



# Application of LLM Causal Inference about Prediction of Korean Economic Growth and The Characteristics Analysis of Causal Inference

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**Abstract:** LLM (large language model) families have a big powerful as one of many AI models that has the potential to revolutionize research and scientific, including general purposes. That is, current LLMs assist not only general purposes but also domains such as scientific research and engineering, the prediction of economic trend, health diagnosis, and policy decision. It also enables graphic works, data analysis, coding workplace. However, unfortunately, the characteristics and application possibilities of the several structure of LLMs did not work through study on application areas. Current LLMs as well as GAI (General AI) models respond to question of user by re-organization these data after learn vast data (Text, Number, Image). That is, inference algorithms of current LLMs do not have the cause on why this task happen. To recover this problem, causal inference is quite important as core technology. The causal inference by structures of LLM such as standard LLM, offline causal RL with backdoor adjustment (Confounder control), offline causal model with explicit confounder, and backdoor adjustment intervention must fully study through step by step of case because these responses is quite different from structures. This paper offers how to apply and what structures of LLMs is useful for user case, depending structure of LLM causal inference. The learning capabilities of LLM is quite different from causal inference model of LLM on application. To research on purpose, what is the core approaches by causal inference model, what is the tuned parameter and structure, and how they obtain practical data for application. These methodologies of LLM causal inference on application should be provided through research and simulation of real-world LLM applications across the target. The prediction of Korea economic growth based on the causal inference of LLM should be performed through a review of current S. Korean situation and data on purpose because we do not fully study and effectively use by the causal inference of LLM for research target. This paper shows the prediction about GDP growth of S. Korea, China, and world, and stock market trend as example, and compares these graphs to see the results by the causal inference of LLM.

**Keywords:** LLM, ChatGPT, Causal Inference, Korean GDP growth prediction, Korean Stock market prediction.

## I. INTRODUCTION

The function of LLM has a powerful trained information but it has also much mistake results for user because of data problems. The generative artificial intelligence (GAI) such as LLM, ChatGPT, and application has significant success for application using the language recognition, image, audio model, and etc. However, because of the complexity of causal inference, the causal inference problems of the large language model (LLM) remain issue in research. The causal problems are difficult to describe in natural language model that the LLM can understand accurately [43-52].

Many have been studying to evaluate the pure causal reasoning abilities of the LLM and obtain their pure causal reasoning. Additionally, some researchers believe that the LLM is merely “parrots” without reasoning really. The causal datasets are typically tabular data, while large models excel in handling natural language data. Therefore, we must draw causal inference based on the data analysis for the LLM. However, LLM could not directly utilize data and this structural problem hinders the inference of LLM from data. This limitation restricts the ability of LLM to solve causal problems effectively.

To recover the difficult problems in improving the causal ability of LLM, there are many researches by using several methods such as a causal problem modeling, causal graphic modeling, and others [48]. They propose a causal agent framework by guiding LLM to invoke causal tools using the variable level, edge level, causal graph level, and causal effect level [1].

This method focuses on the agent’s judgment and understanding of correlations. They propose that the edge level focuses on the agent’s examination of causal relationships between variables, and the causal graph level focuses on the agent’s

ability to generate causal graphs, and the causal effect level focuses on the agent's estimation of causal effects between variables for quantitative expression.

In case of graph, they use graphic representation approach to show inference structure. Basically, the goal of causal inference is to figure out a causal relationship and the lack between two sets of variables, causes and outcomes [1-5].

What we are going to decide how we determine whether any particular variable is a cause or an outcome. It is very important to determine what an outcome variable is done based on our subjective interest as our determination. For example, a typical outcome variable in medical treatment is a disease-free survival rate within some years since diagnosis or treatment because of natural variable of quantity of medicine. However, it is much less clear how to determine which variable should be considered a cause. For instance, in the classical example of 'smoking causes lung cancer', what makes us choose 'whether someone smokes cigarettes' as a cause variable rather than 'a mutation in a particular gene'? It becomes even more mind-boggling once we realize that this choice of 'smoking' as a cause meant that we decided to ignore many variables, such as 'whether a farmer decided to grow tobacco'.

