Economic Decision-Making Under Uncertainty: Towards Efficient Use of Market Data*

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Abstract

Forecasting faces two main obstacles: the data generation process evolves over time, and identifying the most effective model beforehand is challenging due to varying information availability. This research tackles these issues in the context of GDP forecasting. We've introduced an adaptive decision-making framework that evolves over time, utilizing a divide-and-conquer approach across a broad array of possibilities to make informed decisions. This framework is designed to make the most out of the available information, allowing us to explore if financial market expectations accurately reflect changes in economic agents' behaviors promptly. Our aim is to determine if efficient information usage enables us to predict traditional business cycle shocks. Findings indicate that our straightforward yet robust decision-making framework, based on high frequency financial data, matches or exceeds the performance of time series models and others well known machine learning benchmarks, indicating its effectiveness in information utilization. Moreover, the decision-making framework's effectiveness is enhanced when it includes data on financial agents' expectations, outperforming the control set without such data. This suggests that financial agents' expectations are a reliable indicator of immediate shifts in economic behaviors, offering a means to foresee traditional economic model shocks.

Keywords: Adaptive Decision-Making, Financial Market Expectations, Economic Forecasting, Business Cycle

JEL Classification: C5, E3, G17

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1 Introduction

The main challenges in forecasting are that the actual data generation process changes over time and we do not know ex-ante which model is best using the available information. This paper addresses these challenges in forecasting the Gross Domestic Product (GDP) for European Union countries. To this end, we have developed a decision-making process that is adaptive, changes over time, and uses a divide-and-conquer strategy in a large space of possibilities, reflecting relevant information, to make a decision. By ensuring that the performance of the decision process is efficient in using the available information, we use this to infer if financial market expectations can, in time, price changes in the behavior of economic agents ([Deschamps et al., 2020], [Leduc et al., 2023], [Glas and Heinisch, 2023]). Thus, we intend to test whether, with efficient use of available information, we can anticipate shocks in traditional business cycle models.

In traditional macroeconomic models, specifically general equilibrium models ([Smets and Wouters, 2007]), most business cycles are explained by shocks ([Baqaee and Farhi, 2019], [Christiano et al., 2015], [Gali, 1999]). The question is: can we use available information more efficiently to anticipate these shocks? The relevance of this question becomes evident in two scenarios: when macroeconomic models overlook significant dynamics that available information could model, and when we cannot model specific dynamics before observation, necessitating tools like agents' future expectations to predict causal relationship changes.[1].

Specifically, this work will focus on the second possibility. Thus, we test whether the financial market prices, in time, changes in the behavior of economic agents [2]. The expression 'in time' is crucial, as financial markets reflect macroeconomic expectations without always being immediate. In this sense, [Deschamps et al., 2020] argues that high-frequency financial data (particularly credit spreads) are forward-looking and capture market expectations regarding economic conditions. However, the author draws attention to rigidities in the assimilation of information into prices, and therefore, it may be that we cannot capture this information in contracts at the evaluated moment.

In this work, we look at financial futures markets. In the futures market, the future price of the contract is essentially the market consensus on the future price of the asset referenced in the contract. Specifically, we will use the futures market for interest rates.

Future expectations about the economy are priced in the yield curve, which relates interest rates to different maturities. The prices of contracts, or the vertices on the yield curve, reflect expectations about interest rates, monetary policy, and the economy. However, it is important to keep in mind that this relationship between the yield curve and expectations has limitations. The market may not be efficient, investors also price in a premium for their risk perception of the contract, and there are also carrying costs. Thus, the contract price includes other factors besides expectations about the future value of the rate. Therefore, the yield curve does not reflect expectations per se but is a proxy.

The shape of the yield curve is generally used as a proxy for economic expectations. A positive curve (upward) reflects optimistic growth expectations, while a negative (inverted) one indicates pessimism and is generally used as a predictive factor for crises. Finally, a flat curve reflects uncertainties about the economy. The shape of the curve is generally summarized in a few factors like in the Nelson-Siegel Svensson models ([Svensson, 1994]).

Regarding the use of future market information to anticipate movements on the real side of the economy, the literature generally attributes the opposite causality, where macro conditions influence future market expectations ([Ang and Piazzesi, 2003], [Diebold et al., 2006]). Despite this, in this work, we try to establish the transmission channel where the financial market, by quickly incorporating new information into prices, can be used to identify ex-ante changes in the response parameters of economic agents.

To evaluate the stated hypothesis, we conduct forecasts using new data and two distinct groups of predictors: one group that incorporates futures market information to test the effect in question, and

[1]These changes in causal relationships can be endogenously modeled in the model using expectation data and with a grounded theory, but let's clearly separate these situations here to focus the argument.

[2]Besides the financial market, surveys are another source of agents' expectations ([Coibion et al., 2018])

a control group that lacks futures market information. This setup allows us to directly compare the impact of futures market data on our ability to anticipate changes in economic agents' behaviors.

[Elliott and Timmermann, 2016] summarizes the forecasting problem as depending on imprecise models to make predictions about outcomes that can be influenced by evolving processes. Especially [Chiu et al., 2019] draws attention to unexpected changes in the relationships between economic variables and the occasional emergence of structural breaks, such as the 2008 financial crisis. Given the unpredictability, forecasting models need to be adaptive. They must be regularly assessed for accuracy and adjusted when necessary ([Evans and Honkapohja, 2001]). The main concern is that inaccurate predictions can lead to suboptimal policy decisions ([Glas and Heinisch, 2023]). A false positive could mean an exaggerated reaction to an economic signal that is not truly impactful. Conversely, a false negative could involve ignoring a significant economic trend.

With these challenges in mind, we use a decision-making process that aims to use the available information as efficiently as possible to make decisions. In this sense, it is important to define and delimit the term 'as efficiently as possible'. The correct rational form would be to make the decision based on the prediction candidate that best uses the available information given a backward-looking performance metric, on a data base that allows for experimentation.

However, unless the set of relevant variables to be considered in the decision is very restricted, the space of possible decisions tends to be very large. This is indeed true for most economic problems where a certain economic movement can be explained by various causal relationships.

In the case of business cycles, agents can change their behavior over time, and transmission channels can be different in different periods. Thus, causal relationships can take different forms and assume complex relationships ([Acemoglu et al., 2012], [Urquhart and Hudson, 2013], [Urquhart and McGroarty, 2016], [Angeletos and Lian, 2018]).

Another issue is that, for the same dataset, different estimation procedures can lead to different viewpoints on the same set of information ([Hollstein et al., 2019], [Kim and Ko, 2020], [Deschamps et al., 2020]).

With this, there are usually many possible paths to be chosen and, given the limitations of individual model specifications, none is in itself the best representative of the true data generating process. Bearing this in mind, a successful approach in the literature is to combine different models ([Post et al., 2019], [Kourentzes et al., 2019], [Montero-Manso et al., 2020] and [Elliott and Timmermann, 2016]).

