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Technology Gap, Global Value Chain and Carbon Intensity: Evidence from global manufacturing industries

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Abstract: The technological progress of a country may mean that its technology gap compared to the frontier has changed, which will induce a change in its positioning in the global value chain and affect its carbon intensity. Using paten data, Input Output Database and the Global Value Chain Index, we employ systematic Generalized Method of Moments, quantile regression with panel data and multilevel mediation analysis to measure empirically the impact of the technology gap on carbon intensity and positioning on the global value chain. The empirical analysis shows that narrowing the technology gap will reduce significantly a country's carbon intensity. Further, the effect of the technology gap on carbon intensity is more pronounced on

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industries with higher carbon intensity. The mechanism test using the mediation effect model proves that the impact of the technology gap on carbon intensity is achieved by changing in the position of global value chain. The findings suggest that a country's carbon intensity performance is not only affected by its own technological progress, but also by global frontiers. Therefore, a country should not only pay attention to its own technological progress but also to the development of global frontier technologies and speed of technological progress.

Keywords: Technology gap, Carbon intensity, Global Value Chain, Mediation effect model

1. Introduction

Technological progress is an important factor in achieving Intended Nationally Determined Contribution (INDC) to reduce greenhouse gas emissions pursuant to the United Nations Framework Convention on Climate Change (UNFCC). It is estimated that by 2030, global greenhouse gas (GHG) emissions must be approximately 25 percent and 55 percent lower than in 2017 to put the world on a least-cost pathway to limiting global warming to 2^{o}C and 1.5^{o}C, respectively (UNEP, 2018). Current mitigation efforts of the world's majority of emitters are, however, lacking (Gao et al., 2019).

Since the 1980s, the influence of technological progress on emissions reduction has been widely investigated both theoretically and empirically. Some scholars believe that technological progress can reduce energy consumption intensity, change energy consumption patterns, and reduce carbon emissions by developing more efficient and cleaner production technologies (Jordaan et al., 2017; Li et al., 2019; Poumanyvong and Kaneko, 2010; Shuai et al., 2017; Yang and Li, 2017). Other analyses show that technological progress promotes economic growth and induces an increase in energy consumption and carbon emissions (Ganda, 2019; Jaffe et al., 2005; Li and Wang, 2017). Existing studies on the relationship between technological progress and emission intensity are often carried out focusing on a single country. As carbon emissions is a global issue, any study investigating the relationship between the technology gap and emissions intensity should be undertaken at a global level (i.e. cross-country).

Technological progress changes the international production division and trade pattern through narrowing the technology gap with the frontiers, which has an effect on the carbon emissions of the country. If a less developed country increases the speed of technological progress and narrows the technology gap, they can improve their position in the GVC and reduce their emissions. Notwithstanding that the technological progress of a country has improved, the technology gap with the frontiers could be still widened since the faster advancement of the frontiers. In this case, even though the absolute level of technology progress has advanced, the country cannot reduce carbon emissions through improving GVC position. Because there are significant differences in carbon emissions performance between the two groups in terms of not only their mean but also their variance under group-frontier technologies （Zhang et al., 2013）.Therefore, whether technological progress can impact the carbon intensity of the country through GVC position does not depend on absolute technological progress but rather its relative technological progress (that is, the technology gap). A deeper understanding of the impact of the technology gap on emission intensity is important for developing countries that seek to reduce emissions without comprising economic development. For instance, China is the worlds' second-largest economy and the largest GHG emitter in the world and its technology gap is an important consideration for China's emissions reduction. Zhang et al. (2016) found that dynamic carbon emissions performance was mainly driven by the catch-up effect and boosted by innovation in China. Fei and Lin (2017) revealed eastern and central regions in China display a small part of CO2 emission reduction potential derived from the technology gap, while the western region possesses a relatively large part because of the technology gap.

Although the technology gap is important in shaping carbon intensity, there is still very little studies focusing on this topic. Employing the cross-sectional data in Korean, Zhang et al.,(2013) found that the variance under group-frontier technologies can also infect the energy and CO2 performance. However, their study used one country data and did not analyze the mechanism and decompose the direct and indirect effect. To address this gap in the literature, this study considers the technology gap, GVC and carbon intensity in one analytical framework and examines the influence of the technology gap on carbon intensity through GVC. As carbon emissions from production arise predominantly from the manufacturing sector, this paper analyzes empirically the carbon emissions of the global manufacturing sector.

Compared with the general literature on technological progress and carbon emissions, the main contributions of this paper are threefold. First, we study the mechanism of how the technology gap to affect carbon intensity by changing the position of GVC. Differing the previous literatures, in this paper, GVC position is an intermediate variable. Second, we use the technology gap as the main explanatory variable rather than the absolute level of technological progress. Third, we measure and calculate the direct and indirect effects of the technology gap on carbon emissions using the mediation effect model. Because the technology gap also has the indirect effect on carbon emissions, which may be ignored by the absolute level of technological progress to some extent.

The paper proceeds as follow: Section 2 states the mechanism and hypothesis. Section 3 elaborates on the methodology and data. Section 4 presents the empirical results. The concluding section provides policy recommendations and suggestions for further research.

2. Mechanism and Hypotheses

The technology gap influences carbon intensity through two channels: the technological progress effect and the international production division effect. Although the former has been extensively studied in the literature, the latter has received little to no attention as is the focus of this study.

Researches on how technological progress affects carbon emissions are well established. Although it is widely accepted that there exists a relationship between technological progress and carbon intensity, the direction of causality is unclear and worth further studying due to the existence of rebound effect(Yang and Li, 2017). The widely accepted consensus is that technological progress can affect, directly or indirectly, carbon intensity. In terms of direct mechanisms, technological progress can promote energy efficiency, improve production methods, and reduce the use of fossil fuels resulting in lower carbon intensity. Levinson's (2009) research shows that technological progress in the United States has a significant negative impact on carbon emissions. There are also come studies based on the input-output model and Computable General Equilibrium Model confirming that the technological progress is the main driving force of CO2 reduction(Manne and Richels, 2005; Okushima and Tamura, 2010; Timilsina and Shrestha, 2006).

As far as indirect mechanisms are concerned, technological progress impacts carbon emissions by promoting economic growth. Relatedly, there is a large body of empirical research into the Environmental Kuznets Curve (EKC). Many scholars believe that the impact of economic growth on carbon emissions follows an inverted U shape. When emission reduction technologies meet certain conditions, carbon emissions will undergo inverted U transformation (Andreoni and Levinson, 2001; Brock and Taylor, 2010; Grossman and Krueger, 2006).

