



# Industrial agglomeration and industrial SO<sub>2</sub> emissions in China's 285 cities: Evidence from multiple agglomeration types

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## ABSTRACT

The environmental externalities of industrial agglomeration have generated intense debate, yet few studies have considered their effects and inner influence mechanism based on varied agglomeration types. This study distinguished between industrial density and proximity (spatially) and industrial specialization and diversity, as well as related variety and unrelated variety (organizationally). Using the panel data from China's 285 cities from 2003 to 2013, we examined the different effects of multiple agglomeration types of industrial agglomeration on industrial SO<sub>2</sub> emissions, and their inner influence mechanism from two aspects of industrial structure and technological progress. First, we found that various agglomeration types have different environmental externalities and that industrial density and proximity both have significant reduction effects on SO<sub>2</sub> emissions; diversity and related variety effectively reduce SO<sub>2</sub> discharges, but specialization and unrelated variety are linked to increased emissions. Second, technological progress and industrial structure are the critical channels of industrial agglomeration affecting pollution emissions while technological progress plays a greater role in the reducing emission effect of industrial agglomeration. Our findings reveal the importance of different agglomeration types and technological progress between industrial agglomeration and pollution emission.

## 1. Introduction

Since the reforms in and the opening up of China, industrial concentrations have flourished, first in coastal areas and subsequently throughout the country. While the spatial concentration of these developments has enhanced economic growth through agglomeration economies, environmental quality in these locations is threatened (Cheng, 2016; Ji and Zhou, 2020). By 2017, 7000 industrial parks in China had experienced environmental contamination, and only around 20–30% of them met the official environmental standard.<sup>1</sup> Meanwhile, the demand for a higher environmental quality of life has been rising (Guo et al., 2021; Yang et al., 2021). So far, balancing economic growth and environmental quality is a classic dilemma (Grossman and Krueger, 1995), and even remains a vital and urgent issue (Tiba and Omri, 2017). Thus, the in-depth exploration of the impact of industrial agglomeration on pollution emissions and its impact mechanism is becoming a practical and effective approach for this issue (Shen and Peng, 2021).

A large body of research has explored the relationship between

industrial agglomeration and environmental pollution, but no consensus has yet been reached. The first point of view is that industrial agglomeration intensifies environmental pollution (Chen et al., 2020; Cheng, 2016; Virkanen, 1998). The opposing view held by scholars is that industrial agglomeration alleviates environmental pollution (Fang et al., 2020; Karkalakos, 2010). More scholars identify a non-linear relationship, such as an inverse “U” or multiple threshold values (Ang, 2007; He et al., 2014; Neng et al., 2018; Roca et al., 2001; Shen and Peng, 2021). For instance, when exploring the effect of industrial agglomeration on the environment in China's provinces, Shen and Peng (2021) found a U-curved relationship between them (Bowen et al., 2009). This mixed conclusion intrigues scholars to keep thinking about the inner causes and exploring the potential relationship from varied perspectives including agglomeration types.

Although previous studies have found the heterogeneous impacts of several types of industrial agglomeration on pollutant emissions (Shen and Peng, 2020; Yang et al., 2020), the environmental effects of industrial agglomeration have not been comparatively analyzed because

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<sup>1</sup> Please see: <https://www.worldbank.org/en/news/press-release/2019/04/08/green-industrial-parks-critical-for-china-and-the-planet>.

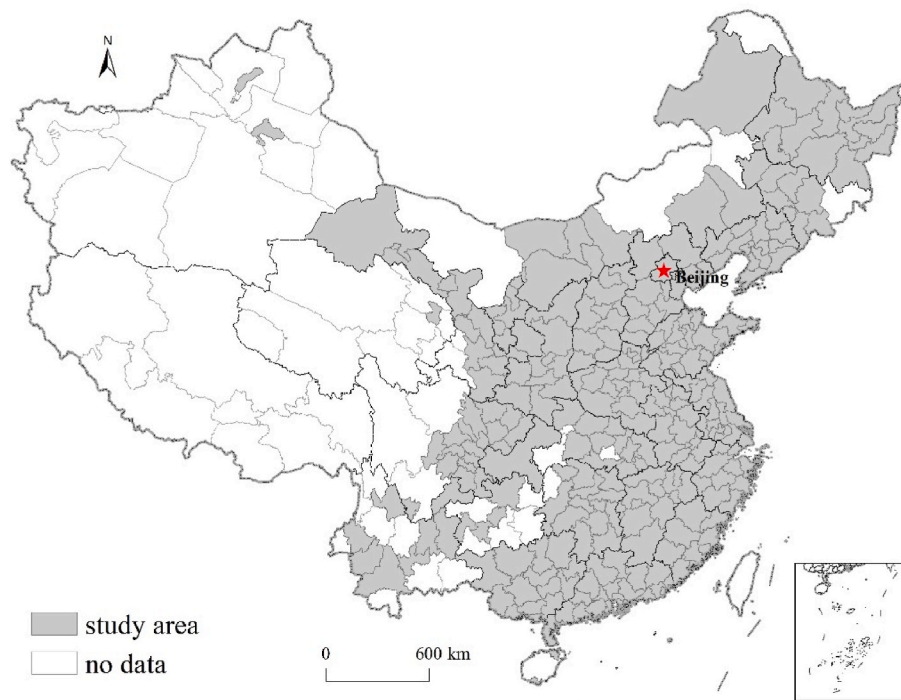


Fig. 1. Study area.

agglomeration types have largely been incomprehensively captured. According to differences in the externalities of agglomeration, agglomeration is categorized into spatial and organizational dimensions (Guo et al., 2016; Shao & Li, 2017). Spatially on one hand, in addition to the agglomeration density of industries, the geographic proximity of enterprises is the other main form of industrial agglomeration at a micro-firm scale that is usually ignored (Duranton and Puga, 2004; Ellison and Glaeser, 1997). The effects of each on environmental pollution may vary based on different scales.<sup>2</sup> Thus, we distinguish, within spatial agglomeration, between agglomeration density and the geographic proximity of enterprises at the macro and micro scales.

