

A Google Trends-Based Spatial Weighting Approach for Space-Time Modeling of Gold Prices during the COVID-19 Pandemic

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ABSTRACT

This study aims to forecast gold prices in Austria, India, South Korea, and Turkiye during the COVID-19 pandemic using an optimal space-time modeling approach. Previous studies have primarily employed conventional spatial weighting matrices based on geographical proximity or economic relationships, with limited attention given to utilizing online search behavior as a source of spatial dependence, particularly when handling incomplete data. To address this research gap, this study proposes a novel framework that integrates Google Trends data as both a data-driven spatial weighting matrix and an exogenous variable within generalized space-time autoregressive (GSTAR)-based models. Missing observations were first imputed using the next observation carried backward (NOCB) method before model estimation. Subsequently, GSTARX and GSTARIX models were developed using Google Trends data from five search categories. Model performance was evaluated using the mean absolute percentage error (MAPE). The results demonstrate that the GSTARX model with a spatial weighting matrix derived from Google Images achieved the highest forecasting accuracy, yielding the lowest MAPE of 4.3%. The forecasts indicate relatively stable gold prices in Austria, declining trends in India and South Korea with a more pronounced decline in South Korea and a substantial increase in Turkiye. These findings demonstrate that Google Trends data can effectively capture dynamic spatial relationships beyond conventional weighting schemes, offering a practical and data-driven alternative for improving space-time forecasting accuracy in the presence of missing values.

KEYWORDS

Exogenous variable, Five search categories, Forecasting, Imputation technique

1. INTRODUCTION

The GSTAR model is widely used in spatial time series analysis due to its ability to simultaneously model temporal and spatial dependencies [1]. To enhance predictive capability, the model has been extended by incorporating exogenous variables, resulting in the generalized space-time autoregressive with exogenous variables (GSTARX) model. Furthermore, if the data do not satisfy the stationarity assumption, differencing can be applied to yield the generalized space-time autoregressive integrated (GSTARI) model. A further extension involving the addition of exogenous variables results in the generalized space-time autoregressive integrated with exogenous variables (GSTARIX) model [1, 2]. Various studies have demonstrated the successful application of the GSTAR model family across diverse fields, such as economics, the environment, health, engineering, agriculture, and

energy [2, 3, 4, 5, 6, 7].

Despite their widespread use, most previous studies still construct spatial weight matrices based on conventional approaches, such as geographic distance, inverse distance, or inter-regional economic relationships [4, 5]. This approach assumes that spatial relationships are static, making it less capable of representing dynamic changes in inter-regional interactions particularly under extraordinary circumstances such as the COVID-19 pandemic. Therefore, a new approach is needed to construct spatial weight matrices more adaptively, based on information that reflects actual public behavior [8, 9, 10, 11, 12, 13].

One potential data source for constructing a spatial weight matrix is Google Trends, which provides an index of internet user search intensity based on specific keywords, regions, and time periods. This data has been widely used as a real-time proxy for public behavior and attention across various fields, such as disease surveillance, public health monitoring, public behavior analysis, and the prediction of economic indicators [14, 15, 16]. In the context of spatial analysis, the use of Google Trends as a basis for constructing spatial weight matrices remains relatively limited. Research by Mubarak et al. (2021) represents an early study exploring this approach [17]. However, it was confined to simulations and did not integrate the resulting weight matrices into spatio-temporal forecasting models. Furthermore, the simultaneous use of Google Trends as both a spatial weight matrix and an exogenous variable within GSTARX or GSTARIX models remains very limited. Therefore, this study proposes integrating Google Trends to fulfill both functions, aiming to better represent dynamic spatial relationships while enhancing forecasting accuracy [15, 18, 19]. Additionally, the study compares various Google Trends search categories namely Google Shopping, Google Images, Google News, Google Search, and YouTube Search to identify the spatial weight matrix that yields the best forecasting performance.

