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# Research on the impact of global economic policy uncertainty on manufacturing: Evidence from China, the United States, and the European Union

**Yifei Li [1], Yuhang Bai [2,*]**

[1] Business School, Zhengzhou University, Zhengzhou 450001, China
[2] School of Economics and Management, Beijing Forestry University, Beijing 100083, China.
* Correspondence: yuhangbai2022@163.com (Y. Bai)

**Abstract:** This study employs the time-varying parameter vector autoregressive (TVP-VAR) model to examine how global economic policy uncertainty (GEPU) affects manufacturing from March 2008 to March 2023. The empirical results show that the effects of GEPU are time varying. Its short-term effects on Chinese manufacturing are slightly greater than its medium- and long-term effects, whereas its medium- and long-term effects on manufacturing in the United States (US) and European Union (EU) are significantly greater than its short-term effects. The impact of European debt crisis, China-US trade war and Russia-Ukraine conflict on the EU manufacturing is higher than that of China and the US, and the impact of COVID-19 pandemic on China's manufacturing is much smaller than that of the US and the EU; thus, Chinese manufacturing has a greater capacity for risk mitigation than US and EU manufacturing.

**Keywords:** global economic policy uncertainty; manufacturing; PMI; TVP-VAR

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## 1. Introduction

The manufacturing industry is an important component of the national economy. As the engine of economic growth, the manufacturing sector is indispensable in increasing employment, advancing technology, and boosting exports [1,2]. Researchers typically use the ratio of manufacturing added value to GDP to assess the contribution of manufacturing to the national economy and use the manufacturing Purchasing Manager Index (PMI) to measure and forecast the trend of manufacturing [3,4]. The manufacturing PMI originated in the United States, this index, which is one of the most widely used in the world to track macroeconomic trends, is compiled from the results of a monthly survey of corporate purchasing managers; it is calculated using data from the manufacturing sector's new orders, inventory, production, supplier delivery and employment domains; it offers effective warning and prediction capabilities[5],is also considered the "leading indicator of overall economic activity in the US ". The manufacturing boom line, which indicates the strength of the manufacturing industry, is often regarded by researchers as the manufacturing PMI of 50; when the PMI is higher than 50, the manufacturing sector of the economy is experiencing prosperity; when the PMI is lower than 50, the manufacturing sector is experiencing a recession. As a result, market economy players can use the manufacturing PMI as a useful decision-making tool [3,4].

The outlook toward the world economy is gloomy, global economic policy uncertainty is rising while manufacturing purchasing manager index is declining. Global economic policy uncertainty (GEPU) evolves from economic policy uncertainty(EPU), economic policy uncertainty (EPU) refers to the fact that in the process of economic policy adjustment, the primary body involved in economic production cannot predict changes in economic policy, thereby leading to a series of unpredictable economic risks[6].The modification of economic policies, such as monetary, fiscal, and national security policies, has a significant impact on the development of EPU. Following Baker [6], Davis [7] weighted the national EPU indexes of 21 major industrial countries according to the proportion of each country's gross domestic product (GDP) and then developed the global economic policy uncertainty (GEPU) method. Global economic recovery has been hampered by numerous uncertainties since the 2008 financial crisis [8], unexpected events led to a rapid rise in global economic policy uncertainty, while the manufacturing purchasing manager index has dropped sharply. For instance, from March 2018 to June 2019, the China-US trade war led to an increase in GEPU from 162.22 to 335.35, in an increase of 2.07 times, meanwhile, China's manufacturing PMI dropped from 51.5 to 49.4, a drop of 4.82%; the US manufacturing PMI dropped from 59.3 to 51.7, a drop of 12.82%; and the EU manufacturing PMI dropped from 56.6 to 47.6, a drop of 15.9%. Based on that, it is worth studying the impact of GEPU on the manufacturing sectors of major economies.

China, the United States, and European Union are the drivers of world manufacturing. According to the data from the World Bank (WB), in 2021, the GDP in China, the US and the EU was 17.73 trillion dollars, 23.32 trillion dollars and 17.09 trillion dollars, respectively, and the world GDP was 96.53 trillion dollars, the three economies account for 60.23% of world GDP; the added value of manufacturing in China, the US, and the EU was 4.87 trillion dollars , 2.50 trillion dollars, and 2.53 trillion dollars, respectively, and the added value of world manufacturing was 16.05 trillion dollars, the three economies account for 61.68% of the added value of world manufacturing, their vigorous development depends on a stable political and economic environment. China is transitioning from low-end to mid-to-high-end manufacturing, especially in the green energy such as photovoltaics, lithium batteries, wind energy, and electric vehicle manufacturing sectors. The US and the EU have long monopolized high value-added manufacturing in sectors such as those concerning automobiles, biomedicine, semiconductors, and materials. Although China, the US, and the EU are the world's three main pillars, its manufacturing industry still struggles with a number of issues brought on by GEPU, in the context of the decoupling of China and the US, the COVID-19 pandemic, and Russia–Ukraine conflict, since 2018, manufacturing in China suffers from the outflow of low-end manufacturing and slowing economic growth rate; manufacturing in the US is subject to labor shortages and high inflation ; manufacturing in the EU endures doubling energy prices . The increase in GEPU led to severe fluctuations in the manufacturing PMI of major global economies, casting a shadow over the global economic recovery.

