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ORIGINAL SCIENTIFIC PAPER

# Exploring the Interrelationship between Scientific Knowledge and Economic Growth in Serbia: Empirical Insights

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**ABSTRACT**
The primary objective of this study is to examine the nature of the relationship between the production of scientific knowledge and economic growth in Serbia during the period 1996-2022. For this purpose, the Vector Autoregression approach, along with the impulse response function and forecast error variance decomposition, was employed. Results suggest an impact of economic growth on the production of scientific knowledge, while no impact in the opposite direction is detected. The Serbian government should persist in investing in science and work closely with the scientific community to overcome barriers to scientific knowledge's full contribution to economic prosperity.

**Keywords:** *scientific knowledge, scientific output, economic growth, VAR, impulse response, Serbia*

**JEL Classification:** O30, O40, C32

## INTRODUCTION

Numerous potential benefits that national economies derive from economic growth, such as increased wages, reduced unemployment, improvements in education and healthcare systems, increased public investments, etc., rightfully position achieving dynamic and intensive economic growth as a priority goal of economic policy. The societal benefits of economic growth also represent the main reasons for decades-long research into economic growth generators. An inference drawn from prior theoretical and empirical investigations is that technological changes, or innovations, serve as one of the major contributors to economic growth.

Technological changes were first explicitly considered as a source of economic growth by proponents of Neoclassical economic theory in the mid-20th century (Solow, 1956; Solow, 1957). By modeling the relationship between labor, capital, technological changes, and economic growth, it was concluded that over 50% of the growth in most countries stems from technological changes. According to this approach, technological changes are exogenously determined. This limitation paved the way for new research aimed at endogenizing technological progress, or discovering the forces driving innovation. In the 1980s, Endogenous Growth theory, also known as New Growth theory, emerged. The endogenous approach to economic growth identifies research and development activities, among others, emphasizing their quantity, as one of the most important

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drivers of economic growth (Lucas, 1988; Romer, 1990; Aghion and Howitt, 1992). Actually, knowledge is seen as a factor generated internally as a result of incentives for research and development (Romer, 1986). Therefore, the increasing research and development, which in large part is constituted by the production of scientific knowledge, plays a role in driving technological advancements and fostering economic growth.

Scientific knowledge facilitates innovation and spurs economic growth through various pathways.

The knowledge created through the process of scientific research boosts the quality of human capital. Researchers expand their knowledge through reading existing literature (Hatemi-J et al., 2016). This facilitates the recognition of existing gaps, thereby motivating researchers to embark on new scientific inquiries aimed at filling these gaps within the existing body of literature. In this way, scientists enhance their expertise and become valuable resources in addressing various social challenges. University professors who are more productive in publishing scientific papers are likely to transfer creative knowledge and skills to their students (Jin and Jin, 2013). Additionally, scientific knowledge is utilized in informal learning programs (e.g., IT retraining programs, advanced level training for programming), enabling continuous enrichment of human capital with current insights. All of this contributes to the development of human capital with the qualifications and capacities necessary to respond to the dynamic changes occurring in the economy and society.

Scientific output enhances the reservoir of valuable knowledge for the business sector. Newly created scientific knowledge amplifies the pool of information accessible to firms for technological endeavors (Martin et al., 1996). The business sector predominantly requires knowledge resulting from problem-solving-oriented scientific activities. These are mainly research in the applied sciences and engineering disciplines (Rosenberg and Nelson, 1994). This kind of scientific knowledge can serve as a foundation for the development or offer ready-made new methods and analytical techniques that can enable firms to raise the productivity of production factors and improve the quality of or produce new products and services, which can enhance their position in domestic and international markets (Antonelli and Fassio, 2016; Azmeh, 2022).

