The Effects of Environment Regulation on Small Low-profit Enterprises

Evidence from the "Air Pollution Prevention and Control Action Plan"*

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January 7, 2025

Abstract

Environmental regulations have become increasingly important in shaping the behavior and performance of firms, particularly small low-profit enterprises (SLEs) that are more vulnerable to external shocks. This study seeks to address the unclear question of whether such external shocks can negatively affect SLEs and, if so, what the underlying mechanisms are. By utilizing the National Tax Investigation Data (2007-2016) within the context of the Air Pollution Prevention and Control Action Plan (APPCAP) regulation introduced in 2013, the study reaches three main conclusions: 1) the regulation directly impacts operating revenue, with a nearly 16% decrease for regulated firms; 2) the negative effects are robust, persistent, and last beyond 2013; and 3) the regulatory shock induces behavioral adjustments among regulated firms, such as changes in energy consumption, labor demand, and capital structure, but does not affect the technology used by SLEs (i.e., no impact on TFP). This research provides insights into the costs borne by SLEs in response to environmental regulations and offers implications for policy-making in the context of green transitions and economic resilience.

*This is the research paper of *Public Economics (1)* instructed by Binzhen Wu. I would like to thank Professor Binzhen Wu for helpful comments and suggestions. I am responsible for all remaining errors.

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1 Introduction

Small Low-profit Enterprises (SLEs) [1] form the cornerstone of China's market-based economy. As of September 2024, the number of registered SLEs and self-employed households surpassed 81.56 million, accounting for over 96.5% of all enterprises in the country.[2] Often referred to as the "blood capillaries" of the economic system, SLEs serve as key vehicles of economic dynamism and essential expressions of private sector vitality. The "56789" framework summarizes the private sector's critical contributions: it accounts for over 50% of tax revenue, 60% of GDP, 70% of technological innovations, 80% of urban employment, and 90% of market entities.[3] For example, regarding employment, data from the National Bureau of Statistics indicate that each small enterprise creates jobs for 7 to 8 individuals, with annual payroll growth of 7.6%, outpacing that of large enterprises (4.1%) and medium-sized enterprises (2.4%).

Despite their critical role, SLEs face significant challenges, particularly in sustainability and resilience to external shocks. The average lifespan of SLEs in China is only three years, implying that just one-third of these businesses remain operational three years post-registration. In comparison, the average lifespan is eight years in the United States and 12 years in Japan. Financing constraints are particularly acute. According to the World Bank's 2018 MSME Finance Gap report (Miriam et al., 2017), the unmet financing demand for medium, small, and micro enterprises (MSMEs) in China is approximately USD 1.9 trillion, equivalent to nearly 17% of the nation's GDP.[4]

The underlying reasons for these financing difficulties are clear: SLEs often lack sufficient collateral or guarantees, and their lower creditworthiness leads to higher perceived investment risks. Consequently, over 60% of their financing comes from private financial institutions, which charge significantly higher interest rates (15–20%, approximately three times that of formal banking institutions). Furthermore, the financing structure is skewed heavily toward short-term liabilities. As of 2014, for a typical SLE, current liabilities requiring repayment within one year comprised 97.5% of total debt, resulting in severe short-term debt pressure and elevated financial risks.

Given the unique status of SLEs, the central government has implemented targeted policies to support their development. These include tax refunds and reductions, deferred payment of social insurance premiums, and ensuring the smooth operation of logistics services, particularly during the COVID-19 pandemic. These measures aim to alleviate financial burdens and enhance the operational resilience of SLEs, underscoring their critical role in the broader economic framework.

To design more targeted policy tools that promote the development of SLEs (small and micro enterprises) in China and enhance their resilience to external shocks, it is critical for economists to identify the specific mechanisms through which these shocks impact the operations of SLEs. However,

[1]In this paper, I arbitrarily let SLEs ("小微企业" in Chinese) to be equivalent to MSMEs (medium, small, and micro enterprises), a term more commonly used in the literature. Actually the differences between these two terms are subtle.

[2]The statistic data refers to the State Council of PRC. (Link)

[3]In detail, the private sector contributes more than 50% of the country's tax revenue. It accounts for more than 60% of GDP. It generates over 70% of technological innovations. It provides over 80% of urban employment. It represents more than 90% of market entities.

[4]You can read this report on the official website of World Bank. (Link).

the existing literature remains opaque on this issue and fails to provide a clear answer.

On one hand, much of the research focuses primarily on the positive effects of government support and favorable policies, such as subsidies and tax cuts (Wang et al., 2020). There is a lack of sufficient attention to the negative shocks and their transmission mechanisms, whether in the short run or the long run. On the other hand, studies that consider negative shocks often center on their effects on large firms and enterprises, with limited attention given to SLEs. This bias may stem from factors such as the greater availability of data on large firms or the more statistically significant regression results when analyzing large firms (Chen et al., 2025).

Despite these challenges, some studies attempt to bridge this research gap by examining the effects of external shocks on SLEs. For instance, Li et al. (2022) utilizes newly incorporated firm registration data to construct new firm entry datasets at urban, monthly, and industry levels, identifying how the first round of Central Environmental Protection Inspections (CEPIs) reshaped China's industrial structure through their impact on firm entry. By leveraging a complete sample of all registered firms in China, this study captures the effects of CEPIs on SLEs. However, it primarily focuses on extensive margin outcomes, such as market entry behavior, rather than on the intensive margin of actual operational performance.

In this research, I aim to complement the literature by providing empirical evidence from an intensive margin perspective, proxied by indices of actual operational performance. This approach seeks to deepen our understanding of the mechanisms through which external shocks affect SLEs and contribute to more effective policy design.

In this paper, the primary research questions are as follows: (1) What are the direct and indirect effects of an external shock on SLEs? (2) How do SLEs adapt and adjust their behavior in response to such shocks? For the external shock, I focus on the Air Pollution Prevention and Control Action Plan (APPCAP), an environmental regulation introduced in 2013. This policy is notable for its strictness and its long-term effects on industrial firms in particular. [5]

This paper contributes to three strands of literature.

