Factor market distortion, technological innovation, and environmental pollution

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Abstract
Factor market distortion is a critical factor that affects environmental pollution, and technological innovation is regarded as a new opportunity to alleviate environmental pollution. Based on panel data from 30 Chinese provinces from 2003 to 2019, this study constructs an intermediary effect model to test the influence mechanism of factor market distortion on regional environmental pollution and the intermediary effect of technological innovation, exploring these effects based on spatial differentiation characteristics. This study shows that factor market distortion protects industries with backward production capacity, high resource consumption, serious pollution, and low production efficiency from elimination; hinders the transformation and upgrading of the regional industrial structure; and forms a lock in the sloppy growth mode, which directly affects the improvement of regional environmental quality. This study reveals the influence of factor market distortions on environmental pollution. This provides empirical evidence for giving play to the decisive role of the market in resource allocation and promoting green technology innovation.

Keywords
Factor market distortion · Technological innovation · Environmental pollution · Intermediary effect model

Introduction
Since its economic reform and opening-up, China has experienced rapid economic growth and become the second-largest economy in the world (Rashidin et al. 2020). However, rapid economic growth has accelerated the exploitation of natural resources and increased the emission of industrial pollutants, resulting in serious environmental pollution problems (Wang et al. 2021). Studies have shown that pollution caused approximately nine million unnatural deaths worldwide in 2015, accounting for 16% of the deaths. Pollution has become the biggest environmental factor causing serious diseases and unnatural deaths (Landrigan et al. 2018), posing a serious hazard to human health, and promoting urgent environmental protection. To mitigate environmental pollution, we must increase pollution control investment, inhibiting rapid economic growth (Hao et al. 2018). The conflict between rapid economic growth and environmental pollution has become increasingly prominent (Gan et al. 2021; Yin et al. 2018a). Environmental pollution has received widespread attention from the international community (Jung et al. 2018). The United Nations Environment Programme (UNEP) advocated solutions to mitigate environmental pollution and promote coordinated environmental and economic development at the 26th United Nations Climate Change Conference (Wyns and Beagley 2021). China has also recognized the importance of controlling environmental pollution. The 19th National Congress of the Communist Party of China proposed implementing sustainable development and formulating strategies to upgrade environmental protection standards and requirements in line with the reality of economic development to win the fight against pollution (Dong et al. 2018).

With the significant acceleration in the pace of innovation (Li et al. 2020), technological innovation, as the main driving force for the coordinated development of the environment and economy, can provide vital support for mitigating environmental pollution (He et al. 2022). Technological innovation provides green technology for production, promotes the transformation and upgrading of
Industrial structures, realizes the greening of production modes, and reduces the consumption of natural resources per output unit, thus improving energy utilization, achieving substantial savings, and recycling of resources, and reducing environmental pollution (Dinda 2018; He et al. 2022; Yuan and Zhang 2020). Technological innovation can also improve technological progress in pollution control by increasing investments. This may, in turn, lead producers to adopt cleaner production processes, clean energy, and use pollution disposal equipment (e.g., exhaust gas purifiers and sewage treatment machines) to achieve terminal treatment and reduce the emission of industrial pollutants at the source, thus improving environmental quality (Bhandari et al. 2019). Therefore, technological innovation positively impacts environmental pollution control and can effectively promote the coordinated development of the environment and economy (Mughal et al. 2022).

In addition, we find that the marketization process of China’s factor market lags far behind that of the product market in the pursuit of environmental pollution control, and factor prices are severely underestimated, leading to increased factor use and irrational allocation, a phenomenon called factor market distortion (Yang et al. 2018). To promote rapid economic growth, governments at all levels intervene and control the price and allocation of various factors such as land, labor, capital, and energy, resulting in obstruction of factor flows, factor price rigidity, factor price differentiation, and factor price underestimation, which ultimately leads to factor market distortion (Zhang et al. 2021). Factor market distortion affects the lock-in effect of the sloppy growth pattern by influencing technological progress, which in turn contributes to environmental pollution. Most studies show that factor market distortion significantly aggravates environmental pollution (Lin and Chen 2018; Liu and Qiu 2020; Que et al. 2018). The environmental effects of factor market distortion cannot be ignored and divided into scale and technology effects. From the perspective of the scale effect, factor distortion makes the factor price lower than the market price, and the increase in factor use inevitably aggravates pollution emissions (Lin and Chen 2018).

Regarding the technology effect, scholars have studied the negative impact of the technological effect of factor market distortion on the environment. The low-cost factor brought about by factor market distortion increases the production scale of non-technological knowledge-intensive products, stimulates the production technology research and development of the traditional manufacturing industry, and has a lock-in effect on the regional crude industrial structure. In contrast, tertiary industries with lower pollution intensity are hindered and not conducive to upgrading industrial structures. This inhibits the improvement in regional environmental quality (Brandt et al. 2013; Zhang et al. 2021).

It is worth noting that factor market distortions can lead to factor resource misallocation. Simultaneously, the elements of the production configuration effect brought about by production technology have a negative effect on the environment (Zhang et al. 2021). However, suppose that factors are allocated to energy conservation and emission reduction, their technological effect will likely lead to green technological innovation, greening production methods, and reducing pollutant emissions, thus alleviating environmental pollution (Du and Li 2019). Therefore, the technological effect of factor market distortion does not necessarily negatively impact the environment. Technological innovation may play an intermediary role in regulating the relationship between factor market distortion and environmental pollution. Most scholars believe that factor market distortions aggravate environmental pollution. However, we found that green technological innovation brought about by factor allocation in energy conservation and emission reduction will play a role in alleviating environmental pollution. What is the effect of factor market distortions on environmental pollution under the intermediary effect of technological innovation? Although many scholars have engaged in fierce discussions on the environmental effect of factor market distortion and the environmental effect of technological innovation, few studies have combined factor market distortion with technological innovation to study their effect on environmental pollution.

