How Does Biased Technological Progress Affect Haze Pollution? Evidence from APEC Economies

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neutral technological progress on haze pollution was the opposite of the effect from output biased technological progress. We also found that increasing renewable energy consumption and reducing energy intensity were separate effective paths for input and output biased technological progress, respectively, to mitigate haze pollution. For neutral technological progress, improving total factor productivity was an important way to mitigate haze pollution. Finally, several policy recommendations are proposed to mitigate haze pollution in APEC economies.

Key words: Haze pollution; Biased technological progress; Neutral technological progress; Marginal rate of substitution; Panel quantile model

1. Introduction

The Asia-Pacific Economic Cooperation (APEC) economy has experienced rapid growth, with gross domestic product (GDP) increasing from 20.36 trillion dollars in 2000 to 48.11 trillion dollars in 2017. The average contribution rate of the APEC economy to global economic growth during this period was 56.6% (World Bank, 2018). However, as a global economic engine, APEC economies have encountered serious environmental pollution, especially haze pollution. Data from the Socioeconomic Data and Applications Center report that the population-weighted average $PM_{2.5}$ concentration of APEC economies (10.85 ug/m^3) exceeded the worldwide average (7.42 ug/m^3) in 2017. To mitigate this increasingly serious problem, APEC economies have committed to doubling renewable energy consumption by 2030 and to reducing

total energy consumption by 45% by 2045, compared with 2010¹. Biased technological progress is an indispensable driving factor for energy conservation and emission reduction. When technological progress leverages less non-renewable energy and more renewable energy, it can achieve the triple goals of energy conservation, emission reduction, and economic growth (Acemoglu et al., 2016).

Since Hicks (1932) proposed the concept of biased technological progress, Kennedy (1964) and Samuelson (1965) further established a theoretical model to describe it. However, lacking a micro-theoretical foundation, the development of biased technological progress theory stalled over the next 30 years. Until around 2000, however, Acemoglu developed a theory of biased technological progress, and elaborated the micro-motivation of biased technological progress (Acemoglu, 1998, 2002, 2007). He emphasized that biased technological progress reflects a change in the marginal rate of substitution. If technological progress leads the marginal productivity of labor to exceed the marginal productivity of capital, for example, then technological progress tends to use more labor. The reverse is also true. Using Acemoglu's studies, researchers developed the measurement method of biased technological progress (Färe et al., 1997), the biased characteristics identification method of technological progress (Weber and Domazlicky, 1999), the environmental performance of biased technological progress (Shao et al., 2016), and the energy conservation performance of biased technological progress (Zha et al., 2017, 2018).

¹Data extracted from: http://iefi.mof.gov.cn/pdlb/dbjgzz/201512/t20151209_1604872.html.

Establishing methods for measuring biased technological progress is a prerequisite for identifying the biased characteristics of technological progress. Originally, the constant elasticity of substitution (CES) production function was applied to measure biased technological progress (David and Van de Klundert, 1965). Using this method, Klump et al. (2007) and Li and Stewart (2014) measured biased technological progress in the United States and Canada. However, assuming the constant elasticity of factor substitution may bias the measurement results. Stochastic frontier analysis (SFA) can address the limitation of constant elasticity of factor substitution by building a parameter model. However, the results may be biased due to the lack of objective parameter settings (Reinhard et al., 2000). Moreover, the SFA method cannot address the problem of multiple outputs (Reinhard et al., 1999). Compared with the CES and SFA methods, data envelopment analysis (DEA) can address the problems of multiple inputs and multiple outputs, without assuming the constant elasticity of factor substitution or setting a specific parameter model (Chung et al., 1997). In the context of these properties, the DEA method is now a preferred approach to measure biased technological progress.

Using the DEA method, Färe et al. (1994) decomposed the Malmquist productivity index into the product of technological change and technological efficiency change. To analyze the biases of technological progress, Färe et al. (1997) further decomposed technological change into the product of neutral technology change, input biased technological change, and output biased technological change. Using the work of Färe et al. (1997), Weber and Domazlicky (1999) developed a method to calculate the biased

characteristics of technological progress, based on the changes in factor growth rate and biased technological progress. This method is simple and easy to calculate, making it a preferred approach for identifying the biased characteristics of technological progress. For example, Chen and Yu (2014) found that technological progress in 99 countries between 1991-2003 was biased toward using more capital, followed by energy and labor. Hampf and Krüger (2017) analyzed the biases of technological progress in 81 countries between 1970-2014, finding that technological progress favored the use of more capital.

The biased characteristics of technological progress play a prominent role in energy conservation and emission reduction. When input biased technological progress uses less fossil energy, or output biased technological progress discharges fewer pollutants, both can significantly impact energy conservation and emission reduction (Li et al., 2019a). Biased technological progress can reduce emissions by controlling fossil energy consumption, reducing energy intensity, or improving the energy structure. For example, Wang and Qi (2014) found that biased technological progress played an important role in reducing energy intensity in Chinese industrial sectors between 1999-2010. Yang et al. (2018) found that improving China's industrial energy structure was an important path by which biased technological progress affected energy conservation and emission reduction. Zha et al. (2018) found that technological progress preferred led to more energy usage in the Chinese industrial period between 1990-2012, hindering energy conservation and emission reduction.

Biased technological progress can change the marginal productivity of energy,

which determines energy consumption. The traditional conclusion is that the lower the energy consumption is, the lower the pollution emissions are (Salahuddin and Gow, 2014). However, the traditional conclusion assumes that the energy structure does not change. The difference between non-renewable energy and renewable energy is that renewable energy discharges minimal pollutants (Yang et al., 2020). If technological progress favors renewable energy instead of non-renewable fossil energy, technological progress can contribute to reducing pollution emissions (Shafiei and Salim, 2014). In this context, we need to distinguish between non-renewable energy and renewable energy when analyzing biased technological progress.

The three primary goals of this study were: (1) to discuss the effect of biased technological progress on haze pollution, based on a panel quantile regression model; (2) to identify the heterogeneity of the effect at different income levels; and (3) to explore the influencing mechanism based on the mediating effects model. In light of previous studies, this study makes three significant contributions to the field. First, we explored the impact of biased technological progress on $PM_{2.5}$ and explained the influencing mechanism². Second, using a framework of capital, labor, and non-renewable energy, we introduced renewable energy to measure biased technological progress, and distinguished the bias between non-renewable energy and renewable energy. Third, we revised the identification method proposed by Weber and Domazlicky

²Sulfur dioxide, nitrogen oxides, and inhalable particulate matter are the main components of haze pollution. The inhalable particulate matter is the culprit of haze pollution. For this reason, we choose $PM_{2.5}$ as the proxy variable of haze pollution.

(1999), which did not address the marginal rate of substitution and nor facilitate comparisons between factors with too large a cardinal difference. To address these gaps, we built a new identification method based on the marginal productivity theory.

The current study is structured as follows. Section 2 introduces the measurement method of biased technological progress. Section 3 describes the biased characteristics of biased technological progress. Section 4 presents the regression results of the effect of biased technological progress on PM_{2.5}. Section 5 explores the influencing mechanism of biased technological progress on PM_{2.5}. Section 6 concludes and gives policy implications.

