Journal of Population Economics (2025) 38:63
https://doi.org/10.1007/s00148-025-01117-z

ORIGINAL PAPER

Air pollution, labor productivity, and individual consumption

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Received: 15 January 2024 / Accepted: 3 July 2025 / Published online: 28 July 2025

Abstract
This paper examines how air pollution affects consumption decisions through income and substitution channels by linking daily air pollution data with monthly records of individual consumption and labor productivity. Exploiting a quasi-experimental setting in a prison in Shenzhen City, China, we find that a 10-unit increase in the daily air pollution index reduces monthly consumption by 3.6%, with 78% of the effect explained by the income channel. The impact is heterogeneous across demographic groups and pollution levels. By jointly analyzing productivity and consumption responses, the paper contributes to a growing literature on the behavioral and economic consequences of environmental exposure.

Keywords Air pollution · Labor productivity · Consumption

JEL Classification Q51 · Q53 · I15 · O15

Responsible editor: Xi Chen

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1 Introduction

A rich literature has documented that air pollution adversely affects individual production, both by reducing labor supply at the extensive margin and by lowering productivity at the intensive margin, and induces more defensive expenditures, i.e., compensatory investments in health.[1] However, the impacts of air pollution exposure on general individual consumption behavior have received comparatively limited attention. Given that consumption is the primary determinant of individual welfare and constitutes the largest component of GDP in most economies, understanding the impacts of air pollution on individuals' general consumption has important implications for welfare and macroeconomic analysis.

In this paper, we use high-frequency data containing comprehensive records of individual consumption and production to examine whether and how air pollution affects consumption behavior. Specifically, we identify two distinct channels through which pollution exposure may alter consumption decisions. First, as both air pollution and consumption goods enter the utility function, certain goods act as substitutes or complements to pollution. Conditional on income, increased pollution exposure may reduce or increase the consumption of specific goods—a mechanism we refer to as the *substitution effect*. Second, since air pollution reduces labor supply and labor productivity, it may also alter an individual's budget for consumption. We refer to this as the *income effect* of air pollution on consumption.

Two clear challenges arise in quantitatively estimating the relationship between air pollution and individual consumption. First, suitable data are difficult to obtain. Such an analysis requires high-frequency, longitudinal records of individual expenditures, ideally over an extended period. In addition, to decompose the overall effect into substitution and income effects, additional information on individual labor supply and productivity is also necessary. Second, identifying the causal effect of air pollution on consumption is challenging. Air pollution exposure can be endogenous to individuals' optimization behaviors, such as residential sorting (Chay and Greenstone 2005; Freeman et al. 2019; Chen et al. 2022; Khanna et al. 2025), avoidance behavior (Neidell 2009; Graff and Neidell 2009; Moretti and Neidell 2011), and even decision making (Chew et al. 2021). Traffic congestion can also be a potential confounder, as it generates both air pollution and emotional stress for individuals (Chang et al. 2019). Daily variation in individual location also complicates exposure assignment (Chen et al. 2020, 2021). A final concern is that the manipulation of official pollution readings can also generate measurement errors (Ghanem and Zhang 2014).

To overcome these challenges, we use a unique dataset that tracks the monthly consumption expenditure and piece-rate wage for 20,334 male inmates incarcerated

[1] See Carson et al. (2011), Hanna and Oliva (2015), and Viard and Fu (2015) for the example of labor supply effect analysis, and see Graff Zivin and Neidell (2012), Fu et al. (2021), Chang et al. (2016, 2018), Archsmith et al. (2018), and He et al. (2019) for the labor productivity effect analysis. Recent studies also have documented that air pollution increases medical (Deschênes et al. 2017; Barwick et al. 2018; Deryugina et al. 2019) and preventive expenditures, such as health insurance (Chang et al. 2018), particulate-filtering facemasks (Zhang and Mu 2018) and home-use air purifiers (Ito and Zhang 2020).

in Shenzhen, China, from July 2004 to August 2015. Within the prison system, all inmates are required to engage in daily manual work, typically assembling industrial parts under contracts with private firms.[2] Inmates receive piece-rate wages and purchase consumption goods at an internal grocery store. Since both production and consumption take place in an isolated and enclosed space, this institutional context provides a quasi-experimental environment ideally suited for our study. It eliminates common sources of endogeneity in pollution exposure, such as residential sorting, avoidance behavior, and daily location changes.

Several institutional features of the prison setting strengthen the validity of our identification strategy. First, inmates work fixed hours and receive monthly piece-rate wages, eliminating the possible impact of air pollution on labor supply choice. Under the piece-rate pay system, monthly income serves as a direct and objective measure of individual labor productivity. Second, inmates receive free meals and medical care, and their expenditures are largely limited to non-defensive goods such as snacks, personal care products, and cigarettes. This removes potential substitution between defensive and non-defensive spending, ensuring that observed changes in consumption are not confounded by endogenous health investments. Hence, the income effect of pollution on consumption operates solely through productivity. Third, inmates can only make purchases once a month on a fixed, predetermined date, which eliminates endogenous timing choices based on pollution conditions. Moreover, the internal grocery store is the sole source of goods, ruling out external choice or market selection.

While our setting rules out most endogeneity concerns raised in the literature, one endogeneity issue may remain: air pollution could be correlated with an inmate's wage income, the primary determinant of individual consumption. To address this, we instrument individual exposure to air pollution using the occurrence of thermal inversions. Thermal inversions arise when a layer of warmer air traps cooler air near the ground, preventing the dispersion of pollutants. Conditional on seasonal effects and weather conditions, including temperature, humidity, wind speed, sunshine duration, and precipitation, thermal inversions are random and independent of economic activities; it has therefore been widely used as a valid instrumental variable (IV) for air pollution (Jans et al. 2018; Hicks et al. 2016; Arceo et al. 2016; Fu et al. 2021; Chen et al. 2020, 2022).

Our IV estimates show that air pollution has a statistically and economically significant negative effect on individual consumption. Specifically, a 10-unit increase in the average daily Air Pollution Index (API) over the month preceding the grocery

[2] Many countries throughout the world have adopted a policy of putting inmates to work. In the U.S. in 2017, approximately a third of the prison population of 2.3 million worked (The Economist, 2018, see https://www.economist.com/united-states/2018/04/12/how-convict-labour-increased-inequality in details), and prisoners employed in manufacturing provided 4.2% of total U.S. manufacturing employment in 2005 (Poyker 2019). Since most prison workers are paid at rates below the federal minimum wage (or even unpaid in some states), the policy of forcing the inmates to work could generate non-negligible impacts on local labor markets. Poyker (2019: Abstract) shows that "competition from cheap prison-made goods led to higher unemployment, lower labor-force participation, and reduced wages (particularly for women) in counties that housed competing manufacturing industries.".

shopping day reduces monthly consumption expenditure by 3.6%. The results are robust across a range of model specifications. Consistent with the environmental productivity literature, we also find that, conditional on the weather variables, air pollution statistically significantly reduced inmates' productivity, measured by their earnings paid under the piece rate system. Moreover, a mediation analysis decomposes the total consumption effect into substitution and income effects. The results show that the income effect is dominant, accounting for 78% of the overall causal effect. We also show that the air pollution impacts on consumption behavior were heterogeneous across demographic groups and with the level of air pollution.

The paper makes three main contributions. First, while existing studies have examined the effects of air pollution on consumption, most estimate partial effects, i.e., the effect on specific defensive goods. By leveraging complete consumption records at the individual level, our study captures the aggregate impact of air pollution on total consumption, particularly non-defensive daily goods that have received little attention in prior research. Since consumption plays an essential role in business cycles and macroeconomic policies, our findings may shed light on the macroeconomic impacts of environmental policies. Secondly, and most importantly, the unique feature of the data set allows us to estimate both the consumption and productivity effects of air pollution and to cleanly decompose the total impact on consumption into substitution and income effects. Thirdly, compared to previous studies on the behavioral impacts of air pollution, our institutional setting offers a cleaner identification of the causal effect of pollution exposure on both consumption and production behaviors.

