

AN EMPIRICAL ANALYSIS ON THE RELATIONSHIP BETWEEN GREEN ECONOMY AND INFLATION IN CHINA

LYU, Y. F.

*School of Banking & Finance, University of International Business and Economics
Beijing 100029, China
(e-mail: 283420976@qq.com; phone: +86-178-1209-6625)*

(Received 18th Mar 2019; accepted 17th May 2019)

Abstract. Targeting the 21 port provinces of China, this paper constructs a panel vector autoregressive (PVAR) model to explore the dynamic relationship between China's green economy and inflation, and to verify whether China's green economy has a negative effect on inflation. Both the global Malmquist-Luenberger (GML) index and the Malmquist-Luenberger (ML) index, which represent the production efficiency under pollution, were adopted to measure China's green economy. It is assumed that the green economy and inflation interact with each other through the output gap, which is associated with pollution, the side-effect of production. The calculated results were tested by impulse response analysis. The final conclusion goes that China's green economy has a weak but long-lasting negative effect on inflation. In other words, China's green economy can alleviate the inflation. Thus, China should speed up pollution control and green economy development to control inflation.

Keywords: *port provinces, global Malmquist-Luenberger (GML) index, Malmquist-Luenberger (ML) index, monetary policy, panel vector autoregressive (PVAR) model*

Introduction

In recent years, the Chinese economy has entered a “new normal” stage, which is characterized by a balanced and manageable growth. According to the National Bureau of Statistics, China's GDP increased 6.6% to RMB 900.309 billion yuan from 2017 to 2018, about 0.1% higher than expected. The fast growth resulted in a hike in China's consumer price index (CPI), an indicator of inflation rate, posing a huge challenge to further economic development (*Figure 1*).

Recent years have also seen growing awareness of global warming across the world. Both the public and the governments are paying more and more attention to the environmental issues induced by global warming. The World Meteorological Organization (WMO) reported that the global mean temperature from January to October in 2018 was $0.98 \pm 0.1^{\circ}\text{C}$ higher than that before the industrial revolution, making 2018 the fourth warmest year on record. If El Niño occurs in the near future, 2019 may be even warmer than 2018 (NOAA, 2019).

Against this backdrop, it is imperative to strike a balance between economic growth and pollution control, even though many countries used to prioritize economic gains over the environmental benefits and perceive the two factors as contradictory. In other words, special efforts should be paid to develop a green economy, which generates output while reducing pollution, aiming to curb global warming. The official definition of green economy is “one that results in improved human well-being and social equity, while significantly reducing environmental risks and ecological scarcities (UNEP, 2011).

Considering the above, this paper examines whether the development of China's green economy has relieved inflation. It is assumed that China's green economy can suppress the pollution in production, and thus the inflation rate. This hypothesis was

tested with the data from the 21 port provinces in China. Meanwhile, a panel vector autoregressive (PVAR) model was employed to study the dynamic relationship between China's green economy and inflation rate.

The port provinces were targeted in this research because they are both transport hubs and industrial centers. In the past three decades, the main coastal economic zones have concentrated 70% of the industries above designated size in China (Chen, 2016). The rapid industrial development, coupled with economic growth, lead to various environmental problems, such as water pollution and land-based wastes (e.g. domestic waste and industrial waste) (Yan et al., 2018). As a result, the port provinces are more polluted than the rest of provinces in the country. Taking SO₂ emissions as an example (Figure 2), more SO₂ was emitted in the port provinces than other Chinese provinces in 2016.

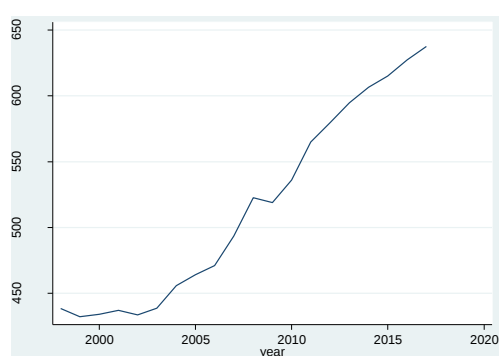


Figure 1. The variation in China's CPI over time (Data source: The National Bureau of Statistics of China)



Figure 2. The distribution of SO₂ emissions across China in 2016 (Data source: The National Bureau of Statistics of China)

Through an impulse response analysis, it is confirmed that the green economy of each port province has a negative effect on inflation. Note that the term “port provinces” refers to provincial administrative regions in Chinese mainland that contains riverside and/or seaside port cities.

The contributions and limitations of this research can be summed up as: (1) The author disclosed the dynamic relationship between China's green economy and the

macroeconomic variable of inflation; (2) It is verified that the green economy interacts with inflation through the output gap, and that China's green economy has a negative impact on inflation, making it possible to control pollution and inflation at the same time; (3) The conclusions are backed up firmly by the actual data from the 21 port provinces in China, which are more polluted than the other Chinese provinces; (4) Due to the lack of a widely accepted way to measure the size of China's green economy, there might be statistical errors in the calculation of the global Malmquist-Luenberger (GML) index or the Malmquist-Luenberger (ML) index; (5) Some biases may exist in the construction of capital stock and output variables.