It is thus an important, if not the most important, job for practitioners of causal inference to convincingly argue why some variables are included and others were omitted. They also must argue why some of the included variables are considered potential causes and why they chose a particular variable as an outcome. This process can be thought of as defining a small universe in which causal inference must be performed. There are many different ways to define causal inference such as a probabilistic graphical model, a corresponding structural causal model, and others. To use LLM for econometrics practically, how to phrase the prompt to lead different parameter to estimates in applications of finance and political economy with coefficients varying in magnitude, sign, and significance. Especially, for mentioning Korean economic growth, which growth will increase more market including image generation of art or drawing, movie, news, u-tube market, and its application. It means the role of LLM is bigger and bigger and will be super generative and will influence economic growth factors [43, 52]. Therefore, this paper provides material for prediction research and motivation to research econometrics. For that, this paper reviews the many materials to build strategy for studying causal inference and to predict the GDP growth in Korean economy.

## II. REVIEW OF CAUSAL INFERENCE FOR PREDICTION RESEARCH OF KOREAN ECONOMETRIC GROWTH

### A. Graphical Model Causal Inference

This method uses probabilistic graphical models in order to describe their statistical and causal relationships among random variables. A probabilistic graphical model is also mentioned as a Bayesian graphical model of graph  $G = (V, E)$ , where  $V$  is a set of vertices/nodes and  $E$  is a set of directed edges. Each node  $v \in V$  corresponds to a random variable, and each edge  $e = (v_s, v_e)$  represents the dependence of  $v_e$  on  $v_s$ . For each node  $v \in V$ , they define a probability distribution  $p_v(v|pa(v))$  over the variable conditioned on all the parent nodes. Furthermore, this prevents us from properly defining a conditional probability  $p_{v'}(v'|v)$ , since:

$$p_{v'}(v'|v) = \frac{p_{v',v}(v'|v)}{p_v(v)}. \quad (1)$$

### B. Structural Causal Inferences

This implies that they can always flip the arrow of the edge between  $v$  and  $v'$  without transforming the joint as well as conditional probabilities. Herein, we can want to use a slightly different way to express the same generative process by a given probability graphical model  $G = (V, E)$ :

$$v \leftarrow f_v(pa(v), E_v). \quad (2)$$

### C. Confounders, Colliders and Mediators

Here, this paper mentions the relationship between the first two variables and an observed confounder for the following probabilistic graphical model, which has  $w$ , shaded and observed.



Fig 1. An observed confounder, an unobserved cofounder, an observed collider, an unobserved collider,



Fig 2. An observed mediator, an unobserved mediator

**D. Example of Active Causal Inference**

When we have a graph G and use variable a, y, and x. The covariate x is a confounder and it may or may not be observed, depending on the situation. A corresponding mention to this graph is vaccination:’

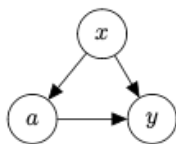


Fig 3. Active causal inference

- a is the individual vaccination;
- y has the individual been infected by the target infectious disease with symptoms;
- x is the underlying health condition of the individual.

The edge  $x \rightarrow a$  is understandable since we often cannot vaccinate an individual with an active underlying health condition. The edge  $x \rightarrow y$  is also understandable since healthy individuals may contract the disease without any symptoms. , while immunocompromised individuals for instance may show a greater degree of symptoms with a higher chance. The edge  $a \rightarrow y$  is also reasonable, as the vaccine must have been developed with the target infectious disease as its goal.

In other words, this graph encodes our structural prior about vaccination. The causal inference refers to figuring out the degree of the causal effect of a on y, with this graph that encodes the reasonable data generating process.

**E. Passive Causal Inference**

When we have an inference, we often face with confounders because of spurious variables. As we use already collected data, we can often avoid the issues arising from actively experimentation, even though we are now faced with another set of challenges, such as the existence of spurious correlations arising from various unobserved confounders that affected the choice of actions earlier.

Here, we consider an alternative approach to RCT (Randomized Controlled Trials) to rely on existing data to infer the causal relationship between the action and outcome by using such as inverse probability weighting method, matching method (we can achieve a similar outcome by manipulating data itself.), instrumental variable method (when confounders were not collected).

