

# **Applied Artificial Intelligence, Big Data Adoption/Avoidance in Public Relations: A Proposed Applied Optimal Macroeconomic Policy Model and Examination**

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## **ABSTRACT**

The advantages and critical challenges of Artificial Intelligence (AI) in cost savings, extreme speed, accuracy, and machine learning to take over some human's less precise performances, all and all, have come into some pronounced stressful and reasonable ambitions as well as fears of the conflicts with the potential as well as some actual damages that AI has imposed and can further impose on society in an enormous number of major events of our lives. Both the topic and the corresponding controversies are appalling. The authors analyze AI through its implications and their own developed applied VAR theoretical model in economic policy and public relations, where massive data are possible to be compiled, labeled, and categorized into segments, and inserted into their proposed VAR econometric model, and Impulse Response Functions, rendering some statistically significant results.

**Keywords:** Artificial Intelligence, Applied Economic Policy, Public Relations, Applied AI Model, VAR Models

## **INTRODUCTION: PUBLIC RELATIONS AND AI**

In this section we have clarified what Public Relations are and focus on some advantages and disadvantages of PR that could be addressed. Also, we have highlighted some - but not all - PR relevant variables, as needed for building AI models that can provide AI analytical contemplations. Given the essence of AI, involving massive data to be marked, labeled, categorized, and organized into the process of machine learning, one would be in need of measurability of distinct variables, either continuous or discrete. Hence, among other cautious practices in applying AI to any field, such as public relations, what one would have to do is define and apply variables that can characterize various aspects of public relations. Redefine public relations through more measurable variables, processes, and functions, as well as

degrees of efficacy and efficiency involved in optimal public relations, given the existing, if not controllable, constraints.

Obviously, to make an AI model on public-relations, some key measurable variables would be needed. Forbes Communication Council (September 14, 2021) recommended 14 Key variables (metrics) to measure the efficacy of a selected PR campaign.

The authors will abbreviate each of them for the theoretical AI model application purposes.

- HCH: How Consumers Heard About the Company
- ACG: Actions Signifying Completed Goals
- CT: Click-Throughs
- IM: Impressions
- CR: Corporate Reputation
- TA: Traffic Analytics
- YSV: Your Share of Voice
- OO: Outputs and Outcomes
- TM: Long-Term, Short-Term and Midterm Metrics
- S: Sales
- DTW: Direct Traffic to the Website
- MPT: Message Pull-Through
- DMO: The Domain Authority of Media Outlets
- MIV: Media Impact Value.

According to Melanie Marten (December 29, 2021), "The role of public relations in 2022 is to foster the authenticity that so many crave in an economy that appears to operate at surface level." p.1.

Obviously, one can think of public relations, inclusive of internal, external, and global public relations, which have even included marketing in several studies for companies and organizations. Assuming that selling an idea, philosophy, and/or goods and services, would all be relevant, then marketing could fit well in the public relations task. As such, the variables to be considered for the design of appropriate AI models would go far beyond the above 14 variables. Costs, sizes of organizations, assets, liabilities, regulations, legal constraints, personnel, etc., would be just a few to think of. Which variables would be most relevant depends on our VAR techniques (Vector Autoregressive models (Hamzaee, 1987) to be analyzed in our upcoming AI application section.

Marten also addresses purpose, responsibility, value, and action of public relations as an integral and cohesive assertion to be extensively and emphatically transpired to the public. Something bigger and more significant than just the bottom line, such as the values of brands, companies, entrepreneurs, and environmental concerns, need to be communicated. Public relations strategies need to include stakeholders as an entity beyond just the investing groups. Grunig (2005, p. 779) developed a theoretical framework, a "situational theory of publics" in which publics are not supposed to be treated equally. There are conceptually "non-publics," who would not face the problem, "latent publics," facing the problem but not recognize it as

such, “aware publics,” who recognize the problem, “active and passive publics,” who may be different on participating in doing something or not much about the problem. The first three mainly defined variables, explaining why some publics get active in certain circumstances, are proposed to reflect levels of involvement, problem identification, and constraint recognition. Artificial Intelligence (AI) is defined by several researchers and practitioners in various, yet cohesive, ways. Nils J. Nilsson AI, the Stanford University’s Kumagai, Professor Emeritus of Computer Science Engineering (Mind Data, 2018) offered: “Artificial intelligence is that activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment.”