Scientific research can equip policymakers with in-depth knowledge about complex societal challenges. It helps understand specific problems, develop policy responses based on evidence, and measure the effects of the policy after its implementation. The recent crisis caused by the COVID-19 pandemic best exemplifies the importance of consulting scientific knowledge in the policymaking process. As stated in the European Commission report, scientific modeling, combining the insights of epidemiology, virology, and mathematics, helped policymakers to foresee the spread of COVID-19, as well as timing the introduction and lifting of restrictions (European Commission, 2022). Science helped policymakers alleviate strain on healthcare systems, achieve a low case fatality rate, and avoid catastrophic economic consequences. In addition to the aforementioned fields of science, accumulated and newly created scientific knowledge in other scientific disciplines was also used to mitigate more serious consequences across various spheres of social life. For instance, economic science played a considerable role in selecting a set of measures to provide support to citizens and businesses during the crisis. One of the measures taken by central banks worldwide was the reduction of the reference interest rate. The decision to adjust the reference rate downwards is definitely based on scientific knowledge grounded in previous research on the implications of the interest rate on consumption and investment.

In the past, scientific research was primarily conducted in the developed world. The availability of substantial financial resources enables developed countries to allocate much more funding towards enhancing the capacity of public research institutions. Governments of advanced economies often allocate significant funds to support the research and development activities of private sector firms. Additionally, private companies themselves (for example, in the fields of pharmacology, IT, etc.) invest considerable resources in creating new knowledge. In comparison to developed countries, developing nations have significantly fewer resources available for scientific research. However, research indicating positive experiences regarding the role of science in achieving economic growth has encouraged governments of developing countries to increasingly allocate funds in collaboration with international donors for the needs of the scientific sector. Greater allocation of resources to research activities, along with increasing access to the internet and other advanced technologies, enables research organizations from developing countries to partner with reputable leading institutions from developed countries and to collaborate more closely with industry (Solarin and Yen, 2016). All of this could contribute to building capacity for generating new scientific knowledge. However, previous papers provide evidence that developing countries have yet to experience noteworthy economic benefits from scientific knowledge. Some of the reasons could be the divergent expectations that policymakers and scientists have, regarding the role of science in socio-economic development (Ogot and Onyango, 2023), the structure of generated knowledge, which is mostly non-applicative (Solarin and Yen, 2016), and unsupportive institutional environment (Oluwatobi et al., 2020).

Over the past decade, there has been a relatively modest number of research endeavors addressing the relationship between scientific knowledge and economic growth in developing countries. This research aims to bridge that gap by providing insights into the relationship between these two phenomena in Serbia, focusing on the time frame from 1996 to 2022. Why Serbia? First, as a developing country with pronounced political and economic turbulence in its recent past, it significantly lags behind the advanced world in terms of innovation performance. Second, Serbia has candidate status for membership in the European Union. In all strategic documents of the European Union since 2000, the creation and advancement of knowledge are among the priority objectives. Accordingly, Serbia must swiftly diminish the share of traditional production factors in economic growth in favor of knowledge to prepare its economy in time for entry into the European Union's single market. Third, the subject of research, as conceived in this paper, has not yet been the focus of interest among researchers. Fourth, there is a noticeable increase in the dynamics regarding the production of scientific knowledge and economic growth. Given all of the above, taking the initial steps in this topic will provide at least indicative insight into the relationship between scientific knowledge and economic growth for policymakers. Additionally, this research may inspire scientists to delve deeper into this issue in Serbia.

The rest of the paper is organized as follows. In section 2, an overview of the empirical literature is presented. Section 3 introduces the methodology. Section 4 provides an analysis of the results. Finally, section 5 concludes the research.

## REVIEW OF THE EMPIRICAL LITERATURE

This section presents empirical literature addressing the relationship between scientific knowledge and economic growth. Since the research aim is to determine how the production of scientific knowledge impacts Serbia's economic growth, the focus is exclusively on reviewing studies that have addressed the same topic in developing countries. To focus on relatively fresh empirical insights, the restrictive criterion for selecting studies was set at the year 2010. All studies conducted before 2010 were not taken into consideration. Some might think that this is a long period to consider from the perspective of freshness of the results. However, even within the chosen time frame, the number of conducted studies on the subject is scant.