Few studies have examined the link between global economic policy uncertainty and manufacturing, nor have they examined the similarities and differences in examining the problems brought on by GEPU on manufacturing in different economies within the same dimension. Understanding how GEPU is affecting the manufacturing sector can help the government alter its industrial policies and give investors decision-making guidelines. In order to determine how GEPU would affect the manufacturing, empirical research is required.

## 2. Literature Review

The existing research on economic policy uncertainty (EPU) primarily concentrates on the fields of financial market volatility and economic growth. It should be clarified that EPU exhibits countercyclicality, and its impact effect increases with the expansion of economic output scale, the degree of positive and negative impact on actual economic output varies by country [9]. The relationship between economic policy uncertainty and US stock returns, Arouri [10] claimed that is nonlinear, with a decrease in stock returns with an increase in EPU. EPU not only lowers stock returns but also exacerbates volatility in exchange rates. For instance, Nilavongse [11] utilized a structural vector autoregressive model to claim that fluctuations in the pound exchange rate are mostly caused by changes in UK economic policies, but uncertainty in US economic policies causes a drop in industrial production capacity in the UK, and the UK's Brexit vote caused the pound to decline significantly; Chen[12]employed quantile regression to discover that the influence of China's EPU on its exchange rate fluctuations is asymmetric and heterogeneous, and that the impact of the US EPU on China's exchange rate fluctuations rises with the quantile, while Hong Kong EPU has no effect on China's exchange rate fluctuations, Japan and the EU EPU have an inverted U-shaped relationship with China's exchange rate changes. Bank lending gives the economy a boost, while high EPU discourages investors from making credit investments. Nguyen[13], who used the generalized least squares method to evaluate the data, claims that there is a negative correlation between bank lending and EPU, with the latter having a larger negative influence on industrialized nations than emerging ones; Phan [14], who studied EPU and financial stability data from 23 countries worldwide from 1996 to 2016, does not appear to share Nguyen's [12] point of view, Phan [13] discovered that EPU has a greater detrimental effect on financial stability for nations with smaller financial systems, lax regulation, and high levels of competition. It is clear from the foregoing that the significant changes in EPU have a negative impact on economic growth, investment, and consumption, high uncertainty causes investment to decline more than output or consumption does [15], However, tools like Bitcoin can be used to hedge EPU risks. Demir [16] discovered that EPU can forecast Bitcoin returns, even though Bitcoin returns and EPU have a negative correlation, however, quantile regression research results reveal that the return rates of Bitcoin and EPU are significant at lower and lower quantile, and investors can use Bitcoin to hedging EPU risks, according to Fang [17], EPU has a negative impact when compared to Bitcoin bonds, but a positive impact when compared to Bitcoin-related commodities and equities. As a result, bitcoin can be used in hedging operations to lower the risk of EPU.

Research on how EPU affects carbon emissions has increased along with the growth of the low-carbon economy. Pirgaip [18] found that there is a one-way causal relationship between Japan's EPU on energy consumption, the US and Germany's EPU on carbon emissions, and Canada's EPU on energy consumption and carbon emissions. In other words, an increase in carbon emissions will result from increased energy use, EPU, and economic expansion. Moreover, he urged the G7 nations to consider the detrimental effects of EPU on energy conservation and emission reduction, as well as to reduce carbon dioxide emissions and consumption. Huang[19]demonstrated that outward direct investment, per capita GDP, and EPU all contribute to rising greenhouse gas emissions; Adams [20]examined how countries with high geopolitical risk emitted carbon, the study's findings demonstrate not only that rising energy consumption raises carbon emissions but also that there is a strong negative correlation between rising EPU and carbon emissions, suggesting that rising EPU will make it more difficult for nations with high geopolitical risks to maintain environmental sustainability. Additionally, some academics examine how EPU affects energy consumption by starting with renewable energy, EPU has an impact on the utilization of renewable energy, Nakhli's[21] study, and there is only a one-way causative relationship between US electricity consumption and EPU, as opposed to a two-way causal relationship between carbon emissions and EPU, and when creating environmental policies, EPU should be taken into account. As research continues to advance, more academics are concentrating on the connection between EPU and carbon emissions at the micro level, Yu[22]asserts that China's provincial EPU have a significant positive impact on the intensity of carbon emissions and that industrial firms are more willing to employ cheap fossil fuels to satisfy the EPUs' continually increasing standards; Luo[23]discovered a strong inverse relationship between the unpredictability of economic policy and green innovation in businesses, while this relationship can be weakened by increasing the transparency of carbon information; Khan[24]found that carbon emissions in China, South Korea, Singapore, and Japan are positively correlated with trade, GDP, and EPU, and the environmental quality of East Asian economies is enhanced by FDI and the use of renewable energy sources.