The international production division effect refers to the impact of the technology gap on carbon emissions through GVC positioning. Studies investigating the technology gap and GVC suggest that technological progress can help manufacturing country shift to higher value-added productive activities (Morrison et al., 2007). Industrial technological innovation can often make inputs to production, such as labor and energy, shift into productive sectors with characterized by higher value-adding and lower carbon emissions, and thereby influence GVC positioning (Sun et al., 2019). In fact, a country's carbon emissions are closely related to its GVC positioning (Pei et al., 2016). As a result, the developing countries exports account for a substantial share of total production-based emissions through trade in final goods compared to developed countries(Meng et al., 2018).

Countries at the high end of the GVC have capital and technological advantages, and predominantly engage in low-carbon and high value-added roles in GVC. In contrast, countries at the lower end of the GVC mainly engaged in low technical and energy intensive processing and intermediate goods assembly(Yu and Luo, 2018; Zhang and Gallagher, 2016). Thus, the developing countries can optimize energy efficiency and reduce emissions when they improve their position in GVC(Sun et al., 2019).

When domestic technological progress outstrips the world technology frontier, it is possible to change the international production division and trade pattern through narrowing the technology gap with the frontiers, which has an effect on the carbon emissions of the country. Therefore, we argue that GVC positioning and carbon emissions are not necessarily dependent on a country’s absolute level of technological progress because international production division is also affected by the conditions of other countries. To analyze the international production division effect, two issues need to be clarified: how changes in the technology gap affect GVC positioning; and how changes in GVC positioning affect carbon intensity, so we propose the hypotheses 1:

Hypothesis 1: *narrowing the technology gap can reduce carbon emissions intensity through improve GVC positioning*.

There are large differences in carbon intensity between different industries, so the impact of technological progress on carbon emissions also has industry heterogeneity. The differences of emissions efficiency and reduction potentials are caused by differences in sectoral and national characteristics(Takayabu et al., 2019). Acemoglu et al. (2012) found that the mechanisms by which technological progress affects carbon emissions depends on the type of initial technology. That is, technological progress in green sector will reduce carbon emissions, while technological progress in the carbon-intensive sectors will increase carbon emissions. The energy efficiency of light industry is generally higher than that of heavy industry(Wang et al., 2019), and the industry heterogeneity is the most important reason for the difference in energy efficiency(Lu and Wang, 2015; Wang et al., 2013).

Concluded from previous studies, there are industry heterogeneity of the impact of technological progress on carbon emissions. The smaller the technology gap of an industry, the stronger its international competitiveness. Thus, an industry can occupy a high-end position in the GVC and engage in cleaner production when it narrowed its technology gap from the technology frontier. This infers that the higher the carbon intensity of the industry, the greater the emissions reduction when production shifts to the high-end of the GVC. According to the above analysis, we propose hypothesis 2.

Hypothesis 2: the impact of the technology gap on carbon emissions differs

among industries due to carbon intensity heterogeneity (industry heterogeneity).

The Porter Hypothesis suggest that environment regulation can affect innovation and technological progress. A large number of researches studied that stringent environmental regulation will induce firms to leave the country for less strict regulatory regimes(Ambec et al., 2013; Porter and Linde, 1995). Concluding from the Porter Hypothesis and pollution haven hypothesis, we find that countries with different level of environment regulation may have different incentive to make innovation and develop cleaner production(Adetutu et al., 2015). Manufacturers subject to environment regulation(cap-and-trade) experience improvements in energy efficiency(Curtis and Lee, 2019). In a country with high innovation incentive, the technology gap can be narrowed than the low innovation incentive country. In a country with cleaner production, the marginal effect of carbon reduction factor may be smaller. For example, Non-Annex I parties in the Kyoto Protocol, due to fewer restrictions, account for relatively more for the emissions resulting from fewer environmental regulations, meaning the technology gap may play a greater role(Kuriyama and Abe, 2018). Thus, the Kyoto Protocol was successful in reducing the emissions of the ratifying countries approximately by 7% below the emissions expected under a “No-Kyoto” scenario, confirming the importance of accounting for the collective nature of the agreement(Maamoun, 2019). Feroz et al.(2009) suggested that the nations that have ratified the Kyoto Protocol are more likely to be environmentally production efficient as compared to the nations that have not ratified the Protocol. China's current environmental regulation policies have played positive roles in reducing carbon emissions(Pei et al., 2019). Wei and Yang (2010) demonstrated that there are obvious regional differences of the impacts of technological progress on CO2 emissions in China, the eastern region is the highest, followed by the central and western regions(Wang et al., 2019). Based on the discussion above, we propose the hypotheses 3:

Hypothesis 3: The technology gap may play a greater role in countries that are not subject to environmental constraints and regulation (country heterogeneity).

3. **Methodology and Data**

3.1 Model design

3.1.1 System GMM

This paper constructs technological progress and the technology gap at the multinational industry level, and employs systematic GMM to explore the impact of the technology gap on carbon intensity. The benchmark model is as follows:

$$lnCO2int_{ijt}=\beta_0+\beta_1 lnCO2int_{ijt-1}+\beta_2 techgap_{ijt}+\beta_3 tech_{ijt}+\beta_4 gvc_{ijt}+\beta_5 Z_{ijt}+\mu_i+\mu_j+\mu_t+\varepsilon_{ijt} \quad (1)$$

where $lnCO2int_{ijt}$ is the logarithm of carbon intensity; $techgap_{ijt}$ is the logarithm of the technology gap; $tech_{ijt}$ is the logarithm of technological progress; $\boldsymbol{Z_{it}}$ is the control variables set including the GVC position, value added production, intra-industry trade index, actual capital stock, labor time structure, labor compensation structure, employees number, gross output, intermediate inputs; i represents industry, j represents country and t represents time. Further definition of these variables is provided in Section 3.2.

3.1.2 Panel data quantile regression

As discussed in Section 2, the effect of the technology gap on carbon emissions can differ among industries with different levels of carbon intensity. This paper uses panel data quantile regression to verify this hypothesis.

Panel data quantile regression estimates coefficients by combining the quantile regression and the panel data model to study the relationship between variables on the different quantiles of the dependent variable and based on the control of individual differences. Consider the following model:

$$y_{it} = \beta_{it} x_{it} + \alpha_i + \mu_{it} \qquad (2)$$

where i is an individual, t is time, μ is a random error term, β_{it} is a coefficient vector of independent variables, and α_i is an unobservable random effect vector of different samples. First, the conditional quantile equation is established to estimate the parameters of the above panel model:

$$q\left(\tau \middle| x_i, \beta(\tau)\right) = \beta(\tau) x_i + \alpha \qquad (3)$$

where $x_i = (x_{i1}, x_{2i}, \ldots, x_{ki})$ is the independent variable vector, and $\beta(\tau) = (\beta_1, \beta_2, \ldots, \beta_k)$ is the coefficient vector at the τ quantile. If there are differences in the estimated coefficients of the technology gap across industries, then the impact of the technology gap on carbon emissions is different among these industries.