**F. Predicting in the IID (Independent and Identically Distributed) Setting**

Statistical model describes a superficial content of reality as it is only required to model related issues for a given set of input examples X and target labels Y. We may describe in approximating  $P(Y|X)$  to answer questions, such as “what is the probability of heart failure when certain blood pressure of a patient is measured?” In this case, these questions can be provably answered by observing a sufficiently large amount of IID data from  $P(X, Y)$ .

**G. Predicting Under Distribution Shifts**

In real situation, interventional problems cannot have a guarantee because of distribution by intervention. For instance, interventions may affect both the value of a subset of causal variables and their relations. For example, “would fewer

people smoke if cigarettes were more socially stigmatized?” As interventions change the joint distribution of the variables of interest, classical statistical learning guarantees.

However, learning about interventions may allow training predictive models that are robust against the changes in distribution that naturally happen in the real world. The robustness of deep neural networks has recently been interested in research topic related to causal inference by learning method.

### H. Answering Counterfactual Questions

Counterfactual problems involve reasoning about why things happened, imagining the consequences of different actions in hindsight, and determining which actions would have achieved the desired outcome.

### I. Causal Model and Inference

The machine learning approaches have produced several products with machine learning applications to big data problems: we have massive amounts of data like large-scale human labeling; we use high-capacity machine learning systems (i.e., complex function classes with many adjustable parameters); we employ high-performance computing systems. The latter can be guaranteed by the construction of a task, including training and test set (e.g., image recognition using benchmark data sets). Alternatively, problems can be made approximately IID.

### J. Structural Causal Models

Let us consider a graph as shown in Fig. 2. Each node has a set of observables (or variables)  $X_1, \dots, X_n$ . We assume that each observable is the result of an assignment;

$$X_i := f_i(\mathbf{PA}_i, U_i) \quad (i=1, \dots, n) \quad (3)$$

using a deterministic function  $f_i$  depending on  $X_i$ 's parents in the graph (denoted by  $\mathbf{PA}_i$ ) and on an unexplained random variable  $U_i$ .

Mathematically, the observables are random variables. The direct edges in the graph of Fig. 2 represent direct causation since the parents are connected to  $X_i$  by directed edges.

The structure of CGM (Causal Graphical Model) The graph structure along with the joint independence of the noises implies a canonical factorization of the joint distribution entailed by (3) into causal conditionals that we refer to as the causal (or disentangled) factorization