The research focus of global economic policy uncertainty (GEPU) is comparable to that of EPU and it examines how GEPU has affected global financial and commodity future markets. Yu[25]contended that as China's integration into the global economy progresses, the unpredictability of global economic policy is one of the main causes of and a substantial contributor to the volatility of the Chinese stock market; Miao[26]was of the opinion that the addition of a regime switching model can increase the precision with which GEPU forecasts changes in the US stock market; Qin [27]thought that gold can be utilized as a hedge against GEPU risks during economic downturns, gold prices fluctuate as a result of GEPU, but GEPU is also impacted by gold prices both favorably and unfavorably; Shao[28]claims that there is an imbalanced relationship between GEPU and the transmission of global grain prices, with the effects of GEPU being more beneficial for soybean prices than maize and wheat prices.

Although prior studies discuss whether and how GEPU affects finance, economic growth, and carbon emissions, they mainly use linear models that cannot capture the time-varying characteristics of the impact caused by GEPU. Therefore, there remain some areas of improvement and innovation in the study of GEPU. First, we switch our research focus from the impact of GEPU on finance to the impact on manufacturing. Second, because 61.68% of the value added in manufacturing worldwide is produced by China, the US, and the EU, understanding how GEPU affects manufacturing in these major economies will help us understand how manufacturing will react if the risk is raised. Third, comparing the impact characteristics of GEPU on manufacturing in China, the US, and the EU will help us verify the anti-risk capabilities of manufacturing in different economies, furthermore, provide reference for capital transfer in the manufacturing industry. Fourth, we discuss the effects of GEPU on manufacturing by employing the time-varying parameter vector autoregressive (TVP-VAR) model and compare the effects of GEPU during critical events, such as the EU debt crisis, China–US trade war, COVID-19 pandemic, and Russia–Ukraine conflict on manufacturing in China, the US, and the EU.

## 3. Materials and Methods

### 3.1. *Time-Varying Parameter Vector Autoregressive*

We utilize the TVP-VAR model to analyze the impact of GEPU on manufacturing. Sims[29] first suggested the standard VAR model, which is frequently employed in the analysis of numerous temporal variables. A multivariate time series regression is used to build the VAR model by regressing all current period variables on several lagged terms of all variables. This allows the model to be used to derive correlations between the variables. The classic VAR model is written as:

$$y_t = A^{-1}c + B_1 y_{t-1} + \cdots + B_s y_{t-s} + A^{-1}\sum \varepsilon_t \qquad (1.)$$

$$t = s+1, s+2, \ldots, n\,;\ \varepsilon_t \sim N(0,1)$$

where $y_t$ is a $k \times 1$ dimensional vector on the observable variables; $s$ denotes the lag period; $B_i = A^{-1}F_i$, A and $F_i$ are k × k coefficient matrices. Assume that A is a lower triangular matrix:

$$A = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \cdots & a_{k,k-1} & 1 \end{pmatrix}$$

And:

$$\sum = \begin{pmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_k \end{pmatrix}$$

where $\sigma_1$ is the standard deviation of the structural shock. The elements in $B_i$ are combined into a $k^2 s \times 1$ dimensional column vector β. In $X_t = I_n \otimes [1, y'_{t-1}, \ldots, y'_{t-1}]$, ⊗ is the Kronecker product. Then equation (1) can be rewritten as:

$$y_t = X_t \beta + A^{-1}\sum \varepsilon_t \qquad (2.)$$

The underlying pattern of change is not entirely captured by typical VAR models since none of the factors in the VAR assumptions are time-varying. In order to solve this issue, Primiceri[30] developed the TVP-VAR model, which builds on the VAR model by adding time-varying parameters and stochastic fluctuations. This model can coefficients follow shock fluctuations; thus, we describe the time-varying relationship among variables from a dynamic perspective. According to Primiceri[30] and Nakajima[31], the specific form of the model is as follows:

$$y_t = X'_t \beta_t + A_t^{-1} \sum_t \varepsilon_t, \qquad t = s+1, \ldots, n \tag{3.}$$