Based on this background, a given economic framework can be described from different points of view. Situations like those described in these examples are relevant to the decision-making problem at hand based on a given set of information and for a decision to be robust, it is important to consider the different possible points of view.

Therefore, our decision-making process addresses the problem using a divide-and-conquer strategy to sequentially reduce the set of available decisions until the final decision is constructed. Our goal is not to make the best decision conditional on the available information, as this, for a given performance metric, would be too costly to find. Moreover, regardless of finding it, using the available information, there is no guarantee that this is the best decision after the realization of the observed GDP. The process also has a stochastic nature and as a result we use controls to ensure consistency of results. With that, our goal is to make a robust and efficient decision as close as possible to the best considering the cost-benefit of the process.

Simply comparing results with and without futures market information does not adequately determine the efficiency of the estimator in utilizing current information. Therefore, we assess the effectiveness of our decision-making process by comparing its outcomes against those generated by other estimators from the literature. A superior performance of our process, which is intentionally kept simple for clarity, over time compared to other estimators that include more complex controls deemed important for the variable under study, would affirm our process's efficiency in leveraging current information.

In the next section, the paper will present the variables to be used, the countries, the performance metrics, and the decision-making process. Next, we will explain better how we will test our hyphotesis, show the results for the different performance metrics in the considered countries and discuss the results. Finally, we will make the conclusion in the next steps, as well as hilight future extensions of the work.

2 Metodology

2.1 Variables and Yield Curve

The dataset employed in this study encompasses data from European Union countries, spanning the period from the first quarter of 2004 (2004 Q1) to the fourth quarter of 2021 (2021 Q4)[3]. We used a balanced panel of countries of EU from 2004 which eliminates United Kingdom that left EU in 2020. The target variable, for both objectives of this work is the quartely variation of the GDP (Equation (1)). The set of explanatory variable is based on the business cycle literature complemented by instruments to controls for state of economy and for expectations.

$$y_t = ln\left(\frac{GDP_t}{GDP_{t-1}}\right) * 100 \tag{1}$$

The business cycles are characterized not only by current information but also by some degree of persistent behavior of previous period, like habits of consumption, delay in adjustment of prices, no depreciated capital stock and so on ([Smets and Wouters, 2007], [Christiano et al., 2015], [Gali, 1999]). Unfortunately, some of this information is not readily available in a timely manner; hence, it won't be utilized in the decision-making process in this work. Instead, for these behaviors, we will employ instruments.

Timely avaiable data are inflation, interest rates and exchange rate. We will use the money base and stock market index as instruments for the state of the economy (e.g., consumption, investment, etc.). To control for anticipated expectations and, consequently, current changes in agent responses, we will draw on information from futures market contracts. It is noteworthy that stock market index contains information about future expectations. This is true since the value today of the stock market index, assuming some degree of market efficiency, is linked to the present value its companies. With this in mind, we will test financial markets as instruments for the state of the economy and as controls for expectations in the Results section. But, to streamline our analysis and coherently organize our variables and argumentation, we will refer from now on data from the futures market as controls for expectations and observed shifts in the current behavior of economic agents meawhile stock market index as instruments for the state of the economy.

Regarding the expectations of financial agents about the future of the economy, we will use the shape of the future interest curve as a proxy. One way to summarize this shape of the interest rate curve is the model Nelson-Siegel model ([Nelson and Siegel, 1987]) factors and it was used in sevel works in the literature ([Diebold et al., 2006], [Diebold and Li, 2006]). This model uses three factors (level, slope and curvature of the yield curve) to fit the yield curve of bond market. A popular extension of this model is the work of [Svensson, 1994] that adds a fourth factor to the Nelson-Siegel model and is used for many Central Banks. This Nelson-Siegel and Svensson model is described in Equation (2).

$$f(\tau) = \beta_0 f_0(\tau) + \beta_1 f_1(\tau) + \beta_2 f_2(\tau) + \beta_3 f_3(\tau) \tag{2}$$

Where

$$\begin{array}{rc} f_0(\tau) = & 1 \\ f_1(\tau) = & \frac{1-e^{-\lambda_1 \tau}}{\lambda_1 \tau} \\ f_2(\tau) = & \frac{1-e^{-\lambda_1 \tau}}{\lambda_1 \tau} - e^{-\lambda_1 \tau} \\ f_3(\tau) = & \frac{1-e^{-\lambda_2 \tau}}{\lambda_2 \tau} - e^{-\lambda_2 \tau} \end{array}$$

[3]Even our effect variables (Svenson factors from ECB yield curve) were available from 2004 Q3, we set the beginning of our training sample to be 2004 Q1 to have more points of data.

$f(\tau)$	foward rate of governmet bond by different maturities
τ	time to maturity
λ_1,λ_2	decay parameters for the model
β_0	long term interest rate
$f_1(\tau)$	slope of the yield curve at shorter maturities
$f_2(\tau)$	responsible for hump-shaped movements in the curve
$f_3(\tau)$	controls the curvature and flexibility of the yield curve

In this work, we will use the estimation of Nelson-Siegel and Svensson factors (Equation (2)) made by the European Central Bank for the countries in the European Union ([Nymand-Andersen, 2018], [ECB, 2008]).

These variables are described in table (1). Given that we intend to study the benefits of considering information on financial agents' expectations about the economy, we defined 2 types of database. The first is the control database ($X_t^{control}$) which contains variables that control for the transmission channels of traditional macroeconomic models and the effect database (X_t^{expect}) which, beyond the variables in $X_t^{control}$, includes the expectation variables we want to test if can anticipate changes in the behavior of economic agents.

These databases ($X_t^{control}$ and X_t^{expect}), formed by the variables in the table (1), are the base sets of informations. These base sets of informations will be the source for the predictor sets used in this work. These precitors set are the 'base level' (X_t^{base}) and the 'base transformed' (X_t^{transf}). Both X_t^{base} and X_t^{transf} depends on the base sets of information ($X_t^{control}$ and X_t^{expect}), and thus they should receive the notation that indicates this ($X_t^{base,k}$ and $X_t^{transf,k}$ where k can be *control* or *expect*), but for simplicity, we will keep the notation X_t^{base} and X_t^{transf}. If it is necessary to define k, the text will make the reference.

With that in mind, the 'base level' (equation 3), for a given X_t (which can be $X_t^{control}$ or X_t^{expect}) in Table (1), for each period, incorporates the base set of information across three dimensions: level (X_t), lag (t-1) (X_{t-1}) and coefficient of variation ($CV_t(X_t)$). In contrast, the 'base transformed' builds upon the 'base level,' applying transformations to extend the predictor set (Table(2)).

$$X_t^{base} = \{X_t, X_{t-1}, CV_t(X_t)\} \tag{3}$$

Finally, in the end of the day, what we intend to do here, to answer the second objective, is similar to a diff in diff approach, where we have a control dataset ($X_t^{control}$) and a data set with the treatment (in this case X_t^{expect}). The difference between the results of $F_{co}^{3stg}\left(X_t^{expect}\right)$ and $F_{co}^{3stg}\left(X_t^{expect}\right)$[4], is the effect that we want to study assuming the efficient use of the available information, or the best feasible use of the current information, which is the assumption of this work given in the 1st objective.

