Macroeconomic forecasting using temporal knowledge graph and machine learning: an application to Colombia

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ABSTRACT

Knowledge graphs (KGs) enable a structured and connected approach to data representation, capturing diverse relationships between different elements of human knowledge [6]. Since future events are unknown, a comprehensive understanding of the semantic correlations and historical evolution patterns of entities and relations is a prerequisite for accurate reasoning [14]. Real-world knowledge continually evolves and remains highly dynamic, which leads to the emergence of Temporal Knowledge Graphs (TKG) to predict future events [14].

My research work analyses how the structure of the economy and how sectors are interconnected in a developing country for macroeconomic forecasting. This relies on extracting macroeconomic variables and using Temporal Knowledge Graphs (TKG) to potentially enhance traditional statistical models. I present limitations and benefits of using Temporal Knowledge Graphs (TKG) in the macroeconomic decision-making process for the forecasting of inflation and Input-Output model in food and energy sectors in Colombia. This academic work contributes to the literature of Temporal Knowledge Graphs (TKG) applied to macroeconomic analysis in developing countries that can be used by governments and private organisations.

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1 INTRODUCTION

Traditional macroeconomic models such as vector autoregression (VAR) or structural vector autoregressive (SVAR) are used by National Statistical Offices to predict economic trends or indicators such as Gross Domestic Product (GDP), Consumer price index (CPI) and others [33]. Governments and Central Banks use these statistical models as one of the inputs to formulate fiscal and monetary policies to improve their national economy and international commerce. For that, they need to collect and use reliable data from each sector to predict macroeconomic indicators that might have an impact on people's lives.

Enhanced computing power, natural language processing, and big data have helped with the agility and accuracy of statistical models [29, 42]. However, there are still some gaps in artificial intelligence that need to be addressed due to the lack of knowledge in machines [7]. For example, Knowledge Graphs (KG)[2] and Machine Learning[3] can provide new opportunities to build sophisticated models to make accurate and informed predictions by managing a large number of variables with human sense and context over time [13, 46]. It is a unification of statistical and symbolic methods [15, 21].

In recent years, there has been an increase in academic studies investigating how to include new variables or relevant sources to help explain macroeconomic indicators. A knowledge graph is a way to capture alternative data variables and create relationships with traditional macroeconomic data variables [11]. There are many studies that have successfully demonstrated that the knowledge graph can capture complex economic relationships (e.g., international trade) and predict macroeconomic indicators [32, 37].

Most academic studies are focused on industrialized economies [36], and this thesis will focus on Colombia, a developing country located in Latin America, and its macroeconomic indicators. Colombia is chosen due to researcher nationality and preference, researcher knowledge on the local economy, and data accessibility from private and public institutions. Furthermore, my research work contributes to the Knowledge Graph theory and macroeconomic forecasting methods in the Global South.

2 PROBLEM STATEMENT

This research work is focused on using temporal knowledge graph reasoning to enrich and improve the prediction of macroeconomic

[2]Organized representations of real-world entities and their relationships
[3]A subset a of artificial intelligence (AI) focused on enabling machines to learn from data to imitate the way that humans learn and make decisions

indicators in Colombia. There is a vast literature on knowledge graphs applied to forecasting stock prices, energy prices, health trends for diseases, among others, in developed countries such as the US, China, UK, etc. [23, 24, 26, 37, 39]. However, I found that there are a limited number of academic studies written and published in English related to knowledge graphs applied in Colombia. Therefore I have identified an opportunity to be a pioneer and contribute to the knowledge graph literature by selecting a developing country to assess their macroeconomic indicators.

We use a temporal knowledge graph reasoning method to assess their accuracy against the Vector Autoregression (VAR) to forecast the Consumer Price Index (CPI) in Colombia [1]. In addition, we will use the Input-Output model [3] to characterize the energy and food sectors in Colombia and extend the inclusion of knowledge graphs to analyse the relationship between energy and food sectors. The objective is to demonstrate the usefulness of temporal knowledge graph reasoning to establish variables that can be used to improve the interdependency assessment between the energy and food sectors.

