.17	DIFPA(2)	3.35	2.20	DINTER(3)	3.25	2.83
DINT2(-1)	-4.64	-3.36	DIFPA(3)	2.93	2.49	DINTER(-2)	2.48	2.45
DIPI(2)	0.55	2.79	DIFPA(-1)	-5.40	-3.80	DP(-2)	-5.63	-2.77
VOTO(2)	0.03	2.29	DIFPA(-3)	7.43	4.19	VOTO(3)	0.06	2.01
			DINT2(2)	-1.93	-2.23	AR(1)	0.12	2.24
			DP(-3)	-8.38	-3.66	AR(2)	-0.07	-1.04
			DPIM(2)	0.39	1.94	AR(3)	-0.09	-1.92
			DPIM(-3)	0.48	2.87			
			VOTO(2)	0.03	2.31			
			MA(1)	-0.29	-2.56			
R^2	0.82		R^2	0.66		R^2	0.79	
S.E. of reg	0.04		S.E. of reg	0.05		S.E. of reg	0.05	
Durb. Watson	1.83		Durb. Watson	2.05		Durb. Watson	2.01	

NOTES:

* Sample 1986:02 - 1996:12; 125 observations after adjusting endpoints
* Estimation Method: Two Stages Least Squares. Instruments: DDJ, DDJ(1),DIFPA(-3), DINT2, DP(3), DP(-1) GI(-2)+all each case explicative variables
* t statistic computed fromWhite Heteroskedasticity-Consistent Standard Errors.

Table 2A. Panels G-I
Regressions for the Sectoral Indexes

PANEL G: Chemicals & Tex.	Coefficient	t-Statistic	PANEL H: Communications	Coefficient	t-Statistic	PANEL I: Others	Coefficient	t-Statistic
C	0.01	0.43	C	0.00	-0.27	C	0.01	0.38
GI	1.43	12.75	GI	0.91	7.58	GI	1.27	16.58
DM4(1)	-3.51	-2.93	DM4(3)	-1.90	-1.95	DM4(1)	4.68	3.60
DM4(2)	4.27	3.55	DIFPA(1)	-4.91	-2.88	DM4(2)	-2.70	-2.93
DEFICIT(3)	0.00	2.25	DIMPORTF(2)	0.08	2.06	DM4(-1)	-5.75	-5.69
DFRAN(-2)	0.21	3.51	DP(1)	7.53	3.48	DEFICIT(1)	0.00	1.96
DP(-2)	-3.96	-2.51	DPIM(-3)	0.47	3.66	DEFICIT(2)	0.00	2.37
DUS(-1)	0.29	2.73	DUS	0.31	1.95	DIFTA(1)	0.89	1.98
DUS(-2)	-0.37	-2.58	DUS(-1)	-0.29	-2.69	DIMPORT	0.19	3.18
VOTO(-2)	0.03	2.23	VOTO(3)	-0.03	-2.38	DIMPORT(-1)	0.20	2.82
MA(1)	0.18	1.71				DIMPORT(-2)	0.22	3.41
						DINT2(3)	4.30	5.04
						DINTER-2)	-1.72	-4.21
						DIPI(2)	0.38	1.97
						DIPI(-3)	-0.38	-2.17
						DP(3)	-6.23	-3.85
						DP(-3)	5.86	3.21
						DPIM(-2)	0.38	2.35
						VOTO(2)	0.03	1.96
R^2	0.82		R^2	0.69		R^2	0.88	
S.E. of reg	0.04		S.E. of reg	0.04		S.E. of reg	0.03	
Durb. Watson	2.00		Durb. Watson	2.04		Durb. Watson	2.33	

NOTES:

* Sample 1986:02 - 1996:12; 125 observations after adjusting endpoints
* Estimation Method: Two Stages Least Squares. Instruments: DDJ, DDJ(1),DIFPA(-3), DINT2, DP(3), DP(-1) GI(-2)+all each case explicative variables
* t statistic computed fromWhite Heteroskedasticity-Consistent Standard Errors.

