Impact of Air Pollution and Environmental Regulations on E-commerce Trends: Evidence from the County-Level Daily Data of a Leading E-commerce Platform

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Abstract: This study investigates the impacts of air pollution on online consumption behavior, using a comprehensive dataset that includes daily e-commerce transaction and daily air quality records across 2,380 counties in China from 2016 to 2019. Employing a fixed-effects panel regression model and an instrumental variable panel regression model, the paper demonstrates that increased air pollution levels are associated with a decrease in online transaction amounts, the number of online consumers, and the number of online orders. Furthermore, the study finds that air pollution has a heterogeneous impact on the purchase of different product categories. These findings account for the influence of environmental factors on consumer behavior and have potential implications for policy-making aimed at addressing air pollution and its socio-economic consequences.

Key words: Air Pollution, Online Consumption, Demonstration Effect, Substitution Effect, Thermal Inversion

1. Introduction

Over the past four decades since its reform and opening up, China has witnessed remarkable economic and social development, while encountering significant pressure on resources and the environment. Since 2012, China has been committed to promoting the transformation of its economic development, focusing on "accelerating ecological civilization system reform and building a beautiful China." China pledges to reach a "carbon peak" by 2030 and achieve "carbon neutrality" by 2060. Leading enterprises have closely aligned their development with addressing social challenges, proactively practicing social responsibility under the "Environmental, Social, and Corporate Governance" (ESG) framework. In the meantime, consumption, known as one of the "three engines" driving economic growth, plays a foundational role in the development of the national economy. However, China is currently facing challenges of slowing domestic demand and sluggish consumption. Against this backdrop, researching the tangible effects of air pollution on consumption has both significant academic value and practical implications. In light of China's efforts in environmental protection and sustainable development, this study aims to examine the impact of air pollution on the purchasing behavior of consumers on the e-commerce platform, thereby evaluating the potential contribution of digital economy in protecting public health, which reduces the health risks associated with air pollution.

This research utilizes transaction data from the Alibaba e-commerce platform to study the effects of air pollution on online consumption. By leveraging the exogenous shocks to air pollution from temperature inversions as an instrument variable, a causal relationship between the two can be established using two-stage least square. The research aims to explore following three aspects: (1) Does air pollution encourage consumers to engage in more online consumption rather than physical one? (2) What are the heterogenous effects of air pollution on the consumption behavior for different types of consumers? (3) What is the long-term impact of air pollution on e-commerce development and the social welfare? This research can be among the first to examine the tradeoff of externalities of air pollution—air pollution may decrease (Sentiment Effect) or increase (Substitution Effect) online consumption. It expects to broaden the understanding of how air pollution affects economic growth channels and further offer policy implications for refining air pollution control policies and market expansion of e-commerce business.

This study mainly correlates with the literature from two fields. Firstly, it is concerned with the research related to the impact of air pollution. Air pollution, being the "byproduct" of economic development, poses a significant challenge that most countries worldwide face during their development process. Due to its extensive reach, difficulty in protection, and invisibility to the naked eye, air pollution often poses more severe threats to human health compared to other types of pollution (Brunekreef and Holgate, 2002). For these reasons, air pollution frequently becomes a focal point of societal concern, prompting numerous scholars to investigate its impact from different angles. Currently, literature concerning the consequences of air pollution can be categorized into three levels: individual, enterprise, and societal. This study will review existing literature following this order.

At the individual level, existing studies primarily focus on the health hazards posed by air pollution. Research has found that air pollution significantly increases the risk and mortality rates of

respiratory diseases, cardiovascular diseases, and excessive obesity (Kenneth and Chay, 2003; Schlenker and Walker, 2011; Deschenes et al., 2020), which in turn lead to rising mortality rates and declining life expectancy across all age groups (Chay and Greenstone, 2003; Chen et al., 2013; Cesur et al., 2018), posing substantial threats to human life and health. Furthermore, air pollution also adversely affects people's mental health, including negative emotions, depression risk, and suicide rate increases due to reduced outdoor activities and social interactions (Arvin and Lew, 2012; Pun et al., 2017). Moreover, air pollution may broadly affect behavioral decisions at the individual level in various ways. For instance, air pollution can lead to a decrease in labor supply and productivity (Lichter et al., 2017), an increase in migration willingness (Qin and Zhu, 2018), deteriorated financial investment performance (Huang et al., 2020; Li et al., 2021), and an overall decline in cognitive ability (Chew et al., 2021; Dong et al., 2021). Overall, air pollution has certain negative impacts on individuals' life health, cognitive ability, and behavioral decisions.

At the enterprise level, existing literature mainly focuses on three aspects of air pollution-related impacts: increased operational costs, interference with company decisions, and decreased operational efficiency. With the rise of environmental awareness, more and more company employees consider air quality as an important basis for choosing their workplace. However, this also means that enterprises in high air pollution areas need to offer better benefits to retain employees (Wang et al., 2021; Yang et al., 2022). This not only increases the human resource costs for enterprises but might also cause a crowding-out effect on their R&D investments, leading to misallocation of corporate funds (Xue et al., 2021). During the specific operational processes, enterprises may respond to the negative impact of air pollution in terms of advertising placements (Shi and Zhang, 2022), ESG performance, and financial robustness (Tan et al., 2021), which overall increases the operational costs for enterprises in high pollution areas. Conversely, the impact of air pollution on enterprise productivity is debatable. On one hand, traditionally, most scholars believe that pollution control would also result in increased costs for enterprises, leading to a decline in productivity (Gollop and Roberts, 1983; Greenstone, 2001). But on the other hand, recent studies found that air pollution not only causes misallocation of human capital in enterprises but also lowers transportation efficiency, leading to increased inventory and efficiency loss, hence improving air quality might also benefit the operational efficiency of enterprises.

At the societal level, existing literature mainly assesses the various societal costs brought about by air pollution. Firstly, given the severe threats air pollution poses to life and health, a large number of studies have evaluated its resulting public health costs (Xia et al., 2022; Barwick et al., 2022). Among them, Barwick et al. (2022), through analyzing the consumption data from China UnionPay between 2013 and 2015, found that a reduction of 10 $\mu g/m^3$ in PM2.5 concentration could decrease medical expenses by about 1.5%, amounting to approximately 60 billion RMB. Secondly, existing literature also studied the impact of air pollution on crime rates, finding that improving air quality helps reduce crime rates, thus lowering social management costs (Bondy et al., 2020). Additionally, air pollution can also affect housing prices in different areas, leading to an increase in socio-economic inequality.

