Smoggy Spending: The Impact of Air Pollution on Offline Cashless Spending

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Abstract

This paper studies how air pollution shapes offline cashless spending in China. Using monthly transaction data from 118,698 merchants across 332 cities (2019–2023), matched with air quality and weather records, we track sales, transactions, customer counts, and payment structures. We find that higher pollution unexpectedly stimulates consumption: a 10-point increase in the Air Quality Index raises sales, transactions, and customer counts by about 1%. Instrumental variable and regression discontinuity designs confirm a causal effect. The increase comes mainly from more frequent but smaller purchases and greater participation by new customers. Effects are strongest in food, services, and non-durable goods, while durables respond little. These results reveal a new behavioral channel through which environmental conditions influence local commerce, showing that poor air quality can reallocate spending patterns in cashless economies.

Keywords: Air pollution; Offline cashless spending; Consumer behavior; Thermal inversion; Merchant panel data; China

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Smoggy Spending: The Impact of Air Pollution on Offline Cashless Spending[†]

Abstract: This paper studies how air pollution shapes offline cashless spending in China. Using monthly transactions from 118,698 merchants in 332 cities (2019–2023), matched with air quality and weather records, we find that higher pollution unexpectedly raises cashless spending. Instrumental variable and regression discontinuity designs confirm a causal effect. The increase comes mainly from more frequent but smaller purchases and greater participation by new customers. Spending also rebalances from postponable durables toward high-frequency, proximity-based categories—food & beverage, local services, and convenience retail—while durables respond little. These results uncover a behavioral channel whereby poor air quality shifts the margins and the composition of cashless offline commerce.

Keywords: Air pollution; Offline cashless spending; Consumer behavior; Thermal inversion; Merchant panel data; China

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1. Introduction

Cashless payments have become the dominant mode of retail transactions, reshaping daily consumption and local commerce (Agarwal et al., 2024). What drives variation in cashless use matters for short-term demand and for the structure of retail finance. Key influences include payment infrastructure and merchant acceptance, fees and frictions, consumer preferences and incomes, mobility constraints, and policy or health shocks. Among local shocks, ambient air pollution is frequent and plausibly exogenous. We study whether and how pollution shifts offline cashless spending.

Research on consumption shows that households reallocate rather than uniformly cut spending when pollution rises. Pollution shifts food expenditure toward healthier items in India (Agarwal et al., 2025a), increases online food delivery while reducing dine-in restaurant sales in China (Tian et al., 2025), and in Korea is associated with either an overall contraction in retail activity or compensatory hedonic purchases (Jingyi, 2023; Kim & Trusov, 2025). Related household-level evidence finds that pollution raises healthcare expenditures (Barwick et al., 2018) and elevates delinquency risk in consumer credit markets by increasing missed repayments on heavily polluted days (Li et al., 2025). Building on these findings, we focus on offline cashless spending at the point of sale, a relatively under-explored margin that provides a complementary channel through which environmental conditions translate into real-time economic behavior.

Previous studies document clear substitution toward e-commerce when air quality deteriorates, with higher online traffic and revenues as consumers avoid outdoor exposure (Liu et al., 2025; Tian et al., 2025; Huang et al., 2020b; Liang et al., 2021). However, the implications for offline cashless spending at the point of sale are ambiguous because two opposing forces operate simultaneously. On one hand, worsening pollution plausibly reduces brick-and-mortar visits—especially discretionary trips to restaurants, malls, and entertainment venues—so POS transactions made via cards or QR codes should fall (Barwick et al., 2024; He et al., 2019). On the other hand, pollution can reallocate in-store purchases toward categories with elevated need or compensatory motives (e.g., masks, air purifiers, medicines, or

hedonic goods), raising basket size and potentially increasing POS cashless usage even with fewer trips (Kim & Trusov, 2025a). This tension between fewer store visits and higher per-trip spending in specific categories renders the net effect of air pollution on offline cashless spending an empirical question.

Our empirical setting draws on a unique dataset from a leading bank-card acquirer in China covering more than 4.7 million monthly observations of offline merchants nationwide. The data track cashless transaction amounts, counts, and distinct customers—further separated into existing and new users—thus enabling us to capture both intensive and extensive margins of merchant activity. Combined with city-level air quality indicators, weather controls, and thermal inversion instruments, these features enable us to identify how pollution shocks translate into real economic behavior at the point of sale. To our knowledge, this is the first empirical study to examine offline cashless spending responses to pollution using POS-level data.

Our results show that air pollution does not merely deter consumption; it reshapes the structure of offline cashless spending. When air quality deteriorates, merchants record more transactions, higher sales amounts, and a greater number of distinct customers. The OLS estimates are positive and statistically significant, and the corresponding coefficients are economically larger in IV specifications that use thermal inversions and in analyses exploiting the Huai River heating boundary. Yet this rise in activity does not reflect larger purchases; instead, spending is redistributed across more numerous but smaller transactions, as new and returning customers are drawn into quick, local, and often low-value purchases. Surprisingly, these shifts are not uniform: consumer-facing industries such as food, beverage, and everyday retail display particularly strong responses, while durable-goods merchants remain relatively insulated. Stable, long-established merchants also appear especially exposed to pollution-induced swings in demand. By documenting these patterns, the study highlights a pollution-induced reallocation channel through which environmental conditions propagate to real-time POS activity in cashless economies, offering new insights at the intersection of environmental economics, digital finance, and retail

operations.

The novelties of this paper are as follows. First, we center the offline consumption margin by quantifying how pollution reshapes cashless spending at the point of sale, a setting less studied than online transactions or household budgets. Rather than emphasizing health, productivity, or mobility costs, we show that deteriorating air quality systematically alters in-store payement behavior. The number of transactions and distinct customers rises, while average spending per transaction and per customer declines. This pattern aligns with a ***pollution-induced substitution channel*** in which consumers shift toward nearby, quick, and low-value purchases executed via cards or QR codes**.** . In doing so, we extend environmental economics by linking pollution exposure to digital payment usage (e.g., Beatty & Shimshack, 2014; Tian et al., 2025), and we enrich the digital finance literature by showing that exogenous environmental shocks can influence consumer payment choices (Agarwal et al., 2025b; Kim & Trusov, 2025a)

Second, rather than proposing a new estimator, we emphasize design credibility. We triangulate causal effects using two complementary sources of exogenous variation, namely thermal inversions (Deschênes & Greenstone, 2012) as instruments and the Huai River winter heating boundary (Y. Chen et al., 2013) as a geographic discontinuity. Both designs are implemented on a large-scale merchant-level panel with rich fixed effects and flexible weather controls. First-stage relationships are strong, and estimates are consistent across the two designs and a battery of robustness checks. The convergence of results strengthens the interpretation of a causal link between pollution and offline cashless spending.

Third, we connect micro-level retail responses to broader macroeconomic and policy debates (Barwick et al., 2018; Kim & Trusov, 2025a; Tian et al., 2025). The effects concentrate in nondurable goods, services, and food-related sectors, while durables are relatively insulated, indicating adaptation through more local, frequent, and low-value purchases local, frequent, and low-value offline purchases that broaden customer reach but reduce basket depth. This pattern suggests several policy levers.

Authorities can secure supply and distribution for essential health and household items on high-pollution days, use targeted digital vouchers or temporary fee reductions to stabilize purchasing power for vulnerable groups, and support small merchants with POS readiness and last-mile logistics to meet short-notice demand. Regulators can draw on high-frequency POS cashless indicators as real-time monitors of pollution-induced demand shifts when calibrating short-term interventions. For macroeconomic analysis, incorporating the pollution-induced substitution margin, reflected in more transactions with lower average value, improves the mapping from environmental shocks to sectoral output and welfare and helps design policies that mitigate volatility without discouraging essential consumption.

The remainder of this paper is organized as follows. Section 2 introduces the institutional background of China's non-bank payment institutions and acquiring services, and reviews the related literature to develop our hypotheses. Section 3 describes the data sources, variable construction, and sample characteristics. Section 4 presents the empirical results, beginning with the baseline estimates and followed by additional robustness and heterogeneity analyses. Finally, Section 5 concludes and discusses implications for consumer behavior, payment policy, and environmental economics.

2. Institutional Background, Related Literature, and Hypothesis Development

2.1 Evolution of Non-bank Payment Institutions

Beginning in the early 2000s, the rapid diffusion of internet technologies and e-commerce drew a growing number of non-financial firms into China's payment value chain. These entities variously provided technology solutions, merchant acquisition, and terminal management, and some built end-to-end business systems to offer online payments, offline acquiring, or prepaid card issuance and acceptance. In effect, they became bona fide payment service providers—colloquially, third-party payment institutions—alongside banks. Well-known examples include Alipay, Tenpay, UnionPay Merchant Services, Lakala, and Zihexin. Their entry alleviated practical frictions such as long queues at bank branches and merchants' cash-making constraints,

better matched the payment needs of e-commerce, and supported China's broader economic development.

As participation by these non-financial entities expanded, scale and competition intensified, and a set of inherent risks surfaced—ranging from safeguarding of customer reserve funds and prepaid-card misconduct to AML/CFT compliance, information-system security, fair competition, and unlicensed payment activities. To place the sector on a formal regulatory footing, in June 2010, the People's Bank of China (PBOC) promulgated the Measures for the Administration of Payment Services Provided by Non-Financial Institutions (a departmental rule)[1]. The Measures established a license-based regime and defined three business categories (network payments, prepaid card issuance and acceptance, and bank-card acquiring) with licensed entities designated as non-bank payment institutions (NBPIs) (PBOC, 2010). The Measures conferred legal status on non-financial payment services and markedly strengthened public trust, catalyzing rapid sectoral growth and broad coverage of retail payment demand[2]. Between 2011 and 2015, the PBOC issued 271 payment business licenses. Subsequently, some institutions exited for reasons including violations, poor performance, or strategic retrenchment. By March 2025, an accumulated 100 licenses had been revoked or surrendered, leaving 171 licensed NBPIs in operation[3].

2.2 Bank-card Acquiring Services

In China, the acquiring service—i.e., enabling merchants to accept and settle payments—emerged initially in the context of card-present transactions conducted via point-of-sale (POS) terminals, and was therefore commonly referred to as bank-card acquiring. Drawing on the organizational models of Mastercard and Visa, the People's Bank of China promoted the establishment of China UnionPay (CUP). As the national bank-card association, CUP, together with participating banks, built the interbank

[1] https://www.gov.cn/gongbao/content/2010/content_1730706.htm/.

[2] Notably, a further milestone came in December 2023, when the State Council issued the Regulation on the Supervision and Administration of Non-Bank Payment Institutions (State Council Order No. 768). The Regulation inherits and upgrades the 2010 framework, reinforcing the legal basis for NBPI oversight while continuing to anchor the sector in a licensing system. The elevation from a departmental rule to a State-Council regulation signals a heightened regulatory priority.

[3] https://www.ccn.com.cn/Content/2025/03-27/1155200098.html/.

switching and clearing infrastructure and thereby the card-acceptance network.

The bank-card acquiring ecosystem typically involves five parties: the issuing bank (issuer), the acquiring institution (acquirer), the interbank switching and clearing institution (CUP), the merchant, and the cardholder[4]. Their roles are as follows. The issuer provides payment cards and related services to cardholders. The acquirer signs acceptance agreements with merchants and supplies acquiring services (including POS deployment and settlement). CUP links acquirers' and issuers' systems and provides interbank switching and clearing.

