Quantification of Survey Expectations by Means of Symbolic Regression via Genetic Programming to Estimate Economic Growth in Central and Eastern European Economies

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Tendency surveys are the main source of agents’ expectations. This study has a twofold aim. First, it proposes a new method to quantify survey-based expectations by means of symbolic regression (SR) via genetic programming. Second, it combines the main SR-generated indicators to estimate the evolution of GDP, obtaining the best results for the Czech Republic and Hungary. Finally, it assesses the impact of the 2008 financial crisis, finding that the capacity of agents’ expectations to anticipate economic growth in most Central and Eastern European economies improved after the crisis.

Keywords: Economic Climate Indicators, evolutionary algorithms, forecasting, genetic programming, symbolic regression, survey-based expectations, tendency surveys

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Expectations about the state of the economy play a major role in economic time series modeling. Business and consumer surveys provide detailed information about agents’ expectations. Survey-based expectations offer several advantages over experimental expectations. First, they are based on the knowledge of respondents operating in the market. Second, they are available ahead of the publication of quantitative official data. Third, they provide detailed information about a wide range of variables. Tendency surveys ask respondents whether they expect a certain variable to increase, to remain constant, or to decrease. Survey results are published as aggregated data. The individual replies can be aggregated as percentages of the respondents in each category, or rescaled by means of a grading procedure. In both cases, the qualitative nature of survey results facilitates the quantification of agents’ responses making use of survey indicators.

The most commonly used indicator to present survey results is the balance statistic. By assuming that the expected percentage change in a variable remains constant over time for all agents, Anderson (1951) defined the balance statistic as the difference between the percentage of agents reporting an increase and the percentage reporting a decrease. As the balance statistic does not take into account the percentage of respondents expecting a variable to remain constant, Claveria (2010) proposes a variation of the balance statistic that accounts for the percentage of respondents reporting a “no change” by weighting it by the proportion of respondents expecting a variable to rise and to fall. The weighted balance makes it possible to discriminate between two equal values of the balance statistic depending on the percentage of respondents who expect a variable to remain constant. By matching individual responses with firm-by-firm outcomes, Müller (2010) finds evidence that the median of the “no change” category is equal to zero. Visco (1984) and Papadia (1983) calculate balances for surveys with more than three answering categories.

The balance statistic is widely used in applied economics as the regressor in quantitative forecast models (Abberger 2007; Batchelor and Dua 1998; Bergström 1995; Biart and Praet 1987; Claveria and Datzira 2010; Claveria, Pons, and Ramos 2007; Franses, Kranendonk, and Lanser 2011; Ghonghadze and Lux 2012; Graff 2010; Guizzardi and Stacchini 2015; Hansson, Jansson, and Löf 2005; Kauppi, Lassila, and Teräsvirta 1996; Klein and Özmucur 2010; Lui, Mitchell, and Weale 2011a, 2011b; Martinsen, Ravazzolo, and Wulfsberg 2014; Mitchell, Smith, and Weale 2005a; Mittnik and Zadrozyń 2005; Parigi and Schlitzer 1995; Rahiala and Teräsvirta 1993; Robinzonov, Tutz, and Horthorn 2012; Schmeling and Schrimpf 2011). On the other hand, balances have also been used to test economic hypotheses (Batchelor and Dua 1992; Girardi 2014; Ilmakunnas 1989; Ivaldi 1992; Jean-Baptiste 2012; Jonsson and Österholm 2011, 2012; Lemmens, Croux, and Dekimpe 2005, 2008; Paloviita 2006; Pehkonen 1992; Pesaran 1984, 1985, 1987; Pesaran and Weale 2006; Schmeling and Schrimpf 2011; Zárate, Sánchez, and Marin 2012).

The balance statistic can be regarded as a qualitative measure of the average changes expected in the variable. As a result, numerous methods to transform balances into a quantitative measure of agents’ expectations have been proposed in the literature. The output of these quantification procedures is a proxy of unobservable expectations, and therefore they inevitably entail a measurement error (Lee 1994).