Besides focusing on the literature related to the impact of air pollution, this study is also directly related to the literature in the field of economics of digitalization. With the rapid development of e-

commerce worldwide, more and more scholars have begun to explore the influencing factors on the development of online consumption. Existing studies show that people's online consumption behavior is influenced by multiple factors, including brand value (Lowry et al., 2008), user reviews (Standifird, 2001; Zhong, 2022), marketing methods (Lu and Chen, 2021; Yang et al., 2023), weather conditions (Steinker et al., 2017), etc., but systemic research on the impact of air pollution on online consumption is still relatively scarce. Two studies are primarily related to this aspect of the research. Zhang and Mu (2018) found that the rise in air pollution levels significantly increases online consumers' demand for protective goods such as masks, while Wang et al. (2023) found that air pollution significantly reduces people's reading time and expenditure on e-books. Notably, these studies only considered specific types of goods, hence may not fully reflect the impact of air pollution on online consumption.

The innovations of this study are mainly manifested in three aspects. Firstly, existing literature on the negative externalities of air pollution has not delved deeply into the potential impact of air pollution on consumption, and this study can fill this gap to a certain extent. Secondly, by analyzing comprehensive and detailed transaction data from the Alibaba e-commerce platform, this study unveils a new channel impacting online consumer behavior—air pollution, thus expanding the relevant literature in the field of online consumption. Thirdly, the online consumption data used in this study comes from the Taobao e-commerce platform, which has good representativeness, and the data on e-commerce transactions at the product category level allows this study to further explore the impact of air pollution on the online demand for different types of goods. This not only helps in clarifying the dominant factors through which air pollution affects online consumption, but also enhances the effectiveness and practicality of policy suggestions.

The remaining parts of this paper are organized as follows. The second section proposes two hypotheses. Data are described in the third section. The fourth section outlines the identification strategy. The fifth section presents the empirical results. Robustness checks are performed in the sixth section. The seventh section displays the results of heterogeneous analysis. The eighth section analyzes the benefits of environmental regulations and discusses policy implications. The final section draws concluding remarks.

2. Hypotheses

In this study, two competing hypotheses are proposed to elucidate how air pollution may impact consumption on the e-commerce platform:

Hypothesis 1: Air pollution may decrease online consumption (Sentiment Effect).

The demonstration effect hypothesis suggests that air pollution could adversely impact consumers' well-being, subsequently reducing their motivation to engage in online consumption. Elevated levels of air pollution may cause individuals to experience physical discomfort, anxiety, and stress, potentially resulting in a decline in their sentiment. Consequently, consumers may become less inclined to participate in online shopping activities, leading to a reduction in online consumption. As articulated in the *Psychological Observer* of American Psychological Association, the haze pervading the sky may not only mar visual field but also leave an indelible mark on psyche. Li et al. (2021) examine the disposition effect among investors in financial markets, employing a difference-in-differences and spatial regression discontinuity model, and using speed of strong wind (above 5m/s) as an instrumental variable. They find that exposure to air pollution might lead individual investors to either consciously engage in mood regulation or unconsciously impair their cognitive abilities, ultimately resulting in irrational "sell-winners and hold-losers" behavior. Lohmann et al. (2023) also find that people more intensely exposed to a public health crisis become more anti-social than those with lower exposure.

Hypothesis 2: Air pollution may increase online consumption (Substitution Effect).

The substitution effect hypothesis posits that air pollution could boost online consumption, as people may be more reluctant to go outdoors and engage in traditional brick-and-mortar shopping when pollution levels are high. In this situation, the overall demand for goods and services remains relatively stable, but the distribution of consumption transitions from offline to online channels. This effect may arise from individuals attempting to minimize their exposure to polluted air in order to safeguard their health. As a result, e-commerce becomes a more appealing option, leading to increased online consumption.

To evaluate these hypotheses, the empirical relationship between air pollution levels and various indicators of online consumption, such as total spending, order volume, and the number of users placing orders, will be examined. By analyzing the data and accounting for the potential influence of diverse control variables, this study will ascertain whether the demonstration effect or substitution effect hypothesis is corroborated by the evidence.

3. Data

The data utilized in this study comprises city-level and individual-level daily e-commerce transaction data, individual-level daily online and physical payment settlement data, and city-level daily air pollution measurements. The e-commerce transaction data encompasses a wide range of indicators at the city level, including Gross Merchandise Volume (GMV), GMV across various product categories, total items purchased, items purchased in different categories, number of orders placed and received, number of orders in distinct categories, and the number of active buyers and sellers. At the individual level, transaction data provides information for both sellers and buyers.

Moreover, air pollution data include environmental factors such as average temperature, precipitation, humidity, sunshine duration, and wind speed, along with city-level daily air quality measurements. Additional variables incorporated in the dataset include order quantity, order quantity for different product categories, order purchase amount, total shopping duration on the platform, return rating, and demographic variables like age and gender.

The sample used for analysis spans 2,380 counties across China, with autonomous regions such as Xinjiang, Tibet, and Ningxia being excluded. The main dependent variables analyzed include daily online purchase amount (Amount), number of consumers (Consumer), order volume (Order), average price per order (Price Per Order, PPO), average expenditure per consumer (Expenditure Per Consumer, EPC), and average order volume per consumer (Orders Per Consumer, OPC) on the Alibaba e-commerce platform for each county between 2016 and 2019. To comply with Alibaba's e-commerce data privacy requirements, the descriptive statistics have been desensitized. Specifically, the original data underwent a linear transformation, with the slope and intercept of the transformation drawn from a uniform distribution ranging between [0,1]. Under the premise of adhering to Alibaba's data privacy standards, this linear transformation still preserves the scale and order of the actual e-commerce transaction data.

Key independent variables encompass PM2.5 concentration (PM2.5), daily average temperature (Temperature), daily average precipitation (Precipitation), daily average wind speed (Wind Speed), daily average relative humidity (Relative Humidity), and daily average sunshine duration (Sunshine Duration) for each county between 2016 and 2019. Descriptive statistics for these variables are presented in Table 1.