Therefore, this study addresses the following questions: First, based on Chinese provincial panel data, we use the intermediary effect model to test whether technological innovation plays an intermediary role in the impact of factor market distortion on environmental pollution. Moreover, if technological innovation has an intermediary effect, it can be measured quantitatively. Third, we discuss the effects of factor market distortions on environmental pollution based on regional characteristics. The remainder of this paper is organized as follows. “Literature review” section is a review of the literature. “Model construction and index selection” section presents the construction of this study’s model and the index selection. “Empirical analysis” section presents the empirical analysis. “Discussion” section presents the discussion of the study. Finally, “Conclusion and policy recommendation” section presents the conclusions and policy recommendations of this study.

**Literature review**

Environmental pollution has become a hot topic, garnering international attention from academia, and many scholars have explored it. The COVID-19 outbreak had a significant moderating effect on environmental pollution, indicating that sudden public social crises can also impact environmental
pollution (Dutheil et al. 2020). Furthermore, considering environmental pollution and rapid economic growth, Li et al. (2019) found a negative correlation between environmental pollution and rapid economic growth. Liu and Lin (2019) established a comprehensive environmental pollution index to measure environmental pollution systematically and found an inverted N-curve between environmental pollution and rapid economic growth. This shows that research exploring the relationship between high economic growth and environmental pollution is continuously being updated. This also indicates that the impact of a particular factor on environmental pollution is uncertain, and it is difficult to reach a definite conclusion. Therefore, exploration of environmental pollution must be conducted continuously.

China’s technological innovation lags behind that of the world, and technological innovation is the main driving force for improving environmental pollution. Therefore, limited by the low level of technological innovation, China’s environmental pollution status has not been effectively controlled (Miao et al. 2018). Existing studies have not reached definite conclusions regarding the impact of technological innovation on environmental pollution. Some scholars believe that many developing countries are likely to fail to achieve the expected level of technological innovation because of a lack of investment funds for technological research and development, leading to low-end production technology and reduced environmental quality (Cheng et al. 2019; Gu and Wang 2018). However, more scholars believe that technological innovation is one of the most effective means of mitigating pollution and is the main driving force for improving environmental quality (Chen and Lee 2020; Yang et al. 2021a). From the perspective of industrial enterprises, the mitigating effect of technological innovation on environmental pollution is based on two main aspects: improving energy utilization through green technological innovation and increasing research and development of clean energy.

On the one hand, technological innovation is one of the fundamental driving forces in improving energy utilization. Miao et al. (2018) mentioned that technological innovation could improve energy utilization by improving the production mode of traditional enterprises, reforming the technological paradigm, and sustaining the development of ecological modes and technologies, thereby improving environmental quality. Ibrahim (2020) argued that technological innovation could improve energy efficiency, leading to energy sustainability and improved environmental quality. Meanwhile, the continuous deterioration of environmental quality stimulates technological progress, and there is a two-way influence between technological innovation and environmental pollution. On the other hand, technological innovation can promote the research and development of clean energy use. Murshed et al. (2021) stated that technological innovation could help develop technologies that can monitor, control, and limit environmentally unfriendly resources; increase R&D investment in clean energy; and reduce pollutant emissions, thus alleviating environmental pollution.

In addition, Zeraibi et al. (2021) suggested that technological innovation can enable the five ASEAN countries to overcome technological barriers that hinder their environmental pollution control in the traditional sense. Technological innovation is expected to play a key role in mitigating environmental pollution during the fourth industrial revolution. Other studies have introduced technological innovations into their relationship with carbon emissions. Khan et al. (2020) studied technological innovation and carbon emissions in China and showed that technological innovation mitigates environmental pollution by reducing carbon emissions. However, we should be aware that although technological innovation plays a role in environmental pollution control, it is not a panacea (Pham et al. 2020). For example, Zhang et al. (2019) suggest that, although technological innovation is positively correlated with technological performance in environmental pollution control, there is significant variability across regions and a large gap between expected and actual technological performance. Therefore, there is still scope for progress in technological innovation for environmental pollution treatment.

There is a close connection between factor market distortion and environmental pollution, with distorted factor markets leading to increased pollution emissions, higher pollution intensity, and lower environmental efficiency (Ji 2020). In China, factor market distortion persists, and environmental pollution is a major problem (Yin et al. 2018b). First, many studies have shown that factor market distortion dampens productivity growth and negatively affects environmental pollution. Lin and Chen (2018) suggested that factor market distortion directly affects total factor productivity by causing pollutant emissions and limiting productivity gains. In terms of pollutant emissions, factor distortion means that the prices of traditional factors, such as traditional energy and hydropower, which serve traditional industries, are seriously underestimated. Low factor prices lead to excessive energy consumption, resulting in excessive pollutant emissions. In terms of productivity, a negative factor price distortion leads to a lack of motivation for product innovation and technological progress. Enterprises fall into a low-cost expansion strategy that hinders the development of production and environmental technology and inhibits productivity improvement.