The coefficient vector $\beta_t$, the parameter matrix $A_t$ and $\sum_t$ in the model all vary with time. To model the time-varying process of these variables, let $\alpha_t$ be the stacked vector of row vectors of non-zero, non-1 elements of matrix $A_t$. For the three vectors $\beta_t$ , $\alpha_t$, and $h_t$ , they obey the following random walk process:

$$\begin{cases} \beta_{t+1} = \beta_t + \mu_{\beta_t} \\ \alpha_{t+1} = \alpha_t + \mu_{\alpha_t}, \\ h_{t+1} = \gamma_t + \mu_{h_t} \end{cases}$$

where $h_{jt} = \log(\sigma_{jt})^2$ and $h_t = (h_{1t}, \ldots, h_{kt})'$. Assume that $\varepsilon_t, \mu_{\beta_t}, \mu_{\alpha_t}, \mu_{\gamma_t}$ follows:

$$\begin{bmatrix} \varepsilon_t \\ \mu_{\beta_t} \\ \mu_{\alpha_t} \\ \mu_{h_t} \end{bmatrix} \sim N\left[0, \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \sum_\beta & 0 & 0 \\ 0 & 0 & \sum_\alpha & 0 \\ 0 & 0 & 0 & \sum_h \end{bmatrix}\right]$$

where $\beta_{s+1} \sim N(\mu_{\beta_0}, \Sigma_{\beta_0})$, $a_{s+1} \sim N(\mu_{a_0}, \Sigma_{a_0})$, $h_{s+1} \sim N(\mu_{h_0}, \Sigma_{h_0})$.It is assumed that shocks to these time-varying parameters are independent of $\beta_t$、$\alpha_t$、$h_t$ and that $\Sigma_\beta, \Sigma_{\alpha_0}, and\ \Sigma_{\gamma_0}$ are diagonal matrices. The addition of a stochastic wandering process to the model allows it to capture a reasonable amount of potential short-term structural changes in the data, making it appropriate for analysis of the monthly data utilized in this research.

Here, $y_t = (Gepu_t, CN_t, US_t, EU_t)$, and $Gepu_t, CN_t, US_t$, and $EU_t$ represent the GEPU, China's PMI, the US' PMI, and the EU's PMI, respectively, in period $t$. The time-varying parameter model follows a random walk process:

This study applies MATLAB to estimate the model through the Bayesian method and uses the Markov chain Monte Carlo simulation to make a posterior estimation of parameters.

### *3.2 Data Source and Description*

Our study empirically analyzes the effects of GEPU on manufacturing using monthly data from March 2008 to March 2023. Global economic policy uncertainty (GEPU) is used to investigate the impact of external factors on different economies[27], and manufacturing Purchasing Manager Index (PMI) covers crucial information of manufacturing sector[5]. Therefore, we use GEPU to represent uncertainty; China's PMI (CN), the US' PMI (US), and the EU's PMI (EU) are used to represent manufacturing sector. GEPU and PMI are obtained from the EPU1 and PMI2 websites.