Gold prices were selected as the subject of this study because gold is a widely used "safe-haven" investment instrument for hedging assets during periods of economic uncertainty [20, 21]. During the COVID-19 pandemic, rising global uncertainty altered investor behavior and caused gold price fluctuations to become more dynamic, thereby necessitating a forecasting method capable of accommodating these changes [22, 23]. On the other hand, gold price data obtained from the World Gold Council contains missing values that occur systematically on Saturdays and Sundays. If not handled appropriately, this condition could compromise the quality of parameter estimation and the accuracy of forecasting results [24]. Therefore, the missing values are first addressed using the NOCB method prior to the modeling process. This method is rarely employed in economics or finance, making its application a novel aspect of this study. Utilizing an imputation technique during the preprocessing stage is a crucial step toward generating a more reliable model, given that missing values remain a common challenge across various fields of research and data analysis [25, 26].

This study makes three key contributions. First, it proposes the use of Google Trends as an alternative data-driven spatial weight matrix capable of representing inter-regional relationships more dynamically than conventional weight matrices. Second, it simultaneously integrates Google Trends as both a spatial weight matrix and an exogenous variable within GSTARX and GSTARIX models. Third, it evaluates the proposed approach using gold price data containing missing values from the COVID-19 pandemic, thereby providing empirical evidence regarding the effectiveness of the developed method. This study has several limitations to maintain the focus of the analysis. First, the autoregressive structure in the GSTARX and GSTARIX models is restricted to the first order, or AR(1). This restriction allows the study to focus on short-term spatiotemporal dependencies while keeping the model specification parsimonious. The use of the first order has also been applied in previous GSTAR studies involving spatiotemporal data, including research on flight forecasting and COVID-19 data [4, 27]. Secondly, the empirical analysis is limited to four countries including Austria, India, South Korea, and Turkiye. These countries were selected to ensure regional representation reflecting diverse economic characteristics and gold market patterns while keeping the number of locations manageable for the construction and evaluation of the spatial weight matrix. Given these limitations, the study aims primarily to evaluate the feasibility of using Google Trends as a source for constructing the spatial weight matrix and as an exogenous variable in gold price forecasting, rather than to generalize the findings to all countries or various autoregressive orders.

2. METHODOLOGY

The gold price data used in this study were obtained from the World Gold Council and represent the daily gold price per troy ounce in Austria, India, South Korea, and Turkiye. The observation period covered January 1, 2020, to December 17, 2021, corresponding to the COVID-19 pandemic. Since the World Gold Council does not report gold prices on Saturdays and Sundays,

the dataset contains systematic missing values on these days. To address this issue, the NOCB imputation method was applied, as described in equation (1).

$$X^{(n)}(s) = X^{(n)}(s+a) \quad (1)$$

where $k = \min\{1, 2, \dots, p-s\}$ such that $X^{(i)}(s+a) \neq NA$.

Daily Google Trends data were collected over the same period. To ensure that the search data accurately reflected local search behavior, the keyword ‘gold price’ was translated into the primary language of each country. The corresponding search keywords and currencies used in this study are summarized in **Table 1**.

Table 1. Keywords and currencies

No	Country	Keyword	Currency
1	Austria	Goldpreis (German)	Euro (EUR)
2	India	Gold price (English)	Rupee India (INR)
3	Korea	(Korean)	South Korean Won (KRW)
4	Turkiye	Altın fiyat (Turkish)	Turkish Lira (TRY)