Studies utilize variations in the number of published scientific papers to quantify the production of scientific knowledge (Table 1). The most commonly used indicator is the total number of published papers. In a few studies, authors have used published scientific papers per million inhabitants and the total number of publications in relation to the rest of the world. Also, one study was identified that used the total number of citations to evaluate the quality of scientific publications and to establish a link between scientific knowledge and economic growth. GDP and GDP per capita, calculated in constant prices to mitigate the influence of price fluctuations, are predominantly used as indicators of economic growth. Only one study used GDP calculated in current prices.

**Table 1.** Review of the selected empirical studies

| Author | Sample | Time frame | Variables | Method | Inference |
|---|---|---|---|---|---|
| Lee et al. (2011) | Western European and Asian countries | 1981-2007 | Total number of publications; Nominal GDP | Granger causality | PUB ⇔ GDP in Brazil; GDP => PUB in China; PUB => GDP in India; PUB <≠> GDP in Poland |
| Inglesi-Lotz & Pouris (2013) | South Africa | 1980-2008 | Publications in relation to the rest of the world; Real GDP | ARDL | PUB => GDP |
| Kim & Lee (2015) | East Asia and Latin America | 1960-2005 | Number of SCI journal articles per million people; Real GDP per capita | OLS, FE | PUB ≠> GDP |
| Inglesi-Lotz, Chang & Gupta (2015) | BRICS | 1981-2011 | Publications in relation to the rest of the world; Real GDP | Bootstap panel causality | PUB <=> GDP in India; PUB <≠> GDP in Brazil, Russia, China, South Africa |
| Ntuli et al. (2015) | 34 OECD | 1981-2011 | Total number of publications; Real GDP | Bootstrap panel causality | PUB => GDP in Mexico and Hungary; GDP => PUB in Poland; PUB <≠> GDP in Turkey, Chile, Czechia, Estonia, Slovakia |
| Odhiambo & Ntenga (2016) | South Africa | 1986-2012 | Total number of publications; Real GDP per capita | ARDL; Granger causality | PUB => GDP in the short and long run |
| Oluwatobi et al. (2018) | Sub-Saharan Africa | 1996–2012 | Scientific and Technical Journal Articles; Real GDP growth rate | System GMM | PUB ≠> GDP |
| Azmeh (2022) | 15 MENA | 2000-2017 | Total number of publications; Total number of citations; Real per capita GDP growth | System GMM | PUB - => GDP; CIT + => GDP |

*Note: + and - are signs of the impact. The arrows indicate the direction of impact. Some countries that are now classified as developed, such as Poland, Czechia, etc., were classified as developing within the time frames considered in the studies.*

*Source: Author compilation.*

The literature encompasses studies that focused on individual countries (only one or a larger number of individual countries) and countries grouped into specific regions and organizations. Depending on this, the methods used to analyze the relationship between scientific knowledge and economic growth differ. Authors who examined these phenomena in individual countries used causality tests and the Autoregressive Distributed Lag (ARDL) approach. In contrast, studies based on panel data relied on the application of the Generalized Method of Moments (GMM) and Fixed Effects (FE) regression approaches.

Authors applying causality tests state varied findings. Lee et al. (2011) reported unidirectional causality from scientific knowledge to economic growth in India, the opposite direction in China, and bidirectional causality in Brazil, while Inglesi-Lotz, Chang & Gupta (2015) found causality (bidirectional) only in India. Lee et al. (2011) and Ntuli et al. (2015) observed different results in Poland. The former indicates the absence of a causal relationship, while the latter emphasizes that there is a unidirectional causality from economic growth to scientific knowledge. One possible reason for the mismatch in results is that Lee et al. (2011) used GDP expressed in current prices, while other studies utilized GDP at constant prices. Additionally, Lee et al. (2011) used the standard Granger causality test, while the other two studies relied on a panel data approach based on Seemingly Unrelated Regressions (SUR) systems and Wald tests with country-specific bootstrap critical values. Except in Poland, Ntuli et al. (2015) provided evidence of causality from scientific knowledge to economic growth in Mexico and Hungary; however, in other countries, there is no evidence of a causal relationship.