2.2 Performance metrics

In this topic, we will discuss the benchmarks and performance metrics to measure the efficiency of the decision-making process. This discussion will take place before the description of the process itself because understanding these comparison parameters facilitates the comprehension of what the process intends to achieve.

As described in more detail in the next topic, the decision-making process used in this work utilizes OLS as an estimator and decides on the space of possibilities for possible specifications in a process with a stochastic nature. These specifications (decisions) consider the time-delayed effect of the predictors but ignore the autoregressive effect of the GDP and other seasonality controls or patterns present in time series estimators. This characteristic is intentionally simplifying in order to highlight the power of more grounded decision-making.

Therefore, to evaluate the performance of the decision-making process used, and thus infer about its efficiency in using the available information, we use 2 groups of benchmarks.

[4] Where F_{co}^{3stg} (.) is the result of the 3 stage process decribed bellow in this paper for the coutntry *co*

Table 1: Base set of information: variables and sources

Group (current varibales)	Variable	Source	Frequency	Code (source)
GDP	*GDP (EUR mi)*	EuroStat	quarterly	NAMQ_10_GDP
Interest Rates (r)	*long term*	EuroStat	daily	IRT_LT_MCBY_D
Prices (π)	*consumer price index*	EuroStat	monthly	PRC_HICP_MIDX
Exchange Rates (e)	*EUR over USD*	FRED	daily	DEXUSEU
Market expectations ($expectations$)	*Nelson-Siegel and Svensson factors*	ECB	daily	BETA0, BETA1, BETA2, BETA3
International Economy ($international$)	*commodities prices*	OECD	quarterly	OILCON, OILSUP, WPBRENT, WPHAMD, WPHD
State of the economy ($state$)	*money base* *main stock market*[1]	ECB YahooFinance	daily daily	BSI.M.U2.Y.V.L10.X.1.U2.2300.Z01.E ^BFX, ^FCHI, ^GDAXI, ^IBEX, ^N100

Note: The table presents the primary data utilized in this study, along with their respective sources. Drawn from business cycle literature, this data is selected for its immediate availability, ensuring its applicability in our decision-making process. Our dataset primarily includes variables related to interest rates (r), prices (π), and exchange rates (e). For variables and dynamics that are not readily available, we resort to using instrumental variables such as the monetary base, financial market indexes ($state$), and data from the international commodity market ($international$). Additionally, to assess the specific effect outlined in our research objectives, we incorporate information from the future interest rate market ($expectations$). This is encapsulated by factors derived from the Nelson-Siegel and Svensson model, known for their relevance in capturing the dynamics of interest rates. [1] The financial market indexes were initially defined as controls for the level of the economy ($state$), but as will be argued throughout the paper, this will also be tested as part of the group of variables that control for the expectations of financial market agents ($expectations$).

Table 2: Base Transformed: Variables transformations

Name of the set	Transformation function and input data set	Data set output description
1. base level	X_t^{base}	$\left\{X_t, X_{t-1}, CV_t(X_t)\right\}$
2. power	$X_t^2 = F^{power}(X_t^{base})$	$\left\{(x_t)^2 \,\vert x_t \in X_t^{base}\right\}$
3. interaction	$X_t^{int} = F^{int}(X_t^{base} \cup X_t^2)$	$\left\{x_t^i * x_t^j \vert x_t^i, x_t^j \in \left\{X_t^{base} \cup X_t^2\right\}\right\}$
4. ratio	$X_t^{ratio} = F^{ratio}(X_t^{base} \cup X_t^2)$	$\left\{x_t^i / x_t^j \vert x_t^i, x_t^j \in \left\{X_t^{base} \cup X_t^2\right\}\right\}$
5. inverse	$X_t^{inv} = F^{inv}(X_t^{base} \cup X_t^2 \cup X_t^{int})$	$\left\{1/x_t^i \vert x_t^i \in \left\{X_t^{base} \cup X_t^2 \cup X_t^{int}\right\}\right\}$
6. difference	$X_t^{dif} = F^{dif}(X_t^{base} \cup X_t^2 \cup X_t^{int} \cup X_t^{inv} \cup X_t^{ratio})$	$\left\{x_t^i - x_{t-1}^i \vert x_t^i \in \left\{X_t^{base} \cup X_t^2 \cup X_t^{int} \cup X_t^{inv} \cup X_t^{ratio}\right\}\right\}$
7. base transformed	$X_t^{transf} = X_t^{base} \cup X_t^2 \cup X_t^{int} \cup X_t^{inv} \cup X_t^{ratio} \cup X_t^{dif}$	

Note: The table describes the construnction of the base set X_t^{base} (step 1. described in equation(3)), from the variables in the table (1), to the construction of the base transformed X_t^{transf} (step 7.). The transformations do not occur linearly from step 1. to step 7., In the intermediate stages, the input for each transformation (column "Transformation function and input data set") may not be the immediate preceding subset, but rather, it depends on which subsets are compatible with that specific transformation.

The first is the baseline, which serves as a parameter to quantify the performance gain when considering more sophisticated controls, in this case, time series estimators. We will use 3 baseline benchmarks that ignores the time series nature of the target variable. The first is a *random walk* process of the target variable. The second is a OLS with a simple decision rule over X_t^{base}, described in the Algorithm(1), which aims only to include a more rational component based on adaptive experience. The last baseline is the $XGBoost$, tunned at each point in time using a grid search in the hyperparameters for the memory window w.

The second group comprises time series estimators that add controls for the seasonal and non seasonal components of the target time series, including the autoregressive effect. These estimators are $SARIMA(p,q,d)(P,Q,D)$ and$SARIMAX(p,q,d)(P,Q,D)$. While $SARIMA(p,q,d)(P,Q,D)$ uses only controls for the seasonal and non-seasonal patterns of the target time serie variable (Equation (1)), $SARIMAX(p,q,d)(P,Q,D)$, in addition to these controls, adds information from the predictors used in$X_t^{base,expect}$ with the same decision rule as the baseline estimator (Algorithm(1)).

Thus, while the baseline includes decision rules for adaptive choice of predictors and $SARIMA(p,q,d)$ (P,Q,D) includes rules for adaptive decision-making of seasonality controls and non seasonal parameters, $SARIMAX(p,q,d)(P,Q,D)$ includes both sets of decision rules and constitutes the most robust benchmark.

Algorithm 1 Variable Selection - base level

1. *map the space of models (set of variables) feasibles*
2. *estimate the validation RMSE (equation (4)) for each model in the time window considered*
3. *rank the models based on the measure in step 2.*
4. *choose the best model and uses its prediction*

Note: The variable selection algorithm consist in map the feasible space of models, rank those with best predicion performance in the given time window and choose the best model in the previous period. The idea of this algorithm is to create a reasoned decision rule that adapts over time according to a memory window.