On the other hand organizationally, the contrast between specialized and diversified agglomeration has been widely discussed in the literature since Glaeser et al. (1992); yet their positive or negative environmental effects are still difficult to identify (Han et al., 2018; Yang et al., 2020). Moreover, research generally overlooks the fact that diversified agglomeration may exert a variety of environmental effects due to the differences in internal linkages between industries. According to evolutionary economic geography, technological linkages are a key factor for technological spillovers between related industries, and unrelated industries do not experience these spillovers. Therefore, diversified agglomeration can be divided into related variety and unrelated variety (Boschma and Iammarino, 2010; Frenken et al., 2007), and their relative impact on pollution emissions needs further exploration. In this context, it is essential to comprehensively capture the agglomeration types and explore their effects on environmental pollution.

Furthermore, given the intricate relationship between industrial agglomeration and environmental pollution, the underlying mechanisms have received little attention in the literature. According to Kuznets's curve theory, structure and technology are important factors behind the impact of economic development on environmental quality (Grossman and Krueger, 1991), yet few studies have shed light on the

role of industrial structure versus technological progress.

Therefore, the main goal of this study is to explore the different effects of industrial agglomeration from the perspective of multiple agglomeration types and further identify their inner influence mechanism from two channels: industrial structure and technological progress. Taking industrial SO<sub>2</sub> emission intensity as a proxy of environmental pollution and China's 285 cities as an example, we examined the various environmental externalities of multiple agglomeration types. We then decomposed industrial SO<sub>2</sub> emissions into an industrial structure index and a technological progress index and used a simultaneous equation model to explore how industrial agglomeration affects industrial SO<sub>2</sub> emissions through industrial structure and technological progress.

The contributions of this paper are twofold. First, we comprehensively captured the multiple agglomeration types from spatial and organizational dimensions to explore their different effects on environmental pollution. Second, we attempted to adopt a simultaneous equation model to identify the two channels (i.e., industrial structural and technological progress) of industrial agglomeration affecting environmental pollution. As a result, the research perspective and approach of our study provide the academic reference for research related to industrial agglomeration, especially in terms of the insights of different externalities of agglomeration based on agglomeration types and in-depth mechanism analysis.

The rest of this paper is structured as follows. The next section presents the research hypotheses. Data and methodology are introduced in Section 3. Section 4 then comprises the empirical results and a discussion. We end our paper with conclusions and policy implications in Section 5.

## 2. Different types of industrial agglomeration and environmental pollution

### 2.1. Spatial agglomeration and environmental pollution

Industrial agglomeration, composed of agglomeration density and geographic proximity, can save costs and boost technology spillovers through face-to-face communication and the sharing of resources and

<sup>2</sup> Although agglomeration density may be higher, the distribution of enterprises may be more scattered. Inversely, although agglomeration density is not high, some enterprises concentrate here.

elements;; this in turn leads to scale economies and further contributes to lowering the intensity and scale of pollutant emissions (He et al., 2017; Lin, 2016). First, such agglomeration can: reduce the costs of transportation and communication; avoid an increase in transaction costs caused by information asymmetry; promote technological innovation and product upgrading; and achieve pollution reduction (He et al., 2017). Second, the diffusion of knowledge and technology decays with increasing geographic distance (known as the decay effect). The increase in geographic distance reduces opportunities for mutual learning among enterprises, especially regarding tacit knowledge, and hinders production technology improvement, and thus exacerbates pollution emissions (Lin, 2016). Third, by improving the utilization efficiency of regional pollution-control facilities and encouraging the construction of pollution-control industries, the concentration of enterprises enables scale economies of pollution control and lowers pollution control costs, and further reduces pollution emissions.

**Hypothesis 1.** Industrial spatial agglomeration—namely geographic agglomeration density and proximity—has positive agglomeration externalities that contribute to reducing industrial pollutant emissions.

## 2.2. Organizational agglomeration and environmental pollution

Organizationally, and based on whether externalities are caused by the same industry type, industrial agglomeration can be divided into specialization and diversity. Specialized agglomeration corresponds with Marshallian externalities (Marshall, 1920), which is derived from the concentration of the same industries (or intra-industries). Specialization is conducive to the sharing of a specialized labor market, intermediate inputs, and knowledge spillovers within the same industries, and thereby reduces pollution emissions by lowering production risks and costs and increasing efficiency. However, the concentration of a single industry is more likely to reduce technology spillover and thereby intensify the level of pollution emissions, because the high level of industrial homogeneity hinders inter-industry exchanges and cooperation (Xie and Yuan, 2016). Thus, it is difficult to identify specialization effects. The notion of diversified agglomeration is that externalities are generated by different industries (or inter-industries) (Jacobs, 1969). An inter-industrial agglomeration provides convenient conditions for exchanging across borders, cooperating across industries, sharing infrastructure, and attracting a skilled labor inflow, all of which contribute to technology spillovers and innovation activities and drive a decline in pollution emissions (Audretsch and Feldman, 1998; Han et al., 2018).

**Hypothesis 2.** Diversified agglomeration produces positive agglomeration externalities through knowledge spillovers and technological spillovers, which contribute to reducing industrial pollutant emissions. However, the environmental effects of specialization depend on the balance between the two opposing forces.

Moreover, from the perspective of evolutionary economic geography, Frenken et al. (2007) and Boschma and Iammarino (2010) stress that technology relatedness is a critical condition for diversified agglomeration to induce technology spillover, and thus related variety and unrelated variety are proposed in terms of shared or complementary competences between industries (the cognitive linkage). Related variety refers to the clustering distribution of a series of industries with strong technological linkages, while unrelated variety is the geographical concentration of industries with weak or no technological linkages.

Under this framework, and compared with the agglomeration distribution of unrelated industries, industries with cognitive linkages strengthen interactive learning and cooperation because of common knowledge; they also promote technological spillovers and stimulate innovation, thus enabling the reduction of pollution emissions. In addition, these industries achieve mutualism by exchanging internal materials, and the byproducts from the production process of an enterprise can be reused as raw materials or intermediate inputs by other

enterprises; thus, material resources are recycled internally and industrial pollution emissions are reduced (Ehrenfeld, 2003). On the other hand, weak cognitive linkages reduce the possibility for mutual learning, and knowledge and technology are difficult to spill over among unrelated industries and thus cannot reduce pollution emissions along the same path as related industries.

**Hypothesis 3.** Related variety is more likely to reduce industrial pollutant emissions based on cognitive proximity, while unrelated variety probably hinders pollution emission reduction.