The first approach for quantifying survey expectations proposed by Theil (1952) is based on the assumption that respondents report a variable to go up or down if the mean of their subjective probability distribution lies above or below a threshold level or indifference interval. This method is known as the probability approach. Carlson and Parkin (1975) suggested using a normal distribution together with symmetric and constant threshold parameters, both across respondents and over time. The proposed extensions of the Carlson-Parkin framework are mainly focused on relaxing some of its
assumptions, as seen in Driver and Urga (2004), Lahiri and Zhao (2015), Nardo (2003), Pesaran and Weale (2006), and Vermeulen (2014), and for an appraisal of the different quantification methods.

This study presents a novel method to empirically model survey data on expectations based on evolutionary computation and symbolic regression (SR). An SR-based approach makes it possible to identify nonlinear dependencies between expectations about different economic variables in large datasets. We estimate the SR model by means of genetic programming (GP), which through Darwinian competition selects the fittest models of interaction between agents’ expectations. With this aim, we use survey data from the World Economic Survey (WES) carried out by the CESIfo Institute to generate quantitative measures of agents’ expectations that we then use to forecast economic growth in ten Central and Eastern European economies.

The relationship between changes in expectations and economic growth has been widely investigated, but never before by means of SR (Abberger 2007; Claveria, Pons, and Ramos 2007; Dees and Brinca 2013; Leduc and Sill 2013; Lui, Mitchell, and Weale 2011a, 2011b; Mitchell, Smith, and Weale 2005a; Mokinski, Sheng, and Yang 2015; Nolte and Pohlmeier 2007; Zanin 2010). By combining an SR approach with GP, we are able to identify the optimal combinations of a wide range of survey variables that best fit the actual evolution of the gross domestic product (GDP) in a set of countries of the Organization for Economic Co-operation and Development (OECD).

Symbolic regression (SR) is an empirical modeling approach especially suitable when the model structure is unknown or changes over time. While conventional regression analysis is based on a certain model specification that optimizes the coefficients in the model, SR does not rely on a specific a priori determined model structure. Symbolic regression can optimize the model structure and the coefficients simultaneously, and finds an appropriate model from a space of all possible expressions defined by a set of given operations and functions. The only assumption made in SR is that the response surface can be described by an algebraic expression. The introduction of GP (Koza 1992) in SR has enabled the use of empirical modeling in a wide range of applications.

Genetic programming (GP), considered as an extension of genetic algorithms (GAs) based on variable-length trees instead of fixed-sized individuals, belongs to the class of evolutionary algorithms (EAs) introduced by Holland (1975) and fostered by evolutionary programming (Fogel, Owens, and Walsh 1966). Zelinka (2015) provides an overview of EAs. See Fogel (2006) and Goldberg (1989) for applications and a comprehensive overview.

Empirical modeling via SR with GP is increasingly attracting interest in different fields due to its wide applicability (Barmpalexis et al. 2011; Cai et al. 2006; Can and Heavey 2011; Ceperic, Bako, and Baric 2014; Sarradj and Geyer 2014; Vladislavleva, Smits, and den Hertog 2010; Yao and Lin 2009). Nevertheless, there have still only been a few applications in economics. Kotanchev, Vladislavleva, and Smits, et al. (2010) identify models between large public datasets and GDP per capita. Kronberger et al. (2011) use SR to identify variable interactions in a large dataset of economic indicators to estimate U.S. inflation. Klůčík (2012) uses GP in the estimation of total exports and imports to Slovakia via SR. Wei (2013) proposes a hybrid model to forecast the stock index in Taiwan. Yang et al. (2015) propose a data-driven approach that uses SR to forecast oil production.

We aim to break new ground by implementing SR via GP in modeling agents’ expectations. This approach allows us to quantify survey expectations and generate estimates of GDP growth.

The structure of the article is as follows. In the next section we review the literature on the quantification of survey expectations, and then we present our methodological approach. The fourth section offers an overview of the experiment, followed by description of the data. In the sixth section, we present the empirical results. This is followed by a brief summary together with conclusions.
LITERATURE REVIEW: THE QUANTIFICATION OF SURVEY-BASED EXPECTATIONS

Business and consumer surveys, also known as tendency surveys, characteristically ask agents whether they expect a variable to rise, to fall, or to remain unchanged. The qualitative nature of agents’ responses made it necessary to quantify the survey indicators. Anderson (1952) was the first to formalize the relationship between quantitative data and respondents’ expectations by regressing the actual average percentage change of an aggregate variable $Y_t$, on the percentage of respondents expecting a variable to rise and fall, denoted by $R_t$ and $F_t$, respectively. Pesaran (1984) later extended this regression approach by allowing the model for an asymmetrical relationship between the actual average percentage change $y_t$ and the change for agent $i(y_{it})$ in periods of growth.