The main measure of performance is the RMSE for out-of-sample predictions calculated using a walk-forward validation approach. With that, in a time period interval (T) using a time window (w) to test the rmse for validation is:

$$F^{rmse}(X,w) = \sqrt{\frac{1}{w}\Sigma_{i=0}^{w-1} e_{T-i}^2} \tag{4}$$

Where, for a given $t \in (w+1):T$, the *mse* of this period t is calculated considering every forecast $(E_{t-1}(y_t|X_t))$, using the information in the time window $(t-1-w)$ up to $t-1$.

Another measure of performance used here is the directional accuracy or sign accuracy. Where the accuracy is the frequency of times the forecast has the same sign of the true value over the total times.

$$F^{accuracy}(X,w) \tag{5}$$

Where the accuracy for each time t, considering the window w, is the sum of times $\left(\frac{E_{t-1}(y_t|X_t)}{y_t} > 0\right)$ over the total number of times.

F^{rmse} (equation (4)) shows a continuos measure in terms of quarterly variation points, $F^{accuracy}$ shows a classification measure where 1 means that y_t^{hat} and y_t^{obs} shares the same sign and 0 otherwise.

2.3 Econometric Specification and Decision Process

The proposed decision making process aims to get as close as possible to the best decision considering the avaiable information (both in data and the model performance). To do so, we adress the 2 most importante problems in forecast mentioned before.

To control for the model uncertainty[5] the strategy is combine several good candidates that tells different histories. In doing so, we try to look at different angles, so when new data comes, we expect to have a lower probability of be surprise. To account for the dynamic nature of the data-generating process over time, the strategy adopted is set a rolling window for the decision in each period.

In turn, the decision in each period is based on "dived and conquer". The core principle is split a large problem into smaller ones, address each problem individually, and integrate their solutions. Anoher way to understand the decision process used is that we are subsetting the original problem in sequence (where each layer of decision uses a different criteria) to come to the final conclusion. The stochastic nature of the process comes from how these groups are formed, and it is necessary to control for the possibility of an unlikely sequence of drops that could bias the results.

With these ideas, the econometric specification is given by Equation (6), where, starting from an initial base X_t, we follow a process of sequential cuts of the space of possibilities in 3 stages until reaching the final decision.

$$\begin{array}{rcl} X_{t-1}^{1st} & = & F^{1st}(y_{t-1}, X_{t-1}, w, \theta_1) \\ X_t^{2nd} & = & F^{2nd}(y_{t-1}, X_{t-1}^{1st}, X_t, w, \theta_2) \\ \hat{y}_t & = & F^{3rd}(y_{t-1}, X_t^{2nd}, \theta_3) \end{array} \tag{6}$$

Where: y_t is the target variable (equation (1)) and $X_{t'}$ can be$X_t^{transf,control}$ or $X_t^{transf,expect}$ (Table(2)) with or without the future market information. $F^{1st}()$, $F^{2nd}()$ and $F^{3rd}()$ are the algorithms for the 1st, 2nd and 3rd stages described bellow, each one with different decision rules. The first 2 stages generates the outputs X_{t-1}^{1st} and X_t^{2nd} and the 3rd the generates the estimate for the target variable ($\hat{y}_t$). These algorithms have 2 others inputs w, that is the time window for the memory of the decision, and θ that is a parameter of robustness that include rules to reduce the noise generate by the stochastic nature o the process. In this work we will set $w = 5$ years or 20 quarters. Despite being a numerically small period of temporal observations, in theory, 5 years seems to be a memory window for making decisions. This window will be used in the decision process and benchmarks. θ takes differentes shapes and values depending on the stage as dicussed bellow.

The decision making process is made in 3 stages : 1) identify the signal variables in a extended base, 2) set good candidates for y^{hat} and 3) emsemble these good candidates and decide the final y^{hat}

In detail:

- Stage 1 - Signals Variables (algorithm (2)): identify the variable signals, or driving forces, for a given time window w. To do so, we subdivide the initial set of variables and apply a rule to classify a variable as relevant.

- Stage 2 - Decision evaluation (algorithm (3)): use signals variables of the 1st stage to find good canditates for predicting the GDP variation in the current quarter and build its prediction candidates. These good candidates are groups of signals variables (instead of individuals ones) with more relevant explanation power in the time window w. Beyond the 'divide and conquer' we also considered the trade off between accuracy and computing power consume. The objective function here, to evaluate the good candidates is the out of sample performance measure (F_t^{rmse} - equation (4)). As we run it 5 times to assure and record the consitency of the decisions (criteria in the robustness parameter $\theta$for this case), the output of the 2nd stage is a multiset since the same good candidate can happens for different stochastic drops.

- Stage 3 - Decisions ensamble (algorithm (4)): combine the candidates of the 2nd stage to do the final decision. The output of 2nd stage, for a given pIntroductioneriod t, is a set of tuples $(V_{n,f}^{*}, rmse_{n,f}, \overline{y}_{n,f})_t$. The 3rd stage seek to combine these forecasts to decide which will be the

[5]Model uncertainty here refers to, for a given basket of good models, or the entire space of possible models, we don't know ex-ante which will perform better. This is a different use of the expression in the literature that refers to the uncertainty about the true parameters of the model

Algorithm 2 Process proposed: 1st stage - signal variables

1. Let V denote the space of explanatory variables. This space comprises I distinct variables, represented as x_i for $i = 1, 2, ..., I$.
- $V = \{x_i | i \in \{1, 2, ..., I\}\}$
2. *Partition V into N non overlapping subsets V_n where*
- $\bigcup_{n \in N} V_n = V$
- $\forall n \neq m | n, m \in N : V_n \cap V_m = \emptyset$
3. *For each interaction d from 1 to D:*
a. *For each subset V_n:*
- *i. identify relevant variables within V_n as x_i^*:*
- *ii: construct $V_{n,c}$: subsets of V_n with low colinearity among its elements (variables):*
- $V_{n,c} = \{x_i | cor(x_i, x_j) \leq k, \forall x_i, x_j \in V_n i \neq j\}$
- *iii: identify the set of relevant variables x_i^* whithin $V_{n,c}$*
- $V_{n,c}^* = \{x_i^* | x_i^* \text{is relevant in } y = F(V_{n,c})\}$
- *iv: create the set of relevant variables from all subsets for this interaction d*
- $V_d^* = \{x_i^* | x_i^* \in \bigcup_{n,c} V_{n,c}^*\}$
4. *Combine the identified relevant variables across all interactions to define the final set of relevant variables V^*. The inclusion criterion for a variable in V^* is that it must be deemed relevant in all interactions (or a frequency equal to D^*):*
- $V^* = \{x_i^* | x_i^* \in V_d^* \forall d \in D\}$

Note: The first stage aims to identify, for a period (time window w), the driving forces or variable signals, to meet the objective function, which in this case is to predict quarterly variations in GDP. To do this, we use 'divide and conquer' to test each candidate predictor. This test is done within the group to which it belongs (V_n – Step 2.) using the 'relevant variables set rule' (Step 3.iii). A variable is deemed 'relevant' in this first stage if it shows a significance level of 90% in internal group testing. These tests are designed to account for multicollinearity, ensuring that the t-statistic is not biased (Step 3.ii). This procedure is iteratively performed to maintain result consistency and mitigate biases that may arise from the stochastic subdivision of variables (Step 3.iv). The final set of 'driving force' or 'signal' variables comprises those consistently deemed relevant across these tests (V^* - Step 4.).