After applying the NOCB imputation method to address the missing values, the dataset was divided into training and testing sets. The training set covered the period from January 1, 2020, to July 31, 2021, while the testing set covered August 1, 2021, to December 17, 2021. The GSTARX and GSTARIX models were subsequently estimated using the training data, as specified in equations (2) and (3):

$$X^{(n)}(s) = \sum_{a=1}^{a=p} \sum_{b=0}^{b=\lambda_a} \delta_{ab}^{(n)} M^b X^{(n)}(s-a) + \sum_{c=1}^{c=q} \gamma_c^{(n)} Q_c^{(n)} + \varepsilon^{(n)}(s) \quad (2)$$

$$\nabla X^{(n)}(s) = \sum_{a=1}^{a=p} \sum_{b=0}^{b=\lambda_a} \delta_{ab}^{(n)} M^b \nabla X^{(n)}(s-a) + \sum_{c=1}^{c=q} \gamma_c^{(n)} Q_c^{(n)} + \varepsilon^{(n)}(s) \quad (3)$$

where $\nabla G^{(i)}(t)$ is the differencing for the i -th region, $\delta_{ab}^{(i)}$ is the order of generalized space time autoregressive for the i -th region, M^b is the spatial weighting matrix, $\nabla G^{(i)}(t-a)$ is the a -th lag of differencing for the i -th region, $\gamma_c^{(i)}$ is the parameter of the exogenous variable for the i -th region, $Q_c^{(i)}$ is the exogenous variable for the i -th region, and $\varepsilon^{(i)}(t)$ is for the i -th region.

To reduce model complexity and maintain computational efficiency, the autoregressive order was restricted to one. In both models, the exogenous variables were derived from five Google Trends categories, namely Google Shopping, Google Images, Google News, Google Search, and YouTube Search. Each category was transformed into a dummy variable before being incorporated into the modeling process, where a value of 1 indicates that search activity was available for the corresponding category on a particular day, whereas a value of 0 indicates that no search activity was recorded.

Also, the spatial weighting matrix has adopted the inverse distance that are shown in equation (4).

$$M_{(n)(j)} = \begin{pmatrix} \frac{1}{m_{(1)(1)}} & \frac{1}{m_{(1)(2)}} & \dots & \frac{1}{m_{(1)(j)}} \\ \frac{1}{m_{(2)(1)}} & \frac{1}{m_{(2)(2)}} & \dots & \frac{1}{m_{(2)(j)}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{m_{(n)(1)}} & \frac{1}{m_{(n)(2)}} & \dots & \frac{1}{m_{(n)(j)}} \end{pmatrix} \quad (4)$$

where $m_{(n)(j)} = m_{(j)(n)}$, i is the i -th location, j is the j -th location, and when $n = j$ then $m_{(n)(j)} = 0$.

The model with the lowest MAPE was selected as the best-performing model among all model specifications evaluated. The MAPE for each model was calculated using equation (5).

$$\forall_n \in Accuracy_{MAPE} = 100\% \left(1 - \left(\frac{1}{T} \sum_{s=1}^{s=T} \left| \frac{X^{(n)}(t) - X'^{(n)}(t)}{X^{(n)}(t)} \right| \right) \right) \quad (5)$$

where $G^{(n)}(s)$ is actual value dan $G'^{(n)}(s)$ is predicted value.

Based on the selected model, gold prices in Austria, India, South Korea, and Turkiye were forecast for the period from December 18, 2021, to March 31, 2022. Because the modeling procedure involved differencing, the fitted and forecasted values were back-transformed to their original scale to facilitate interpretation and comparison with the actual gold prices.

3. RESULT & DISCUSSION

The gold price data in Figure 3.1 reveals varying patterns of price movement across the countries, although a general price increase was observed during the early phase of the pandemic.