3 HYPOTHESIS FORMULATION

In this study, we attempt to address the following research questions: 1) whether alternative variables can be captured in a macroeconomic graph for a Latin American country; 2) whether entities from a new macroeconomic graph add value to macroeconomic forecasting in a Latin American country over time; 3) how the interdependency of both energy and food sectors is reflected in the economic activity of a Latin American country over time. Consequently, we formulate the following hypotheses:

HYPOTHESIS 1. *Alternative variables and traditional macroeconomic variables merged in a Temporal Knowledge Graph (TKG) improve macroeconomic forecasting.*

HYPOTHESIS 2. *Temporal Knowledge Graph (TKG) can explain the interdependency between energy and food in the economic activity of a country .*

4 LITERATURE REVIEW

This section covers a selection of macroeconomic indexes and statistical models used in Colombia, knowledge extraction methods, and the literature on knowledge graphs used for macroeconomic forecasting.

4.1 Macroeconomic forecasting in Colombia

Public and private institutions rely on macroeconomic data for their decision-making process. Market analysts describe, summarize, forecast, and advise on economic trends [33].

4.1.1 Input–output model. The input-output analysis is a theoretical framework to represent transactions among various industries of the economy [28]. These relations can be represented by tables or matrices. This representation helps to predict and analyze the effects of changes in one sector on the other sectors for policy analysis [38]. Wassily Leontief was awarded the Nobel Prize in Economics in 1973 for his development of this model [31, 38]. Economists regularly use input–output models to examine the economic interrelationship between the agricultural sector and other sectors of the economy, such as the manufacturing and energy sector [17, 25, 40].

4.1.2 Input–output analysis of energy use in agriculture. Energy has a fundamental role in economic and social development, but there is a general lack of rural energy development policies that focus on agriculture [30]. The efficient use of energy is one of the principal requirements of sustainable agriculture in the world [30]. The agricultural sector has become increasingly dependent on energy resources such as electricity and natural gas[17]. The use of energy in agriculture has also become more intensive in response to an increasing population and a desire for higher standards of living [30]. This consumption pattern demands an increase in food production that causes a higher demand and use of chemical fertilizers, pesticides, agricultural machinery, and electricity[30].

For example, Bonet-Morón et al. (2020) analysed how the COVID-19 outbreak and the collapse of international oil prices affected Colombian regions. Each region has their own economic structure such as level of informality in the labour market and the economic links across their different sectors. They used a multiregional input–output model (Colombian economic structure and prices in 2015 and 2019, respectively) to assess the shock of these factors in Colombian regions [3]. As a result, they provided some recommendations on how to make better policy decisions and minimize the economic impact of these economic disruptions [3].

I identified that there is a literature gap in the use of temporal or traditional knowledge graph reasoning and Input-Output analysis to forecast changes between the energy and agriculture sectors. Therefore, my thesis will assess and provide insights on how to combine those elements, knowledge graph and Input-Output model, to enrich macroeconomic analysis.

4.1.3 Vector Autoregressive (VAR) model. A Vector Autoregressive (VAR) model, developed by Christopher Sims [8], is a statistical model widely used in macroeconomic research to explain rich dynamics in multiple time series. Univariate forecasting algorithms (AR, ARMA, ARIMA) predict only one time-dependent variable, while a VAR model is bidirectional (predictors variable influence target variable and vice versa) [33]. For example, a univariate autoregression VAR(p) can be modeled as follows:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + ... + \alpha_k y_{t-k} + \varepsilon_t \tag{1}$$

where α_0 is the intercept, a constant and α_1, α_2 until α_k are the coefficients of the lags of y_t up to order p. The ε_t is the error, which is considered as noise.

4.1.4 Forecasting inflation using VAR Analysis. One of the macroeconomic indicators for assessing the stability of a country's economy is indicated by inflation [18]. Changes in this indicator will affect the dynamics of economic growth. The advantage of the VAR approach is that their usefulness in forecasting inflation can be directly evaluated despite multiple factors that may affect it [10]. Multiple academic studies have used vector autoregression (VAR) models to study the determinants of inflation expectations associated with demand and supply shocks and the dynamic relationship between economic activity and monetary policy [27].

Several attempts have been made to investigate the determinants of inflation in several countries using VAR analysis [2]. Coloni and Madera (2008) used a structural co-integrated VAR model for the G-7 countries to study the direct effects of oil price shocks on output and prices, and the reaction of monetary variables to external shocks [9]. Bandara (2011) found that money supply growth and rice price increases are the main determinants of inflation in Sri Lanka in the long run [2].

Samuel and Ussif (2001) found that in Tanzania, output and monetary factors are the main determinants of inflation. In addition, the exchange rate also becomes a significant variable in inflation in the long run [19]. Chaudhry and Chaudhry (2005) found that the growth rate of import prices and the growth rate of output are the most important determinants of inflation in Pakistan both in the short and long term [5]. Therefore, my research in temporal knowledge graphs will enrich and expand the existing literature on the variables used for the prediction of inflation in a developing country.