When τ varies over (0, 1), solving the weighted absolute residual minimization problem can obtain the estimated parameter of the quantile regression. The minimum weighted absolute residual is:

$$\hat{\beta} = arg\min_{\alpha,\beta} \sum_{j=1}^{J} \sum_{t=1}^{T} \sum_{i=1}^{N} \rho_{\tau_j} \left(y_{it} - x_{it}\beta\left(\tau_j\right) - \alpha_i\right) \quad (4)$$

where ρ_{τ_j} is the weight of each quantile.

3.1.3 Mediation effect test

Under open economy conditions, a country can bridge the technology gap, raise its position in the GVC and reduce carbon emissions. Therefore, the model's mediated variable is GVC position. The mediation effect tests whether the technology gap affects carbon emissions through the GVC position as well as the magnitude of the impact.

Assuming that all variables are centralized, the mediation effect model can be illustrated as follows:

Figure 1 Illustration of Mediation Effect Model

In Figure 1, the coefficient c is the total effect of the independent variable X on the dependent variable Y; the coefficient a is the effect of the independent variable X on the mediated variable M; the coefficient b is the effect of the mediated variable M on the dependent variable Y after controlling for the independent variable X；and c' is the direct effect of the independent variable X on the dependent variable Y after controlling the mediated variable M. The "mediation effect" is the product a and b, and the total effect is equal to the sum of the direct effect and the mediation effect, that is $c = c'+ab$.

Baron and Kenny's stepwise regression is the most commonly used mediation test method (Zhao et al., 2010). The test is applied as follows: the first step is to test the coefficient c; the second step is to test the coefficients a and b in order, and if c is significant, a and b are also significant, the mediation effect is significant; if c' is not significant, the mediation effect is a complete mediation effect. In recent years, the robustness of this approach has been questioned by some studies and as an alternative, some studies use the bootstrap method to directly test the coefficient's product.

In this study, we apply the mediation effect test using the stepwise regression method and the bootstrap method. The mediation effect model can further explore the internal interaction mechanism when the X and Y relationships are known. More importantly, the total effect of X on Y can be decomposed into direct effects and indirect effects, and their scale can be measured. As we use panel data in our study, the mechanism analysis is based on the multi-level mediation method of Krull and MacKinnon (2001).

3.2 Data and variable construction

3.2.1 Industry consolidation and unifying

The industry carbon emissions and input-output data in this paper are obtained from environmental and socio-economic accounts of World Input-Output Database (WIOD) (2013). The GVC data is sourced from the GVC indicators published by University of International Business and Economics (UIBE)[†]. There are some papers had been published using this database (Mouanda-Mouanda, 2019; Pan, 2019; Qiu, 2019). We use the GVC index calculating from the WIOD2013 and use the international standard industrial classification ISIC_Rev3.0. We source detailed

[†] RIGVC UIBE, 2016, UIBE GVC Index, http://rigvc.uibe.edu.cn/english/D_E/database_database/index.htm

information of patents granted by the U.S. Patent and Trademark Office (USPTO) from the Harvard Business School Patent Inventor Database of Li et al. (2014) to construct the proxies of technological progress at the industry-level. Following Hsu et al.(2014) and Bhattacharya et al.(2017) which have matched the three-digit technical classification code of the USPTO patent with the US double-digit industry code, and calculate the industry technology gap and technological progress indicators using the US industry classification standard. Our sample spans from 1975 to 2010.

In order to combine the data for empirical analysis, we first need to match the US standard industrial classification (SIC) and the ISIC_Rev3.0. The specific matching details are shown in Table 1.

Table 1. The unifying of ISIC_Rev3.0 and US standard industry classification

3.2.2 Variable construction and descriptive statistics

In this paper, we focus on the carbon emission of a country, and develop the theoretical basis for a relationship between the technology gap and carbon intensity at the cross-country level and examine empirically the direct effects and indirect effects of the technology gap on emissions. So, the dependent variable is carbon emission intensity, calculated as total carbon emissions divided by industrial value-added output. The WIOD2013 publish emissions and energy use data at the country and industry level from 1995 to 2009 for the European Union and 13 major countries and regions.

The core independent variable - the technology gap - is calculated as follows:

$$Technology\ Gap_{ijt} = (Technology\ Frontier_{it} - Technological\ progress_{ijt})/Technology\ Frontier_{it} \quad (5)$$

where *i* denotes the industry, *j* denotes the country and *t* denotes time. The technology gap lies between 0 and 1. The smaller the value, the smaller the gap. We use the number of patent applications to measure technological progress and construct two kinds of proxies for the technology gap: the "quality indicator" (measured by the number of patent citations) and the "quantity indicator" (measured by the number of patent applications).

Technological progress is represented by the number of patents approved by the USPTO and the maximum number of patents represents the world's technology frontier. Employing patent data as a "technological" proxy indicator has several advantages: First, the patent data is open; Second, it provides a wealth of information and longer time series data, including all countries and technology types; Third, inventions are relatively standardized data, which gives us the comparable cross country and industry. This paper uses the Harvard Business School patent inventor database (Lai et al., 2011)[‡] to construct industrial patent data as a proxy for industrial technological progress. The number of patents in each industry is calculated based on the time that patent is approved. Since there is a lag between patent application and approval, this paper uses the lagged value to characterize the technological variables in the model (Bhattacharya et al., 2017).

[‡]The Harvard Business School Patent Applicant Database contains detailed information on patents approved by the US Patent and Trademark Office (USPTO) from 1976 to 2010.

The number of approved patents does not fully reflect the level of technological progress of an industry since the overall quantity does not always account for the quality. The patent citation better reflects the influence of patents and captures quality and market value (Aghion et al., 2013; Harhoff et al., 1999; Trajtenberg, 1990). It is hard to conclude that the patents approved in 2000 and cited 10 times in 2010 are of higher quality than those approved in 2008 but only cited 5 times, which is the truncation error. In this paper, the weighting factor developed by Hall et al.(2001) is used to adjust the number of patent citations.

Figure 2. Technological progress and technology gap

Source: Collating from USPTO and WIOD databases by author.

As can be seen in Figure 2, between 1995 and 2009, the average level of technological progress at the world industry level fluctuated and simultaneously the technology gap expanded. This means that the gap between the level of technological progress of an industry and the international frontier are not narrowing. Between 1995 and 2009, technological progress improved globally on average, whereas the technology gap enlarged.