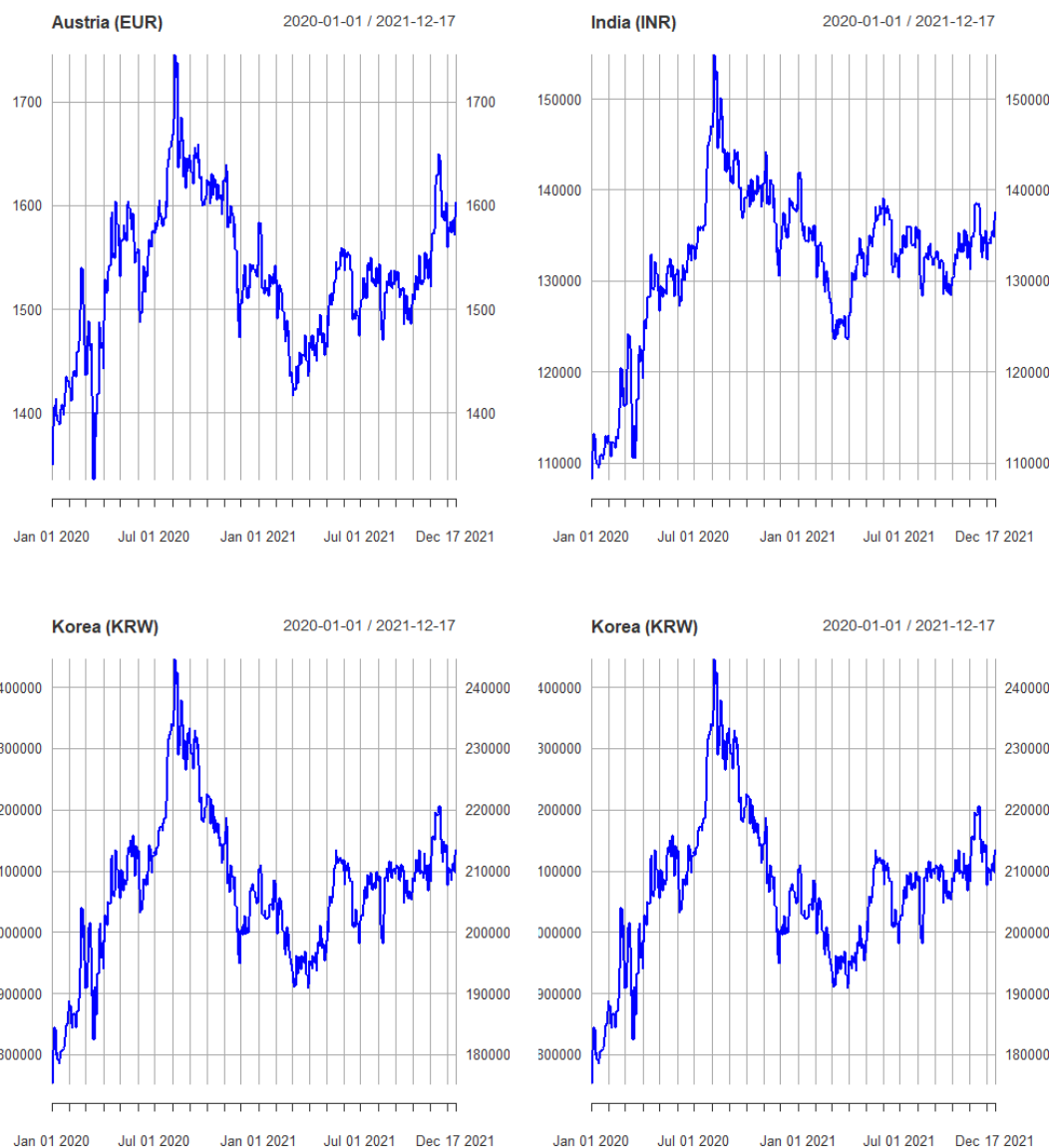


Figure 1. The price of gold

Throughout the observation period, gold prices ranged from 1,335.64 to 1,745.46 EUR in Austria, 108,120.04 to 154,901.87 INR in India, and 1,751,732.56 to 2,446,368.45 KRW in South Korea. Meanwhile, Turkiye exhibited the widest range of fluctuation, spanning 9,014.28 to 29,642.66 TRY. These differences in scale reflect the use of local currencies, necessitating caution when directly comparing price levels across countries. Temporally, all four countries showed a rise in gold prices from

the early to mid-pandemic periods. Average prices in the first quarter of 2020 were 1,434.55 EUR for Austria, 114,693.69 INR for India, 1,889,377.44 KRW for South Korea, and 9,682.27 TRY for Türkiye. By the Q3 of 2020, these values had risen to 1,633.35 EUR, 142,074 INR, 2,268,990.36 KRW, and 13,839.34 TRY, respectively. This pattern indicates that the onset of the pandemic was followed by a rise in gold prices across all study locations. After reaching relatively high levels in 2020, Austria, India, and South Korea experienced a price correction in the Q1 of 2021 before showing renewed increases in subsequent periods. In contrast, Türkiye displayed more pronounced dynamics during the second half of 2021, with the average price rising from 15,287.09 TRY in the Q3 to 19,573.94 TRY in the Q4.