The most common approach for quantifying survey expectations assumes that respondents report that variable goes up or down if the mean of their subjective probability distribution lies above or below a threshold level (indifference interval). This theoretical framework, proposed by Theil (1952), is denoted as the probability approach. Carlson and Parkin (1975) developed the method by using a normal distribution. Several authors have used alternative distributions (Batchelor 1982; Foster and Gregory 1987; Visco 1984). Balcombe (1996), Berk (1999), Fishe and Lahiri (1981), and Mitchell (2002) have found evidence that normal distributions provide as accurate expectations as other stable distributions. The Carlson-Parkin method assumes a constant and symmetric indifference interval across respondents and over time.

Batchelor (1981, 1982), Bennett (1984), Defris and Williams (1979), and Pesaran (1987) note some of the restrictions of the Carlson-Parkin framework. Abberger (2007) uses probit analysis to estimate a quantitative threshold for employment expectations that allows differentiation between a decrease and an increase in actual employment. Several refinements of the probabilistic approach have been proposed in order to reduce the measurement error introduced by restrictive assumptions (Batchelor and Orr 1988; Batchelor 1986; Berk 1999; Breitung and Schmeling 2013; Claveria, Pons, and Suriñach 2003, 2006; Dasgupta and Lahiri 1992; Kariya 1990; Lahiri and Zhao 2015; Löffler 1999; Łyziak 2013; Mitchell, Mouratidis, and Weale 2007; Mitchell, Smith, and Weale 2002; Mitchell et al. 2005b; Müller 2010; Seitz 1988; Smith and McAleer 1995; Toyoda 1979).

By making the threshold dependent on time-varying quantitative variables, Batchelor (1986) and Berk (1999) develop a variant of the Carlson-Parkin procedure. Seitz (1988) uses Cooley and Prescott’s (1976) time-varying parameter (TVP) model, in which the parameter vector is subject to permanent and temporary shocks. Claveria, Pons, and Suriñach (2006) present a more general model based on a state-space representation that allows for asymmetric and dynamic response thresholds generated by a first-order Markov process.

A certain portion of the literature focuses on individual expectations. Mitchell, Smith, and Weale (2002) develop an indicator based on firm-level responses. By comparing individual responses with firm-by-firm realizations, Müller (2010) develops a variant of the Carlson-Parkin method with asymmetric and time-invariant thresholds. The author introduces the “conditional absolute null” property, which is based on the empirical finding that the median of realized quantitative values corresponding to the “no change” category is zero. The main advantage of this new procedure is that it solves the zero response problem and provides variance estimates closer to the sample variances. As opposed to the results obtained by Lui, Mitchell, and Weale (2011a), Müller (2009) finds that business expectations provide useful information. For an appraisal of individual firm data on expectations, see Zimmermann (1997).
Recent studies for Central and Eastern European countries are those of Sorić, Škrabić, and Čizmešija (2013), who assess the predictive properties of the composite indicators of the business and consumer surveys of the European Commission for the EU. The authors compare the forecasting performance of old EU member states vs. the new member states by means of panel vector autoregressive models, finding no significant differences between the two groups. These results are in line with those obtained by Lyziak and Mackiewicz-Lyziak (2014), who use panel data analysis and find that the expectational errors in transition and developed economies are similar, being lower in the former during the 2008 financial crisis.

In a recent study, Lahiri and Zhao (2015) propose a generalization of the Carlson-Parkin method that allows time-varying and heterogeneous thresholds. The authors examine the quality of quantified expectations by comparing them to quantitative realizations at the firm level. They find that allowing for cross-sectional heterogeneity and asymmetric and time-varying thresholds obtains significant improvements, particularly during periods of uncertainty, with high levels of disagreement between respondents.

As stated by Lee (1994), the differences between the actual values of a variable and quantified expectations may arise from three different sources: measurement or conversion error due to the use of quantification methods, expectational error due to the agents’ limited ability to predict the movements of the actual variable, and sampling errors. Since survey-based expectations are approximations of unobservable expectations, they inevitably entail a measurement error.