The remainder of this paper is organized as follows: Section 2 reviews the previous studies on China's green economy and inflation; Section 3 introduces the main variables and estimation methods in our research; Section 4 empirically analyzes the dynamic relationship between China's green economy and inflation, measures China's green economy with its GML index, and tests the robustness by the ML index; Section 5 wraps up this paper with several conclusions.

Materials and methods

Relationship between inflation and output gap

Much research has been done to disclose the relationship between inflation and output gap. For instance, the Phillips curve (1958) reflects the negative correlation between the inflation rate and the unemployment rate, while the New Keynesian Phillips curve (NKPC) reveals the intrinsic causal link between economic output and inflation (Taylor, 1980; Calvo, 1983).

In addition, Jarociński and Lenza (2018) employed a Bayesian dynamic factor model to estimate the output gap in the Eurozone and illustrated the model's predictive power of inflation. With the aid of discrete and continuous wavelet transforms, Tiwari et al. (2014) explored the relationship between inflation and output gap in France, suggesting that the inflation rate can be predicted by economic output in the short and medium terms. Justiniano et al. (2013) confirmed the significant correlation between output gap and inflation through the analysis of the economic data of the US from 1954 to 2009. Based on the NKPC and hybrid NKPC, Bian and Hu (2016) designed the sticky information Phillips curve (SIPC) and double sticky Phillips curve (DSPC) for China, and proved the significance of output gap coefficients in the models, thus validating the Phillips curve.

Measure of China's green economy

There is not yet a widely accepted way to accurately measure the green economy, despite repeated attempts to do so. This is partially attributable to the significant country differences in the status and policies of green economy. On China's green economy, the existing research methods can be divided into four categories: data envelopment analysis (DEA) (Guo et al., 2017; Bao, 2017; Marino et al., 2017; Wang and Zhao, 2017; Yan, 2017, 2018; Shen et al., 2017; Han et al., 2018; Song, 2018), the stochastic impacts by regression on population, affluence and technology (STIRPAT) (Wang, 2017; He, 2017), the logarithmic mean Divisia index (LMDI) model (Wang and Feng, 2018; Chen, 2018), and the GML/ML index.

Coupling the DEA and the directional distance function (DDF), the ML index was modified from the Malmquist index (Chung et al., 1997), which is traditionally calculated from the output distance between different technologies. Compared with the Malmquist index, the ML index is still applicable when undesired outputs like CO₂ emissions or pollution are considered. The index was adopted by Li et al. (2018) to measure the carbon productivity of 36 industrial sectors in from 2003 to 2015. However, the ML still has certain shortcomings, such as the inability to solve linear prediction, non-transferability and additivity.

In 2010, the ML index was further improved by Oh into the GML index. Since then, the GML index has been widely adopted to measure economic output. For example, Emrouznejad and Yang (2016) employed the GML index to evaluate China's manufacturing industry between 2004 and 2012, and built a framework to measure the industrial eco-efficiency in terms of CO₂ emissions. Based on the GML index, Lei et al. (2017) constructed a carbon-weighted economic development indicator for 30 Chinese provinces between 1998 and 2014, and evaluated the economic performance of the carbon emissions-aware economy. Ren et al. (2018) relied on the GML index to incorporate undesirable outputs into the measurement of total factor productivity (TFP) for 11 coastal regions of China between 2006 and 2014, and assessed the efficiency of China's marine economy under environmental constraints. With the aid of the GML index, Pan et al. (2018) designed a measure of the green economy of 30 provinces in China between 1999 and 2016, and evaluated the provincial green economic development. In this paper, the GML index proposed by Oh (2010) is taken as a measure of China's green economy.

The effects of China's green economy

Several scholars have studied the drivers and impacts of China's green economy. Among them, Zeng et al. (2017) built a structural vector autoregressive (SVAR) model to analyze the dynamic relationship between carbon subsidy price, stock price and energy price in Beijing between 2014 and 2015. Lin and Zhu (2017) created a PVAR model to investigate the relationship between urbanization, industrial structure, energy density and carbon density in 30 Chinese provinces between 2000 and 2015. Ouyang and Li (2018) probed into the dynamic relationship between energy consumption, M2 money supply, credit, income, and stock price from Q1, 1996 to Q4, 2015. Using the panel data of 30 Chinese provinces between 1998 and 2014, Lei et al. (2017) investigated the dynamic relationship between the industrial structure, energy structure, low carbon index, foreign direct investment (FDI) and trade, using the PVAR model. In fact, the PVAR is the most frequently used model for the dynamic relationship between China's green economy and other variables. Thus, this model was selected for our research.

The price impact of China's green economy has long been a research hotspot. For example, Zeng et al. (2014) found that, while other factors are under control, land pollution induces a net loss of 31% in the value of nearby plots. On the provincial data in 2001~2010, Leng and Du (2016) verified the positive correlation between energy price distortion and haze pollution in China. Zhang (2018) suggested that the pollution control costs of key monitoring enterprises in China has a significant causal effect on the marginal cost and price of multi-product enterprises.

Drawing from the previous research, the author assumed that pollution, as an externality, will affect the production output, and thus the price (Mas-Colell et al., 1995).