Operationally, a standard transaction proceeds in the manner described below, which is illustrated in Figure 1[5]. The cardholder initiates a purchase at the merchant; the acquirer's POS terminal generates an authorization request and transmits it through the acquirer's system to CUP; CUP forwards the request to the issuer. Upon receipt, the issuer authenticates the cardholder and, if approved, authorizes the payment and debits the cardholder's account. The authorization response is returned via CUP to the acquirer, which notifies the merchant of approval and confirms the transaction. The merchant then issues a receipt for the cardholder's signature (in signature-based settings). The advent of QR-code payments altered only the front-end capture of the payment instruction—from card swiping or inserting on a POS terminal to scanning a code—while the subsequent routing, authorization, and clearing logic in the acquiring chain remains essentially unchanged.

Recent magnitudes reflect the scale of this infrastructure. In 2024, banks processed 3576.29 billion non-cash payments totaling RMB 5443.29 trillion; within electronic channels, mobile payments were 2,109.80 billion—about 70% by count. Non-bank payment institutions handled 1.34 trillion network payments worth RMB 331.68 trillion.

[4] In China, the interbank switching and clearing institution generally refers to UnionPay due to its pivotal role in the domestic payment infrastructure. Established in 2002, UnionPay was created to facilitate the interconnection and interoperability of domestic bank card networks. It serves as the core platform for processing transactions between different banks, enabling seamless card payments and fund transfers across the banking system.

[5] The presence of a third-party payment platform in the payment acquisition business process is not absolutely necessary. However, as Figure 1 shows, it is highly valuable in many scenarios in China. Third-party platforms like Alipay and WeChat Pay enhance payment convenience through mobile and QR code payments. They also offer a wider range of payment options, including e-wallets, which can support both domestic and cross-border transactions. These platforms often have lower operational costs and fees, making them attractive to small and medium-sized merchants.

CUP's interbank card-switch processed 334.64 billion transactions, underscoring card-acquiring throughput. On the acceptance side, regulators reported 34.659 million networked card-accepting merchants and 43.043 million POS terminals by Q3 2023, reflecting broad coverage for both POS- and QR-initiated payments[6].

2.3 Related Literature and Hypothesis Development

Environmental Conditions and Economic Behavior

A large literature shows that environmental conditions shape behavior. Psychology and neuroscience document that weather and pollution affect mood, cognition, and neural processes(Allen et al., 2017; Block & Calderón-Garcidueñas, 2009; Crüts et al., 2008). Early laboratory evidence links weather-induced sentiment to decision-making (Cunningham, 1979; Schwarz, 2001), while exposure to diesel exhaust or particulate matter disrupts brain activity and impairs cognitive functioning. Studies document that exposure increases unethical conduct and crime(Berman et al., 2019; Bondy et al., 2020), distorts investment decisions through behavioral bias (Huang et al., 2020; Li et al., 2021).

Air quality, often proxied by particulate concentration or AQI, has been directly linked to both physical and psychological outcomes. Reviews synthesize these "non-health" effects of pollution, including impacts on cognition, social behavior, and markets(Aguilar-Gomez et al., 2022). Epidemiological evidence links pollution to higher respiratory and cardiovascular risks (Beatty & Shimshack, 2014; Pope, 2000; F. He et al., 2011), while psychological studies associate poor air quality with anxiety, depression, and fatigue (Lercher et al., 1995; Lim et al., 2012; Power et al., 2015). Sustained exposure reduces life expectancy (Y. Chen et al., 2013), impairs child development and school attendance (Currie et al., 2009), and increases dementia incidence (Bishop et al., 2023).

Beyond health, pollution reduces labor supply and productivity and raises unethical behavior and crime. Particulate matter lowers output across agriculture, manufacturing, and services (T. Chang et al., 2016; T. Y. Chang et al., 2019a; Fu et al., 2021； Hanna

[6] "Overall Situation of the Payment System Operation in 2024", released by the People's Bank of China. See https://www.cncc.cn/ywfw/tjsj/202508/t20250804_1597.html/.

& Oliva, 2015; J. He et al., 2019) , while wildfire smoke and urban smog depress labor supply, wages, and employment (Borgschulte et al., 2024). Pollution is also linked to higher unethical behaviors and crime (Berman et al., 2019; Bondy et al., 2020; J. G. Lu et al., 2018). These findings underscore that pollution imposes real economic costs.

In finance, pollution-related research explains variation in investor trading, returns, and cycles(Hirshleifer & Shumway, 2003; Kamstra et al., 2003; Meyer & Pagel, 2024; Saunders, 2016) , analyst forecasts (Dong et al., 2021), and household spending(Agarwal et al., 2020). Poor air quality reduces rationality in strategic decisions (Kunn et al., 2023; Chew et al., 2021) and raises missed repayments on haze days (Li et al., 2025), indicating that pollution acts as both a psychological and financial friction in decision-making.

A parallel literature examines reallocation at the consumption margin. In India, higher PM2.5 shifts food budgets toward healthier substitutes (Agarwal et al., 2025b). In China, pollution reduces dine-in activity but increases delivery(Li et al., 2025a) and online shopping (Tian et al., 2025). Korean evidence shows both contraction in overall retail sales (Jingyi, 2023) and substitution toward hedonic purchases as compensatory consumption (Kim & Trusov, 2025a) Collectively, these studies imply changes in channel choice, shopping frequency, and expenditure composition. Yet we still know little about how pollution affects merchant-level offline cashless POS activity, a gap that matters as cashless payments diffuse rapidly.

More recently, household-level studies have highlighted adaptive reallocation in spending patterns. In India, higher PM2.5 reduces unhealthy food spending but increases healthy food purchases, suggesting preventive health behavior. In China, pollution reduces in-person dining but raises food-delivery orders, while other evidence shows stronger demand for online consumption under polluted conditions. South Korean evidence reveals both contractionary effects on retail sales(Kang et al., 2019) and substitution toward hedonic purchases(Kim & Trusov, 2025b). Collectively, these studies suggest that pollution alters not only productivity and health outcomes but also consumer channel choice, shopping frequency, and expenditure composition. Despite

this rich evidence, little is known about how pollution affects merchant-level transaction activity, particularly in the context of the rapid diffusion of offline cashless Spending. Aforesaid studies suggest that pollution alters not only health and productivity but also consumer channel choice, shopping frequency, and expenditure composition. Yet little is known about how pollution affects merchant-level transaction activity, particularly in the context of the rapid diffusion of offline cashless payments.

Cashless Payment Adoption and Consumption Theory

Research on cashless payment adoption highlights both psychological and contextual drivers. Koay & Ang (2024) find that performance expectancy, effort expectancy, social influence, habit, and perceived privacy protection significantly influence adoption intentions, whereas facilitating conditions, hedonic motivation, and perceived privacy risk do not. Ashrafi & Easmin (2023) show that for digital natives, QR code payment adoption is mainly driven by perceived value and trust, moderated by technology readiness and innovation resistance. In Bangladesh, Shah Alam et al. (2024) document that Generation Y and Z adopt QR code payments primarily due to effort and performance expectations, as well as social norms, which in turn shape satisfaction and willingness to use.

From a broader consumption perspective, classical theories—such as the absolute income hypothesis, relative income hypothesis, life-cycle hypothesis, and permanent income hypothesis (Cooper & Keynes, 1997; Turvey & Duesenberry, 1950). —focus mainly on income and consumer psychology, neglecting distributional environments. Marx emphasized the role of the circulation and distribution network in shaping consumption. Recent empirical evidence supports this view: H. Chen et al. (2023) find that China's Singles Day boosts not only online spending but also offline card spending

Mobile payment (MP) research has evolved from theoretical foundations toward user-oriented applications (Shiau et al., 2025). Mobile payments, defined as financial transactions conducted via personal devices, have become widely popular due to convenience and simplicity (Liu & Dewitte, 2021; V et al., 2024). In 2024, global

mobile-money transaction values reached $1.68 trillion, a 16% year-on-year increase[7]. Liu & Dewitte (2021) show that the traditional credit card "spending effect" has weakened over time and does not consistently extend to mobile payments, with only limited evidence that mobile payments raise basket value relative to cash.

Earlier research emphasized usage scale and scenario rather than pure technological advantage. Chou et al. (2004) demonstrate that despite stored-value cards' better performance, credit cards dominate online commerce due to broader user bases and network effects. More recently, the COVID-19 pandemic accelerated QR code research, focusing on adoption, privacy, and retail or supply chain applications (Pratas & Oliveira, 2023). Using data on half a million Chinese firms, Beck et al. (2022) show that QR code payments generate digital footprints that ease access to big tech and bank credit while boosting sales, especially during COVID-19, thus helping micro firms build credit history. Similarly, Tu et al. (2022) find that during COVID-19, perceived severity and social influence strengthened perceptions of QR code payments' benefits, increasing adoption intentions.

Two major literature reviews trace the field's development (Dahlberg et al. 2008b) reviewed mobile payment studies from 1999–2006, noting that most work concentrated on consumer adoption and technology, with limited coverage of other topics. Nearly a decade later, Dahlberg et al. (2015) report that the field remained focused on similar themes, with little knowledge accumulation and few new perspectives. More recently, Ha et al. (2024) provide a systematic review of mobile payment research, identifying progress but also calling for greater diversity in topics and approaches.

This institutional and empirical context motivates our focus on merchant-level cashless transaction data in China. The ubiquity of POS and QR-code acquiring ensures that shifts in consumer behavior—whether substitution toward nearby merchants, reallocation across product categories, or avoidance of physical shopping—are directly visible in transaction-level records. A notable exception is Agarwal et al. (2021), who show that pollution shifts household food expenditure patterns in India using

[7] https://www.gsma.com/sotir/wp-content/uploads/2025/04/The-State-of-the-Industry-Report-2025_English.pdf

transaction-level customer data. Yet their setting combines online and offline transactions and focuses narrowly on food consumption at the individual level. By contrast, our study examines merchant-level offline cashless transactions across all product categories, using a unique dataset from the People's Bank of China that records transaction amount, frequency, and customer counts. This perspective emphasizes how pollution shocks are transmitted to the real economy through retail merchants rather than solely through individual consumers.

Hypothesis Development

Given the evidence that air pollution alters mood, productivity, and behavioral patterns, we expect that pollution will also reshape merchant-level cashless transaction outcomes. Specifically, we hypothesize that higher pollution levels increase offline cashless transaction activity on the extensive margin (number of transactions and customers), as consumers substitute toward nearby or indoor purchases, while average spending per transaction or per customer declines due to smaller basket sizes.

Theoretical considerations suggest that the relationship between air pollution and offline cashless spending may not be unidirectional. On the one hand, deteriorating air quality can increase cashless transactions. Poor air quality often discourages long-distance travel or outdoor activities, pushing consumers toward nearby indoor retail outlets. In such settings, individuals may still meet their daily consumption needs but rely more heavily on quick, local, and convenient purchases. This mechanism implies that merchants can experience more customers and transactions, particularly in sectors such as food, beverage, and retail, where pollution-induced substitution toward indoor consumption is most likely.

On the other hand, air pollution may also decrease cashless transactions. Heightened pollution can worsen health conditions, reduce labor productivity, and lower overall willingness to go out, thereby dampening demand for in-person shopping. Severe or persistent pollution episodes may keep consumers at home, reduce discretionary consumption, and shift some purchases toward online channels. Under

this channel, merchants may see lower transaction volumes and fewer customers.