2. Methodology

2.1 Malmquist-Luenberger productivity index

We assume that $x^t = (x_1^t, \dots, x_N^t) \in R_N^+$, $y^t = (y_1^t, \dots, y_M^t) \in R_M^+$, and $b^t = (b_1^t, \dots, b_O^t) \in R_O^+$ represent an input vector set, a desirable output vector set, and an undesirable output vector, respectively, set in time t . Based on Färe et al. (1997), for any $x^t \in R_N^+$, the production technology of input possibility set is defined as follows:

$$L^t(y^t, b^t) = \{x^t : x^t \text{ can produce } (y^t, b^t)\}, \quad t = 1, \dots, T \quad (1)$$

where the input possibility set is assumed to be closed, bounded, convex, and strongly disposable. According to the input possibility set, the Shephard input distance function is defined as follows:

$$D_i^t(y^t, b^t, x^t) = \sup\{\theta : (x^t/\theta) \in L^t(y^t, b^t)\}, \quad t = 1, \dots, T \quad (2)$$

where the reciprocal of the Shephard input distance function represents the ratio of the minimum input to the actual input when the output is constant. Using Färe et al. (1994), the Malmquist-Luenberger (ML) productivity index with constant returns to

scale is defined as follows:

$$ML = \left[\frac{D_0^t(y^t, b^t, x^t)}{D_0^t(y^{t+1}, b^{t+1}, x^{t+1})} \times \frac{D_0^{t+1}(y^t, b^t, x^t)}{D_0^{t+1}(y^{t+1}, b^{t+1}, x^{t+1})} \right]^{\frac{1}{2}} = \sqrt{K^t \times K^{t+1}}, \quad t=1, \dots, T-1 \quad (3)$$

where K represents the change in total factor productivity from time t to time $t+1$. To avoid being arbitrary by choosing one of the two reference technologies, we used the geometric mean of two production technologies, consistent with Chung et al. (1997).

2.2 Input biased technological progress

Based on Färe et al. (1994), the ML productivity index is decomposed into two components: technological efficiency change (TE) and technological change (TC), as follows:

$$ML = \frac{D_0^t(y^t, b^t, x^t)}{D_0^{t+1}(y^{t+1}, b^{t+1}, x^{t+1})} \times \left[\frac{D_0^{t+1}(y^t, b^t, x^t)}{D_0^t(y^t, b^t, x^t)} \times \frac{D_0^{t+1}(y^{t+1}, b^{t+1}, x^{t+1})}{D_0^t(y^{t+1}, b^{t+1}, x^{t+1})} \right]^{\frac{1}{2}} = TE \times TC \quad (4)$$

TC is written as:

$$TC = \left[\frac{D_0^{t+1}(y^t, b^t, x^t)}{D_0^t(y^t, b^t, x^t)} \right] \times \left[\frac{D_0^t(y^{t+1}, b^{t+1}, x^{t+1})}{D_0^{t+1}(y^{t+1}, b^{t+1}, x^{t+1})} \right]^{\frac{1}{2}} = MATC \times BTC \quad (5)$$

where $MATC$ represents the neutral technological change, which is used to describe the translation effect of the production frontier; and BTC represents a biased technological change, which is used to characterize the rotation effect of the production frontier. BTC is further defined as follows:

$$BTC = \left[\frac{D_0^{t+1}(y^{t+1}, b^{t+1}, x^{t+1})}{D_0^t(y^{t+1}, b^{t+1}, x^{t+1})} \times \frac{D_0^t(y^{t+1}, b^{t+1}, x^t)}{D_0^{t+1}(y^{t+1}, b^{t+1}, x^t)} \right]^{\frac{1}{2}} \times \left[\frac{D_0^{t+1}(y^{t+1}, b^{t+1}, x^t)}{D_0^t(y^{t+1}, b^{t+1}, x^t)} \times \frac{D_0^t(y^t, b^t, x^t)}{D_0^{t+1}(y^t, b^t, x^t)} \right]^{\frac{1}{2}} \quad (6)$$

$= IBTC \times OBTC$

where $IBTC$ is input biased technological change, which represents the impact of

input biased technological progress on the marginal rate of substitution when output is constant. $IBTC > 1$ (or < 1) indicates that the input biased technological change increases (or decreases) total factor productivity and tends to use more (or fewer) factors. $IBTC = 1$ indicates that input biased technological change is Hicks neutral. The input biased technological change is calculated by solving the following linear programming problem:

$$\begin{aligned}
 & \left[D_0^{t+i}(y^{t+j}, b^{t+p}, x^{t+q}) \right]^{-1} = \min \theta \\
 & s.t. \sum_{n=1}^N \gamma_n^{t+i} y_m^{t+i} \geq y^{t+j}, m=1, \dots, M \\
 & \sum_{n=1}^N \gamma_n^{t+i} b_o^{t+i} = b^{t+p}, o=1, \dots, O \\
 & \sum_{n=1}^N \gamma_n^{t+i} x_n^{t+i} \leq \theta x^{t+q}, n=1, \dots, N \\
 & \gamma_n^{t+i} \geq 0
 \end{aligned} \tag{7}$$

where $\left[D_0^t(y^t, b^t, x^t) \right]^{-1}$, $\left[D_0^{t+1}(y^{t+1}, b^{t+1}, x^{t+1}) \right]^{-1}$, $\left[D_0^{t+1}(y^t, b^t, x^t) \right]^{-1}$, $\left[D_0^t(y^{t+1}, b^{t+1}, x^{t+1}) \right]^{-1}$, $\left[D_0^t(y^{t+1}, b^{t+1}, x^t) \right]^{-1}$, $\left[D_0^{t+1}(y^{t+1}, b^{t+1}, x^t) \right]^{-1}$ are calculated with $(i, j, p, q) = (0, 0, 0, 0)$, $(i, j, p, q) = (1, 1, 1, 1)$, $(i, j, p, q) = (1, 0, 0, 0)$, $(i, j, p, q) = (0, 1, 1, 1)$, $(i, j, p, q) = (0, 1, 1, 0)$, $(i, j, p, q) = (1, 1, 1, 0)$, respectively.

2.3 Output biased technological progress

Some previous studies have assumed that multiple inputs could produce only a single desirable output (Weber and Domazlicky, 1999; Färe et al., 2001). However, based on the assumption of weak disposability, each desirable output must be accompanied by an undesirable output (Chung et al., 1997). For this reason, we constructed the production technology of output possibility set as:

$$P^t(x^t) = \left\{ (y^t, b^t) : (y^t, b^t) \text{ is obtainable from } x^t \right\}, \quad t=1, \dots, T \tag{8}$$

According to the output possibility set, the Shephard output distance function is

defined as follows:

$$D_o^t(x^t, y^t, b^t) = \inf \left\{ \beta : (y^t / \beta) \in P^t(x^t) \right\}, \quad t = 1, \dots, T \quad (9)$$

where the output distance function represents changes in both desirable and undesirable outputs in the same direction. However, due to the constraints of several external factors, such as environmental regulations, we need to achieve the win-win goal of increasing desirable output while reducing undesirable output. To this end, we create a directional distance function that considers both desirable and undesirable outputs. The general form is expressed as follows:

$$D_o^t(x^t, y^t, b^t; g) = \sup \left\{ \beta : (y^t, b^t) + \beta g \in P^t(x^t) \right\} \quad (10)$$

where g is a set of vectors describing the change in the direction of desirable and undesirable outputs; g is expressed as $g = (y, -b)$. Thus, formula (10) is expressed as follows:

$$\begin{aligned} D_o^t(x^t, y^t, b^t; y^t, -b^t) &= \sup \left\{ \beta : D_o^t(x, (y^t, b^t) + \beta(y^t, -b^t)) \leq 1 \right\} \\ &= \sup \left\{ \beta : \beta \leq \frac{1}{D_o^t(x, y^t, b^t)} - 1 \right\} \end{aligned} \quad (11)$$