Table 1. Summary Statistics

Variables	Observations	Mean	S.D.	Min	Max
E-commerce Variables					
Amount	2,608,480	1,798,096.32	6,293,680.68	0.04	1,905,467,270.01
Consumer	2,608,480	9,227.36	17,396.22	1.00	1,373,472.00
Order	2,608,480	20,384.36	52,737.52	1.00	12,272,560.00
Price Per Order	2,608,480	57.40	45.44	0.02	44,372.93
Expenditure Per Consumer	2,608,480	117.20	95.03	0.04	66,840.24
Orders Per Consumer	2,608,480	1.42	0.30	0.71	70.43
Pollution and weather variables					
PM2.5 ($\mu g/m^3$)	2,608,480	45.02	35.49	1.59	774.88
Temperature (℃)	2,608,480	14.38	11.07	-38.25	36.09
Precipitation (mm)	2,608,480	2.88	6.36	0.00	393.28
Wind Speed (m/s)	2,608,480	2.17	0.97	0.01	18.92
Relative Humidity (%)	2,608,480	69.06	17.15	7.08	99.00
Sunshine Duration (hours)	2,608,480	5.46	3.91	0.00	14.35

Note: This table reports the summary statistics of all variables considered in this study. The descriptive statistics for the e-commerce indicators have been desensitized accordingly. The dataset covers 2380 counties from Jan 1, 2016 to December 31, 2019, and the unit of observation is county-day.

4. Identification Strategy

4.1 Baseline Model

Initially, the following fixed-effects panel regression is estimated as a baseline model:

$$Outcome\ Variable_{c,t} = \alpha + \beta \cdot \text{PM2.5}_{c,t} + W'_{c,t}\gamma + \delta_t + \theta_{c,y} + \varepsilon_{c,t}, \quad (1)$$

where $\text{PM2.5}_{c,t}$ denotes the average PM2.5 concentration in county c on date t; $W_{c,t}$ represents a set of control variables for county c on date t, including daily average temperature, precipitation, wind speed, relative humidity, and sunshine duration; δ_t signifies date fixed effects; $\theta_{c,y}$ indicates county-year fixed effects; and $\varepsilon_{c,t}$ is the error term in the regression model. Notably, the date fixed effects δ_t account for nationwide common shocks across all counties, such as macroeconomic conditions and holidays, while the county-year fixed effects $\theta_{c,y}$ control for potential interference from annually varying county-level variables, including local population, GDP, education level per capita, and inherent consumption habits. The estimation results are reported in Table 2.

Model (1) assumes that the PM2.5 concentration is exogenous to the daily online consumption variables at the county level. However, this assumption might be overly restrictive, as omitted county-level variables could affect both online consumption and air pollution levels simultaneously, thereby leading to omitted variable bias and potentially underestimating the impact of air pollution. For example, short-term macroeconomic factors at the county level may influence both online consumption decisions and local air pollution levels. To address these potential endogeneity concerns, the instrumental variable panel regression model is further considered. The estimation results are reported in Table 2.

4.2 Instrumental Variable Estimation

To mitigate potential endogeneity, the following first-stage regression for the endogenous variable PM2.5 concentration and instrumental variable is estimated:

$$\text{PM2.5}_{c,t} = \mu + \rho \cdot \text{Thermal Inversion}_{c,t} + W'_{c,t}\vartheta + \sigma_t + \tau_{c,y} + e_{c,t} \quad (2)$$

where $W'_{c,t}$ denotes a set of control variables for county c on date t, including daily average temperature, precipitation, wind speed, relative humidity, and sunshine duration; σ_t represents date fixed effects; $\tau_{c,y}$ represents county-year fixed effects; and $e_{c,t}$ is the error term.

This paper adopts thermal inversion as an instrumental variable for PM2.5 concentration, which is commonly used in existing economic literature (Chen et al., 2022). The data are sourced from the Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2) dataset. This dataset divides the whole world into regions of 0.5° × 0.625° grids and records air temperatures every 6 hours for 42 atmospheric layers, ranging from 110 m to 36,000 m. This data is aggregated at the county level and matched with the online transaction data. A thermal inversion phenomenon occurs when the temperature of the second atmospheric layer (320 m) is higher than that of the first atmospheric layer (110 m) simultaneously. Consequently, this paper calculates the temperature difference between the second and first atmospheric layers, retain the original value if the difference is positive and assigning it to zero if the difference is negative, and take the average of this difference

value within 24 hours (the original data has a 6-hour frequency) to obtain the daily thermal inversion variable (Thermal Inversion$_{c,t}$) for each county-level region. The two-stage least square estimation results are reported in Table 3 and Table 4.

5. Empirical Results

5.1 Baseline: Fixed-effects Panel Estimation

The primary findings of the fixed-effects panel regression model are detailed in Table 2. Upon controlling for weather variables, date fixed effects, and county-year fixed effects, a 10 $\mu g/m^3$ increase in PM2.5 concentration within a county-level region results in a 0.07% decrease in online transaction amount, a 0.07% decrease in the number of online consumers, and a 0.12% decrease in the number of online orders. If converted to the standard deviation of PM2.5, this effect implies that a single standard deviation increases in PM2.5 concentration (35.49 $\mu g/m^3$) in county-level regions corresponds to reductions of 0.25%, 0.25%, and 0.43% in online transaction amount, the number of online consumers, and the number of online orders, respectively, which is economically significant.

Table 2. The Effect of PM2.5 on Online Consumption

	log(Amount)		log(Consumer)		log(Order)	
	(1)	(2)	(3)	(4)	(5)	(6)
PM2.5	-0.0007***	-0.0007***	-0.0009***	-0.0007***	-0.0017***	-0.0012***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Weather controls	No	Yes	No	Yes	No	Yes
County-year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Date FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.986	0.987	0.991	0.992	0.993	0.994
Observations	2,608,480	2,608,480	2,608,480	2,608,480	2,608,480	2,608,480

Note: This table reports the estimation results of the effect of PM2.5 on online consumption based on fixed-effect panel regressions. The dependent variables are the logarithm of county-level transaction amount, the logarithm of county-level unique consumer volume, and the logarithm of county-level order amount. Weather controls include temperature bins within 5℃, second-order polynomial in precipitation, humidity, wind speed, and sunshine durations. All regressions include county-year fixed effects and date fixed effects. Standard errors are reported in the parentheses and are two-way clustered by county and date. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

5.2 Instrumental Variable Estimation

Due to potential issues such as omitted variables and measurement errors, a simple linear panel regression model faces potential endogeneity problems. In light of this, the paper utilizes temperature inversion as an instrumental variable for the daily average PM2.5 concentration to perform a two-stage least squares estimation (2SLS). The first-stage regression primarily investigates the impact of temperature inversion on the daily average PM2.5 concentration (Equation 2), with the relevant estimation results detailed in Table 3.