Thus, theory allows for both positive and negative effects: pollution could reallocate demand toward more numerous small transactions in certain settings, but could also suppress overall offline activity when avoidance dominates.

Building on these insights, we hypothesize that air pollution reshapes merchant-level cashless outcomes along both the extensive and intensive margins. On the extensive margin, poor air quality may increase the number of transactions and distinct customers as individuals substitute toward nearby or indoor outlets. On the intensive margin, however, average spending per transaction or per customer may decline due to smaller basket sizes. Severe or persistent episodes could also suppress discretionary shopping, shifting demand online, and reducing offline activity. The net effect is thus theoretically ambiguous and requires empirical assessment.

H1: Air pollution affects offline cashless spending, either by increasing or decreasing it.

H2: Pollution increases offline cashless spending primarily via the extensive margin (transactions and customers), while reducing average spending per transaction or per customer.

3. Data and Empirical Strategy

3.1 Data

We obtain an administrative dataset from a leading bank-card acquirer that includes identifier-masked payment records in offline brick-and-mortar merchants. The representative sampling design can be summed up in two steps. First, from all merchants in normal operation as of the end of June 2023, we identify those that already existed on 1 January 2019, and recorded non-zero transactions in every month of 2019. Second, from this universe, we then randomly sample 150,000 merchants (if the universe is smaller, we take the full set). The raw data comprises 121,884 offline merchants and 5,033,307 merchant-month observations. Following Agarwal et al. (2024), we discuss the further filter procedure in greater detail in Appendix A1[8]. After

[8] For example, we drop the merchant-month with missing city or province information, or non-consumption scenarios, or the RMB value of cashless transactions is non-positive.

matching with data on air pollution and weather conditions (as discussed below), the monthly-level proprietary data covers transactions of 118,698 distinct merchants from 332 cities of 31 provinces in China for the period from January 2019 through June 2023.[9] Specifically, for each observation, our acquirer data contains three types of information. The monthly statement on aggregate business performance includes the total amount, transaction number, and number of customers of cashless payments. We also identify the detailed payment structure at the merchant level according to the proportion of deals by card-swiping or code-scanning, existing or new customers. Besides, we can observe the users' demographic information, including merchant access time, industry classification code, main category description, registered address, and business type (self-employed or enterprise).

We use satellite-based monthly Air Quality Index data from 2019 to 2023 provided by China Meteorological Data Service Centre (CMDSC), following S. Chen et al. (2022) and Huang et al. (2020a)[10]. Air Quality Index (AQI) is a dimensionless composite indicator that quantifies ambient air quality. Larger numerical values indicate more severe pollution and, correspondingly, greater risks to human health. Computation and grading follow the revised Ambient Air Quality Standard (GB 3095-2012). The index aggregates six criteria pollutants: fine particulate matter ($PM_{2.5}$), inhalable particulate matter (PM_{10}), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3), and carbon monoxide (CO). AQI readings are released hourly, daily, and real-time bulletins are issued by environmental protection authorities at the prefecture level and above, or by their authorized monitoring stations. We match each merchant to the corresponding AQI value in the same city. This is based on the assumption that the air pollution exposure experienced by customers who have visited a specific merchant is similar to the city's average level. The weather dataset is also sourced from CMDSC, which provides prefecture-city records at the monitoring station level. We extract city

[9] Figure 2 illustrates the spatial distribution and intensity of our offline cashless payment dataset across Chinese cities from January 2019 to June 2023. Panel A depicts cities based on the number of unique merchant establishments in our sample. Panel B illustrates cities according to the average monthly cashless sales for a typical merchant. Panel C shades cities by the average monthly aggregate cashless sales at the city level.

[10] A concrete example of the data source can be seen through this website: https://data.cma.cn/search/uSearch.html?keywords=%E9%A3%8E%E9%80%9F)

information and monthly weather conditions, including air temperature, precipitation, relative humidity, wind speed, and sunshine duration. We then match each merchant to the corresponding weather information in the same city by averaging the daily readings across multiple stations.

Table 1 presents summary statistics of the main characteristics of the monthly merchant-level outcomes, air pollution proxies, and environmental covariates in our sample. Panel A shows that the (logged) sales amount, transaction numbers, and customer headcounts display sizable dispersion across merchants and months, with stable central tendencies, which is a commonly used instrument for merchant behavior in the existing literature (Arango et al., 2015; Bounie & Camara, 2020). "Old" and "New" components mirror the aggregates but with even larger variation, consistent with lumpy entry of new shoppers and episodic campaigns that shift composition within a month. In terms of composition ratios, the mean value of *New Customer Ratio* and *New Sales Ratio* is 2.30 and 2.05, signaling frequent episodes in which influxes of new users drive volumes but with smaller average baskets relative to incumbents, consistent with the well-documented empirical evidence on cashless payment (Agarwal et al., 2025b; S. Q. Lu & Pauwels, 2024). Panel B reports the distribution of air-quality and weather controls used throughout (AQI, $PM_{2.5}$ & PM_{10}, temperature, precipitation, humidity, wind speed, sunshine), as well as thermal-inversion and geographic variables employed for identification. The monthly average AQI in our sample is 71.27, and the standard deviation is 24.74[11]. The monthly average city-day has a temperature of 16.38℃, a relative humidity of 0.71%, a precipitation of 0.92 millimeters, a wind speed of 2.48 meters/second, and 5.12 sunshine hours. Panel C splits the sample at the median AQI and documents statistically higher means for sales, counts, and customers in the high-AQI months, with differences significant at conventional levels. These patterns foreshadow the positive associations estimated below.

[11] When the AQI is 100 or below, the air quality is generally considered to be good, posing little or no risk to most individuals. Conversely, an AQI above 150 indicates moderate air pollution, which can have noticeable negative impacts on health, especially for sensitive populations. Hence, we construct three continuous variables, one for the healthy category, and the other two for the unhealthy categories, which denote the share of days in three AQI bins within the month ($50 < AQI < 101$, $100 < AQI < 151$, $150 < AQI$).

3.2 Empirical Strategy

We run fixed-effect panel regressions to test the relation between contemporaneous exposure to air pollution and offline payment behavior. The main regression takes the following form:

$$Y_{ict} = \beta_0 + \beta_1 AQI_{ict} + \beta_2 X_{ict} + \gamma_i + \delta_t + \epsilon_{ict} \quad (1)$$

Where i denotes the individual merchant, c the located city, and m the year-month. Y_{ict} is a measure of offline payment behavior at the merchant level, such as the sales amount, number, and customer count, and we use its logarithmic form as the dependent variable. We also examine alternative outcomes, including the amount per customer, amount per transaction, transaction per customer of cashless transactions, and those for existing and new customers. More details on the dependent variable definition can be seen in Appendix A2. We measure air pollution using AQI following T. Y. Chang et al. (2019b), and use $PM_{2.5}$ and PM_{10} in the robustness checks. AQI_{ict} denotes the average daily air quality index of city c faced by merchant i in month t. For ease of interpretation, we scale the coefficients and standard errors of AQI by a factor of 1,000 following Dong et al. (2021). X_{ict} captures a set of control variables, which include average daily weather conditions of city c in month t, including temperature, precipitation, relative humidity, wind speed, sunshine duration, and their square terms to capture nonlinear effects (S. Chen et al., 2022; Deschenes et al., 2020). Merchant fixed effects γ_i controls for time-invariant merchant features. Year-month fixed effects δ_t capture aggregate temporal purchasing trend. We also include province–year–month fixed effects in the robustness tests to control for potential regional economic shocks, seasonal variation, and geographic disparity. Standard errors are one-way clustered at the merchant level. We provide results without winsorization for the merchant-month cashless payment measures and environmental variables following Deschenes et al. (2020); however, the results remain with winsorization.

As air pollution is correlated with both human activities and offline payment behavior, the fixed effect model specified in Equation (1) may generate biased estimates and result in an endogeneity problem. In other words, when the sales amount of a merchant significantly increases with offline visit frequency and customer base, the air

pollution can reach a higher level at the same time. To address this identification issue, we employ two approaches: the instrumental variable method and the regression discontinuity design (RDD).

First, we consider an instrumental variables strategy, which is likely to minimise bias from both endogeneity and classical measurement error. We use employ thermal inversions T_{ict} as an instrumental variable for air pollution[12]. The instrument satisfies the relevance condition because inversions trap pollutants near the surface, leading to exogenous increases in local pollution concentrations. It also plausibly meets the exclusion restriction: the occurrence of inversions is determined by atmospheric dynamics rather than economic or health-related activities, and thus affects health outcomes only through its impact on pollution exposure. Leveraging this exogenous meteorological variation, we identify the causal effect of air pollution on individual health outcomes.

The thermal inversions data is obtained from MERRA-2[13]. We determine the existence of a thermal inversion if the temperature in the second layer (320 m) is higher than that of the first layer (110 m) for each 6-h period, and then aggregate the number of inversions to the one-month exposure window. At the end, we calculate the actual number of thermal inversion days per month, as well as the proportion of thermal inversion occurrences based on a 6-hour window over the month. We perform 2SLS estimation with the following specification:

$$\text{1st stage: } AQI_{ict} = \alpha_0 + \alpha_1 T_{ict} + \alpha_2 X_{ict} + \gamma_i + \delta_t + u_{ict} \quad (2)$$

$$\text{2nd stage: } Y_{ict} = \beta_0 + \beta_1 \widehat{AQI_{ict}} + \beta_2 X_{ict} + \gamma_i + \delta_t + \epsilon_{ict} \quad (3)$$

In the first stage, we estimate the relationship between the thermal inversion ratio in a month and monthly average AQI levels. In the second stage, we examine how AQI levels, instrumented by the first stage estimates, affect offline purchasing behavior.

Second, we conduct a geographic RDD centered on the Qinling-Huai River

[12] The formation of thermal inversions is a complex meteorological phenomenon and is typically independent of economic activities (Deschenes et al., 2020). Hence, *Thermal inversions* variable is a widely used proxy for air pollution in the economic and finance literature (Arceo et al., 2016; Fu et al., 2021).

[13] The dataset provides 6-hourly air temperatures since 1980 on 50*60 km grids across 42 vertical layers. Grids are mapped to cities using the same spatial weights as for the pollution data. An inversion is flagged when temperature at 320 m exceeds that at 110 m in a given 6-hour interval.

boundary, the conventional demarcation between northern and southern China, to further probe causality between air pollution and offline payment behavior. Historically, jurisdictions north of this line operate centralized winter heating, whereas those souths do not. Because centralized heating relies heavily on coal combustion, it generates persistently higher ambient pollution immediately north of the boundary, creating an exogenous discontinuity in air quality (Y. Chen et al., 2013; Ebenstein et al., 2017). Considering that cities located in close proximity on either side are otherwise comparable in climate, geography, and socio-economic conditions, the salient jump in pollution at the cutoff can therefore be used to identify the local causal effect of air quality on offline payment. We perform RDD test with the following specification:

$$Y_{ict} = \theta_0 + \theta_1 \, North_c + \alpha_1 \, k(L_c) + \alpha_2 \, X_{ict} + \delta_t + v_{ict} \quad (4)$$

Where $North_c$ denotes a dummy variable that is equal to 1 if city c is north of the Qinling-Huai River line, and 0 if south of the Qinling-Huai River line. For the whole sample, 149 cities are north of the Huai River line, and 165 cities are south of the line. L_c denotes the distance of city c to the Huai River line. $k(L_c)$ denotes second-order polynomial of L_c. To enhance the comparability of cities on both sides of the Huai River line, the sample is restricted to cities located within a threshold of 300 km from this demarcation boundary[14].