We use the UIBE GVC Index that was constructed by the GVC Research Team of the UIBE combing the GVC accounting and other indicators[§]. Based on the original world ICIO table, the UIBE indicator system uses the current value-added

[§]RIGVC UIBE, 2016, UIBE GVC Index, http://rigvc.uibe.edu.cn/english/D_E/database_database/index.htm trade accounting and analysis method to generate the database. Based on the input-output data at the national and industrial level from 1995 to 2009, we construct control variables including forward linkage (based GVC participation index), backward linkage (based GVC participation index); capital density, labor time structure, labor compensation structure, number of employees, industry value added output, total industry output and intermediate inputs to production. The data is sourced from the social economic database published by WIOD in 2013 and the UIBE GVC Index.

Capital density is equal to the ratio of capital stock to industrial value-added production. Labor time structure is equal to the ratio of the working hours of high-skilled workers to the working hours of low and medium technical workers. Labor compensation structure is the ratio of labor compensation of high-skilled workers to labor compensation of low and medium technical workers. This paper constructs cross-national data from 39 countries, 15 years, and 14 manufacturing industries. Descriptive statistics of all the variables are reported in Table 2.

Table 2. Descriptive statistics

Sources: WIOD, UIBE GVC Index, WDI Database

4. Empirical Analysis

4.1 Unit root test

We first perform a panel unit root test on the variables using the LLC, HT and Fisher criteria to avoid the pseudo-regression problem. It can be seen from Table 3 that total output value, intermediate input, employees, energy use, and per capita GNI failed are non-stationary in levels and stationary in first-difference. The remaining variables are stationary in levels.

Table 3. Panel unit root test

4.2 Benchmark estimation and panel quantile regression

The benchmark estimation focuses on the effect of the technology gap on carbon emissions intensity using the systematic GMM. This estimation method controls for industry, country and year fixed effects of. The estimation results are presented in the first column of Table 4.

Table 4. Benchmark estimation

The benchmark estimates show that an improvement GVC position will significantly reduce the carbon emissions intensity. The increase in GVC positioning helps a country's industry to engage in cleaner and higher-end production in the international production division, thereby reducing carbon intensity. These results confirm Hypothesis 1. The backward linkage will significantly increase carbon intensity, which may be conducive to economic growth and energy use, thereby increasing carbon emissions. Intermediate inputs and emissions-related energy use significantly increase carbon intensity, as would be expected.

We now proceed to investigate whether the technology gap, GVC position and carbon emissions vary by industry (industry heterogeneity). As we can see in Table 4, the estimated coefficients of technology gap are not statistically significant before the 50th quantile and are statistically significant from 50th to 90th quantile. The value of estimated coefficients increases with the increase of quantiles. That is, the higher the carbon intensity of the industry, the greater the effect of the technology gap, which confirms Hypothesis 2. We find that the coefficient of GVC position is significantly negative in both SYS-GMM estimation and panel data quantile regression, which means the promotion of GVC position have negative effect on carbon emission intensity. The coefficient of backward linkage based GVC participation is significantly positive, which means the more an industry embodied in the GVC production from the backward, the higher carbon emission intensity the industry has. The coefficient of forward linkage based GVC participation is not statistically significant. These results are consistent in SYS-GMM estimation and panel data quantile regression.

4.3 Mechanism analysis

We use a multilevel mediation method in order to verify further what's role the technology gap plays in influencing carbon emissions. We presented the results of the stepwise regression method and the bootstrap method to test the mediation effect in Table 5 and Table 6, respectively. Before running the estimates, we center all the variables to avoid multi-collinearity effects.

Table 5 presents three sets of estimation results, corresponding to the three formulas of the mediation effect test using the stepwise regression method. The first tests whether the effect of the technology gap on carbon emissions is significant, the second tests the effect of the technology gap on the GVC position, and the third tests the effect of these two variables on carbon emissions intensity. The direct effect is the coefficient of the technology gap, and the mediation effect is equal to the coefficient of the technology gap in the second estimate multiplied by the coefficient of the GVC position in the third estimates. The total effect of technology gap on carbon emission intensity is 0.349, the direct effect of the technology gap on carbon emissions is 0.811, and the indirect effect is (-1.406) *(-0.031), or 0.043. The proportion of total effect mediated is about 11.7%. Therefore, the expansion of the technology gap will significantly increase carbon emissions, reduce the GVC position, and increase carbon emissions. The results confirm Hypothesis 2, that the division effect of the technology gap influences GVC positioning.

Table 5. Median effect test of stepwise regression

Since the stepwise regression method has many criticisms for the mediation effect (Zhao et al., 2010), a growing studies use the bootstrap method to directly test whether the mediation effect is significant, that is, whether the product of coefficient of technology gap in the estimates 3 and the estimates 2 is significant. In order to provide more robust mediation evidence, this paper also uses the bootstrap method to test the mediation effect, repeat sampling 500 times, the test results are listed in Table 6. The direct effects, indirect effects, and total effects are presented in Table 6. We find all effects are significant, and the scale of coefficients are consistent with the stepwise method. This finding provides robustness to the earlier results indicating that the mediation effect is significant.

Table 6. Bootstrap mediation effect test

4.4 Robustness test

To confirm the robustness of our results, we substitute the patent quantity indicator (citations) with the quantity indicator (the number of patent applications). The results are presented in Table 7.

The panel quantile regression robustness test is consistent with our previous results. The results of the mediation effect test show that the total effect of the technology gap on carbon emissions, direct effect and indirect effect, are significant. The results are also very similar to those presented in Table 6. Above all, these findings demonstrate that the empirical results of this paper are robust, and the expansion of the technology gap will significantly increase carbon emissions by affecting GVC positioning.

Table 7. Robustness test

4.5. Extended discussion

In order to verify the country heterogeneity hypothesis, we classify the baseline model according to whether they are the Annex I countries. The results are presented in Table 8 (in this instance the technology gap and technological progress in equations (1) and (3) are constructed by using patent citation). In equations (2) and (4), they are constructed using the number of patents. The estimates are still based on the system GMM (to control for time, industry and national fixed effects), and the standard error is the robust according to national industry and time clustering. There are no second-order sequence correlations for the four estimated residuals.

The results show that the expansion of the technology gap drives increases in carbon emissions, but this effect varies across country categories. This provides prima facie evidence in support of Hypothesis 3.