As in prediction of the Impacts of AI on 2023 evolutions, some of what Express Computer (2022) highlighted as key areas, include the following:

- Intelligent automation, and its impacts on the business processes and information technology adopted, will benefit all industries.
- The emergence of cyber assistants is critical in confronting the growing cyber-security risks and threats.
- The growth of interest in the usage and concept of Foundation Models, which would enable businesses not to worry too much about the lack of a specific behavioral model to their data, and the ability to use and reuse AI. This is just a new wave in the AI landscape.
- Treatment of problematic data privacy in healthcare, financial fields, and the high-cost data these days through usage of synthetic data, created by computers, in which some computer-generated examples that enable the augmentation and/or replacement of the real data for making the appropriate decisions.
- More reliance on artificial intelligence for transparency and traceability of data and cleaner environment.

As to a resolution to the challenges of the necessity of massively huge data for an effective establishment of AI in any reliable predictions, MIT Sloan School of Management’s Rama Ramakrishnan, Professor of the Practice, has articulated in his “How to Build Good AI Solutions When Data Is Scarce” (Winter 2023). He offers a logical and less expensive method of utilizing some already established and utilized models that can be comfortably applied to businesses with similar and related problems and activities. While he has clarified how a good reliable AI modeling would work through time consuming labor of extremely big data management experts in their classification, accumulation, and labeling data in most cases, he asserts that: “Data-efficient AI techniques are emerging – and that means you don’t always need large volumes of labeled data to train AI systems based on neural networks.” (p. 48)

Ada (2022), in its “Top 6 AI trends in 2023,” proposed that in 2022 there were some warnings and predictions about the events of 2023, as summarized below:

- It is expected that in 2023 some jobs will be eliminated, and some new ones will replace the fading ones.
- It is expected that AI will be democratized.
- The increasing growth of comparative intelligence, especially repeated ones will facilitate the improvement of experiences.

- AI will be adopted and implemented more and more in almost all industries and domains.

Hence, business and organizations must use such experiences and evolutions to create the needed competitive advantage in the future.

Ransbotham, Sam, et al. (November 2021) in *MIT Sloan Management Review*, proposed a cohesive approach to AI's contribution to cultural benefits within an enterprise. As demonstrated in Figure 1 (extrapolated here by Hamzaee and Salimi), that approach would entangle the usage of AI, while enhancing a team culture and the task of effectiveness uplifting. All that, as suggested by the authors, would necessitate a comprehensive improvement plan, through which trust, understanding, collective learning, clarity of roles, collaborations, morale boosting, efficiency, and decision quality would be simultaneously improved.

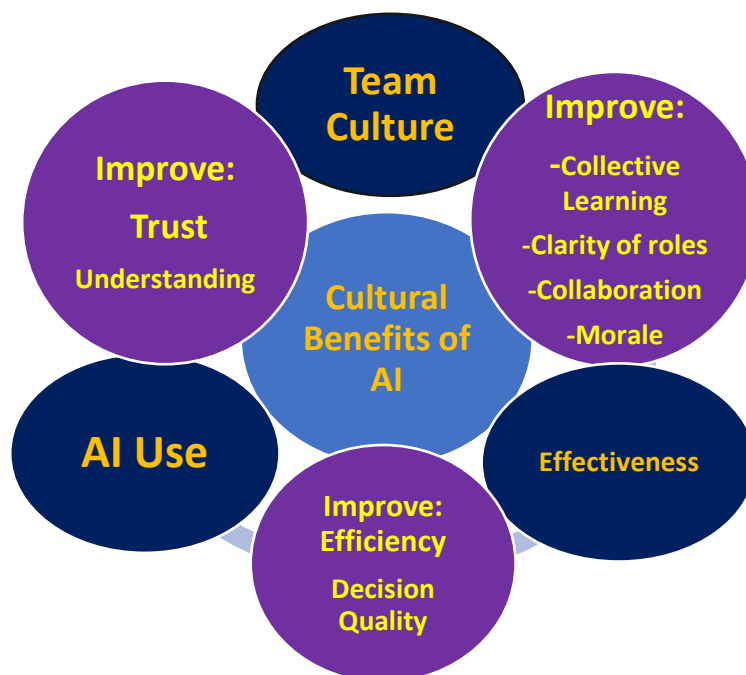


**Figure 1: Cultural Benefits of Artificial Intelligence**

Source: Authors' Revision for Some Extrapolation of Ransbotham, Sam, et al. (November 2021). "Cultural Benefits of Artificial Intelligence in the Enterprise." *MIT Sloan Management Review*.