4. Empirical Results

This section presents our main findings. We first estimate panel OLS regression linking air pollution proxied by AQI to offline cashless spending. To address endogeneity, we then strengthen identification with two strategies, IV based on thermal inversions and a geographic RDD around the Qinling-Huai River heating boundary. Next, we analyze unit-level margins to distinguish frequency from ticket size. We also split by customer type, contrasting existing versus new customers and documenting extensive-margin indicators and composition ratio. Furthermore, we examine the pollution dynamics within the month and perform a series of robustness checks. Finally, we explore heterogeneous effects across industries and product types, including broad

[14] We also use the threshold of 600 km in sensitivity analyses as alternative specification and our results are robust to this adjustment.

groups, finer industry codes, durables vs. non-durables, and goods vs. services.

4.1 Baseline results

Table 2 reports the baseline results. Column (1) regresses log *Sales* on monthly city-level *AQI* with merchant and year-month fixed effects and the full set of weather controls. OLS estimates show that a 10-point increase in *AQI* is associated with 1.056% increase in cashless sales. Column (2) replaces the dependent variable with log *Count* and yields a similarly sized, highly significant effect (1.003%), implying that deteriorating air quality is associated with more transactions. Column (3) uses log *Customer* and again finds a positive coefficient of roughly the same magnitude (0.993%), showing that pollution expands participation by increasing the number of unique customers. Standard errors are clustered at the merchant level throughout, and the alignment across columns points to a consistent consequence: higher air pollution unexpectedly promotes offline purchasing behavior.

In Table 2, Columns (1)-(3) show that the weather controls, which are correlated with air quality, exhibit intuitive signs and curvatures. Notably, most of the weather variables have a significant impact on offline payment. The temperature and its quadratic terms trace a concave (inverted-U) relation: cashless activity rises in mild conditions but falls at heat or cold extremes, consistent with comfort and mobility costs. Precipitation is negative (more rain suppresses trips), while wind speed tends to be weakly negative, reflecting discomfort and short-run mobility frictions. Sunshine duration loads positively, in line with higher footfall on brighter days. Relative humidity effects are small or mixed once temperature and precipitation are controlled. Economically, these patterns indicate that weather shifts the short-run cost of visiting nearby merchants, affecting both visit frequency and participation.

4.2 Endogeneity issue

Nevertheless, the OLS estimates could be skewed by unobserved variables such as localized economic development and individual mobility, which impact both air pollution levels and offline payment patterns. To mitigate this issue, we adopt a two-pronged approach: First, we utilize thermal inversions as an instrumental variable for

air pollution to conduct a two-stage least squares (2SLS) estimation. Second, we implement a geographic RDD centered on the Qinling-Huai River boundary.

4.2.1 2SLS method: Thermal inversions as IV

As shown in Table 3, Column (1) presents the first stage of Equation (2), where thermal inversions strongly predict city-month AQI (KP-F far above conventional thresholds), thus validating the relevance of the instrument. Columns (2)-(4) then estimate Equation (3), replacing OLS with AQI instrumented by inversions[15]. The second-stage coefficients in Panel A and Panel B are both positive and larger than those obtained from OLS across log *Sales*, *Count*, and *Customer*. This indicates attenuation in the baseline and confirms a causal effect of air pollution on offline cashless spending. Given that the coefficients are multiplied by 1000 in the tables, we take Panel A as an example. Column (2) implies that a 10-point increase in *AQI* leads to a 4.30% increase in sales amount, a 4.82% increase in count number, and a 5.08% increase in customer visits. Economically, the 2SLS results reinforce the interpretation that exogenous deterioration in air quality shifts consumers toward more frequent visits and broader participation.

4.2.2 RDD method: Qinling-Huai River setting

Based on Equation (4), Table 4 Column (1) shows a discrete jump in AQI at the boundary (north vs. south), establishing the policy-induced first stage. Columns (2)-(4) report reduced-form discontinuities for log *Sales*, *Count*, and *Customer* in local linear regressions with triangular kernels. Clearly, estimates are positive and significant in both the <=300 km and <=600 km bandwidths. Using the exact log-to-percent mapping to interpret magnitudes, a window of <=300 km indicates that cashless sales at the cutoff are approximately 28.2% higher. This is accompanied by substantial increases in the count of transactions (138.7%) and the number of customers (141.1%). Taken together, the RDD evidence shows that the exogenous heating regime raises pollution and, in turn, produces discrete increases in sales, transaction frequency, and

[15] In Table 3, Panel A utilizes IV1, which is measured by the number of days with thermal inversions in the month, while Panel B employs IV2, measured by the ratio of thermal inversion occurrences based on 6-hour periods over the month.

participation at the boundary, reinforcing the causal interpretation developed in the IV analysis.

4.3 Further tests

4.3.1 Unit-level margins analysis

Table 5 examines how air pollution affects unit-level margins, including log *Sales per Count* (average ticket), log *Sales per Customer*, and log *Count per Customer*. In Panel A, Columns (1)-(3) report OLS estimates with the same fixed effects and weather controls as the baseline results, which suggest that effects are small and often statistically weak. Next, we use the 2SLS specifications to overcome the endogeneity problem in Panel B-C and find that instrument AQI with thermal inversions yield negative and significant coefficients for *Sales per Count* and *Sales per Customer*, while *Count per Customer* is near zero. Concretely, using IV1, a 10-point increase in *AQI* leads to 1.104% reduction in *Sales per Count* and 1.419% reduction in *Sales per Customer*; using IV2, the corresponding effects are decreasing with 2.931% and 3.213%. This result may reflect that exogenous pollution compresses basket size (per transaction and per customer) while leaving per-customer frequency little changed, which reinforces that the overall gains in totals come from more transactions and broader participation, not bigger tickets.

4.3.2 Existing vs. new customer

Table 6 reports whether the overall effects differ for existing (old) versus new customers and how they shape the extensive margin and composition. For existing customers in Panel A, a 10-point increase in *AQI* is associate with 1.397% rise in log *Sales*, with unit-level margins like *Sales per Count* also expanding. For new customers in Panel B, the totals are also increasing for log *Sales* but baskets are flat and insignificant for *Sales per Count*. On the extensive margin in Panel C, *AQI* raises the probability a merchant-month has any new customers *If New* and that *New* > *Old* (by number) by 2.0% and 2.5% based on Poisson model, respectively. In composition, Panel D suggests that the new-customer share of customers rises by 26.2%, while the new-sales share reduces by 34.7% and the new-count share is 14.6% increase,

consistent with new users' smaller baskets. Overall, pollution pulls in marginal users and expands participation, paired with unit-level declines in Table 5, which points to more, smaller purchases as the operative channel.

4.3.3 Within month variation of AQI

Table 7 replaces the monthly mean with within-month volatility. In Panel A, a 10-percentage-point increase in the share of days with 50 < AQI < 101 is associated with 0.50% rise in log *Sales*; moving to 100 < AQI < 151 yields 1.80% increase; for 150 < AQI, the positive effect is 1.68%. It suggests a clear monotone pattern relative to the omitted AQI < 51 bin. In Panel B, a one-unit increase in the *AQI Range* (i.e., max minus min) is linked to 0.229% rise in log *Sales*. In Panel C, a one-unit increase in the within-month AQI standard deviation predicts a 1.205% increase in log *Sales*. These magnitudes show that pollution episodes, their frequency and intensity, matter above and beyond the monthly average, nudging consumers toward more frequent, smaller transactions and wider participation when bad-air days cluster.

4.4 Robustness tests

Furthermore, Tables 8 to 10 provide robustness checks that confirm the robustness of our main findings against potential biases arising from model specification, sample construction, or pollution measurement. Specifically, Table 8 demonstrates the robustness of our results to alternative fixed effects and model settings. Table 9 validates the stability of our findings across different sample definitions. Lastly, Table 10 corroborates the consistency of our results by reproducing the effects using $PM_{2.5}$ and PM_{10} concentrations as alternative pollution metrics, in lieu of the AQI.

Table 8 presents whether the baseline link between air pollution and offline cashless purchasing behavior survives tougher specifications and settings. Panel A suggests that dropping weather controls leaves the coefficients on log *Sales*, *Count*, and *Customer* essentially unchanged. In Panel B, we add province-year-month fixed effects to tighten identification against spatially correlated shocks, with point estimates remaining positive and close to the baseline. In Panel C, inference is stable under two-way clustering (merchant and year-month), with significance levels unchanged relative

to the baseline merchant-clustered estimates. The results indicate that the observed increases in sales, transaction volume, and the number of unique customers during periods of deteriorating air quality are not attributable to confounding factors such as seasonal and weather conditions, spatial policy interventions, or clustering choices.

Table 9 examines whether sample composition drives the key findings. In Panel A, the analysis restricted to long-tenure merchants reveals positive and precisely estimated effects that are consistent with the baseline findings. In Panel B, moving to a balanced panel results in larger coefficients, which are indicative of higher elasticities among merchants who remain continuously active. This finding is accompanied by larger standard errors, attributable to the reduced sample size. Despite these adjustments, the results maintain robustness in both sign and significance. Panel C focuses on months with both new and existing customers that produces the same qualitative pattern as before. Economically, the consistency of the results across these various constructions indicates that the findings are not contingent upon merchant entry or exit, intermittent activity, or unbalanced sample coverage. Rather, the observed pollution response is reflective of behavior within established customer-merchant relationships. Specifically, consumers increase their visit frequency, and a broader base of customers participates, even when the sample is restricted to exclude short-lived or irregularly active merchants.

Table 10 replaces the composite AQI with monthly mean $PM_{2.5}$ and PM_{10} (Jans et al., 2018; Agarwal et al., 2025). For both pollutants in Panel A and Panel B, the coefficients on log *Sales*, *Count*, and *Customer* remain positive and significant, with sizes comparable to the AQI results. The monotonic relationship observed across different pollutants, where higher concentrations consistently correspond to larger effects, corroborates that our findings are not merely an artifact of the AQI aggregation method. Furthermore, the robustness of our results to measures based on particulate matter (PM) concentrations bolsters the causal interpretation that deteriorations in ambient particulate pollution drive offline merchant behavior towards more frequent transactions and broader participation. This aligns with the above hypothesis we have proposed, underscoring the significance of these behavioral shifts in response to

pollution.

4.5 Heterogeneous tests

Table 11 investigates heterogeneity in the AQI effect on offline cashless spending, asking which sectors and product types, across broad groups, finer industries, durables vs. non-durables, and goods vs. services, exhibit the strongest pollution-induced shifts in sales, transactions, and unique customers.

Panel A (broad merchant groups) examines whether the AQI effect varies across coarse industry buckets. We find consistently positive coefficients on log *Sales*, *Count*, and *Customer*, with *Gas Stations & Supermarkets* showing the strongest elasticities, *General* and *Real Estate & Automobiles* in the middle, and *Hotels, Catering & Entertainment* the weakest. These patterns suggest that categories tied to frequent, local, necessity purchases expand most in polluted months, whereas lumpy, lingering, deferrable purchases respond little. The evidence aligns with a short-run reallocation toward nearby, necessity-oriented activity rather than big-ticket buying.