The price change will in turn cause changes in inflation. On the one hand, the mitigation of pollution, a side-effect of production, drags down the output of the whole society and pushes up the marginal production cost, resulting in economic losses (Xi et al., 2013). On the other hand, pollution control also affects the marginal cost of enterprises, e.g. the cost of power generation is influenced by effective energy policies (Zhang et al., 2007; Bianco et al., 2017; Borchellini et al., 2017; Silvestro et al., 2017; Domenico et al., 2018). In other words, the overall societal cost is subjected to the impacts of externalities. Being a developing country, China tends to suffer greater loss in economic output, which stems from pollution control, than developed countries (Maradan and Anatoli, 2005). Hence, the PVAR model is selected here to study the dynamic relationship between China's green economy and price changes, i.e., inflation.

Methodology of main variables

ML index

The ML index was proposed by Chung et al. (1997) and modified by Oh (2010) to overcome suboptimal properties. In this paper, this index is employed in the robustness test. The ML index of country i can be defined by two contemporaneous continuous reference vectors, as in Equation (1):

$$ML^S(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) = \frac{1 + D^S(x^t, y^t, b^t)}{1 + D^S(x^{t+1}, y^{t+1}, b^{t+1})} \quad (\text{Eq.1})$$

where, D^S is the DDF. The DDF can be defined by the synchronous technology set (P^S) in Equation (2):

$$D^S(x, y, b) = \max\{\beta \mid (y + \beta y, b - \beta b) \in P^S(x)\}, \quad s = t, \quad t+1 \quad (\text{Eq.2})$$

If the production activity achieves higher output and lower externalities in year $t+1$, then $ML^S > 1$ and production efficiency increases. Otherwise, $ML^S < 1$ and the production efficiency declines. So in Equation (3):

$$ML^t(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) \neq ML^{t+1}(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) \quad (\text{Eq.3})$$

The ML index can also be defined as the geometric mean of two consecutive periods, as in Equation (4):

$$\begin{aligned} ML^{t,t+1}(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) &= \left[\frac{1 + D^t(x^t, y^t, b^t)}{1 + D^t(x^{t+1}, y^{t+1}, b^{t+1})} \times \frac{1 + D^{t+1}(x^t, y^t, b^t)}{1 + D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})} \right]^{1/2} \\ &= \frac{1 + D^t(x^t, y^t, b^t)}{1 + D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})} \times \left[\frac{1 + D^{t+1}(x^t, y^t, b^t)}{1 + D^t(x^t, y^t, b^t)} \cdot \frac{1 + D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{1 + D^t(x^{t+1}, y^{t+1}, b^{t+1})} \right]^{1/2} \\ &= \frac{TE^{t+1}}{TE^t} \times [TG_t^{t,t+1} \cdot TG_{t+1}^{t,t+1}]^{1/2} \\ &= EC^{t,t+1} \times TC^{t,t+1} \end{aligned} \quad (\text{Eq.4})$$

where, TE^s is technical efficiency of period s ; $TG^{t, t+1}$ is the technical gap between periods t and $t+1$; $EC^{t, t+1}$ is the variation in technical efficiency gap between periods t and $t+1$; $TC^{t, t+1}$ is the variation in technical boundary gap between periods t and $t+1$. Obvious, $EC^{t, t+1} > 1$ indicates an increase in technical efficiency, and $EC^{t, t+1} < 1$ indicates the opposite; $TC^{t, t+1} > 1$ means the technical boundary increases with the growth in output and the reduction of externalities.

GML index

The GML index can be defined in Equation (5):

$$GML^{t, t+1}(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) = \frac{1 + D^G(x^t, y^t, b^t)}{1 + D^G(x^{t+1}, y^{t+1}, b^{t+1})} \quad (\text{Eq.5})$$

where, D^G is the DDF. The DDF can be defined by the global technology set (P^G) in Equation (6):

$$D^G(x, y, b) = \max\{\beta \mid (y + \beta y, b - \beta b) \in P^G(x)\} \quad (\text{Eq.6})$$

If production activities achieve higher output and lower externalities, then $GML^{t, t+1} > 1$ and productivity increases. Otherwise, $GML^{t, t+1} < 1$ and productivity decreases. The GML index can be broken down in Equation (7):

$$\begin{aligned} GML^{t, t+1}(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) &= \frac{1 + D^G(x^t, y^t, b^t)}{1 + D^G(x^{t+1}, y^{t+1}, b^{t+1})} \\ &= \frac{1 + D^t(x^t, y^t, b^t)}{1 + D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})} \times \left[\frac{(1 + D^G(x^t, y^t, b^t)) / (1 + D^t(x^t, y^t, b^t))}{(1 + D^G(x^{t+1}, y^{t+1}, b^{t+1})) / (1 + D^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}))} \right] \\ &= \frac{TE^{t+1}}{TE^t} \times \left[\frac{BPG_{t+1}^{t, t+1}}{BPG_t^{t, t+1}} \right] \\ &= EC^{t, t+1} \times BPC^{t, t+1} \end{aligned} \quad (\text{Eq.7})$$

where, TE^s is technical efficiency of period s ; $EC^{t, t+1}$ is the variation in technical efficiency gap between periods t and $t+1$; $BPG^{t, t+1}$ is the optimal practice gap between the synchronous technology boundary and the global technology boundary.

Output gap

The potential output can either be estimated from the time series data of actual output or be determined by the production function. The former approach needs to detrend the data and extrapolate growth rates. However, the estimation is too simple to derive the exact amount of potential output. The latter method mainly considers the factor utilization and the impact of technical progress on output, revealing the supply-side of potential output. The production function method has been adopted by many scholars (Guo and Jia, 2004).