## 3. Data sources and measurements

### 3.1. Estimation of industrial sulfur dioxide (SO<sub>2</sub>) emissions

We chose industrial SO<sub>2</sub> emission intensity as a proxy of environmental pollution for the following reasons. First, the emission of SO<sub>2</sub> originates from fossil fuel consumption, especially for industrial activities, which is closely related to technological progress and industrial structure. In China, SO<sub>2</sub> pollution is among the most severe in the world, mainly driven by rapid industrial development. The effects of pollution emissions may be more evident for SO<sub>2</sub> emissions. Second, industrial SO<sub>2</sub> emissions have been widely used to represent environmental pollution in previous research, both in China and in other countries (He et al., 2018). It is convenient for our analysis to dialogue with the previous results and findings, adding to the research implications. Finally, and based on the completed accessibility, the data cover 285 prefectural-level cities in China.

#### 3.1.1. Industrial SO<sub>2</sub> emissions intensity

Similar to previous studies, we calculated industrial SO<sub>2</sub> emission intensity by dividing industrial SO<sub>2</sub> emissions  $w_{i,t}$  by the total industrial output  $Y_{i,t}$  ( $Y_{i,t} = \sum_{j=1}^J Y_{i,t}^j$ ) in city  $i$  in year  $t$ , namely,

$$Plu_{i,t} = w_{i,t} / Y_{i,t} (\text{unit : ton / 100 million yuan}) \quad (1)$$

#### 3.1.2. Decomposing industrial SO<sub>2</sub> emissions: industrial structure and technological progress

The decline in pollution intensity in a city may be based on two aspects, namely an adjustment of the industrial structure (from heavily to less polluting industries) and the upgrading within industries of technologies to control industrial pollution (Zhang and Jiang, 2014). To further explore the potential mechanisms by which industrial agglomeration affects environmental pollution, we decomposed industrial SO<sub>2</sub> emission intensity into an industrial structure index and a technological progress index. This follows Zhang and Jiang (2014) who examined the influence of foreign direct investment (FDI) on water pollution.

The proportion of industry  $j$  accounting for the total industrial output value of city  $i$ ,  $s_{i,t}^j$  ( $s_{i,t}^j = Y_{i,t}^j / Y_{i,t}$ ) is generally used to represent the industrial structure. However, given that pollution emission intensities differ across industries, we took the national average emission intensity coefficient of industry  $j$  in the base period ( $t = 0$ ) as the benchmark weight ( $Plu_{A,0}^j = w_{A,0}^j / Y_{A,0}^j$ ), and defined the industrial structure index related to SO<sub>2</sub> pollution as

$$polstr_{i,t} = \frac{1}{\sum_{j=1}^J (s_{i,t}^j \times Plu_{A,0}^j)} = \frac{Y_{i,t}}{\sum_{j=1}^J (w_{A,0}^j Y_{i,t}^j / Y_{A,0}^j)} \quad (2)$$

The higher the  $polstr$ , the lower the proportion of heavily polluting industries in the industrial sector in city  $i$ . Conversely, the lower the index, the higher the proportion of heavily polluting industries.

The national average SO<sub>2</sub> emission intensity  $Plu_{A,0}^j$  of industry  $j$  in the base year ( $t = 0$ ) is regarded as a technical benchmark. The theoretical SO<sub>2</sub> emissions  $\bar{w}_{i,t}^j$  of industry  $j$  in city  $i$  is measured by  $Plu_{A,0}^j$  multiplied

by the industrial output ( $Y_{i,t}^j$ ) in city  $i$  in year  $t$ , namely,  $\bar{w}_{i,t}^j = Plu_{A,0}^j * Y_{i,t}^j$ . Thus, the theoretical total SO<sub>2</sub> emission volume in city  $i$  is calculated by summing the SO<sub>2</sub> emissions of all industries, namely  $\bar{w}_{i,t} = \sum_{j=1}^J \bar{w}_{i,t}^j$ .

Based on this, we defined the ratio of the actual SO<sub>2</sub> emissions and its theoretical value as the technical progress indicator related to SO<sub>2</sub> pollutants in city  $i$ ,

$$poltec_{i,t} = \frac{\bar{w}_{i,t}}{w_{i,t}} = \frac{\sum_{j=1}^J (w_{A,0}^j Y_{i,t}^j / Y_{A,0}^j)}{w_{i,t}} \quad (3)$$

in which  $poltec_{i,t} > 1$  indicates that the actual SO<sub>2</sub> emissions in city  $i$  are lower than the theoretical emissions, meaning that the actual pollution control technology in city  $i$  surpasses the reference technology level. This means that the higher the  $poltec_{i,t}$  s, the more advanced the environmental control technology in city  $i$ .

Lastly, combining Equations (1)–(3) for industrial pollution, we obtained the decomposition identities of industrial SO<sub>2</sub> emissions,

$$Plu_{i,t} = \frac{w_{i,t}}{Y_{i,t}} = \frac{1}{polstr_{i,t} \times poltec_{i,t}} \quad (4)$$

As this equation shows, reducing industrial SO<sub>2</sub> emissions can be achieved both by upgrading the industrial structure ( $polstr$ ) and by improving environmental protection technologies ( $poltec$ ).

### 3.2. Industrial spatial and organizational agglomeration

#### 3.2.1. Spatial agglomeration

##### (1) Industrial density

We included the relative industrial density in city  $i$ ,

$$den_i = \frac{ind_i / area_i}{\sum ind_i / \sum area_i} \quad (5)$$

where  $ind_i$  and  $area_i$  represent the total industrial output and land area of city  $i$ , respectively, normalized by the average industrial density over all observations.

##### (2) Geographic proximity

Following Duranton and Overman (2005), we computed the geographic distance between enterprises by the geographic location of enterprises, which indicates the physical proximity or degree of spatial clustering between firms across all sectors. For this, we calculated the coefficient of variation for latitude and longitude of each enterprise point as

$$proximity = -\ln(CV_{latitude-firm} \times CV_{longitude-firm}) \quad (6)$$

The larger the  $proximity$ , the more concentrated the distribution of enterprises within each city.

#### 3.2.2. Organizational agglomeration

##### (1) Specialization and diversity

Following the methodology of Duranton and Puga (2000), we measured the specialization and diversity of a city through the output value among industries. To compare specialization between cities, it is necessary to compare the employment sector with the largest share in each city. Therefore, specialization is expressed by the location quotient of the largest industry. Although the reciprocal of the Herfindahl index is generally used to measure diversification, we set the inverse of the Krugman Dissimilarity Index to measure regional diversity, allowing optimal horizontal comparison between cities.

$$rzi = \frac{Max}{j} (s_{ij} / s_j), rdi = 1 / \sum_j |s_{ij} - s_j| \quad (7)$$

Where  $s_{ij}$  indicates the proportion that the total output value of industry  $j$  in city  $i$  accounts for in the total industrial output value of city  $i$ , and  $s_j$  is the ratio of the total output value of industry  $j$  to the national output value of all industries. The larger the  $rzi$  ( $rdi$ ), the higher the level of specialization (diversity).