Despite these contributions, we acknowledge that using a prison sample from a single city limits the external validity of our findings. However, this design choice is deliberate and serves a clear empirical purpose. Our primary goal is to identify and disentangle the causal channels through which air pollution affects consumption behavior—specifically, separating the income effect (via productivity) from the substitution effect (via preferences). Achieving this decomposition requires detailed, high-frequency data on both earnings and consumption, as well as a setting where labor supply is inelastic and avoidance behavior is minimal. The prison environment offers precisely such conditions. This approach represents a standard trade-off between internal and external validity.[3] Similar to other influential studies that

[3] First, existing researches on the impact of air pollution on individual labor productivity are mainly limited to jobs with low labor supply elasticity, such as agricultural work during peak seasons (Graff-Zivin and Neidell 2012), call center operators (Chang et al. 2019), or piece-rate jobs (Chang et al. 2016; He et al. 2019). These roles make it difficult for workers to opt out or reduce hours due to air pollution, allowing for effective measurement of the intensive margin of labor as an indicator of productivity. However, this focus on specific industries may also reduce the generalizability of the findings. Second, researches on the impact of air pollution on individual consumption mainly cover defensive spending, like buying masks (Wang and Zhang 2023), air purifiers (Sun et al. 2017; Ito and Zhang 2020), and health insurance (Chang et al. 2018), or measures of non-defensive consumption via credit card spending (Barwick et al. 2024). These researches have not fully captured all of an individual's consumption choices, while we do. Lastly, previous studies have not simultaneously measured individuals' labor productivity and consumption choices within the same population, missing the chance to establish an empirical relationship between air pollution exposure and individual productivity and consumption in a unified framework.

rely on special populations to study hard-to-measure behaviors—for instance, Graff Zivin and Neidell (2012), who used data from a single piece-rate farm to examine pollution's impact on productivity—our use of a specialized institutional context enhances causal identification. The study's qualitative insights and methodological contributions remain broadly applicable, even if the quantitative magnitudes are context-specific.

The paper proceeds as follows. Section 2 presents a conceptual model. Section 3 and Sect. 4 introduce the data and the empirical strategy. Section 5 presents the estimation results. Section 6 concludes the paper.

2 Conceptual framework

This section develops a simple conceptual model to illustrate how air pollution affects inmates' consumption decisions. Since each inmate's labor supply is fixed, we consider a representative individual with preferences over consumption goods c and health H,

$$u(c, H), \tag{1}$$

where $c = \left(c_1, c_2, \ldots, c_n\right)$ is a vector of the consumption goods.[4] The utility function is strictly concave and twice continuously differentiable, satisfying the following standard properties: $\frac{\partial u}{\partial c_i} > 0$ and $\frac{\partial^2 u}{\partial {c_i}^2} \leq 0, (i = 1, 2, \ldots, n)$; $\frac{\partial u}{\partial H} > 0$ and $\frac{\partial^2 u}{\partial H^2} \leq 0$. Without loss of generality, we assume independent demands so that $\frac{\partial^2 u}{\partial c_i \partial c_j} = 0$ for $i \neq j$ $(i, j = 1, 2, \ldots, n)$, but preference of good i $(i = 1, 2, \ldots, n)$ may depend on the consumer's health status $\frac{\partial^2 u}{\partial c_i \partial H} \neq 0$. Consumption good i is a complement to health if $\frac{\partial^2 u}{\partial c_i \partial H} > 0$, and is a substitute for health if $\frac{\partial^2 u}{\partial c_i \partial H} < 0$.

To focus on the pollution-consumption channels, we abstract from defensive expenditure and medical treatment and assume health is a function of pollution only: $H = H(A)$, where A denotes air pollution. The individual faces a budget constraint:

$$\sum\nolimits_{i=1}^{n} p_i c_i = y(H) \tag{2}$$

where p_i is the price of good i, and $y(H)$ is the income from piece-rate work, increasing with health at a decreasing rate. Without changing the model's structure, we can normalize the price of good 1 to one and interpret it as savings. This allows the model to be embedded in a consumption-saving framework, treating saving as a proxy for future consumption utility. Accordingly, the utility function $u(c, H)$ is interpreted such that c_1 represents the amount allocated to future use, and the present total consumption expenditure is given by $\sum\nolimits_{i=2}^{n} p_i c_i$.

[4] While our model does not explicitly include psychological mood, a known determinant of consumption, we view emotional responses to air pollution, such as stress, as part of an individual's psychological well-being. Since well-being is inherently embedded in the health component H, mood-related effects are conceptually incorporated in the model through the health-related utility channel.

The individual chooses c to maximize utility subject to the budget constraint. The corresponding Lagrangian function is $L = u(c, H) + \lambda\left[y(H) - \sum_{i=1}^{n} p_i c_i\right]$, and the first-order conditions are:

$$\frac{\partial u(c^*, H)}{\partial c_i} = \lambda^* p_i (i = 1, 2, \ldots, n) \tag{3}$$

$$y(H) - pc^* = 0 \tag{4}$$

where λ is the Lagrange multiplier, and the superscript $*$ denotes the optimal solutions. At the optimum, consumption and the Lagrange multiplier are functions of prices, income, and health (which is itself a function of air pollution), $c_i^*(p, y(H), H)$ and $\lambda^*(p, y(H), H)$ $(i = 1, 2, \ldots, n)$. Substituting the optimal values into the utility function yields the indirect utility function: $V(p, y(H), H)$.

To examine the effects of air pollution on consumption, we totally differentiate Eq. (3) with respect to air pollution A:

$$\frac{\partial c_i^*}{\partial A} = \underbrace{\frac{p_i \frac{\partial \lambda^*}{\partial A}}{\frac{\partial^2 u}{\partial c_i^2}}}_{\textit{income effect}} + \underbrace{\frac{-\frac{\partial^2 u}{\partial c_i \partial H} H'(A)}{\frac{\partial^2 u}{\partial c_i^2}}}_{\textit{substitution effect}}, (i = 1, 2, \ldots, n) \tag{5}$$

Note that $\frac{\partial^2 u}{\partial {c_i}^2} < 0$ and $H'(A) < 0$. By the envelope theorem, we have $\frac{\partial V}{\partial y(H)} = \frac{\partial L}{\partial y(H)} = \lambda^*$, so λ^* measures the marginal utility (or shadow price) of income. The first term in Eq. (5) therefore reflects the income effect of air pollution on consumption good i. It can be shown that $\frac{\partial \lambda^*}{\partial A} > 0$, implying a negative income effect.[5] That is, the decline in labor productivity caused by air pollution exposure reduces consumption of any good i. Moreover, $\frac{\partial \lambda^*}{\partial A} > 0$ means that the marginal utility of income increases with pollution. This is consistent with the concavity of utility in income: as air pollution worsens and overall utility falls, each additional unit of income becomes more valuable to the individual under environmental stress.

The second term in Eq. (5) reflects the substitution effect of air pollution. As air pollution reduces health status, consumption of good i declines further if it is a complement to health, i.e., $\frac{\partial^2 u}{\partial c_i \partial H} > 0$. In contrast, this substitution effect could be positive if good i is a substitute for health, i.e.,$\frac{\partial^2 u}{\partial c_i \partial H} < 0$. This substitution effect is primarily determined by the individual's inherent consumption preferences, which are likely to reflect biologically driven responses to changes in physical well-being.

[5] Totally differentiating Eq. (4) with respect to A yields $\sum_{i=1}^{n} p_i \frac{\partial c_i^*}{\partial A} = y^{'}(H) \bullet H^{'}(A)$. Given that $y^{'}(H) > 0$ and $H^{'}(A) < 0$, the total effect of pollution on consumption (and savings, if c_1 is interpreted as savings) is negative: $\sum_{i=1}^{n} p_i \frac{\partial c_i^*}{\partial A} < 0$. Since the substitution effect in Eq. (5) can be either sign, maintaining a negative total effect across all pollution levels requires the income effect to be negative, which in turn requires $\frac{\partial^*}{\partial A} > 0$.

The model can be further generalized by allowing health to depend not only on air pollution but also on consumption choices, i.e., $H = H(c, A)$. Under this generalization, consumption goods can be classified into three categories. (1) A pure utility-generating good that contributes directly to utility but has no effect on health, i.e., $\frac{\partial u}{\partial c_i} > 0$ and $\frac{\partial H}{\partial c_i} = 0$. This corresponds to the setting in the baseline model above. (2) A pure defensive good, such as medical treatment, does not enter the utility function directly but improves health, i.e., $\frac{\partial u}{\partial c_i} = 0$ and $\frac{\partial H}{\partial c_i} > 0$. Since pollution deteriorates health, optimal consumption of such goods increases with pollution, $\frac{\partial c_i}{\partial A} > 0$. (3) A hybrid good affects both utility and health, such that $\frac{\partial u}{\partial c_i} > 0$ and $\frac{\partial H}{\partial c_i} \neq 0$. For instance, cigarette consumption may yield utility while simultaneously harming health. The impact of pollution on the consumption of hybrid goods reflects the combined effects identified for pure utility-generating and pure defensive goods.

3 Data

This data contains prison inmates' consumption and piece-rate wage incomes and the data on air pollution and other weather variables.

3.1 Tracking records of inmates

The inmate data used in this study were obtained through a special research collaboration with the Shenzhen Male Prison authorities, who granted part of the author team access to administrative records and permissions to conduct extensive in-prison surveys. Earlier studies by part of the author team (Cameron et al. 2019; 2022) utilized a random sample of 1200 male inmates and a matched sample of rural-to-urban migrants outside the prison system to study the effects of sex ratios and childhood "left-behind" experiences on criminal behavior. In contrast, the present study draws on comprehensive administrative data covering the full male prison population over a longer time horizon, enabling us to investigate productivity and consumption behavior in greater depth.