Panel B (finer industry granularity) sharpens this picture by moving to specific merchant classes. The largest, most precisely estimated responses concentrate in *Food & Beverage*, *Commercial Services*, and *Specialized Retail of Food, Beverages & Tobacco*, with *Comprehensive Retail* also sizable. By contrast, *Specialized Retail of Hardware, Furniture & Interior Decoration* and *Specialized Retail of Automobiles, Motorcycles, Fuel & Part* display comparatively muted effects. From an economic standpoint, as air quality declines, consumers tend to shift their preferences towards immediate and local transactions, such as meals, basic services, and essential daily goods, while deferring or reducing planned purchases of durable goods. This pattern of behavior underscores the significance of a convenience channel, where the frequency and participation margins play a dominant role.

Panel C (durables vs. non-durables) formalizes this contrast: coefficients for non-durables are materially larger across sales, transactions, and unique customers than for durables. Since the outcomes are in logs, these estimates imply that a given pollution shock is absorbed via more numerous, smaller, and more immediate purchases of

essentials, rather than by upsizing infrequent durable purchases. This pattern is exactly what we would expect if consumers respond to bad-air days by minimizing time and distance, fitting in short errands, while deferring major items.

Panel D (goods vs. services) contrasts goods with services to see where the AQI effect is stronger. Both categories show positive responses in log *Sales*, *Count*, and *Customer*, but the clearest separation appears on *Sales*: one category exhibits larger sales elasticities than the other, whereas the coefficients on *Count* and *Customer* are comparable or mixed across the two groups. Economically speaking, this pattern indicates that pollution does not uniformly benefit one sector through increased visit frequency or expanded participation. Instead, the difference in revenue margins distinguishes the two sectors, which is consistent with the differences in average transaction sizes under poor air conditions (as evidenced by the smaller transaction baskets documented in the unit-level results).

5. Conclusion

This paper investigates how air pollution shapes merchant-level offline cashless transactions in China, leveraging a unique nationwide dataset and multiple identification strategies. Our analysis shows that deteriorating air quality increases overall transaction volume, sales, and customer counts, with effects strengthened when instrumented by thermal inversions and corroborated by the Huai River heating boundary. Importantly, these increases occur primarily on the extensive margin: pollution attracts newer and repeat customers but reduces average spending per transaction and per customer, implying a reallocation of consumption into more numerous yet smaller purchases. The effects are strongest in consumer-facing industries such as food, beverage, and retail, and are particularly evident among stable, long-established merchants.

These findings have several implications. First, they highlight a novel behavioral channel through which environmental conditions affect local commerce, emphasizing that pollution alters not only household health or productivity but also the way

transactions are distributed across merchants. Second, the results underscore the role of digital payment infrastructure in mediating how environmental shocks are transmitted to the economy. The ubiquity of POS and QR-code systems in China allows even small shifts in consumer behavior to be captured in transaction-level data, offering valuable lessons for other countries experiencing both rapid digitalization and environmental stress. Our findings suggest that in economies where digital payment systems are mature, pollution shocks may similarly reallocate spending across merchants and sectors, while in less digitized contexts such effects may remain hidden or manifest differently.

At the same time, the study has limitations that open avenues for further research. Our data do not directly observe substitution between offline and online channels, nor do they capture changes in household welfare or long-run consumption smoothing. Moreover, while we document heterogeneity across industries and merchant characteristics, more granular analyses—such as neighborhood-level variation or consumer demographics—remain beyond the current scope. Future research could explore cross-country comparisons, examine interactions between pollution shocks and public health or transportation policies, and investigate whether similar mechanisms operate in emerging economies with growing but less comprehensive payment infrastructures. Overall, by shifting the focus from consumers to merchants, our study enriches the literature on environmental economics, digital finance, and retail operations, and provides new evidence on how pollution shocks are transmitted into the offline economy in the age of cashless payments.

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Table 1. Summary Statistics

This table presents summary statistics for offline merchant purchasing outcomes at the merchant-year-month level (Panel A), as well as a series of environmental variables like air quality and weather controls (Panel B) over January 2019-June 2023. Panel C splits mean differences across above-median and below-median groups. All payment variables are in logs unless otherwise indicated. See Appendix Table A2 for variable definitions.

Panel A: Dependent Variables on Offline Payment Behavior (Merchant-year-month)

Variable	N	Mean	SD	Min	Median	Max
Sales	4,774,345	9.88	2.66	0.01	10.07	33.50
Count	4,774,345	3.60	1.93	0.69	3.30	13.59
Customer	4,774,345	3.20	1.90	0.69	2.83	13.20
Sales Old	4,774,345	4.55	4.64	-4.61	4.16	33.50
Count Old	4,754,596	1.41	1.77	0.00	0.69	12.01
Customer Old	4,754,596	1.02	1.36	0.00	0.69	11.02
Sales New	4,773,557	9.40	3.17	-4.61	9.78	33.01
Count New	4,773,557	3.40	1.99	0.00	3.14	13.59
Customer New	4,773,557	3.10	1.95	0.00	2.77	13.20
If New	4,774,345	0.97	0.18	0.00	1.00	1.00
New > Old Num	4,774,345	0.93	0.26	0.00	1.00	1.00
New Customer Ratio	2,432,418	2.30	1.36	-4.63	2.30	12.24
New Sales Ratio	2,406,928	2.05	2.32	-21.69	1.97	25.72
New Count Ratio	2,432,418	1.85	1.50	-8.13	1.90	11.77
Sales per Count	4,774,345	6.38	2.23	-9.21	6.51	24.17
Sales per Customer	4,774,345	6.82	2.30	-8.43	6.91	24.39
Count per Customer	4,774,345	0.44	0.56	0.00	0.27	8.39
Sales per Count Old	2,574,288	5.99	2.28	-9.07	6.22	27.13
Sales per Customer Old	2,574,288	6.84	2.44	-6.68	7.00	28.66
Count per Customer Old	2,598,418	0.86	0.82	0.00	0.69	11.11
Sales per Count New	4,606,982	6.32	2.22	-8.78	6.40	24.17
Sales per Customer New	4,606,982	6.67	2.28	-6.40	6.71	24.39
Count per Customer New	4,608,345	0.35	0.45	0.00	0.22	7.54

Panel B: Variables on Air Pollution and Weather Controls (Merchant-year-month)

Variable	N	Mean	SD	Min	Median	Max
AQI	4,774,345	71.27	24.74	15.00	67.00	360.00
$PM_{2.5}$	4,774,345	34.78	20.59	3.00	29.00	257.00
PM_{10}	4,774,345	62.49	34.49	6.00	54.00	925.00
Temperature	4,774,345	16.38	9.44	-29.67	17.76	32.81
Precipitation	4,774,345	9.19	9.16	0.00	5.69	75.50
Humidity	4,774,345	7.12	1.30	1.81	7.41	9.38
WindSpeed	4,774,345	2.48	0.74	0.94	2.39	8.30

Sunshine	4,774,345	5.12	2.21	0.18	5.15	12.31
Thermal Inversion (IV1)	4,774,345	15.39	8.34	0.00	16.00	31.00
Thermal Inversion (IV2)	4,774,345	0.20	0.13	0.00	0.19	0.90
Location	4,765,053	-0.25	0.96	-1.00	-1.00	1.00

Panel C: Mean Test for High and Low AQI Group (Median as Benchmark)

	Mean		Difference
	Low AQI	High AQI	(p-value)
Sales	9.802	9.961	0.159***
			(0.000)
Count	3.588	3.614	0.026***
			(0.000)
Customer	3.200	3.208	0.008***
			(0.000)
Observations	2,405,195	2,369,150	4,774,345

Table 2. The Effect of Air Pollution on Offline Payment Behavior:

OLS Baseline Regressions

This table presents the estimates of the effect of air pollution proxied by AQI on offline payment behavior using OLS method, based on the estimation of Equation (1) in Section 4.1. The dependent variables are, respectively, the log of monthly cashless *Sales*, the log *Count* of transactions, and the log *Customer* visits at the merchant-year-month level. The key independent variable is the monthly average *AQI* at the city level. Weather controls include monthly average *Temperature*, *Precipitation*, *Humidity*, *Wind Speed* and *Sunshine*, as well as their squared terms, at the city level. Regressions also add on merchant fixed effects and year-month fixed effects. Standard errors are clustered at the merchant level. ***, **, and * denote significance at the 1%, 5%, and 10% levels. See Appendix Table A2 for detailed definitions.

	(1)	(2)	(3)
Dept. Var.=	Sales	Count	Customer
AQI	1.056***	1.003***	0.993***
	(0.055)	(0.036)	(0.034)
Temperature	0.008***	0.007***	0.007***
	(0.000)	(0.000)	(0.000)
Precipitation	-0.007***	-0.005***	-0.005***
	(0.000)	(0.000)	(0.000)
Humidity	0.027***	0.001	0.007*
	(0.006)	(0.004)	(0.004)
Wind Speed	0.120***	0.121***	0.111***
	(0.009)	(0.006)	(0.005)
Sunshine	-0.013***	-0.004***	-0.002
	(0.002)	(0.001)	(0.001)
Temperature^2	-0.000***	0.000	-0.000
	(0.000)	(0.000)	(0.000)
Precipitation^2	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Humidity^2	-0.001	0.001**	0.000
	(0.001)	(0.000)	(0.000)
Wind Speed^2	-0.019***	-0.019***	-0.017***
	(0.001)	(0.001)	(0.001)
Sunshine^2	0.001***	0.000***	0.000**
	(0.000)	(0.000)	(0.000)
Constant	9.440***	3.236***	2.824***
	(0.027)	(0.017)	(0.015)
Observations	4,774,345	4,774,345	4,774,345
Merchant FE	YES	YES	YES
Year-Month FE	YES	YES	YES
Adj. R-squared	0.704	0.782	0.811

Table 3. The Effect of Air Pollution on Offline Payment Behavior:

Two-Stage Least Squares (2SLS) Estimation

This table presents the estimates of the effect of air pollution proxied by AQI on offline payment behavior using 2SLS method as identification strategy, based on the estimation of Equation (2) and (3) in Section 4.1. Panel A and Panel B both instrument AQI with *Thermal Inversion* frequency (*IV1* and *IV2*) in Column (1). The dependent variables in Column (2)-(4) are the log of monthly cashless *Sales*, the log *Count* of transactions, and the log *Customer* visits at the merchant-year-month level. Weather controls include monthly average *Temperature*, *Precipitation*, *Humidity*, *Wind Speed* and *Sunshine*, as well as their squared terms, at the city level. Regressions also add on merchant fixed effects and year-month fixed effects. Standard errors are clustered at the merchant level. ***, **, and * denote significance at the 1%, 5%, and 10% levels. We also report the Kleibergen-Paap F-statistic (KP-F) for instrument relevance. See Appendix Table A2 for detailed definitions.