##### (2) Related variety and unrelated variety

Following Frenken et al. (2007), we used an entropy indicator method to measure related variety and unrelated variety. Using the method of Pan et al. (2012), we classified 37 two-digit industries in China into four aggregated sets based on the input–output relationship across industries.<sup>3</sup> As in Frenken et al. (2007), the inter-industries within each large category are related but the four large categories are unrelated, and unrelated variety ( $uv$ ) is the entropy of the large category, while related variety ( $rv$ ) is represented by the weighted sum of the entropies of the subsectors in each large category,

$$uv = \sum_{g=1}^4 p_{gi} \log_2 \left( \frac{1}{p_{gi}} \right), rv = \sum_{g=1}^4 p_{gi} h_{gi} \quad (8)$$

$$h_{gi} = \sum_{j \in g} \frac{p_{ji}}{p_{gi}} \log_2 \left( \frac{1}{\frac{p_{ji}}{p_{gi}}} \right) \quad (j = 1, \dots, 37; g = 1, 2, 3, 4.)$$

In eq. (8),  $j$  is the 37 chosen industries,  $g$  refers to the four industry categories,  $p_j$  represents the ratio of the output of industry  $j$  to the total output, and  $p_g$  represents the ratio of the output of category industry  $g$  to the total output;  $h_{gi}$  is the entropies of variety of industry  $i$  in category  $g$ . The larger the  $uv$ , the higher the noncorrelation degree of the industry agglomeration. The larger the  $rv$ , the higher the correlation degree of the agglomeration industry.

#### 3.3. Model specification

In accordance with the theoretical framework presented in Section 2, we constructed a panel regression model to examine the impact of different agglomeration types on industrial SO<sub>2</sub> emissions,

$$\ln pol_{it} = \alpha_0 + \beta_1 aggl_{it} + \beta_2 \ln pop_{it} + \beta_3 str_{it} + \beta_4 open_{it} + \beta_5 tec_{it} + \beta_6 \ln er_{it} + r_t + \tau_i + \varepsilon_{it} \quad (9)$$

<sup>3</sup> Category I: coal mining and washing, oil and natural gas exploration industry, non-ferrous metal mining, ferrous metal mining, non-metallic mining and other mining industry, non-metallic mineral product industry and production and supply of electric power and heating; Category II: food processing, food manufacturing, beverage manufacturing, tobacco products, the textile industry, textile and apparel, footwear, headgear, leather, fur, feathers (down) and its products, wood processing and wood, bamboo, and straw products, furniture manufacturing, paper and paper product industry, printing and recording media reproduction, educational and sports goods, oil processing, coking and nuclear fuel industry, pharmaceutical manufacturing and gas production and supply; Cluster III: chemical material and chemical product manufacturing, chemical fiber manufacturing industry, rubber products and plastic products; Cluster IV: ferrous metal smelting and rolling processing industry, non-ferrous metal smelting and pressing industry, fabricated metal products, general equipment manufacturing, special equipment manufacturing, transportation equipment manufacturing industry, electrical machinery and equipment manufacturing, communication equipment, computer and other electronic equipment manufacturing, and instruments and cultural and office equipment manufacturing.



where  $\ln pol_{it}$  is the logarithm of SO<sub>2</sub> emission intensity in city  $i$  and year  $t$ ,  $aggl_{it}$  represents the indicators of different agglomeration types in city  $i$  and year  $t$ . As control variables we included population size  $\ln pop$ , industrial structure  $str$ , openness to the outside world  $open$ , local technological level  $tec$ , and environmental regulation  $ln er$ .  $r_t$  and  $\tau_i$  stand for the fixed effects for each year and city, respectively, and  $\varepsilon_{it}$  is the usual error term.

Furthermore, adopting a simultaneous equation model, we identified the two channels (industrial structural and technological progress) that may influence industrial SO<sub>2</sub> emissions. Specifically, we analyzed the effects of different spatial and organizational agglomerations on the industrial structure of the city in Equation (10a), and on the technological advancement of the city in Equation (10b).

$$\{polstr_{it} = c(1) + c(2) * aggl_{it} + c(3) * rgdp_{it} + c(4) * open_{it} + c(5) * er_{it} + c(6) * for_{it} \quad (10a)$$

$$\{poltec_{it} = c(7) + c(8) * aggl_{it} + c(9) * rgdp_{it} + c(10) * open_{it} + c(11) * er_{it} + c(12) * for_{it} \quad (10b)$$

where industrial structure index  $polstr$  and technological progress index  $poltec$  are decomposed from SO<sub>2</sub> emissions.  $rgdp$  refers to the economic development of the city, and  $for$  to the green rate of the built-up area.

### 3.4. Data

The study area includes 285 prefecture-level cities over the 2003–2013 period. Two reasons were considered: First, the existing related research about the linkage between industrial agglomeration and environmental pollution mainly focus at the province level or on part of city regions in China (Hao et al., 2021; Wang et al., 2020); there is a shortage of empirical evidence on prefecture-level cities which may exert different effects. Thus, our study provided one empirical case at the smaller scale covering 285 prefecture-cities. Secondly, in order to match sector data and prefecture-level cities, we chose the 2003–2013 dataset during, considering data accessibility.<sup>4</sup>

Industrial data were drawn from the Annual Survey of Industrial Firms (ASIFs) published by the Chinese National Bureau of Statistics (NBS). We collected the industrial output value of 39 two-digit sectors (SIC codes 06–46) and the total industrial output of each city. The chosen sectors cover industries such as mining, manufacturing, electricity, gas, and water production; they also cover all state-owned industrial enterprises and nonstate-owned enterprises with sales revenues greater than RMB 5 million (USD 78,000). Abnormal values in the database were removed to ensure accurate results. Independent variables (i.e., industrial SO<sub>2</sub> emissions) and other control variables (e.g., per capita GDP, the actual use of FDI, industrial SO<sub>2</sub> production and treatment, and greening rate in built-up areas) were obtained from the China City Statistical Yearbook (2004–14). The definitions and descriptive statistics of variables are shown in Table 1.