Table 2. Search centers for the keyword “gold price” across google trends categories

Country	Google Shopping	Image search	News search	Web search	Youtube search
Austria	Lower Austria	Carinthia	Tyrol	Upper Austria	Carinthia
India	Dadra and Nagar Haveli	Dadra and Nagar Haveli	Arunachal Pradesh	Punjab	Andaman and Nicobar Islands
South Korea	-	Gyeonggi	-	Gyeonggi	Seoul
Türkiye	Bitlis	Gümüşhane	Van	Adıyaman	Balıkesir

Table 3.1 presents the geographic centers of search activity for the keyword "gold price" across five Google Trends categories. The results reveal substantial spatial variation across countries and search categories. In Austria, search centers are distributed across Lower Austria, Carinthia, Tyrol, and Upper Austria, depending on the specific Google Trends category. India also exhibits significant variation, with search centers located in Dadra and Nagar Haveli, Arunachal Pradesh, Punjab, and the Andaman and Nicobar Islands. In South Korea, Gyeonggi emerges as the search center for Image Search and Web Search, while Seoul is identified for YouTube Search; no search centers were identified for Google Shopping or News Search. Türkiye displays the greatest variation in search centers, encompassing Bitlis, Gümüşhane, Van, Adıyaman, and Balıkesir across the five categories. These differences indicate that the spatial distribution of public interest in gold prices varies across both search platforms and countries. This variation in search centers provides an empirical basis for constructing a Google Trends-based spatial weighting matrix. Unlike conventional spatial weights determined primarily by geographic distance or fixed regional relationships, this proposed approach reflects the spatial distribution of online search activity. Consequently, each Google Trends category can yield a distinct spatial weighting structure, enabling an evaluation of forecasting performance for various forms of online search behavior within the GSTARX and GSTARIX frameworks. This approach is particularly relevant for identifying which types of search activity provide the most informative representation of spatial dependencies in gold prices.

Analysis of Google Trends data reveals heterogeneity in "gold price" search activity across countries and search categories. In Austria, Web Search was the most consistent category, showing activity on 576 out of 578 days (99.65%), whereas Google Shopping, Image Search, News Search, and YouTube Search showed activity during only 0.17%, 1.90%, 2.08%, and 1.38% of the observation period, respectively. India exhibited broader search activity across categories: Web Search was recorded throughout the entire period (100%), followed by Google Shopping (89.45%), Image Search (86.33%), YouTube Search (72.32%), and News Search (41.87%). In South Korea, search activity was relatively limited; Web Search reached 12.80%, while Google Shopping and Image Search stood at only 0.17% each, YouTube Search at 0.87%, and News Search showed no activity. Meanwhile, Türkiye displayed a pattern dominated by Web Search (100%), with Google Shopping, Image Search, News Search, and YouTube Search recording 11.94%, 7.96%, 1.56%, and 1.04%, respectively.

These variations in search activity proportions indicate that Google Trends provides information that is spatially and temporally heterogeneous. This heterogeneity is significant for the construction of spatial weight matrices, as each category can yield a distinct spatial relationship structure. Categories with more consistent search activity potentially offer more stable information for representing inter-regional relationships, whereas categories with very limited activity provide comparatively less information. Consequently, this study evaluates each Google Trends category as an alternative source for spatial weight matrices and as an exogenous variable within GSTARX and GSTARIX models. Further evaluation is based on each model's ability to generate accurate gold price forecasts.