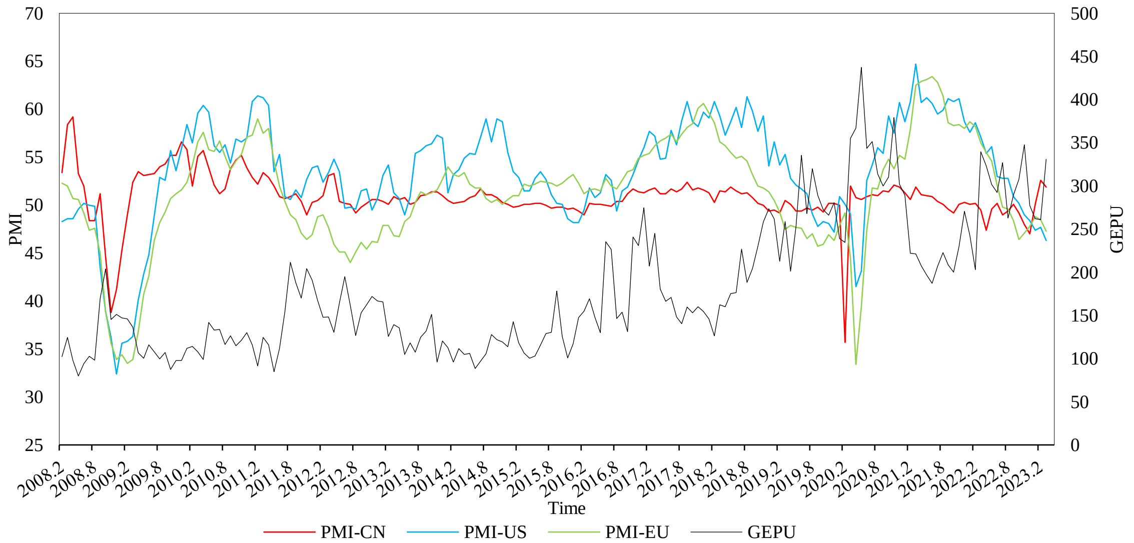
1 Economic Policy Uncertainty Index

2 Investing.com - Stock Market Quotes & Financial News

Manufacturing PMIs in China, the US and the EU have experienced significant swings as a result of global economic policy uncertainty. Overall, Figure 1 demonstrates that when the GEPU varies significantly, the manufacturing PMIs for China, the US, and the EU similarly vary, and that the impact of the GEPU on the PMI may have a time-lag effect. In terms of stages, first, the European debt crisis in December 2009 led to a rise in GEPU, and the PMIs of China, the US and the EU fluctuated sharply above 50, but they still maintained a certain upward trend, the reason may be that the manufacturing is getting rid of the 2008 financial crisis, while the impact of the European debt crisis is more reflected in the debt area; but the European debt crisis has caused a decline in the EU manufacturing PMI that is significantly greater than that of China and the US, as the sovereign credit crisis in Greece, Spain, Italy and other European nations has gotten worse. Second, the China-US trade war began in March 2018, which led to a spike in GEPU and a steep decline in the PMIs of the US and the EU, but just a minor change in China's manufacturing PMI. Then, in December 2019, the COVID-19 outbreak caused a sharp increase in GEPU, which peaked in May 2020 at 437.31; at the same time, the manufacturing PMIs of China, the US, and the EU all experienced significant fluctuations, the shutdown had a substantial negative influence on China’s manufacturing PMI, which fell to 35.7 and indicated a severe recession, while the manufacturing PMIs for the US and the EU also dropped below 50. Finally, the Russia-Ukraine crisis caused the GEPU, which had been in a downward trend, to sharply surge again in February 2022, this led to the manufacturing PMIs of the US and the EU collapsing quickly and steeply, whereas China's manufacturing PMI only experienced a very modest fall.

Figure 1 Status of changes in GEPU and PMI

Descriptive analysis of logarithmic variables. Table 1 reports the descriptive statistics of the sample variables. In terms of mean and standard deviation, except for the GEPU, the PMI mean levels across economies are ranked from high to low by the US, the EU and China; and the volatility levels are ranked from high to low by the EU, the US and China.




The skewness coefficient of the GEPU is positive in comparison to the other indicators' negative skewness, it shows that a greater proportion of GEPU data samples are above the mean whereas a greater proportion of PMI data samples are below the mean. The kurtosis of the indicators shows a peak below 3 for the GEPU, but a peak above 3 for the PMI of China, the US, and the EU, especially China's PMI, which has a peak above 10, it shows that the probability density distribution curve for the PMI for the three economies, except for the GEPU, has a steeper form, particularly for the PMI for China.

Table 1 Descriptive Statistics

| Variable | N | Mean | Std | Min | Max | skewness | kurtosis |
|---|---|---|---|---|---|---|---|
| GEPU | 175 | 175.985 | 5397.808 | 79.854 | 437.238 | 0.911 | 2.990 |
| CN | 175 | 50.873 | 6.180 | 35.7 | 59.2 | -1.678 | 14.59 |
| US | 175 | 53.638 | 30.708 | 32.4 | 64.7 | -1.050 | 4.866 |
| EU | 175 | 51.415 | 33.290 | 33.4 | 63.4 | -0.729 | 4.350 |

## 4. Results

### *4.1Empirical Testing*

First, logarithmic the variables and test the stability. In Table 2, the Phillips & Perron and Augmented Dickey–Fuller tests indicate that the LNCN and LNGEPU are stationary series, whereas the LNUS and LNEU are first-order difference stationary series, meet the requirements for further building TVP-VAR model.

Table 2 Stationary Test

| Variable | ADF test statistic | Prob.* | PP test statistic | Prob.* |
|---|---|---|---|---|
| LNCN | -5.690536 | 0.0000 | -6.913705 | 0.0000 |
| ΔLNCN | -10.051150 | 0.0000 | -22.548040 | 0.0000 |
| LNEU | -2.719834 | 0.0727 | -2.861398 | 0.0521 |
| ΔLNEU | -9.276044 | 0.0000 | -9.279564 | 0.0000 |
| LNUS | -2.749221 | 0.0679 | -3.053498 | 0.0321 |
| ΔLNUS | -12.331430 | 0.0000 | -12.340520 | 0.0000 |
| LNGEPU | -4.965404 | 0.0004 | -4.842320 | 0.0006 |
| ΔLNGEPU | -16.295340 | 0.0000 | -19.865730 | 0.0000 |

Note: *MacKinnon (1996) one-sided p-values; PP test: Phillips & Perron test; ADF test:Augmented Dickey–Fullerton test.

Second, determine the lag order of the time series. According to the minimum criteria of SC and AIC, it can be seen from table 3 that the lag order of the model is three.