## 4. Results and discussion

### 4.1. The influence of industrial agglomeration on environmental pollution

We used a panel regression with city-fixed effect<sup>5</sup> to investigate the influence of the agglomeration types of indicators from different industrial spatial and organizational agglomeration types on industrial

SO<sub>2</sub> emission intensity, and the results are shown in Table 2. There is no strong correlation between the independent variable and different indicators of agglomeration types and other control variables, based on correlation analysis of variables in Table A1. The VIFs in all models are less than 2, signifying there are no serious collinear problems. The values of  $R^2$  demonstrate that all models are significant and have good explanatory power.

The results of Models 1 and 2 show the effects of industrial agglomeration density and geographic proximity on pollution emissions. The coefficient of agglomeration density ( $den$ ) is significantly negative, indicating that expansion of the agglomeration scale reduces SO<sub>2</sub> emission intensity. This result may arise from the increased level of corporate sharing and technology spillover caused by agglomeration. It also offers support for the conclusion of Shuang et al. (2011) that positive environmental externalities caused by an increase in industrial agglomeration levels play an important role in reducing industrial pollution. The negative and significant coefficient of geographic proximity ( $pro$ ) indicates that the spatial closeness of enterprises reduces the intensity of regional pollution discharge, which lends support to the finding by Lin and Xiong (2012) that the geographic proximity of automobile enterprises promotes a decline in pollutant emissions through its spillover effects on enterprise innovation. Therefore, the effects of agglomeration density and geographic proximity on industrial SO<sub>2</sub> emissions in this paper are consistent with Hypothesis 1.

Models 3 and 4 show the influence of organizational agglomeration on industrial SO<sub>2</sub> emissions. In Model 3, the estimated coefficient of specialization ( $rzi$ ) is significantly positive, meaning the specialized agglomeration of industries intensifies industrial SO<sub>2</sub> emissions. Based on Hypothesis 2, it implies that the crowding effect exceeds positive environmental externalities. Based on the industry life cycle, the reason may be that industries within specialized agglomeration are in a mature phase and achieve standardization (i.e., industrial homogeneity) through sharing, matching, and learning. The negative overcrowding effect tends to dominate, compared with the declined positive externality in pollution reduction (Neffke et al., 2011), which is consistent with the findings of Hong et al. (2020) while the estimated coefficient of diversity ( $rdi$ ) is negative at a 99% significance level. As expected with Hypothesis 2, diversified agglomeration reduces pollution effects. The knowledge spillovers between different industries contributes to improved innovation of pollution-reduced technology and environmental efficiency (Shen and Peng, 2021).

In Model 4, the coefficient of related variety ( $rv$ ) is significantly negative, while the coefficient of the unrelated variety ( $uv$ ) is significantly positive. This indicates that a diversified agglomeration with technical connections is conducive to reducing SO<sub>2</sub> emissions, while the concentration of unrelated industries could increase SO<sub>2</sub> emissions, as Hypothesis 3 clarified. Compare with unrelated variety, related variety with the strong linkage of technology and interindustry input-output induces the promotion of economic growth and industry development (Boschma and Iammarino, 2010). In line with the findings of Li et al. (2021), related variety has a positive reduction effect on SO<sub>2</sub> emissions through stronger technology spillovers, while unrelated variety has a negative environmental effect.

In Models 5 and 6, the coefficient direction and significance of the regression results are consistent with the results of Models 1–4 when all variables of agglomeration types are included in a single model. That is, agglomeration density, geographic proximity of enterprises, diversification, and related variety are conducive to reducing industrial SO<sub>2</sub> emission intensity, while specialization and unrelated variety intensifies emissions.

In terms of control variables, the estimated coefficients of population size ( $\ln pop$ ), technological level ( $tec$ ), and environmental regulation ( $er$ ) are significantly negative in all models, which means the three factors are negatively associated with industrial SO<sub>2</sub> emissions. That is, population concentration, increasing scientific and technological investment, and environmental regulation contribute to reducing industrial SO<sub>2</sub>

<sup>4</sup> This dataset is extracted from the Annual Survey of Industrial Firms (ASIFs) provided by the State Statistical Bureau in China, last updated in 2013.

<sup>5</sup> Based on the Hausman-test (see Table 2), the panel regressions with fixed effect are recommended in our study.

**Table 1**  
Variable definitions and summary statistics.

Variables	Definition	Measure	Observe	Mean	Std. Dev.	Min	Max
<i>SO<sub>2</sub></i>	SO <sub>2</sub> emission intensity	Logarithm of SO <sub>2</sub> emission intensity	3,135	4.004	1.260	−3.929	10.89
<i>den</i>	Industrial density	Relative industrial density	3,135	2.194	4.807	0.0106	71.414
<i>pro</i>	Firm proximity	Variable coefficient for latitude and longitude of each enterprise point	3,135	10.52	1.229	2	15.24
<i>rzi</i>	Specialization	Location quotient of the largest industry	3,135	11.30	10.18	1.823	133.7
<i>rdi</i>	Diversity	The inverse of the Krugman Dissimilarity Index of industries	3,135	1.065	0.299	0.538	2.332
<i>rv</i>	Related variety	Weighted sum of the entropies of the subsectors in each sector of 37 two-digit sectors	3,135	1.302	0.393	0.0243	2.276
<i>uv</i>	Unrelated variety	Entropy across 4 large sectors	3,135	1.107	0.186	0.220	1.385
<i>lnpop</i>	Population density	Logarithm of population density	3,135	5.711	0.910	1.547	7.887
<i>open</i>	Opening-up level	Actual use of FDI as a percentage of GDP	3,135	0.0217	0.0247	0	0.376
<i>tec</i>	Technological level	Ratio of science and technology expenditure to fiscal expenditure	3,135	0.00992	0.0109	0	0.163
<i>str</i>	Industrial structure	Proportion of output value of industries with high SO <sub>2</sub> emissions <sup>1</sup> in GDP	3,135	0.418	0.192	0	1
<i>lnr</i>	Environmental regulation	Logarithm of treatment rate of industrial SO <sub>2</sub>	3,135	0.351	0.693	−35.06	0.998
<i>lnrgdp</i>	Economic development	Logarithm of per capita GDP	3,135	9.788	0.817	7.634	13.13
<i>for</i>	Green rate	Green rate of the built-up area	3,135	35.94	15.65	0	386.6
<i>polstr</i>	Industrial structure index	Industrial structure index	3,135	0.0159	0.0083	0.00179	0.109
<i>poltec</i>	Technological progress index	Technological progress index	3,135	7.563	164.7	0.00711	7.596

<sup>1</sup> To ensure the accuracy of the regression results, we controlled for the proportion of polluting industries. According to the industrial SO<sub>2</sub> emission intensity value at the national level, 10 industries (i.e., non-ferrous metal mining and dressing industry, non-metallic mining and dressing industry, paper and paper product industry, petroleum processing, coking and nuclear fuel, chemical raw material and chemical product manufacturing industry, chemical fiber manufacturing, non-metallic mineral products, ferrous metal smelting and rolling processing industry, non-ferrous metal smelting and rolling processing industry, electric power, heat production and supply industry) were set as industrial SO<sub>2</sub> pollution-intensive industries.