As shown in Table 3, the estimated coefficient for the temperature inversion variable is positively significant at the 1% statistical level, indicating a high positive correlation between temperature inversion and daily average PM2.5 concentration.

Table 3. First-Stage Regression Results of the Two-Stage Least Squares (2SLS) Method

	PM2.5	
	(1)	(2)
Thermal Inversion	3.5931***	4.6563***
	(0.4250)	(0.4090)
Weather Controls	No	Yes
County-year FEs	Yes	Yes
Date FEs	Yes	Yes
Observations	2,608,480	2,608,480
R^2	0.517	0.558

Note: The table reports the first-stage regression results of the 2SLS method. The dependent variable is the daily average PM2.5 concentration. The key independent variable is temperature inversion. Both models control for weather conditions and fixed effects for county-year and date. Standard errors are reported in parentheses and are two-way clustered by county and date. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Based on the first-stage regression, the paper further conducts a second-stage regression, with the relevant estimation results reported in Table 4. This table displays the results of instrumental variable regression. After controlling for weather conditions, county-year fixed effects, and date fixed effects, the Kleibergen-Paap Wald F-statistic for the first-stage regression is 24,315.4, which far exceeds the 10% critical value of 16.38 for the Stock-Yogo weak identification test, indicating that there is no issue of weak instrumental variables. It is observed that a 10 $\mu g/m^3$ augmentation in PM2.5 concentration within a county-level region causes a 0.24% decrease in online transaction amounts, a 0.20% decrease in the number of online consumers, and a 0.60% decrease in the number of online orders. When this effect is converted to the standard deviation of PM2.5, it indicates that a single standard deviation increase (35.49 $\mu g/m^3$) in PM2.5 concentration in a county-level region corresponds to decreases of 0.85%, 0.71%, and 2.13% in online transaction amounts, the number of online consumers, and the number of online orders, respectively. Compared to the outcomes of the baseline fixed-effects panel regression in Table 2, the effects derived from the instrumental variable

regression are approximately 3-5 times larger. It is worth noting that this is a common phenomenon in instrumental variable regression, as endogeneity can lead to downward omitted variable bias, causing the underestimation of results, while the instrumental variable amends the endogeneity issue to obtain a more accurate estimation of the effect. Another crucial point is that the direction of the coefficients obtained from the instrumental variable regression remains consistent with the direction of the coefficients derived from the fixed-effects panel regression, which further validates the robustness of the findings above.

Table 4. The Effect of PM2.5 on Online Consumption with the 2SLS Method

	log(Amount)		log(Consumer)		log(Order)	
	(1)	(2)	(3)	(4)	(5)	(6)
PM2.5	-0.0114***	-0.0024***	-0.0100***	-0.0020***	-0.0171***	-0.0060***
	(0.0015)	(0.0009)	(0.0011)	(0.0007)	(0.0013)	(0.0008)
Weather controls	No	Yes	No	Yes	No	Yes
County-year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Date FEs	Yes	Yes	Yes	Yes	Yes	Yes
KP *F*-statistics	10,545.1	24,315.4	10,545.1	24,315.4	10,545.1	24,315.4
Observations	2,608,480	2,608,480	2,608,480	2,608,480	2,608,480	2,608,480
R^2	0.986	0.987	0.991	0.992	0.993	0.994

Note: This table reports the estimation results of the effect of PM2.5 on online consumption based on fixed-effect panel IV regressions. The dependent variables are the logarithm of county-level transaction amount, the logarithm of county-level unique consumer volume, and the logarithm of county-level order amount. Weather controls include temperature bins within 5℃, second-order polynomial in precipitation, humidity, wind speed, and sunshine durations. All regressions include county-year fixed effects and date fixed effects. Standard errors are reported in the parentheses and are two-way clustered by county and date. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

To deepen our understanding of how air pollution affects individual consumers' online consumption behavior at the individual level, this paper substitutes the dependent variable in the regression with daily county-level average price per order (PPO), average expenditure per consumer (EPC), and average number of orders per consumer (OPC) respectively. Utilizing a similar identification strategy (fixed effects panel regression model and fixed effects instrumental variable panel regression model), this paper explores the economic relationship between PM2.5 concentration and these three dependent variables. The estimation results are presented in Table 5.

Table 5. The Effect of PM2.5 on Online Consumption: Alternative Dependent Variables

	log(1+PPO)		log(1+EPC)		log(1+OPC)	
	OLS	IV	OLS	IV	OLS	IV
PM2.5	0.0005***	0.0033***	-4.37×10^{-5}	-0.0007	-0.0003***	-0.0028***
	(0.0001)	(0.0010)	(0.0002)	(0.0010)	(0.0001)	(0.0005)
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
County-year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Date FEs	Yes	Yes	Yes	Yes	Yes	Yes
KP *F*-statistics	-	24,315.4	-	24,315.4	-	24,315.4
Observations	2,608,480	2,608,480	2,608,480	2,608,480	2,608,480	2,608,480
R^2	0.570	0.568	0.718	0.717	0. 772	0.767

Note: This table reports the estimation results of the effect of PM2.5 on individual-level and order-level dependent variables. The dependent variables are the logarithm of county-level price per order, the logarithm of county-level expenditure per consumer, and the logarithm of county-level order per consumer. Weather controls include temperature bins within 5℃, second-order polynomial in precipitation, humidity, wind speed, and sunshine durations. All regressions include county-year fixed effects and date fixed effects. Standard errors are reported in the parentheses and are two-way clustered by county and date. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 5 shows the results of instrumental variable regression. Controlling for weather variables, date fixed effects, and county-year fixed effects, a 10 $\mu g/m^3$ increase in PM2.5 concentration at the county level results in a significant 0.33% increase in the average price per order and a substantial 0.28% decrease in the average number of orders per consumer. Conversely, air pollution does not affect the average expenditure per consumer. When converted to the standard deviation of PM2.5, this effect indicates that a single standard deviation increase (35.49 $\mu g/m^3$) in PM2.5 concentration at the county level precipitates a 1.17% increase in the average price per order and a 0.99% decrease in the average number of orders per consumer. In the meantime, the estimates obtained from the instrumental variable regression are larger than those obtained from the fixed effects panel regression model, but the directions of both are consistent, which attests to the robustness of the findings.