Firstly, the development of SLEs in China has garnered significant interest among researchers, as it is both a popular and policy-relevant topic. In recent years, SLEs have faced considerable challenges, including macroeconomic downturns, geopolitical tensions, disrupted international trade, and the interruptions caused by COVID-19 (Zhu et al., 2020). These challenges have been particularly severe for SLEs, which often lack resilience. In response, the central government has introduced a series of favorable policies aimed at supporting SLEs. Many studies evaluate the effectiveness of these policies using robust empirical frameworks, focusing on initiatives such as tax cuts (Wang et al., 2020, Li, 2021, Feng et al., 2023) and improved access to financing through tax credit-backed bank loans

[5]Initially, I considered examining the impacts of extreme weather events, such as heavy rainfall and the resulting floods, or typhoons in coastal cities. However, after discussing with Professor Wu, I realized that incorporating gradual or slow-changing variables poses challenges for empirical identification and makes it difficult to construct treatment and control groups. To ensure cleaner identification and more robust results, I chose to use the APPCAP as a case study.

(Yang et al., 2021). In other developing, especially low-income, countries, tools like microfinance, microcredit, and microinsurance are regarded as effective mechanisms for fostering the growth of SLEs and boosting local economies. The Grameen Bank, founded by Muhammad Yunus and awarded the Nobel Peace Prize in 2006, serves as a prominent example of the success of such strategies. The development economics literature extensively analyzes the impacts of these tools across different regions and countries (Angelucci et al., 2015, Attanasio et al., 2015, Banerjee et al., 2015a,b, Blattman et al., 2016, Brooks et al., 2018, Bruhn et al., 2018, De Mel et al., 2008, Field et al., 2013, Meager, 2019, Groh and McKenzie, 2016).

Secondly, this paper contributes to the literature on the effects of environmental regulation policies on enterprises. In environmental economics, numerous studies have analyzed various types and scales of regulations to uncover their potential impacts and underlying mechanisms. For example, He et al. (2020) estimates the effect of water quality regulations on firm productivity using a spatial regression discontinuity design embedded in China's water quality monitoring system. The study finds that immediate upstream polluters experience a more than 24% reduction in total factor productivity (TFP), exacerbating spatial disparities and offering regulators insights into mitigating such strategic behaviors. Similarly, Liu et al. (2021) examines the employment and labor demand impacts of China's Key Cities for Air Pollution Control (KCAPC) program. The findings reveal that the mechanism driving these changes is a combination of production technology upgrades and reduced labor demand, disproportionately affecting low-skilled workers in domestic manufacturing firms.

Other studies have also provided interesting insights into the effects of environmental regulations. For instance, private firms are found to bear a larger share of pollution fees (Cai et al., 2016), while regulated firms strategically shift production under energy conservation programs (Chen et al., 2025). This paper builds on this body of work by focusing on how air pollution regulations, such as the APPCAP, have influenced the operational variables of SLEs. Given the extensive impact of this regulation in China over the past decade, the findings will add a valuable perspective to the existing literature.

Thirdly, this paper seeks to contribute to the growing literature on adaptation behavior in response to external shocks, a topic that has gained increasing attention in economics research, particularly in the context of climate change. Several studies offer valuable insights into potential adaptation mechanisms. For instance, Cui and Tang (2024) highlights how households smooth consumption by utilizing precautionary savings as a buffer against extreme weather events, while Lane (2024) explores how rural households rely on "Emergency Loans" provided by microfinance institutions to cope with shocks. Additionally, Barrot and Sauvagnat (2016) examines how firms' production networks are reshaped in response to external disruptions, shedding light on the structural adjustments firms make under such conditions. This paper aims to build on these studies by investigating how SLEs adapt to environmental shocks, providing a new perspective on resilience and behavioral adjustments.

The following sections are organised as follows. Section 2 covers the background and policy details of APPCAP. Section 3 explains the data and variables used in the empirical analysis. Section 5 covers the baseline empirical strategies and illustrates the possible mechanisms based on the baseline results. Section 6 concludes.

2 Background of the APPCAP

The Air Pollution Prevention and Control Action Plan (APPCAP) was launched by the Chinese government in 2013 as a comprehensive policy to address severe air pollution and improve air quality nationwide. In September 2013, the first action plan document for pollution control was released, marking the beginning of APPCAP, often referred to as China's "Clean Air Act". This regulatory program set ambitious goals, including reducing PM10 concentrations by over 10% nationwide by 2017 and achieving significant improvements in air quality in regions with the most critical air pollution, such as the Beijing-Tianjin-Hebei area, the Yangtze River Delta, and the Pearl River Delta.[6]

APPCAP outlined detailed policies and measures to combat air pollution, collectively known as the "Ten Measures for Air" (often referred to as "大气十条" in Chinese). These ten key measures included reducing emissions from industrial sources, controlling coal consumption, promoting clean energy alternatives, optimizing the energy structure, enhancing industrial pollution control, strengthening environmental enforcement (e.g., monitoring systems), and making substantial investments in green technologies, among others.

The implementation of APPCAP has had far-reaching effects on industrial operations, urban planning, and environmental awareness in China. For instance, by 2017, PM2.5 concentrations had dropped by 38.2% in the Beijing-Tianjin-Hebei area, 31.7% in the Yangtze River Delta, and 25.6% in the Pearl River Delta, surpassing the initial goals of 25%, 20%, and 15%, respectively (Figure 1).

[6]Other goals included significant reductions in PM2.5 concentrations, improved air quality days, and the elimination of outdated industrial capacities.