The inmates' data are collected in the city of Shenzhen, China. Shenzhen lies in the Pearl River Delta, in the southern province of Guangdong, where much of China's manufacturing occurs and borders Hongkong from the north. It has long been a magnet for migrant workers, and its present population of 20 million makes it the fourth-largest city in China. The study can thus provide some insights into the impacts of air pollution on the productivity and daily consumption behavior of low-wage manufacturing workers in a metropolitan city.

We have access to all of the administrative records of 20,334 inmates imprisoned in the male prison between July 2004 and August 2015—a total of 433,369 inmate-month observations. The prison warden records each inmate's monthly spending in the prison store and wage income. The prison takes inmates arrested in Shenzhen and the neighboring city of Dongguan. The average age of inmates was 34, amongst whom 86.3% held rural household registration (*Hukou*) before incarceration. On

Table 1 Summary statistics

Variable	Definition (units)	Mean	SD	Min	Max
Total commodity expenditure					
Expenditure	Monthly expenditure (CNY/month)	205.43	144.34	0.102	1586.0
Piece-rate wage	Monthly piece-rate wage income (CNY/month)	65.87	76.92	0	3882.9
Monthly balance	Monthly account balance before placing the order (CNY)	1228.1	4042.8	0	98,618.8
Initial balance	Initial account balance upon incarceration (CNY)	2027.3	4744.9	0	98,618.8
Air pollution					
API	Air pollution index (0–500, index)	52.82	15.07	27.07	105.95
Thermal inversions					
Inversions	Number of thermal inversions (1st layer, number)	5.687	7.958	0	38

Number of observations = 433,369; number of prisoners = 20,334. Summary statistics on inmates' characteristics and weather controls can be seen in Tables 1–3 in the Appendix

average, they had received 9 years of education, and their average sentence length was 4.3 years.

The inmates' incomes include wages from the prison factory and family transfers. Inmates work for the prison factory 6 days a week doing manual assembly work. The final products are mainly electronic, such as USB ports and circuit boards. They are paid at a fixed piece rate for each unit of product produced and receive income monthly as a deposit into a personal prison trust account. Given the piece-rate pay system, each inmate's monthly wage perfectly measures his productivity in the corresponding working period.

Inmates were allowed to purchase consumption goods using their account balance once a month. The purchase dates differ across prison districts and are exogenously given to inmates. On the purchase day, an inmate places an order by submitting a paper listing the quantities and prices of all consumer goods. The insider grocery store sells around 200 consumption goods, categorized into foods, personal care, stationery, phone cards, and cigarettes (see Table 1 in the Online Appendix for summary statistics).[6] The dataset specifies who placed the order and when, and the quantities and prices of ordered commodities. The data allows us to calculate each inmate's monthly expenditure and categorize it (see Table 2 in the Online Appendix for summary statistics).

The data also includes detailed demographic information for each inmate. This includes age, education level, crime type, sentence length, and occupation before being incarcerated. The information is summarized in Figure A1 and Table 3 in the Online Appendix.

[6] Foods and personal care are the two largest choice sets for inmates. There are around 130 food items including drinks, cookies, noodles, canned food, sweets, snacks and fruits. Personal care has around 40 products including soap, shampoo, body wash, facial cleanser, toothpaste, toilet paper, face towels and other personal care items.

Table 2 2SLS estimates of thetotal effect of API on log(expenditure)

	(1)	(2)	(3)	(4)
Panel A: 1st-stage estimates, dependent variable is API				
Thermal inversions	0.455***	0.472***	0.386***	0.420***
	(0.0052)	(0.0060)	(0.0045)	(0.0049)
1st-stage *F*-statistics	495.5	123.5	154.3	38.72
KP *F*-statistics	77.76	60.94	74.19	74.63
Panel B: 2nd-stage estimates, dependent variable is log(expenditure)				
API	−0.053***	−0.0036***	−0.0034***	−0.0036***
	(0.0014)	(0.0005)	(0.0008)	(0.0007)
Model specifications				
Weather controls	Yes	Yes	Yes	Yes
Inmate *FE*	No	Yes	Yes	Yes
Year-month-weekdays *FE*	No	No	Yes	Yes
Sample weight	No	No	No	Yes

Number of observations = 433,369; number of prisoners = 20,334. All regressions control for inmate fixed effects, year/month/weekday fixed effects and weather controls, and are weighted by the number of inmates in the jail across different days. Weather controls include temperature bins and second-order polynomials in average humidity, wind speed, total sunshine duration, and cumulative precipitation. Standard errors are clustered by the date and are listed in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

3.2 Air pollution

Air pollution data is from the China National Environmental Monitoring Center (CNEMC). Before 2013, CNEMC published a daily Air Pollution Index (API) for 120 cities in China. The API ranges from zero to 500 and is divided into six levels, namely excellent (0–50), good (51–100), lightly polluted (101–150), moderately polluted (151–200), heavily polluted (201–300), and severely polluted (above 300).

Since January 2013, CNEMC has published a real-time hourly Air Quality Index (AQI) and the concentrations of air pollutants, including $PM_{2.5}$, PM_{10}, O_3, SO_2, NO_2, and CO, in around 1400 monitoring stations, 11 of which are located in Shenzhen City.[7] To obtain an air pollution measure for the period 2013 to 2015, we use the inverse-distance weighting (IDW) method to match air pollution data from monitoring stations to Shenzhen Male Prison. The IDW method is widely used in the literature when calculating pollution measures (Currie and Neidell 2005; Deschênes and Greenstone 2007; Schlenker and Walker 2016).[8] The basic

[7] The data can be viewed at http://106.37.208.233:20035/. One may need to install Microsoft Silverlight.

[8] This method has been recently criticized by Sullivan (2017) in the context of point pollution sources. In the context of a difference in difference design that uses opening and closing of point sources as the source of random variation in air pollution, the interpolation created by the IDW may smooth out sharp spatial differences in exposure, creating bias in the estimates in either direction. However, when using thermal inversions as the source of variation for air pollution, there are no sharp spatial differences and IDW will not distort the estimates.

algorithm is to take the weighted average of all monitoring stations within the circle with a radius for the centroid of Shenzhen Male Prison. We choose 100 km as our radius, and the results are robust to different radii. The computation of AQI differs from that of API. Since Shenzhen's daily AQI was not available before 2013, we computed daily APIs from 2013 to 2015 so that we could have a balanced and uniform measure for air pollution across the whole sample period.[9]

3.3 Thermal inversions

We obtained thermal inversion data from the Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2) released by the National Aeronautics and Space Administration (NASA) in the U.S.[10] MERRA-2 divides the earth using a 0.5×0.625-degree grid (approximately 50×60-km grid), and reports the air temperature for each 42 sea-level pressure layers every 6 h starting from 1980. We aggregate every 6-h temperature for each layer in the grids located in Shenzhen Male Prison. We define a thermal inversion as occurring in 6 h if the temperature in the first layer (110 m) is lower than that in the second layer (320 m). We also conduct a robustness check by coding inversions using differences in temperature between the first and third layers (540 m).

3.4 Weather

The weather data are taken from the China Meteorological Data Service Center (CMDC).[11] The CMDC records daily maximum, minimum, and average temperatures, precipitation, relative humidity, wind speed, and sunshine duration for 820 weather stations in China, one of which is located in Shenzhen City. Following the same method used for matching API data, we applied IDW to match site-level temperature, humidity, wind speed, sunshine duration, and aggregate precipitation for the month preceding each inmate's order to Shenzhen Male Prison. To capture the flexible non-linearity of temperature, we discretize the daily temperature distribution using five °C temperature bins.

4 Summary statistics

Table 1 presents summary statistics of key variables. There are 433,369 inmate/month observations in the sample period from July 2004 to August 2015. On average, each inmate placed 16 monthly purchase orders during incarceration.

[9] See http://kjs.mep.gov.cn/hjbhbz/bzwb/dqhjbh/jcgfffbz/201203/W020120410332725219541.pdf for detailed AQI calculation formula and explanation.

[10] The data we use is M2I6NPANA (version 5.12.4) and can be downloaded at https://disc.sci.gsfc.nasa.gov/uui/datasets/M2I6NPANA_V5.12.4/summary?keywords=\%22MERRA-2\%22\%20M2I6NPANA\&start=1920-01-01\&end=2017-01-16.

[11] The data can be seen at http://data.cma.cn/.