Table 2B
Regressions for the General Index

PANEL A: Best fit

	Coefficient	t-Statistic
C	-0.02	-1.64
GI(-2)	-0.14	-2.38
DDJ	0.74	5.58
DDJ(1)	0.25	2.96
DDJ(-1)	0.42	5.12
DEXPORT(1)	0.13	2.69
DFRAN	0.17	1.85
DIFPA(-1)	3.64	3.13
DIFPA(-3)	2.70	2.93
DIMPORT(2)	0.16	3.06
DIMPORT(3)	0.09	2.15
DINT2	-2.60	-2.82
DINTER(1)	-3.26	-5.02
DIPI	-0.31	-1.99
DP(3)	4.12	3.11
DP(-1)	-5.20	-2.85
VOTO	-0.02	-3.44
R^2	0.68	
S.E. of reg	0.04	
Durbin-Watson	2.23	

PANEL B: Best forecast

	Coefficient	t-Statistic
C	0	-0.32
GI(-2)	-0.18	-2.19
DDJ	0.79	6.13
DDJ(1)	0.32	3.20
DIFPA(-3)	2.59	1.93
DINT2	-4.09	-4.11
DP(3)	3.85	1.91
DP(-1)	-3.93	-2.18
R^2	0.44	
S.E. of reg	0.05	
Durbin-Watson	2.22	

NOTES:
* Sample 1986:02 - 1996:12; 125 observations after adjusting endpoints
* t statistic computed fromWhite Heteroskedasticity-Consistent Standard Errors.
* Estimation Method: Ordinary Least Squares.

Tabla 3A. Forecasting Comparison. Panels A-C

Panel A: Banks

RMSE

	Model 1	Model 2	Model 3	CAPM	AR(3)	Ran. Walk
n=1	0.7737	1.0477	0.5923	0.5774	0.8767	0.8792
n=2	0.6417	0.7778	0.4705	1.0509	1.0128	0.6330
n=3	0.9197	0.6407	0.6933	0.9021	1.0839	0.5658
n=4	0.8159	0.7277	0.6329	0.8154	1.0522	0.6718
n=5	0.7309	0.7647	0.5705	0.7387	1.0219	0.7125

e_n

	Model 1	Model 2	Model 3	CAPM	AR(3)	Ran. Walk
n=1	0.7737	1.0477	0.5923	0.5774	0.8767	0.8792
n=2	0.6154	0.9574	0.5556	0.6778	0.9091	0.7891
n=3	0.4805	0.9006	0.4466	0.5965	0.9305	0.7058
n=4	0.4109	0.9230	0.4211	0.5255	0.9416	0.8228
n=5	0.3956	0.9170	0.3592	0.4637	0.9295	0.8306

Model 1: see table 3B, panel A; Model 2: Model 1 without GI; Model 3: GI, DINT2(-1), DINT2(-2), DP(-1), DPIM(-3)

Panel B: Electricity

RMSE

	Model 1	Model 2	Model 3	CAPM	AR(3)	Ran. Walk
n=1	2.8574	1.1033	1.3322	2.7225	2.1887	1.6371
n=2	2.1847	1.2026	1.2432	2.0452	1.7784	1.4572
n=3	1.7838	1.0697	1.0282	1.6715	1.5044	1.1932
n=4	1.5517	1.0032	0.9917	1.4476	1.3687	1.1076
n=5	1.3965	0.9672	0.9583	1.2961	1.2691	1.0398

e_n

	Model 1	Model 2	Model 3	CAPM	AR(3)	Ran. Walk
n=1	2.8574	1.1033	1.3322	2.7225	2.1887	1.6371
n=2	1.6513	1.2402	1.1996	1.4710	1.5079	1.3608
n=3	1.9590	1.3337	1.3691	1.7663	1.6609	1.6413
n=4	41.1385	9.4492	8.1253	31.8831	14.0602	14.5071
n=5	3.2156	0.0854	0.1827	2.3651	0.2940	0.3637

Model 1: see table 3B, panel B; Model 2: Model 1 without GI; Model 3: DINT2(-2), DPIM(2).

Panel C: Food, Drinks and Tobacco

RMSE

	Model 1	Model 2	Model 3	CAPM	AR(3)	Ran. Walk
n=1	0.6819	0.8806	0.5786	0.6539	0.6502	0.9586
n=2	0.8878	0.8116	0.7930	0.9704	0.7232	0.9105
n=3	0.8562	0.8872	0.7866	0.9222	0.8432	0.9136
n=4	0.9315	0.9004	0.8248	0.9696	0.8832	0.9028
n=5	2.1215	0.8521	1.8697	2.0431	0.8556	0.8490

e_n

	Model 1	Model 2	Model 3	CAPM	AR(3)	Ran. Walk
n=1	0.6819	0.8806	0.5786	0.6539	0.6502	0.9586
n=2	0.7666	0.8477	0.6856	0.7797	0.6819	0.9361
n=3	0.7731	0.8974	0.6964	0.7904	0.7847	0.9315
n=4	0.4899	0.9036	0.4542	0.5089	0.8158	0.9222
n=5	0.2721	0.8910	0.2613	0.3003	0.8122	0.9072

Model 1: see table 3B, panel C; Model 2: Model 1 without GI; Model 3: GI, DAPL(-1), DIMPORT(-1), DP(3), DPIM(1), MA(1)