国务院关于印发大气污染防治行动计划的通知

国发〔2013〕37 号

各省、自治区、直辖市人民政府，国务院各部委、各直属机构：

现将《大气污染防治行动计划》印发给你们，请认真贯彻执行。

国务院

2013 年 9 月 10 日

（此件公开发布）

奋斗目标：经过五年努力，全国空气质量总体改善，重污染天气较大幅度减少；京津冀、长三角、珠三角等区域空气质量明显好转。力争再用五年或更长时间，逐步消除重污染天气，全国空气质量明显改善。

具体指标：到 2017 年，全国地级及以上城市可吸入颗粒物浓度比 2012 年下降 10%以上，优良天数逐年提高；京津冀、长三角、珠三角等区域细颗粒物浓度分别下降 25%、20%、15%左右，其中北京市细颗粒物年均浓度控制在 60 微克/立方米左右。

Figure 1: The APPCAP notice and detailed goals set by the document

Note: This figure illustrates the specific requirements and goals set by APPCAP. The term "可吸入颗粒物" refers to PM10, while "细颗粒物" refers to PM2.5.

Source: Ministry of Ecology and Environment and State Council of PRC.

（十二）控制煤炭消费总量。制定国家煤炭消费总量中长期控制目标，实行目标责任管理。到 2017 年，煤炭占能源消费总量比重降低到 65%以下。京津冀、长三角、珠三角等区域力争实现煤炭消费总量负增长，通过逐步提高接受外输电比例、增加天然气供应、加大非化石能源利用强度等措施替代燃煤。

京津冀、长三角、珠三角区域以及辽宁中部、山东、武汉及其周边、长株潭、成渝、海峡西岸、山西中北部、陕西关中、甘宁、乌鲁木齐城市群等“三区十群”中的 47 个城市，新建火电、钢铁、石化、水泥、有色、化工等企业以及燃煤锅炉项目要执行大气污染物特别排放限值。各地区可根据环境质量改善的需要，扩

（三十四）强化企业施治。企业是大气污染治理的责任主体，要按照环保规范要求，加强内部管理，增加资金投入，采用先进的生产工艺和治理技术，确保达标排放，甚至达到“零排放”；要自觉履行环境保护的社会责任，接受社会监督。

（二十四）加大环保执法力度。推进联合执法、区域执法、交叉执法等执法机制创新，明确重点，加大力度，严厉打击环境违法行为。对偷排偷放、屡查屡犯的违法企业，要依法停产关闭。对涉嫌环境犯罪的，要依法追究刑事责任。落实执法责任，对监督缺位、执法不力、徇私枉法等行为，监察机关要依法追究有关部门和人员的责任。

（三十）制定完善应急预案。空气质量未达到规定标准的城市应制定和完善重污染天气应急预案并向社会公布；要落实责任主体，明确应急组织机构及其职责、预警预报及响应程序、应急处置及保障措施等内容，按不同污染等级确定企业限产停产、机动车和扬尘管控、中小学校停课以及可行的气象干预等应对措施。开展重污染天气应急演练。

京津冀区域城市建成区、长三角城市群、珠三角区域要加快现有工业企业燃煤设施天然气替代步伐；到 2017 年，基本完成燃煤锅炉、工业窑炉、自备燃煤电站的天然气替代改造任务。

对布局分散、装备水平低、环保设施差的小型工业企业进行全面排查，制定综合整改方案，实施分类治理。

Figure 2: More details about the APPCAP

Source: Ministry of Ecology and Environment.

3 Data

In this paper, the primary dataset utilized is the National Tax Investigation Data (2007–2016), collected by the Chinese State Administration of Taxation (SAT). Each year, the SAT stratified a sample of nearly 700,000 enterprises of varying sizes and collected detailed tax-related data through questionnaires. This dataset includes a wide range of variables related to basic firm information, operational performance, profits, and taxation records.

The dataset offers several advantages:

1. High Representativeness: The stratified sampling process ensures coverage across different firm sizes while considering other key characteristics, such as whether a firm is a key tax-source enterprise or export-oriented.

2. Rich Operational Variables: The dataset includes detailed metrics such as energy consumption, employment, revenue, profit, liabilities, and assets, making it a valuable resource frequently analyzed in economic research.

The definition of SLEs in this study is based on the *New Enterprise Income Tax Law* first released in 2008. According to this law:

- For industrial firms, an SLE is defined as having annual taxable income less than 300,000 yuan, fewer than 100 employees, and total assets under 30 million yuan.

- For non-industrial firms, an SLE is defined as having annual taxable income less than 300,000 yuan, fewer than 80 employees, and total assets under 10 million yuan.

The figure 3 illustrates the ratio of SLEs across different waves of the survey sample, which remains relatively stable from 2007 to 2016, demonstrating the reliability of this dataset.

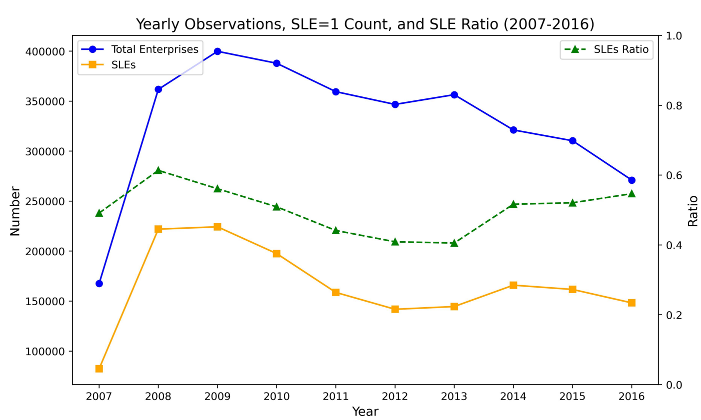


Figure 3: Summary Description

Note: Enterprises with self-reported taxable revenue equal to zero were excluded when generating this figure.

Additional city-level control variables are sourced from the China City Statistical Yearbook.

4 Empirical Strategies

4.1 Design

Defining treatment and control groups for this regulation policy is somewhat challenging, as it was not a pilot initiative but one implemented nationwide. Generally, existing studies classify treatment and control groups by leveraging differences in the intensity of pollution control measures inferred from the policy documents.

There are two common approaches for classification:

- Setting the Beijing-Tianjin-Hebei region as the treatment group and other regions (excluding the two additional key regions) as the control group.
- Defining all three key regions as the treatment group and the remaining regions as the control group.

In essence, these two classifications share the same control group, but the treatment groups differ slightly. Following Li et al. (2019), I adopt the first classification, as it creates a more pronounced difference in policy intensity between the two groups. Additionally, I use the second classification later as a robustness check.