Table 3 Lag Length Criteria

| Lag | LogL | LR | FPE | AIC | SC | HQ |
|---|---|---|---|---|---|---|
| 1 | 986.3979 | NA | 1.29e-10 | -11.41645 | -11.12131 | -11.29668 |
| 2 | 1028.416 | 80.08187 | 9.53e-11 | -11.72254 | -11.13228 | -11.48302 |
| 3 | 1074.669 | 85.97497 | 6.68e-11* | -12.07845* | -11.19305* | -11.71917* |
| 4 | 1088.187 | 24.49297 | 6.89e-11 | -12.04926 | -10.86873 | -11.57022 |
| 5 | 1103.391 | 26.83033* | 6.97e-11 | -12.0399 | -10.56423 | -11.44109 |

Note: * indicates lag order selected by the criterion. LR: sequential modified LR test statistic (each test at 5% level); FPE: Final prediction error; AIC: Akaike information criterion; SC: Schwarz information criterion; HQ: Hannan–Quinn information criterion.

Third, perform cointegration testing to prevent the issue of pseudo regression in time series. The Johansen test results in Table 4 indicate that there are at least two sets of cointegration relationships among the variables, which is consistent with the modeling requirements.

Table 4 Johansen Cointegration Test

| Hypothesized No. of CE(s) | Eigenvalue | Trace Statistic | 0.05 Critical Value | Prob.** |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| None * | 0.310988 | 95.77258 | 47.85613 | 0 |
| At most 1 * | 0.098185 | 31.7032 | 29.79707 | 0.0298 |
| At most 2 | 0.06295 | 13.9277 | 15.49471 | 0.0849 |
| At most 3 | 0.015829 | 2.744419 | 3.841466 | 0.0976 |

Note: * denotes the rejection of the hypothesis at the 0.05 level.

Fourth, Estimating model parameters. The Markov chain Monte Carlo (MCMC) algorithm is first employed for 10,000 iterations; this article discards the results of the first 1,000 iterations to improve the accuracy of the estimation findings. Obtain the posterior distribution of Markov chain convergence after eliminating the first 1000 iterations, and then take a sample from the posterior distribution to create the mean estimation of each parameter. Table 5 displays the outcomes of the estimation. The posterior mean is within the 95% confidence interval, and the standard deviation of the parameter estimation results obtained from model sampling is small, indicating that the results are good. The values of the CD statistic do not exceed 1.96, indicating that discarding the prior 1000 results is sufficient to cause the Markov chain to converge and cannot disprove the initial hypothesis that the parameters follow a posterior distribution. Additionally, the last column of the table's invalid factors all have values lower than 100, demonstrating the success of the TVP-VAR model's parameter estimation.

### *4.2 Empirical Results*

The effect of GEPU on manufacturing PMI in China, the US, and the EU can be investigated using the TVP-VAR model. The equal interval dynamic impulse response function (Figure 2) and impulse response function at various time points (Figure 3) were used [31,32] to empirically analyze the impact of GEPU on manufacturing.

Figure 2a displays the equal interval dynamic impulse response results, which demonstrate that GEPU initially had a negative impact on China’s manufacturing from 2008 to 2013 before changing to a positive impact in 2013 and peaking in 2015; thereafter, the impact effect continued to wane and eventually changed to a negative impact in 2017, with a relatively small overall amplitude. Figures 2(b and c) show that GEPU has a similar effect on US and EU manufacturing, respectively. Specifically, it has a negative impact on US manufacturing from March 2008 to April 2013, but after that there is a significant fluctuation above the zero axis; from March 2008 to June 2013, the impact of GEPU on EU manufacturing is negative, but after that there is a significant fluctuation above the zero axis most of the time. According to empirical findings, the direction and size of GEPU’s effects on manufacturing change over time. For example, GEPU’s short-term impact on China’s manufacturing is slightly greater than its medium- and long-term effects, whereas GEPU’s medium- and long-term effects on manufacturing in the US and the EU are much greater than its short-term effects. China’s manufacturing has a risk resilience advantage because the impact of GEPU is much lower than that of the US and the EU.