Investigating the case of South Africa, Inglesi-Lotz & Pouris (2013) and Odhiambo & Ntenga (2016) found that there is a long-term impact of scientific output on economic growth, and the latter also identified short-run causality in the same direction. In a study conducted two years later, using different research methods, Inglesi-Lotz & Pouris (2015) found no connection between scientific output and economic growth, despite using the same set of indicators.

Kim & Lee (2015) and Oluwatobi et al. (2018) did not find a causal relationship between scientific knowledge production and economic growth in East Asia and Latin America, and in Sub-Saharan Africa. Azmeh (2022) reports that in MENA countries, scientific production leads to a decline in economic growth, while the increased quality of scientific knowledge positively influences economic growth.

Summarizing the results of the listed studies, it can be concluded that the relationship between scientific production and economic growth may be multifaceted. Most evidence supports the absence of any relationship between scientific knowledge and economic growth, followed by results confirming the existence of a relationship where scientific production influences changes in economic growth. An equal number of pieces of evidence confirm the existence of bidirectional causality and causality from economic growth to scientific production. There is the least evidence suggesting that scientific knowledge negatively impacts economic growth.

All studies, except one, focused on examining the direction of causality, without determining the magnitude and type of relationship, which is a gap that this paper aspires to fill.

## Methodology

The annual data used in this study cover the period from 1996 to 2022 for the Republic of Serbia. The variables include real GDP, as a proxy for economic growth, and the total number of published scientific papers (PUB), which is used as a measure of scientific production. Data on scientific publications are from the Scopus database (SCImago, n.d.), while data on real GDP comes from the World Development Indicators (World Bank, 2024). All data were transformed into a natural logarithm.

The econometric approach utilized in this paper is a Vector Autoregression (VAR) model. VAR model depicts the progression of multivariate time series involving $m$ numbers of endogenous variables. The behavior of these variables within the system depends on their own lagged values and the past values of all endogenous variables.

The VAR model with $p$ number of lags for $m$ number of variables can be expressed as:

$$\mathcal{Z}_t = c_0 + \sum_{i=1}^{p} \omega \mathcal{Z}_{t-i} + \pi_t \quad (1)$$

Where: $\mathcal{Z}_t$ is a (m × 1) vector of endogenous variables; $c$ is a (m × 1) vector of constants; $\omega$ is the i[th] (m × m) matrix of autoregressive parameters for $i$ = 1, 2, 3,..., $p$, and $\pi_t = (\pi_{1t},..., \pi_{kt})$ represents the (m × 1) vector of serially uncorrelated error terms.

This study applies the VAR model specified in levels, which is considered valid even in cases where the underlying variables are non-stationary, as confirmed in previous studies (Gospodinov et al., 2013; Ashley & Verbrugge, 2009; Kilian & Lütkepohl, 2017).

To analyze the dynamic behavior of the estimated bivariate VAR(p) model, we utilized the impulse response function and forecast error variance decomposition.

We selected the cumulative impulse response function to demonstrate the accumulation of disturbance effects on our variables over time. Utilizing Cholesky decomposition to orthogonalize the covariance matrix in the VAR model alleviates the issue of contemporaneous correlation among the variables. Within this methodological framework, the variables are arranged in a specific order (Sims, 1980). Given our case, the variables are arranged as follows: [GDP PUB]. By arranging the variables in this order, we proceeded from the assumption that changes in GDP in the current period may directly influence publications in the same period, while for scientific production, it takes some time for the impact on GDP to materialize. To draw appropriate conclusions based on the impulse response function, confidence intervals were calculated using a two-stage bias-adjusted approach with 1,000 bootstrap replications and 500 double-bootstrap replications. The primary advantage of this method is its explicit accommodation of the bias and skewness inherent in the small-sample distribution of the impulse response estimator (Killian, 1998).