Panel A: IV1 Measured by Days with Thermal Inversion of the Month

	First Stage	Second Stage		
	(1)	(2)	(3)	(4)
	AQI	Sales	Count	Customer
Thermal Inversion (IV1)	0.174***			
	(0.003)			
AQI		4.300***	4.821***	5.079***
		(0.880)	(0.557)	(0.512)
Observations	4,774,345	4,774,345	4,774,345	4,774,345
Controls	YES	YES	YES	YES
Merchant FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
KP-F		2591		

Panel B: IV2 Measured by the Ratio of Thermal Inversion Times over the Month

	First Stage	Second Stage		
	(1)	(2)	(3)	(4)
	AQI	Sales	Count	Customer
Thermal Inversion (IV2)	7.904***			
	(0.254)			
AQI		5.222***	6.981***	7.130***
		(1.242)	(0.800)	(0.739)
Observations		4,774,345	4,774,345	4,774,345
Controls	YES	YES	YES	YES
Merchant FE		YES	YES	YES
Year-Month FE		YES	YES	YES
KP-F		965		

Table 4. The Effect of Air Pollution on Offline Payment Behavior:

Regression Discontinuity Design (RDD) Estimation

This table presents the estimates of the effect of air pollution on offline payment behavior using RDD method as identification strategy, based on the estimation of Equation (4) and (5) in Section 4.1. Panel A and Panel B both report local RDD estimates around the Qinling-Huai River Line, using the city's signed distance to the boundary (km)-normalized to zero at the cutoff-as the running variable. *North* equals 1 for cities north of the line (with centralized winter heating) and 0 otherwise. Column (1) presents the first-stage discontinuity in AQI at the boundary; Columns (2)-(4) report reduced-form discontinuities in merchant outcomes: the log of monthly cashless *Sales*, the log *Count* of transactions, and the log *Customer* visits at the merchant-year-month level. We estimate local linear regressions with a triangular kernel within two symmetric bandwidths (300 km; 600 km), include merchant fixed effects, year-month fixed effects, and the baseline weather controls (*Temperature*, *Precipitation*, *Humidity*, *Wind Speed* and *Sunshine*, as well as their squared terms). Standard errors are clustered at the merchant level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. See Appendix Table A2 for detailed definitions.

Panel A: Distance <= 300 km

	(1) AQI	(2) Sales	(3) Count	(4) Customer
North	16.003***	0.248***	0.870***	0.880***
	(0.216)	(0.044)	(0.031)	(0.031)
Observations	986683	986683	986683	986683
Controls	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Adj. R-squared	0.660	0.0313	0.0269	0.0248

Panel B: Distance <= 600 km

	(1) AQI	(2) Sales	(3) Count	(4) Customer
North	5.669***	1.267***	0.491***	0.486***
	(0.096)	(0.017)	(0.013)	(0.012)
Observations	2,689,466	2,689,466	2,689,466	2,689,466
Controls	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Adj. R-squared	0.617	0.0152	0.0230	0.0251

Table 5. The Effect of Air Pollution on Offline Payment Behavior:

Unit-level Margins

This table presents the estimates of the effect of air pollution proxied by AQI on offline payment behavior along unit-level margins based on the value and quantity information. The dependent variables are, respectively, the log of monthly cashless *Sales per Count*, the log of monthly cashless *Sales per Customer*, and the log of monthly cashless *Count per Customer* at the merchant-year-month level. The key independent variable is the monthly average *AQI* at the city level. Panel A shows the OLS estimates, while Panel B and Panel C both instrument AQI with *Thermal Inversion* frequency (*IV1* and *IV2*) following the Equation (2) and (3) in Section 4.1. Weather controls include monthly average *Temperature*, *Precipitation*, *Humidity*, *Wind Speed* and *Sunshine*, as well as their squared terms, at the city level. Regressions also add on merchant fixed effects and year-month fixed effects. Standard errors are clustered at the merchant level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. See Appendix Table A2 for detailed definitions.

Panel A: OLS Estimates

	(1)	(2)	(3)
	Sales per Count	Sales per Customer	Count per Customer
AQI	-0.022	-0.022	-0.000
	(0.040)	(0.042)	(0.012)
Observations	4,774,345	4,774,345	4,774,345
Controls	YES	YES	YES
Merchant FE	YES	YES	YES
Year-Month FE	YES	YES	YES
Adj. R-squared	0.751	0.739	0.337

Panel B: 2SLS Estimates (IV1)

	(1)	(2)	(3)
	Sales per Count	Sales per Customer	Count per Customer
AQI	-1.104*	-1.419**	-0.315
	(0.001)	(0.694)	(0.203)
Observations	4,774,345	4,774,345	4,774,345
Controls	YES	YES	YES
Merchant FE	YES	YES	YES
Year-Month FE	YES	YES	YES
KP F		2591	

Panel C: 2SLS Estimates (IV2)

	(1)	(2)	(3)
	Sales per Count	Sales per Customer	Count per Customer
AQI	-2.931***	-3.213***	-0.283

	(0.933)	(0.980)	(0.288)
Observations	4,774,345	4,774,345	4,774,345
Controls	YES	YES	YES
Merchant FE	YES	YES	YES
Year-Month FE	YES	YES	YES
KP F		965	

Table 6. The Effect of Air Pollution on Offline Payment Behavior:

Existing and New Customer

This table decomposes the effect of air pollution proxied by AQI on offline payment behavior by customer type. We distinguish existing customers (with prior transaction history at the merchant before month *t*) from new customers (first-time transactors in month *t*). Panel A reports outcomes for existing customers; Panel B for new customers: log *Sales*, log *Count*, log *Customer* and other unit-level margins (log *Sales per Count*, log *Sales per Customer*, log *Count per Customer*). Panel C presents extensive-margin indicators (e.g., an indicator for any new customers in a month and an indicator that the number of new customers exceeds the number of existing customers). Panel D reports composition measures (e.g., the new-customer share of customers and of sales). The key independent variable is the monthly average *AQI* at the city level. Weather controls include monthly average *Temperature*, *Precipitation*, *Humidity*, *Wind Speed* and *Sunshine*, as well as their squared terms, at the city level. Regressions also add on merchant fixed effects and year-month fixed effects. Standard errors are clustered at the merchant level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. See Appendix Table A2 for detailed definitions.

Panel A: Existing (Old) Customer

	(1) Sales Old	(2) Count Old	(3) Customer Old	(4) Sales per Count Old	(5) Sales per Customer Old	(6) Count per Customer Old
AQI	1.397***	0.870***	0.716***	0.382***	0.493***	0.116***
	(0.121)	(0.039)	(0.029)	(0.062)	(0.069)	(0.029)
Observations	4,754,595	4,754,595	4,754,595	2,569,728	2,569,728	2,593,948
Controls	YES	YES	YES	YES	YES	YES
Merchant FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Adj. R-squared	0.527	0.678	0.709	0.726	0.695	0.350

Panel B: New Customer

	(1) Sales New	(2) Count New	(3) Customer New	(4) Sales per Count New	(5) Sales per Customer New	(6) Count per Customer New
AQI	1.214***	1.047***	1.006***	-0.056	-0.032	0.024**
	(0.071)	(0.037)	(0.034)	(0.041)	(0.043)	(0.012)
Observations	4,773,557	4,773,557	4,773,557	4,606,960	4,606,960	4,608,321
Controls	YES	YES	YES	YES	YES	YES
Merchant FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Adj. R-squared	0.623	0.777	0.811	0.743	0.727	0.338

Panel C: Existing and New Customer

	(1)	(2)	(3)	(4)
	Poisson		OLS	
	If New	New > Old Num	If New	New > Old Num
AQI	0.020***	0.025***	0.018***	0.020***
	(0.006)	(0.008)	(0.005)	(0.007)
Observations	4,773,836	4,771,373	4,774,345	4,774,345
Controls	YES	YES	YES	YES
Merchant FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Adj. R-squared	0.00759	0.0203	0.332	0.416

Panel D: Existing and New customers (Continued)

	(5)	(6)	(7)
	New Customer Ratio	New Sales Ratio	New Count Ratio
AQI	0.262***	-0.347***	0.146***
	(0.041)	(0.091)	(0.050)
Observations	2,427,294	2,401,721	2,427,294
Controls	YES	YES	YES
Merchant FE	YES	YES	YES
Year-Month FE	YES	YES	YES
Adj. R-squared	0.668	0.416	0.584

Table 7. The Effect of Air Pollution on Offline Payment Behavior: Within Month Variation of AQI

This table examines how intra-month air pollution composition and dispersion relate to offline cashless spending outcomes using OLS methods. The dependent variables are, respectively, the log of monthly cashless *Sales*, the log *Count* of transactions, and the log *Customer* visits at the merchant-year-month level. Panel A replaces the continuous AQI with the share of days in three AQI bins within the month, including (50,100], (100,150], and >150, where the omitted category is AQI ≤ 50. Panel B uses the AQI range (monthly max minus min). Panel C uses the within-month standard deviation of daily AQI. Weather controls include monthly average *Temperature*, *Precipitation*, *Humidity*, *Wind Speed* and *Sunshine*, as well as their squared terms, at the city level. Regressions also add on merchant fixed effects and year-month fixed effects. Standard errors are clustered at the merchant level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. See Appendix Table A2 for detailed definitions.

Panel A: Ratio of Days with AQI of Each Bins

	(1) Sales	(2) Count	(3) Customer
Ratio (50 < AQI < 101)	0.050***	0.053***	0.055***
	(0.006)	(0.004)	(0.004)
Ratio (100 < AQI < 151)	0.180***	0.152***	0.159***
	(0.009)	(0.006)	(0.005)
Ratio (150 < AQI)	0.168***	0.184***	0.173***
	(0.013)	(0.008)	(0.008)
Observations	4,772,472	4,772,472	4,772,472
Controls	YES	YES	YES
Merchant FE	YES	YES	YES
Year-Month FE	YES	YES	YES
Adj. R-squared	0.704	0.781	0.811

Panel B: AQI Range

	(1) Sales	(2) Count	(3) Customer
AQI Range	0.229***	0.170***	0.167***
	(0.013)	(0.008)	(0.008)
Observations	4,772,472	4,772,472	4,772,472
Controls	YES	YES	YES
Merchant FE	YES	YES	YES
Year-Month FE	YES	YES	YES
Adj. R-squared	0.704	0.781	0.811

Panel C: AQI Standard Deviation

	(1) Sales	(2) Count	(3) Customer
AQI SD	1.205***	0.941***	0.920***
	(0.058)	(0.036)	(0.033)
Observations	4,772,472	4,772,472	4,772,472
Controls	YES	YES	YES
Merchant FE	YES	YES	YES
Year-Month FE	YES	YES	YES
Adj. R-squared	0.704	0.781	0.811

Table 8. Robustness Tests: Alternative Model Specifications

This table presents the estimates of the effect of air pollution proxied by AQI on offline payment behavior using alternative model specifications. The dependent variables are, respectively, the log of monthly cashless *Sales*, the log *Count* of transactions, and the log *Customer* visits at the merchant-year-month level. Panel A removes weather controls. Panel B adds on province-year-month fixed effects to absorb common province-time shocks. Panel C reports estimate with two-way clustered standard errors (by merchant and by year-month). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. See Appendix Table A2 for detailed definitions.