Moreover, factor market distortions can aggravate industrial production pollution severely. According to Ji (2020), factor market distortion is positively correlated with industrial pollution intensity, whereas foreign and public ownership moderate this positive correlation. Similarly, Tan et al. (2019) pointed out that factor market distortion affects
production pollution in two ways. First, low prices make enterprises invest more factors in production to increase output instead of promoting green technological progress and increasing energy consumption. Second, low prices can hardly reflect scarcity and external costs, making optimizing factor allocation difficult, and reducing energy utilization. The above two paths will impact the total-factor energy efficiency, which is closely related to environmental pollution. Most studies are based on total factor market distortion, whereas Sun et al. (2020) extend the framework of the mechanism of factor price distortion on environmental pollution. Research shows that factor price distortion contributes significantly to environmental pollution, and institutional quality becomes the threshold of factor price distortion affecting environmental pollution. In addition, Zhang et al. (2021) found that factor market distortion had an intermediary effect on the impact of local government competition on environmental pollution. Therefore, the effect of factor market distortion on environmental pollution is not always direct but may have indirect effects on environmental pollution through other influencing factors.

Thus, both technological innovation and factor market distortions can affect environmental pollution. Is there a connection between technological innovation and factor-market distortions? Several scholars have conducted relevant studies in this regard. Yin et al. (2018a) pointed out that factor market distortion affects environmental pollution in four aspects: land, labor, capital, and the energy market. Liang (2022) analyzed the impact of capital market distortion and labor market distortion on technological innovation based on the factors mentioned above. The results show a significant negative correlation between the factor misallocation caused by capital and labor market distortions and technological innovation. Jia and Lin (2021) study the impact of factor market distortion on enterprises’ technological innovation. Jia and Lin (2021) indicated that, before the transformation of economic momentum, local governments caused factor market distortion due to rapid economic development, which weakened and inhibited enterprises’ technological innovation capability. After the transformation of economic momentum, the government pays more attention to the quality of economic development, the distortion of the factor market improves significantly, the market mechanism plays its full role, and enterprises’ technological innovation ability gradually appears.

Furthermore, some studies examine the impact of technological innovation and factor market distortion on firm productivity. Dai and Sun (2021) showed that technological innovation and factor market distortion affect resource allocation; however, technological innovation has not yet become the dominant determinant of resource allocation. Factor market distortion may offset the resource reallocation associated with technological innovation and cause an overall loss of productivity. This theory can also be extended to environmental pollution. What is the impact of technological innovation and factor market distortions on environmental pollution? Although there is a lack of relevant literature, energy is closely related to environmental pollution, as indicated by Yin et al. (2018a). They study the mechanism of the impact of technological innovation and factor market distortion on environmental pollution. Yin et al. (2018b) divided technological innovations into traditional and green types. Traditional technological innovations can increase energy consumption by improving production activities. By contrast, green innovation can reduce energy consumption by lowering per product unit and changing the energy consumption structure. Technological innovation has an inverted U-shaped effect on energy consumption, that is, a rebound effect (Lu and Wang 2017). Factor market distortion increases the inverted U-shaped effect of technological innovation. Interestingly, Yang et al. (2021b) found that technological innovation has an intermediary effect on synergistic government-led and market-driven industrial agglomeration on environmental pollution control and that industrial agglomeration can indirectly contribute to environmental pollution control through the intermediary role of technological innovation. Therefore, we conjecture that technological innovation has an intermediary effect on the impact of factor market distortions on environmental pollution.

There are theoretical studies on technological innovation and environmental pollution, factor market distortion and environmental pollution, technological innovation and factor market distortion; however, few studies have examined the relationship between these three factors, and the research angle is relatively narrow. Therefore, this study uses panel data from Chinese provinces to consider the relationship between technological innovation, factor market distortion, and environmental pollution. Based on this analysis, we can speculate an interaction between technological innovation and factor market distortion on environmental pollution and an intermediary effect.

Model construction and index selection

The following recursive evaluation model of the direct and intermediary effects of factor market distortion was constructed to further identify the intermediate mechanism of factor market distortion affecting environmental pollution, as shown in Eqs. (1)–(3):

\[
\ln Pol_{it} = c + \alpha \ln R_{it} + \sum_{j=1}^{n} \gamma \ln Control_{it} + \mu + \delta + \varepsilon_{it}
\]  

(1)
lnTi \_pt = c + \beta lnFmd \_pt + \sum_{j=1}^{n} \gamma \lnControl \_pt + \mu_p + \theta_i + \varepsilon_{pt} 

(2)

lnPol \_pt = c + \theta_i lnFmd \_pt + \theta_2 lnTi \_pt + \sum_{j=1}^{n} \gamma \lnControl \_pt + \mu_p + \theta_i + \varepsilon_{pt} 

(3)

where Pol represents the degree of environmental pollution; Fmd represents factor market distortion; \( \sum_{j=1}^{n} \) Control represents the control variables; Ti represents the intermediate variable, namely technological innovation; p represents province and t represents year; \( \mu, \theta, \) and \( \varepsilon \) represent the error term; and c represents the constant term. These variables were treated logarithmically to overcome the impact of heteroscedasticity on the model regression results.

This study selected provincial panel data from 2003 to 2019, covering various dimensions, such as energy, economy, industry, and education. The explained variable is the degree of environmental pollution, and the explanatory variables are technological innovation and factor market distortion. The control variables were selected by considering the urban characteristic variables that affect environmental pollution based on the differences between the samples in different provinces. Government expenditure, human capital level, urbanization level, secondary industry agglomeration level, opening-up level, infrastructure, and foreign direct investment were chosen as control variables. Finally, the data included 510 samples for 2003–2019 from 30 Chinese provinces (Tibet was omitted due to missing data for some years). The data were obtained from China Statistical Yearbook, China Marketization Process Index Report, and China Population and Employment Statistical Yearbook from 2004 to 2020.