Combining formulas (6) and (11), $OBTC$ is defined as follows:

$$OBTC = \left[\frac{1 + D_o^t(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})}{1 + D_o^t(x^{t+1}, y^t, b^t; y^t, -b^t)} \times \frac{1 + D_o^{t+1}(x^{t+1}, y^t, b^t; y^t, -b^t)}{1 + D_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})} \right]^{\frac{1}{2}} \quad (12)$$

where $OBTC$ represents the effect of output biased technological progress on desirable or undesirable outputs when the input is constant. $OBTC > 1$ (or < 1) indicates that output biased technological change increases (or decreases) output. $OBTC = 1$

indicates that output biased technological change is Hicks neutral³. The output biased technological change is obtained by solving the following linear programming problem:

$$\begin{aligned}
D_0^{t+i}(x^{t+j}, y^{t+p}, b^{t+q}; y^{t+p}, -b^{t+q}) = \max \beta \\
s.t. \sum_{n=1}^N z_n^{t+i} y_m^{t+i} \geq (1 + \beta) y^{t+p}, m = 1, \dots, M \\
\sum_{n=1}^N z_n^{t+i} b_o^{t+i} = (1 - \beta) b^{t+q}, o = 1, \dots, O \\
\sum_{n=1}^N z_n^{t+i} x_n^{t+i} \leq x^{t+j}, n = 1, \dots, N \\
z_n^{t+i} \geq 0
\end{aligned} \tag{13}$$

where $D_0^t(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})$, $D_0^t(x^{t+1}, y^t, b^t; y^t, -b^t)$, $D_0^{t+1}(x^{t+1}, y^t, b^t; y^t, -b^t)$, $D_0^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})$ are calculated with $(i, j, p, q, p, q) = (0, 1, 1, 1, 1, 1)$, $(i, j, p, q, p, q) = (0, 1, 0, 0, 0, 0)$, $(i, j, p, q, p, q) = (1, 1, 0, 0, 0, 0)$, $(i, j, p, q, p, q) = (1, 1, 1, 1, 1, 1)$, respectively.

2.4 Biased characteristics identification method

2.4.1 Biased characteristics identification method of input biased technological progress

Weber and Domazlicky (1999) proposed a method to identify the biased characteristics of technological progress, by comparing the changes in factor growth rate and *IBTC* from period S to period T . Fig. 1 shows that four different input sets, $L^1(y, b)$, $L^n(y, b)$, $L^{21}(y, b)$, and $L^{22}(y, b)$ can produce the same output. Different input sets represent different technological levels. When output is constant and $IBTC > 1$ from period S to period T , then $L^n(y, b)$, $L^{21}(y, b)$, and $L^{22}(y, b)$ require fewer input factors than $L^1(y, b)$. In production theory, technological progress

³More details about output biased technological progress can be found in Färe et al. (1997).

can drive the isoquant curve to “translate” or “rotate”. Technological progress is Hicks neutral when the marginal rate of substitution is constant. This can drive the translation of isoquant curves $L^1(y,b)$ to $L^n(y,b)$. Technological progress tends to use more x_1 or x_2 when the marginal rate of substitution changes. This can drive the rotation of isoquant curves $L^1(y,b)$ to $L^{21}(y,b)$ or $L^{22}(y,b)$.

Neutral technological progress and biased technological progress can exist in the same production process. This requires us to separate the “translation effect” and the “rotation effect” from the total effect of technological progress (Chen and Yu, 2014). Based on Weber and Domazlicky (1999), when $x_2^{t+1}/x_1^{t+1} < x_2^t/x_1^t$, x_1 -using biased technical change is associated with $IBTC > 1$, and x_2 -using biased technical change is associated with $IBTC < 1$. When $x_2^{t+1}/x_1^{t+1} > x_2^t/x_1^t$, x_1 -using biased technological change is associated with $IBTC < 1$, and x_2 -using biased technological change is associated with $IBTC > 1$. Regardless of whether $x_2^{t+1}/x_1^{t+1} < x_2^t/x_1^t$ or $x_2^{t+1}/x_1^{t+1} > x_2^t/x_1^t$, input biased technological progress is Hicks neutral when $IBTC = 1$.

Fig. 1 Input biased technological change

However, this method does not identify biased characteristics when there are differences in the marginal productivity of factors. Technological progress can change the marginal productivity of factors, so we need to find a comparable “reference surface” for all factors. To this end, the marginal productivity of all input factors is estimated based on the Cobb-Douglas production function, as follows:

$$\ln(y) = \alpha + \pi_1 \ln(x_1) + \pi_2 \ln(x_2) + \varepsilon \quad (14)$$

where x_1 and x_2 represent two different production factors; y represents output; π represents the marginal productivity of factors; and ε is the random disturbance term. The contribution of x_1 and x_2 to y is calculated using formula (14), expressed as $\pi_1(x_1^{t+1} - x_1^t)$ and $\pi_2(x_2^{t+1} - x_2^t)$, respectively. From period t to period $t+1$: (1) When $\pi_2(x_2^{t+1} - x_2^t) < \pi_1(x_1^{t+1} - x_1^t)$, x_1 -using biased technical change is associated with $IBTC > 1$, and x_2 -using biased technical change is associated with $IBTC < 1$. (2) When $\pi_2(x_2^{t+1} - x_2^t) > \pi_1(x_1^{t+1} - x_1^t)$, x_1 -using biased technological change is associated with $IBTC < 1$, and x_2 -using biased technological change is associated with $IBTC > 1$. (3) Regardless of whether $\pi_2(x_2^{t+1} - x_2^t) < \pi_1(x_1^{t+1} - x_1^t)$ or $\pi_2(x_2^{t+1} - x_2^t) > \pi_1(x_1^{t+1} - x_1^t)$, the input biased technological progress is Hicks neutral when $IBTC = 1$. See Table 1 for more details.

Table 1 Input biased technological change direction

Previous method	Our method	$IBTC < 1$	$IBTC = 1$	$IBTC > 1$
$x_2^{t+1}/x_1^{t+1} < x_2^t/x_1^t$	$\pi_2(x_2^{t+1} - x_2^t) < \pi_1(x_1^{t+1} - x_1^t)$	x_2 -using (x_1 - saving)	Neutral	x_1 -using (x_2 - saving)
$x_2^{t+1}/x_1^{t+1} > x_2^t/x_1^t$	$\pi_2(x_2^{t+1} - x_2^t) > \pi_1(x_1^{t+1} - x_1^t)$	x_1 -using	Neutral	x_2 -using

Note: The traditional method refers to the method proposed by Weber and Domazlicky (1999).