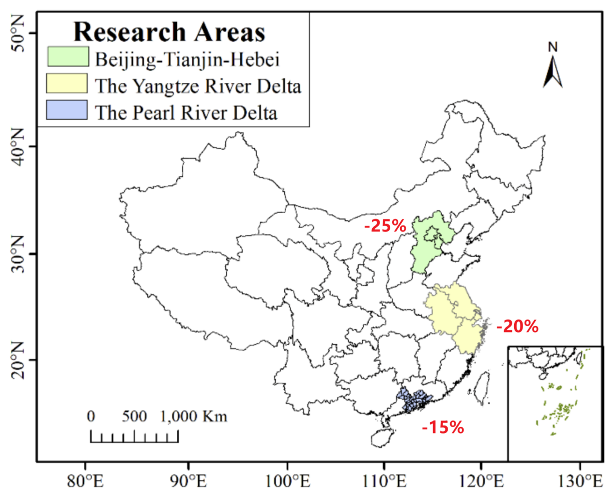


Figure 4: the illustration of Treatment & Control groups

Note: This figure is adapted from a paper, with modifications to include the target goal values.

In addition, because there are so many different industries covered in the survey, I refer to some statistics to classify the regulated and unregulated industries for better focused on the effects on the targeted SLEs.

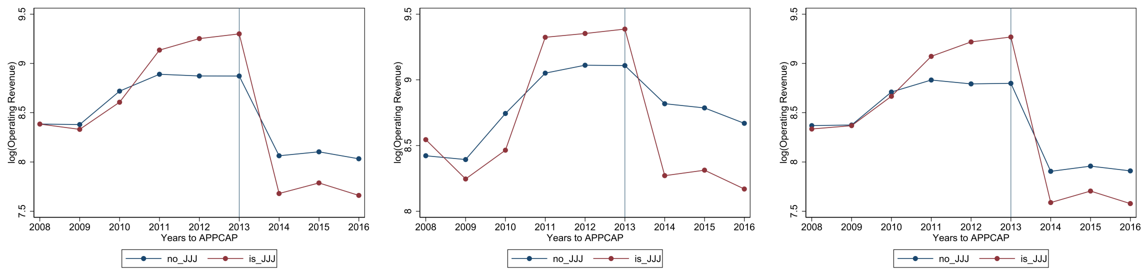
The classification refers to the table of industrial gas emission in 2012 from National Bureau of Statistics. And the key variable for classification is "Industrial Waste Gas Emission (100 million cu.m)". The following table 1 shows all regulated industries, other industries are considered as unregulated. In this paper, I only focus on the regulated SLEs.

Table 1: Regulated Sectors and Industries under APPCAP

Sector	**Industry**
Mining industry (4)	coal mining and washing (B06), oil and natural gas extraction (B07), ferrous metal ore mining (B08), non-ferrous metal ore mining (B09)
Manufacturing industry (19)	agricultural and sideline food processing (C13), food manufacturing (C14), textile industry (C17), textile and garment manufacturing (C18), leather, fur, feather, and related products and footwear manufacturing (C19), paper and paper product manufacturing (C22), petroleum, coal, and other fuel processing (C25), chemical raw materials and chemical product manufacturing (C26), pharmaceutical manufacturing (C27), chemical fiber manufacturing (C28), rubber and plastic product manufacturing (C29), non-metallic mineral product manufacturing (C30), ferrous metal smelting and rolling processing (C31), non-ferrous metal smelting and rolling processing (C32), special equipment manufacturing (C35), automobile manufacturing (C36), electrical machinery and equipment manufacturing (C38), and computer, communication, and other electronic equipment manufacturing (C39)
Construction industry (1)	residential building construction (E47)
Others (2)	transportation industry (G54), and catering industry (H62)

Note: The number after the name of each industry is the corresponding "Chinese National Economic Industry Classification" (CNEIC)

The figure 5 below shows the dynamics of the operating revenue of regulated, unregulated and all of the SLEs from the dataset. It is easy to see the difference between the SLEs in Jingjinji (JJJ) region and the SLEs in other regions. After the strict regulation in 2013, the operation of SLEs in JJJ region (treatment group) experienced more serious shock than other SLEs, which can provide a preliminary evidence for further empirical analysis.



(a) All SLEs (b) Regulated (c) Unregulated

Figure 5: The dynamics of operating revenue between treatment and control group

Note: This figure shows the basic parallel trend before the treatment (APPCAP) and the significant drop of operating revenue of SLEs after APPCAP (Although the pre-trend parallel is not so perfect, which means the existence of potential selection bias and other endogeneity issues). Intuitively, the SLEs in treated group will experience a more significant negative shock than control group.

4.2 Specification

From the introduction above, I leverage the basic two-way fixed effects (TWFE) model as the baseline specification of the the Average Treatment Effect (ATE) of APPCAP on Operating Revenue and other outcome variables.

$$\ln Y_{ijt} = \alpha + \beta_1 APPCAP_{jt} \times Treat_j + \gamma X_{it} + \mu_j + \eta_t + \varepsilon_{ijt} \tag{1}$$

Where $\ln Y_{ijt}$ represents the natural logarithm of the outcome variable (e.g., operating revenue) for SLE i in city j and year t; $Treat_j$ is a binary variable equal to 1 if city j belongs to the treatment group; $APPCAP_{jt}$ is a binary variable equal to 1 for years after 2013; and X_{ijt} includes time-invariant control variables, such as city-level factors (temperature, rainfall, cloud amount, tertiary sector ratio, and infrastructure investment) and firm-level factors (assets and liability, used as proxy for firm size). Additionally, μ_j denotes city fixed effects, and η_t represents year fixed effects.

To ensure robustness (because β_1 is not guaranteed to recover an interpretable causal parameter), I employ two additional specifications: the intensity-based DiD and the PSM-DiD (propensity score matching difference-in-differences). The intensity-based DiD accounts for varying levels of regulatory enforcement by modifying the initial regression to replace the interaction term $treat \times post$ with $treat \times post \times PM2.5$, where $PM2.5$ denotes the annual concentration of PM2.5. This allows for capturing the heterogeneity in regulatory impacts across cities.