AI in public relations, according to Keith Peterson (October 21, 2022), would help in recognizing the identities of individuals, the business names, outputs, services, etc., that would all exist in images. It is also possible to register and identify the visual communications related to one's business, as well as compiling information about good and bad customers' experiences. As to limitations and challenges, Cade Metz (May 1, 2023) reported more than one thousand tech leaders, researchers, and AI pundits submitted an open group-signed warning letter, calling for a moratorium against the AI development blends' "profound risks to society and humanity." That letter was signed by 27,000 by the beginning of May 2023.

Meanwhile, Brooking Institute, in its Governance Studies, provided a report (C. F. Kerry, February 10, 2020) alongside a group of studies that were focused on identification of key governance and AI issues, followed by some proposed corresponding policy resolutions in highlighting some complex emerging technologies. The report begins as: "Our world is undergoing an information Big Bang, in which the universe of data doubles every two years and quintillions of bytes of data are generated every day." p. 1. (A quintillion is a 1 followed by 30 zeroes).

He suggested that volume, variety, and velocity of data, altogether, would make the impact of data much stronger. With such rapid growth of data and evolution of AI, the ability to use personal information in intruding on privacy domains would boost up the speed and power of personal information analyses.

### A PROPOSED THEORETICAL AI MODEL FOR MACROECONOMIC POLICY APPLICATION

To study the impact of excessive government budget deficits on the economy, Hamzaee (1987) presented the following systems of simultaneous structural equations, the first 2 representing the behavioral functions of demand for and supply of loanable funds, where all the variables are defined in the subsequent pages.

$$DF = a_0 - a_1i - a_2i^* + a_3dy + a_4dy^* - a_5dp - a_6dp^* + a_7DEF + a_8DEF^* + a_9de \quad (1)$$

$$SF = b_0 + b_1i + b_2i^* + b_3dy + b_4dy^* + b_5dp + b_6dp^* + b_7dMB + b_8dMB^* + b_9de \quad (2)$$

Then taking the percentage growth or change in the money base (high-powered money), which are the monetary policy variables (dMB, and dMB\*) for the domestic as well as

$$dMB = c_0 + c_1i + c_2dy - c_3dp - c_4dRES \quad (3)$$

$$dMB^* = k_0 + k_1i^* + k_2dy^* - k_3dp^* - k_4dRES^* \quad (4)$$

$$dRES = l_0 - l_1dp + l_2dp^* + l_3de - l_4dy + l_5dy^* + l_6i - l_7i^* \quad (5)$$

$$dRES = l_0 - l_1dp + l_2dp^* + l_3de - l_4dy + l_5dy^* + l_6i - l_7i^* \quad (6)$$

$$dRES = l_0 - l_1dp + l_2dp^* + l_3de - l_4dy + l_5dy^* + l_6i - l_7i^* \quad (7)$$

$$dRES = l_0 - dRES = l_0 - l_1dp + l_2dp^* + l_3de - l_4dy + l_5dy^* + l_6i - l_7i^* \quad (8)$$

$$dRES^* = m_0 + m_1dp - m_2dp^* - m_3de + m_4dy - m_5dy^* - m_6i + m_7i^* \quad (9)$$

$$I = f(i^*, dy, dy^*, dp, dp^*, DEFA, DEFA^*, de) \quad (10)$$

Assuming that all those relationships are linear, Hamzaee (1987) derived the following reduced form equation for interest rate estimation through OLSQ method. The time period of 1966, I – 1983, IV (applying quarterly data) has been applied. The source of data was International

Financial Statistics (IFS). Moreover, the interest rate data included the 3-month interbank rates from Morgan Trust Company, Morgan International Data.