2.4.2 Biased characteristics identification method of output biased technological progress

We applied the method used by Barros et al. (2010) to identify the biased characteristics of output biased technological progress; the core principle for this is shown in Fig. 2. Direction vectors g^1 and g^2 indicate that technological progress tends to yield more desirable output and less undesirable output. Four different output sets, $P^1(x)$, $P^n(x)$, $P^{12}(x)$, and $P^{21}(x)$, were used to represent different technological levels. From period t to period $t+1$: (1) When $P^1(x)$ moves to $P^{21}(x)$ (i.e. $y^{t+1}/b^{t+1} < y^t/b^t$), y -increasing biased technical change is associated with $OBTC < 1$, and b -increasing biased technical change is associated with $OBTC > 1$. (2) When $P^1(x)$ moves to $P^{12}(x)$ (i.e. $y^{t+1}/b^{t+1} > y^t/b^t$), b -increasing biased technical change is associated with $OBTC < 1$, and y -increasing biased technical change is associated with $OBTC > 1$. (3) Regardless of whether $y^{t+1}/b^{t+1} > y^t/b^t$ or $y^{t+1}/b^{t+1} < y^t/b^t$, the output biased technological progress is Hicks neutral when $OBTC = 1$. See Table 2 for more details.

Fig. 2 Output biased technological change

Table 2 Output biased technological change direction

	$OBTC < 1$	$OBTC = 1$	$OBTC > 1$
$y^{t+1}/b^{t+1} > y^t/b^t$	b -increasing (y -decreasing)	Neutral	y -increasing (b -decreasing)
$y^{t+1}/b^{t+1} < y^t/b^t$	y -increasing (b -decreasing)	Neutral	b -increasing (y -decreasing)

3. Data and biased characteristics

3.1 Data

We used a balanced panel dataset for 17 APEC economies for the years 2000-2017 to measure biased technological progress. We defined input and output variables as follows:

(1) Input variables. The study's input variables were capital (K), labor (L), non-renewable energy (NRE), and renewable energy (RE). The variable K was

represented by the capital stock of Federal Reserve Economic Database; L was represented by the proportion of the population aged 15-64 compared to the total population, as reported in the APEC database; NRE represented coal, oil, and natural gas consumption; and RE represented the sum of hydropower, and other renewable energy consumption. All energy consumption data were obtained from BP2018.

(2) Output variables. GDP (at fixed prices in 2010) served as a proxy variable for desirable output; the data were collected from the APEC database. There was no uniform standard for selecting undesirable output variables. Based on Zha et al. (2019), the CO₂ emissions of APEC economies served as the proxy variable for undesirable output, and the data were collected from the BP2018.

3.2 Biased characteristics of input biased technological progress

Table 3 shows the biased characteristics of input biased technological progress in APEC economies between 2000-2017. There are several interesting findings. First, with the exception of China, Indonesia, Thailand, and Peru, many APEC economies tended to use more capital instead of other factors; capital use was followed by labor, non-renewable energy, and renewable energy. China, Indonesia, and Thailand tended to use more renewable energy, followed by non-renewable energy, labor, and capital. Input biased technological progress in Peru was Hicks neutral.

Second, input biased technological progress tended to use more labor compared to non-renewable energy and renewable energy. China, Indonesia, Japan, and Thailand tended to use more energy (non-renewable energy and renewable energy) instead of labor. With the exception of Japan, all high-income economies demonstrated a

preference for energy conservation⁴.

Third, with the exception of China, Indonesia, and Thailand, low-income economies tended to use more renewable energy instead of non-renewable; however, all high-income economies tended to use more non-renewable energy. Finally, input biased technological progress in APEC economies from 2000 to 2017 showed relative energy conservation, but did not support improvements in energy structure.

Table 3 Biased characteristics of input biased technological progress (2000-2017)

Economies	Bias _{K-L}	Bias _{K-NRE}	Bias _{K-RE}	Bias _{L-NRE}	Bias _{L-RE}	Bias _{NRE-RE}	Bias-order
A. Low-income economies							
China	L	NRE	RE	NRE	RE	RE	RE-NRE-L-K
Indonesia	L	NRE	RE	NRE	RE	RE	RE-NRE-L-K
Malaysia	K	K	K	L	L	NRE	K-L-NRE-RE
Mexico	K	K	K	L	L	NRE	K-L-NRE-RE
Peru	Neutral	Neutral	Neutral	Neutral	Neutral	Neutral	Neutral
Philippines	K	K	K	L	L	NRE	K-L-NRE-RE
Russia	K	K	K	L	L	NRE	K-L-NRE-RE
Thailand	L	NRE	RE	NRE	RE	RE	RE-NRE-L-K
Vietnam	K	K	K	L	L	NRE	K-L-NRE-RE
B. High-income economies							
Australia	K	K	K	L	L	NRE	K-L-NRE-RE
Canada	K	K	K	L	L	NRE	K-L-NRE-RE
Chile	K	K	K	L	L	NRE	K-L-NRE-RE
Japan	K	K	K	NRE	RE	NRE	K-NRE-RE-L
Korea	K	K	K	L	L	NRE	K-L-NRE-RE
New Zealand	K	K	K	L	L	NRE	K-L-NRE-RE
Singapore	K	K	K	L	L	NRE	K-L-NRE-RE
the United States	K	K	K	L	L	NRE	K-L-NRE-RE
APEC	K	K	K	L	L	NRE	K-L-NRE-RE

Note: Bias_{K-L} is the biased direction of input biased technological progress between capital and labor, and so on; Bias-order represents the biased ordering of input biased technological progress among capital, labor, non-renewable energy, and renewable energy; K indicates that input biased

⁴According to the International Monetary Fund, low-income economies include China, Malaysia, Mexico, Peru, Philippines, Russia, Thailand, Indonesia, and Vietnam; high-income economies include Australia, Canada, Chile, Japan, South Korea, New Zealand, Singapore, and the United States.

technological progress tends to use more capital, and so on; Neutral stands for Hicks neutral.

3.3 Biased characteristics of output biased technological progress

Table 4 shows the biased characteristics of output biased technological progress in APEC economies between 2000-2017. Output biased technological progress had a stronger effect on desirable output compared to undesirable output, and there were significant differences in the biased characteristics when comparing low-income and high-income economies. Overall, low-income economies tended to produce more undesirable output. Among these, Indonesia, Philippines, Russia, Thailand, and Vietnam tended to produce more undesirable output; in contrast, China, Malaysia, Mexico, and Peru tended to produce more desirable output. With the exception of Canada, which tended to produce more undesirable output, most high-income economies produced more desirable output overall.

Table 4 Biased characteristics of output biased technological progress (2000-2017)

Economies	Bias _{Y-B}	Bias-order	Economies	Bias _{Y-B}	Bias-order
A. Low-income economies			B. High-income economies		
China	Y	Y-B	Australia	Y	Y-B
Indonesia	B	B-Y	Canada	B	B-Y
Malaysia	Y	Y-B	Chile	Y	Y-B
Mexico	Y	Y-B	Japan	Y	Y-B
Peru	Y	Y-B	Korea	Y	Y-B
Philippines	B	B-Y	New Zealand	Y	Y-B
Russia	B	B-Y	Singapore	Y	Y-B
Thailand	B	B-Y	the United States	Y	Y-B
Vietnam	B	B-Y	APEC	Y	Y-B

Note: Bias_{Y-B} is the biased direction of output biased technological progress between desirable output and undesirable output; Bias-order represents the biased ordering of output biased technological progress between desirable output and undesirable output.