Environmental pollution level (Pol)

Industrial production and consumption cause environmental pollution. Currently, most scholars exclude domestic pollutants when studying environmental pollution (Song et al. 2020). Studies have shown that verifying the environmental Kuznets curve based on the pollutants generated by living consumption is invalid. Therefore, it is unreasonable to include domestic pollutants as a measurement index of environmental pollution. Because of the lack of a unified index to measure the degree of comprehensive pollution indicators, including air, water, and solid waste pollution, based on the fact that China’s current environmental pollution mainly comes from industrial production, and sulfur dioxide is the most typical pollutant in industrial pollution emissions, referring to the practice of Xu et al. (2021), industrial sulfur dioxide emissions were selected as the measurement index of environmental pollution.

Technological innovation (Ti)

Technological innovation is measured by the total number of domestic patent authorizations. Many studies have used the number of patent applications to measure the enterprises’ technological innovation (Yuan and Zhang 2020). However, enterprises’ actual technological innovation level is affected by various external factors. The quality of patent applications is uneven. There is a time lag between patent applications and authorization. A patent application may not be granted if it has not passed the examination. Therefore, this study used the patent authorization index rather than the patent application index. Moreover, some scholars only consider invention patents as the statistical basis of patent authorization (He et al. 2022) while ignoring the fact that other forms of patents also have utility and novelty, which can also reflect the ability of technological innovation. Based on this analysis and data availability, this study selects the total number of domestic patent authorizations to eliminate one-sidedness as a measure of technological innovation. Technological innovation improves environmental pollution by increasing energy utilization and promoting the transformation and upgrading of industrial institutions; thus, the prediction coefficient of this variable is negative.

Factor market distortion (Fmd)

It is difficult to directly measure factor market distortion in each region of China. Therefore, this study considers the relevant scores in the China Marketization Process Index Report to construct a factor market distortion index. The measures constructed by most studies are \( FAC1 = (\text{marketization index of product market} - \text{factor market development index})/\text{marketization index of product market}; \) \( FAC2 = (\text{marketization index of the overall market} - \text{factor market development index})/\text{marketization index of the overall market} \) (Ji 2020). Although the two measures consider that the factor marketization process lags behind the product marketization process, we find that regions with a lower factor market development index also have a lower marketization index for their product market and the overall market, thus smoothing out the relative factor market distortion between regions. Referring to Lin and Chen (2018), this study uses the relative gap between the development degree of the factor market in each region and the highest development degree of the factor market in the sample to measure the factor market distortion. This measure reflects the relative differences in factor market distortion among regions and regional market distortion characteristics over time. The specific formula is shown in (4):

\[ \text{factor market distortion} = \frac{\text{development degree of factor market in region} - \text{highest development degree of factor market in sample}}{\text{highest development degree of factor market in sample}} \]
\[ F_{md_{pt}} = \frac{\max \{ \text{factormarket}_{pt} \} - \text{factormarket}_{pt}}{\max \{ \text{factormarket}_{pt} \}} \]  

(4)

where factormarket represents the factor market index, \( \max \{ \text{factormarket} \} \) represents the maximum value of the factor market index of all provinces during the sample period. In this study, the factor market index of Beijing in 2019 is chosen as \( \max \{ \text{factormarket} \} \) and the factor market distortion of Beijing in 2019 is expressed as \( F_{md_{+1}} \) to facilitate the logarithmic processing of the variables. Factor market distortion increases the energy consumption of traditional enterprises through low factor costs and inhibits the incentive for technological innovation, thus aggravating environmental pollution; thus, the prediction coefficient of this variable is positive.

**Government expenditure (Ge)**

This variable is measured by the proportion of government fiscal expenditure to GDP (Zhang et al. 2017). Government fiscal expenditure from 2003 to 2006 was measured using the fiscal expenditure index, and government fiscal expenditure from 2006 to 2019 was measured using the general budget expenditure index. To achieve an outstanding performance assessment, local governments prefer to spend fiscal expenditure on productive investment projects with immediate economic benefits and low environmental standards to introduce highly polluting and energy-consuming enterprises, which directly leads to an increase in pollution emissions. A higher government fiscal expenditure may mean stronger environmental regulation and environmental protection investment, which can alleviate environmental pollution. Therefore, the impact of government expenditure on environmental pollution is uncertain, and this variable’s prediction coefficient is unknown.

**Human capital level (Hc)**

Years of education per capita were used for the measurements. Domestic and foreign scholars primarily use income, cost, and educational index methods to evaluate the level of human capital. It is difficult to collect data on income methods. The income level is affected by various other factors, such as distribution policies and the effectiveness of the labor market, which leads to some bias in the calculation results. Although the cost method can better reflect the different forms and compositions of human capital, it only considers its monetary value and ignores the time value of investment currency. The education index method can reflect the degree of workers’ knowledge and skill acquisition, which play a decisive role in forming human capital. In addition, it can exclude the influence of price factors and maintain a strong positive correlation with the knowledge accumulation of human capital, which can objectively reflect the level of human capital. Following the method of Bano et al. (2018) with slight modifications, this study calculated the years of education per capita by assigning different weights according to education level, as shown in Formula (5).

\[ Edu_{pt} = \frac{6 \times \beta_{pt} + 9 \times \gamma_{pt} + 12 \times \delta_{pt} + 16 \times \varepsilon_{pt}}{\omega_{pt}} \]  

(5)

where \( Edu \) represents years of education per capita; \( \beta \), \( \gamma \), \( \delta \), and \( \varepsilon \) represent the number of people with primary school education, junior high school education, high school and technical secondary school education, junior college education, and above, respectively. Considering China’s educational system, the number of years of education is determined as 6 years, 9 years, 12 years, and 16 years, respectively. The improvement in educational quality brings about increased awareness of environmental protection. Meanwhile, the growth mode supported by human capital can more effectively promote economic development in an innovation-driven pattern, thus reducing environmental damage. Therefore, the prediction coefficient of this variable was negative.