The PSM-DiD, on the other hand, addresses identification concerns related to sample selection bias and endogeneity—particularly the concern that whether an SLE belongs to the treatment or control group may be endogenous. I match different SLEs based on their assets, liabilities, and profits to ensure comparability between groups. The figure 6 below illustrates the differences before and after applying PSM, demonstrating that the treatment and control groups become more balanced post-matching.

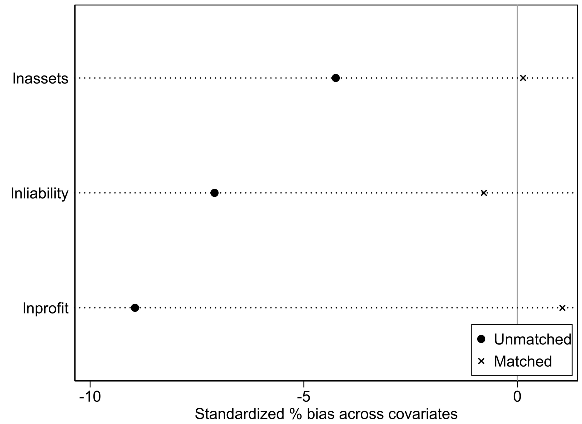


Figure 6: PSM Balance Check

Note: This figure shows that after PSM, the differences between two groups reduce a lot and the two groups become more comparable and balanced.

5 Results

5.1 Baseline Regression

The table 2 shows the baseline regression results with and without PSM. Take the results with PSM correction as the most robust results, the APPCAP leads to a 8% drop in operating revenue for regulated SLEs and the policy has no significant effects on unregulated SLEs, which aligns with our expectation.

To estimate the dynamic treatment effects of APPCAP on SLEs, I run the standard event study regression as equation . The figure 7 shows that pre the treatment, the two groups have nearly parallel trends (insignificant coefficient) while post the regulation, the difference becomes more significant, with a little sign of reverting back, which proves the negative effects induced by this regulation is long-lasting.

$$\ln Y_{ijt} = \alpha + \sum_{y=\underline{y}, y\neq -1}^{y=\bar{y}} \beta_y APPCAP_t \times Year_y + \gamma X_{ijt} + \mu_j + \eta_t + \varepsilon_{ijt} \tag{2}$$

where $[\underline{y}, \bar{y}] = [-6, 3]$ and the base year is $y = -1$ ($\beta_y = 0$), $Year_y$ is a binary variable, equal to 1 when the city j would be treated after y years, the coefficients when $y \geqslant 0$ correspond the average accumulation effects of operating revenue relative to the former year, then the β_y is expected to be negative when $y \geqslant 0$.

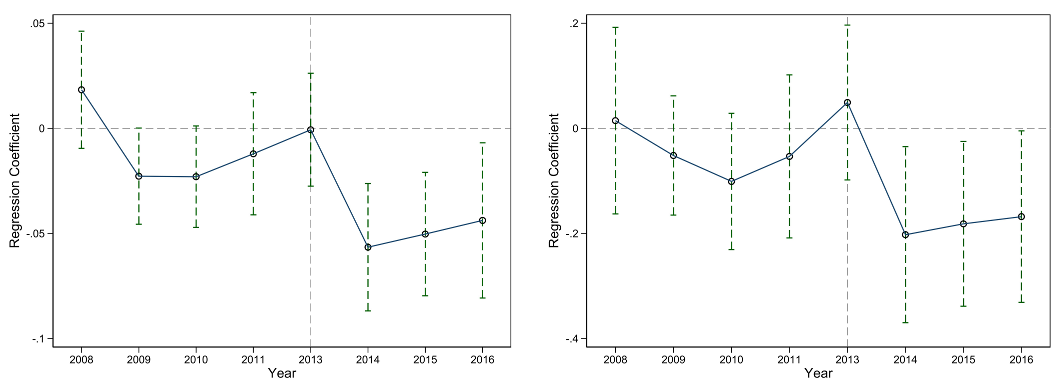
As for the placebo test, I follow the classic way of "permutation", which means I randomly assign treatment vs. control groups, and run the baseline regression for 200 times repeatedly to estimate the coefficients and draw the distribution. The figure shows the kdensity distribution estimates and the corresponding p-values, and the p-values of most estimates are greater than 0.1, which means the results unlikely to be obtained by chance or influenced by other policies or random factors, i.e. the estimate above is a significant outlier and reliable.

Table 2: Baseline Estimates **w/o and w/ PSM**

	Dependent variable: Log (Operating Revenue)			
	Two-way FE		**PSM-DiD**	
	(1) Regulated	(2) Unregulated	(3) Regulated	(4) Unregulated
APPCAP×Treat	-0.183***	-0.133**	-0.159***	-0.049
	(0.051)	(0.062)	(0.052)	(0.066)
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	214,750	690,269	82,788	260,539
R-squared	0.434	0.412	0.374	0.374

Note: The dependent variable is the natural logarithm of operating revenue. Robust standard errors are in parentheses, clustered at the industry-year level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.



(a) Intensity DiD

(b) PSM-DiD

Figure 7: the Event Study of two specification strategies

Note: Scatter plots with error bars of 95% CI. 2012 is the base year dropped in the event study regression.

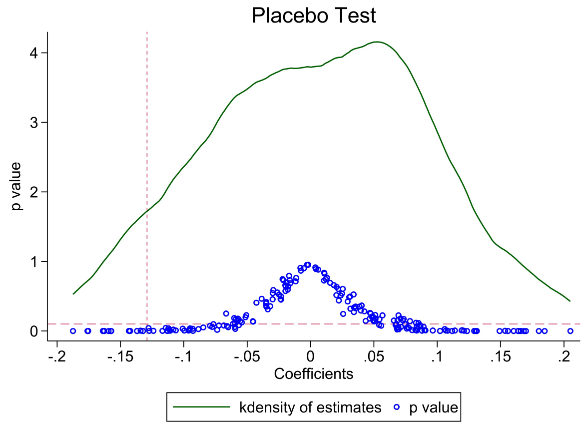


Figure 8: the Placebo Test

Note: This figure shows the density distribution of coefficient of each baseline regression for 200 times repeatedly. The red dash line shows the coefficient in this paper's estimation, which is obviously the outliers of the total distribution.