Algorithm 3 Process proposed: 2nd stage - blocks prediction power

1. *Let V^*, the outp of the 1st stage described in Algorithm (2), be the input of the second stage*
2. *Partition V into N_2 non overlapping subsets V_n^* where:*
- $\bigcup_{n \in N_2} V_n^* = V^*$
- $\forall n \neq m | n, m \in N_2 : V_n^* \cap V_m^* = \emptyset$
3. *For each interaction d_2 from 1 to D_2:*
a. *For each subset V_n^*:*
- *i. identify relevant block of variables ($V_{n,f}^*$):*
- *ii. construct $V_{n,f}^*$: combine the variables of V_n^* in feasible structures*
- $V_{n,f}^* = \{x_i | x_i \in V_n^*\}$
- *iii. construct $V_{n,f}^{rmse}$: map the prediction power (equation (4)), in the time window, for each $V_{n,f} \in V_n^*$*
- $V_{n,f}^{rmse} = \{(V_{n,f}^*, rmse_{n,f}) | V_{n,f}^* \in V_n^*, rmse_{n,f} = F^{rmse}(V_{n,f}^*, T, w)\}$
- *iv. contruct $V_{n,f}^*$: choose the structures of each $V_{n,f}^{rmse}$ according to the criteria given by $F()$ and the threshold k*
- $V_{n,f}^* = \{V_{n,f,j}^* | F(V_{n,f,j}^{rmse}) \leq k, \forall V_{n,f,j}^{rmse} \in V_{n,f}^{rmse}\}$:
4. *construct V_f^{**}: combine $V_{n,f}^*$ in different blocks*
- 4.1: *construct V_f^*: as the set of $V_f^* = \bigcup_{n \in N_2} V_{n,f}^*$*
- 4.2: *construct $V_f^{**} = \bigcup_{j=k_1}^{k2} \bigcup_i \binom{V_{f,i}^*}{j}$*
- 4.3: *map the prediction power (equation (4)) of each $V_l^{**} \in V^{**}$*
5. *contruct V^{**}: V^{**} is set of tuples:*
- $V^{**} = \left\{(V_l^{**}, rmse_l, \overline{y}_l)_t \,|V_l^{**} \in V^{**}, rmse_l = F^{rmse}(V_l^{**}, w), \overline{y}_l = F(V_l^{**}), t \in T\right\}$

Note: The 2nd stage algorithm aims to create specifications by grouping into blocks the 1st stage variables that have strong predictive capacity according to the performance metric of Equation (4). The goal is to reduce the complexity of the search space for decisions while increasing search efficiency. Thus, for a given set of signal variables from the first stage (V^*), we once again use 'divide and conquer' and within each subgroup we apply a 'feasible structures' rule. In this case, empirical evidence from the work showed that the best performing predictor blocks have between 4 and 6 predictors, so our rule of 'feasible structures' includes blocks with predictors of 1 to 5 predictors since the marginal gain of considering 6 predictors is not relevant. The end result (V^{**}) is the sets of tuples with the set of predictors (V_l^{**}), the performance metric ($rmse_l$) and the prediction candidate ($\overline{y}_l$).

Algorithm 4 Process proposed: 3rd stage - ensamble good candidates

1. *Let V^{**}, the output of the 2nd stage described in Algorithm (3), be the input in the 3rd stage*
2. *construct $V^{**}_{\{emsamble.base\},k}$: where k is a subset of V^{**}*
a. *V^{**} is a multiset*
b. *Construct $V^{**}_{\{base-m\}}$: subsets of V^{**}*
- $V^{**}_{\{base-total\}} = V^{**}$
- $V^{**}_{\{base-unique\}} = \{tuple_i \neq tuple_j | tuple_i, tuple_j \in V^{**}\}$
c *Construct $V^{**}_{\{best\},n}$: subset the best models of $V^{**}_{\{base-m\}}$ (defined in b.) following the rule n as $F^{best}_n()$)*
- $V^{**}_{\{best\},n} = F^{best}_n(V^{**}_{\{base-m\}})$
d. *Construct $V^{**}_{\{ensamble.base\},k}$: subset of $V^{**}_{\{best\},n}$(defined in c.) following the rule k $F^{e.base}_k()$*
- $V^{**}_{\{ensamble.base\},k} = F^{e.base}_k(V^{**}_{\{best\},n})$
3. *Set the ensemble estimator $V^{**}_{\{ensamble.estimator\}}$:*
- $V^{**}_{\{ensamble.estimator\}} = F^{estimator}(V^{**}_{\{ensamble.base\}})$

Note: The algorithm of the 3rd stage gets the multiset of good candidates for predictions (output of the 2nd stage) and set strategies to ensemble these predictions. In doing so, I consider: (i) the density of predictions in an area, both in the multset and in a set (only unique values) (2.6), (ii) different threshold approaches to the most relevant subsets of predictions (2.c), (iii) the existence of outlier (2.d) and (iv) implementing an ensamble approach that combines both individual candidates and a representative from a densely populated prediction area.

decision in each period. Whith that, the 3rd stage is about makes consitent decisions over time in a stochastic process. Its ains to build the final decision considering the uncertainty about it. A decision process that is not consistent is not a good one. To do that, we analyze the density (a cloud) of forecast (generated by the 2nd stage) in different ways and we decide, in each period, based on past uncertainty and error of each approach.

The 3rd stage algorithm (Algorithm (4)) aims to propose the prediction by combining the candidates indicated by the 2nd stage (Algorithm (3)). To do so, it uses different paths with 4 decision nodes (candidate base (2.b - $V^{**}_{\{base-m\}}$), best candidates within each base (2.c - $V^{**}_{\{best\},n}$), base for ensemble (2.d $-$ $V^{**}_{\{ensamble.base\},k}$) and the base ensamble rule of 2.d (3. $-$ $V^{**}_{\{ensamble.estimator\}}$)). We apply 2 rules to each of these decision nodes within the 3rd stage algorithm, which generates 16 candidates for each period and for the structure used in this work.

The estimator's final decision is to choose, among these 16 candidates, the one that has the best past performance, for a given memory window[6]. This final decision (choice) rule had a relevant impact on the consistency of decisions.