**Urbanization level (urban)**

The urbanization rate is measured by the proportion of the urban population in the total population (Nathaniel et al. 2020). Urbanization is accompanied by an increase in population and an improvement in people’s consumption levels, which increases urban household waste, changes the urban microclimate, and enhances the heat island effect, thereby causing environmental harm. Therefore, the prediction coefficient for this variable was positive.

**Industrial agglomeration level (Sia)**

This variable is measured by the number of location entropy in the secondary industry. There are various methods for measuring the level of industrial agglomeration, and location entropy has a professional advantage. Some scholars have used the spatial autocorrelation coefficient and spatial Sydney index to measure. However, measuring each province’s secondary industry agglomeration level must reflect the specialization advantages and spatial distribution patterns among provinces and eliminate scale differences. Therefore, the location entropy is more reasonable (Zheng and Lin 2018). The specific formula is shown in (6):
where \( S_{ia_{pt}} = \frac{P_{pt}}{P_t} / \frac{Q_{pt}}{Q_t} \)

\[(6)\]

where \( S_{ia} \) refers to the location entropy of the secondary industry; \( P_{pt}, Q_{pt}, P_t \), and \( Q_t \) refer to the added value of the secondary industry of province \( p \), the regional GDP of province \( p \), the added value of the national secondary industry, and the national GDP at time \( t \). Secondary industry agglomeration will lead to the expansion of the industrial scale, the increase in energy demand, the emission of pollutants due to the congestion effect, and environmental pollution. Therefore, the prediction coefficient for this variable was positive.

**Opening-up level (OU)**

This variable is measured by trade dependence, total imports proportion, and GDP exports. The greater the value, the higher the degree of economic openness. The degree of trade dependence reflects a region’s participation in the international division of labor. This indicates the degree of dependence of national economic development on import and export trade over a certain period. Scholars use it concisely and intuitively (Lin and Chen 2018). Trade openings have led to a free flow of international and domestic factors. China’s vigorous development of an export-oriented trade economy can give full play to the improvement of technological innovation and skill spillover brought by opening up to the outside world to alleviate environmental pollution effectively. Therefore, the prediction coefficient for this variable was negative.

**Infrastructure (infra)**

It is measured in highway kilometers per 10,000 people. The index of highway kilometers per 10,000 people can reflect the capacity of urban transportation infrastructure to provide services to urban populations and the development of urban transportation infrastructure, which can evaluate the level of regional infrastructure. The higher the development level of the urban transportation infrastructure, the greater the energy consumption, further increasing the emission of pollutants and aggravating environmental pollution. Therefore, the prediction coefficient for this variable was positive.

**Foreign direct investment (Fdi)**

This is measured by the FDI of the RMB exchange rate against the dollar to GDP. The environmental effects of FDI have always been the focus of debate in academia. FDI transfers heavily polluting enterprises to countries with weak environmental regulations through cross-border capital flows, thus aggravating local environmental pressure and leading to the emergence of a “pollution paradise.” Some scholars believe that FDI brings advanced production technology and management experience, thus reducing the emission of pollutants and the “pollution halo” (Liu et al. 2018). Therefore, FDI is an essential factor affecting regional environmental pollution, but its impact on environmental pollution remains uncertain. Therefore, the predictive coefficient of the variable is unknown (Table 1).

**Empirical analysis**

The results of the stepwise regression of Formulas (1)–(3) of the intermediary effect model, using technological innovation as the intermediary variable, are shown in Table 2. The regression results in column 2 show that factor market distortion significantly aggravates environmental pollution. The third column shows that factor market distortion significantly inhibits technological innovation improvement. The coefficient of \( Ti \) in column 4 is significantly negative, indicating that technological innovation is conducive to alleviating environmental pollution. The coefficient of \( Fmd \) is still significantly positive after \( Ti \) is controlled for; therefore, the increase in factor market distortion has a direct promotion effect on environmental pollution. The coefficients of the

| Variable | N  | Mean   | Sd    | Min   | Max   | Coef |
|----------|----|--------|-------|-------|-------|------|
| lnPol    | 510| 3.676  | 1.062 | −2.257| 5.208 | /    |
| lnTi     | 510| 9.176  | 1.688 | 4.248 | 13.176| −    |
| lnFmd    | 510| 4.133  | 0.407 | 0.000 | 4.582 | +    |
| lnGe     | 510| 3.029  | 0.424 | 2.131 | 4.328 | ?    |
| lnHc     | 510| 2.161  | 0.116 | 1.798 | 2.540 | −    |
| lnUrban  | 510| 3.932  | 0.266 | 3.210 | 4.495 | +    |
| lnSia    | 510| −0.039 | 0.221 | −1.009| 0.345 | +    |
| lnOu     | 510| 2.943  | 0.975 | 0.245 | 5.143 | −    |
| lnInfra  | 510| 3.285  | 0.645 | 1.332 | 4.926 | +    |
| lnFdi    | 510| 0.491  | 1.084 | −4.534| 2.493 | ?    |
intermediary effect models $\alpha$, $\beta_1$, and $\theta_2$ in Table 2 are all significant. Thus, there is a significant positive direct effect of factor market distortion on environmental pollution and a significant negative intermediary effect of technological innovation.