4. Empirical results and analysis

4.1 Econometric model

The panel model simultaneously controls the individual effect and the time effect,

and is effective for samples with significant individual differences. For these reasons, we applied a panel model to explore the effect of input biased technological progress on $PM_{2.5}$, in the following way:

$$PM_{2.5it} = \alpha_0 + \alpha_1 IBTC_{it} + \alpha_2 OBTC_{it} + \alpha_3 MATC_{it} + \sum_{j=4}^k \alpha_j X_{it}^j + \varepsilon_{it} \quad (15)$$

where $PM_{2.5}$ represents the population-weighted average $PM_{2.5}$ concentration, and measures haze pollution; $IBTC$, $OBTC$, and $MATC$ represent input biased technological progress, output biased technological progress, and neutral technological progress, respectively; and ε is a random disturbance term. We are most interested in the coefficients of α_1 , α_2 , and α_3 , which reflect the effects of different biased technological progress on $PM_{2.5}$ ⁵. The variable X represents control variables, including population structure, foreign direct investment, industrial structure, and economic development level. The definitions of terms and data sources were as follows:

(1) Population structure (PS). Early studies found that population structure significantly impacts $PM_{2.5}$ (Hixson et al., 2012). As such, we set population structure as a control variable, expressed by the proportion of the population aged 15-64 compared to the total population.

(2) Foreign direct investment (FDI). An increase in the proportion of FDI to GDP reduces $PM_{2.5}$ (Xie and Sun, 2020). Thus, we set foreign direct investment as a control variable, expressed by the ratio of FDI to GDP (%).

⁵The largest variance expansion factor in this model is 4.24, this indicates that there is no obvious multicollinearity.

(3) Industrial structure (IS). The higher the proportion of the secondary industry is, and the lower the proportion of the tertiary industry is, the more serious the haze pollution problem will be (Shi et al., 2020). Therefore, we set industrial structure as a control variable, expressed by the ratio of the secondary industry GDP to total GDP (%).

(4) Economic development level ($PGDP$). $PM_{2.5}$ is the undesirable output of economic growth, and economic growth leads to a long-term increase in $PM_{2.5}$ emissions (Li et al., 2016). As such, the economic development level was set as a control variable, with GDP per capita as a proxy variable for the economic development level.

The $PM_{2.5}$ data were collected from the Socioeconomic Data and Applications Center; the data of FDI and secondary industry GDP were collected from the World Bank; and the other data are the same as discussed in Section 3.1. Table 5 lists the descriptive statistics of the variables.

Table 5 Descriptive statistics of the variables from 2000 to 2017

Variable	Unit	Mean	Std. dev.	Min	Max
$PM_{2.5}$	mg/m ³	11.290	9.896	0.000	50.300
IBTC	-	1.078	0.278	0.989	3.295
OBTC	-	1.014	0.033	0.989	1.162
MATC	-	0.987	0.119	0.609	1.355
PS	%	67.530	3.649	58.260	73.750
FDI	%	3.707	4.521	-3.812	26.520
IS	%	32.490	7.361	18.670	48.530
PGDP	\$10000	2.354	1.778	0.203	9.391

The quantile regression method is an extended form of the ordinary least squares regression method, and addresses the issues of outliers, heteroscedasticity, and skewness in the independent variables. As such, it is widely used in empirical analyses

(Koenker and Hallock, 2001). Moreover, the panel quantile regression model is also used to estimate the effect of an independent variable on a dependent variable under different conditional distributions. Drawing on Koenker (2004), the general form of the panel quantile regression model was set as follows:

$$Q_{y_{it}}(\tau|x_{it}) = \alpha(\tau) + \beta(\tau)x'_{it}; \quad i = 1, 2, \dots, I, \quad t = 1, 2, \dots, T \quad (16)$$

Equation (16) is estimated by solving the following linear programming problem:

$$\min_{(\alpha, \beta)} \sum_{k=1}^K \sum_{i=1}^I \sum_{t=1}^T \omega_k \rho_{\tau_k} (y_{it} - \alpha(\tau_k) - x'_{it} \beta(\tau_k)) \quad (17)$$

Following the formulas (15) and (16), we established the following panel quantile regression model:

$$Q_{\tau}(PM_{2.5it}|x_{it}) = \beta_0^{\tau} + \beta_1^{\tau} IBTC_{it} + \beta_2^{\tau} OBTC_{it} + \beta_3^{\tau} MATC_{it} + \sum_{j=4}^k \beta_j^{\tau} X_{it}^j + \varepsilon_{it}^{\tau} \quad (18)$$

We set seven quantiles, namely $\tau = (0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95)$.

4.2 Empirical results

4.2.1 Benchmark regression results

First, we needed to test the stability of the variables before analyzing the benchmark regression results. To this end, we performed LLC and Fisher-PP tests; the results are shown in columns (1) and (2) of Table 6. All variables were found to be stationary and suitable for regression analysis. Columns (3) to (5) in Table 6 show the regression results of fixed effects (FE), random effects (RE), and feasible generalized least squares (FGLS), respectively. The regression results of RE and FE differed from the results of FGLS. This was particularly true with respect to the effects of both input and output biased technological progress on $PM_{2.5}$.

The coefficients of input biased technological progress were negative, but not significant, in the regression results of FE and RE. However, the coefficient was significantly positive in the regression results of FGLS. The coefficients of output biased technological progress were positive at the 1% significance level in the regression results of FE and RE. However, the coefficient was negative at a 1% significance level in the regression results of FGLS. The coefficients of neutral technological progress were significantly negative in the three regression results; however, the coefficients of FE and RE were significantly larger compared to the coefficients of FGLS.

These differences in the regression results can be explained by the test results in column (5). The results of the Modified Wald test, the Wooldridge test, and the Frees test indicated that FE and RE models showed intergroup heteroscedasticity, intragroup autocorrelation, and intergroup contemporaneous correlation. This indicated that the RE and FE regression results may be biased (Greene, 2012). In this context, the regression coefficients of FGLS are reliable.

The FGLS regression results showed input biased technological progress significantly increased $PM_{2.5}$ (coefficient=4.425, P value<0.01). This differed from the conclusion that traditional technological progress supports reductions in pollution emissions (Grossman and Krueger, 1991; Acemoglu et al., 2016). A review of the biased characteristics of input biased technological progress found that between 2000-2017, APEC economies tended to use more capital, followed by labor, non-renewable energy, and renewable energy. This shows that input biased technological progress had the

characteristics of relative energy conservation, which mitigated haze pollution.

However, there was continued growth in the consumption of both non-renewable and renewable energy in APEC economies from 2000 to 2017. Input biased technological progress tended to use more non-renewable energy compared to renewable energy. For these reasons, the energy structure did not improve as a result of energy conservation, increasing pollution emissions (York and Bell, 2019). This may have also occurred because input biased technological progress can improve marginal productivity, expanding the scale of production. The scale effect increases demand for fossil energy, generating more pollutant emissions (Yang et al., 2019). Moreover, input biased technological progress can significantly reduce energy costs, which also contributes to the increase in non-renewable energy consumption (Yi et al., 2020).

Output biased technological progress significantly decreased $PM_{2.5}$ (coefficient=-7.515, P value<0.01). The output biased technological progress of APEC economies from 2000 to 2017 tended to produce more desirable output and less undesirable output, significantly contributing to mitigating $PM_{2.5}$. Neutral technological progress also mitigated $PM_{2.5}$ (coefficient=-1.957, P value<0.01). This may be because neutral technological progress can improve total factor productivity, which supports the mitigation of haze pollution. The effect of output biased technological progress on $PM_{2.5}$ was significantly stronger than neutral technological progress (7.515>1.957). This demonstrated that output biased technological progress is a more effective way to mitigate $PM_{2.5}$.