Monte Carlo simulations make it possible to distinguish between these three sources of error. Nevertheless, there have been few attempts in the literature to compare quantification methods in a simulation context. Common (1985) and Nard and Cabeza-Gutés (1999) analyze different quantification methods, focusing on rational expectation testing rather than on their forecasting ability. Nardo (2003) and Claveria, Pons, and Suriñach (2006) assess the forecasting performance of different quantification methods in simulation experiments. By means of simulation-based expectations, Terai (2009) and Löffler (1999) estimate the measurement error introduced by the probabilistic method.

**METHODOLOGY: SYMBOLIC REGRESSION VIA EVOLUTIONARY COMPUTATION**

Symbolic Regression

Symbolic regression attempts to find relationships that bind together the variables of a given dataset. It is a regression method where no model is assumed beforehand. Therefore, SR is particularly indicated when there is little information available about the process under consideration. The solution is based on discrete optimization, searching for the most fitting algebraic expression of the data in the space of all possible expressions. There are different strategies for solving an SR. Koza (1992) proposed the application of GP to implement SR. Genetic programming is the most common approach, due to its versatility.

The wide applicability of this empirical modeling approach has attracted researchers from different fields (Barmpalexis et al. 2011; Cai et al. 2006; Ceperic, Bako, and Baric 2014; Sarradj and Geyer 2014; Wu, Chou, and Su 2008). Symbolic regression plays an increasingly important role in many engineering applications, such as signal processing (Yao and Lin 2009), industrial data analysis (Vladislavleva, Smits, and den Hertog 2010), and experimental design of manufacturing systems (Can and Heavey 2011).
The first application of SR via GP in economics is that of Koza (1992), who uses hierarchical genetic algorithms to analyze the nonlinear “exchange equation” relating price level, GNP, money supply, and the velocity of money. The author finds the relationship between quarterly values of the price level in the United States (from 1959 to 1988) and the three other elements of the equation. Since then, there have been only a few applications to economics. Álvarez-Díaz and Álvarez (2005) make use of GP to generate predictions of exchange rates of the yen and the pound to the U.S. dollar.

Kotanchek, Vladislavleva, and Smits, et al. (2010) detect outliers and identify models in large public datasets. The authors use SR via Pareto GP to identify records which are systematically under- or over-predicted by diverse ensembles of nonlinear SR models, providing some insight into economic properties anticipating GDP per capita. Kronberger et al. (2011) use SR to identify variable interactions in a large dataset of economic indicators to estimate U.S. CPI inflation. Kříček (2012) uses GP in the estimation of foreign trade (total exports and imports to Slovakia) via SR. Acosta-González, Fernández, and Sosvilla (2012) apply GP to select the best econometric model for explaining the severity of the 2008 crisis.

More recently, Wei (2013) proposes a hybrid model that uses an adaptive expectation GA to optimize a fuzzy inference system to forecast stock price trends (the stock index in Taiwan). Yang et al. (2015) use SR to predict oil production. Hao et al. (2015) develop a GA-based learning approach to analyze survey data related to customer satisfaction with online travel agency websites. Chen et al. (2015) also use an adaptive GA to hybridize a support-vector regression (SVR) model. The authors find that the proposed seasonal SVR model outperforms nonseasonal SVR and artificial neural network (ANN) models to forecast holiday daily tourist flows to a site in China (Mount Huangshan).

Genetic Programming

Genetic programming belongs to the broader class of evolutionary algorithms, which can be classified into GAs and GP. While basic GAs use fixed-length binary string representation to code potential solutions of a problem, and do not allow the model structure to vary during the evolution, GP uses a more general representation scheme, using tree-structured, variable-length representations suitable to nonlinear modeling. A recent economic application of GAs is that of Acosta-González and Fernández (2014), who use a GA to forecast the financial failure of firms.

Genetic programming can be considered as an extension of GAs and was introduced by Cramer (1985). The works of Koza (1992, 1995) enabled the application of GAs to other areas, such as artificial intelligence (AI) and machine learning. Koza (1992) first proposed the use of GP to find a regression tree defining analytical functions that best fit the data. The author proposes finding the best single computer program that solves a given problem by applying an evolutionary method that imitates aspects of biological evolution, such as the principle of survival and reproduction of the fittest.