These results are consistent with intuitive expectations. Factor market distortion protects industries with backward production capacity, high resource consumption, serious pollution, and low production efficiency from elimination; hinders the transformation and upgrading of the regional industrial structure; and forms a lock in the sloppy growth mode, which directly affects the improvement of regional environmental quality. Factor market distortion makes enterprises more reliant on low-cost factors for profit, and the incentive mechanism of enterprise technology R&D innovation is weakened, which not only makes it difficult to improve the resource utilization rate by promoting technological innovation but also lacks the incentive to adopt clean production processes, clean energy, and pollution treatment equipment, thus inhibiting the regulatory effect of technological innovation on environmental pollution. Therefore, although technological innovation moderates the effect of factor market distortion on environmental pollution, its positive effect of factor market distortion on environmental pollution still dominates.

The following robustness tests were conducted to further confirm the above findings’ reliability, which did not change the original research findings. First, the explained variable $Pol$ was replaced by the per capita index, $rPol$, and the test results are listed in Table 3. After replacing it with the per capita pollution index, factor market distortion still has a significant promoting effect on environmental pollution. Technological innovation still has a significant negative intermediary effect between factor market distortion and environmental pollution, indicating that the intermediary effect of technological innovation also has strong robustness. Therefore, the overall robustness of the model results was excellent.

The conclusions of this study may be affected by the sample selectivity bias. As there are various measures for the two explanatory variables, it is impossible to be exhaustive.

### Table 2 Test results of the intermediary effect of technological innovation

| Variable | $lnPol$ | $lnTi$ | $lnPol$ |
|----------|---------|--------|---------|
| $lnFmd$  | 0.2757*** | -0.0904** | 0.2677*** |
| $lnTi$   | -0.0893*  | 0.0000 | 0.0000 |
| $lnGe$   | 0.4940*** | 0.0556  | 0.4989*** |
| $lnHc$   | -0.6501 | 2.0242*** | -0.4694 |
| $lnUrban$ | 1.4918*** | 1.4514*** | 1.6214*** |
| $lnSia$  | 0.3753**  | 0.5097*** | 0.4208** |
| $lnOut$  | -0.3233*** | -0.0226 | -0.3244*** |
| $lnInfra$ | 0.1538*  | 0.0494  | 0.1582* |
| $lnFdi$  | -0.0513**  | -0.0102 | -0.0522** |
| Constant | -2.3299  | -1.6837  | -2.4802* |

Year-fixed Yes Yes Yes
Province-fixed Yes Yes Yes
$N$ 510 510 510
$R^2$ 0.9475 0.9835 0.9478
$F$ 90.0524 403.9840 86.9237
$P$ 0.0000 0.0000 0.0000

Note: Figures in brackets are $p$ values of the corresponding test statistics. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

### Table 3 Robustness test results (replace the explained variable)

| Variable | $lnrPol$ | $lnTi$ | $lnrPol$ |
|----------|---------|--------|---------|
| $lnFmd$  | 0.2838*** | -0.0904** | 0.2729*** |
| $lnTi$   | -0.1205** | -0.0000 | -0.0000 |
| $lnGe$   | 0.5279*** | 0.0556  | 0.5346*** |
| $lnHc$   | -0.6762 | 2.0242*** | -0.4324 |
| $lnUrban$ | 1.6869*** | 1.4514*** | 1.8617*** |
| $lnSia$  | 0.4485**  | 0.5097*** | 0.5099*** |
| $lnOut$  | -0.3074**  | -0.0226 | -0.3101*** |
| $lnInfra$ | 0.3174*** | 0.0494  | 0.3233*** |
| $lnFdi$  | -0.0492*  | -0.0102 | -0.0504** |
| Constant | -11.7180*** | -1.6837 | -11.9208*** |

Year-fixed Yes Yes Yes
Province-fixed Yes Yes Yes
$N$ 510 510 510
$R^2$ 0.9190 0.9835 0.9199
$F$ 96.1688 403.9840 93.3438
$P$ 0.0000 0.0000 0.0000

Note: Figures in brackets are $p$ values of the corresponding test statistics. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.
Therefore, this study selected the most appropriate measure for the focused analysis, which may have caused the problem of the self-selection of samples. This study also used the FACI proposed by Ji (2020) to measure factor market distortion and the total number of domestic patent applications Ti’ to measure technological innovation, to control for the adverse influence of sample selectivity bias, as shown in Scheme I. Table 4 presents the robustness test results. These results indicate that the main conclusions of this study have not changed. Finally, this study not only replaces Pol with rPol but also replaces Fmd with FACI and Ti’ with Ti, denoted as Scheme II. The regression results also demonstrate the robustness of the conclusions of this study.

**Discussion**

First, the results were similar to those of previous studies. Empirical results show that factor market distortion has a positive effect on environmental pollution (Lin and Chen 2018; Liu and Qiu 2020; Que et al. 2018) and that technological innovation can effectively alleviate environmental pollution (Dinda 2018; He et al. 2022; Yuan and Zhang 2020). Second, based on existing research, this study creatively analyzes the relationship between factor market distortion, technological innovation, and environmental pollution and discusses the intermediary effect mechanism of technological innovation in the impact of factor market distortion on environmental pollution. It was found that technological innovation has a significant negative effect on mediation, which can alleviate, but cannot eliminate, the positive impact of factor market distortion on environmental pollution. Thus, the current factor of market distortion that aggravates environmental pollution has not effectively improved.