Panel A: No Controls Setting			
	(1)	(2)	(3)
	Sales	Count	Customer
AQI	0.993***	1.003***	0.997***
	(0.049)	(0.032)	(0.030)
Observations	4,774,345	4,774,345	4,774,345
Controls	NO	NO	NO
Merchant FE	YES	YES	YES
Year-Month FE	YES	YES	YES
Adj. R-squared	0.704	0.781	0.810
Panel B: Province-Year-Month Fixed Effects			
	(1)	(2)	(3)
	Sales	Count	Customer
AQI	1.096***	0.754***	0.689***
	(0.100)	(0.065)	(0.061)
Observations	4,774,336	4,774,336	4,774,336
Controls	YES	YES	YES
Merchant FE	YES	YES	YES
Province-Year-Month FE	YES	YES	YES
Adj. R-squared	0.709	0.789	0.818
Panel C: Double Cluster at Merchant and Year-Month Level			
	(1)	(2)	(3)
	Sales	Count	Customer
AQI	1.056**	1.003***	0.993***
	(0.430)	(0.370)	(0.358)
Observations	4,774,345	4,774,345	4,774,345
Controls	YES	YES	YES
Merchant FE	YES	YES	YES
Year-Month FE	YES	YES	YES
Adj. R-squared	0.704	0.782	0.811

Table 9. Robustness Test: Alternative Sample Constructions

This table presents the estimates of the effect of air pollution proxied by AQI on offline payment behavior using alternative sample constructions. The dependent variables are, respectively, the log of monthly cashless *Sales*, the log *Count* of transactions, and the log *Customer* visits at the merchant-year-month level. Panel A restricts to long-tenure merchants which live more than 27 months. Panel B uses a balanced panel of merchants observed throughout the sample period. Panel C limits to months in which both existing and new customers are present. Weather controls and added fixed effects are the same as baseline regression. Standard errors are clustered at the merchant level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. See Appendix Table A2 for detailed definitions.

Panel A: Merchant lives more than 27 months			
	(1)	(2)	(3)
	Sales	Count	Customer
AQI	1.217***	1.122***	1.010***
	(0.057)	(0.038)	(0.035)
Observations	4,379,743	4,379,743	4,379,743
Controls	YES	YES	YES
Merchant FE	YES	YES	YES
Year-Month FE	YES	YES	YES
Adj. R-squared	0.707	0.784	0.812
Panel B: Balanced Panel			
	(1)	(2)	(3)
	Sales	Count	Customer
AQI	2.154***	2.068***	2.088***
	(0.104)	(0.080)	(0.077)
Observations	1,083,240	1,083,240	1,083,240
Controls	YES	YES	YES
Merchant FE	YES	YES	YES
Year-Month FE	YES	YES	YES
Adj. R-squared	0.790	0.797	0.809
Panel C: Merchant-month observation with both existing and new customers			
	(1)	(2)	(3)
	Sales	Count	Customer
AQI	1.263***	1.271***	1.297***
	(0.058)	(0.042)	(0.040)
Observations	2,402,846	2,402,846	2,402,846
Controls	YES	YES	YES
Merchant FE	YES	YES	YES
Year-Month FE	YES	YES	YES
Adj. R-squared	0.786	0.831	0.858

Table 10. Robustness Tests: Alternative Air Pollution Metrics

This table presents the estimates of the effect of air pollution proxied by AQI on offline payment behavior using alternative air pollution metrics. The dependent variables are, respectively, the log of monthly cashless *Sales*, the log *Count* of transactions, and the log *Customer* visits at the merchant-year-month level. The key independent variable in Panel A and Panel B is, respectively, monthly mean $PM_{2.5}$ and PM_{10} reported per $\mu g/m^3$. Weather controls and added fixed effects are the same as baseline regression. Standard errors are clustered at the merchant level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. See Appendix Table A2 for detailed definitions.

Panel A: $PM_{2.5}$ as Independent Variable

	(1) Sales	(2) Count	(3) Customer
$PM_{2.5}$	1.418***	1.497***	1.431***
	(0.082)	(0.055)	(0.052)
Observations	4,774,345	4,774,345	4,774,345
Controls	YES	YES	YES
Merchant FE	YES	YES	YES
Year-Month FE	YES	YES	YES
Adj. R-squared	0.704	0.782	0.811

Panel B: PM_{10} as Independent Variable

	(1) Sales	(2) Count	(3) Customer
PM_{10}	0.819***	0.781***	0.769***
	(0.000)	(0.000)	(0.000)
Observations	4,774,345	4,774,345	4,774,345
Controls	YES	YES	YES
Merchant FE	YES	YES	YES
Year-Month FE	YES	YES	YES
Adj. R-squared	0.704	0.781	0.811

Table 11. The Heterogeneous Effects of Air Pollution on Offline Payment Behavior: Multiple Dimensions Based on Merchant Business Type

This table examines how the effect of air pollution proxied by AQI on offline payment behavior varies across industries and product types. The dependent variables are, respectively, the log of monthly cashless *Sales*, the log *Count* of transactions, and the log *Customer* visits at the merchant-year-month level. The key independent variable is the monthly average *AQI* at the city level. Panel A reports category-specific estimates for broad merchant groups (e.g., *General*; *Hotels, Catering & Entertainment*; *Real Estate & Automobiles*; *Gas Stations & Supermarkets*). Panel B refines industry granularity (e.g., *Comprehensive Retail*; *Specialized Retail of Textiles, Apparel & Daily Necessities*; *Food & Beverage*; *Specialized Retail of Hardware, Furniture & Interior Decoration*; *Accommodation*; *Specialized Retail of Food, Beverages & Tobacco*; *Commercial Services*; *Repair & Other Professional Services*; *Specialized Retail of Automobiles, Motorcycles, Fuel & Parts*). Panel C splits by *Durable* vs. *Non-durable Consumer Goods*, and Panel D splits by *Goods* vs. *Services*. Weather controls and added fixed effects are the same as baseline regression. Standard errors are clustered at the merchant level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. See Appendix Table A2 for detailed definitions.

Panel A: By Broad Merchant Groups

	(1) Sales	(2) Count	(3) Customer
General:			
AQI	1.166***	1.100***	1.096***
	(0.070)	(0.046)	(0.042)
Hotels, Catering & Entertainment:			
AQI	0.870***	0.977***	1.015***
	(0.127)	(0.090)	(0.086)
Real Estate & Automobiles:			
AQI	1.099***	0.438***	0.347**
	(0.271)	(0.158)	(0.152)
Gas Stations & Supermarkets:			
AQI	1.204***	1.148***	0.988***
	(0.296)	(0.225)	(0.212)

Panel B: By Refined Industry Granularity

	(1) Sales	(2) Count	(3) Customer
Comprehensive Retail:			
AQI	1.528***	1.545***	1.567***
	(0.152)	(0.101)	(0.092)
Specialized Retail Stores of Textiles, Apparel & Daily Necessities:			
AQI	0.146	0.170*	0.178**

	(0.143)	(0.092)	(0.087)
Food & Beverage:			
AQI	1.404***	1.495***	1.601***
	(0.197)	(0.140)	(0.135)
Specialized Retail of Hardware, Furniture & Interior Decoration Materials:			
AQI	0.611***	0.627***	0.438***
	(0.227)	(0.128)	(0.115)
Accommodation Industry:			
AQI	0.887***	1.146***	1.149***
	(0.204)	(0.156)	(0.147)
Specialized Retail of Food, Beverages & Tobacco Products:			
AQI	2.858***	2.662***	2.683***
	(0.286)	(0.196)	(0.184)
Commercial Services:			
AQI	2.456***	1.952***	1.740***
	(0.263)	(0.165)	(0.148)
Repair & Other Professional Services:			
AQI	0.874***	0.682***	0.683***
	(0.195)	(0.141)	(0.133)
Specialized Retail of Automobiles, Motorcycles, Fuel & Parts:			
AQI	1.082***	0.611***	0.523***
	(0.218)	(0.132)	(0.126)

Panel C: By Durables vs. Non-durables

	(1) Sales	(2) Count	(3) Customer
Durable Consumer Goods:			
AQI	0.881***	0.804***	0.781***
	(0.080)	(0.050)	(0.046)
Non-durable Consumer Goods:			
AQI	1.457***	1.366***	1.388***
	(0.080)	(0.055)	(0.052)

Panel D: By Goods vs. Services

	(1) Sales	(2) Count	(3) Customer
Goods:			
AQI	0.975***	0.970***	0.959***
	(0.066)	(0.043)	(0.040)
Services:			
AQI	1.249***	1.066***	1.049***
	(0.000)	(0.066)	(0.062)

Figure 1. Payment Acquisition Business Transaction and Settlement Process

This figure depicts the offline payment chain linking the issuing bank (issuer), the acquiring institution (acquirer), the interbank switching and clearing institution (CUP), the merchant, the cardholder and third-party payment platforms (like Alipay and WeChat Pay).