$$P(X_1, \dots, X_n) = \prod_{i=1}^n P(X_i | X_{i+1}, \dots, X_n). \quad (4)$$

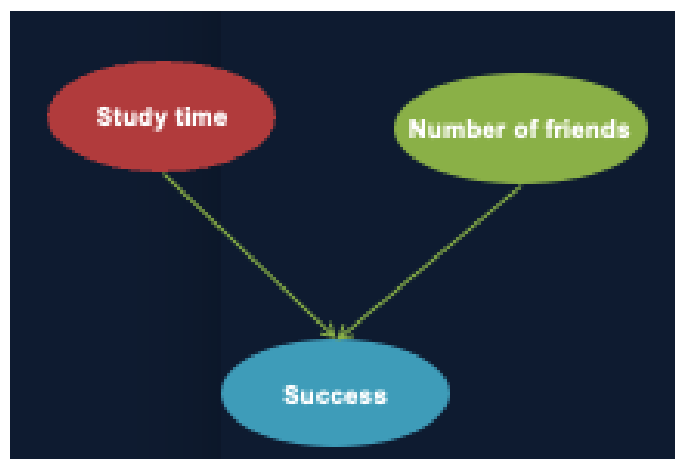


Fig 4. The basic of causal graphical model

Statistical Model (Colorful Illustration): Data → Probability Distribution

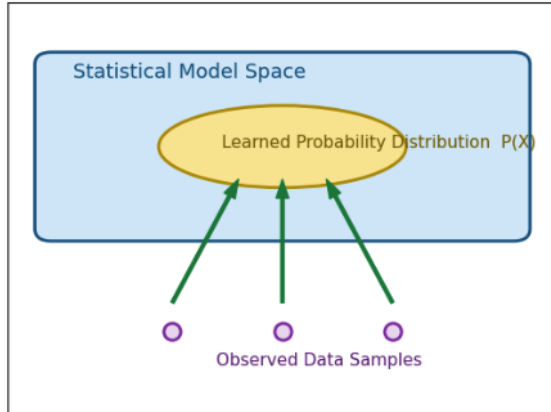


Fig 5 (a). The example of statistical model

3D Statistical Model: Data → Probability Distribution

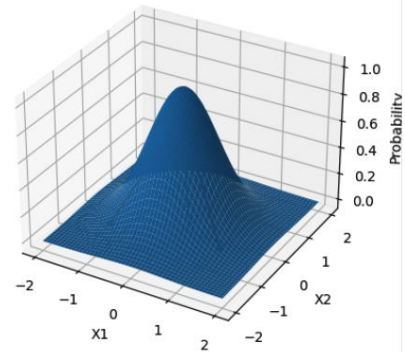


Fig 5 (b). The 3D of statistical model

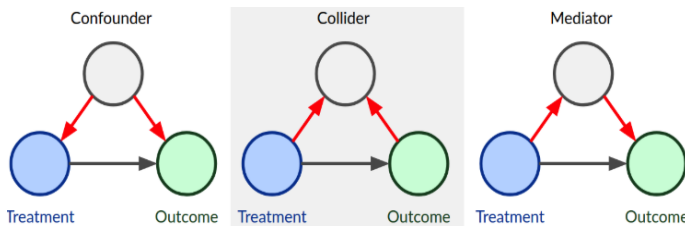


Fig 6 (a). The basic of causal inference model

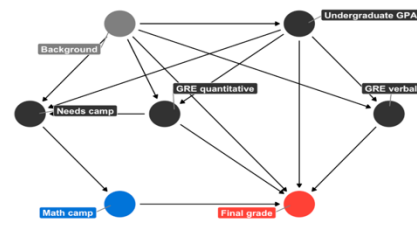


Fig 6 (b). The causal inference model (Confounding)

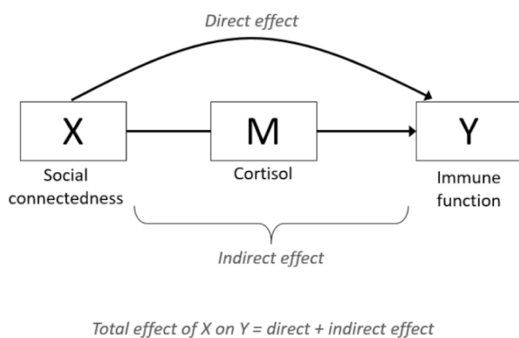


Fig 6 (c). The causal inference model (Mediation)

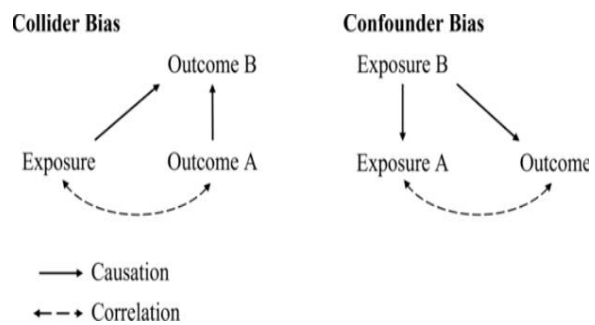


Fig 6 (d). The causal inference model (Collider)

Fig 5 shows the statistical distribution and Fig 6 illustrates the basic, Cofounding, Mediation, Collider of causal inference model with graph (Fig 5. and Fig 6. draw by ChatGPT).

**K. Independent Causal Mechanism**

This factorization according to the causal graph is always possible when  $U_i$  is independent, but we will now consider an additional notion of independence relating the factors in (4) to one another.

Whenever we perceive an object, our brain assumes that the object and the mechanism by which the information contained in its light reaches our brain are independent. We can violate this by looking at the object from an accidental viewpoint, which can give rise to optical illusions [188]. The above independence assumption is useful because, in practice, it holds most of the time, and our brain, thus, relies on objects being independent of our vantage point and the illumination. Likewise, there should not be accidental coincidences, such as 3-D structures lining up in 2-D, or shadow boundaries coinciding with texture boundaries. In vision research, this is called the generic viewpoint assumption.

L. Off-Line Reinforcement Learning

The success of deep learning methods in the case of supervised learning can be largely attributed to the availability of large data sets and methods that can scale to large amounts of data. In the case of RL, collecting large amounts of high-fidelity diverse data from scratch can be expensive and, hence, becomes a bottle-neck.