In non-Annex I countries, the estimated coefficient of the technology gap is significantly positive and the larger than Annex I countries (for Annex I countries, the estimated coefficient is not statistically significant). Non-Annex I countries have a relatively loose environmental constraint, and subsequently, higher carbon emissions. In industries with higher carbon intensity, the technology gap plays a greater role, which is consistent with the previous analysis. However, we find that the technology gap in Annex I countries is not significant. The reason is that most Annex I countries are developed countries, which not only have strict environmental constraints, but also occupy a high-end position in the GVC and undertake cleaner production. The coefficients of other control variables are consistent with the baseline estimates.

Table 8. Group estimates

We now test whether the change in the technology gap affects carbon emissions through GVC positioning using the bootstrap mediation test. The estimated results are presented in Table 9. Technology (citation) represents the quality of patent that is measured by number of patent citations, and the technology(number) represents the quantity of patent that is measured by the number of patent applications.

The results reveal that the technology gap of non-Annex I countries has a meditation effect, but no direct effect. The median effect of Annex I countries is significant, and the proportion of the total effect mediated is about 5%, less than the full sample result. This result is also consistent with the estimates in Table 8, further confirming that for countries with higher carbon intensity, the technology gap can affect carbon emissions by affecting the GVC positioning.

Table 9. Mediation effect test

5. Conclusion and Policy Implications

Technological progress is an important factor for countries to achieve Intended Nationally Determined Contribution. Existing studies on the relationship between technology gaps and emission intensity generally only focus on a single country. As GHG emissions are an international concern, a proper examination of how technological progress influences carbon intensity should be conducted at the cross-country level. Technological progress changes the international production division and trade pattern through narrowing the technology gap with international frontiers, which has an effect on the country level carbon emissions. From the perspective of the global economy, technological progress of a country infers a change in the technology gap, resulting in changes to GVC positioning, international production division and industrial competition, which in turn influences trade patterns. Industrial structure and trade patterns directly affect the carbon emissions of the economy.

Although the technology gap is important in shaping energy intensity, there is very little research on the relationship between the technology gap and carbon intensity. We posit that technology gap can change carbon intensity with GVC positioning as a meditating factor. We further posit that this relationship varies across industries with different levels of carbon intensity and across Annex I and non-Annex I countries.

This paper combines theories relating to the technology gap, GVC and carbon intensity into a single analytical framework. Compared with the literature on general technological progress and carbon emission, the main contribution of this paper is that it decomposes the direct effects and indirect effects through the mediation effect model and quantifies the mediation role of GVC positioning in the relationship between the technology gap and carbon emissions intensity.

The empirical results show that narrowing the technology gap significantly reduces carbon emissions, and the higher the carbon intensity, the greater the effect of technology gap on reducing emissions intensity. The mediation effect model proves that the impact of the technology gap on the carbon emission can be achieved by improving GVC positioning. The results of the country group estimates indicate that technology gap can play a significant role in carbon emissions in Non-Annex I countries, and that it has the greatest mediation effect through changing GVC.

The policy implications of this paper are summarized as follows: First, mitigating emissions needs a global framework due to the presence of carbon leakage along the GVC. Second, in order to pursue green development, national governments must not only focus on their own technological progress, but also pay attention to the gap between their technology level and the world's frontiers. Third, in order to effectively advance technological progress for emission reduction, priority should be given to carbon intensive industries. Last, Annex I countries needs to work harder than non-Annex I countries in advancing their technological progress and reducing technology gaps. Non-Annex I countries, which have high abatement potential, could collaborate with Annex I countries through measures such as regional cooperation and trade (Han et al., 2018) in order to promote cost effective emission mitigation.

The present study could be further improved in the future in the following areas: Technology gap can be differentiated into clean technology gap and dirty technology gap, and explore how technology gaps in different technology categories affect carbon intensity.

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Table(s)

Tables

Table 1. The unifying of ISIC_Rev3.0 and US standard industry classification

ISIC/REV3.0		US SIC[1]	Unified industry code
Food, beverages and tobacco	sec15t16	20，21	1
Textiles and textile	sec17t18	22,23	2
Leather, leather and footwear	sec19	31	3
Wood and of wood and cork	sec20	24	4
Pulp, paper, paper, printing and publishing	sec21t22	26、27	5
Coke, refined petroleum and nuclear fuel	sec23	29	6
Chemicals and chemical	sec24	28	7
Rubber and plastics	sec25	30	8
Other non-metallic mineral	sec26	32	9
Basic metals and fabricated metal	sec27t28	33、34	10
Machinery, nec	sec29	35	11
Electrical and optical equipment	sec30t33	36、38	12
Transport equipment	sec34t35	37	13
Manufacturing nec; recycling	sec36t37	25、39	14

Table 2. Descriptive statistics

variable	Variable content	Obs	mean	std	min	max
CO2int	log of CO2 intensity	8190	2.031	2.63	-11.543	6.313
GVC	GVC position	8190	0.927	0.134	0.646	1.687
lntechnum	log of technology progress (number)	8190	4.079	3.624	0.000	13.710
lntechgapp	log of technology gap (number)	8190	0.818	0.369	0.000	1.000
lntechcit	log of technology progress(citation)	8190	3.332	3.295	0.000	13.397

[1] For details of the US industry classification code and corresponding name, see: https://mckimmoncenter.ncsu.edu/2digitsiccodes/

lntechgapc	log of technology gap(citation)	8190	0.824	0.368	0.000	1.000
lncap	log of capital density	8190	-0.983	0.720	-7.643	8.259
laborhs	work hours structure	8190	0.163	0.121	0.004	0.850
laborcs	labor compensation structure	8190	0.276	0.190	0.006	1.711
lnvalue	log of value added	8190	4.843	0.516	0.000	7.624
lninter	log of Intermediate inputs	8190	4.864	0.557	0.000	7.793
lngross	log of Gross output by industry	8190	5.021	0.852	2.447	10.825
lnenergy	log of energy use	8190	4.331	2.001	0.000	10.017
lnemployee	log of number of persons engaged	8190	9.724	2.510	0.000	16.035
lngni	log of GNI per capital	8190	9.76	0.717	7.293	11.197
forward	Forward linkage based GVC participation	8190	0.293	0.194	0	3.87
backward	Backward linkage based GVC participation	8190	0.299	0.140	0	0.93