$$i = k_1 i_{-1} + k_2 i_{-2} + k_3 GNP_{-1} + k_4 GNP_{-2} + k_5 DEFA_{-1} + k_6 DEFA_{-2} + e^i \quad (11)$$

$$GNP = \beta_1 i_{-1} + \beta_2 i_{-2} + \beta_3 GNP_{-1} + \beta_4 GNP_{-2} + \beta_5 DEFA_{-1} + \beta_6 DEFA_{-2} + e^{GNP} \quad (12)$$

$$DEFA = \partial_1 i_{-1} + \partial_2 i_{-2} + \partial_3 GNP_{-1} + \partial_4 GNP_{-2} + \partial_5 DEFA_{-1} + \partial_6 DEFA_{-2} + e^{DEFA} \quad (13)$$

Taking the first lag of each of the last three equations, the following three will be derived:

$$i_{-1} = A_1 i_{-2} + A_2 i_{-3} + A_3 GNP_{-2} + A_4 GNP_{-3} + A_5 DEFA_{-2} + A_6 DEFA_{-3} + e^{i_{-1}} \quad (14)$$

$$GNP_{-1} = B_1 i_{-2} + B_2 i_{-3} + B_3 GNP_{-2} + B_4 GNP_{-3} + B_5 DEFA_{-2} + B_6 DEFA_{-3} + e^{GNP_{-1}} \quad (15)$$

$$DEFA_{-1} = C_1 i_{-2} + C_2 i_{-3} + C_3 GNP_{-2} + C_4 GNP_{-3} + C_5 DEFA_{-2} + C_6 DEFA_{-3} + e^{DEFA_{-1}} \quad (16)$$

Application of artificial intelligence in the monetary policy would involve huge categorical data testing through a model of impulse response functions, in which categories of data for various economic conditions, such as recessionary, expansionary, and inflationary eras could be appropriately considered. One may get into the estimated functions that have been constructed through massive data behavior, as opposed to any traditional models of monetary policy formulation, where data are only used to test a predetermined mathematical model. Yet as indicated by Rama Ramakrishnan in MIT Sloan Management Review (Winter 2023, pp. 48-53), the traditional models can be applied in case the massive data inclusion would be prohibitive in countries or cases, where data availability might be a challenge.

### Description of Variables

- $i$  = domestic real interest rate in each country
- $de$  = percentage change in the foreign exchange rate in each country
- $dy$  = percentage change in the real GDP in each country
- $dp$  = inflation rate in each country
- $DEFA$  = seasonally adjusted real budget deficits for each country.

Similar variables with asterisk represent those of foreign country, which is treated to be the United States for each country in this study. So, it will be clear that:

- $i^*$  = domestic real interest rate in the U.S.
- $dy^*$  = percentage change in the real GDP in the U.S.
- $dp^*$  = inflation rate in the U.S.
- $DEFA^*$  = seasonally adjusted real budget deficits for the U.S. government.
- $H$  = the stock of high-powered money (money base)
- $RES$  = the stock of foreign reserves
- $dp^e$  = expected inflation rate
- $de^e$  = expected change in the foreign exchange rate

- $e$  = the foreign exchange rate
- $dH$  = the percentage change in the stock of high-powered money
- $dRES$  = percentage change in the stock of foreign reserves holdings.

Also,  $H^*$ ,  $RES^*$ ,  $dp^*$ ,  $dH^*$ , and  $dRES^*$  are similar variables for the foreign country (the U.S.A.). The variable  $i$ , which has been based on the Inter Bank Rates (with three months of duration) data, is calculated through:

$$i_T = r_T - dp_{T+1},$$

where:

- $i_T$  = real interest rates (3-month Inter Bank Rates) in period  $T$
- $r_T$  = nominal interest rates (3-month Inter Bank Rates) in period  $T$
- $dp_{T+1}$  = Future inflation rated (one period later)

Assuming expectations are made rationally,

$$dp^e_{T+1} = dp_{T+1} + v_{T+1}$$

Assuming rational expectation,  $v_{T+1}$ , the error term in period  $T+1$ , is a white noise, and  $E(v_{T+1}) = 0$ . In that case, the actual and expected rates of inflation one period ahead would be the same, which means:  $dp^e_{T+1} = dp_{T+1}$

## THE EMPIRICAL ANALYSES OF FINDINGS

The source of adopted data for variable  $i$  has been Morgan Guaranty Trust Company. For all other variables, International Financial Statistics has been the provider of the IFS data tape, made by the Bureau of Economics and Business Administration at Arizona State University. The time frame designated for the estimation (Hamzaee, 1987), was 1966, I – 1983, IV (quarterly data). Any other data are adopted from the corresponding data lines of IFS (International Financial Statistics).