Off-line RL [73], [150] tries to address this concern by learning a policy from a fixed data set of trajectories, without requiring any experimental or interventional data (i.e., without any interaction with the environment). The effective use of observational data (or logged data) may make real-world RL more practical by incorporating diverse prior experiences. To succeed at it, an agent should be able to infer the consequence of different sets of actions compared to those seen during training (i.e., the actions in the logged data), which essentially makes it a counterfactual inference problem. The distribution mismatch between the current policy and the policy that was used to collect off-line data makes off-line RL challenging as this requires us to move well beyond the assumption of independently and identically distributed data. Incorporating invariances by factorizing knowledge in terms of ICMs can help make progress toward the off-line RL setting.

III. PREDICTION OF KOREAN ECONOMETRIC GROWTH BY LLM MODEL

In this section, this paper shows ChatGPT response to experiment the performance of ChatGPT. The purpose of this experiment is to see how it is correct response about our question for research. Fig 7 shows the prediction of S. Korean GDP growth with Standard LLM and our target is to make:  $P(Y_{t+1}|X_t)$ .

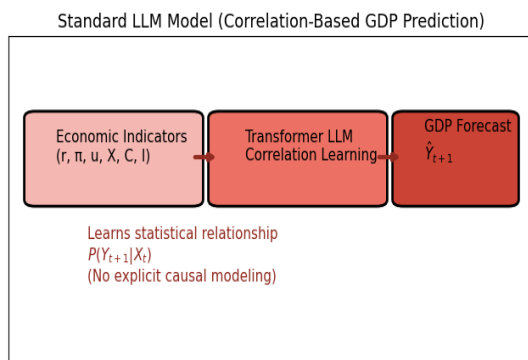


Fig 7 (a). Standard LLM model for the prediction

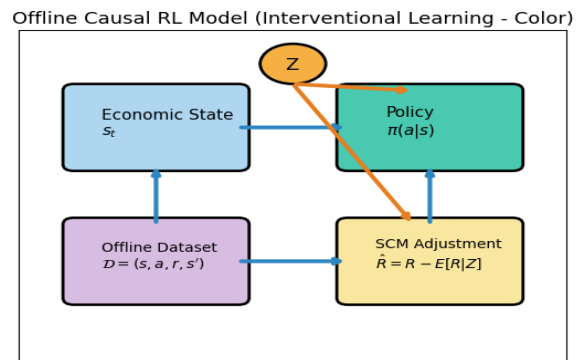


Fig 7 (b). Offline causal RL model for the prediction

Here in standard model, we can obtain process; put data economic indicators --> Transformer LLM --> GDP forecast. Mathematically,  $\hat{Y} = f_x(X_t)$  and learn  $P(Y_{t+1}|X_t)$  for prediction of S. Korean GDP growth.

On the other hand, offline causal RL model (intervention learning) is shown in Fig 7(b).

Here,

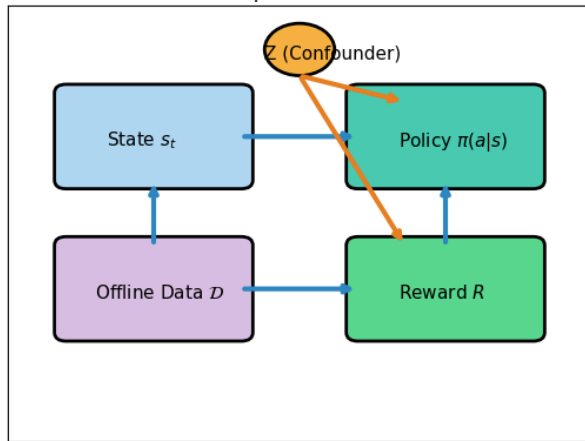
1.  $\mathcal{D} \rightarrow s_t$
2.  $s_t \rightarrow \pi(a|s)$
3.  $\mathcal{D} \rightarrow \text{SCM}$
4.  $\text{SCM} \rightarrow \pi$
5.  $Z \rightarrow \pi, Z \rightarrow \text{SCM}$

Our final target is to make:

$$\pi^* = \arg \max_{\pi} \mathbb{E} \left[ \sum_t \gamma^t \hat{R}_t \mid do(\pi) \right]$$

That is, it is interventional optimization of policy.