The first-order differencing applied to gold price data to achieve mean stationarity prior to the estimation of the GSTARX and GSTARIX models (**Figure 2**).

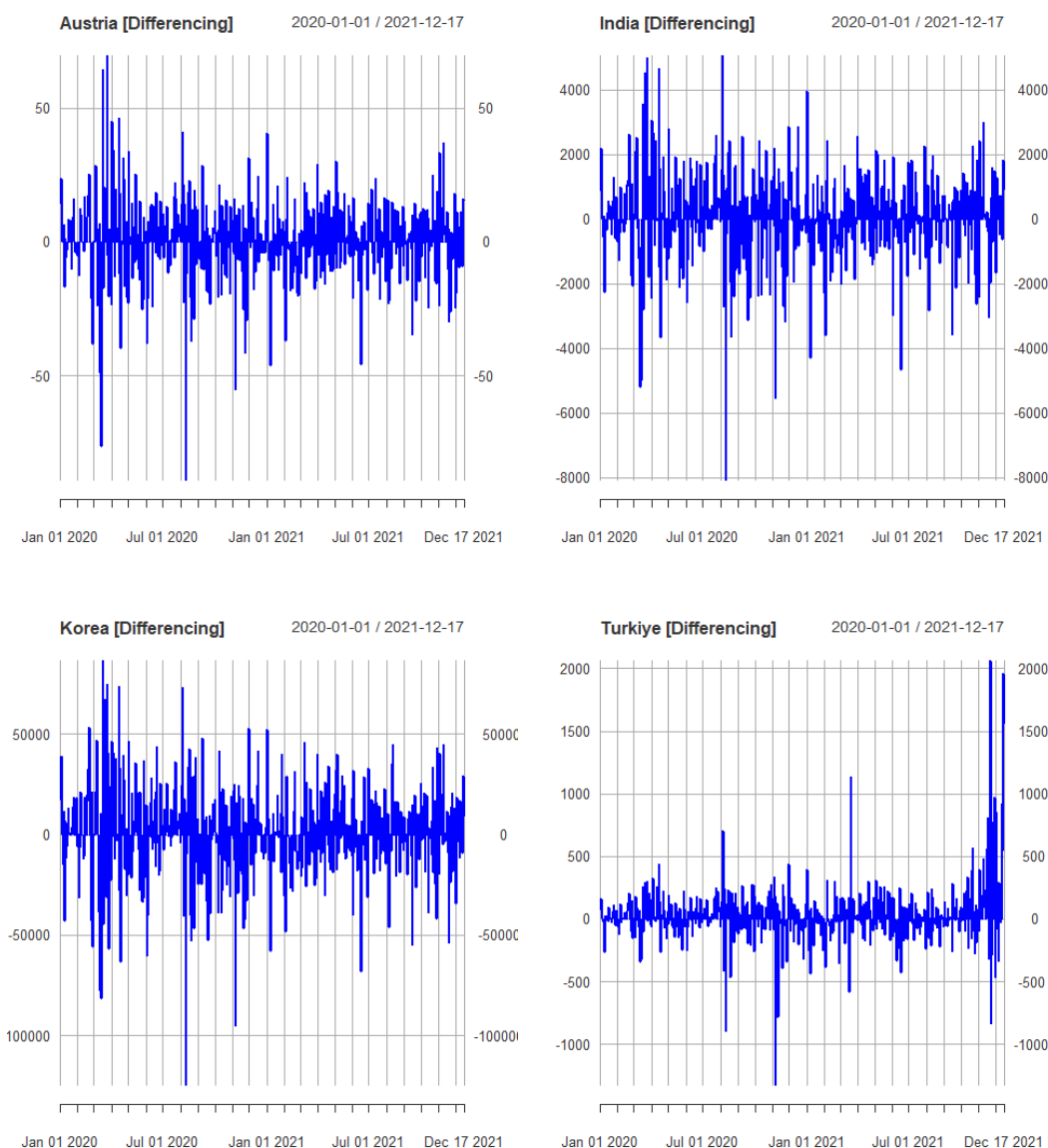


Figure 2. Differencing results

The differencing results indicate that the gold price data for Austria, India, South Korea, and Turkiye fluctuate around relatively stable mean values of 0.355, 41.085, 535.015, and 28.811, respectively.