In this paper, the production function method is selected to measure the potential output, such as to determine the output gap of each port province in China. Firstly, the

aggregate production function was estimated based on the data on the actual output, labor and capital stock, laying the basis for acquiring the TFP. The Cobb-Douglas production function is adopted in *Equation (8)*:

$$Y_t = AK_t^\alpha L_t^\beta \quad (\text{Eq.8})$$

where, Y_t is the actual output; L_t is the actual labor; K_t is the capital stock; α and β are the output elasticities for capital and labor, respectively. Taking the natural logarithm on both sides of *Equation (8)*, we have *Equation (9)*:

$$\ln Y_t = \ln A + \alpha \ln K_t + \beta \ln L_t \quad (\text{Eq.9})$$

If the production has constant scale of returns, then $\alpha + \beta = 1$. In this case, a double logarithmic model can be constructed in *Equation (10)*:

$$\ln(Y_t/L_t) = \ln A + \alpha \ln(K_t/L_t) + \gamma_t \quad (\text{Eq.10})$$

The TFP can be obtained from the residual term of this regression (γ_t). Secondly, the TFP was decomposed by the Hodrick–Prescott (HP) filter, and the potential employment was estimated under the potential output in *Equation (11)*:

$$L_t^{\text{Potential}} = L_{St} \times Tr_{p,t} \times (1 - NAWRU_t) \quad (\text{Eq.11})$$

where, L_{St} is the number of people in the working age; $Tr_{p,t}$ is the trend participation rate; $NAWRU_t$ is the unemployment rate induced by non-wage factors. Thirdly, the potential output was established from the estimated TFP trend, potential employment and potential output. Finally, the output gap was determined as the difference between the estimated output and the potential output.

Research data and calculation results

Research data

The 21 port provinces in China were taken as the research objects. As shown in *Table 1*, some of these provinces have both riverside and seaside port cities, and some have either riverside or seaside port cities.

The annual data of these provinces in 2006~2015 were collected to reduce the regression bias in PVAR model estimation. The annual data were selected for three reasons: the large-scale changes in macroeconomic variables are unlikely to occur within a monthly or quarterly range (Beetsma et al., 2008), the macroeconomic variables may change systematically under the expectation effect, which is more prevalent in shorter time windows, and the annual data do not contain any potential seasonal effect.

Calculation of the GML index

The GML index was computed by the method of Oh (2010) according to the annual data of the 21 provinces in 2006~2015. The following variables were covered in the computing process.

(i) The desirable output: the annual GDP of the 21 port provinces. This variable was converted into a constant price by the GDP deflator (unit: RMB 100 million yuan). Data source: CEInet Statistics Database.

(ii) The undesirable output: the annual SO₂ emissions (unit: ton) and wastewater discharge (unit: ton). Data source: The National Bureau of Statistics of China.

(iii) The inputs of production technology: the inputs were measured by three indices, namely, capital stock (unit: RMB 100 million yuan), labor force (unit: 10,000 people) and energy consumption (unit: TCE).

The capital stock was calculated by the method of Shan (2008), who computed the capital stock of China and its provinces in 1952~2006 using the perpetual inventory method (PIM). The PIM assumes that the relative efficiency is geometrically decreasing, while the reset rate is constant. Here, the calculation formula of the capital stock can be expressed in *Equation (12)*:

$$K_t = (1 - \delta)K_{t-1} + I_t / P_t \quad (\text{Eq.12})$$

where, K_{t-1} is the capital stock of the year $t-1$; δ is the economic depreciation rate; I_t is the investment amount in year t ; P^I is the investment price index used to convert the investment amount into constant price. Here, the investment amount is measured by the fixed capital formation amount of each province, which comes from the China Economic and Trade Network, while the investment price index of each province was extracted the CEInet Statistics Database. Under the PIM assumption, the economic depreciation rate of the 21 provinces was set to 10.96%.

Table 1. List of 21 port provinces in China

No.	Province	Type	No.	Province	Type	No.	Province	Type
1	Anhui	Riverside	8	Hebei	Seaside	15	Liaoning	Seaside
2	Chongqing	Riverside	9	Heilongjiang	Riverside	16	Shandong	Riverside and seaside
3	Fujian	Seaside	10	Henan	Riverside	17	Shanghai	Riverside and seaside
4	Guangdong	Riverside and seaside	11	Hubei	Riverside	18	Sichuan	Riverside
5	Guangxi	Riverside and seaside	12	Hunan	Riverside	19	Tianjin	Seaside
6	Guizhou	Riverside	13	Jiangsu	Riverside and seaside	20	Yunnan	Riverside
7	Hainan	Seaside	14	Jiangxi	Riverside	21	Zhejiang	Riverside and seaside

Data source: Chinese Ministry of Transport

In addition, the labor force in each province was obtained by adding up the urban residents employed in the public sector, in the private sector, and self-employed, without considering the employment of rural residents. The employment data before 2008 were drawn from the China Stock Market & Accounting Research (CSMAR) Database, and those after 2008 were extracted from the National Bureau of Statistics of China. The provincial data on annual energy consumption were also downloaded from the CSMAR database.