Tabla 3A. Forecasting Comparison. Panels D-F

Panel D: Building and Construction

RMSE

	Model 1	Model 2	Model 3	CAPM	AR(3)	Ran. Walk
n=1	0.3308	0.7894	0.7830	0.4687	0.7825	0.8941
n=2	0.8014	0.6408	0.7263	1.0269	0.8410	0.6847
n=3	2.3515	1.1887	0.8719	2.4092	1.2393	1.7570
n=4	2.0895	1.1289	0.9049	2.1311	1.1619	1.5735
n=5	1.8731	1.0984	0.9257	1.9128	1.1237	1.4654

e_n

	Model 1	Model 2	Model 3	CAPM	AR(3)	Ran. Walk
n=1	0.3308	0.7894	0.7830	0.4687	0.7825	0.8941
n=2	0.4394	0.7398	0.7659	0.5993	0.7988	0.8188
n=3	0.2641	0.6838	0.7487	0.4321	0.7489	0.7145
n=4	0.1250	0.7626	0.8294	0.0103	0.7948	0.7428
n=5	0.0471	0.8491	0.9036	0.1580	0.8629	0.8147

Model 1: see table 3B, *panel* D; Model 2: Model 1 without GI; Model 3: DDJ(2), DIPI(2), VOTO(2) + one lag of the sectoral index

Panel E: Investment

RMSE

	Model 1	Model 2	Model 3	CAPM	AR(3)	Ran. Walk
n=1	4.5736	2.5994	1.2038	3.3128	2.0098	1.6590
n=2	3.2697	1.8902	1.0781	2.4618	1.5535	1.3149
n=3	2.8234	1.5505	0.9839	2.0112	1.2841	1.0740
n=4	2.4479	1.4147	0.9810	1.7441	1.2030	1.0281
n=5	2.1896	1.3149	0.9675	1.5603	1.1426	0.9855

e_n

	Model 1	Model 2	Model 3	CAPM	AR(3)	Ran. Walk
n=1	4.5736	2.5994	1.2038	3.3128	2.0098	1.6590
n=2	0.5660	0.0099	0.8496	0.3520	0.5278	0.5775
n=3	0.7377	0.0513	0.8348	0.2733	0.4974	0.4724
n=4	0.1679	0.5016	0.9155	0.2193	0.7440	0.7093
n=5	0.1365	0.5789	0.9144	0.1454	0.7739	0.7310

Model 1: see table 3B, panel E; Model 2: Model 1 without GI; Model 3: DIFPA, DIFPA(2), DIFPA(3), DIFPA(-1), DIFPA(-3), DPIM(2), DPIM(-3), MA(1).

Panel F: Mining and Metal

RMSE

	Model 1	Model 2	Model 3	CAPM	AR(3)	Ran. Walk
n=1	5.3884	2.4268	0.0134	5.407	3.6723	0.2922
n=2	3.8946	1.9348	0.5763	3.906	2.7067	0.6840
n=3	3.2078	2.3607	0.4869	3.192	2.5658	0.6255
n=4	2.7802	2.1437	0.6205	2.788	2.2874	0.7047
n=5	2.4888	1.9715	0.6876	2.494	2.0911	0.7567

e_n

	Model 1	Model 2	Model 3	CAPM	AR(3)	Ran. Walk
n=1	5.3884	2.4268	0.0134	5.4071	3.6723	0.2922
n=2	0.4937	0.8980	0.7354	0.4801	0.6086	0.8597
n=3	0.5222	1.1559	0.6207	0.3924	0.8074	0.8148
n=4	0.2358	1.2075	0.7324	0.0353	0.9144	0.8483
n=5	0.2319	1.1397	0.7978	0.0318	0.9342	0.8812

Model 1: see table 3B, panel F; Model 2: Model 1 without GI; Model 3: DFRAN(1), DIMPORT(-2), DINT2(-2), DP(-2).

Tabla 3A. Forecasting Comparison. Panels G-I

Panel G: Chemical and Textiles

RMSE

	Model 1	Model 2	Model 3	CAPM	AR(3)	Ran. Walk
n=1	0.2722	0.9826	0.1917	0.4471	1.0421	0.9124
n=2	0.5381	1.6880	0.2396	0.4795	0.8004	1.3269
n=3	0.5337	1.4878	0.4705	0.5472	0.8576	1.1835
n=4	0.7881	1.3988	0.6709	0.6690	0.8598	1.1069
n=5	12.2883	1.4661	10.9494	10.1867	0.8956	1.2146

e_n

	Model 1	Model 2	Model 3	CAPM	AR(3)	Ran. Walk
n=1	0.2722	0.9826	0.1917	0.4471	1.0421	0.9124
n=2	0.2026	0.7932	0.1778	0.4371	1.1374	0.7969
n=3	0.3208	0.8584	0.3847	0.5197	1.0729	0.8072
n=4	0.1290	0.9232	0.0238	0.1074	1.0147	0.8153
n=5	0.6102	0.9370	0.4542	0.2952	0.9787	0.7732

Model 1: see table 3B, panel G; Model 2: Model 1 without GI; Model 3: DM4(1), DM4(2), DEFICIT(3), DFRAN(-2), DUS(-1), DUS(-2).