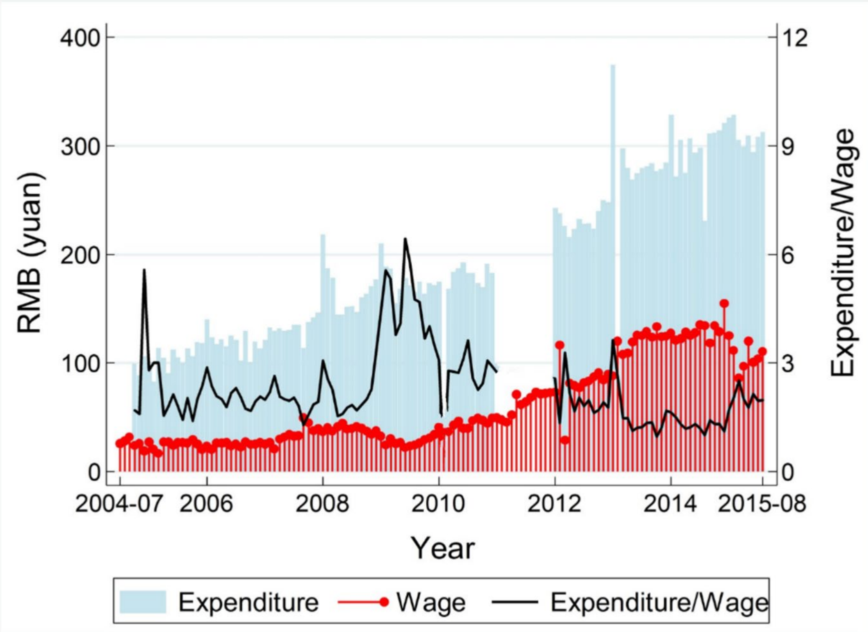

Fig. 1 Time trend of inmates' monthly expenditure and piece-rate wage. Notes: The light-blue bar denotes the total monthly consumption expenditure of inmates. We have missing expenditure records from Jul. 2004 to Sep. 2004 and the whole year of 2011. The red dropline depicts inmates' average monthly piece-rate wage. The black line presents the ratio of expenditure/wage

The average monthly expenditure was 205.4 Chinese Yuan (CNY), while the average monthly piece rate wage was 65.9. According to prison administration data, inmates typically bring an initial sum of external funds upon incarceration, which is used to establish their "Initial Balance." In our sample, this balance averages 2027 CNY. This amount is intended to support their ongoing in-prison expenses. Notably, when inmates' monthly expenses exceed their wage income, the initial balance helps ensure their account remains sufficiently funded. Figure 1 plots the time trends of nominal monthly expenditure and earnings. It is evident that monthly expenditure and wage income monotonically increase over time.

Air pollution, thermal inversions, and other weather variables are individual-specific monthly measures constructed by averaging the daily data in the entire month prior to the purchase date of each inmate. Recall that inmates could purchase goods once a month, with purchase dates varying across prison districts, typically between the 7th and 10th. These dates are exogenously assigned and determined by the prison's monthly notification. Thus, we define "the month prior to each inmate's purchase date" as the period between 2 consecutive monthly purchase dates. The mean of the individual-specific monthly average APIs was 52.8 on average, with a maximum monthly average of 106.0.[12] Recall that the occurrence of thermal inversion is calculated every 6 h. In an average month, there were 5.7 6-h periods in which a thermal inversion was recorded. Summary weather statistics for the area are presented in Table 4 of the Online Appendix.

Finally, we present the summary statistics of inmate consumption in Table 2. The two most frequently purchased consumption goods were cigarettes and snacks, the expenditures on which averaged 49.6 CNY and 62.9 CNY per month, respectively.

5 Empirical strategy

The following equation is used to estimate the effect of air pollution on the consumption expenditures of inmates:

$$Log(c_{i,t(i)}) = \beta_0 + \beta_1 P_{i,t(i)} + f\left(W_{i,t(i)}\right) + \theta_i + g(t(i)) + \varepsilon_{i,t(i)}, \tag{8}$$

where $c_{i,t(i)}$ is inmate i's consumption expenditure at the order placement date $t(i)$, $P_{i,t(i)}$, and $W_{i,t(i)}$ are respectively the average daily API and other weather variables to which inmate i is exposed in the entire month before date $t(i)$—Note that $t(i)$ is exogenously assigned for each inmate. The function $f\left(W_{i,t(i)}\right)$ resets the daily weather measures to monthly figures, which include temperature-day bins and second-order polynomials of all other weather variables, including average daily relative humidity, average daily wind speed, average daily sunshine duration, and cumulative precipitation in the entire month before date $t(i)$. Temperature-day bins are constructed by calculating the number of days when the daily mean temperature is in the j^{th} of 5 °C bins in the month before date $t(i)$. We include a range of weather variables that might be correlated with thermal inversions or influence prisoner health (Arceo et al. 2016; Adhvaryu et al. 2015) and labor productivity (Graff Zivin and Neidell 2012; Chang et al. 2016). Our results are robust to alternative weather constructs such as finer temperature bins and higher-order polynomials. θ_i is an individual fixed effect that captures all time-invariant characteristics of an inmate, such as preference and physique. $g(t(i))$ denotes time fixed effects of inmate i's order placement date t, including year fixed effects, month fixed effects, and weekday fixed effects, controlling for time trends and any seasonal patterns or weekday effects.

[12] Shenzhen's air pollution levels might be moderate compared to other Chinese cities, but they are still sizable. For instance, in a similar setting, Chang et al. (2016) examined the impact of outdoor air pollution on the productivity of indoor workers at a pear-packing factory in Northern California, U.S. Their data sample's mean, minimum and maximum $PM_{2.5}$ concentrations are 10.42, 1.9, and 59.7 μg/m^3, respectively. Since the Chinese government only started to monitor concentration levels of $PM_{2.5}$ after 2013, we have to rely on API to implement our study. However, the Shenzhen Municipal Bureau of Ecology and Environment (https://meeb.sz.gov.cn/) estimated the city's concentration levels of $PM_{2.5}$ before 2013 using satellite-derived monthly data. Using the estimated and monitored $PM_{2.5}$ data in Shenzhen, we found that mean, minimum and maximum $PM_{2.5}$ concentrations in our sample period are 76.8, 47.1, and 113.3 μg/m^3, respectively, substantially higher than those in Chang et al. (2016). These values also exceed China's national PM2.5 standards (15 μg/m^3 for primary and 35 μg/m^3 for secondary thresholds) by a wide margin. To the extent that marginal effects may rise at higher pollution levels, our estimates—though comparable to prior international studies—could plausibly understate the impact in more severely polluted regions in China.

All production and consumption occur in an isolated and closed environment; therefore, our study excludes most endogeneity problems relating to air pollution. However, one endogeneity issue may remain: air pollution could be correlated with the inmate's wage income. First, as the literature and our model suggested, air pollution may depress worker productivity and the inmate's piece-rate wage income. Second, prison production is contingent on external orders, which may be positively linked to the intensity of local economic activity, a source of air pollution. Considering the positive relationship between income and consumption, the linear regression estimates of pollution's impact on consumption could be upward biased by the first of these explanations and downward biased by the second.

Following the literature (Jans et al. 2018; Hicks et al. 2016; Arceo et al. 2016; Fu et al. 2021; Chen et al. 2020, 2022), we use thermal inversion as an instrument for air pollution to solve this potential endogeneity issue. Thermal inversion can be treated as an exogenous shock because its formation only depends on meteorological factors and is independent of local economic activities and human health (Arceo et al. 2016). However, the daily weather variation generally influences a thermal inversion phenomenon (Chen et al. 2022), which should be controlled in the IV analysis.

Figure 2 shows Shenzhen's monthly API and thermal inversion trend between July 2004 and August 2015. The thermal inversions variable is the number of thermal inversions to which inmate i is exposed the entire month before date $t(i)$. Since thermal inversions are recorded in 6 h intervals, the number of inversions can range from zero to four on a 24-h day. A strong positive correlation between thermal inversion and API can be observed in the figure. Using thermal inversions as the IV for air pollution, we estimate the following generalized 2SLS model:

$$ln(c_{i,t(i)}) = \beta_0 + \beta_1 \widehat{P}_{i,t(i)} + f\left(W_{i,t(i)}\right) + \theta_i + g(t(i)) + \varepsilon_{i,t(i)}, \tag{9}$$

$$P_{i,t(i)} = \alpha_0 + \alpha_1 I_{i,t(i)} + f\left(W_{i,t(i)}\right) + \theta_i + g(t(i)) + \varphi_{i,t(i)}, \tag{10}$$

where $I_{i,t(i)}$ is the number of thermal inversions to which inmate i is exposed in the entire month before date $t(i)$.

All the regressions were weighted by the number of inmates each month; however, the results were robust to the omission of regression weights. Standard errors were clustered at the date on which orders were put in. This allowed the error terms of inmates shopping on the same day to be correlated.