Factor market distortion prevents backward industries from eliminating and forms a lock in sloppy growth mode. Factor market distortion makes enterprises more reliant on low-cost factors for profit and weakens the incentive mechanism of enterprise technology R&D innovation. Therefore, we must change the situation of factor market distortion to release the capacity of technology, which can improve the environment.

Besides, there are still some limitations of the research done in this paper. First, when measuring the explained

| Variable | Scheme I | Scheme II |
|----------|----------|-----------|
| lnFACI   | 0.6229*** (0.000) | 0.6607*** (0.000) |
| lnTi’    | -0.2340** (0.031) | -0.2340** (0.031) |
| lnPol    | 0.6029*** (0.000) | 0.6364*** (0.000) |
| lnGe     | 0.5507*** (0.000) | 0.5860*** (0.000) |
| lnHc     | -0.5486 (0.000) | -0.5668 (0.000) |
| lnUrban  | 1.4992*** (0.000) | 1.6814*** (0.000) |
| lnSta    | 0.3463*** (0.004) | 0.4216*** (0.002) |
| lnOu     | -0.3415*** (0.000) | -0.3276*** (0.000) |
| lnInfra  | 0.1567** (0.089) | 0.3198*** (0.001) |
| lnFdi    | -0.0492* (0.051) | -0.0588*** (0.019) |
| Constant | -0.0608*** (0.014) | -11.6174*** (0.000) |
| Year-Fixed | Yes | Yes |
| Province-Fixed | Yes | Yes |
| N        | 510 | 510 |
| R²       | 0.9473 | 0.9191 |
| F        | 89.7676 | 96.3266 |
| P        | 0.0000 | 0.0000 |

Note: Figures in brackets are p values of the corresponding test statistics. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.
variable, only a single pollutant, industrial sulfur dioxide, was measured, failing to consider realistic pollutants from various sources, such as wastewater, smoke, and solid waste, and did not consider the self-purifying capacity of nature and the ecological carrying capacity of each region. In a follow-up study, we can use different data layers to examine one or more pollutants separately and adopt different theories and models to comprehensively assess the environmental effects of factor market distortion and technological innovation. Second, only domestic patent authorizations are used as proxy variables to investigate the effects of technological innovation on environmental pollution. It may be more realistic if technological innovation can be divided into production and green technological innovation to study their effects on environmental pollution separately.

Currently, different regions in China have different levels of environmental pollution, factor market distortion, and technological innovation development speeds. Tests were conducted for regional inspections to analyze the reliability of the results further. Scholars usually use policy-based criteria published by the government to divide China into 12 provinces in the east, nine provinces in the middle, and ten provinces in the west. This division considers geographical location and economic development level without considering environmental factors. Factors such as factor market distortion and technological innovation vary significantly among the provinces within the three regions. Therefore, the test results based on this division are likely unreasonable. For the above reasons, this study proposes a new way to classify the 30 provincial regions into developed, developing, and backward regions by considering the geographic location and economic development level, as well as the factors of market distortion, technological innovation, and environmental pollution indices of each region, as shown in Table 5.

Next, we test whether technological innovation in the three regions has an intermediary effect on the impact of factor market distortions on environmental pollution. The test results are listed in Table 6. From the perspective of the direct effect, factor market distortion in developed regions exacerbates environmental pollution, which is consistent with the findings of previous studies. The direct effect in developing regions was $-0.3511$, implying that factor market distortion exerts a significantly negative effect on environmental pollution. The indirect effects show that the intermediary effects in the developed and developing regions are $-0.0176$ and $-0.0686$, respectively. This means that factor market distortion in developed and developing regions negatively affects environmental pollution through technological innovation. The internal mechanisms of the intermediary effects of both are identical. Overall, the developed and developing regions have significant intermediary effects of

### Table 5 Regional classification table

| Region            | Provinces, autonomous regions, and municipalities                                                                 |
|-------------------|-------------------------------------------------------------------------------------------------------------------|
| Developed regions | Shanghai, Beijing, Tianjin, Anhui Province, Shandong Province, Guangdong Province, Jiangsu Province, Hebei Province, Zhejiang Province, Hubei Province, Hunan Province, Fujian Province, and Chongqing Municipality |
| Developing regions| Jilin Province, Sichuan Province, Shanxi Province, Jiangxi Province, Henan Province, Hainan Province, Liaoning Province, Shaanxi Province, and Heilongjiang Province |
| Backward regions  | Yunnan Province, Inner Mongolia Autonomous Region, Guangxi Zhuang Autonomous Region, Ningxia Hui Autonomous Region, Xinjiang Uygur Autonomous Region, Gansu Province, Guizhou Province, and Qinghai Province |

### Table 6 Intermediary effect results of regional inspection

| Region         | Variable | $lnPol$     | $lnTi$     | $lnPol$ | Direct effect | Intermediary effect |
|----------------|----------|-------------|------------|---------|---------------|---------------------|
| Developed regions | $lnFmd$   | 0.1476***   | $-0.1202^*$ | 0.1652*** | 0.1652         | $-0.0176$          |
|                 | $lnTi$    |             |            |         |               |                     |
| Developing regions | $lnFmd$   | $-0.4197^{**}$ | $-0.3827^*$ | $-0.3511^{**}$ | $-0.3511$     | $-0.0686$          |
|                 | $lnTi$    |             |            |         |               |                     |
| Backward regions  | $lnFmd$   | 0.5153*     | 0.4587**   | 0.5410*  | 0.5410        | $-0.0258$          |
|                 | $lnTi$    |             |            |         |               |                     |

Note: Figures in brackets are $p$ values of the corresponding test statistics. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

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technological innovation on the impact of factor market distortion on environmental pollution. In contrast, the backward regions did not pass the significance tests. Thus, regional differences exist in the impact of factor market distortions on environmental pollution.