6. Robustness Check

To further examine the reliability of the above findings, this paper conducts a series of robustness checks, including: (1) removing the observations corresponding to the top and bottom 0.1% of transaction amounts to eliminate the interference of potential extreme value; (2) defining thermal inversion using the temperature difference between the third layer (540 m) and the first layer (110

m); (3) controlling two-way fixed effects for both date and counties; (4) clustering standard errors at the county level; (5) substituting the air pollution with the AQI index as key independent variable, because the AQI index is highly correlated with PM2.5 levels, with a Pearson correlation coefficient of 0.953. These results are reported in Table 6.

Table 6. Robustness Checks for IV Regressions

	log(Amount)	log(Consumer)	log(Order)	log(1+PPO)	log(1+EPC)	log(1+OPC)
Panel A: excluding observations of top 0.1% and bottom 0.1% online transaction values						
PM2.5	-0.0041***	-0.0030***	-0.0069***	0.0028***	-0.0012	-0.0027***
	(0.0008)	(0.0007)	(0.0008)	(0.0010)	(0.0011)	(0.0005)
Panel B: alternative layers for IV						
PM2.5	-0.0067***	-0.0031***	-0.0060***	0.0022**	-0.0015	-0.0019***
	(0.0016)	(0.0012)	(0.0013)	(0.0011)	(0.0011)	(0.0006)
Panel C: alternative specification of fixed effects						
PM2.5	-0.0015***	-0.0014***	-0.0052***	0.0035***	-0.0003	-0.0026***
	(0.0005)	(0.0004)	(0.0016)	(0.0011)	(0.0010)	(0.0005)
Panel D: alternative clustering of standard errors						
PM2.5	-0.0024***	-0.0020***	-0.0060***	0.0033***	-0.0007*	-0.0028***
	(0.0004)	(0.0003)	(0.0004)	(0.0006)	(0.0004)	(0.0003)
Panel E: AQI as the key independent variable						
AQI	-0.0025***	-0.0039***	-0.0013*	0.0022***	-0.0013**	-0.0018***
	(0.0009)	(0.0008)	(0.0007)	(0.0006)	(0.0006)	(0.0003)
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
County-year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Date FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observation	2,608,480	2,608,480	2,608,480	2,608,480	2,608,480	2,608,480

Note: This table reports the results of robustness checks. Weather controls include temperature bins within 5℃, second-order polynomial in precipitation, humidity, wind speed, and sunshine durations. All regressions control for weather, county-year fixed effects and date fixed effects. Standard errors are reported in the parentheses and are two-way clustered by county and date. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

Table 6 demonstrates that the previous findings persist across various robustness checks, and the direction and magnitude of the estimated effects align closely with the estimates in the baseline regression. Therefore, the findings based on instrumental variable regression prove to be robust.

7. Heterogeneity Analysis

To understand how air pollution affects online consumption, this paper further conducts heterogeneity analysis from three perspectives: product categories, economic development levels, and regional differences between northern and southern areas.

7.1 Product Categories Differentiation

This paper further scrutinizes the impact of air pollution on the purchase of different categories of goods. Specifically, based on the first-level categories of commodity classification of 2013 by the National Bureau of Statistics of China, this paper examines the impact of air pollution on Clothing, Transportation and Communication, Furniture, Health and Medication, Education and Entertainment, Household Items, and Others.

As depicted in Table 7, air pollution has the most significant inhibitory effect on the online purchase of Transportation and Communication, Education and Entertainment, and Clothing. However, there is no significant inhibitory effect on Health and Medication, Furniture, and Household Items; on the contrary, it promotes the purchase of these categories of commodities. These findings align intuitively with consumer behavior: when air pollution intensifies, consumers are more likely to remain indoors, which leads to a decrease in demand for Transportation and Communication, Education and Entertainment, and Clothing, while the demand for Health and Medication, Furniture, and Household Items may increase.

Table 7. Categorical Analyses for the Effect of PM2.5 on Online Consumption

	log(Amount)		log(Consumer)		log(Order)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Clothing						
PM2.5	-0.0277***	-0.0084***	-0.0105***	-0.0043***	-0.0089***	-0.0045***
	(0.0022)	(0.0011)	(0.0017)	(0.0010)	(0.0018)	(0.0010)
Panel B: Food and Beverage						
PM2.5	0.0162***	0.0075***	0.0098***	0.0062**	0.0059**	0.0034**
	(0.0052)	(0.0027)	(0.0035)	(0.0028)	(0.0023)	(0.0016)
Panel C: Transportation and Communication						
PM2.5	-0.0358***	-0.0187***	-0.0321***	-0.0116***	-0.0360***	-0.0127***
	(0.0069)	(0.0034)	(0.0059)	(0.0023)	(0.0065)	(0.0024)
Panel D: Furniture						
PM2.5	0.0112*	0.0078**	0.0019	0.0040	0.0014	0.0037
	(0.0063)	(0.0038)	(0.0044)	(0.0030)	(0.0045)	(0.0030)
Panel E: Health and Medication						
$PM_{2.5}$	0.0133**	0.0095***	0.0091	0.0078	0.0032	0.0024
	(0.0053)	(0.0031)	(0.0058)	(0.0049)	(0.0043)	(0.0022)
Panel F: Education and Entertainment						
PM2.5	-0.0206***	-0.0137***	-0.0140***	-0.0067***	-0.0284***	-0.0173***
	(0.0045)	(0.0027)	(0.0034)	(0.0019)	(0.0051)	(0.0028)
Panel G: Household Items						
PM2.5	0.0018	0.0024	-0.0020	0.0038**	-0.0042	0.0041**
	(0.0039)	(0.0026)	(0.0028)	(0.0018)	(0.0032)	(0.0019)
Panel H: Others						
PM2.5	-0.0146***	-0.0085***	-0.0106***	-0.0041**	-0.0186***	-0.0089***
	(0.0040)	(0.0025)	(0.0031)	(0.0018)	(0.0041)	(0.0023)
Weather controls	No	Yes	No	Yes	No	Yes
County-year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Date FEs	Yes	Yes	Yes	Yes	Yes	Yes
KP *F*-statistics	10,545.1	24,315.4	10,545.1	24,315.4	10,545.1	24,315.4
Observations	2,608,480	2,608,480	2,608,480	2,608,480	2,608,480	2,608,480

Note: This table reports the estimation results of categorical analyses for the effect of $PM_{2.5}$ on online consumption based on fixed-effect panel IV regressions. The dependent variables are the logarithm of county-level transaction amount, the logarithm of county-level unique consumer volume, and the logarithm of county-level order amount. Weather controls include temperature bins within 5℃, second-order polynomial in precipitation, humidity, wind speed, and sunshine durations. All regressions control for county-year fixed effects and date fixed effects. Standard errors are reported in the parentheses and are two-way clustered by county and date. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

7.2 Economic Development Discrepancy

Residents' awareness and concern about air pollution might differ significantly across regions of different economic development levels, potentially leading to heterogeneous effects of air pollution

on online consumption. To test this, the paper gathers per capita GDP data for each county from 2016 to 2019 from the *China County Statistical Yearbook* and splits the full sample into two subsets based on the median per capita GDP of each year: higher economic development level (top 50%) and lower economic development level (bottom 50%). Then, using the instrumental variable panel regression model, the paper separately estimates the impact of air pollution on online consumption for each subsample at different economic development levels, with results shown in Table 8.