For the control variables, population structure was significantly positively

correlated with PM_{2.5}, indicating that a high labor participation rate aggravates haze pollution. This finding was consistent with the conclusion in Li et al. (2019b). Foreign direct investment supported reductions in PM_{2.5}, which contradicts the conclusion of the “pollution paradise” hypothesis. Our conclusion was consistent with Chen et al. (2019). Industrial structure was positively correlated with PM_{2.5}, which was consistent with the finding of Ji et al. (2018). There was a significant negative correlation between economic development level and PM_{2.5}, demonstrating that countries with higher income levels had less haze pollution (Chen et al., 2018).

Table 6 Stationary test and benchmark regression results (dependent variable: PM_{2.5})

	(1)	(2)	(3)	(4)	(5)
	LLC	Fisher-PP	FE	RE	FGLS
IBTC	-3.70*** [0.0001]	2.01** [0.0224]	-0.534 (-0.90)	-0.447 (-0.75)	4.425*** (17.60)
OBTC	-1.67** [0.0474]	3.27*** [0.0005]	27.692*** (3.01)	27.881*** (3.02)	-7.515*** (-3.77)
MATC	-15.86*** [0.0000]	3.73*** [0.0001]	-7.000*** (-5.11)	-7.004*** (-5.09)	-1.957*** (-10.09)
PS	-8.16*** [0.0000]	4.54*** [0.0000]	0.730*** (9.81)	0.750*** (10.11)	1.421*** (64.13)
FDI	-8.90*** [0.0000]	37.40*** [0.0000]	0.042 (0.87)	0.034 (0.70)	-0.0248*** (-6.03)
IS	-3.37*** [0.0004]	3.77*** [0.0001]	0.012 (0.25)	0.028 (0.61)	0.297*** (42.07)
PGDP	-3.32*** [0.0004]	6.59*** [0.0000]	-0.854*** (-3.74)	-0.867*** (-3.79)	-1.607*** (-39.40)
PM _{2.5}	-6.903*** [0.0000]	11.591*** [0.0000]			
Constant			-57.094*** (-5.11)	-59.220*** (-5.22)	-85.70*** (-38.39)
Hausman FE-RE Modified Wald test			10.56 [0.2280]		1350.81 [0.0000]

Wooldridge			54.103
test			[0.0000]
Frees test			729.410
			[0.0000]
<i>N.obs</i>	306	306	306

Note: T statistics in parentheses; P value in square brackets; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.2.2 Robustness test

To avoid pseudo regression results, we tested the robustness of the benchmark regression results. First, there was a potential two-way causal relationship between biased technological progress and $PM_{2.5}$, which could lead to errors in the regression results. To this end, we applied the first-order lag term of the dependent variable to test the robustness of benchmark regression results. We assumed that $PM_{2.5}$ in the t period could not contribute to the biased technological progress in the $t-1$ period. Compared with the coefficients in column (5) of Table 6, the signs and significance of the coefficients in columns (1) and (2) of Table 7 were consistent with the benchmark regression results, with only a slight change in the size.

Second, China is the country with the most severe haze pollution in the APEC economies. As such, the population-weighted average $PM_{2.5}$ concentration in China was significantly higher compared to other economies. To address this, we removed China from the total sample to avoid the interference of a special sample on the regression results. The impact of biased technological progress on $PM_{2.5}$ remained significant, and the signs were consistent with the benchmark regression results (see columns (3) and (4) in Table 7).

Third, sulfur dioxide (SO_2), nitrogen oxides (NO_x), and inhalable particulate matter are the main components of haze pollution. The first two are gaseous pollutants,

and the last is a particulate pollutant. These pollutants are generated by energy consumption, and are closely related (Cereceda-Balic et al., 2017). As such, we replaced PM_{2.5} with SO₂ and NO_x for the robustness test. The signs and significance of the coefficients in columns (5) to (8) of Table 7 remained consistent with the benchmark regression results.

Table 7 Robustness test results

	PM _{2.5}		PM _{2.5}		SO ₂		NO _x	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Coef.	t-value	Coef.	t-value	Coef.	t-value	Coef.	t-value
IBTC(-1)	3.108**	2.92						
OBTC(-1)	-25.673*	-2.09						
MATC(-1)	-3.085*	-2.00						
IBTC			1.944***	11.80	1.395***	410.73	0.553***	14.97
OBTC			-12.870***	-8.07	-15.907***	-409.57	-1.983***	-5.03
MATC			-1.257***	-10.23	-7.563***	-1174.49	-1.778***	-24.38
CV	yes		yes		yes		yes	
YFE	yes		yes		yes		yes	
CFE	yes		yes		yes		yes	
N	288		288		306		306	

Note: (-1) represents the first-order lag of the variable; CV, YFE, and CFE represent the control variable, time fixed effect, and individual fixed effect, respectively; * p < 0.1, ** p < 0.05, *** p < 0.01.

4.2.3 Panel quantile regression results

The benchmark regression results revealed the average effect of biased technological progress on PM_{2.5}. There were significant differences in the population-weighted average PM_{2.5} concentration in different APEC economies. As such, the resulting average effect potentially differed from the individual effect. In this context, a panel quantile regression model was used to estimate the impact of biased technological progress on different PM_{2.5} concentrations. We set seven quantiles, labeled Q05, Q10, Q25, Q50, Q75, Q90, and Q95, to indicate the different levels of haze pollution. The quantiles Q05, Q10, and Q25 were used to test the effect of biased

technological progress on low concentration $PM_{2.5}$. Q50 was used to test the effect of biased technological progress on medium concentration $PM_{2.5}$. The quantiles Q75, Q90, and Q95 were used to test the effect of biased technological progress on high concentration $PM_{2.5}$. Table 8 presents the key findings.

First, input biased technological progress had a significant positive effect on $PM_{2.5}$ for all quantiles except for Q90 and Q95. This demonstrates that input biased technological progress had a very weak effect when the $PM_{2.5}$ concentration was high. The effect of input biased technological progress on $PM_{2.5}$ decreased as the $PM_{2.5}$ concentration increased. This may be because severe haze pollution is subject to strict environmental regulation, and the high cost of environmental regulation crowds out technology innovation investment. This leads to input biased technological progress having a limited impact on $PM_{2.5}$ (Wang and Wei, 2019).

Second, output biased technological progress only had a significant negative effect on the $PM_{2.5}$ concentration for Q25 and Q95; this result depends on the biased characteristics of the economies. For high concentration $PM_{2.5}$ economies, such as China, South Korea, Vietnam, and Malaysia, output biased technological progress from 2013 to 2017 tended to produce more desirable output. For economies with low $PM_{2.5}$ concentrations, such as Singapore, New Zealand, and Australia, output biased technological progress from 2000 to 2017 tended to produce more desirable output.

Third, the effect of neutral technological progress on $PM_{2.5}$ varied across the $PM_{2.5}$ concentrations. Neutral technological progress had a significant positive effect on low concentration $PM_{2.5}$ economies, but a significant negative effect on high concentration

PM_{2.5} economies. Finally, we tested the heterogeneity of the coefficients in the seven quantiles regression; the results are reported in column (8) of Table 8. The null hypothesis was that the coefficients were equal under different quantiles. This hypothesis could be rejected, because the impacts of biased technological progress on PM_{2.5} were heterogeneous across quantiles.