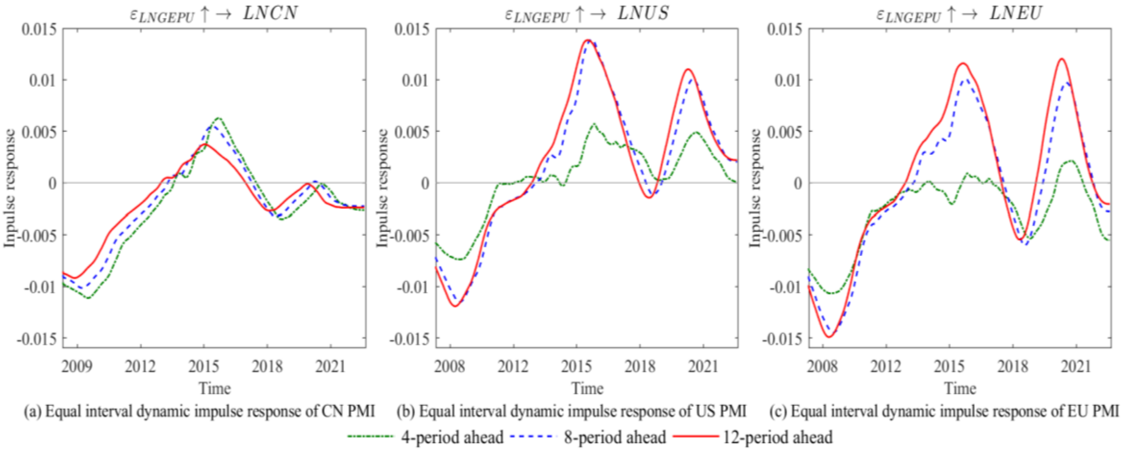



Figure 2 Equal interval dynamic impulse response of PMI to GEPU

Manufacturing is also impacted by critical GEPU events that occurred at various times. Our study selects four crucial time points in GEPU, including the European debt crisis (December 2009), China–US trade war (March 2018), COVID-19 pandemic (December 2019), and Russia–Ukraine conflict (February 2022). The results are displayed in Figure 3 China was negatively impacted at these four time points, with the European debt crisis having a higher impact on China's manufacturing than the China–US trade war and Russia–Ukraine conflict, whereas the COVID-19 pandemic had the least impact on China's manufacturing. The US manufacturing industry was most adversely affected by the European debt crisis and most favorably by the COVID-19 pandemic; the US–China trade war and Russia–Ukraine conflict had less impact on US manufacturing. The EU manufacturing sector was most negatively impacted by the European debt crisis, followed by the China–US trade war and Russia–Ukraine conflict, and most favorably by the COVID-19 pandemic.

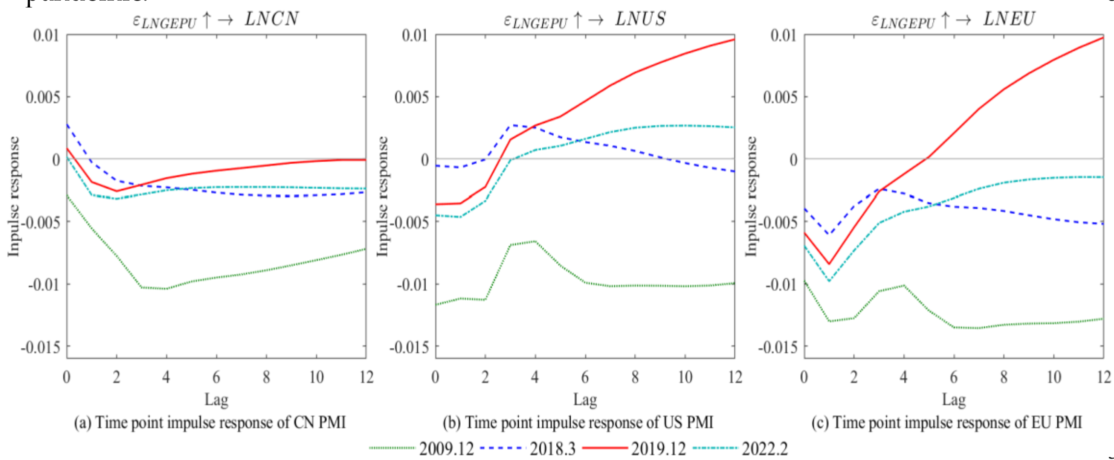



Figure 3 Time point impulse response of PMI to GEPU

Comparing the effects of GEPU on the manufacturing sectors of the three major economies at various times, we can see that: First, the European debt crisis has a larger detrimental impact on the EU industry than on the US or Chinese industries. Second, the negative impact of the China–US trade war on EU manufacturing is greater than that on China and the US. Third, the COVID-19 pandemic's influence on China's manufacturing is infinitesimally close to the zero axis, thereby indicating that COVID-19 has almost no impact on China's manufacturing, but it has a greater positive impact on manufacturing in the EU and the US. Finally, the impact of the Russia–Ukraine conflict on the EU is higher than that on the US and China. Regarding the effects of GEPU on manufacturing at different time points, the impact on China's manufacturing is the least and that on EU manufacturing is greater than that on the US. This phenomenon indicates that when facing the impact of GEPU, China's manufacturing industry has a higher ability to resist risks than the United States and the European Union, the reason may be that China is the only country in the world with all industrial sectors[3]; and has a full industry chain advantage, which significantly enhances the risk resistance ability of China's manufacturing. As a result of the high degree of industrial chain overlap, the manufacturing sectors of the US and the EU now have a more substitutive relationship, which has increased competition between the two. At the same time, China's manufacturing sector is complementary to the manufacturing sectors of the US and the EU, meaning that China's low-end consumer goods can satisfy the market demand of the US and the EU, when compared to the US and China, the industrial sector in the EU has much lower risk resilience.