Offline Causal RL with Explicit Confounder Z (Color Version)



State  $s_t$ : current state, Policy  $\pi(a|s)$ : Policy, Reward  $R$ : result/reward, Offline data:  $\mathcal{D}$ , log data,  $Z$ : Confounder.

Blue Line: main line

- $\mathcal{D} \rightarrow s_t$
- $s_t \rightarrow \pi(a|s)$
- $\pi \rightarrow R$
- $\mathcal{D} \rightarrow R$

Orange Line: Confounding path

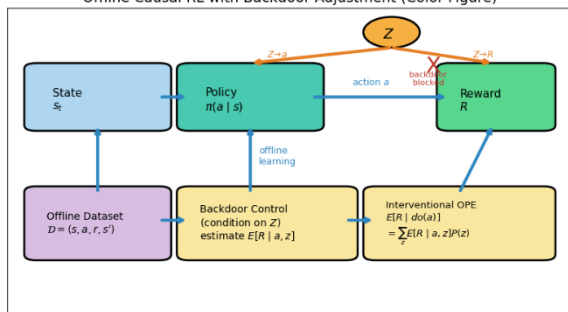
- $Z \rightarrow \pi(a|s)$
- $Z \rightarrow R$

The results are biased because of these two paths.

Fig 7 (c). Offline causal RL with explicit confounder z

Here, we need to obtain  $E[R | do(a)]$  in observer state. Therefore, SCM/Backdoor adjustment (This response is mentioned by ChatGPT. So, we need confirm it is true or not).

Offline Causal RL with Backdoor Adjustment (Color Figure)



Here, it is causal path is  $S_t \rightarrow \pi(a|s) \rightarrow R$  (It is what we want to obtain) and backdoor paths is  $\pi(a|s) \leftarrow Z \rightarrow R$ . The block path of Fig (d) is  $\pi(a|s) \rightarrow SCM \text{ adjustment}, SCM \rightarrow R$ . Fig 8 shows the prediction of S. Korea, China, and world by standard LLM, offline causal RL, and offline causal with explicit made by ChatGPT. This experiment is to confirm and compare graph made by each model of ChatGPT.

Fig 9 illustrates the prediction of stock market by each method (standard LLM, Offcausal RL, Offcausal model with explicit, and Backdoor adjustment: Cofounder control) as mentioned in

Fig 7 (d). Offline causal RL with backdoor it is correct.

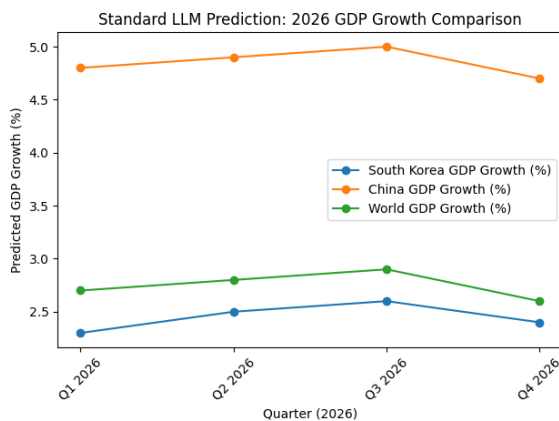


Fig 8 (a). The prediction of GDP by standard LLM

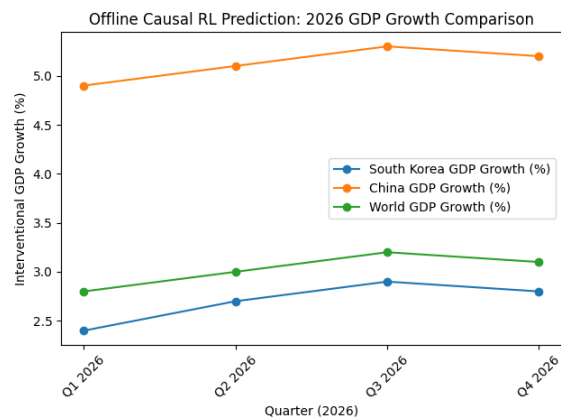
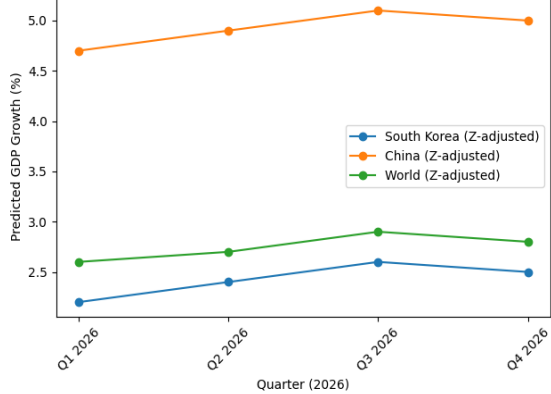