Table 8 Panel quantile regression results (dependent variable: PM_{2.5})

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Q05	Q10	Q25	Q50	Q75	Q90	Q95	Equality test
IBTC	7.088*** (7.23)	7.022*** (7.52)	6.674*** (7.26)	5.329*** (3.72)	4.960** (2.08)	1.637 (0.71)	3.573 (1.07)	0.90** [0.017]
OBTC	19.365 (0.75)	-14.334 (-0.81)	-22.241** (-2.49)	-8.928 (-0.34)	5.697 (0.10)	-0.385 (-0.01)	-126.424* (-1.65)	3.18*** [0.005]
MATC	6.521*** (3.59)	6.032*** (3.23)	7.564*** (3.79)	6.553 (1.40)	12.450 (1.10)	4.870 (0.34)	-21.825* (-1.84)	8.45*** [0.000]
PS	0.955*** (4.89)	0.993*** (6.80)	0.912*** (9.19)	0.881*** (4.73)	1.423*** (5.81)	1.869*** (7.08)	1.822*** (6.38)	9.34*** [0.000]
FDI	-0.103 (-0.74)	-0.262*** (-2.97)	-0.304*** (-3.90)	-0.308** (-2.15)	-0.515** (-2.20)	-1.055*** (-4.03)	-0.670** (-1.97)	2.19** [0.044]
IS	0.177*** (4.13)	0.244*** (6.96)	0.314*** (5.31)	0.499*** (6.25)	0.625** (2.12)	1.372*** (6.65)	1.232*** (5.54)	14.66*** [0.000]
PGDP	-1.499** (-2.00)	-0.498 (-1.00)	-0.060 (-0.32)	0.034 (0.06)	-0.320 (-0.46)	1.448 (1.37)	1.793 (1.46)	3.59*** [0.002]
Constant	-95.000*** (-3.40)	-66.109*** (-3.21)	-55.531*** (-3.87)	-68.522** (-2.02)	-122.712 (-1.51)	-155.689* (-1.69)	3.771 (0.04)	- -
<i>N.obs</i>	306	306	306	306	306	306	306	-
Adj. R ²	30.36%	32.67%	29.04%	25.07%	32.07%	53.23%	65.26%	-

Note: T statistics in parentheses; P value in square brackets; * p < 0.1, ** p < 0.05, *** p < 0.01.

4.2.4 Heterogeneity analysis

This section discussed the heterogeneity of the effects of biased technological

progress on PM_{2.5} at different levels of economic development. Using the estimation methods above, the FGLS and panel quantile regression methods were performed to generate the estimates. The regression results are reported in Table 9, where column (1) includes the regression results of the FGLS method, and columns (2) to (8) include the regression results of the panel quantile method.

For the FGLS regression results, input biased technological progress significantly increased PM_{2.5} in high-income economies; however, there was only a limited impact in low-income economies. Output biased technological progress significantly reduced PM_{2.5} in high-income economies, but increased PM_{2.5} in low-income economies. Neutral technological progress significantly reduced PM_{2.5} only in low-income economies; the impact in high-income economies was not statistically significant.

For panel quantile regression results, input biased technological progress only had a significant positive impact on economies with a high-income and low and medium PM_{2.5} concentration (Q05, Q10, Q25, and Q50). All quantile regression results failed to pass the significance test for low-income economies. This demonstrated that input biased technological progress played a more prominent role in economies having a high-income and low PM_{2.5} concentrations. Output biased technological progress had a significant negative impact on economies with a high-income and low PM_{2.5} concentration. This had a significant positive effect on PM_{2.5} in low-income economies, with the effect increasing as the PM_{2.5} concentration increased. In addition to Q95, neutral technological progress had a significant negative impact on PM_{2.5} in high-income economies; this effect increased with an increase in PM_{2.5} concentration.

Although it had a significant negative effect on PM_{2.5} in low-income economies, this effect only passed a significance test in quantiles Q25, Q50, and Q90.

Table 9 Panel quantile regression results at different income levels (dependent variable: PM_{2.5})

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FGLS	Q05	Q10	Q25	Q50	Q75	Q90	Q95
A. Low-income economies								
IBTC	-7.110 (-0.70)	93.086 (1.30)	66.783 (1.15)	21.076 (0.68)	24.073 (1.15)	22.259 (0.41)	-36.592 (-0.78)	-76.250 (-1.48)
OBTC	148.621*** (3.21)	192.551 (1.37)	244.432* (1.80)	256.057** (2.26)	304.654** (2.51)	481.190 (1.56)	810.002*** (3.25)	984.472*** (4.94)
MATC	-4.472*** (-4.67)	1.153 (0.40)	-1.553 (-0.55)	-5.675** (-2.45)	-11.160*** (-5.09)	-10.265 (-1.41)	-14.713* (-1.88)	-11.787 (-1.64)
CV	yes	yes	yes	yes	yes	yes	yes	yes
<i>N.obs</i>	162	162	162	162	162	162	162	162
Adj. R ²	-	31.85%	28.71%	28.05%	30.11%	44.32%	69.88%	70.45%
B. High-income economies								
IBTC	5.197*** (6.68)	3.991*** (2.92)	4.516*** (3.69)	5.959*** (3.12)	8.006*** (4.38)	6.873 (1.40)	9.074 (1.17)	4.403 (0.54)
OBTC	-41.770*** (-5.83)	-13.339 (-0.69)	-22.754* (-1.74)	-2.287 (-0.13)	13.623 (0.57)	18.294 (0.51)	20.077 (0.35)	38.268 (0.51)
MATC	0.958 (0.66)	9.635* (1.83)	8.015** (2.06)	13.909*** (3.04)	20.117*** (4.24)	20.670*** (2.68)	28.301** (2.00)	24.572 (1.24)
CV	yes	yes	yes	yes	yes	yes	yes	yes
<i>N.obs</i>	144	144	144	144	144	144	144	144
Adj. R ²	-	30.43%	34.23%	40.03%	45.61%	52.41%	59.61%	59.63%

Note: T statistics in parentheses; CV represent control variable; * p < 0.1, ** p < 0.05, *** p < 0.01.

5. Influencing mechanism

5.1 Mediating effect model

Section 4 discussed the impact of biased technological progress on haze pollution; however, we still need to scientifically explain the associated influencing mechanism.

To this end, the general form of the mediating effect model is expressed as follows:

$$\begin{cases} A_{it} = a_0 + a_1 B_{it} + \sum_{j=2}^k a_j X_{it} + \mu_{it}^1 \\ M_{it} = b_0 + b_1 B_{it} + \sum_{j=2}^k b_j X_{it} + \mu_{it}^2 \\ A_{it} = c_0 + c_1 B_{it} + c_2 M_{it} + \sum_{j=3}^k c_j X_{it} + \mu_{it}^3 \end{cases} \quad (19)$$

where A_{it} represents the dependent variables, including $PM_{2.5}$, energy structure, energy intensity, and total factor productivity; and B_{it} represents the independent variables, including input biased technological progress, output biased technological progress, and neutral technological progress. The variable M represents the mediating variables, including energy structure, energy intensity, and total factor productivity; X represents a set of control variables; a_1 represents the effect of biased technological progress on $PM_{2.5}$; b_1 represents the effect of biased technological progress on mediating variables; and c_1 represents the residual effect of biased technological progress on $PM_{2.5}$ after excluding the mediating effect. Finally, the product of b_1 and c_2 is defined as the mediating effect, which is created to investigate the effect of biased technological progress on $PM_{2.5}$ through mediating variables.