6 Estimation results

Since we rely on two-stage least square (2SLS) to estimate the effects of air pollution on inmates' consumption decisions, we begin by examining the first-stage estimation of 2SLS. Panel A in Table 2 reports the regression results of Eq. (10). The coefficient of thermal inversions is always positive and statistically significant under different model settings. In Columns (1)–(3), we add weather controls, inmate fixed effects, and year/month/weekday fixed effects in sequence. After controlling for the group of time-fixed effects, the coefficient of thermal inversions decreases slightly but remains significant at the 1% level. In Column (4), we consider the weighted regression using the total number of purchase orders placed by inmates on each order placement day; the result remains unchanged. The estimated coefficient in Column (4) suggests that one more occurrence of thermal inversion would increase the average daily API by 0.42 units the entire month before the order placement day. One standard deviation (8.0) increase in thermal inversion increases the average daily API by 6.1 percentage points or 0.2 standard deviations. In Columns (1)–(4), the Kleibergen-Paap (KP) Wald *F*-statistics (Kleibergen and Paap 2006) are all larger than the Stock-Yogo weak identification test critical values at 10% maximal IV size of 16.4 (Stock and Yogo 2005), suggesting that the IV is strong and valid. We will now focus on 2SLS results in all that follows.

6.1 Results of the overall causal effects

Panel B in Table 2 presents our main results, i.e., the total causal effect of air pollution on inmates' consumption expenditure. It is evident from Panel B that the coefficient of air pollution estimated by 2SLS not only consistently keeps the same negative sign but also varies little in magnitude across different model settings. Indeed, the stability of the 2SLS results suggests that the IV is exogenous. Column (4) shows that, after controlling for weather conditions, inmate individual effects, year/month/weekdays fixed effects, and using weighted regression, a rise in API in the entire month prior to the order placement date significantly reduces the inmates' total consumption expenditure. This suggests that every 10-unit increase in monthly average API reduces a typical inmate's consumption expenditure by 3.6%. In contrast, the OLS results presented in Table 5 in the Online Appendix 1 are very sensitive to the model settings, and the air pollution effect becomes insignificant after controlling for the time-fixed effects. Moreover, the OLS systematically underestimates the air pollution impact on inmates' consumption.

We conducted a sensitivity analysis to check the robustness of our analysis to variations in the measurement used when specifying the regression variables. As shown in Table 3 and Fig. 3, the estimated coefficients of API are robust to variations in the measurement of standard errors, inversions/expenditure, weather, and time window exposure.

Firstly, in the baseline, the standard errors are clustered at the date level with the underlying assumption that the model residuals are homogeneous within each date but heterogeneous across different dates. This is an appropriate assumption as the variations of air pollution are at the individual-specific monthly level. Nevertheless, our results are robust to alternative standard errors, i.e., the robust standard errors without any pre-assumptions in a large sample case (Column (1) of Table 3) and the standard errors clustered by an inmate (Column (2) of Table 3). Secondly, in our baseline, we treat a thermal inversion as existing whenever the temperature in the second layer (320 m) is higher than the temperature in the ground layer (110 m) and use 5 °C wide temperature-day bins ranging

Table 3 Robustness check

Dep. var	Log(expenditure)					Expenditure/wage
Scenarios	Alternative standard errors		Alternative layer of inversions	Flexible temperature controls		Measurement of consumption
	(1)	(2)	(3)	(4)	(5)	(6)
API	− 0.0036***	− 0.0036***	− 0.0038***	− 0.0032***	− 0.0028***	− 0.5201***
	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0010)	(0.1173)
Temperature	5 °C bins	5 °C bins	5 °C bins	3 °C bins	Quadratic	5 °C bins
IV-inversions	Layer 1	Layer 1	Layer 2	Layer 1	Layer 1	Layer 1
KP *F*-statistics	153.05	150.40	153.33	76.08	93.47	74.63
S.E. clustered by	Robust	Prisoner	Date	Date	Date	Date
API composition	Composite	Composite	Composite	Composite	Composite	Composite

Number of observations = 433,369; number of prisoners = 20,334. Less than 0.1% of observations are missing in Column (5) regression as expenditure/wage (%) cannot be defined when piece rate wage income equals to zero. All regressions control for inmate fixed effects, year/month/weekday fixed effects, and weather controls and are weighted by the number of inmates in the jail across different days. Standard errors are clustered by date unless otherwise stated and are listed in parentheses. *$p<0.1$; **$p<0.05$; ***$p<0.01$

from ≤ − 10 to ≥ 35 °C. Column (3) in Table 3 presents results obtained when the definition of a thermal inversion uses the 540-m layer rather than the layer at 320 m. Thirdly, Column (4) in Table 3 reports the results using finer temperature-day bins, i.e., 3 °C-wide bins. The results hardly change (− 0.0032). The temperature-day bins reflect the nonlinear impacts of temperature. To highlight their importance, Column (5) of Table 3 presents the regression results obtained when the bins are replaced by a quadratic term reflecting the average daily temperature in the month prior to the order placement date. The coefficient for air pollution is still significantly negative under the more straightforward temperature control but is slightly reduced (− 0.0036). Fourthly, in Column (6), we use the ratio (%) of total consumption expenditure relative to the piece-rate wage as an alternative measure of consumption. The ratio reflects the relative changes between the total consumption expenditure and wage income and is negative at the 1% significance level.

Figure 3 presents the 2SLS results obtained using different time windows to indicate inmates' exposure to air pollution. Since inmates are only allowed to order consumption goods once a month, it is natural to use the average daily API in the entire month before the order placement date to measure inmates' exposure to air pollution. We used the mean API in a range of time windows to test sensitivity to the duration and intensity of pollution. These included contemporaneous daily API; average daily API in the past 1 month, 2 months, 3 months, 6 months, and 1 year before the day of placing the order; and future average daily API in the 1 month, 2 months, 3 months, 6 months, and 1 year after the day of placing the order. Future air pollution should not affect current consumption decisions and is used as a placebo test. While doing these tests of sensitivity to the API period, the window used for inversion and weather matched that used for the API.

There are several findings worth noting. First, the contemporaneous API does not significantly impact inmates' consumption expenditure. Since inmates make the consumption decision after a month's exposure to air pollution and need to consume the ordered goods over the coming month, the current air pollution should have little impact on their consumption plan. Second, all past average daily APIs had a significant inverse relationship with inmates' total consumption expenditure, but the magnitude and significance of the effect were at their greatest when using a 1-month time window, i.e., average daily API in the month preceding order placement. Although average daily APIs in more extended periods were still significant, their significance and magnitude fell sharply, suggesting that the additional time was decision-irrelevant. The result is consistent with He et al. (2019), who show that worker outcome is responsive to day-to-day variation in air pollution with up to 30 days of delay. Finally, Fig. 3 also suggests that future exposure to air pollution has no impact on today's consumption decisions. The regression using future average daily API is a placebo test, and our study passes all placebo tests, validating the results of the study.[13]

6.2 Channel decomposition: substitution effect and income effect

As discussed in our theory model, air pollution may affect an individual's consumption through two channels: a direct substitution effect driven by the substitution between damaged health and utility-generating consumption goods and an indirect income effect driven by depressed productivity and wage income. We now explore these two channels. Our primary results are presented in Table 4.

We firstly check whether air pollution reduces inmates' piece-rate wage income by estimating

$$ln(w_{i,t(i)}) = \beta_0^w + \beta_1^w \widehat{P}_{i,t(i)} + f\left(W_{i,t(i)}\right) + \theta_i + g(t(i)) + \varepsilon_{i,t(i)}, \tag{11}$$

where $w_{i,t(i)}$ is the wage income inmate i receives in the month of $t(i)$ and $\widehat{P}_{i,t(i)}$ is estimated from Eq. (9). The inmates are paid monthly, and the pay period starts on the 1st day of the month and ends on the last day of the month. All paydays are at the beginning of the following month. Our purpose is to decompose the substitution and income effects of air pollution on individual consumption, with the piecework income used as a control in the consumption regression (i.e., Column (4) in Table 4). Accordingly, in Column (2), we present the regression results using the same air pollution variable used in the consumption regression, i.e., average daily

[13] We must acknowledge the unobservable noise in the lead results, resulting in low estimation efficiency, and we can neither reject the hypothesis that these lead values are zero nor that they are equal to the main estimates. Since these lead APIs have not yet occurred on the inmates' purchase day, they are irrelevant to inmates' expenditure and may contain significant noise.