3 Results

Based on what we discuss so far, we will set our performance metric:

$$F^{performance}(X, w, estimator) \tag{7}$$

Where:

- $performance$ can be $rmse$ or $accuracy$ (equations (4) and (5) respectively),
- X can be $X^{control}_t$ or X^{expect}_t and
- $estimator$ can be $3-control$, $3-expect$ and $benchmark_i$ (where the benchmark i can be OLS, $SARIMA$ or $SARIMAX$). $3-control$ and $3-expect$ are the output of the 3 stage econometric specification in Equation (6) when the inputs X_t in the 1st step are $X^{control}_t$ and X^{expect}_t respectively.

With that, we tested:

[6]This memory window, here, is 4 quarters (1 year). We also consider a control for the sensitivity, of a given path, to the stochastic component of the 2nd stage

Table 3: Algorithms for Estimators

Code	Estimator	Bechmark group	DecisionRule
ols	OLS	Baseline	Algorithm(1)
$sarima$	$SARIMA(p,q,d)(P,Q,D,s)$	Time Serie	Algorithm to tune the params $(p,q,d)(P,Q,D,s)$ where wich one can be $[0,1]$
$sarimax$	$SARIMAX(p,q,d)(P,Q,D,s)$	Time Serie	Algorithm(1) + Algorithm to tune the params $(p,q,d)(P,Q,D,s)$ where wich one can be $[0,1]$
$3-control$	*3stgSig in* $X_t^{control}$)	Decision Process	Algorithms(2, 3 and 4)
$3-expect$	*3stgSig in* (X_t^{expect})	Decision Process	Algorithms(2, 3 and 4)

Note: The work uses 3 groups of estimators as described in the 'Bechmark group' column. The first is Baseline, represented by OLS and uses a simple decision rule (Algorithm (1)), which aims to include a more rational component based on adaptive experience. The second group is Team Serie, and uses SARIMA and SARIMAX. Both use an adaptive algorithm to decide, for the memory window w, the best seasonality (P,Q,D,s) and non-seasonality (p,q,d) parameters of the time series. Furthermore, SARIMAX uses the same algorithm as Baseline (Algorithm (1)) to decide on exogenous variables. Thus, while the baseline includes decision rules for the adaptive choice of predictors and SARIMA includes rules for the adaptive decision of seasonality controls and time series patterns, SARIMAX includes both decision rules and constitutes the most robust benchmark.

1. $F^{performance}(X,w,3-j)$ outperforms $F^{performance}(X,w,benchmark_i)$: suggest that our decision-making framework utilizes current information more effectively than conventional benchmarks.
2. $F^{performance}(X,w,3-expect)$ outperforms $F^{performance}(X,w,3-control)$: indicate that expectations can indeed serve as a precursor to predicting shifts in economic agents' behavior.

Therefore, the results of the work highlight the relative performance of our proposed decision-making process (section 2.3) against the benchmarks (section 2.2). The estimators and algorithms employed are detailed in Table (3). Moreover, in light of the discussion in Section 2.1 regarding financial market indexes—how, in the context of market efficiency, they reflect the present value of future cash flows of firms and thus price in future expectations—we also explore the inclusion of financial market indexes in our predictive models. This exploration is segmented into two scenarios: where these indexes are part of the control variables group ($X_t^{control}$) and where they are considered among the effect variables (X_t^{expect}).

Results are methodically presented in Tables (4) and (6) for scenarios where financial market indexes act as control variables, and in Tables (5) and (7) where they are part of the effect variables group, with metrics of RMSE and accuracy assessed respectively. To enhance understanding, Tables (8) and (9) succinctly summarize these findings, distinguishing between models that exclude and include financial market indexes as part of the effect variables group, respectively.

It is pertinent to note that the sample period, encompassing two major global economic crises (2008 and COVID-19 in 2020), exhibits a broad range in the maximum and minimum values across countries, as shown in the 'Min' and 'Max' columns in Tables (4) and (5). Furthermore, the data did not receive any smoothing treatment.

Consequently, our study's findings are delineated as follows:

1. Employing Financial Market Indexes for Expectation Controls: Our analysis reveals that incorporating financial market indexes within the control group for market expectations (X_t^{expect}) yields more coherent and definitive conclusions compared to when they are grouped to control for the economy's overall level ($X_t^{control}$). This distinction becomes particularly evident as financial market indexes, when categorized within the expectation control group (effect group), enable estimators with expectations ($3-expect$) to outperform those without ($3-control$) in nearly all instances within our sample. This outcome underscores the efficacy of utilizing financial market indexes as a dual control for market expectations—both within the control and effect groups—since these indexes inherently encapsulate market anticipations, the very effect under scrutiny. Initially, when financial markets were positioned as controls for the economy's level

Table 4: Benchmarks for RMSE by Country - Financial Markets Indexes as instruments for economy state

$Country$	$3-control$	$3-expect$	ols	$sarima$	$sarimax$	Min^*	Max^*
AUT	4.19	4.6	9.53	5.12	8.75	-9.17	9.49
BEL	5.45	5.28	8.75	6.69	7.4	-9.59	10.76
ESP	5.25	5.67	14.79	9.1	4.84	-14.44	11.6
FIN	6.71	6.25	16.05	4.43	7.99	-8.46	9.12
FRA	3.83	3.59	6.25	4.64	4.45	-10.63	11.21
GER	2.27	2.49	3.97	3.85	4.55	-9.63	9.01
HOL	3.19	3.26	5.58	3.02	3.23	-4.95	7.66
IRL	10.9	6.61	13.09	6.74	10.1	-9.43	24.18
ITA	7.33	7.54	10.51	7.02	10.74	-16.17	12.55
PRT	4.84	4.32	8.34	5.3	7.18	-10.43	12.41

Note: The table shows the rmse (equation(4)) for the estimations procedures used in this work when financial market indexes are included in $X_t^{control}$ *and therefore* $3-control$*. There were 3 sets of estimators. (1) OLS is the baseline, uses full current variables (table (1)) and ignores the time serie nature of the target variable. (2) Time Series models with exogenous variables* ($SARIMAX\,(p,q,d)\,(P,Q,D,s)$) *and with out it* ($SARIMA\,(p,q,d)\,(P,Q,D)$) *uses ML and consider and tune the time serie struture of the target variable. SARIMAX are used with and without a variable selection. (3)* $3-control$ *and* $3-expect$ *use the decision making process proposed (section 2.3) using OLS and ignores the time serie nature. With that, the difference in performance between the time serie estimatiors (set (2)) and the baseline ones (sets (1)) shows the importance of the time serie nature of the target serie. The difference between the* $3-control$ */* $3-expect$ *and the time series (set (3)) shows the advantage of a well-structured decision process, ignoring an important component of the target variable, over the best baseline. The errors and max and min are measure in quarterly % variation of EUR million (1).*

Table 5: Benchmarks for RMSE by Country - Financial Markets Indexes as instruments for expectations