5.2 Mechanism

To dive into the mechanism behind the negative effects caused by APPCAP in 2013. I leverage the rich variables in National Tax Investigation Data and try to find the possible operational performance change after this policy.

The first channel I examine is energy use, which is directly affected by the implementation of the APPCAP, particularly in the case of fossil fuels. The figure below presents the coefficients of the regression equation (1) after substituting the outcome variables with the consumption of different fuel types: coal, oil, and electricity[7]. The results indicate that the consumption of coal and oil decreased significantly following the APPCAP, while the change in electricity use was not statistically significant. This finding aligns with expectations, as electricity usage itself does not directly contribute to air pollution; rather, its environmental impact is tied to the generation process. In contrast, coal and oil consumption directly emit substantial amounts of air pollutants, making their reduction a clear target under the APPCAP.

In more detail, a comparison of the coefficients between regulated and unregulated SLEs reveals some interesting findings. First, the change in oil usage for production is significantly negative for both groups, with the coefficients being quite similar. However, the coefficient for oil use in regulated SLEs is significantly more negative than that in unregulated SLEs. Additionally, while the change in electricity usage is not statistically significant, unregulated SLEs show a slight reduction in electricity consumption. This suggests a substitution pattern between different energy sources, highlighting the spillover effects of policy. Specifically, although the government primarily targets regulated SLEs, unregulated ones also adjust their operational strategies to align with the policy, demonstrating the

[7]Because there are a lot of zero value in the self-reported variable of coal, oil and electricity use, I take the natural logarithm of the value plus 1 to generate the $\ln Y$.

broader influence of the regulation.

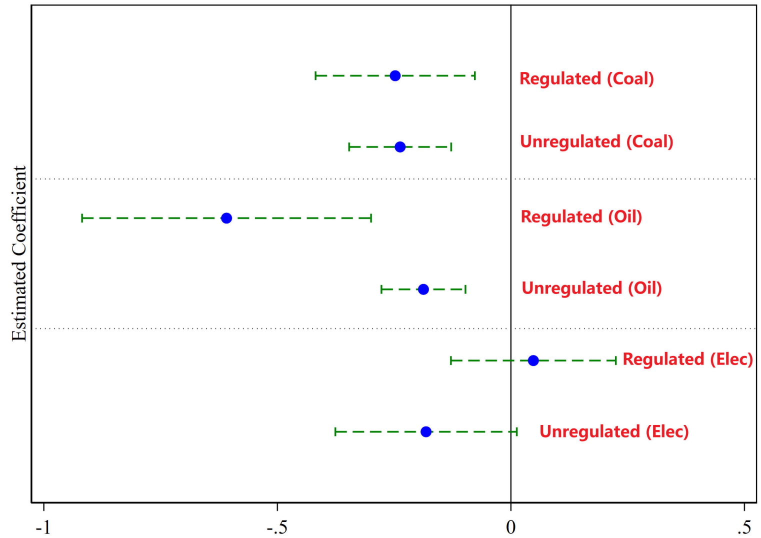


Figure 9: the coefficients of different energy type

Note: Scatter plots with error bars of 90% CI.

The second channel I examine is employment, which is critically important for two main reasons. First, SLEs are labor intensive and serve as a reservoir of employment in the Chinese economy. They play a pivotal role in ensuring basic living standards and quality of life for a large segment of grass-roots, ordinary people during the rapid urbanization process. Second, external regulations often have regressive redistribution or reallocation effects, disproportionately impacting vulnerable groups, such as the labor force employed by SLEs. These workers typically lack advanced skills and face challenges in securing better-paying or more suitable jobs. Under the pressure of regulations and the ensuing green transition, many SLEs struggle with basic operations and may be inclined to reduce their labor demand, potentially exacerbating unemployment issues (Liu et al., 2021).

The structural changes occurring in the Chinese economy as a result of these dynamics warrant further research and exploration. The table 3 below shows that there is a significant effect on the labor demand for regulated SLEs, with a nearly 7.4% drop, whereas no such effect is observed for unregulated SLEs. However, the coefficient for unregulated SLEs is not statistically significant. This finding offers a positive perspective, suggesting that the transition costs and unemployment pressures on the government may be less severe than initially anticipated during the processes of pollution reduction and green development. A reasonable conjecture is that the reduced demand in regulated SLEs may be absorbed by unregulated SLEs, potentially offsetting any negative outcomes.

Table 3: Estimates of the Employment Channel **w/ PSM**

	Employment	
	(1) Regulated	(2) Unregulated
APPCAP×Treat	-0.074*	-0.037
	(0.041)	(0.047)
Controls	Yes	Yes
City FE	Yes	Yes
Year FE	Yes	Yes
Observations	51,037	180,726
R-squared	0.375	0.278

As for the capital components and their structure, the table 4 below shows that the APPCAP indeed affects the capital accumulation or depletion process for regulated SLEs. Regulated SLEs will experience an almost 18% increase in their liability levels; however, the liabilities-to-assets ratio will not be significantly affected by this policy. [8]

The intriguing point is that while liabilities increase, the liabilities-to-assets ratio remains unaffected by the regulation. A possible explanation for this could be the accelerated asset accumulation process following the APPCAP. The government may encourage enterprises to upgrade their equipment, renovate production lines, or even expand their scale through subsidies, low-interest loans, or funding for environmental projects. Such support fosters the growth of enterprises' assets, particularly the increase in fixed assets like machinery and equipment. The simultaneous increase in both assets and liabilities results in an insignificant change in the ratio, meaning that financial risk and debt burden are not amplified to a significant degree.

[8] To calculate the liabilities-to-assets ratio, I divide the liabilities of each firm by the value of its assets and then take the natural logarithm to derive the outcome variable.