We used forecast error variance decomposition to estimate how much of a variable's change can be attributed to its own disturbances and those from other variables within the system. The standard error distribution for the forecast error variance decomposition was derived from 1000 Monte Carlo simulations.

*Results*

The optimal lag order for the VAR model, performance indicators, residual and stability tests are given in Table 1. The lag length was determined using the Akaike information criterion (AIC)[1]. It indicates that the optimal number of lags in the model is one. Adjusted $R^2$ values imply that the model has a good fit. Residual tests confirmed that there is no evidence that residuals are not independent of each other, nor is there evidence that the variance of the residuals is not consistent across all predicted values. The stability of the VAR(1) was checked by estimating the inverse roots of the autoregressive characteristic polynomial. The results satisfy the stability conditions of the model as all the roots of the characteristic polynomial have a modulus of less than one.

[1] Kilian (1998) and Berkowitz & Kilian (2000) suggest using the AIC because it does not exhibit bias in underestimating the genuine lag order, especially in small samples. This is of great importance, particularly in the context of sampling with replacement, where the lag length is estimated twice, potentially aggravating any downward bias.

**Table 1.** Optimal lag order, performance of VAR model, residual and stability tests

| Lag selection criterion | **Value** | |
|---|---|---|
| *AIC* | -5.133 (1) | |
| Goodness of fit | **Value** | |
| *Adjusted* $R^2$ | 0.97; 0.99 | |
| Residual tests | **Value** | |
| *LM – p-value* | 0.897 | |
| *White – p-value* | 0.362 | |
| Stability test | Root | Modulus |
| | 0.948 | 0.948 |
| | 0.839 | 0.829 |

*Note: 0.97 and 0.99 are values for equations where GDP and PUB are dependent variables, respectively. () – selected number of lags.*

Table 2 presents the results of the impulse response function. The corresponding bootstrap confidence intervals are shown in the APPENDIX. The positive reaction of scientific production occurs two years after the shock in economic growth and continues throughout the entire observed period. On the other hand, scientific production does not contribute to Serbia's economic growth.

**Table 2.** Two-stage bias-adjusted bootstrap cumulative impulse response function

| *Impulse => response* | **¥** | **τ** |
|---|---|---|
| GDP => PUB | + | 2-12 |
| PUB => GDP | - | / |

*Note: ¥ is a sign of the cumulated impulse response parameters. τ – the time interval within the forecast horizon (f = 12) during which the impact has been recorded.*

The results of the forecast error variance decomposition are reported in Table 3. The initial impact of economic growth on the forecast error variance of scientific production is approximately 7%, after which it continues to increase until it reaches its peak in the 12th period, when it amounts to around 88%. Scientific knowledge explains an extremely small part of the forecast error variance of economic growth, accounting for around 3% in the long term.

**Table 3.** Forecast error variance decomposition of GDP and PUB in %

| **Variables** | **FEVD of PUB** | | | | |
|---|---|---|---|---|---|
| | **f = 1** | **f = 3** | **f = 6** | **f = 9** | **f = 12** |
| PUB | 93.35 | 62.11 | 27.69 | 15.62 | 11.55 |
| GDP | 6.65 | 37.89 | 72.32 | 84.38 | 88.45 |
| Variables | **FEVD of GDP** | | | | |
| | **f = 1** | **f = 3** | **f = 6** | **f = 9** | **f = 12** |
| PUB | 0 | 0.52 | 1.69 | 2.69 | 3.44 |
| GDP | 100 | 99.48 | 98.31 | 97.3 | 96.57 |

*Note: f – forecast horizon.*

## CONCLUSION

The study adopted the impulse response function and forecast error variance decomposition to investigate the relationship between scientific knowledge and economic growth in Serbia. The empirical estimations have shown that economic growth, expressed in real GDP, stimulates the production of scientific knowledge, measured by the total number of published scientific papers. On the other hand, generating scientific knowledge does not lead to economic growth. Similar results were reported by Lee et al. (2011), Kim & Lee (2015), Ntuli et al. (2015), Oluwatobi et al. (2018).