Table 8 indicates that air pollution suppresses online consumption in counties at both higher and lower economic development levels, but there is a notable difference in the scale of negative impacts. Specifically, in counties with relatively developed economies, the negative impact of air pollution on online consumption is greater. For instance, after controlling for weather conditions and all fixed effects, a daily average increase of 10 $\mu g/m^3$ in PM2.5 concentration leads to a 0.36% decrease in online consumption amounts in economically developed counties, while in less developed counties, the magnitude is only 0.11%, which is two thirds lower. Moreover, the estimated coefficient of daily average PM2.5 concentration is negatively significant at the 1% statistical level in economically developed counties, whereas its significance is substantially weakened in the subset of less developed counties. These findings reflect that the overall suppressive effect of air pollution on online consumption is mainly driven by consumers from economically developed areas.

Table 8. Heterogeneity Analysis of Impact of Air Pollution on Online Consumption: Economic Development Level

	log(Amount)		log(Customer)		log(Order)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Economically Developed Counties						
PM2.5	-0.0124***	-0.0036***	-0.0105***	-0.0029***	-0.0201***	-0.0068***
	(0.0025)	(0.0013)	(0.0017)	(0.0008)	(0.0029)	(0.0013)
Panel B: Economically Underdeveloped Counties						
PM2.5	-0.0105***	-0.0011*	-0.0078*	-0.0015	-0.0132***	-0.0044***
	(0.0034)	(0.0006)	(0.0042)	(0.0011)	(0.0047)	(0.0020)
Weather controls	No	Yes	No	Yes	No	Yes
County-year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Date FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,608,480	2,608,480	2,608,480	2,608,480	2,608,480	2,608,480

Note: This table reports the estimation results of economic development discrepancy for the effect of PM2.5 on online consumption based on fixed-effect panel IV regressions. The dependent variables are the logarithm of county-level transaction amount, the logarithm of county-level unique consumer volume, and the logarithm of county-level order amount. Weather controls include temperature bins within 5℃, second-order polynomial in precipitation, humidity, wind speed, and sunshine durations. All regressions control for county-year fixed effects and date fixed effects. Standard errors are reported in the parentheses and are two-way clustered by county and date. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

7.3 Differences between North and South

The household heating system is exclusively operated by the government in North China during the cold winter, while the large consumption of coal has led to more severe air pollution compared to the southern regions. This systematic difference in air pollution levels may cause heterogeneous impacts on online consumption between North and South. For example, long-term and frequent air pollution events in northern areas may stimulate residents to adopt more comprehensive preventative measures against air pollution, thus mitigating its suppressive effect on online consumption. However, it is also possible that residents in the north are more affected by extreme air pollution, leading to a more pronounced negative impact on online consumption. To reveal potential north-south heterogeneity in the impact of air pollution on online consumption, the full sample is split into two subsets according to the *Qinling-Huaihe* line that demarcates North and South. Then the impacts of air pollution are estimated using the instrumental variable panel regression model, with the regression results provided in Table 9.

Comparing the results in panels A and B of Table 9, it is evident that air pollution has a significantly negative impact on online consumption in both southern and northern regions, but the impact is relatively smaller in the north than in the south. Specifically, every 10 $\mu g/m^3$ increase in daily average PM2.5 concentration leads to a 0.32% decrease in online consumption amounts in the south and a 0.20% decrease in the north. However, the impact on the number of consumers (0.26% vs 0.18%) and the quantity of orders (0.55% vs 0.46%) is relatively close to each other, with t-tests showing that the differences are not statistically significant at the 10% level. Thus, difference in the negative impact of air pollution on online consumption between north and south exists, while its scale is not substantial.

Table 9. Heterogeneity Analysis of Impact of Air Pollution on Online Consumption: Differences between North and South

	log(Amount)		log(Customer)		log(Order)	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: North						
PM2.5	-0.0102**	-0.0020***	-0.0069**	-0.0018***	-0.0127***	-0.0046***
	(0.0044)	(0.0006)	(0.0032)	(0.0005)	(0.0039)	(0.0015)
Observations	1247248	1247248	1247248	1247248	1247248	1247248
Panel B: South						
PM2.5	-0.0143***	-0.0032***	-0.0154***	-0.0026***	-0.0177***	-0.0055***
	(0.0041)	(0.0009)	(0.0038)	(0.0005)	(0.0047)	(0.0012)
Observations	1361232	1361232	1361232	1361232	1361232	1361232
Weather controls	No	Yes	No	Yes	No	Yes
County-year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Date FEs	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the estimation results of northern and southern counties for the effect of PM2.5 on online consumption based on fixed-effect panel IV regressions. The dependent variables are the logarithm of county-level transaction amount, the logarithm of county-level unique consumer volume, and the logarithm of county-level order amount. Weather controls include temperature bins within 5℃, second-order polynomial in precipitation, humidity, wind speed, and sunshine durations. All regressions control for county-year fixed effects and date fixed effects. Standard errors are reported in the parentheses and are two-way clustered by county and date. *, **, and *** denote significance at 10%, 5%, and 1%, respectively.