Sources: WIOD, UIBE GVC Index, WDI Database

Table 3. Panel unit root test

Variables	LLC Criteria		HT Criteria		Fisher Criteria	
	Statistic	P Value	Statistic	P Value	Statistic	P Value
CO2int	-33.864***	0.000	-5.57***	0.000	40.297***	0.000
GVC	-76.6***	0.000	-21.855***	0.000	43.206***	0.000
lntechnum	-50.182***	0.000	-61.706***	0.000	66.217***	0.000
lntechgapp	-540***	0.000	-62.186***	0.000	85.624***	0.000
lntechcit	-50.182***	0.000	-61.706***	0.000	66.217***	0.000
lntechgapc	-570***	0.000	-62.344***	0.000	93.718***	0.000
lncapital	-27.738***	0.000	-49.63***	0.000	49.46***	0.000
laborhs	-15.448***	0.000	-15.689***	0.000	13.452***	0.000
laborcs	-22.654***	0.000	-16.106***	0.000	23.666***	0.000
lnvalue	-81.990***	0.000	-3.647***	0.0001	51.457***	0.000
forward	-12.36***	0.000	-37.901***	0.000	40.4***	0.000
backward	-8.931***	0.000	-15.386***	0.000	43.152***	0.000
lngross	-5.796***	0.000	3.8594	0.9999	35.998***	0.000
lninter	-6.242***	0.000	4.536	1	35.909***	0.000

lnenergy	-13.002***	0.000	-0.793	0.214	37.051***	0.000
lnemployee	-6.677***	0.000	-0.717	0.2367	27.1967***	0.000
lngni	-3.18***	0.001	16.168	1	19.742***	0.000
FODlngross[2]	-35.802***	0.000	-27.624***	0.000	55.466***	0.000
FODlninter	-39.039***	0.000	-26.299***	0.000	58.102***	0.000
FODlnenergy	-54.576***	0.000	-46.066***	0.000	77.416***	0.000
FODlnemployee	-29.7995***	0.000	-39.964***	0.000	59.503***	0.000
FODlngni	-22.473***	0.000	-9.187***	0.000	45.801***	0.000

Table 4. Benchmark estimation

Dependent variable:CO2int	SYS-GMM	Quantile regression with panel data				
	Baseline	q(10)	q(30)	q(50)	q(70)	q(90)
CO2int 1st order lag	0.137***	0.989***	0.993***	0.994***	0.992***	0.986***
	(3.59)	(391.80)	(790.98)	(765.10)	(651.99)	(281.71)
lntechcit	0.00413*	0.000995	-0.000917	-0.000649	-0.00147**	-0.0119***
	(1.72)	(0.46)	(-0.72)	(-0.85)	(-2.15)	(-4.50)
lntechgapc	0.0395*	0.0137	0.0104	0.0101*	0.0119**	0.0206***
	(1.89)	(1.59)	(1.45)	(1.88)	(2.04)	(2.80)
GVC position	-1.439**	-0.112***	-0.105***	-0.101**	-0.0980**	-0.0769*
	(-2.50)	(-2.71)	(-2.59)	(-2.47)	(-2.40)	(-1.83)
forward	0.482***	-0.0490	-0.0487	-0.0463	-0.0460	-0.0478
	(2.59)	(-1.61)	(-1.64)	(-1.59)	(-1.56)	(-1.61)
backward	0.770*	0.0775*	0.0812*	0.0832*	0.0856**	0.0925**
	(1.91)	(1.77)	(1.88)	(1.94)	(2.01)	(2.17)
lncapital	-0.00735	-0.0125	-0.00393	-0.00280	-0.000154	0.00214
	(-0.59)	(-1.64)	(-0.64)	(-0.51)	(-0.03)	(0.31)
laborhs	0.345	-0.174**	-0.177**	-0.178***	-0.179***	-0.179**
	(0.85)	(-2.51)	(-2.57)	(-2.58)	(-2.61)	(-2.57)
laborcs	-0.167	0.113***	0.109***	0.108***	0.108***	0.108***
	(-0.78)	(3.24)	(3.04)	(3.01)	(2.90)	(3.08)
FODlngross	-0.968***	-0.114***	-0.0700***	-0.0463***	-0.0284***	0.0175*
	(-5.54)	(-9.36)	(-15.19)	(-9.30)	(-5.76)	(1.72)

[2]FODinter means first order difference of inter.

FODlninter	0.569***	-0.101**	-0.0976*	-0.0915*	-0.0872*	-0.0528
	(4.35)	(-2.00)	(-1.91)	(-1.80)	(-1.72)	(-1.04)
FODlnenergy	0.304***	0.0484	0.0552	0.0610	0.0657	0.0980**
	(7.61)	(1.03)	(1.19)	(1.33)	(1.44)	(2.17)
FODlnemployee	-0.241***	0.0134***	0.0121***	0.00771***	0.00839***	0.0178***
	(-4.00)	(3.17)	(4.79)	(3.36)	(2.94)	(3.25)
lnvalue	-0.469***	-0.00101	-0.00601	-0.00649	-0.0134***	-0.0183***
	(-4.72)	(-0.13)	(-1.38)	(-1.59)	(-2.90)	(-2.70)
FODlngni	-0.244	0.0588***	0.0510***	0.0443***	0.0394***	0.101***
	(-1.04)	(4.34)	(5.43)	(5.28)	(4.85)	(7.61)
Time fixed effect	YES	-	-	-	-	-
Country fixed effect	YES	-	-	-	-	-
Industry fixed effect	YES	-	-	-	-	-
Constant	0	-0.107	-0.104	-0.102	-0.100	-0.0821
	(.)	(-1.01)	(-0.98)	(-0.96)	(-0.95)	(-0.77)
N	7606	7606	7606	7606	7606	7606

Notes: Z values are in parentheses, and *, **, and *** indicate significant levels at 10%, 5%, and 1%, respectively. q (10)-q (90) represent the estimated results of the 10th, 30th, 50th, 70th, and 90th positions, respectively.

Table 5. Median effect test of stepwise regression

	(1)	(2)	(3)
Dependent variable	CO2int	GVC position	CO2int
GVC position			-1.406***
			(-5.84)
lntechgapc	0.349***	-0.031***	0.326***
	(6.92)	-12.76	(6.38)
lntechcit	0.02***	-0.001***	0.0191***
	(3.11)	-2.91	(2.94)
lncapital	0.198***	0.004***	0.193***
	(8.33)	3.9	(8.10)
lnvalue	-0.335***	-0.003	-0.343***
	(-8.67)	-1.5	(-8.88)
FODlninter	0.842***	0.001	1.382***
	(3.5)	0.07	(5.16)
FODlngni	-1.015***	0.011	-1.014**