Technological innovation in developed and developing regions aggravates environmental pollution, which is inconsistent with the findings of the full sample. One possible explanation is that industrial enterprises agglomerate in the developed regions. For pollution-intensive industries, the input of technological innovation into production technology may be higher than that of green pollution control technology, leading to increased production pollutant emissions and thus aggravating environmental pollution. Although developing regions process labor-intensive products to obtain higher economic benefits, they also try to introduce advanced production technology from developed domestic regions and foreign countries at the primary processing stage, resulting in the extension of the industrial chain and increasing the production of capital-intensive products, which has a negative impact on the environment. Additionally, we find that factor market distortion in developing regions has a significantly negative effect on environmental pollution. One possible explanation is that developing regions have relatively fewer production-intensive enterprises compared to developed regions. Factor market distortion allocates more factor resources from production to energy conservation and emission reduction, offsetting the adverse environmental impact of pollutants emitted from production. Developing regions primarily develop their economies by exploiting natural resources, processing raw products, and agglomerating natural resource-led industries with environmentally friendly characteristics. Assuming that the distortion of the factor market is reduced, and the free flow of factors is promoted, to achieve the optimal allocation of factor resources and pursue higher economic benefits, the factors in developing regions are bound to flow to heavy industries with strong pollution, thus aggravating environmental pollution. Therefore, the misallocation of resources caused by the distortion of the factor market can maintain the current situation of the factor flow of natural resources in developing regions, thus playing a role in alleviating environmental pollution.

Conclusion and policy recommendation

Based on China’s provincial panel data, taking the relationship between factor market distortion, technological innovation, and environmental pollution as the research starting point, this study analyzes the direct effect of factor market distortion and environmental pollution and examines the key role of technological innovation in the mechanism of factor market distortion on environmental pollution. The results show that technological innovation has a significant negative intermediary effect on the impact of factor market distortions on environmental pollution. Factor market distortion significantly increases pollution emissions, hindering the improvement of regional environmental quality. The above conclusions depend on the robustness test. Further regional tests show that technological innovation in developed and developing regions still has a significant negative intermediary effect, whereas the effect in backward regions is insignificant. Based on the above conclusions, this study offers the following policy recommendations.

First, we strengthen the factor market reform process. One of the main drawbacks of China’s current market-oriented reform process is distortion of the factor market. Factor resources have become a tool for maintaining local interests and government officials’ performance, so they are not allocated to the best economic subjects, hindering regional environmental pollution improvement. Only by fully improving the factor market and reducing administrative intervention can the efficiency of factor use be fundamentally improved, and the goal of improving environmental pollution be achieved. Governments should further liberalize the factor price mechanism based on market orientation, break down barriers to the flow of factors among regions, and channel factors to enterprises with higher production efficiency. In addition, to avoid the possible negative impact of regional industrial structure and economic scale, local governments should avoid blindly following the trend in dealing with the relationship between factor market distortion and environmental pollution and take measures according to local conditions.

Second, we implement an innovation-driven development strategy and optimize the investment structure for technological innovation. The regional test results show that technological innovation investment’s impact on environmental pollution is two-sided. Therefore, local governments should take a long-term view, pay attention to the relationship between environmental pollution and economic growth, and plan the scale of technological innovation investment and resource allocation reasonably so that technological innovation can play a better role in pollution prevention and control in all fields and regions. Simultaneously, enterprises should constantly conduct research and technological upgrades, encouraging technological innovation in pollution control, including clean production technology, end-of-pipe treatment technology, new energy, and new materials. Enterprises should focus on introducing and cultivating innovative talent in high technology to improve China’s level of technological innovation continuously and develop a green economy, strengthening cooperation with scientific research institutions and universities, giving full play to the collaborative innovation spillover effect, promoting the...
transformation of scientific and technological achievements into real productivity, and continuously solving the problem of environmental pollution.

Third, a reasonable environmental regulation system should be established. Different regions in China have different levels of economic development, resource endowments, and technology; and different environmental regulation systems should be established for each region, combining governmental environmental regulation, market-based environmental regulation, and public participation in environmental regulation to establish a rational and standardized environmental regulation system and strengthen the supervision of relevant environmental protection departments. The government should promote technological innovation and optimize industrial structure upgrades when formulating environmental protection policies. They provide more preference and support for inland places. Inland areas should not simply pursue economic benefits and ignore environmental pollution but should also appropriately raise the environmental access threshold and effectively screen and attract foreign investment. In general, when the government is committed to controlling environmental pollution, it should take a two-pronged approach by reducing the degree of distortion in the factor market and enhancing the ability of green technological innovation, giving full play to the interactive effect of both, improving the efficiency of emission reduction of enterprises, and promoting green technological innovation of enterprises, which can eventually promote green economic development and high-quality growth.

Author contribution Shuhong Wang: conceptualization, methodology, writing, and submission of the manuscript. Huikang Wang: Software, data processing, investigation, supervision, and writing.

Data availability The data used in this study are available from the corresponding author upon request.

Declarations

Ethics approval Ethical approval was obtained from the National Natural Science Foundation of China.

Consent to participate All authors of this paper consent to participate.

Consent for publication All authors of this manuscript have consented to its publication.

Conflict of interest The authors declare no competing interests.

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