Table 4 Mechanisms and mediating effect

	Mechanisms			*Mediating effect*
Dep. var	Log(expenditure)	Log(piece-rate wage)	Log(balance – wage)	Log(expenditure)
	(1) Baseline	(2)	(3)	(4)
API	–0.0036***	–0.0042***	–0.0002	–0.0008***
	(0.0007)	(0.0010)	(0.0029)	(0.0003)
Log(piece-rate wage)				0.6622***
				(0.1742)
KP *F*-statistics	74.63	74.63	74.63	29.84
Mediating effect (%)				78

Number of observations = 433,369; number of prisoners = 20,334. All regressions control for inmate fixed effects, year/month/weekday fixed effects, and weather controls and are weighted by the number of inmates in the jail across different days. Standard errors are clustered by date and are listed in parentheses. *$p<0.1$; **$p<0.05$; ***$p<0.01$

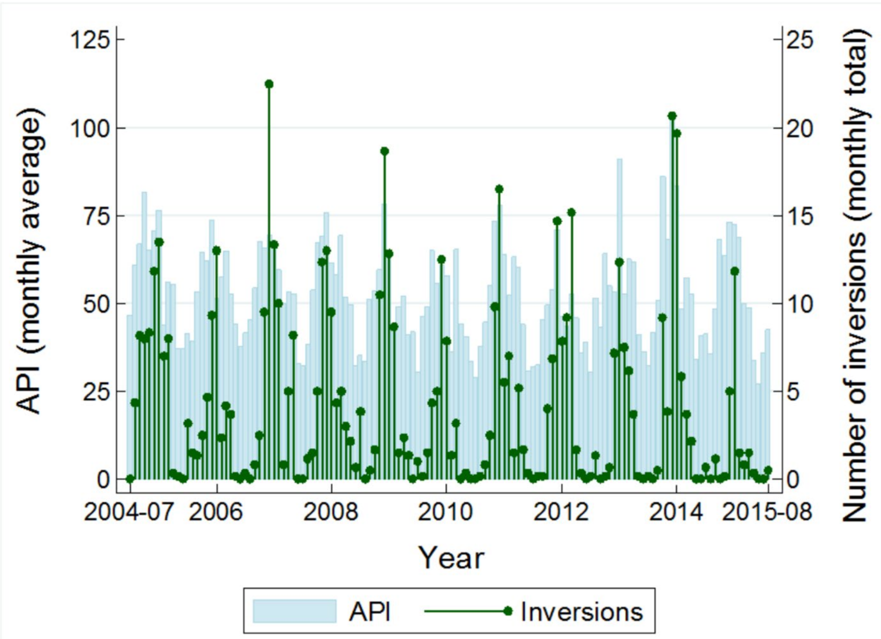

Fig. 2 Positive correlation between thermal inversion and API. Notes: The light-blue bar denotes the monthly average API that inmates were exposed to. The dark-green dropline depicts the corresponding monthly number of thermal inversions

Table 5 Heterogeneous analyses: by age cohort and education level

Dep. var	Log(expenditure)				
	(1)	(2)	(3)	(4)	(5)
Age cohort	*<30*	*30–40*	*40–50*	*50–60*	*> =60*
Panel A: By age cohort					
API	−0.0042***	−0.0037***	−0.0021	0.0053	0.0123
	(0.0010)	(0.0013)	(0.0019)	(0.0035)	(0.0111)
KP *F*-statistics	254.3	397.0	209.7	42.85	44.52
Observations	199,946	157,781	62,755	10,989	1522
Education level	*Below primary*	*Primary school*	*Junior high school*	*Senior high school*	*College or above*
Panel B: By education level					
API	−0.0010	−0.0016	−0.0037***	−0.0078***	−0.0059**
	(0.0072)	(0.0014)	(0.0010)	(0.0022)	(0.0030)
KP *F*-statistics	227.7	350.2	444.4	155.2	67.04
Observations	7319	118,525	245,003	47,132	14,525

All regressions control for inmate fixed effects, year/month/weekday fixed effects, and weather controls and are weighted by the number of inmates in the jail across different days. Standard errors are clustered by date and are listed in parentheses. *$p<0.1$; **$p<0.05$; ***$p<0.01$

API in the entire month before the order placement day.[14] These show that a 10-unit increase in the average daily API reduces prisoners' monthly earnings by 4.2%. The result is directly comparable to previous studies—Graff and Neidell (2012) and Chang et al. (2016)—that used U.S. data to study the effect of concurrent air pollution on work productivity.

An inmate receives income from two sources: wage income and family transfers. Both are directly deposited into his personal trust account at the prison. When buying grocery items on the scheduled date, the budget available to an inmate will be his total account balance. If air pollution were related to inmates' *non*-wage income, the complexity of the above-discussed income effect of air pollution could be compounded by non-productivity factors. To test whether there is any correlation between air pollution and outside transfer, we subtract the inmate's last month's wage income from his account balance on the order placement date and regress the residual on the average daily API the month before the order placement date. The

[14] Note that in Column (2) of Table 4, the time window of the air pollution measure differs from the time window of the working time, which is the inmate's pay period, but they coincide if the allowed shopping date is on the 1st day of the month. The data show that the inmates' order placement days tend to be clustered at the beginning of each month (the mean and median of the date is the 7th of a month). Hence the measurement error of the air pollution measure used in Column (2) is limited. Moreover, since both the payday and shopping day in each month are fixed for all inmates, the measurement error is completely exogenous and should not bias the regression results. We also estimate the impact of average daily API in the month of the pay period on the inmate's pay received at the start of the following month. The 2SLS estimator is −0.0040, almost the same as that in Column (2), and also significant at the 1% level.

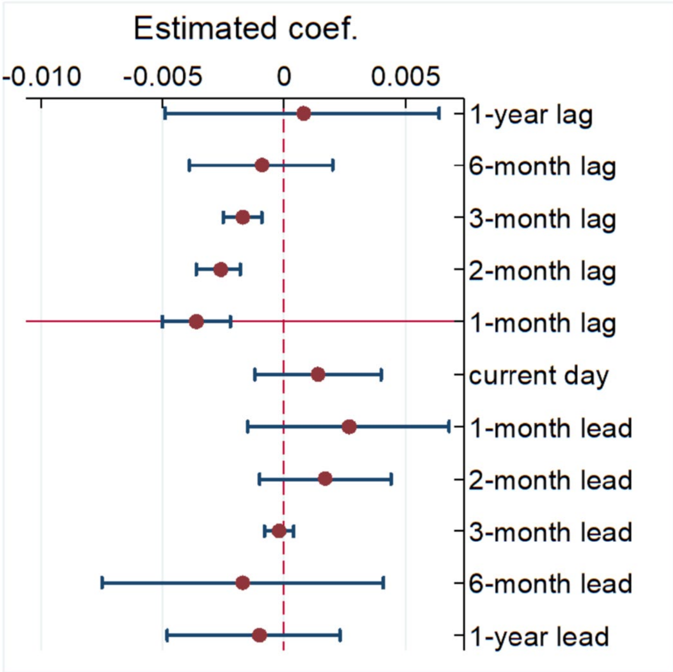

Fig. 3 The effect of API on the total consumption expenditure by different time windows of air pollution exposure. Notes: This figure presents the effects of air pollution on inmates' total monthly consumption expenditure by different time windows of air pollution exposure. API is calculated by averaging the daily APIs in these different time windows. The circle denotes the point estimate of the total causal effect, and the whisker denotes the 95% confidence interval. Our baseline (average daily API the entire month before the shopping day) is highlighted in a red horizontal line

results (see Column (3) in Table 4) show that income transfers outside the prison are independent of inmates' air pollution exposure. This verifies the use of prisoners' piece-work-based earnings as the sole mediator in the following mediation analysis.[15]

We next decompose the total causal effect of air pollution on inmates' consumption expenditure into the direct substitution and indirect income effects. If air pollution is randomly assigned, we can easily decompose the total effect into

[15] The result is also consistent with the practice of outside transfer. As discussed above, inmates generally brought a few thousand CNY to set up an initial account balance upon incarceration. The account balance then increases in the deposit of piece-rate wages and decreases in consumption expenditures. When the account balances approach zero, external transfers after imprisonment may occur. The data shows inmates rarely overdraw their initial accounts, indicating infrequent receipt of external funds after imprisonment. Prison management indicates that family transfers typically happen once a year, usually after Chinese New Year, with occasional deposits during family visits. This infrequency aligns with the prison's provision of basic needs (meals and necessities), suggesting that additional monthly expenditures do not significantly impact primary living conditions. Overall, external funds are received infrequently and irregularly, making it difficult to logically or statistically link them to monthly air pollution levels.

two causal ones using traditional mediation analysis.[16] However, once air pollution is endogenous, the two regressors in the mediation model—wage income and air pollution—are both endogenous and a complex causal chain arises. The endogenous treatment (air pollution) and its outcome (inmates' piece-rate wage income) jointly cause a second outcome of interest, inmates' consumption. Conventionally, a separate dedicated instrument for the wage income is required to achieve identification, but we only have one instrumental variable, which cannot unpack the causal chain with standard IV estimation. However, Dippel et al. (2020) show that if air pollution is endogenous in the regression of consumption on air pollution only because of omitted variables that affect wage income, and through wage income also affects consumption, a single instrumental variable is enough to identify the total effect, direct effect, and indirect effect. That is to say, in the following first-stage regression, we can use the temperature inversion to instrument the wage income conditional on the air pollution,

$$ln\left(w_{i,t(i)}\right) = \alpha_0^w + \alpha_1^w I_{i,t(i)} + \alpha_2^w P_{i,t(i)} + f\left(W_{i,t(i)}\right) + \theta_i + g(t(i)) + \varphi_{i,t(i)} \tag{12}$$

and then estimate the second-stage mediation model using the following equation,

$$ln(C_{i,t(i)}) = \beta_0^C + \beta_1^C P_{i,t(i)} + \beta_2^C ln\widehat{w}_{i,t(i)} + f\left(W_{i,t(i)}\right) + \theta_i + g(t(i)) + \varepsilon_{i,t(i)} \tag{13}$$

where $\widehat{w}_{i,t(i)}$ are the estimated values of $w_{i,t(i)}$ in the first stage—Eq. (12).