5.2 Influencing mechanism of input biased technological progress

Non-renewable energy has consistently been viewed as the source of pollution emissions, whereas renewable energy consumption does not discharge pollutants. To this end, replacing non-renewable energy with renewable energy is the most effective approach to save energy and reduce emissions (Bilgili et al., 2016). Input biased technological progress can change the marginal rate of substitution, and the cost of

production. Both can lead to changes in the energy structure (Acemoglu, 2002). In this regard, when input biased technological progress uses less non-renewable energy and more renewable energy, the energy structure generally improves. The proportion of non-renewable energy and renewable energy consumption changed significantly in APEC economies from 2000 to 2017. This indicated that energy structure is a candidate path for technological progress to affect haze pollution.

The ratio of non-renewable energy consumption to total energy consumption was used to represent energy structure. The results are reported in columns (1) to (3) of Table 10; the control variables were the same as the benchmark regression model. The results in column (1) show that input biased technological progress was significantly positively correlated with $PM_{2.5}$ concentration. The results in column (2) show that input biased technological progress was significantly positively correlated with energy structure. The results in column (3) show that energy structure had a significantly positive effect on the $PM_{2.5}$ concentration. In these contexts, input biased technological progress can affect $PM_{2.5}$ concentration through energy structure.

5.3 Influencing mechanism of output biased technological progress

As discussed in Section 2.4.2, if output biased technological progress has a greater effect on desirable output when the energy input is constant, the energy intensity must be smaller (Shahbaz et al., 2015). The energy intensity declined in APEC economies from 2000 to 2017, indicating that the energy intensity was a potential path affecting haze pollution through technological progress.

Energy intensity is expressed as the ratio of energy consumption to GDP; the

associated regression results are shown in columns (4) to (6) of Table 10. To address the endogeneity problem, GDP per capita was removed from the control variables. The results in column (4) show that output biased technological progress was significantly negatively correlated with $PM_{2.5}$. The results in column (5) indicate that output biased technological progress significantly reduced energy intensity. The results in column (6) show that energy intensity was significantly positively correlated with $PM_{2.5}$. These results demonstrate that output biased technological progress impacted $PM_{2.5}$ through energy intensity.

5.4 Influencing mechanism of neutral technological progress

In contrast with biased technological progress, neutral technological progress does not change the marginal rate of substitution. Thus, neutral technological progress does not reduce non-renewable energy consumption when other factors remained constant. Neutral technological progress also does not reduce undesirable outputs when desirable outputs remained constant. The role of neutral technological progress in energy conservation and emission reduction is to improve total factor productivity. If total factor productivity is high, it means that the input is small when output is constant, or the output is large when the input is constant (Amri et al., 2019). We propose that total factor productivity is a potential path for neutral technological progress to mitigate haze pollution.

Total factor productivity is an important force driving economic growth. Total factor productivity and GDP growth are strongly positively correlated (Wang and Fang, 2016). As such, we used GDP (at fixed prices in 2010) as a proxy variable for total

factor productivity. Similarly, GDP per capita was removed from the control variables to address the problems of endogeneity and multicollinearity. The regression results are shown in columns (7) to (9) of Table 10. The results in column (7) show there was a significant negative correlation between neutral technological progress and PM_{2.5}. The results in column (8) show there was a significant positive correlation between neutral technological progress and total factor productivity. The results in column (9) show that the total factor productivity and PM_{2.5} were significantly negatively correlated. Therefore, total factor productivity was a mediating variable for output biased technological progress to mitigate PM_{2.5}.

Table 10 Test results of the influencing mechanism

	Energy structure			Energy intensity			Total factor productivity		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	PM ₂	ES	PM _{2.5}	PM _{2.5}	EI	PM _{2.5}	PM _{2.5}	TFP	PM _{2.5}
	.5								
IBTC	4.34 3*** (19.04)	0.067** * (18.44)							
ES			1.547** * (4.04)						
OBT				-	-				
C				20.271* ** (-10.93)	0.014** * (-7.39)				
EI						126.951* ** (26.47)			
MATC							- 1.587** * (-6.07)	0.691** * (53.76)	
TFP									- 0.835** *

								(-67.92)	
CV	yes	yes	yes	yes	yes	yes	yes	yes	yes
YFE	yes	yes	yes	yes	yes	yes	yes	yes	yes
CFE	yes	yes	yes	yes	yes	yes	yes	yes	yes
<i>N.obs</i>	306	306	306	306	306	306	306	306	306

Note: CV, YFE, and CFE represent the control variable, time fixed effect, and individual fixed effect, respectively; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6. Conclusions and policy implications

This paper provided insights about how biased technological progress affects haze pollution, and identified the influencing mechanism. We first introduced renewable energy into a framework of capital, labor, and non-renewable energy to measure biased technological progress, and then developed a new method to identify biased characteristics, based on marginal productivity theory. Finally, using a balanced panel dataset of 17 APEC economies between 2000-2017, we conducted an empirical analysis using the panel quantile model and mediating effect model. Our main conclusions are summarized as follows.

(1) Overall, input biased technological progress in 17 APEC economies tended to use more capital, followed by labor, non-renewable energy, and renewable energy. With the exception of China, Indonesia, and Thailand, all economies tended to use more capital and labor compared to non-renewable and renewable energy; however, they still tended to use more non-renewable energy than renewable energy. Input biased technological progress aggravated haze pollution, but this effect decreased as the $PM_{2.5}$ concentration increased.

(2) Output biased technological progress significantly reduced haze pollution in high-income economies, but aggravated haze pollution in low-income economies.

These differences stemmed from the heterogeneity of biased characteristics at different income levels. With the exception of China, Malaysia, Mexico, and Peru, low-income economies tended to produce more undesirable output. In contrast, with the exception of Canada, high-income economies tended to produce more desirable output.

(3) Increasing renewable energy consumption and reducing energy intensity were effective paths for input and output biased technological progress, respectively, to mitigate haze pollution. For neutral technological progress, improving total factor productivity was an important way to mitigate haze pollution.

This study highlights several policy recommendations for mitigating haze pollution in APEC economies. Input biased technological progress tended to use more capital and labor compared to energy. Within the energy variable, there was a tendency to use non-renewable energy over renewable energy. Based on this, APEC economies should invest more in renewable energy technology innovation to promote renewable energy consumption, especially in the United States, Australia, New Zealand, and Chile. Total non-renewable energy consumption is also growing. To avoid an economic downturn, the most effective measure may be to promote non-fossil energy to replace fossil energy. Also, more attention should be paid to investing in renewable energy projects, especially in large energy-consuming countries such as China, the United States, and Russia. This would facilitate the energy transition in the APEC economies, and would contribute to sustainable development.

The biased characteristics of output biased technological progress determine its prominent role in mitigating haze pollution. Another important way to mitigate haze

pollution in the APEC economies is to promote emission-reducing biased technological innovation. Moreover, APEC economies should commit to improving energy efficiency so that output biased technological progress can play the largest role in mitigating haze pollution. This is particularly true for China, Australia, and the United States. To maximize the role of neutral technological progress in mitigating haze pollution, APEC economies should strengthen their independent research and development capabilities, and actively pursue advanced technologies for energy conservation and emission reduction to improve total factor productivity.

Appendix

Appendix A. Input biased technological change, output biased technological change, and neutral technological change in APEC economies from 2000 to 2017.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

The datasets used or analyzed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare no competing interests.

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Authors Contributions

All authors contributed to the article and approved the submitted version. GLY was involved in drafting the manuscript. DLZ was involved in the designing, conception, and revising of the manuscript critically for intellectual content.

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