Calculation of the output gap

The annual output gap of each port province in 2006~2015 was calculated by the method of Guo and Jia (2004), using the following variables:

- (i) The actual output: the annual GDP of each port province.
- (ii) The actual labor force: the annual urban labor force of each province.
- (iii) The capital stock: this variable was computed the same as in the preceding subsection.
- (iv) $L_{St} \cdot Tr_{p,t}$: the number of people in the working age multiplied by the trend value.
- (v) $NAWRU_t$: the number of laborers divided by the total number of people involved in social and economic activities. The latter was defined as the sum of the number of laborers and the number of registered unemployed urban residents. The data were collected from the National Bureau of Statistics of China.
- (vi) Constant return on scale: The assumption that the scale of return is constant was verified by the Wald test. The original hypothesis H_0 can be expressed as $\alpha + \beta = 1$. The test results are listed in *Table 2* below.

Table 2. The results of the Wald test

H_0	$\chi^2 (1)$	$P > \chi^2$
$\alpha + \beta = 1$	1.17	0.2803

The results in *Table 2* show that the P-value is greater than 0.05, revealing the validity of the original hypothesis. Thus, the production mode of China's economy was considered as having constant returns to scale between 2006 and 2015.

PVAR model

The PVAR model was established to analyze the relationship between China's green economy and the inflation rate. The variables were treated as endogenous and interdependent. To reflect the real interaction between the variables, the lag term of all variables was included in the model. The basic form of the PVAR model is established as *Equation (13)*:

$$y_{it} = \alpha_0 + \sum_l^L \alpha_l y_{i,t-l} + I_i + T_t + \mu_{it} \quad (\text{Eq.13})$$

where, y_{it} is the column vector containing endogenous variables; i is the serial number of port provinces; t is the year; L is the post-order; I_i is the individual effect vector; T_t is the time effect vector; μ_{it} is a random disturbance term (i.e. the white noise).

The individual effect vector does not change with time, and the right side of *Equation (13)* contains the lag term of the dependent variables. Thus, the mean differencing was adopted to prevent the estimation bias from potential endogeneity. More specifically, the forward-mean-differencing method was adopted to remove the fixed effect in the model (Arellano and Bover, 1995). Besides, the generalized method of moments (GMM) was used to obtain a consistent estimator of the coefficient of the explanatory variable, with the lag term of the explanatory variables as the instrumental variables. Furthermore, an impulse response analysis was conducted through Monte-Carlo simulation.

Results

The dynamic relationship between GML index and inflation

Basic regression

Considering the negative correlation between pollution and the GML, it is assumed that the GML has a negative effect on the CPI. The orthogonal impact response function is the disturbance term of the Cholesky decomposition. By exogenous nature, the Cholesky decomposition variables can be ranked as output gap (*outgap*), China's green economy (*GML*) and inflation (*CPI*). The regression model can thus be established as Equation (14):

$$y_{it} = (outgap_{it}, GML_{it}, CPI_{it})^T \quad (\text{Eq.14})$$

Prior to the regression, the Fisher-Phillips-Perron (PP) test, the Im-Pesaran-Shin (IPS) test and the Levin-Lin-Chu (LLC) test were carried out, proving that the level values of all variables can be directly used for the regression of the PVAR model. The level values of all variables rejected the null hypothesis at a significance level of 1%, that is, the level values of all variables do not possess unit roots, and all sequences are stationary. Moreover, the optimal lag order (2) was determined by the Akaike information criterion (AIC), Bayesian information criterion (BIC) and Hannan & Quinn information criterion (HQIC). The test results are shown in Table 3 below.

Table 3. The results on the optimal lag order

Lag	AIC	BIC	HQIC
1	6.18901	7.04927	6.53857
2	4.62324*	6.16506*	5.23567*
3	4.63834	6.81804	5.46838

Note: ***, ** and * stand for the significance levels of 1%, 5% and 10%, respectively

As such, the PVAR (2) model was selected for our research.

Impulse response analysis

Through Cholesky decomposition, the author analyzed the interaction between China's green economy and inflation, after excluding the effects of other endogenous variables. Since the data run from 2006 to 2015, a total of 10 years, the impact duration was divided into 10 periods. The impulse response function (IRF) graph of the CPI to the GML was obtained through 1,000 random Monte-Carlo simulations.

Robustness test

Basic regression

The same analysis was performed using the ML index, assuming that the ML also has a negative impact on the CPI. The variables were the same as those in the analysis based on the GML. In the ML-based analysis, the PVAR model was still adopted, and the Cholesky decomposition variables were still ranked as the output gap (*outgap*),

China's green economy (*ML*) and inflation (*CPI*). Thus, the regression model is parallel to *Equation (13)*.

Prior to the regression, the PP-Fisher test, IPS test and LLC test were conducted as well, and the optimal lag order (3) was determined by the AIC, BIC and HQIC criteria. These results are displayed in *Table 4* below.

Table 4. The results on the optimal lag order

Lag	AIC	BIC	HQIC
1	6.00907	6.86933	6.35863
2	9.7832	11.325	10.3956
3	2.53134*	4.71105*	3.36139*

Note: ***, ** and * stand for the significance levels of 1%, 5% and 10%, respectively

As such, the PVAR (3) model was selected for our research.