$Country$	$3-ctrl$	$3-exp$	ols	rw	xgb	$sarima$	$sarimax$	Min^*	Max^*
AUT	4.64	4.37	9.53	9.01	5.42	5.12	8.75	-9.17	9.49
BEL	5.13	5.13	8.75	11.75	6.46	6.69	7.4	-9.59	10.76
ESP	6.26	5.58	14.79	10.97	6.77	9.1	4.84	-14.44	11.6
FIN	7.6	6.12	16.05	10.76	7.65	4.43	7.99	-8.46	9.12
FRA	4.06	3.67	6.25	6.35	4.47	4.64	4.45	-10.63	11.21
GER	2.44	2.42	3.97	4.27	3.06	3.85	4.55	-9.63	9.01
HOL	4.4	3.39	5.58	7.65	3.95	3.02	3.23	-4.95	7.66
IRL	7.0	7.1	13.09	9.83	7.87	6.74	10.1	-9.43	24.18
ITA	7.33	7.52	10.51	12.76	7.48	7.02	10.74	-16.17	12.55
PRT	5.72	4.78	8.34	7.51	5.43	5.3	7.18	-10.43	12.41

Note: The table shows the rmse (equation(4)) for the estimations procedures used in this work when financial market indexes are included in X_t^{expect} *and therefore* $3-expect$*. There were 3 sets of estimators. (1) Baseline estimators given by OLS (uses full current variables (table (1)) and ignores the time serie nature of the target variable), a random walk process (rw) and a XGBoost tunned at each point in time (xgb). (2) Time Series models with exogenous variables* ($SARIMAX\,(p,q,d)\,(P,Q,D,s)$) *and with out it* ($SARIMA\,(p,q,d)\,(P,Q,D)$) *uses ML and consider and tune the time serie struture of the target variable. SARIMAX are used with and without a variable selection. (3)* $3-control$ *and* $3-expect$ *use the decision making process proposed (section 2.3) using OLS and ignores the time serie nature. With that, the difference in performance between the time serie estimatiors (set (2)) and the baseline ones (sets (1)) shows the importance of the time serie nature of the target serie. The difference between the* $3-control$ */* $3-expect$ *and the time series (set (3)) shows the advantage of a well-structured decision process, ignoring an important component of the target variable, over the best baseline. The errors and max and min are measure in quarterly % variation of EUR million (1).*

Table 6: Benchmarks for Accuracy by Country - Financial Markets Indexes as instruments for economy state

$Country$	$3-control$	$3-expect$	ols	$sarima$	$sarimax$
AUT	0.8	0.76	0.53	0.65	0.45
BEL	0.71	0.72	0.41	0.92	0.8
ESP	0.71	0.72	0.47	0.88	0.9
FIN	0.63	0.57	0.41	0.92	0.65
FRA	0.61	0.69	0.45	0.74	0.76
GER	0.71	0.72	0.63	0.57	0.61
HOL	0.86	0.84	0.43	0.92	0.82
IRL	0.45	0.47	0.37	0.61	0.43
ITA	0.69	0.69	0.41	0.71	0.61
PRT	0.51	0.67	0.59	0.47	0.61

Note: The table shows the accuracy (equation(5)) for the estimations procedures used in this work when financial market indexes are included in $X_t^{control}$ and therefore $3-control$. The bechmarks are described in Tables (4) and (5).

Table 7: Benchmarks for Accuracy by Country - Financial Markets Indexes as instruments for expectations

$Country$	$3-control$	$3-expect$	ols	$sarima$	$sarimax$
AUT	0.78	0.8	0.53	0.65	0.45
BEL	0.71	0.71	0.41	0.92	0.8
ESP	0.72	0.74	0.47	0.88	0.9
FIN	0.59	0.55	0.41	0.92	0.65
FRA	0.67	0.71	0.45	0.74	0.76
GER	0.72	0.76	0.63	0.57	0.61
HOL	0.84	0.78	0.43	0.92	0.82
IRL	0.43	0.47	0.37	0.61	0.43
ITA	0.69	0.67	0.41	0.71	0.61
PRT	0.53	0.59	0.59	0.47	0.61

Note: The table shows the accuracy (equation(5)) for the estimations procedures used in this work when financial market indexes are included in X_t^{expect} and therefore $3-expect$. The bechmarks are described in Tables (4) and (5)

Table 8: Summary of results - Financial Markets Indexes as instruments for economy state

$Country$	$RMSE$	$Accuracy$
AUT	$3-control$	$3-control$
BEL	$3-expect/3-control$	$sarima$
ESP	$sarimax$	$sarimax/sarima$
FIN	$sarima$	$sarima$
FRA	$3-expect/3-control$	$sarimax/sarima$
GER	$3-control/3-expect$	$3-expect/3-control$
HOL	$sarima/3-control/sarimax/3-expect$	$sarima/3-expect/sarimax/3-control$
IRL	$3-expect/sarima$	$sarima$
ITA	$sarima/3-control/3-expect$	$sarima/3-expect$
PRT	$3-expect$	$3-expect$

Note: This table summarizes the results from tables (4) and (6) pointing out the best performing estimators in the sample by country. The countries that show more than one estimate are because the difference between their performance was not very significant and therefore it is not possible to conclude with certainty about the dominance of one over the other. When more than one estimator is indicated, the estimator on the left will be the one that performed best.

Table 9: Summary of results - Financial Markets Indexes as instruments for economy expectations

Country	Rmse	Accuracy
AUT	$3-expect$	$3-expect$
BEL	$3-expect/3-control$	$3-expect/3-control$
ESP	$sarimax$	$sarimax/sarima$
FIN	$sarima$	$sarima$
FRA	$3-expect$	$sarimax/sarima/3-expect$
GER	$3-expect/3-control$	$3-expect/3-control$
HOL	$sarima/sarimax/3-expect$	$sarima/3-control/sarimax/3-expect$
IRL	$sarima/3-control/3-expect$	$sarima$
ITA	$sarima/3-control/3-expect$	$sarima/3-control/3-expect$
PRT	$3-expect$	$sarimax/3-expect$

Note: This table summarizes the results from tables (5) and (7) pointing out the best performing estimators in the sample by country. The countries that show more than one estimate are because the difference between their performance was not very significant and therefore it is not possible to conclude with certainty about the dominance of one over the other. When more than one estimator is indicated, the estimator on the left will be the one that performed best.

rather than for its future expectations, the results pertaining to leveraging financial agents' expectations to predict economic behavior shifts were inconclusive. This phenomenon is attributed to the intrinsic nature of financial market indexes, which are tied to the present value of firms' anticipated future cash flows, thereby embodying expectations related to economic dynamics and agent behaviors.

2. Future Markets as Predictors of Economic Behavior Changes: Significantly, the $3-expect$ estimator consistently outperformed the $3-control$ across our sample for scenarios excluding financial market indexes from the $3-control$ (control group). This pattern suggests that expectations reflected within the financial market preemptively indicate shifts in financial agents' behavior.