8. Environmental Regulations and Economic Benefits Analysis

8.1 Institutional Background: Central Ecological and Environmental Protection Inspection

Within China's administrative framework, local governments bear the primary responsibility for environmental oversight. As mandated by the *Chinese Environmental Protection Law*, "local governments at all levels shall be accountable for the environmental well-being of their administrative jurisdictions." Nevertheless, these local authorities are often preoccupied with multifaceted objectives, such as fostering GDP growth and safeguarding fiscal revenue (Li and Zhou, 2005), which can diminish their motivation to rigorously implement environmental regulations. A notable decrease in regulatory stringency is observed when the share of secondary sector (manufacturing) in GDP is minimal, coinciding with an increase in industrial activities. This has led to instances of collusion between local governments and businesses in environmental regulation. As per capita income rises, public expectations for environmental quality are escalating. In response, centrally administered environmental protection inspections have emerged as a pivotal strategy for strengthening the nation's governance capabilities and harmonizing the objectives of environmental stewardship with those of economic progression. The establishment of a formal environmental protection inspection apparatus was affirmed by the Central Leading Group for Deepening Overall Reform at their 14th meeting in July 2015, which adopted the *Environmental Protection Inspection Plan (Trial)*. The inaugural series of such inspections spanned from December 31, 2015, to September 15, 2017, systematically executed by central teams in four successive phases across all 31 provincial administrative divisions (see Table 1). This extensive undertaking has left a discernible impact across regions, from the eastern seaboard to the western hinterlands.

The scope of environmental protection inspections in China is broad, addressing a spectrum of issues that include air and water pollution, solid waste and soil contamination, unauthorized construction within protected natural areas, and the perpetuation of obsolete industrial operations. These inspections cast a wide range of accountability, extending beyond the confines of environmental regulatory bodies to encompass grassroots community organizations and a host of sectors integral to environmental governance such as land administration, forestry, water resources, housing and urban-rural development, agriculture, urban oversight, occupational safety, industrial policy, transportation, public security, economic planning, and tourism, among others. While the scrutiny primarily targets the efficacy of local party committees and governmental bodies, the ambit of these inspections also involves local businesses, holding them to account for violations of environmental laws. The inaugural round of central environmental protection inspections culminated in punitive actions against 29,000 enterprises, levying fines that cumulatively amounted to roughly 1.43 billion RMB.

Throughout the environmental protection inspection initiative, the conduct of numerous large-scale corporations was scrutinized as a consequence of public reporting. Upon the Second Central Environmental Protection Inspection Team's deployment to the Ningxia Hui Autonomous Region, they were immediately met with allegations from residents. These concerned Company *X*'s operational practices, specifically, ceasing production by day but resuming nocturnally without activating necessary environmental safeguards, resulting in the direct emission of pollutants into the atmosphere. Similarly, in Yunnan Province, Enterprise *Y* found itself repeatedly accused of releasing noxious gases, the byproduct of yellow phosphorus production, untreated and continuous, both day and night. These accusations, documented and lodged with the Seventh Central Environmental Protection Inspection Team on July 22, 2016, prompted a directed inquiry by the environmental agency of Xuanwei municipality. It has been observed that the involvement of the central inspection teams correlates with a marked enhancement in the ambient air quality of the provinces inspected, suggesting that the central oversight has effectively incentivized industrial entities to curtail their pollutant discharge.

Table 10. First Round of Central Environmental Protection Inspection Schedule

Batch	Duration	Inspected Areas
First	2015.12.31 - 2016.2.4	Hebei
Second	2016.7.12 - 2016.8.19	Inner Mongolia, Jiangsu, Jiangxi, Henan, Guangdong, Guangxi, Yunnan
Third	2016.11.24 - 2016.12.30	Beijing, Shanghai, Hubei, Chongqing, Gansu, Qinghai
Fourth	2017.4.24 - 2017.5.28	Liaoning, Anhui, Fujian, Hunan, Guizhou, Shaanxi
Follow-up	2017.8.7 - 2017.9.15	Hebei, Inner Mongolia, Jiangsu, Jiangxi, Guangdong, Yunnan

Note: For more details on the timetable of the "Environmental Protection Inspection Plan", please visit the website of the Ministry of Ecology and Environment.

8.2 Model Specification

Using the Central Ecological and Environmental Protection Inspection as an exogenous policy shock, this paper utilizes a staggered difference-in-indifferences (DiD) approach to evaluate the effect of improvement of air quality on online consumption.

$$Outcome\ Variable_{c,t} = \alpha + \beta \cdot \text{Inspection}_{c,t} + W'_{c,t}\gamma + \delta_t + \theta_{c,y} + \varepsilon_{c,t}, \quad (3)$$

where $\text{Inspection}_{c,t}$ equals to 1 if the central inspection team came to county c on date t; $W_{c,t}$ represents a set of control variables for county c on date t, including daily average temperature, precipitation, wind speed, relative humidity, and sunshine duration; δ_t signifies date fixed effects; $\theta_{c,y}$ indicates county-year fixed effects; and $\varepsilon_{c,t}$ is the error term in the regression model. Notably, the date fixed effects δ_t account for nationwide common shocks across all counties, such as macroeconomic conditions and holidays, while the county-year fixed effects $\theta_{c,y}$ control for potential interference from annually varying county-level variables, including local population, GDP, education level per capita, and inherent consumption habits. $\text{Inspection}_{c,t}$ is the variable of primary interest. Based on the analysis above, air quality is expected to improve during periods of environmental inspections, thereby increasing local residents' consumption on e-commerce

platforms. Hence, this paper anticipates the coefficient sign to be positive.

The necessary condition for identification in a DiD analysis is that in the absence of the intervention, the difference in the explained variable between the treatment and control groups should not vary over time. In the context of this paper, this means that, under the counterfactual condition of no environmental protection inspection, there should be no difference in online consumption patterns between counties that experienced environmental inspections and those that did not. In empirical studies, this is often substantiated through event study methodology. Specifically, this paper adopts the following regression equation setup:

$$Outcome\ Variable_{c,t} = \alpha + \beta_1 \cdot \text{Inspection}_{c,t}^{-6} + \beta_2 \cdot \text{Inspection}_{c,t}^{-5} + \cdots + \beta_{12} \cdot \text{Inspection}_{c,t}^{6} + W_{c,t}'\gamma + \delta_t + \theta_{c,y} + \varepsilon_{c,t}, \quad (4)$$

where $\text{Inspection}_{c,t}^{-k}$ equals to 1 if the date is k days before central inspection team come to county c on date t; $\text{Inspection}_{c,t}^{k}$ equals to 1 if the date is k days after central inspection team come to county c on date t. This regression does not include $\text{Inspection}_{c,t}^{-1}$, which serves as the benchmark, so it estimates the difference in the impact of inspection day and that 1 day before. The rest of setting remain the same.