Table 4: Estimates of Three Channels **w/ PSM**

	Liabilities-to-Assets Ratio		**Liability**	
	(1) Regulated	(2) Unregulated	(3) Regulated	(4) Unregulated
APPCAP×Treat	-0.001	0.028	0.179**	0.134
	(0.032)	(0.031)	(0.074)	(0.100)
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	82,788	260,539	82,788	260,539
R-squared	0.017	0.013	0.074	0.044

Note: The dependent variable is the natural logarithm of liabilities-to-assets ratio and liabilities at the end of the year. Robust standard errors are in parentheses, clustered at the industry-year level.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The final channel concerns an unobservable factor for an SLE: total factor productivity (TFP), which is a critical measure of the technological level of an SLE. To derive this variable, I borrow the methodology from Giannetti et al. (2015) by regressing the SLE's operating revenue on the number of employees, total assets, and cash payments for goods and services (all in logarithms). I then generate the residual, which is denoted as TFP (i.e., the portion of output unexplained by labor, capital, and other production factors).

Table 5 below shows the effects of the APPCAP on TFP for both types of SLEs. These effects are statistically insignificant, which alleviates concerns that the APPCAP could result in a significant negative shock, hindering technological progress among regulated SLEs. A possible explanation is that SLEs typically have limited resources to invest in more advanced or environmentally friendly technologies for improving productivity, which distinguishes them from larger firms.

Table 5: the TFP Estimates **w/ PSM**

	Dependent variable: TFP	
	(1) Regulated	(2) Unregulated
APPCAP×Treat	-0.007	-0.033
	(0.033)	(0.024)
Controls	Yes	Yes
City FE	Yes	Yes
Year FE	Yes	Yes
Observations	20,453	65,499
R-squared	0.041	0.029

Note: The dependent variable is the residual term (TFP). Robust standard errors are in parentheses, clustered at the industry-year level.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

6 Conclusion

In this research, I aim to address a question that remains somewhat unclear: whether an external shock can have negative effects on small and labor-intensive enterprises (SLEs), and if so, what the potential mechanisms are. By leveraging the National Tax Investigation Data (2007-2016) and placing this within the context of the APPCAP regulation introduced in 2013, I draw three main conclusions: 1) the regulation has direct effects on operating revenue (nearly 16% and only for regulated firms); 2) the negative effects are robust, persistent, and last beyond 2013; 3) the regulatory shock induces a series of behavioral adjustments among regulated firms, such as changes in energy consumption, labor demand, and capital structure, but does not affect the technology used by SLEs (no impact on TFP).

From these preliminary conclusions, several policy implications can be drawn. The production decrease induced by the APPCAP leads to economic loss, but the reduction in pollutants also brings benefits such as fewer related diseases and lower mortality rates. For policymakers, it is crucial to understand how to strike a balance between local costs (borne by firms, especially small and micro enterprises) and broader social/global benefits (such as improved public health and avoided environmental disasters). This research provides some evidence on the cost side for SLEs, which is critical, as they form the backbone of the Chinese economy.

There are certainly several limitations in this paper. The primary challenge to the results stems from the reliability of the dataset, as all the values used in this research are derived from the National Tax Investigation, which consists of self-reported data that may be subject to potential manipulation during the data collection process. Other concerns include the possibility of SLEs switching sectors within or across industries (e.g., moving from a regulated to an unregulated sector), as well as informal adaptations (such as concealing production and pollution behaviors), which may not be fully captured in this study. To address these issues, cross-sectional sampling data would be a valuable supplement. In the future, more robust and detailed analyses focusing on heterogeneous effects would be highly beneficial. Such analyses could help us better understand which industries are more heavily impacted and identify the most effective ways to support them.

To extend this research and address additional potential questions, I believe there are several valuable data sources that could be considered for future studies. First, patent application data from the State Intellectual Property Office could be used to measure innovation performance, particularly in terms of more sustainable or "greener" innovations (Cui et al., 2023). However, a foreseeable challenge is the limited number of data points available that could be matched with the SLEs in the National Tax Investigation data. Second, the China Micro and Small Enterprise Survey (CMES) focuses specifically on SLEs in China and could be a powerful dataset for research related to SLEs. However, the major limitation is that only data from a single year (2015) is accessible, and there is no detailed information regarding the name or address of the firms included in that survey. Third, insurance transaction and issuance data could be a useful source, as it is designed and provided by either the government or commercial insurance companies to help boost the resilience of SLEs. A direct question that could be addressed is how to improve the efficiency of insurance products, which would be valuable for insurance providers, especially in the context of climate change.[9]

Finally, I would like to share a related NBER working paper, Grover and Kahn (2024), which can be seen as a potential extension of this research and the related literature. The figure 10 below is taken from this paper and illustrates the relationship among different components when studying the behavioral adjustments of firms in response to external shocks (in this case, a climate change shock). There are many strategies available to adapt to the negative effects of climate change. From the firm's perspective, potential methods include adjusting the firm's size, improving managerial quality, and modifying ownership structures—all of which can help firms respond to climate challenges and enhance their resilience in the future.

From a broader sectoral perspective, strategies might include resource reallocation and more frequent and adaptive transactions in informal markets. These adjustments offer valuable insights for policymakers, helping them strengthen government capabilities and implement more supportive policies for firms in vulnerable sectors or regions.

[9] Another intriguing issue I am eager to explore is the proactive versus passive adaptation strategies adopted by firms. However, a significant challenge lies in how to rigorously define and identify what constitutes "proactive" versus "passive" adaptation.