3. Comparative Efficacy of Decision Rules and Time Series Estimators: The simplistic framework of our decision-making process did not conclusively outperform traditional time series estimators, nor was the inverse observed. Notably, the decision-making process exhibited superior performance in certain sample segments, while time series estimators excelled in others. Given the rudimentary nature of our approach, especially considering the GDP series characteristics previously discussed, we infer that the decision-making process has been effectively utilizing current information. Extrapolating from our results, one might infer a tendency for the decision-making process to surpass time series methodologies in effectiveness when employing RMSE as the performance metric. Although this inference aligns with expectations, given RMSE's incorporation within the decision-making framework (unlike accuracy), it remains a tentative conclusion, hence described as 'tends to be more successful.'

4. SARIMAX Versus SARIMA Performance: Anticipating SARIMAX to outshine SARIMA, due to its more complex structure and alignment with business cycle predictors and a structured decision rule, was intuitive. However, the anticipated superiority was not empirically supported, reinforcing the notion that business cycles are predominantly influenced by shocks.

5. Behavioral Distinctions in Complex Economies: In referring to 'more complex economies,' we imply those with a larger GDP. The underlying assumption suggests that, particularly within European contexts, larger economies are proportionally less susceptible to external shocks or movements than their smaller counterparts. Consequently, financial market information in larger economies is presumed to reflect a more significant portion of the behavior pertinent to the economy in question. This assumption led to the expectation of the decision-making process's enhanced performance in larger economies, with a converse likelihood in smaller economies favoring time series models. Yet, the introduction of an annual GDP column in the result tables does not substantiate this hypothesis.

In summary, despite the simplicity of our decision-making process, which overlooks time series controls, the time series estimator does not exhibit superiority over the decision-making approach implemented with OLS. This observation accentuates the pivotal role of decision-making components, namely expectations, complex interactions, and the exploration of an expanded possibility space. Thus, it becomes evident that time series estimators are not inherently more efficacious than a process meticulously applying current information in an optimally efficient manner ex-ante.

Highlighting our methodology, this study incorporates OLS within its decision-making framework. It is crucial to acknowledge that our focus extends beyond mere forecasting, aiming instead at decision-making within a deliberately simplified context. With this premise, the 'optimal estimator' may vary across different economic landscapes and over time, prompting an intriguing inquiry into the conditions underpinning the superior performance of one estimator over another.

4 Conclusion

The challenges of forecasting economic cycles primarily stem from two factors: firstly, the difficulty in knowing ex-ante the best possible decision with the information available at a given moment, and secondly, the evolving nature of the actual data generation process over time.

Against this backdrop, our study pursued two main objectives. The initial goal was to develop a decision-making process that improves the efficiency of using available information over time, mindful of these challenges. Achieving this laid the groundwork for our second objective: evaluating whether financial market agents' expectations could predict changes in economic agents' behavior and, consequently, in the data generation process itself. We sought to determine if the financial market is capable of pricing information that accurately forecasts shifts in economic behaviors timely enough to facilitate proactive decision-making.

We designed our decision-making process to maximize the utility of an initial dataset, expanding the range of relevant possibilities as broadly as possible. This approach leads to a subdivision process, culminating in the final decision. The process is structured into three distinct stages, each defined by an objective function that strikes a balance between processing costs and outcome precision, aiming for the most effective decision-making pathway.

Our analytical framework centers around the use of Ordinary Least Squares (OLS), focusing on the persistent components of business cycles, such as consumption trends, past investment depreciation, and sustained inflation, through the application of lagged variables. Nevertheless, it intentionally overlooks the seasonal and non-seasonal aspects of time series, including autoregressive components. Recognizing the importance of these seasonal factors in GDP analysis, we compare our method against SARIMA and SARIMAX models as benchmarks. These models are notable for their comprehensive approach, addressing both persistent elements and explicitly adjusting for seasonal and non-seasonal fluctuations.

The empirical evidence from a selection of Eurozone countries between 2004 and 2021 indicates that time series estimators, despite being calibrated for seasonal and non-seasonal patterns, do not outperform our decision-making process, which eschews these specific time series elements. This observation confirms the efficacy of our framework in efficiently harnessing available information for sound decision-making.

Moreover, our findings suggest that financial agents' expectations effectively incorporate part of the anticipated changes in economic agents' behaviors and can preempt some shocks described in traditional macroeconomic models. It's important to note that such expectations are manifested not only in futures contracts but also in financial market indexes. Given a certain degree of market efficiency, these indexes reflect the present value of firms' anticipated future cash flows and, by extension, the financial agents' future outlooks. The term 'part of the changes' is highlighted due to a noted incremental improvement in our decision-making process's performance when analyzing data with expected effects versus without. However, our analysis concludes that no method consistently dominates across all benchmarks or when comparing data samples with and without expected effects.

In conclusion, our results are not only promising but also highlight the effectiveness of our decision-making process and the anticipatory power of financial market expectations. This opens new avenues for further research, emphasizing the complex interplay between economic forecasting and market efficiency. These findings point to both the challenges and opportunities in improving the predictive accuracy of economic models.

These encouraging outcomes pave the way for further exploration and refinement of our results, as well as for pursuing additional lines of research. The detailed analysis, both cross-sectional and longitudinal, reveals that no single method can be deemed definitively superior based on aggregate measures alone. In our study, these measures involve calculating performance metrics, as outlined in our conclusion tables. For individual countries, we use an aggregated metric that averages all forecast errors, while our assessment across countries is based on instances where one estimator notably outperforms others. This methodology highlights the difficulty of establishing clear dominance among forecasting methods, underscoring the necessity for a nuanced approach to evaluate the effectiveness of various estimators.

A promising direction for future comparison with time series estimators involves disaggregating results by country and time period. Such an analysis could illuminate the conditions under which certain estimators excel, offering deeper insights into their relative strengths.

Moreover, we envisage several extensions to this work. An immediate step is to broaden our database to include a wider range of countries and extend the analysis to periods beyond the Euro era for the countries studied. Adding more financial market variables and futures market data, such as credit spreads or other assets traded in futures markets, could significantly enrich our analysis. Additionally, exploring the marginal effect of each variable within the decision-making process offers a promising avenue for deepening our understanding of these complex dynamics.

Furthermore, comparing our process with other estimators like SVM or *XGBoost* could provide insights into the conditions under which each estimator excels, shedding light on their respective strengths and limitations. While our decision-making process currently utilizes OLS, exploring alternatives such as $SARIMAX$ or incorporating seasonality controls within OLS might reveal more nuanced or efficient forecasting methods.

Finally, the application of our findings could extend beyond predicting changes in economic agents' response parameters. If expectations are indeed capable of anticipating these changes, it opens the door to using this predictive capability as a foundation for constructing risk measures. The forecast error itself, derived from a process that optimally utilizes available information, could serve as a novel indicator of risk, offering a valuable tool for economic and financial analysis.

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