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The Green Costs of Debt Overhang: Evidence from Local Government Debt Restructuring

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Abstract

The pursuit of causes with positive externalities is, unfortunately, often constrained by debt burdens. We investigate the environmental costs of debt overhang by examining China's massive debt restructuring in 2015. Cities with heavier pre-restructuring debt burdens experienced greater improvements in local air quality after their costly debt was swapped for municipal bonds backed by higher-level governments. These patterns cannot be fully explained by tightened top-down environmental regulations or trends driven by initial pollution levels. Previously more debt-constrained cities also saw larger increases in clean energy production, penalties imposed on polluting firms, closures of coal-fired power plants, and green patents filed by listed firms. Our findings underscore the role of public debt constraints in shaping local green transition.

Keywords: Debt restructuring, local governments, debt overhang, air pollution
JEL classification: H63, H74, Q51, Q52, Q53, Q58

The Green Costs of Debt Overhang: Evidence from Local Government Debt Restructuring

Jiayin Hu Xiaokang Hu Yuchao Peng Yingguang Zhang*

Abstract

We investigate the environmental implications of debt overhang using China's large-scale local government debt restructuring in 2015 as a natural experiment. We find that after the debt restructuring, cities with previously heavier debt burdens experience greater improvements in air quality. These cities also become more likely to close coal-fired power plants, increase clean energy production, and raise pollution penalties. Listed firms in these cities file more green patent applications. Alternative explanations, such as top-down environmental inspections and pre-existing trends, cannot explain the findings. Our study highlights the critical role of governments' financial constraints in shaping environmental regulations and outcomes.

Keywords: Debt restructuring, local governments, green finance, air pollution

JEL classification: G34, H74, Q53, Q58

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1 Introduction

Governments worldwide have become increasingly indebted. According to a United Nations (UN) report, global public debt reached a staggering $92 trillion in 2022, with 40% of developing countries classified as being in "serious debt trouble."[1] Meanwhile, this debt crisis is intertwined with an environmental crisis, as many countries facing debt problems also exhibit acute environmental vulnerabilities.[2] The interplay between the public debt and environmental crises presents a major challenge: countries highly exposed to environmental risks often have budgets strained by debt, limiting their ability to invest in measures that enhance environmental resilience.[3] Understanding the relationship between public debt burdens and environmental issues is hence essential for addressing this dual crisis effectively.

However, few studies have rigorously examined the environmental implications of public debt burdens. One major obstacle is the lack of suitable empirical settings. In particular, cross-country comparisons and nationwide time-series analyses are often confounded by country-specific characteristics and macroeconomic trends. Natural experiments involving shocks to public debt with regional variations are hard to find.

This paper addresses the gap by leveraging a large-scale public debt restructuring program implemented in China in 2015, which allowed local governments to issue low-cost municipal bonds to replace high-cost existing debts.[4] The program effectively alleviated

[1]See A World of Debt Report by the UN Crisis Response Group. The International Monetary Fund (IMF) forecasts that global public debt will continue to rise, particularly in emerging market economies and low-income countries. See IMF Global Debt Database.

[2]See Tackling debt and climate challenges in tandem: A policy agenda, UNCTAD Policy Brief No. 104.

[3]See Kristalina Georgieva, Marcos Chamon, Vimal Thakoor, "Swapping Debt for Climate or Nature Pledges Can Help Fund Resilience", December 14, 2022, the IMF blog.

[4]Prior to the restructuring program, much of the local government debt was off-budget and accumulated through local government financing vehicles (LGFVs). LGFVs are special-purpose entities backed by local governments to raise funding through commercial debts. Since local governments in China had long been prohibited from issuing municipal bonds or borrowing from banks, LGFVs played a critical role in financing

local governments' financial constraints by lowering interest payments, extending repayment horizons, and expanding debt capacity through strengthened implicit guarantees from upper-level governments. Importantly, the debt swap program was designed to contain local governments' default risks and was not directly motivated by environmental objectives. Thus, this shock to local government indebtedness provides a well-suited empirical setting to investigate the causal impact of public debt capacity on local environmental issues.