**Table 2**  
Impact of different types of industrial agglomeration on SO<sub>2</sub> emission intensity.

	M1	M2	M3	M4	M5	M6
<i>den</i>	−0.0503*** (0.0130)				−0.0281** (0.0127)	−0.0428*** (0.0127)
<i>pro</i>		−0.0512*** (0.0147)			−0.0523*** (0.0142)	−0.0553*** (0.0143)
<i>rzi</i>			0.0131*** (0.00279)		0.0131*** (0.00279)	0.0167*** (0.00278)
<i>rdi</i>			−1.310*** (0.115)		−1.281*** (0.115)	
<i>rv</i>				−1.164*** (0.111)		−1.052*** (0.111)
<i>uv</i>				0.483*** (0.156)		0.539*** (0.155)
<i>lnpop</i>	−3.940*** (0.284)	−3.995*** (0.284)	−3.472*** (0.277)	−3.666*** (0.280)	−3.518*** (0.276)	−3.574*** (0.278)
<i>open</i>	−2.145** (0.989)	−2.218** (0.989)	−1.253 (0.960)	−2.021** (0.973)	−1.145 (0.958)	−1.556 (0.964)
<i>tec</i>	−27.61*** (1.632)	−26.92*** (1.603)	−23.79*** (1.546)	−25.68*** (1.562)	−25.45*** (1.604)	−27.21*** (1.606)
<i>str</i>	1.586*** (0.176)	1.597*** (0.176)	1.243*** (0.173)	1.048*** (0.181)	1.226*** (0.173)	1.074*** (0.179)
<i>er</i>	−0.0771*** (0.0184)	−0.0816*** (0.0184)	−0.0741*** (0.0178)	−0.0726*** (0.0180)	−0.0775*** (0.0178)	−0.0769*** (0.0179)
Constant	26.52*** (1.638)	27.25*** (1.655)	25.06*** (1.597)	26.03*** (1.616)	25.94*** (1.607)	25.79*** (1.625)
City Fixed Effect	YES	YES	YES	YES	YES	YES
<i>N</i>	2923	2923	2923	2923	2923	2923
Hausman ( <i>chi</i> 2)	173.92***	178.00***	183.48***	179.20***	140.06***	138.18***
<i>R-squared</i>	0.247	0.247	0.295	0.273	0.300	0.291

Notes: \*\*\* stands for  $p < 0.01$ , \*\* stands for  $p < 0.05$ , and \* stands for  $p < 0.1$ . Robust standard errors are reported in parentheses.

emissions, which is consistent with the results of most related studies (Chen et al., 2020; Dong et al., 2019). Except for Model 3, the coefficients of opening to the outside world (*open*) are significant and negative, showing its negative linkage with SO<sub>2</sub> emission intensity. Opening to the outside world enables technological spillovers across the region, which in turn leads to reduced industrial SO<sub>2</sub> emissions. The coefficient of industrial structure (*str*) is significantly positive, indicating that the increase in the proportion of industrial SO<sub>2</sub> pollution-intensive industries will increase industrial SO<sub>2</sub> emissions.

To ensure the robustness of the results, a sensitivity check was conducted by choosing industrial dust instead of industrial SO<sub>2</sub> emissions as

a proxy of pollution emission. Table A2 in the appendix shows the different effects of agglomeration types on industrial dust, which are all consistent with those of SO<sub>2</sub>, although the coefficients of unrelated variety are insignificant. These results most probably offer evidence for the effects of industrial agglomeration on pollution emissions.

#### 4.2. Mechanism analysis

We further used the simultaneous equations to test how different types of industrial agglomeration affect industrial SO<sub>2</sub> emissions through industrial structure and technological progress. The results are

**Table 3**  
Mechanism analysis according to industrial structure and technological progress.

	M7			M8			M9			M10			M11			M12		
	polstr	poltec	polstr	poltec	polstr	poltec	polstr	poltec	polstr	poltec	polstr	poltec	polstr	poltec	polstr	polstr	poltec	poltec
<i>den</i>	0.000505*** (0.0000325)	0.130*** (0.0370)											0.000501*** (0.0000329)	0.132*** (0.0373)		0.000423*** (0.0000321)		0.126*** (0.0378)
<i>pro</i>			0.000347*** (0.000119)	-0.0785 (0.131)									0.0000712 (0.000116)	-0.139 (0.132)		0.0000331 (0.000112)		-0.135 (0.132)
<i>rzi</i>					-0.0000355* (0.0000181)	-0.0160 (0.0198)							-0.0000277* (0.0000174)	-0.0142 (0.0198)		-0.0000300* (0.0000164)		-0.0161 (0.0193)
<i>rdi</i>					-0.000574 (0.000583)	1.962*** (0.638)							-0.000652 (0.000561)	1.920*** (0.637)				
<i>rv</i>							0.00464*** (0.000422)	2.125*** (0.482)								0.00384*** (0.000429)		1.831*** (0.505)
<i>uv</i>							-0.0136*** (0.000841)	-1.043 (0.962)								-0.0120*** (0.000835)		-0.671 (0.983)
<i>lnrgdp</i>	0.00153*** (0.000205)	1.206*** (0.233)	0.00276*** (0.000196)	1.547*** (0.215)	0.00279*** (0.000199)	1.380*** (0.217)	0.00273*** (0.000187)	1.517*** (0.213)					0.00152*** (0.000207)	1.069*** (0.236)		0.00161*** (0.000199)		1.192*** (0.234)
<i>open</i>	0.0502*** (0.00626)	-5.002 (7.123)	0.0696*** (0.00641)	1.436 (7.037)	0.0732*** (0.00671)	-8.300 (7.340)	0.0533*** (0.00636)	-9.229 (7.274)					0.0512*** (0.00665)	-12.69* (7.550)		0.0363*** (0.00634)		-13.13* (7.461)
<i>er</i>	-0.000404** (0.000190)	0.366* (0.216)	-0.000438** (0.000197)	0.363* (0.216)	-0.000411** (0.000198)	0.320 (0.216)	-0.000339* (0.000189)	0.331 (0.216)					-0.000391** (0.000190)	0.331 (0.216)		-0.000325* (0.000183)		0.343 (0.216)
<i>for</i>	0.0000166* (0.000000)	-0.0107 (0.0104)	0.0000247*** (0.00000944)	-0.00825 (0.0104)	0.0000244*** (0.0000)	-0.00967 (0.0103)	0.0000176* (0.000)	-0.0122 (0.0104)					0.0000159* (0.00000)	-0.0116 (0.0103)		0.0000106 (0.00000)		-0.0141 (0.0104)
Constant	-0.00166 (0.00190)	-9.304*** (2.160)	-0.0170*** (0.00209)	-11.76*** (2.291)	-0.0126*** (0.00191)	-12.61*** (2.089)	-0.00337* (0.00192)	-13.56*** (2.192)					-0.00136 (0.00231)	-8.213*** (2.622)		0.00649*** (0.00240)		-8.930*** (2.823)
<i>N</i>	2943			2943		2943		2943					2943			2943		
<i>R-squared</i>	0.248			0.187		0.189		0.259					0.253			0.305		