Following Dippel et al. (2020), β_1^C, $\beta_2^C\beta_1^w$ and $\beta_1^C + \beta_2^C\beta_1^w$ would be, respectively, the direct, indirect and total causal effects of air pollution on the inmates' consumption expenditure. Intuitively, the identification approach implies that if the following two conditions are satisfied, the air pollution would be exogenous in Eq. (13), and therefore, the parameters of the mediation model can be well estimated. First, the correlation between wage income and air pollution is the only channel for air pollution to be endogenous in regression (9). Second, a temperature inversion is a valid instrument to identify the causal effect of wage income on consumption when conditional on air pollution. As already discussed, air pollution can correlate with wage income through a direct environmental productivity effect and outside-world economic activities in the isolated and closed prison environment. Hence, in Eq. (13), when conditional on air pollution, the endogeneity can only arise from the omitted outside-world economic activities, which affect consumption through the wage income. This is exactly the setting required by Dippel et al. (2020).

Column (4) in Table 4 presents the regression results of Eq. (13). Based on the estimators from Eqs. (11) and (13), we can calculate the direct, indirect, and total causal effects of air pollution on the inmates' consumption expenditure, $\beta_1^C = -0.0008$, $\beta_2^C\beta_1^w = -0.0028$, and $\beta_1^C + \beta_2^C\beta_1^w = -0.0036$. The total causal effect $\beta_1^C + \beta_2^C\beta_1^w$ estimated by Eq. (13) can be shown to equal β_1, which

[16] That is, estimating the direct causal effect from the mediation model, i.e., regressing consumption on both the mediator, i.e., piece-rate wage income, and the air pollution, and calculating the indirect causal effect by differencing the total causal effect and the direct causal effect.

Table 6 Heterogeneous analyses: by work type and wage level

	Dep. var.: log(expenditure)			
	Wage level		*Work type in the jail factory*	
Subsample	Above average	Below average	Management and logistics	Production work
	(1)	(2)	(3)	(4)
API	−0.0016**	−0.0062***	−0.0005	−0.0042***
	(0.0007)	(0.0016)	(0.0017)	(0.0008)
KP *F*-statistics	178.95	34.53	43.54	69.33
Observations	171,118	261,875	24,532	408,461

All regressions control for inmate fixed effects, year/month/weekday fixed effects, and weather controls and are weighted by the number of inmates in the jail across different days. Standard errors are clustered by date and are listed in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

is estimated by Eq. (9) and presented in Column (1) in Table 4. The comparison shows that the total causal effects estimated by the two different approaches are exactly the same, confirming that the identification approach proposed by Dippel et al. (2020) is valid for our study. The direct substitution effect and indirect income effect, respectively, account for 78% and 22% of the total effect of air pollution on inmates' consumption expenditure, and the income effect is the main force driving the impacts of air pollution on individual daily consumption. To our knowledge, the above analysis could be the first in the literature to decompose the total causal effect of air pollution on individual consumption into two different channels.

6.3 Heterogeneity analysis

The impact of air pollution on the amount prisoners spend each month may vary across the prison population and product categories. To assess how inmates' consumption choices are differentially affected by air pollution, we explore the potential heterogeneity by running regressions on subsamples separated by inmates' characteristics and product categories.

6.3.1 Heterogeneity amongst inmates

We first explore these variations in terms of prisoner age, education, and productivity level.[17] As shown in Table 5, air pollution significantly reduces total spending by inmates younger than 40 but does not impact inmates above 40. Moreover, although

[17] We examined the correlations among age, education, and sentence length, as shown in Table 6. The analysis reveals that an inmate's age is positively correlated with education, sentence length, and time served. However, education is not significantly related to sentence length or time served, likely because it is determined prior to incarceration.

air pollution has no impact on spending by illiterate inmates (see Column (1) in Panel B of Table 5), it reduces the total consumption expenditure of all other education levels, with the contraction increasing with prisoner education. The results in Table 6 further suggest that the total consumption expenditure of more productive inmates is more sensitive to air pollution. These results show that the consumption expenditures of younger, more educated, and productive inmates are more likely to be negatively affected by increased air pollution.

Second, inmates who are younger, more educated, and more productive are also more likely to be high earners and, therefore, to spend more on consumption. To understand the source of the heterogeneity, we explore whether differences in inmates' consumption levels can explain these patterns. To assess this, we run a subsample regression, splitting the whole sample into 10 decile consumption groups based on the consumption expenditure of each inmate. Figure 4 presents the results of the subsample regression for each decile. It shows that air pollution significantly reduces the total consumption expenditure of the three largest spending decile groups, i.e., the 8th, 9th, and 10th, but has no significant effect on spending by the other seven deciles. The finding suggests that the variations in the pattern of spending by prisoners depend on the variations in the amounts they spend.

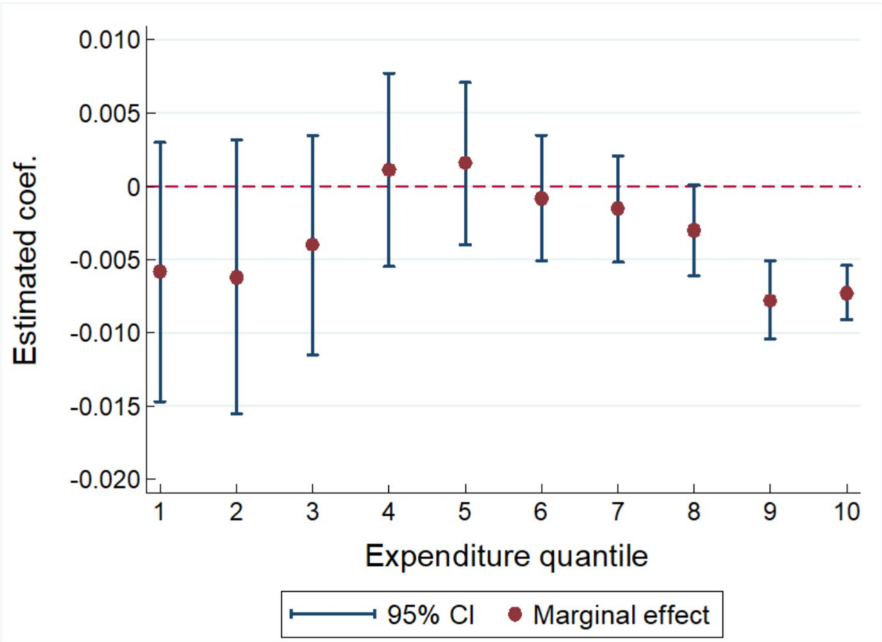

Fig. 4 The effect of API on total expenditure by expenditure quantiles. Notes: This figure presents the effects of air pollution on inmates' consumption expenditure by 10 quantile consumption subsamples (Q1–Q10). The quantile is divided by the average monthly expenditure of each inmate during our research period. The circle denotes the point estimate of the effect, and the whisker denotes the 95% confidence interval

Table 7 Heterogeneous analyses: by sentence length and served time

Dep. var	Log(expenditure)			
	Sentence length		Served time	
	< 42 month	> = 42 month	< 32 month	> = 32 month
	(1)	(2)	(3)	(4)
API	−0.0065***	−0.0032***	−0.0057***	−0.0032***
	(0.0018)	(0.0008)	(0.0017)	(0.0008)
KP *F*-statistics	32.58	89.84	29.12	87.27
Observations	127,152	305,841	128,667	304,326
Mean [SD] of age	31.92 [7.74]	34.25 [8.22]	32.03 [8.08]	34.14 [7.95]
Mean [SD] of education	2.86 [0.73]	2.87 [0.79]	2.89 [0.75]	2.84 [0.78]

All regressions control for inmate fixed effects, year/month/weekday fixed effects, and weather controls and are weighted by the number of inmates in the jail across different days. Standard errors are clustered by date and are listed in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Finally, we perform subsample regressions based on whether inmates' sentence length and served time are above or below the 50th percentile, as shown in Table 7. We find that for inmates with below-average sentence lengths and less than the average time served, air pollution has a more significant impact on their consumption. The results are intuitive as inmates with above-average sentence lengths and more than the average time served may have adapted to the production and consumption in the prison, leading to a smaller response to air pollution.