Panel H: Communications

RMSE

	Model 1	Model 2	Model 3	CAPM	AR(3)	Ran. Walk
n=1	0.3113	0.6900	0.2983	0.4022	0.9329	0.8179
n=2	2.3046	15.9789	0.3528	6.0460	6.6374	16.9280
n=3	1.8817	13.0480	0.2886	4.9463	5.4479	13.8255
n=4	1.6298	11.3081	0.2536	4.2845	4.7393	11.9810
n=5	1.4656	10.1219	0.2771	3.8370	4.2578	10.7234

e_n

	Model 1	Model 2	Model 3	CAPM	AR(3)	Ran. Walk
n=1	0.3113	0.6900	0.2983	0.4022	0.9329	0.8179
n=2	0.3325	0.5212	0.2932	0.4612	0.9939	0.6384
n=3	0.2289	0.4611	0.1981	0.4837	0.9851	0.6171
n=4	0.1436	0.6553	0.1436	0.3333	0.9421	0.7370
n=5	0.2124	0.7346	0.2190	0.3683	0.9256	0.7880

Model 1; see table 3B, panel H; Model 2: Model 1 without GI; Model 3: DM4(3), DIMPORT(2), DP(1), DPIM(-3), DUS, DUS(-1), VOTO(3).

Panel I: Others

RMSE

	Model 1	Model 2	Model 3	CAPM	AR(3)	Ran. Walk
n=1	2.3461	0.3533	0.4824	3.3542	1.5285	0.9821
n=2	1.9181	0.8497	0.6552	2.5453	1.3489	0.9943
n=3	1.6342	1.5618	0.6610	2.1029	1.3827	1.0035
n=4	1.6644	1.5996	0.8028	2.0611	1.3225	1.0053
n=5	1.4975	1.5109	0.8422	1.8522	1.2688	1.0048

e_n

	Model 1	Model 2	Model 3	CAPM	AR(3)	Ran. Walk
n=1	2.3461	0.3533	0.4824	3.3542	1.5285	0.9821
n=2	0.8119	1.9874	0.9634	0.1621	0.9253	1.0200
n=3	0.8108	2.1259	0.8710	0.2874	1.0912	1.0205
n=4	0.1831	1.9638	0.9698	0.5728	1.1035	1.0167
n=5	0.1386	1.4472	0.9783	0.0001	1.0579	1.0086

Model 1: see table 3B, panel I; Model 2: Model 1 without GI; Model 3: DM4(1), DM4(2), DM4(-1), DIMPORT, DIMPORT(-1), DIMPORT(-2),DINT2(3),DINTER(-2),DIPI(2,-3),DPIM(2,-2).

Tabla 3B. Forecasting Comparison

General Index

RMSE

	Model 1	Model 2	Model 3	AR(3)	Ran. Walk	Composite
n=1	0.9530	0.9781	0.7158	0.5774	0.7666	0.3908
n=2	10.5709	3.5064	0.5858	1.0509	9.2921	5.0484
n=3	8.6312	2.8635	0.5287	0.9021	7.5899	4.1248
n=4	7.4852	2.5100	0.6112	0.8154	6.5874	3.5781
n=5	6.7030	2.2706	0.6550	0.7387	5.9037	3.2052

e_n

	Model 1	Model 2	Model 3	AR(3)	Ran. Walk	Composite
n=1	0.9530	0.9781	0.7158	0.5774	0.7666	0.3908
n=2	0.6788	0.9018	0.7217	0.6778	0.5241	0.2585
n=3	0.5158	0.6809	0.6314	0.5965	0.4806	0.2598
n=4	0.6697	0.7348	0.7329	0.5255	0.7022	0.3470
n=5	0.6904	0.7428	0.7558	0.4637	0.7430	0.3615

Model 1: see Table 3B, panel A; Model 2: DDJ, DDJ(1), DDJ(-1), DINT2, DP(3), DP(-1), DIFPA(-3), GI(-1); Model 3: see Table 3B, panel B.