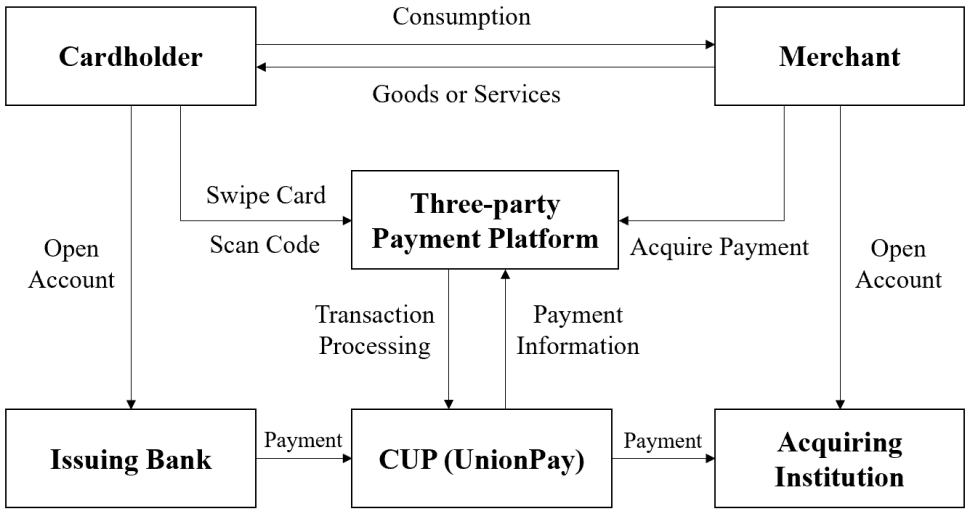
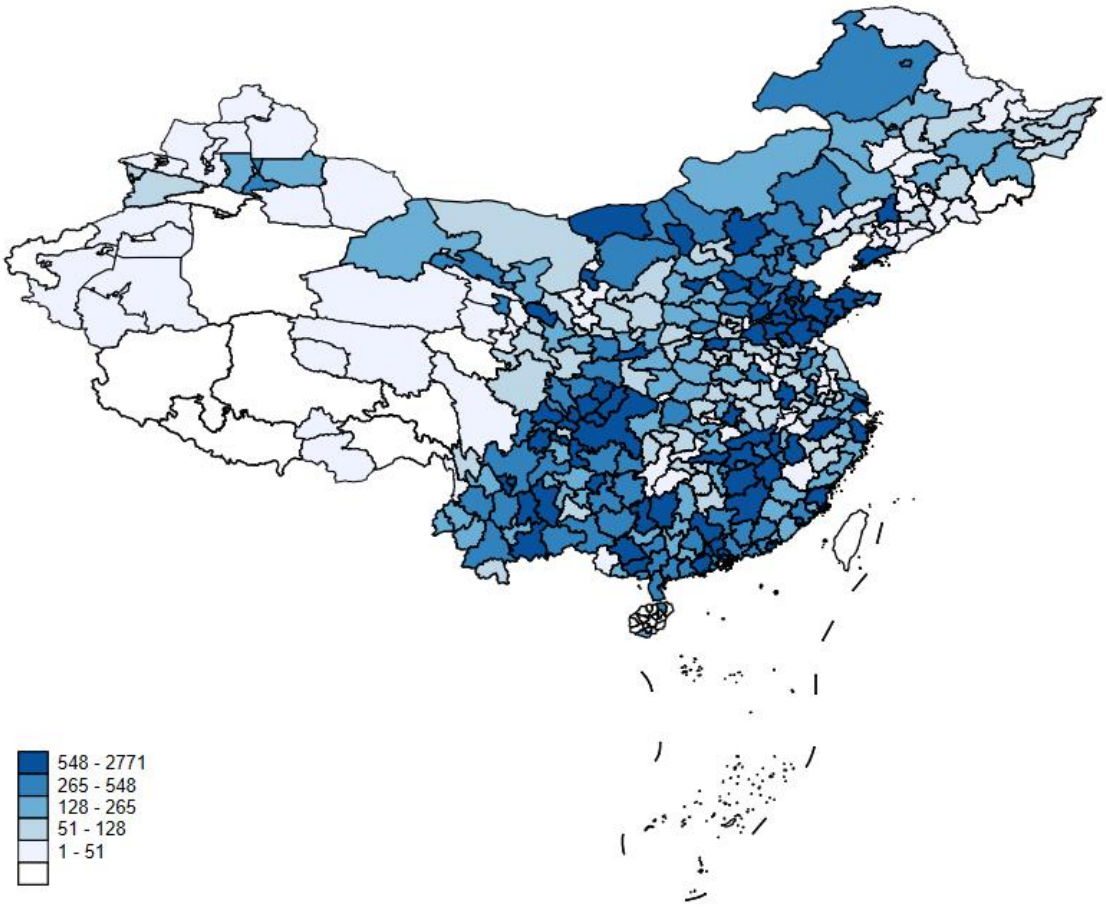
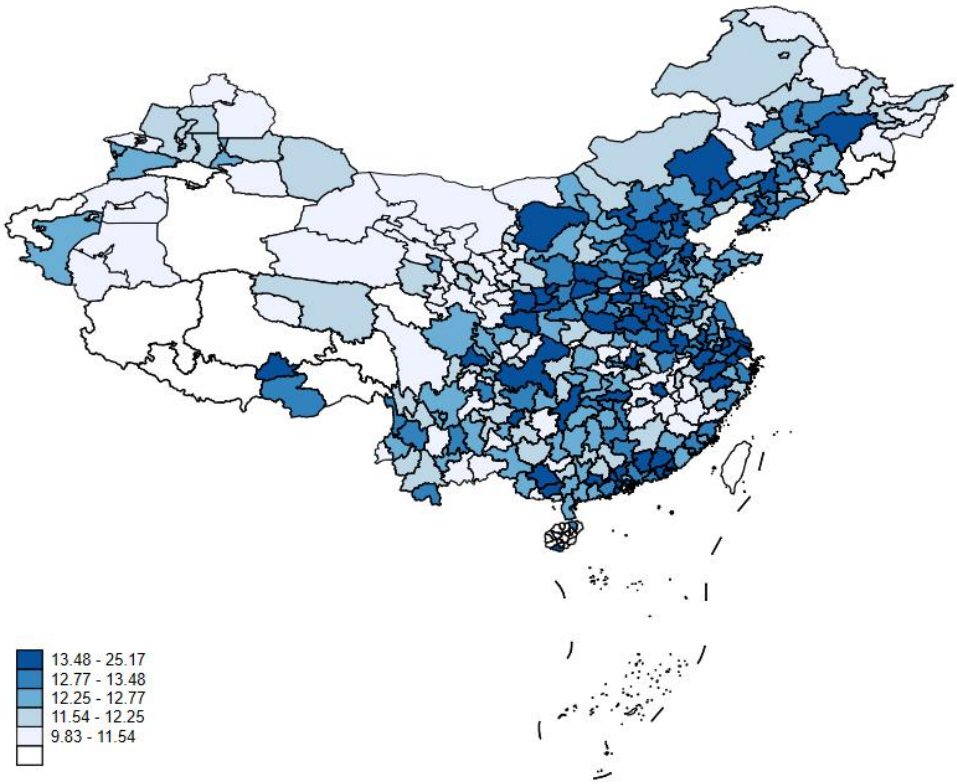


Figure 2. Geographic Distribution of Merchant Establishment and Transaction Sales Metrics

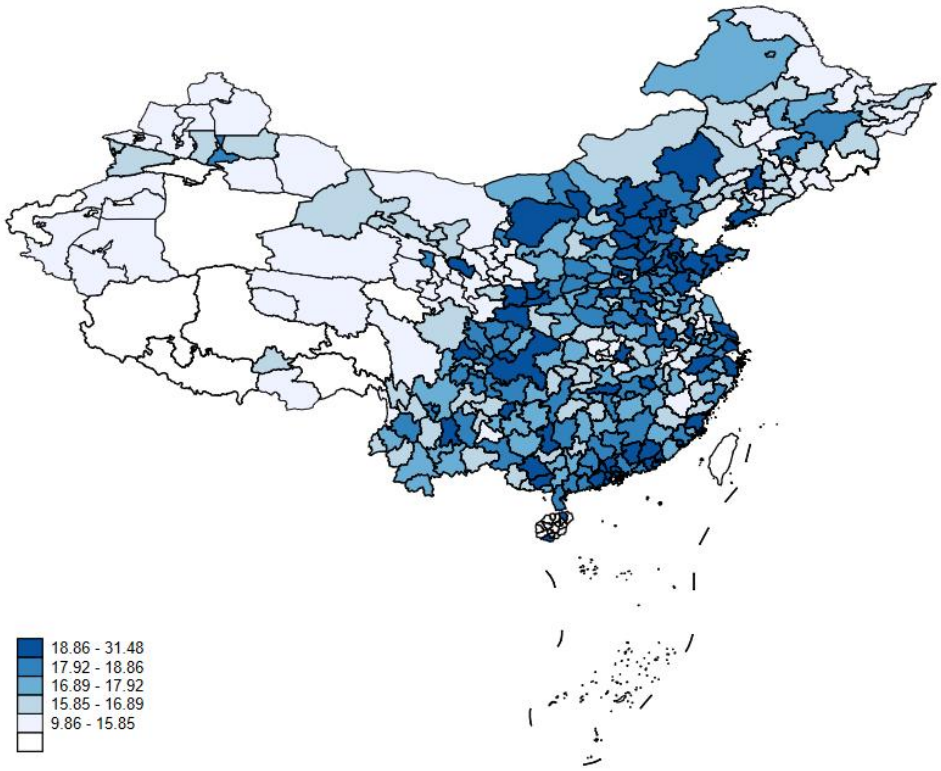
This figure maps the spatial coverage and intensity of our offline cashless payments dataset across Chinese cities from January 2019 to June 2023. Panel A shades cities by the number of distinct merchant establishments in our sample. Panel B shades cities by the average monthly cashless sales in log CNY for a representative merchant. Panel C shades cities by the average monthly aggregate cashless sales in log CNY at the city level. Darker colors indicate higher values, and color scales are comparable within each panel only. City-level measures pool all merchant-month observations matched to that city. Observations with missing location are dropped. The sample covers 118,698 merchants in 332 cities across 31 provinces. See Appendix A2 for variable definitions.



Panel A: Distinct Merchant establishments distribution in each city



Panel B: Average monthly cashless transaction sales for a representative merchant



Panel C: Average monthly aggregate cashless transaction sales at the city level

Appendix A1. Sample Construction

This appendix table documents the unit of analysis, sample coverage, and data filter procedures used throughout the paper.

	Observations
Total merchant-month sample	5,033,300
Less:	
Non-positive total sales amount of cashless transactions	134,053
Missing city or province information	8,311
Non-consumption scenarios	116,591
Final sample	**4,774,345**

Appendix A2. Variable Description

This appendix table provides precise and detailed descriptive definitions of all variables used in estimation, tables and figures.

Panel A: Dependent variables

Variable	Definition
Sales	Logarithmic form of total sales amount of cashless transactions
Count	Logarithmic form of number of cashless transactions
Customer	Logarithmic form of cashless payments customer count
Sales Old	Logarithmic form of total sales amount of cashless transactions of existing customers
Count Old	Logarithmic form of number of cashless transactions of existing customers
Customer Old	Logarithmic form of existing customer count with cashless payments
Sales New	Logarithmic form of total sales amount of cashless transactions of new customers
Count New	Logarithmic form of number of cashless transactions of new customers
Customer New	Logarithmic form of new customer count with cashless payments
If New	Dummy variable equal to 1 if the merchant-month has new customers with cashless payments, 0 otherwise
New > Old Num	Dummy variable equal to 1 if the quantity of new customers is greater than that of existing users, 0 otherwise
New Customer Ratio	New customers count with cashless payments divided by existing customers count with cashless payments
New Sales Ratio	Total sales amount of cashless transactions of new customers divided by total sales amount of cashless transactions of existing customers
New Count Ratio	New customer count with cashless payments divided by existing customer count with cashless payments
Sales per Count	Logarithmic form of total sales amount of cashless transactions divided by number of cashless transactions
Sales per Customer	Logarithmic form of total sales amount of cashless transactions divided by cashless payments customer count
Count per Customer	Logarithmic form of number of cashless transactions divided by cashless payments customer count
Sales per Count Old	Logarithmic form of total sales amount of cashless transactions divided by number of cashless transactions for existing customers
Sales per Customer Old	Logarithmic form of total sales amount of cashless transactions divided by cashless payments customer count for existing customers
Count per Customer Old	Logarithmic form of number of cashless transactions divided by cashless payments customer count for existing customers
Sales per Count New	Logarithmic form of total sales amount of cashless transactions divided by number of cashless transactions for new customers
Sales per Customer New	Logarithmic form of total sales amount of cashless transactions divided by cashless payments customer count for new customers
Count per Customer New	Logarithmic form of number of cashless transactions divided by cashless payments customer count for new customers

Panel B: Air pollution and weather conditions

Variable	Definition	Source
AQI	Air quality index	CSMAR
$PM_{2.5}$	Particulate matter with a diameter of less than 2.5 micrometers ($\mu g/m^3$)	CSMAR
PM_{10}	Particulate Matter with a diameter of less than 10 micrometers ($\mu g/m^3$)	CSMAR
Temperature	Average daily temperature over the year-month (℃)	CSMAR and China Meteorological Data Service Centre (CMDSC)
Precipitation	Average daily precipitation over the year-month (10 mm)	CSMAR and CMDSC
Humidity	Average daily relative humidity over the year-month (%*10)	CSMAR and CMDSC
WindSpeed	Average daily 10-meter wind speed over the year-month (m/s)	CMDSC
Sunshine	Average daily sunshine duration over the year-month (hour)	CSMAR and CMDSC
Location	Dummy variable equal to 1 if the city is north of the Huai River line, -1 if the city is south of the Huai River line, 0 otherwise	Authors' calculation
Thermal Inversion (IV1)	Days with thermal inversions of the month	MERRA-2 and authors' calculation
Thermal Inversion (IV2)	Aggregate the number of thermal inversions for each 6-h period to the one-month exposure window, and then calculate the ratio of thermal inversion times over the month	MERRA-2 and authors' calculation