The economic growth that Serbia achieved in the previous period enabled it to allocate considerably more resources to the scientific sector. In response to this favorable stimulus, scientists have drastically increased their productivity in terms of the number of published scientific papers. However, what emerged as output did not contribute to a higher growth of the Serbian economy. Just as there are numerous channels through which scientific knowledge finds its way to economic growth, there are equally many reasons why it may fail to do so.

One of the potential reasons for the absence of a positive impact of scientific knowledge on economic growth is the pronounced outward migration, characterized by a predominance of highly educated people. Through emigration, individuals with advanced education carry the knowledge they have acquired during their studies at Serbian universities, thus contributing to the economic growth of the destination country. In recent years, the Serbian government has been making considerable efforts to create conditions that would primarily retain young highly educated people, but also to attract back those who already live abroad. If these efforts yield results, it will reflect on the strengthening of the innovation potential of the Serbian economy, further contributing to its more dynamic growth.

The modest level of collaboration between universities and industries in the domain of research and development can serve as an additional argument for elucidating the absence of a significant contribution of scientific knowledge in promoting economic growth. In 2023, Serbia scored 44.5/100 on this indicator, positioning it at the 65th rank out of a total of 129 countries for which data on this indicator are available (WEF, 2023). The lack of communication and consequent cooperation between the industry and the scientific sector can lead to research activities that fail to address specific industry-related problems. One possible explanation may be what experiences from developing countries show, namely that their economies rely much more on foreign than on domestic research for innovation and growth (Barrett et al., 2021). The business sector in these countries may recognize that customizing foreign knowledge to indigenous conditions is a more effective strategy for development than investing in domestic scientific production. A potential approach for addressing this issue involves increasing the number of project calls from the Science Fund of the Republic of Serbia, aimed at fostering collaboration between universities and industries.

It is also questionable to what extent policymakers rely on scientific knowledge in formulating policies. Responsibility in this segment is twofold. The practice, especially in developing countries, is that policymakers more often rely on the input from political staff and senior civil servants when formulating policies (Ogot & Onyango, 2023), than on scientists. On the other hand, there may be difficulties for policymakers to find common ground with researchers. For example, researchers may simply lack the inclination to participate in the development of public policy documents, such as strategies as fundamental documents, and specific documents such as reform programs, action plans, etc., but are primarily interested in scientific research. Accordingly, aiming for the country's economic progress, both sides should make adjustments to their current practices.

The Serbian government needs to continue investing in science and, in close collaboration with the scientific community, strive to find effective mechanisms to address the issues that hinder scientific knowledge from making its full contribution to economic prosperity.

The research has several limitations that simultaneously serve as a roadmap for future endeavors in this field in Serbia. The study employs the total number of published scientific papers across all scientific fields as an indicator of scientific knowledge. This may lead to a loss of insight into the specificity and role of various scientific fields in economic growth. Therefore, it would be desirable to examine the relationship between scientific knowledge from different scientific fields and economic growth. Furthermore, the empirical results are based on a bivariate VAR model, which means that some variables that could be related to both the production of scientific knowledge and economic growth are omitted. By including human capital and institutional environment-related variables, a more holistic picture could be provided. Additionally, alternative proxies for scientific knowledge could be used. Relying solely on the number of published papers, no distinction is made among them in terms of impact. Therefore, as an alternative, the total number of papers published in the most reputable journals (Q1 in Scopus), and the total number of citations or cited papers should be considered.