In GP, populations of computer programs are bred using Darwinian competition and genetic operations (crossover and mutation). The structure is then evolved and optimized for model approximation. Computer programs are mated so as to create potentially more fit new offspring programs. The best single individual program produced by this process after many generations may be a satisfactory solution to the problem. Dabhi and Chaudhary (2015) and O’Neil et al. (2010) review the main issues related to GP.
New improved versions of GP have been proposed in the literature. Ferreria (2001) introduced gene expression programming (GEP). Peng et al. (2014) proposed an improved GEP algorithm especially suitable for dealing with SR problems. Zelinka, Oplatkova, and Noelle (2005) introduce analytical programming, and shows its ability to synthesize suitable solutions (programs) in SR. Gandomi and Roke (2015) compare the forecasting performance of ANN models to that of GEP techniques. Poli et al. (2010) review the state of the art in GP.

A GP approach is particularly indicated to find patterns in large data sets where little or no information is known about the system. Genetic programming is capable of evolving the structure of the models in combination with the parameters of the model. In our case, the use of GP is justified by the fact that there is an arbitrary functional relationship between a large data set of variables, which are ordinal variables from surveys, and a macroeconomic objective measure, which is the GDP. This way, we are able to find the “fittest” combinations of survey variables that are more adequate to track the evolution of the economy.

**EXPERIMENTAL SETUP**

In this study we estimate economic growth by means of quantitative measures of agents’ expectations generated by a new quantification procedure of survey expectations. The new method is based on SR via GP. This flexible approach finds optimal combinations of responses or survey variables that describe a quantitative variable used as a yardstick—in our case, the year-on-year growth of GDP. In the present study, we use agents’ expectations from the CESifo World Economic Survey and GDP data retrieved from the OECD website (https://data.oecd.org/gdp/quarterly-gdp.htm#indicator-chart).

The main objective of the experiment is twofold. On the one hand, we aim to quantify agents’ expectations expressed in the form of survey indicators, whether balances or other composite indicators, by means of an SR approach. Given the functional expression, we obtain building blocks that can be regarded as part of the formula, and are defined as simple combinations of input variables by means of basic functions. We extract building blocks for the top twenty functions returned by the GP algorithm for twenty-eight countries of the OECD, and focus the analysis on ten Central and Eastern European economies. On the other hand, we combine the most fitted empirical expressions to generate forecasts of GDP, and we test whether there are changes in the ability of agents to anticipate the evolution of economic growth after the 2008 financial crisis.

The application of GP is based on the following steps:

1. The selection of the independent variables. In our case, the twelve variables of the WES presented in Table 1.
2. The set of functions to be used. We have restricted the experiment to the mean, the maximum, the minimum, the ratio, and the logarithm.
3. The definition of a fitness measure that reflects to what extent the individual function reproduces the data used for the regression. As an error metric, we have applied the root mean squared error (RMSE).
4. The setting of the parameters that control the run, and a termination criterion. We have chosen a population of 1,000, and have limited the maximum number of generations to 150.
As a result, the best individual functions from all generations are selected. In this study we have applied a fully configurable simple EA set up using the open source Distributed Evolutionary Algorithms Package (DEAP) framework implemented in Python.

**DATA**

The World Economic Survey (WES) is carried out quarterly by the CESifo Institute for Economic Research in cooperation with the International Chamber of Commerce. The survey questionnaire focuses on qualitative information. Respondents are asked to assess their country’s general situation and expectations regarding important economic indicators (overall economy, foreign trade, inflation, interest rates, share prices, etc.). The individual replies are combined for each country without weighting. The grading procedure consists in giving a rank of 9 to positive replies, of 5 to indifferent replies, and of 1 to negative replies. The survey results are published as aggregated data. The aggregation procedure is based on country classifications. Within each country group or region, the country results are weighted according to the share of the specific country’s exports and imports in total world trade (CESifo 2011). For a detailed analysis of WES data, see Henzel and Wollmershäuser (2005), Hutson, Joutz, and Stekler (2014), and Stangl (2007, 2008). Table 1 shows all the variables used in this study. As can be seen, six of the exogenous variables are leading indicators as they refer to the expected situation of a variable in the next six months. We conduct the experiment from the second quarter of 2000 to the first quarter of 2014.