4.2 Knowledge graph reasoning

Reasoning is a form of human logical thinking that has become an artificial intelligence (AI) goal. It focuses on enabling machines to have a reasoning ability similar to human beings [7]. Reasoning technology based on knowledge graphs is considered a key technology to give AI the same level of reasoning and decision-making ability as human logical thinking [7, 22]. In addition, knowledge graph reasoning improves the completeness of a knowledge graph by inferring new knowledge [35].

4.3 Temporal knowledge graph

The knowledge graphs with temporal information are called temporal knowledge graphs (TKGs) [44]. A TKG can be viewed as a natural extension of a knowledge graph in the time dimension, in which each knowledge representation is expressed as a quadruple *TKG = (E,R,O,T)* where E, R, O and T are the sets of entities, relations, objects, and timestamps, respectively, [4]. All events that occurred at the same time can be formulated as a snapshot of TKGs. Thus, TKGs can be viewed as a sequence of snapshots where each snapshot has an individual timestamp, to express the evolution over time [45]. Temporal Knowledge Graphs (TKGs) enable effective modeling of knowledge dynamics and event evolution, facilitating deeper insights and analysis into temporal information [45].

4.3.1 Temporal knowledge graph reasoning. From 2012, Temporal knowledge graph reasoning has garnered considerable attention, driven by the time sensitive nature of real-world knowledge [41, 43]. However, traditional or static Knowledge graphs and Temporal knowledge graph commonly have missing facts due to the expense of labeling facts. As a result, predicting missing facts through TKG reasoning has become a critical task in natural language processing [14].

Assuming that the known time interval is $[t_0, t_N]$, according to the timestamp $t$of the predicted facts, the TKG reasoning methods can be divided into two settings: interpolation ($t\ \varepsilon\ [t_0, t_N]$) and extrapolation ($t > t_N$) [16, 22, 45]. The goal of interpolation is to predict missing facts in a sequence of known facts, whereas extrapolation is to predict future facts based on a known historical sequence [20].

4.4 Knowledge graph for macroeconomic forecasting

The Knowlegde graph approach is particularly relevant for studying economic and social development in the globalized economy [32, 36]. Rincon-Yanez et al. (2023) suggest that by integrating the gravity model, which is used to predict trade relations between entities based on factors such as size, into the knowledge base development process, it will allow the prediction of trade patterns [32]. This is a major support for policy makers and economists who need to estimate the potential effects of local changes such as new trade agreements or tariff changes on the overall trade scenario [32].

Tilly and Livan (2021) highlight the work of Guo and Vargo (2020) that uses themes and location data from the GDELT (Global Database of Events, Language and Tone) to show that population, trade, cultural proximity, and geographic closeness drive international news attention [12, 36]. Tilly and Livan (2021) suggest that there are opportunities for research on macroeconomic forecasting that incorporates news narrative-based features to improve the predictions of macroeconomic indicators [36]. Yang et al. builds a knowledge graph from traditional economic variables but also new alternative big data variables to achieve significantly higher forecast precision [42]. Thorsrud found that central bank predictions are improved by extracting themes from newspaper articles and using them to create sentiment indices that are included in GDP growth forecasting [34].

4.5 Textual Data for Knowledge Graph Construction

We build the temporal knowledge graph for macroeconomic indicators that help us forecast the Consumer Price Index (CPI) and analyse the interdependency between food and energy through the Input-Output (IO) analysis. For this purpose, we will extract variables from market reports, press releases, and academic papers from the following sources:

- Colombian Central Bank (*Banco de la República* in Spanish)
- National Administrative Department of Statistics (*Departamento Administrativo Nacional de Estadística*
- Fedesarrollo (Colombian Think Tank)
- BBVA (Commercial Bank - Colombian branch)
- National Association of Financial Institutions (ANIF)
- La República (National newspaper)
- Portafolio (National newspaper)

5 DISCUSSION

This research work will provide insights on how temporal knowledge graphs enhance and enrich macroeconomic forecasting models. It is a step forward on how Semantic Web can help with human decision-making processes in real-time in developing countries. Our findings will contribute the literature of knowledge graphs in Latin America, and how knowledge graphs have a wide range of applications across several disciplines. Most of the academic studies are focused on developed economies which give an opportunity to this research work to be a novelty in the Global South. My study will also present knowledge graphs limitations and how this study could be a baseline for future works on macroeconomic forecasting.

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