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## APPENDIX

**Table A1.** 99% Two-Stage Bias-Adjusted Bootstrap Confidence Intervals with 1,000 Bootstrap Replications and 500 Double-Bootstrap Replications

| | f = 1 | f = 2 | f = 3 | f = 4 | f = 5 | f = 6 |
|---|---|---|---|---|---|---|
| GDP => PUB | 0, 0.1 | 0, 0.2 | 0, 0.3 | 0, 0.5 | 0, 0.7 | 0, 0.9 |
| PUB => GDP | / | -0.01, 0.01 | -0.04, 0.03 | -0.07, 0.05 | -0.11, 0.07 | -0.17, 0.09 |

**Table A1.** (Continued)

| | f = 7 | f = 8 | f = 9 | f = 10 | f = 11 | f = 12 |
|---|---|---|---|---|---|---|
| GDP => PUB | 0, 1.2 | 0.1, 1.6 | 0.1, 1.9 | 0.1, 2.3 | 0.1, 2.6 | 0.1, 3 |
| PUB => GDP | -0.23, 0.11 | -0.3, 0.14 | -0.38, 0.17 | -0.47, 0.2 | -0.57, 0.23 | -0.69, 0.27 |

*Note: f – forecast horizon.*

**Table A2.** 95% Two-Stage Bias-Adjusted Bootstrap Confidence Intervals with 1,000 Bootstrap Replications and 500 Double-Bootstrap Replications

| | f = 1 | f = 2 | f = 3 | f = 4 | f = 5 | f = 6 |
|---|---|---|---|---|---|---|
| GDP => PUB | -0.01, 0.05 | 0, 0.14 | 0.03, 0.27 | 0.07, 0.42 | 0.12, 0.6 | 0.17, 0.82 |
| PUB => GDP | / | -0.01, 0.01 | -0.03, 0.02 | -0.06, 0.03 | -0.1, 0.04 | -0.15, 0.06 |

**Table A2.** (Continued)

| | f = 7 | f = 8 | f = 9 | f = 10 | f = 11 | f = 12 |
|---|---|---|---|---|---|---|
| GDP => PUB | 0.23, 1.07 | 0.3, 1.34 | 0.37, 1.61 | 0.44, 1.9 | 0.48, 2.22 | 0.54, 2.53 |
| PUB => GDP | -0.2, 0.08 | -0.27, 0.09 | -0.33, 0.11 | -0.41, 0.13 | -0.48, 0.15 | -0.56, 0.17 |

*Note: f – forecast horizon.*

**Table A3.** 90% Two-Stage Bias-Adjusted Bootstrap Confidence Intervals with 1,000 Bootstrap Replications and 500 Double-Bootstrap Replications

| | f = 1 | f = 2 | f = 3 | f = 4 | f = 5 | f = 6 |
|---|---|---|---|---|---|---|
| GDP => PUB | -0.01, 0.05 | 0.02, 0.14 | 0.05, 0.25 | 0.09, 0.4 | 0.15, 0.57 | 0.21, 0.77 |
| PUB => GDP | / | -0.01, 0.01 | -0.03, 0.02 | -0.05, 0.03 | -0.08, 0.04 | -0.12, 0.06 |

**Table A3.** (Continued)

| | f = 7 | f = 8 | f = 9 | f = 10 | f = 11 | f = 12 |
|---|---|---|---|---|---|---|
| GDP => PUB | 0.26, 0.99 | 0.33, 1.24 | 0.39, 1.5 | 0.45, 1.76 | 0.51, 2.06 | 0.56, 2.37 |
| PUB => GDP | -0.17, 0.07 | -0.21, 0.08 | -0.27, 0.1 | -0.32, 0.11 | -0.39, 0.13 | -0.46, 0.15 |

*Note: f – forecast horizon.*



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