6.3.2 Heterogeneity amongst products

Table 8 presents the 2SLS estimates of air pollution's effects on each production category. As shown in the table, when inmates are exposed to more polluted air during the month before they place their purchase orders, they reduce their spending on food and cigarettes but increase their expenditure on personal care. Expenditure on personal stationery, however, is unresponsive to air pollution. Within the category of food, more heterogeneity is observed. Specifically, air pollution induces inmates to consume more sweets and fruits and fewer beverages, cookies, noodles, and canned food, and has little effect on pre-packaged snacks such as nuts.

Our results might suggest several patterns whereby air pollution impacts consumption. First, the discomfort caused by greater air pollution exposure may lead individuals to be depressed and lose their appetite, which in turn reduces their consumption of carbohydrate foods and meats, such as cookies, noodles, and canned food. Still, it may increase their consumption of stress-relieving foods such as sweets. Second, air pollution-induced discomfort may incline people to consume fewer unhealthy goods, such as cigarettes, and more healthy goods, such as fruits. Thirdly, air pollution may make daily physical activity less attractive, reducing the beverage demand. Fourthly, people may increase their spending on personal toiletries in response to the dirty air. Finally, as Table 8 shows, cigarettes are the most sensitive to air pollution—a 10-unit increase in average daily API leads to a nearly

Table 8 Heterogeneous analyses: by product category

Dep. var	Log(expenditure)					
Category	*Total food*	Beverage	Cookies, noodles, and canned food	Sweets	Snacks	Fruits
	(1)	(2)	(3)	(4)	(5)	(6)
API	−0.0059**	−0.0130***	−0.0148***	0.0226***	0.0033	0.0128***
	(0.0024)	(0.0027)	(0.0028)	(0.0029)	(0.0028)	(0.0026)
Observations	264,971	133,356	168,317	74,596	237,222	78,059
KP *F*-statistics	40.88	28.95	28.75	18.66	34.51	28.83
	Office supplies	*Personal care*	*Phone cards*	*Cigarettes*		
	(7)	(8)	(9)	(10)		
API	−0.0007	0.0056***	−0.0072**	−0.0081***		
	(0.0027)	(0.0013)	(0.0028)	(0.0028)		
Observations	305,003	305,003	265,019	158,651		
KP *F*-statistics	39.37	39.37	28.68	19.10		

All regressions control for inmate fixed effects, year/month/weekday fixed effects and weather controls, and are weighted by the number of inmates in the jail across different days. Standard errors are clustered by date and are listed in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

8.1% reduction in expenditure. Since cigarettes are the prisoners' second largest expenditure item (behind snacks), accounting for 22.7% of inmates' total consumption expenditure, this response to air pollution has a much more significant impact than other consumption goods.

In addition to analyzing demographic heterogeneity among inmates, we use spline regression to examine the nonlinear impacts of air pollution on individual consumption, i.e., how the estimates of the effects change over six different API intervals: < 30, [30, 40], [40, 50], [50, 60], [60, 70], [70, 80], and > 80. The results show that air pollution negatively affects consumption only when the average daily API in the month before the order exceeds 40. Moreover, inmate spending decreases at an accelerating rate as pollution levels rise. For detailed technical information and results, see Online Appendix 2.

6.4 External validity

One may argue that inmates could be very different from the national population, limiting the generalization of the results. Since 86.3% of the inmate samples are rural migrants and all inmates engage in production, we believe our sample population may be closest to the 300 million Chinese rural migrant workers, who are generally less educated and low-skilled. In the following, we use individual sampling data from the 2010 National Population Census of China to compare the individual characteristics of our samples to those of national rural migrant workers.[18]

[18] The results are same even if we focus on national male rural migrant workers in manufacturing. These results are available upon request.

Table 9 Characteristics of inmates and migrant workers

Variables		Inmates	Migrant workers (males in China)	Difference (1)–(2)	Migrant workers (males in Guangdong Province)	Difference (1)–(4)
		(1)	(2)	(3)	(4)	(5)
Age	Mean	33.77	33.50	0.270	31.39	2.380
(Years > = 18)	(SD)	(8.174)	(10.474)	Ha: diff! = 0	(9.602)	Ha: diff! = 0
	Obs	20,334	146,144	$p = 0.0004$	34,321	$p = 0.0000$
Education level	Mean	2.863	3.125	−0.262	3.228	−0.365
(1–5)	(SD)	(0.767)	(0.735)	Ha: diff! = 0	(0.671)	Ha: diff! = 0
	Obs	20,334	146,144	Pr(|T| > |t|) = 0.0000	34,321	Pr(|T| > |t|) = 0.0000

Definitions of education levels: 1, below primary school; 2, primary school; 3, junior high school; 4, senior high school; 5, college and above

The individual sampling data of the 2010 National Population Census of China are from the Population Department of the National Bureau of Statistics of China and include 44 million individuals generated by proportionate stratified random sampling from the general population. We use the following criteria to select rural migrant workers from 44 million individual samples and then compare their characteristics to those of the prisoner population. Firstly, we define an individual as a rural migrant if he lives in cities, but his residence is registered as rural *Hukou*. Secondly, the rural migrant is employed. Thirdly, the rural migrant worker has to be male to match the gender of our inmate samples.

We focus on the two most important individual characteristics, i.e., age and education, and present the results of the comparison in Table 9. Column (1) (Column (2)) presents the mean and standard deviation of age and education of inmates (national male rural migrant workers), and Column (3) reports the *p*-value of the *T*-test for the differences in characteristics between the two samples. Since the prison is located in Guangdong province, Column (4) also presents the statistics of age and education of male rural migrant workers in Guangdong province and reports the *p*-value of the *T*-test for the differences between their characteristics and inmates in Column (5). The *T*-test shows that inmates' age and education level are statistically indifferent from those of national or Guangdong's male rural migrant workers, confirming that the characteristics of inmates are at least comparable to the large population of male rural migrant workers.

We recognize that the prison population may not fully represent the broader migrant worker population due to inherent selection bias, but the two population groups are relatively the most comparable. Previous research utilizing the same dataset (Cameron et al. 2019, 2022) conducted parallel surveys and economic experiments with inmates and a randomly selected sample of non-inmate rural-to-urban migrants in Shenzhen. It was shown that these incarcerated individuals exhibited significant differences from the general migrant population in terms of parental absence, cognitive scores, marital status, and behavioral preferences, although they had similar backgrounds of education and age. These distinctions underscore the selection bias and the challenges in generalizing our findings. However, these distinctions may not necessarily lead to different consumption responses to air pollution. By providing comprehensive background information and explicitly discussing these limitations, we aim to offer a balanced interpretation of our results.

7 Conclusion

This paper investigates how air pollution affects individual consumption through income and substitution channels. Using a unique dataset that links daily air quality data to monthly records of inmates' piece-rate wages and consumption, we find that a 10-unit increase in the Air Pollution Index (API) reduces monthly consumption by 3.6 percentage points. Approximately 78% of this effect is explained by the income channel, as pollution lowers productivity and wage income. The consumption response is heterogeneous: it is concentrated among high spenders and becomes significant only when pollution exceeds an API threshold of 40.

Our findings reveal a subtle but pervasive morbidity cost of pollution: reduced economic activity through suppressed labor productivity and consumption, even in the absence of severe health shocks. In this sense, clean air functions as an economic stimulus by enabling both higher labor productivity and greater consumption. While our data comes from a specific institutional setting, the productivity estimates align with previous studies, and the inmates share characteristics with China's rural migrant workers. Thus, our results likely reflect a lower bound of the impact on broader populations.

A key contribution of the study is to isolate and quantify the relative strength of the income and substitution effects, providing new micro-level evidence on how environmental shocks affect individual behavior. Although prison data may limit representativeness, it offers a quasi-experimental setting with clean consumption measurement and minimal behavioral confounding, free from avoidance, self-selection, or timing effects. The setting thereby enhances the internal validity of our findings.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s00148-025-01117-z.

Acknowledgements We would like to thank the editor (Xi Chen), and the three anonymous referees for their extremely valuable suggestions. The authors declare that they have no conflicts of interest. This research is supported by the National Natural Science Foundation of China (Nos. 72273131, 71,973,003, 71,973,004), and the National Social Science Fund of China (Nos. 20AZD086, 24&ZD100). Ethics approval was obtained from the Australian National University (Protocol number: 2013/494). The approval was granted by the Australian National University Human Research Ethics Committee to Dandan Zhang, Xin Meng, and Lisa Cameron. We are grateful to the prison authorities for granting us access to the data used in this study.

Funding National Natural Science Foundation of China,72273131,Shuai Chen,71973003,Min Wang,71973004,dandan zhang,National Social Science Fund of China,No.20AZD086,dandan zhang,24&ZD100,Shuai Chen

Data availability The paper used administrative data from Shenzhen Male Prison, which did not grant written consent for public data sharing. As a result, the supporting data on inmates' consumption and wages are not publicly available. However, replication code and the corresponding output log file are available in the supplementary material attached to this article.

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