Impulse response analysis

The IRF graph of the CPI to the ML was obtained through 1,000 random Monte-Carlo simulations.

Discussion

As shown in *Figure 3*, the effect of the GML on the CPI was not observable at the start, decreased in the first period, and slightly increased in the second period. After that, the effect continued to decline until the fourth period, and then tended to be stable through the tenth period. Overall, China's green economy has a weak negative effect on inflation in the long run, which agrees with our hypothesis.

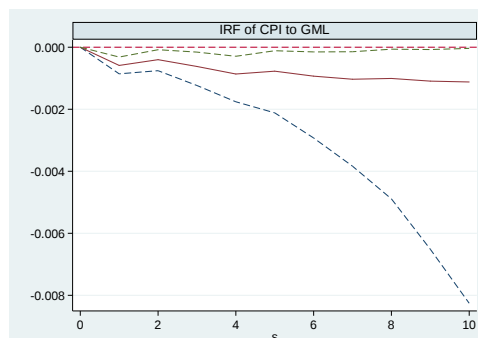


Figure 3. The IRF graph of the CPI to the GML (Note: The red line is the impulse response curve; the green dotted line stands for the points in the confidence interval of 5%; the blue dotted line stands for the points in the confidence interval of 95%)

As shown in *Figure 4*, the effect of the ML on the CPI was not observable at the start, decreased in the first period, and slightly increased in the second period. After that, the effect continued to decline until the fourth period, and then tended to be stable through the tenth period. In general, China's green economy has a weak negative effect on inflation in the long run.

To sum up, China's green economy has a weak but long-lasting negative effect on inflation. In other words, China's green economy can alleviate the inflation.

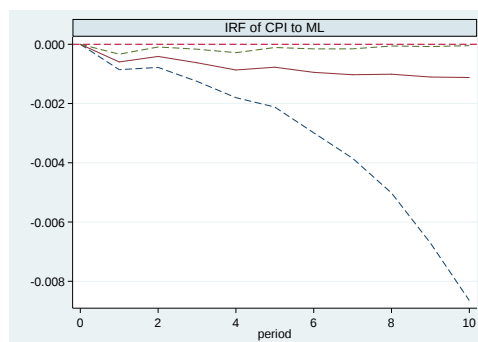


Figure 4. The IRF graph of the CPI to the ML (Note: The red line is the impulse response curve; the green dotted line stands for the points in the confidence interval of 5%; the blue dotted line stands for the points in the confidence interval of 95%)

Conclusions

Targeting the most polluted 21 port provinces in China, this paper attempt to disclose the dynamic relationship between China's green economy and inflation, and verify the hypothesis that China's green economy can alleviate the inflation through the output gap. Specifically, a PVAR model was constructed to explore the relationship, and the result was tested by impulse response analysis. It is proved that China's green economy has a causal relationship with inflation, whether it is calculated by the GML or the ML. The final conclusion goes that China's green economy has a weak but long-lasting negative effect on inflation. In other words, China's green economy can alleviate the inflation. Thus, the pollution is positively correlated with inflation.

In light of the findings, China should speed up pollution control and green economy development, such as to complete the 2020 climate targets ahead of schedule and lay the foundation for implementing the 2030 climate targets. Meanwhile, proper monetary policy should be rolled out to enhance the suppression effect of green economy over inflation.

The conclusion about the relationship between the green economy and inflation could indicate that the green economy can be a good signal for monetary policy. So further studies about the analysis of effects of monetary policy signalling within green economy over the clarity of central bank communication could be recommended.

REFERENCES

- [1] Arellano, M., Bover, O. (1995): Another look at the instrumental variable estimation of error-components models. – Journal of Econometrics 68(1): 29-51.
- [2] Bao, Z. B. (2017): Construction of the evaluation system of regional agricultural circular economy and TOPSIS application. – Environmental and Earth Sciences Research Journal 4(1): 12-16.
- [3] Beetsma, R., Giuliodori, M., Klaassen, F. (2008): The effects of public spending shocks on trade balances and budget deficits in the European Union. – Journal of the European Economic Association 6(2-3): 414-423.