	(-2.6)	0.57	(-2.56)
FODlngross	-1.274***	-0.007	-1.882***
	(-4.81)	-0.48	(-6.10)
laborhs	-2.141***	0.178***	-1.953***
	(-3.62)	6.46	(-3.29)
laborcs	0.222***	-0.047***	0.176
	(0.7)	-3.14	(0.55)
FODlnenergy	0.251***	-0.003	0.256***
	(3.22)	-0.67	(3.21)
FODlnemployee	-0.569***	0.007	-0.502***
	(-3.26)	0.85	(-2.87)
forward	1.279***	0.243***	1.652***
	(12.6)	50.11	(14.07)
backward	-1.073***	0.198***	-0.562***
	(-6.36)	23.76	(-3.07)
Constant	-0.028***	-0.001	-0.0361
	(-0.08)	-0.15	(-0.10)
N	7606	7606	7606
Meditator Variable:GVC position, it is level 1 variable			
c_path = 0.34851033			
a_path = -0.03073396			
b_path = -1.4059667			
c_prime = 0.32600969 same as dir_eff			
ind_eff = 0.04321093	proportion of total effect mediated =		0.11703281
dir_eff = 0.32600969	ratio of indirect to direct effect =		0.13254491
tot_eff = 0.36922062	ratio of total to direct effect =		1.1325449

Note: Z values are in parentheses, and *, **, and *** indicate significant levels at 10%, 5%, and 1%, respectively.

Table 6. Bootstrap mediation effect test

	Observed Coef.	Bootstrap Std. Err.	z	P>z	Normal based [95% Conf.Interval]	
Indirect effect	0.043	0.014	3.020	0.003	0.015	0.071
Direct effect	0.326	0.051	6.360	0.000	0.226	0.426
Total effect	0.369	0.049	7.490	0.000	0.273	0.466

Table 7. Robustness test

Dependent variable:CO2int	SYSGMM	Quantile regression with panel data				
	Baseline	q(10)	q(30)	q(50)	q(70)	q(90)
CO2int 1st order lag	0.138***	0.989***	0.993***	0.994***	0.992***	0.986***
	(3.63)	(395.75)	(584.99)	(645.50)	(570.50)	(276.87)
lntechnum	0.00314	0.00164	-0.000379	-0.000306	-0.000947	-0.00814***
	(1.53)	(0.90)	(-0.62)	(-0.56)	(-1.49)	(-2.89)
lntechgapp	0.0304	0.0121	0.0105	0.0101	0.0124**	0.0254***
	(1.19)	(1.41)	(1.58)	(1.58)	(1.98)	(3.48)
GVC position	-1.438**	-0.112*	-0.107*	-0.103*	-0.0990*	-0.0574
	(-2.50)	(-1.95)	(-1.87)	(-1.82)	(-1.74)	(-0.96)
forward	0.481***	-0.0489*	-0.0484*	-0.0461*	-0.0454*	-0.0467*
	(2.59)	(-1.90)	(-1.93)	(-1.81)	(-1.80)	(-1.92)
backward	0.770*	0.0787**	0.0822**	0.0841**	0.0866**	0.0981***
	(1.91)	(2.07)	(2.18)	(2.23)	(2.30)	(2.60)
lncapital	-0.0073	-0.0125**	-0.00403	-0.00295	-0.000194	0.00390
	(-0.59)	(-2.10)	(-0.94)	(-0.68)	(-0.04)	(0.91)
laborhs	0.342	-0.181**	-0.184**	-0.184**	-0.186**	-0.188**
	(0.85)	(-2.21)	(-2.25)	(-2.27)	(-2.28)	(-2.30)
laborcs	-0.165	0.116**	0.111**	0.111**	0.110**	0.109**
	(-0.77)	(2.41)	(2.27)	(2.24)	(2.22)	(2.20)
FODlngross	-0.969***	-0.101**	-0.0970**	-0.0912**	-0.0867**	-0.0492
	(-5.54)	(-2.44)	(-2.42)	(-2.27)	(-2.18)	(-1.23)
FODlninter	0.570***	0.0482	0.0552	0.0606	0.0657	0.0972**
	(4.34)	(1.20)	(1.35)	(1.50)	(1.63)	(2.41)
FODlnenergy	0.304***	0.0132**	0.0122***	0.00765***	0.00833***	0.0145*
	(7.6)	(2.35)	(3.49)	(2.74)	(2.94)	(1.91)
FODlnemployee	-0.241***	-0.00118	-0.00670	-0.00685*	-0.0139***	-0.0183***
	(-3.98)	(-0.14)	(-1.32)	(-1.93)	(-4.30)	(-3.77)
lnvalue	-0.469***	-0.112***	-0.0700***	-0.0464***	-0.0277***	0.0232***
	(-4.72)	(-8.82)	(-10.74)	(-6.78)	(-4.31)	(4.15)
FODlngni	-0.242	0.0568***	0.0497***	0.0436***	0.0381***	0.0907***
	(-1.03)	(3.24)	(10.28)	(9.05)	(6.81)	(11.55)

Time fixed effect	YES	-	-	-	-	-
Country fixed effect	YES	-	-	-	-	-
Industry fixed effect	YES	-	-	-	-	-
Constant	7.143***	-0.0961	-0.0928	-0.0911	-0.0892	-0.0574
	(5.66)	(-1.27)	(-1.22)	(-1.20)	(-1.17)	(-0.74)
N	7606	7606	7606	7606	7606	7606

	Observed Coef.	Bootstrap Std. Err.	z	P>z	Normal based [95% Conf.Interval]	
Indirect effect	0.042	0.007	6.02	0	0.029	0.056
Direct effect	0.343	0.031	11.23	0	0.283	0.403
Total effect	0.385	0.025	15.8	0	0.338	0.433
proportion of total effect mediated =			0.117			
ratio of indirect to direct effect =			0.133			
ratio of total to direct effect =			1.133			

Notes: Z values are in parentheses, and *, **, and *** indicate significant levels at 10%, 5%, and 1%, respectively.