Notes: \*\*\* stands for  $p < 0.01$ , \*\* stands for  $p < 0.05$ , and \* stands for  $p < 0.1$ . Robust standard errors are reported in parentheses.

shown in Models 7–12 of Table 3. In M7 and M10, for the industrial structure index (*polstr*) and the technological progress index (*poltec*), the estimated coefficients of agglomeration density and related variety are both significantly positive. This indicates that the agglomeration scale expansion and industrial relatedness enhancement contribute to reducing SO<sub>2</sub> emission intensity, which can be caused by lowering the proportion of regional polluting industries and improving the technological level of pollution control.

In M9 and M10, the influences of specialized agglomeration and unrelated variety on industrial structure index are both significantly negative, but on technological progress, those are negative but insignificant. This means that the concentration of a single industry and unrelated industries may increase industrial SO<sub>2</sub> emissions by increasing the proportion of polluting industries while diversity is significantly positively associated with the technological progress index but is insignificant regarding the industrial structure index. This indicates that diversity exerts the pollution reduction effect by improving environmental protection technology. In M8, the influence of geographic proximity on industrial structure is positively significant, while its influence on technological progress is negative but insignificant. This means that geographical proximity contributes to reducing pollution emissions through optimizing industrial structure, but has no significant role in pollution control technology improvement. The magnitudes and signs of the estimated coefficients in M12 and M13 are mostly consistent with those of M7–11. In sum, the above results confirm that industrial structure and pollution control technology are important determinants of industrial SO<sub>2</sub> emissions, and the effects of different agglomeration types on industrial structure and pollution control technology vary.

Moreover, the influence mechanism between agglomeration types is different. Technological progress is the main factor in agglomeration density, diversity, and related variety to promote pollution reduction. It shows that the above three agglomeration types achieve technological spillovers through mutual learning between industries, and then promotes the level of industrial-technological (Castaldi et al., 2015; Frenken and Boschma, 2007). Conversely, industrial structure improvement is not sensitive to these interactions between industries. On the other hand, an increase in the proportion of polluting industries is a key channel for specialization and unrelated variety aggravating pollution emissions, while geographical proximity reduces pollution emissions. It is more difficult to form technological spillovers and promote industrial innovation when a single industry or unrelated industries concentrate, which is in line with Gao et al. (2020) and Neng et al. (2018). Rather, geography proximity of the polluting industries is more conducive to building a green cooperation network and reducing pollution through communicating and sharing (Peng et al., 2021). Therefore, the proportion of polluting industries most likely increases in the first two agglomeration types and decreases in geography proximity.

Finally, the effects of industrial structure and technological progress on industrial SO<sub>2</sub> emission intensity are different. The estimated coefficients of agglomeration density, and related variety for the technology progress index (i.e., 0.130, 2.125) are significantly larger than those for the industrial structure index (i.e., 0.000505, 0.00464). The results show that agglomeration density and related variety are more likely to improve pollution control technology and reduce industrial SO<sub>2</sub> emissions through technological spillovers. The significant and positive coefficient of diversity for technology progress index and its nonsignificant coefficient for industrial structure index support the positive role of technological progress as well. Compared to the nonsignificant coefficient for the technology progress index, the significantly negative coefficients of specialized agglomeration and unrelated variety for the industrial structure indicate that specialized agglomeration and unrelated variety can affect industrial SO<sub>2</sub> emissions through the role of industry structure, but not through pollution control technology. Therefore, industrial agglomeration mainly promotes the reduction of industrial SO<sub>2</sub> emission intensity through the improvement of pollution control technology.

## 5. Conclusions and policy implications

While a large body of research has focused on the environmental effects of industrial agglomeration, the agglomeration types of industries have been ignored. This is unfortunate as each exert different externalities on industrial pollution emissions. Therefore, using the 2003 to 2013 panel data on 285 Chinese cities, we explored the different influences of multiple industrial agglomeration types on industrial SO<sub>2</sub> emissions from spatial and organization dimensions. Further, we clarified how industrial agglomeration affects industrial SO<sub>2</sub> emissions through industrial structure and technological progress.

### 5.1. Contribution

Our findings indicate that both agglomeration density and geographic proximity promote a reduction in industrial SO<sub>2</sub> emissions. Organizationally, diversified agglomerations and related variety are conducive to a decline in SO<sub>2</sub> emissions, while specialized agglomeration and unrelated variety increase SO<sub>2</sub> emissions. To a certain extent, these findings offer support for previous studies on industrial agglomeration concerning the traditional density and geographical proximity and the prevalent specialization and diversity (Hong et al., 2020; Lin and Xiong, 2012; Shen and Peng, 2021; Shuang et al., 2011). That is, the increase in agglomeration density, geographic proximity of enterprises, and diversity are conducive to pollution reduction, while specialization aggravates pollution emissions.