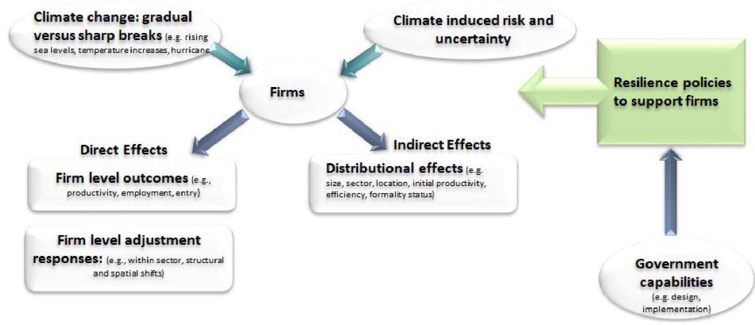


Figure 10: Key themes for firms in the context of climate change adaptation

References

Angelucci, M., Karlan, D., and Zinman, J. (2015). Microcredit impacts: Evidence from a randomized microcredit program placement experiment by compartamos banco. *American Economic Journal: Applied Economics*, 7(1):151–182.

Attanasio, O., Augsburg, B., De Haas, R., Fitzsimons, E., and Harmgart, H. (2015). The impacts of microfinance: Evidence from joint-liability lending in mongolia. *American Economic Journal: Applied Economics*, 7(1):90–122.

Banerjee, A., Duflo, E., Glennerster, R., and Kinnan, C. (2015a). The miracle of microfinance? evidence from a randomized evaluation. *American economic journal: Applied economics*, 7(1):22–53.

Banerjee, A., Karlan, D., and Zinman, J. (2015b). Six randomized evaluations of microcredit: Introduction and further steps. *American Economic Journal: Applied Economics*, 7(1):1–21.

Barrot, J.-N. and Sauvagnat, J. (2016). Input specificity and the propagation of idiosyncratic shocks in production networks. *The Quarterly Journal of Economics*, 131(3):1543–1592.

Blattman, C., Green, E. P., Jamison, J., Lehmann, M. C., and Annan, J. (2016). The returns to microenterprise support among the ultrapoor: A field experiment in postwar uganda. *American economic journal: Applied economics*, 8(2):35–64.

Brooks, W., Donovan, K., and Johnson, T. R. (2018). Mentors or teachers? microenterprise training in kenya. *American Economic Journal: Applied Economics*, 10(4):196–221.

Bruhn, M., Karlan, D., and Schoar, A. (2018). The impact of consulting services on small and medium enterprises: Evidence from a randomized trial in mexico. *Journal of Political Economy*, 126(2):635–687.

Cai, H., Chen, Y., and Gong, Q. (2016). Polluting thy neighbor: Unintended consequences of china's pollution reduction mandates. *Journal of Environmental Economics and Management*, 76:86–104.

Chen, Q., Chen, Z., Liu, Z., Serrato, J. C. S., and Xu, D. Y. (2025). Regulating conglomerates: Evidence from an energy conservation program in china.

Cui, J., Huang, S., and Wang, C. (2023). The impact of air quality on innovation activities in china. *Journal of Environmental Economics and Management*, 122:102893.

Cui, X. and Tang, Q. (2024). Extreme heat and rural household adaptation: Evidence from northeast china. *Journal of Development Economics*, 167:103243.

De Mel, S., McKenzie, D., and Woodruff, C. (2008). Returns to capital in microenterprises: evidence from a field experiment. *The Quarterly Journal of Economics*, 123(4):1329–1372.

Feng, C., Liu, B., and Ye, Y. (2023). Tax cuts incentives and heterogeneous investment responses: Evidence from micro and small enterprises (in chinese). *Journal of Management World*, 11.

Field, E., Pande, R., Papp, J., and Rigol, N. (2013). Does the classic microfinance model discourage entrepreneurship among the poor? experimental evidence from india. *American Economic Review*, 103(6):2196–2226.

Giannetti, M., Liao, G., and Yu, X. (2015). The brain gain of corporate boards: Evidence from china. *the Journal of Finance*, 70(4):1629–1682.

Groh, M. and McKenzie, D. (2016). Macroinsurance for microenterprises: A randomized experiment in post-revolution egypt. *Journal of Development Economics*, 118:13–25.

Grover, A. and Kahn, M. E. (2024). Firm adaptation to climate change. Technical report, National Bureau of Economic Research.

He, G., Wang, S., and Zhang, B. (2020). Watering down environmental regulation in china. *The Quarterly Journal of Economics*, 135(4):2135–2185.

Lane, G. (2024). Adapting to climate risk with guaranteed credit: Evidence from bangladesh. *Econometrica*, 92(2):355–386.

Li, H. (2021). The way to improve the efficiency of tax reduction: The evidence from the elasticity of taxable income of small and micro enterprises in structural tax reduction period (in chinese). *Journal of Management World*, 11.

Li, S., Wang, M., and Zhang, d. (2022). Environmental Inspection and Firm Entry: Evidence from Firm Registration Data (in Chinese). *The Journal of World Economy*, 45(1):110–132.

Li, X., Qiao, Y., and Shi, L. (2019). Has china's war on pollution slowed the growth of its manufacturing and by how much? evidence from the clean air action. *China Economic Review*, 53:271–289.

Liu, M., Tan, R., and Zhang, B. (2021). The costs of “blue sky”: Environmental regulation, technology upgrading, and labor demand in china. *Journal of Development Economics*, 150:102610.

Meager, R. (2019). Understanding the average impact of microcredit expansions: A bayesian hierarchical analysis of seven randomized experiments. *American Economic Journal: Applied Economics*, 11(1):57–91.

Miriam, B., Martin, H., Mahima, K., Sandeep, S., Aksinya, S., and Joshua, S. W. (2017). *MSME finance gap: Assessment of the shortfalls and opportunities in financing micro, small, and medium enterprises in emerging markets*. World Bank.

Wang, W., Li, X., and Lu, Y. (2020). Tax reduction incentives and corporate debt burden: Evidence from the policy of halving the income tax on small low-profit enterprises (in chinese). *Economic Research Journal*, 55(8):105–120.

Yang, L., Wu, B., Li, S., and Peng, F. (2021). Can using tax credit for financing help small businesses access bank loans? empirical evidence from the policy of tax credit bank loans (in chinese). *Economic Research Journal*, 56(7):96–112.

Zhu, W., Zhang, P., Li, P., and Wang, Z. (2020). Firm crisis, government support and policy efficiency under the epidemic shock: Evidence from two waves of questionnaire on smes (in chinese). *Journal of Management World*, 4.