Based on **Table 3**, the distances between search centers in Austria, India, South Korea, and Turkiye based on Google Trends categories for which search activity data is available. Only the Image Search, Web Search, and YouTube Search categories were considered, as these provide identifiable search centers for the countries included in the study. For Image Search, the shortest distance was observed between Austria and Turkiye (2,194.37 km), while the longest was between Austria and South Korea (8,531.35 km). A similar pattern was observed for Web Search, with the shortest distance between Austria and Turkiye (2,292.23 km) and the longest between Austria and South Korea (8,383.41 km). For YouTube Search, Austria and Turkiye also showed the shortest distance (1,410.47 km), whereas Austria and South Korea showed the longest (8,531.35 km).

Table 4 presents the model evaluation results indicate that all GSTARX and GSTARIX models achieved relatively high accuracy, exceeding 90% for most specifications. For the GSTARX model, the use of Image Search yielded the highest average accuracy at 95.69%, followed by Web Search at 94.16% and YouTube Search at 93.55%. Meanwhile, for the GSTARIX

Table 3. Distance between search centers across google trends categories (km)

Image Search				
	Austria	India	South Korea	Turkiye
Austria	-	6081	8531	2194
India	6081	-	5514	3888
South Korea	8531	5514	-	7233
Turkiye	2194	3888	7233	-
Web Search				
	Austria	India	South Korea	Turkiye
Austria	-	5432	8383	2292
India	5432	-	4733	3463
South Korea	8383	4733	-	7473
Turkiye	2292	3463	7473	-
Youtube Search				
	Austria	India	South Korea	Turkiye
Austria	-	8316	8531	1410
India	8316	-	4539	7181
South Korea	8531	4539	-	8117
Turkiye	1410	7181	8117	-

model, the average accuracies obtained from Image Search, Web Search, and YouTube Search were 95.17%, 95.16%, and 95.16%, respectively. These results demonstrate performance variations based on the Google Trends categories used to construct the spatial weight matrix. Thus, search activity characteristics on each platform can yield distinct representations of spatial relationships when modeling gold prices. These differences also highlight that Image Search provides the most informative spatial data when utilized in the GSTARX model. The GSTARX model employing a weight matrix based on Image Search achieved an average accuracy of 95.69%, leading to its selection as the best-performing model in this study. These results indicate that image-based search patterns offer additional insights into inter-regional interdependencies relevant to gold price movements. The findings support a research approach that utilizes Google Trends as an alternative for constructing spatial weight matrices. Unlike conventional spatial matrices which typically rely on geographic distance or relatively static economic relationships Google Trends-based matrices can represent connectivity patterns derived from public search activity. However, these results demonstrate the predictive superiority of the Image Search-based matrix rather than providing causal evidence that search activity directly drives changes in gold prices.

A comparison between GSTARX and GSTARIX reveals that no single specification consistently yielded the highest accuracy across all Google Trends categories. For Image Search, GSTARX achieved an average accuracy of 95.69%, surpassing the 95.17% accuracy achieved by GSTARIX. Conversely, for Web Search, GSTARIX achieved an accuracy of 95.16%, surpassing GSTARX's 94.16%. A similar pattern was observed in YouTube Search, where GSTARIX yielded 95.16% accuracy compared to GSTARX's 93.55%. These results indicate that the benefits of using Google Trends depend on the model specifications and the characteristics of the data employed. GSTARX performed better with Image Search, whereas GSTARIX delivered relatively

Table 4. Model accuracy (%)