### Impulse Response Functions

All possible variables that may influence each public relations and/or economic policy formulation models are inserted into many regression equations of each given variable, regressed on several lagged values of itself as well as those of other relevant hypothetically possible variables.

Among many impulse response functions that the pertinent autoregressive policy functions would necessitate to adopt, six countries' Impulse response functions for  $i$  (a country's real interest rate) with respect to a DEFA shock (a one standard-deviation change, or shock, in a country's own seasonally adjusted budget deficits) are depicted in Figure 2. Imagine how AI would come into exciting considerations with the already compiled, marked, entitled, and registered massive data. Potentially, only if our substantiated 9-variable response functions are adopted, there would be 362,880 possible autoregressive functions (9 variables' permutations, 9 by 9 variables) for the maximal number of groups of option to consider. The calculation is simply from the following well-known arithmetic formula:

$$A_9^9 = \frac{9!}{(9-9)!} = 362,880$$

One may wonder why one should even discuss that potential number of impulse response functions. Simply because the ordering of the variables would render different levels of statistical significance. In the literature it is an understanding that earlier appearance of each variable, as contrasted with the other ones, implies a relatively stronger explanatory power for that variable (Hamzaee, 1987, p. 87; Litterman and Weiss, 1984).

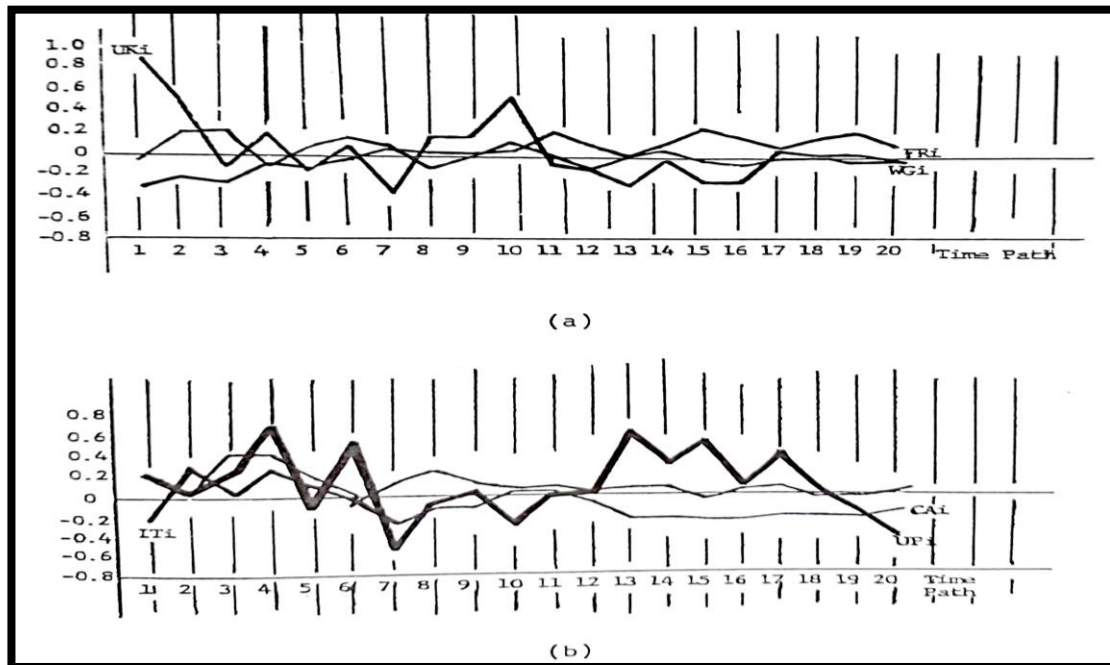


**Figure 2: Responses of Each Country's Interest Rates to One Standard-Deviation Shock in Its Own Budget Deficits Focused Countries: U.S.A., West Germany (WG), France (FR), United Kingdom (UK), Canada (CA), Italy (IT), Japan (JP)**

In Figure 3, each country's interest rate responses to one standard-deviation shock in the U.S. budget deficits are demonstrated.