The Economic Climate Index (ECI) is an aggregate indicator obtained as the arithmetic mean of assessments of the general economic situation and expectations for the economic situation in the next six months. As a rule, the trend in the Ifo ECI correlates closely with the actual business-cycle trend measured in annual growth rates of real GDP. Franses, Kranendonk, and Lanser (2011) compare forecasts by expert with pure model forecasts. Robinzonov, Tutz, and Hothorn (2012) use the Ifo Business Climate and other aggregate indicators from surveys as exogenous variables for industrial production forecasting. In Table 2, we present a descriptive

| Variable | Expectation |
|----------|-------------|
| GSON     | Present economic situation—overall economy |
| GSCN     | Present economic situation—capital expenditures |
| GSPN     | Present economic situation—private consumption |
| GSOP     | Economic situation last year—overall economy |
| GSCP     | Economic situation last year—capital expenditures |
| GSPP     | Economic situation last year—private consumption |
| GSOF     | Economic situation next 6 months—overall economy |
| GSCF     | Economic situation next 6 months—capital expenditures |
| GSPP     | Economic situation next 6 months—private consumption |
| TVEX     | Foreign trade volume next 6 months—exports |
| TVIM     | Foreign trade volume next 6 months—imports |
| TBAL     | Trade balance next 6 months |
analysis of the ECI for the ten Central and Eastern European economies evaluated in this study: Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovak Republic.

RESULTS

In this section we present the results of the experiment, evaluating the ability of the quantified measures of agents’ expectations to approximate the evolution of the GDP in ten Central and Eastern European countries. Using as a criterion the correlation coefficients between the elements of the population (formula) and the dependent variable (year-over-year GDP growth rates), we select a set of building blocks (Table 3) linearly combined to generate a survey-based

| Building blocks |
|-----------------|
| Log(GSOP)       |
| Log(GSCP)       |
| Log(TBAL)       |
| Log(TVEX)       |
| GSCN/GSCP       |
| GSPN/GSPP       |
| GSON/GSOF       |
| Log[(GSOP+GSCP+GSPP)/3] |
| Log[(GSOF+GSCF+GSPF)/3] |
| Log[Max(TVEX/GSPN,TVEX/GSON,TVEX/GSCN)] |
| TVEX/TVIM-TBAL  |
| TBAL/TVIM       |
| Log[(GSON+GSPN)/2] |
indicator to approximate economic growth. First, we visually compare the evolution of the proposed SR-generated indicator to that of the ECI (Figure 1) and the GDP (Figure 2). Second, we analyze the forecasting performance of the quantified expectations by comparing them to a naive model used as a benchmark to compute the mean absolute scaled error (MASE). Results of this comparison are presented in Tables 4 and 5.

Figure 1 shows that the proposed SR-generated indicator and the CESifo ECI show similar patterns of evolution. The main difference resides in the scale. This is especially evident during the 2008 financial crisis, when the downward reaction of the quantified expectations is of greater magnitude. With the aim of assessing the ability of the proposed proxy of agents’ expectations to approximate GDP growth, in Figure 2 we compare the evolution of the quantified expectations via SR to the evolution of the year-on-year growth rates of GDP in the ten Central and Eastern European economies analyzed.

Regarding the differences across countries, while in most economies agents’ expectations seem to advance the turning points, especially regarding the 2008 financial crisis, the opposite holds in Bulgaria, Hungary, Latvia, and the Slovak Republic. The crisis does not start uniformly in all countries; the first signs of recession show in the economies of Croatia, the Czech Republic, Estonia, Latvia, and Poland. While in most countries we observe at least one full business cycle, in the Czech Republic and Poland we observe two complete business cycles.

As a rule, SR-quantified expectations seem to correlate closely with the actual oscillations of GDP. These results are in line with those of Lahiri and Zhao (2015), who note the potential gains in forecast accuracy of quantified expectations under more relaxed assumptions.

In Table 4 we evaluate the forecast accuracy of the generated survey-based indicators used as a proxy for GDP growth, using the naive method as a benchmark. In order to do so, we use the Mean Absolute Scaled Error (MASE) proposed by Hyndman and Koehler (2006). This measure of forecast accuracy scales the errors by the in-sample MAE obtained with a random walk. As official data are published with a delay of more than a quarter with respect to survey data, we use two-step-ahead naive forecasts as a benchmark. This measure is independent of the scale of the data, and it does not suffer from some of the problems presented by other relative measures of forecast accuracy, such as the relative MAE (Hyndman and Koehler 2006).