GTSARX with image search				GTSARX with web search			
Austria	India	South Korea	Turkiye	Austria	India	South Korea	Turkiye
97.90	97.00	97.59	90.29	98.16	97.92	90.02	90.52
		95.69				94.16	
GTSARX with youtube search				GTSARIX with image search			
Austria	India	South Korea	Turkiye	Austria	India	South Korea	Turkiye
97.89	98.09	87.47	90.74	98.06	93.63	98.53	90.47
		93.55				95.17	
GTSARIX with web search				GTSARIX with youtube search			
Austria	India	South Korea	Turkiye	Austria	India	South Korea	Turkiye
98.06	93.56	98.56	90.47	98.06	93.55	98.57	90.47
		95.16				95.16	

superior performance for Web Search and YouTube Search. Thus, incorporating a differencing process into GSTARIX does not automatically result in higher accuracy; its effectiveness depends on the structure of the Google Trends information used in the model.

Model performance also exhibited heterogeneity at the country level. For Austria, the highest accuracy (98.16%) was achieved using GSTARX with Web Search, while for India, the peak accuracy (98.09%) was obtained using GSTARX with YouTube Search. South Korea saw its highest accuracy (98.57%) with GSTARIX and YouTube Search, whereas Turkiye achieved its highest accuracy (90.52%) with GSTARX and Web Search. These differences demonstrate that the relationship between online search activity and gold price dynamics is not uniform across countries. Nevertheless, when performance was evaluated in aggregate across all countries, GSTARX using an Image Search-based weighting matrix yielded the highest average accuracy at 95.69%. Consequently, this model was selected as the optimal model for gold price forecasting.

4. CONCLUSION

This study demonstrates that Google Trends can serve as an alternative source for constructing spatial weight matrices and as an exogenous variable in gold price modeling using GSTARX and GSTARIX. The analysis reveals that "gold price" search activity exhibits distinct patterns across countries and search categories, resulting in varying spatial structures. These differences indicate that information based on public search behavior offers a potentially more adaptive representation of spatial relationships than relying solely on geographic data. Among the available Google Trends categories, Image Search, Web Search, and YouTube Search yielded spatial weight matrices suitable for application in the models.

Evaluation based on MAPE indicates that the GSTARX model utilizing a spatial weight matrix derived from Image Search performed best, achieving an average accuracy of 95.69%. Comparative results show that GSTARX excelled when using Image Search data, whereas GSTARIX demonstrated relatively better performance with Web Search and YouTube Search data. Thus, the application of differencing in GSTARIX does not automatically result in higher accuracy. Overall, the findings support the use of Google Trends as a digital information source to represent spatiotemporal dependencies in gold price forecasting, particularly amidst the uncertainty of the COVID-19 pandemic. The best-performing model identified in this study can subsequently be used to forecast gold prices in Austria, India, South Korea, and Turkiye.

Based on these findings, several avenues for future research are proposed. First, the geographical scope could be expanded

to include more countries or regions, allowing the spatial dependency structures derived from Google Trends to be tested in more diverse contexts. Second, future studies could consider longer observation periods including the post-pandemic era to determine whether the advantages of Google Trends-based weight matrices remain consistent across varying economic conditions. Third, the range of Google Trends categories and keywords could be broadened to include terms related to gold investment, economic uncertainty, inflation, or financial market conditions. Fourth, future research could compare Google Trends-based weight matrices with conventional ones such as inverse distance, binary contiguity, or economic linkage matrices to more comprehensively test the advantages of the search behavior-based approach. Fifth, this study was limited to the AR(1) autoregressive order; consequently, subsequent research could evaluate higher autoregressive orders to determine whether accounting for longer-term temporal dependencies improves forecasting accuracy. Finally, given that this study employed binary coding for Google Trends data (1 for the presence of searches and 0 for their absence), future studies could explore more informative measures of search intensity or volume provided such data are available thereby ensuring that the information used to construct weight matrices and exogenous variables reflects not only the occurrence of search activity but also its intensity level.

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