- [4] Bian, Z., Hu, H. (2016): Sticky Prices, Sticky Information and Chinese Phillips Curve. – *The Journal of World Economy* 4: 22-43.
- [5] Bianco, V., Piazza, G., Scarpa, F., Tagliafico, L. A. (2017): Energy, economic and environmental assessment of the utilization of heat pumps for buildings heating in the Italian residential sector. – *International Journal of Heat and Technology* 35(S1): S117-S122.
- [6] Blundell, R., Bond, S. (1998): Initial conditions and moment restrictions in dynamic panel data models. – *Journal of econometrics* 87(1): 115-143.
- [7] Borchellini, R., Corgnati, S. P., Becchio, C., Delmastro, C., Bottero, M. C., Dell'Anna, F., Acquaviva, A., Bottaccioli, L., Patti, E., Bompard, E., Pons, E., Estebarsari, A., Verda, V., Santarelli, M., Leone, P., Lanzini, A. (2017): The Energy Center Initiative at Politecnico di Torino: Practical experiences on energy efficiency measures in the municipality of Torino. – *International Journal of Heat and Technology* 35(S1): S196-S204.
- [8] Calvo, G. A. (1983): Staggered prices in a utility-maximizing framework. – *Journal of Monetary Economics* 12(3): 383-398.
- [9] Chen, L. (2016): Marine Pollution, Preventing and Treating Status and Its Countermeasures in China. – *Environmental Protection* 5(65): 1674-1021.
- [10] Chen, J. (2018): Estimation and factor decomposition of carbon emissions in China's tourism sector. – *Problems of Sustainable Development* 13(2): 91-101.
- [11] Chung, Y. H., Färe, R., Grosskopf, S. (1997): Productivity and undesirable outputs: a directional distance function approach. – *Journal of Environmental Management* 51(3): 229-240.
- [12] Davis, J. S., Fujiwara, I., Wang, J. (2018): Dealing with time-inconsistency: Inflation targeting vs. exchange rate targeting. – Working paper Australian National University.
- [13] Domenico, G., Carla, C. G., Margherita, M. (2018): Integrated urban regeneration policy and soft mobility planning for transport energy-saving. – *Instrumentation Mesure Métrologie* 17(4): 527-547.
- [14] Emrouznejad, A., Yang, G. L. (2016): CO2 emissions reduction of Chinese light manufacturing industries: A novel RAM-based global Malmquist–Luenberger productivity index. – *Energy Policy* 96: 397-410.
- [15] Emrouznejad, A., Yang, G. L. G. R. (2018): A novel inverse DEA model with application to allocate the CO2 emissions quota to different regions in Chinese manufacturing industries. – *Journal of the Operational Research Society*: 1-12.
- [16] Guo, Q., Jia, J. (2004): Estimating Potential Output and the Output Gap in China. – *Economic Research Journal* 5: 31-39.
- [17] Guo, X. (2017): Applying the dynamic DEA model to evaluate the energy efficiency of OECD countries and China. – *Energy* 134: 392-399.
- [18] Han, Y., Long, C., Geng, Z., Zhang, K. (2018): Carbon emission analysis and evaluation of industrial departments in China: An improved environmental DEA cross model based on information entropy. – *Journal of environmental management* 205: 298-307.
- [19] He, Z., Xu, S., Shen, W., Long, R., Chen, H. (2017): Impact of urbanization on energy related CO2 emission at different development levels: Regional difference in China based on panel estimation. – *Journal of cleaner production* 140: 1719-1730.
- [20] Jarociński, M., Lenza, M. (2016): An Inflation-Predicting Measure of the Output Gap in the Euro Area. – *Journal of Money, Credit and Banking* 50(6): 1189-1224.
- [21] Justiniano, A., Primiceri, G. E., Tambalotti, A. (2013): Is there a trade-off between inflation and output stabilization? – *American Economic Journal: Macroeconomics* 5(2): 1-31.
- [22] Lei, M. (2017): Carbon-weighted economic development performance and driving force analysis: Evidence from China. – *Energy Policy* 111: 179-192.
- [23] Leng, Y., Du, S. (2016): Energy Price Distortion and Haze Pollution: The Evidence from China. – *Industrial Economics Research* 1: 71-79.

- [24] Li, H., Shi, J. F. (2014): Energy efficiency analysis on Chinese industrial sectors: An improved Super-SBM model with undesirable outputs. – *Journal of Cleaner Production* 65: 97-107.
- [25] Li, W. (2018): Historical growth in total factor carbon productivity of the Chinese industry-A comprehensive analysis. – *Journal of Cleaner Production* 170: 471-485.
- [26] Lin, B., Zhu, J. (2017): Energy and carbon intensity in China during the urbanization and industrialization process: A panel VAR approach. – *Journal of Cleaner Production* 168: 780-790.
- [27] Love, I., Zicchino, L. (2006): Financial development and dynamic investment behavior: Evidence from panel VAR. – *The Quarterly Review of Economics and Finance* 46(2): 190-210.
- [28] Maradan, D., Vassiliev, A. (2005): Marginal costs of carbon dioxide abatement: empirical evidence from cross-country analysis. – *Revue Suisse d'Economie et de Statistique* 141(3): 377.
- [29] Marino, C., Nucara, A., Nucera, G., Pietrafesa, M. (2017): Economic, energetic and environmental analysis of the waste management system of Reggio Calabria. – *International Journal of Heat and Technology* 35(S1): S108-S116.
- [30] Mas-Colell, A., Whinston, M. D., Green, J. R. (1995): *Microeconomic Theory*. Vol. 1. – New York: Oxford university press.
- [31] NOAA National Centers for Environmental Information, State of the Climate (2018): *Global Climate Report for Annual 2018*.
- [32] Oh, D. H. (2010): A global Malmquist-Luenberger productivity index. – *Journal of Productivity Analysis* 34(3): 183-197.
- [33] Ouyang, Y., Li, P. (2018): On the nexus of financial development, economic growth, and energy consumption in China: New perspective from a GMM panel VAR approach. – *Energy Economics* 71: 238-252.
- [34] Pan, W., Pan, W., Hu, C., Tu, H., Zhao, C., Yu, D., Xiong, J., Zheng, G. (2019): Assessing the green economy in China: An improved framework. – *Journal of Cleaner Production* 209: 680-691.
- [35] Phillips, A. W. (1958): The relation between unemployment and the rate of change of money wage rates in the United Kingdom, 1861-1957. – *Economica* 25(100): 283-299.
- [36] Ramey, V. A. (2011): Identifying government spending shocks: It's all in the timing. – *The Quarterly Journal of Economics* 126(1): 1-50.
- [37] Ren, W. (2018): Evaluation of China's marine economic efficiency under environmental constraints—an empirical analysis of China's eleven coastal regions. – *Journal of Cleaner Production* 184: 806-814.
- [38] Shan, S. (2008): Reestimating the Capital Stock of China:1952-2006. – *The Journal of Quantitative & Technical Economics* 25(10): 17-31.
- [39] Shen, Z., Balezentis, T., Chen, X., Valdmanis, V. (2018): Green growth and structural change in Chinese agricultural sector during 1997–2014. – *China Economic Review* 51: 83-96.
- [40] Silvestro, F., Bagnasco, A., Lanza, I., Massucco, S., Vinci, A. (2017): Energy efficient policy and real time energy monitoring in a large hospital facility: A case study. – *International Journal of Heat and Technology* 35(S1): S221-S227.
- [41] Song, S. L. (2018): Application of gray prediction and linear programming model in economic management. – *Mathematical Modelling of Engineering Problems* 5(1): 46-50.
- [42] Soon, S. V., Baharumshah, A. Z., Wohar, M. E. (2018): Exchange rate pass-through in the Asian countries: does inflation volatility matter? – *Applied Economics Letters* 25(5): 309-312.
- [43] Taylor, J. B. (1980): Aggregate dynamics and staggered contracts. – *Journal of Political Economy* 88(1): 1-23.