## 5. Robust Test

The TVP-VAR model is frequently incorrectly set, which compromises the validity of empirical data by leaving out crucial factors or ranking variables incorrectly. As a result, the benchmark TVP-VAR model in this study needs to undergo a robustness test. This study refers to existing research[33], when doing robustness analysis, change the variable order from the original $y_t = (Gepu_t, US_t, CN_t, EU_t)$, to $y_t = (Gepu_t, US_t, EU_t, CN_t)$, Select the same lead time and time point as above, and the robustness test results are shown in Figure 4 and Figure 5.

Figure 4 shows that the medium- and long-term impact of GEPU on the manufacturing PMI in the US and the EU is greater than the short-term impact; the short-term impact on China's manufacturing PMI is higher than the medium- and long-term impact, consistent with the results of equal interval pulse response mentioned above. Figure 5 shows that the response strength of the manufacturing PMI for China, the US and the EU at various time intervals is comparable to the corresponding strength above. This demonstrates that the TVP-VAR model employed for robustness testing exhibits comparable dynamic changes, demonstrating the robustness of the above empirical findings.

Figure 4 Robustness test: equal interval impulse response results

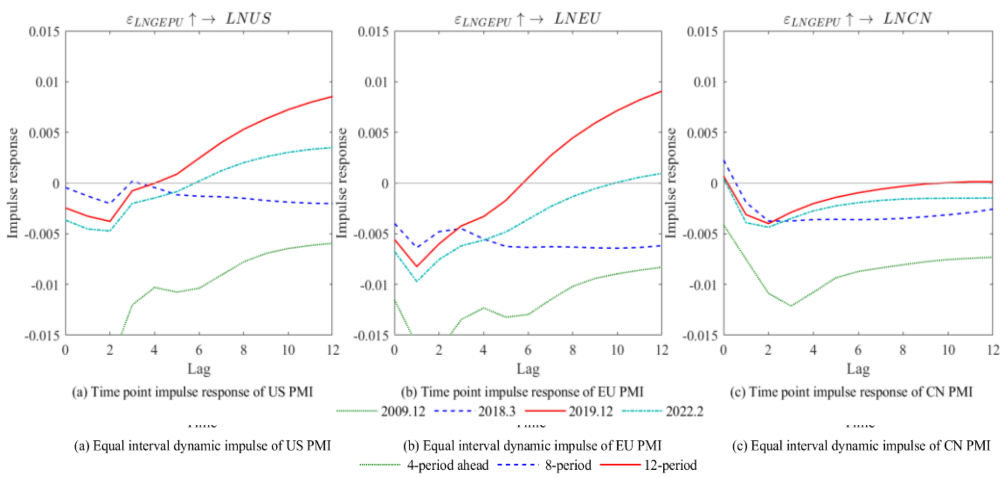



Figure 5 Robustness test: time point impulse response results

## 6. Discussion and Conclusion

Against the background of increasing global political and economic volatility, we employ the TVP-VAR model to empirically test the impact of GEPU on manufacturing

[3] China is the only country in the world with all industrial sectors

from March 2008 to March 2023 in China, the US, and the EU. We confirm that the impact of GEPU on manufacturing is time varying and aggravates the volatility of global manufacturing. We conclude that manufacturing in the EU is more fragile than that in the US and China, thereby making it more susceptible to the harsh effects of GEPU; moreover, manufacturing in China has a higher anti-risk capacity than the US.

Former studies reveal that the impact of GEPU on finance is mainly reflected in the short- term [34,35], conversely, our research posits that the impact of GEPU on manufacturing is mainly reflected in the medium- and long-term. The blockade measures of the COVID-19 pandemic drastically lowered demand and caused factories to closedown [36]; however, our research argues that China's manufacturing has benefited from its dynamic Zero-COVID policy and is almost unaffected by COVID-19. The Russia–Ukraine conflict has increased the uncertainty of German economic policy and negatively impacted its financial and economic systems [37–39], while we find that the EU manufacturing suffered most from the Russia–Ukraine conflict. Furthermore, depending on data availability, the impact of the Russia–Ukraine conflict on world manufacturing patterns needs to be further explored.

## 7. Patents

**Author Contributions:** Yifei Li: Conceptualization, Methodology, Data curation, coding, Empirical analysis, Writing- Original draft preparation. Yuhang Bai: Conceptualization, Methodology, Data curation, Empirical analysis, writing- Reviewing and Editing.

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