Table 8. Group estimates

Dependent variable:CO2int	No Annex I Countries		Annex I Countries	
	(1)	(2)	(3)	(4)
CO2int 1st order lag	0.547***	0.547***	0.0683	0.0691
	(6.89)	(6.87)	(1.57)	(1.59)
lntechcit	0.0135***	0.0129***	0.00211	0.00132
	(2.77)	(2.71)	(0.88)	(0.63)
lntechgapc	1.875***	2.117**	0.0169	0.00508
	(2.58)	(2.26)	(0.76)	(0.25)
GVC position	-1.309**	-1.308**	-0.694	-0.693
	(-2.45)	(-2.44)	(-0.92)	(-0.92)
forward	-0.0424	-0.0436	1.056***	1.055***
	(-0.39)	(-0.40)	(4.5)	(4.50)
backward	0.103	0.104	0.949*	0.948*
	(0.3)	(0.30)	(1.94)	(1.94)
lncapital	-0.014	-0.0134	-0.0114	-0.0113
	(-0.44)	(-0.42)	(-0.81)	(-0.80)
laborhs	-0.543	-0.455	0.528	0.525
	(-0.80)	(-0.68)	(1.12)	(1.11)

laborcs	-0.00956	-0.0488	-0.196	-0.194
	(-0.02)	(-0.12)	(-0.80)	(-0.80)
FODlngross	-1.278***	-1.278***	-0.872***	-0.872***
	(-6.54)	(-6.52)	(-4.10)	(-4.10)
FODlninter	0.562***	0.564***	0.488***	0.488***
	(3.96)	(3.93)	(3.21)	(3.20)
FODlnenergy	0.731***	0.728***	0.241***	0.241***
	(7.06)	(6.99)	(5.52)	(5.52)
FODlnemployee	-0.598***	-0.595***	-0.191***	-0.191***
	(-3.94)	(-3.90)	(-2.71)	(-2.71)
lnvalue	-0.347***	-0.350***	-0.468***	-0.467***
	(-3.50)	(-3.51)	(-3.74)	(-3.74)
FODlngni	0.499**	0.484*	-0.686**	-0.684**
	(2.00)	(1.91)	(-2.14)	(-2.13)
Time fixed effect	YES	YES	YES	YES
Country fixed effect	YES	YES	YES	YES
Industry fixed effect	YES	YES	YES	YES
Constant	1.154	0.925	0	0
	(1.26)	(0.93)	(.)	(.)
N	1364	1364	6242	6242
ar1p	0.000	0.000	0.156	0.151
ar2p	0.319	0.432	0.571	0.567
hansenp	.	.	1	1

Notes: Z values are in parentheses, and *, **, and *** indicate significant levels at 10%, 5%, and 1%, respectively.

Table 9. Mediation effect test

	No Annex I Countries: N=1364						
		Observed Coef.	Bootstrap Std. Err.	z	P>z	Normal based [95% Conf.Interval]	
Technology (citation)	Indirect effect	0.085	0.034	2.510	0.012	0.019	0.152
	Direct effect	0.060	0.120	0.500	0.618	-0.175	0.294
	Total effect	0.145	0.085	1.700	0.090	-0.022	0.313
Technology (number)	Indirect effect	0.084	0.034	2.450	0.014	0.017	0.151
	Direct effect	0.067	0.139	0.480	0.629	-0.205	0.340
	Total effect	0.151	0.105	1.440	0.150	-0.055	0.356

	Annex I Countries: N=6242						
Technology (citation)	Indirect effect	0.021	0.003	8.110	0.000	0.016	0.027
	Direct effect	0.378	0.003	120.910	0.000	0.372	0.384
	Total effect	0.399	0.000	838.360	0.000	0.398	0.400
Technology (number)	Indirect effect	0.021	0.003	8.130	0.000	0.016	0.026
	Direct effect	0.399	0.006	71.420	0.000	0.388	0.410
	Total effect	0.420	0.003	141.580	0.000	0.414	0.426

Figure(s)

Figures

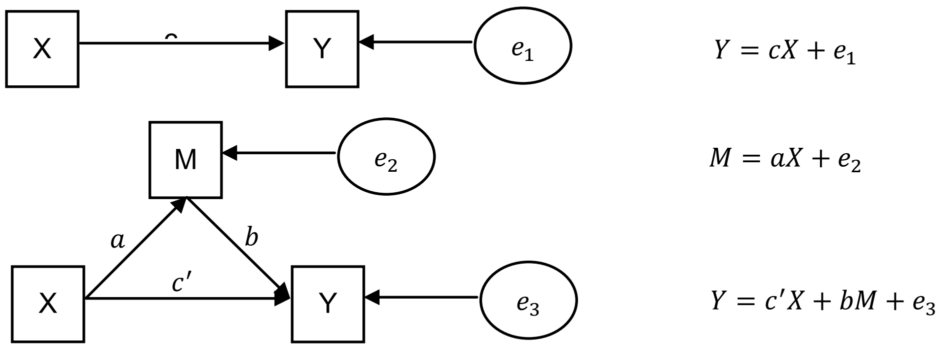

Figure 1. Illustration of Mediation Effect Model

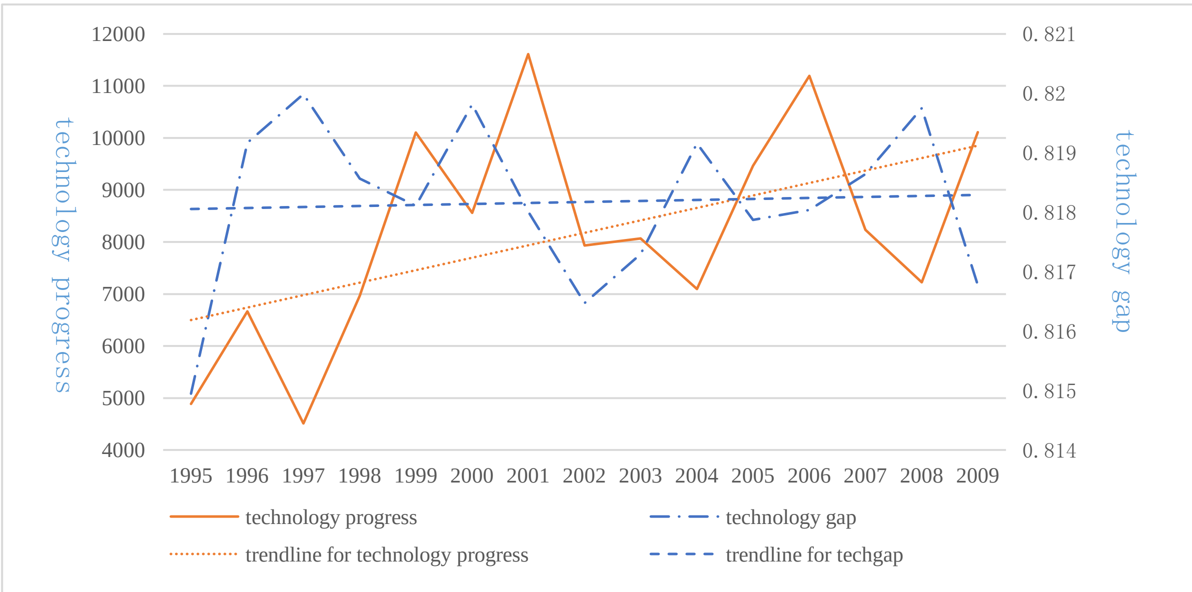

Figure 2. Technology progress and technology gap

Source: Collating from USPTO and WIOD databases by author.