Additionally, this statistic is easy to interpret: values larger than 1 are indicative that the survey-based forecasts are worse than the average prediction computed in-sample with the benchmark model. Symbolic regression quantified expectations show the best forecasting performance in the Czech Republic and Hungary, where SR-based estimates outperform the naive model used as a benchmark.

Given that the 2008 financial crisis influenced the forecasting accuracy of survey-based measures of economic expectations (Łyziak and Mackiewicz-Łyziak 2014), we recompute the MASE, differentiating between the pre-crisis subperiod (2000–2007), the crisis (2007–2010), and the post-crisis subperiod (Table 5).

The results in Table 5 show that the forecast accuracy of survey-based expectations significantly worsened during the crisis in all countries except the Czech Republic. Agents’ expectations are more accurate in the post-crisis than in the pre-crisis years in all countries except Lithuania and Poland. These results are in line with those of Łyziak and Mackiewicz-Łyziak (2014), who also find that the 2008 financial crisis period has led to a decrease in expectational errors in transition economies.

In the last subperiod, SR-quantified expectations outperform the naive model in six of the ten countries. At the opposite end, in Croatia and Lithuania, agents’ expectations are less able to
FIGURE 1 Evolution of the Ifo Economic Climate Indicator vs. the Proposed Survey-Based Economic Indicator.

Notes: Compiled by the author. The black line represents the evolution of the Ifo Economic Climate Indicator in each country. The dotted line represents the evolution of the proposed survey-based economic indicator via symbolic regression.
FIGURE 2 Evolution of the Ifo Economic Climate Indicator vs. the Proposed Survey-Based Economic Indicator.

Notes: Compiled by the author. The dotted line represents the year-on-year growth rate of GDP in each country. The black line represents the evolution of the proposed survey-based economic indicator via symbolic regression.
anticipate the year-on-year growth rates of GDP. This result can be explained in part by the high dispersion observed in the Economic Climate Index of these two economies (Lithuania presents the highest range, and Croatia the second-highest variation coefficient). Additionally, in the case of Lithuania, mean square errors values are very high, indicating that forecast errors are highly concentrated in a few periods.

**CONCLUSION**

Economic expectations have become essential in assessing the current state of the economy. Survey expectations are a primary source of agents’ economic expectations. However, qualitative expectations are usually quantified in order to forecast macroeconomic aggregates or to test economic hypotheses. In this study, we propose an empirical approach to quantifying qualitative survey responses. This data-driven method of modeling survey-based agents’ expectations avoids making assumptions about the subjective probability distribution of respondents.
With this aim, we use symbolic regression via genetic programming to derive a set of mathematical functional forms that link survey expectations of the World Economic Survey to economic growth. By linearly combining these expressions, we generate estimates of GDP growth in ten Central and Eastern European economies. Finally, we analyze the impact of the 2008 financial crisis on agents’ expectations by assessing the capacity of survey-based expectations to anticipate future economic growth. This analysis finds that the crisis period has led to an improvement in the forecasting performance of agents’ expectations in Central and Eastern European economies.

We find that the SR-quantified expectations correlate closely with the actual oscillations of economic activity and with the CESifo Economic Climate Index. This result suggests that our assumption-free approach to quantifying survey expectations in the direction of change may provide gains in forecast accuracy. Since empirical modeling with symbolic regression via genetic programming makes it possible to select the fittest models of interaction between agents’ expectations and the official quantitative series they refer to, this framework may prove very useful both for researchers and practitioners.

Despite the usefulness of the proposed approach for quantifying survey-based expectations and forecasting economic growth, this study is not without limitations. One aspect not addressed is the use of our approach to search for the optimal proxy indicator of the quantitative variable used as a yardstick. Another issue left for future research is the use of this new set of quantified expectations to test economic hypotheses, which would provide new insight into the formation of expectations or the behavior of the Phillips curve.

Extending the analysis to the rest of the countries in the World Economic Survey would facilitate analyzing differences across countries worldwide. It would also be of interest to replicate the experiment using microdata. A comparison with other questionnaires would make it possible to test whether the obtained functional forms are extensive to different survey data. Another question to be considered in further research is whether the implementation of alternative evolutionary algorithms may improve the forecasting performance of symbolic regression-based quantified expectations.

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