- [44] Tiwari, A. K., Oros, C., Albulescu, C. T. (2014): Revisiting the inflation–output gap relationship for France using a wavelet transform approach. – *Economic Modelling* 37: 464-475.
- [45] United Nations Environment Programme (2011): Towards a green economy: Pathways to sustainable development and poverty eradication.
- [46] Wang, Q., Zeng, Y. E., Wu, B. W. (2016): Exploring the relationship between urbanization, energy consumption, and CO2 emissions in different provinces of China. – *Renewable and Sustainable Energy Reviews* 54: 1563-1579.
- [47] Wang, Y., Zhang, C., Lu, A., Li, L., He, Y., Tojo, J., Zhu, X. (2017): A disaggregated analysis of the environmental Kuznets curve for industrial CO2 emissions in China. – *Applied Energy* 190: 172-180.
- [48] Wang, J., Zhao, T. (2017): Regional energy-environmental performance and investment strategy for China's non-ferrous metals industry: a non-radial DEA based analysis. – *Journal of Cleaner Production* 163: 187-201.
- [49] Wang, J., Zhao, B., Wang, S., Yang, F., Xing, J., Morawska, L., Ding, A., Kulmala, M., Kerminen, V. M., Kujansuu, J., Wang, Z., Ding, D., Zhang, X., Wang, H., Tian, M., Petäjä, T., Jiang, J., Hao, J. (2017): Particulate matter pollution over China and the effects of control policies. – *Science of The Total Environment* 584: 426-447.
- [50] Wang, M., Feng, C. (2018): Decomposing the change in energy consumption in China's nonferrous metal industry: An empirical analysis based on the LMDI method. – *Renewable and Sustainable Energy Reviews* 82: 2652-2663.
- [51] Yan, Q. (2017): Economic and technical efficiency of the biomass industry in China: A network data envelopment analysis model involving externalities. – *Energies* 10(9): 1418-1437.
- [52] Yan, Q. (2018): Energy–economy–environmental (3E) performance of Chinese regions based on the data envelopment analysis model with mixed assumptions on disposability. – *Energy & Environment* 29(5): 664-684.
- [53] Yan, D., Zhang, H., Fu, D. (2018): Survey on ship pollution source. – *Ship Science and Technology* 40(11): 9-12.
- [54] Yang, X., Teng, F., Wang, G. (2013): Incorporating environmental co-benefits into climate policies: a regional study of the cement industry in China. – *Applied Energy* 112: 1446-1453.
- [55] Zeng, X., Chen, Y., Miao, Z. (2014): The Impacts of Contamination on the Price of Adjacent Land: An Empirical Study in Wuhan Downtown Area. – *China Land Sciences* 28(11).
- [56] Zeng, S., Nan, X., Liu, C., Chen, J. (2017): The response of the Beijing carbon emissions allowance price (BJC) to macroeconomic and energy price indices. – *Energy Policy* 106: 111-121.
- [57] Zhang, Q., Tian, W., Wei, Y., Chen, Y. (2007): External costs from electricity generation of China up to 2030 in energy and abatement scenarios. – *Energy Policy* 35(8): 4295-4304.
- [58] Zhang, W., Li, K., Zhou, D., Gao, H. (2016): Decomposition of intensity of energy-related CO2 emission in Chinese provinces using the LMDI method. – *Energy Policy* 92: 369-381.
- [59] Zhang, Z. (2018): Environmental regulation, price transfer and pollution burden of Chinese manufacturers: evidence based on pollution fees of key monitoring firms. – *Industrial Economics Research* 4: 65-75.
- [60] Zhang, L. P., Zhou, P. (2018): A non-compensatory composite indicator approach to assessing low-carbon performance. – *European Journal of Operational Research* 270(1): 352-361.