In addition, regarding related and unrelated varieties, attention has been given to their effects on regional economic development and innovation but less to their environmental effects. The opinion of many scholars, that related variety is more conducive to regional development and innovation through technology spillovers, can support our findings (Boschma and Iammarino, 2010; Content and Frenken, 2016). Namely, related variety causes technology spillovers due to inter-industry linkages, and then contributes to reducing pollution emissions via improved industrial technology. While unrelated variety, due to the low degree of industrial relatedness, hinders technological spillovers and innovation improvement, which in turn aggravates pollution emissions.

Moreover, in terms of the influence mechanism, we confirmed that industrial structure and pollution control technology (technological progress) are two important channels industrial agglomeration effects SO<sub>2</sub> emissions. Correspondingly, agglomeration density and related variety may reduce SO<sub>2</sub> emissions through industrial structure optimization and technological progress, in which the role of the latter is greater. On the other hand, specialization and unrelated variety may aggravate SO<sub>2</sub> emissions by increasing the proportion of polluting industries in regional industries, but geographic proximity may reduce the emissions. While the pollution intensifying effect of diversified agglomeration and related variety is mainly via declining pollution control technology. The exploration of the influence mechanism in our study shows the role of industrial structure and technological progress in the effect of industrial agglomeration on pollution emission.

Some future research projects can be drawn from this paper. First, because of data limitations, our sample only covered the 2003 to 2013 period. The main aim of our study was to uncover the different effects of agglomeration types; as such, the validity of our conclusions is not time sensitive. However, it is necessary to use the latest available data to test the reliability of our conclusions. Second, in our current work, we only

analyze the effects of industrial agglomeration on global pollution emissions. Future work can investigate whether heterogeneity effects exist among segments of industry or regions. Third, industrial SO<sub>2</sub> emissions are chosen as a proxy for pollution emission in our study and other previous research. Further research should comprehensively consider multiple pollutants such as liquids, gases, and solids.

### 5.2. Policy implications

While industrial agglomeration benefits economic growth, it also results in environmental pollution. How to address the incompatible relationship between economic development and environmental protection and realize the transformation from “centralized emissions” to “centralized treatment” of pollution in industrial agglomeration regions is always a tricky issue in China. The following policy suggestions are proposed based on the findings of this study.

First, the Chinese government should insist on the development path of industrial agglomeration based on their positive environment and economic effects. Specifically, the government should actively guide firms to centralize layout, to plan industrial parks and the construction of development zones as well as improve the diversified agglomeration of related industries and avoid spatial concentration among single or unrelated industries. Second, more attention should be paid to the role of pollution control technology. To improve pollution control technology, it is critical to promote diversity and relatedness between industries and strengthen cooperation and exchange. Finally, the government should support financial and tax incentives and motivate firms to voluntarily improve pollution control technology.

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### CRediT authorship contribution statement

**Yuanyuan Cai:** Software, Visualization, Validation, Writing - Original draft preparation, Review, Rewriting & Editing. **Zhiqiang Hu:** Conceptualization, Methodology, Software, Data curation, Visualization, Investigation, Writing - Original draft preparation.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendices.

**Table A.1**

Correlation between variables.

	So <sub>2</sub>	den	pro	rzi	rdi	rv	uv	lnpop	open	tec	str	er
So <sub>2</sub>	1											
den	−0.379	1										
pro	−0.159	0.238	1									
rzi	0.234	−0.170	−0.0526	1								
rdi	−0.418	0.238	0.0780	−0.491	1							
rv	−0.390	0.163	0.0412	−0.414	0.766	1						
uv	−0.0288	−0.102	−0.0597	−0.272	0.473	0.444	1					
lnpop	−0.400	0.397	0.440	−0.306	0.446	0.417	0.162	1				
open	−0.320	0.362	0.204	−0.197	0.399	0.320	0.0295	0.300	1			
tec	−0.489	0.403	0.0597	−0.194	0.322	0.230	0.0270	0.286	0.229	1		
str	0.392	−0.222	−0.0524	0.115	−0.262	−0.406	0.0574	−0.265	−0.188	−0.178	1	
er	−0.0961	0.044	0.0353	−0.0165	0.0773	0.0512	0.0521	0.149	0.0229	0.118	0.00880	1

**Table A.2**

Robustness check for the effects of agglomeration types on pollution emission based on industrial dusty.

	M1r	M2r	M3r	M4r	M5r	M6r
den	−0.0847*** (0.0155)				−0.0568*** (0.0150)	−0.0761*** (0.0152)
pro		0.0530*** (0.0175)			0.0514*** (0.0167)	0.0478*** (0.0171)
rzi			0.0210*** (0.00331)		0.0204*** (0.00330)	0.0258*** (0.00333)
rdi			−1.658*** (0.136)		−1.602*** (0.137)	
rv				−0.994*** (0.134)		−0.795*** (0.133)
uv				−0.179 (0.188)		−0.0610 (0.186)
pop	−6.229*** (0.338)	−6.204*** (0.339)	−5.601*** (0.328)	−5.985*** (0.337)	−5.565*** (0.327)	−5.736*** (0.333)
open	−5.464*** (1.179)	−5.732*** (1.183)	−4.296*** (1.137)	−5.270*** (1.172)	−4.251*** (1.133)	−4.685*** (1.153)
tec	−42.53*** (1.944)	−39.25*** (1.917)	−36.91*** (1.830)	−39.31*** (1.882)	−37.89*** (1.897)	−39.98*** (1.922)
str	1.808*** (0.209)	1.860*** (0.210)	1.387*** (0.205)	1.396*** (0.218)	1.389*** (0.204)	1.474*** (0.215)
er	−0.108*** (0.0219)	−0.105*** (0.0220)	−0.104*** (0.0211)	−0.106*** (0.0217)	−0.1000*** (0.0210)	−0.103*** (0.0214)
Constant	39.07*** (1.952)	38.12*** (1.979)	36.92*** (1.890)	39.12*** (1.946)	36.25*** (1.901)	36.65*** (1.945)
N	2923	2923	2923	2923	2923	2923
R-squared	0.340	0.335	0.389	0.349	0.395	0.373

Notes: \*\*\* stands for  $p < 0.01$ , \*\* stands for  $p < 0.05$ , and \* stands for  $p < 0.1$ . Robust standard errors are reported in parentheses.

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