Fig 8 (b). The prediction of GDP by offline causal RL

Offline Causal Model with Explicit Confounder (Z): 2026 GDP Growth Comparison



Backdoor Adjustment (Confounder Control): 2026 GDP Growth Comparison

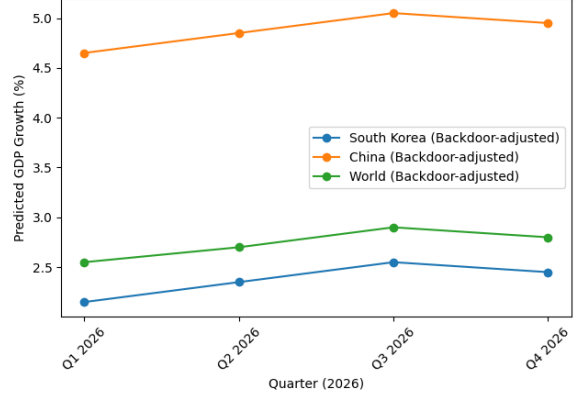
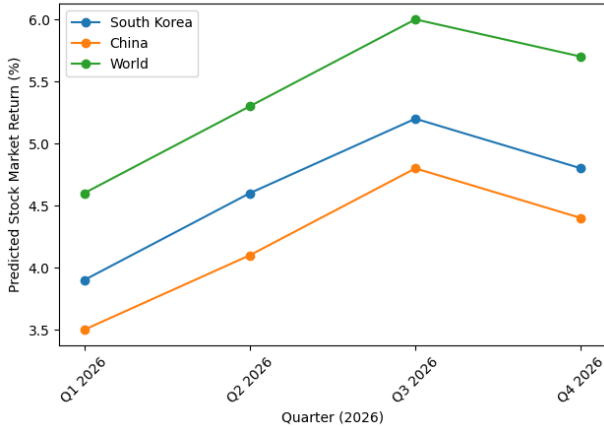


Fig 8 (c). The prediction of GDP by offline causal with explicit

Fig 8 (d). The prediction of GDP by backdoor adjustment

Standard LLM Model: 2026 Stock Market Prediction Comparison



Offline Causal (Explicit Confounder Model): 2026 Stock Market Prediction

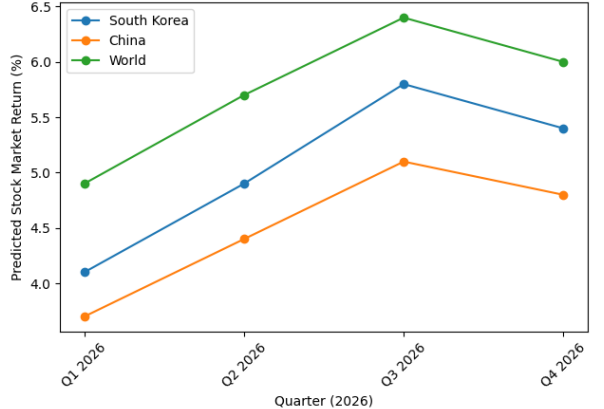
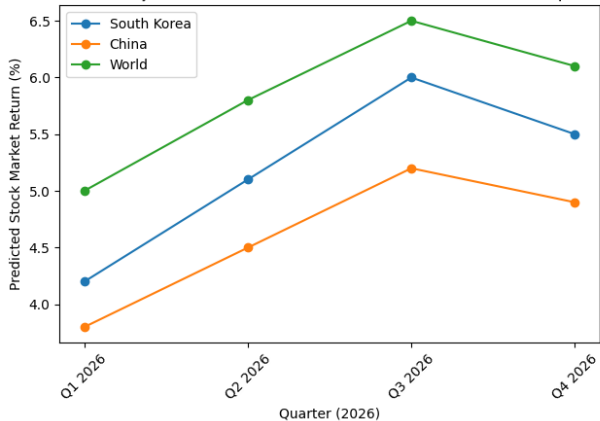