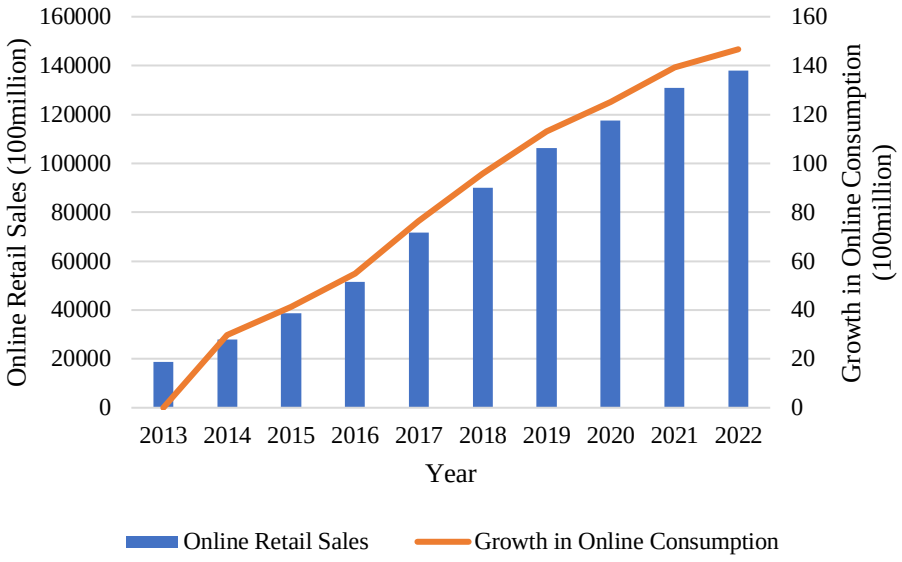
8.3 Policy Implication

Data from the Ministry of Ecology and Environment of China shows that between 2013 and 2022, the average daily concentration of PM2.5 in China decreased from $70.1\mu g/m^3$ to $30.2\ \mu g/m^3$, a reduction of 57%. During the same period, China's online consumption grew rapidly, with e-commerce sales rising from 1.89 trillion yuan in 2013 to 13.79 trillion yuan in 2022. Using these two data points, this paper can roughly estimate the increase in online consumption due to improved air quality. For simplicity, let's assume a linear decline in China's daily average PM2.5 concentration between 2013 and 2022, with an average decrease of about $4.4\ \mu g/m^3$per year. According to the results of the instrumental variable regression, this is equivalent to a 0.11% increase in online consumption. By combining the e-commerce sales of each year, one can estimate the growth in online consumption due to air quality improvement. Figure 1 shows the estimated results of online consumption growth due to improved air quality from 2013 to 2022. Overall, the incremental part of online consumption is still relatively small compared to the total e-commerce sales, but it is still considerable in absolute terms. Estimates show that from 2013 to 2022, the cumulative scale of increased online consumption due to air pollution improvement in China is about 82.2 billion yuan.

Furthermore, this paper has made a preliminary estimate of the increase in online consumption that could result from further improvements in air quality in China's future. Although China's air quality has improved greatly in the past decade, there is still room for further improvement compared to developed countries. For example, the World Health Organization (WHO) recommends a safe standard of $10\ \mu g/m^3$ for PM2.5 in its *Air Quality Guidelines*, while China's average daily PM2.5 concentration in 2022 was still three times this standard. If China's future PM2.5 levels further decrease to $10\ \mu g/m^3$, meeting the WHO recommended standard, then according to the instrumental variable estimation results, the scale of online consumption is expected to increase by

0.485%. Assuming the current proportion of e-commerce sales to total GDP (11.4%), this could contribute approximately 0.06% to GDP growth. Additionally, as the proportion of e-commerce sales increases, the consumption growth from improved air quality will also correspondingly contribute more to China's economic growth. It is worth mentioning that although the proportion of consumption increase due to improved air quality may not be prominent, it is still significant in absolute terms and has durability over time. Therefore, the conclusions of this paper also indirectly confirm the positive effect that China's vigorous air pollution control efforts over the past decade have had on promoting long-term economic growth.

Figure 1. Estimated Growth in Online Consumption Attributable to Improvement of Air Quality



9. Concluding Remarks

This study investigates the impact of air pollution on online consumption in China, utilizing daily city-level and individual-level e-commerce transaction data, coupled with air pollution data from 2,380 counties between 2016 and 2019. By employing fixed effects panel regression models and instrumental variable panel regression models, this paper estimates the causal relationship between PM2.5 concentration and various measures of online consumption, including transaction amounts, the number of consumers, and the number of orders.

The empirical results indicate that an increase in air pollution significantly reduces online consumption in terms of transaction amounts, the number of consumers, and the number of orders. These results suggest that the "sentiment effect" of air pollution predominates over the "substitution effect" in the context of online consumption. Furthermore, the analysis of different product categories reveals that air pollution significantly depresses online purchases of Transportation and Communication, Education and Entertainment, and Clothing, while it stimulates purchases of Health and Medication, Furniture, and Household Items. In addition, the negative impact of air pollution on online consumption is more pronounced in the southern regions and economically developed areas. Lastly, based on the empirical analysis results, this paper makes a preliminary

estimation of the increase in online consumption attributable to the improvement in air quality. The findings confirm that air pollution control not only benefits the health level of residents in China but also has a direct and positive effect on growth.

The findings of this study hold substantial implications for policymakers, e-commerce platforms, and sellers. Policymakers should recognize the detrimental consequences of air pollution on online consumption and prioritize policies that aim to reduce air pollution. E-commerce platforms and sellers on the platforms should be aware of the heterogeneous effects of air pollution on different categories of products and adjust their marketing strategies accordingly. For instance, they could focus on promoting products related to indoor activities and health during periods of severe air pollution. Moreover, from the perspective of online consumption, this paper estimates the economic benefits of further improving China's air quality to the levels recommended by the WHO, thereby providing a reference for policy formulation.。

In conclusion, this study sheds light on the previously unexplored causal relationship between air pollution and online consumption, underlining the importance of reducing air pollution not only for environmental and public health purposes but also for the prosperity of the e-commerce sector. Future research could delve deeper into the underlying mechanisms of the observed effects, evaluate the welfare implications for consumers, businesses, and society, and explore the impact of air pollution on online consumption in other countries or regions, utilizing consumer behavior around air quality index thresholds for regression discontinuity designs, employing the Qinling Mountains and Huai River heating demarcation line for regression discontinuity designs, or analyzing the impact of major air pollution events.

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