#### **AN EXTENDED APPLICATION OF ARTIFICIAL INTELLIGENCE IN PUBLIC RELATIONS**

If the focal AI application model would be on public relations of any kind, then we are going to apply time series data and a procedure like the economic policy application, yet with different variables, applicable to PR. One may identify and use or even insert the 14 or much more variables in this segment, while applying the same procedures (as used in the economic policymaking model) to get into predictions and relationships among the adopted variables. As the applied PR campaign model, the process of PR-AI campaign model, would necessitate the right variables. As a simpler example, the following variables, as defined previously, would be our adopted variables: HCH, ACG, CT, IM, CR, TA, YSV, OO, TM, S, DTW, MPT, DMO, MIV. This by itself, would be a separate VAR-focused model, pretty much like the first one above.

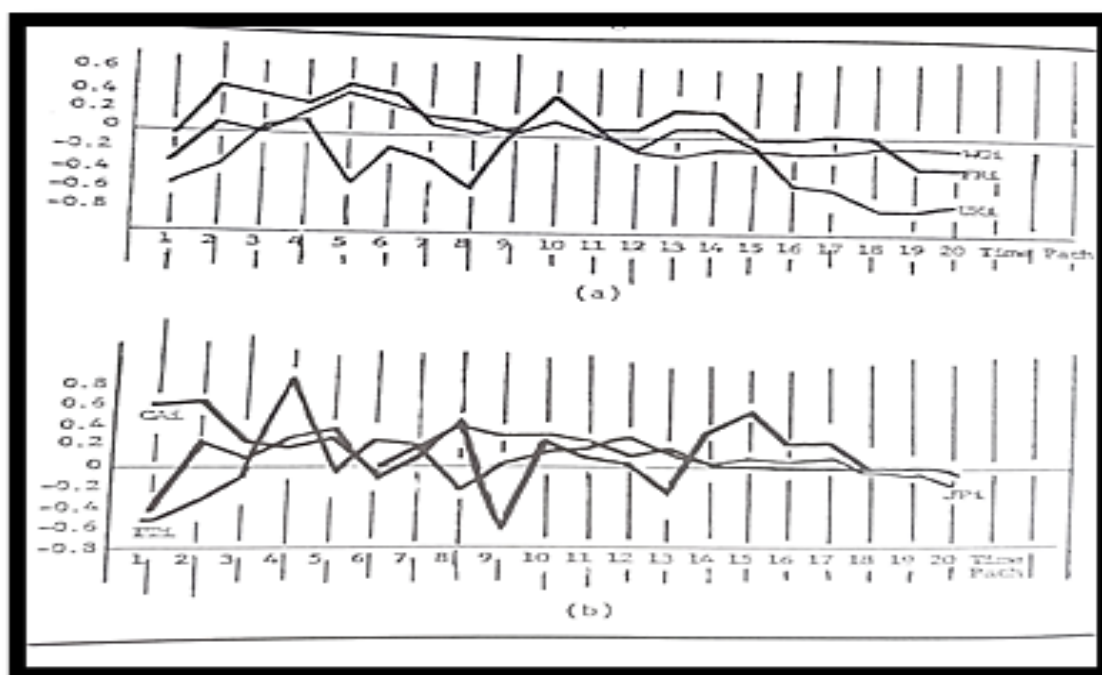


**Figure 3: Responses of Each Country's Interest Rate to One Standard-Deviation Shock in the U.S. Budget Deficits Focused Countries: U.S.A., West Germany (WG), France (FR), United Kingdom (UK), Canada (CA), Italy (IT), Japan (JP)**

## CONCLUSIONS AND SUMMARY

It must be noted that the illustrated functions are drawn for the estimated responses at the end of each quarter over five years in Figure 2 and Figure 3. The significance of the shapes of the graphs is highlighted in two important statistical characteristics:

1. Applying Friedman's (1983) characterization, the stability of the relationships between each variable (taken separately) and lagged values of all variables in the system, including the variable itself is dominant in magnitudes (the height if each graph at various quarters of the 5 years).
2. As Porter and Offenbacher (1983) suggested, a relationship stability necessitates some smooth response patterns that would fade away and converge around 0 values over a time path.
3. Hence, our adopted VAR technique would be especially for times series and models, in which lagged values of the corresponding variables are relevant and mandatory to include.

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