Fig 9 (a). The stock prediction by Standard LLM

Fig 9 (b). The stock prediction of GDP by offline causal

Backdoor Adjustment Model: 2026 Stock Market Prediction Comparison



2026 Stock Market Index Prediction Comparison

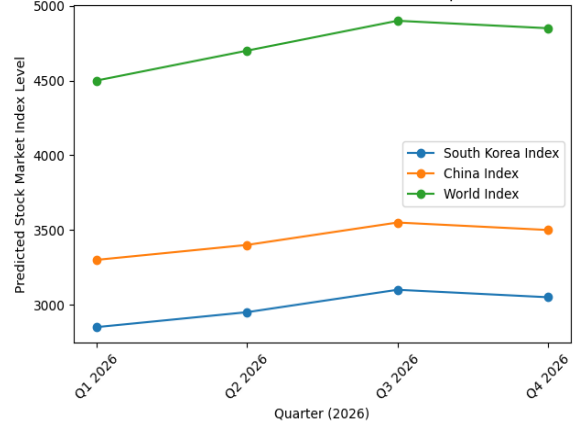


Fig 9 (c). The stock prediction by backdoor adjustment model

Fig 9 (d). The stock prediction of GDP by standard LLM

These figures from Fig. 4 to Fig. 9 is made by ChatGPT to see how it is correct and true for study. Therefore, I do not believe all these Figures are true of correct. We need to review more detail to see those.

#### IV. DISCUSSION

The key importance of Large Language Models (LLMs) is trained on vast datasets and provides a new milestone for addressing research and search. LLMs has a wide range of knowledge, common sense, specialized domains, and advanced reasoning abilities about fact and data. Leveraging LLMs for causal discovery has gained traction due to their ability to replicate expert knowledge in a cost-effective and accessible manner. Many recent materials have explored LLM-based approaches for causal discovery, focusing on meta-data and knowledge-driven reasoning similar to human experts. However, these methods largely treat LLMs as single-agent systems, which may limit their reasoning capabilities, especially when handling complex causal relationships or large-scale, dense causal graphs. When we want to compare the structure of LLM how it is, we review the results of learning through Fig. 8 and Fig. 9.

To illustrate the implications of these results and its relation to these models, we can select key research challenges and topics.

#### V. CONCLUSION

This paper provides the several materials to give the study motivation and the strategy of Korean econometric by LLM (K-EcoLLM). Nowadays, the possibility of LLM application is wider and deeper in science and engineering as well as general purpose because of model ability such as text reading, image recognition function, translation ability of image and text, including general topics. Herein, applications of LLM increases more for economic and science. Many research materials predict that LLM will change higher labour market, K-12 education, and others. It means the role of LLM is bigger and bigger and will be super generative and influence economic growth factors. Therefore, this paper offers materials for study structure of LLM. As we can see Fig. 7, there are many structures of LLM and the learning results are different like Fig. 8 and Fig 9., through the prediction of GDP growth and stock market (S. Korean economic growth, China, and world) by structures of several LLM.

Unfortunately, we cannot use the LLM that developed for the general purpose because the situation of economic growth is so complex and dynamically change in real-time. As shown in Fig. 8 and Fig. 9, LLM (Large language model) have a strong necessary for study. However, unfortunately, all structure of was done out of S. Korea.

That is why they should offer application of LLM design, training, adaptation, evaluation, and application for both researchers and practitioners for Korean econometric research. Unfortunately, in Korea, there are few application materials of several LLMs in econometrics. To accomplish this, this paper provides the necessary material for user that they are interested in econometrics by application of LLM. The research of LLM should mention the evolution of language models, core approaches, PEFT (Parameter-Efficient Fine-tuning), and practical data for application through research process for the several structures of LLM models. The methodology of LLM application depending LLM models should be mentioned the survey of real-world LLM applications across the scientific area, engineering field, healthcare issues, and creative topic and method through a review of current Korean environment situation.

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