In this paper, we examine whether relaxed financial constraints for governments lead to improvements in environmental outcomes and, if so, how. We hypothesize that governments with greater alleviation of debt burdens are more likely to transition toward projects with positive environmental externalities, thereby improving environmental outcomes. Our economic rationale parallels the argument by Hong, Kubik and Scheinkman (2012), who posit that financial constraints are a key determinant of corporate goodness, as spending on socially responsible initiatives is often limited by the degree of a firm's financial slack. Moreover, we study the mechanisms through which the environmental improvements, if any, might be achieved. In particular, this transition needs not manifest as direct spending or subsidies for green investments; disinvestments from "brown" projects may also play a critical role, such as shutting down coal-fired power plants and imposing environmental penalties on polluting firms. These plant closures and pollution penalties can be particularly difficult to enforce for financially distressed governments, which may prioritize financial and economic concerns over environmental objectives.

To study our research questions, we compile a comprehensive database by integrating

fiscal expansion through infrastructure investments to counteract the negative effects of the 2008 financial crisis. However, this shadow banking mechanism could quickly spiral out of control, accumulating substantial unsupervised debt. Most importantly, LGFVs' commercial debts were often short-term and costly, with an average yield of 8%, far exceeding the yields paid by government agencies.

data from multiple sources, including grid-level air pollution data derived from satellite images, environmental penalties scraped from local government websites, operational activities of coal-fired and clean-energy power plants, and green patent applications filed by local firms. We acquire a dataset on local governments' debt burdens from Qu et al. (2023), who collect the data through legally binding inquiries sent to prefecture-level governments. We exploit the debt restructuring program in 2015 and the cross-sectional variations in pre-restructuring debt overhang to conduct a difference-in-differences (DID) analysis.

Our primary finding is that cities with tighter debt constraints in the pre-restructuring period experienced greater improvements in air quality after the debt swap. Specifically, our estimates indicate that a doubling of local governments' pre-swap debt-to-GDP ratio (hence a larger benefit from debt swap) leads to an additional 1.8 percent decrease in PM2.5 (the sample mean of PM2.5 is 43.33 $\mu g/m^3$). Put another way, the most indebted city (with a debt-to-GDP ratio of 2.94) is expected to see a 22.25 percent additional reduction in PM2.5 compared to a city with an average debt-to-GDP ratio (0.22). In terms of economic significance, Barwick et al. (2024a) estimate that a 10 $\mu g/m^3$ decrease in PM2.5 translates into a reduction of over $9.2 billion in China's annual healthcare spending. Therefore, our estimates suggest that the effects of financial constraint relaxation on air quality improvement are economically meaningful.

Moreover, the effects remain statistically and economically significant after controlling for contemporaneous environmental regulations (e.g., a city's inclusion in the central environmental inspection list), local weather conditions (e.g., precipitation), economic activities (e.g., population density and nighttime lights), and a series of fixed effects (e.g., geographic grid, city, and province). The results are consistent under alternative air quality measures (e.g., PM1, PM10, and carbon emissions) and debt burden measures (e.g., debt-to-fiscal-revenue ratio). Furthermore, we do not find statistically significant associations between pre-restructuring debt burdens and economic activities (proxied by nighttime lights and GDP growth), indicating that the reduction in air pollution is not driven by decreases in local economic activities.

We then investigate the potential mechanisms underlying the observed environmental improvements. First, we find that the green impact of debt restructuring is more pronounced in areas with higher initial pollution levels, suggesting a targeted approach by local governments for pollution reduction. Second, a higher pre-restructuring debt burden predicts a faster transition from coal-fired power plants to clean-energy power plants. Third, cities with higher pre-restructuring debt burdens more aggressively increase pollution penalties on firms. These findings indicate that local governments' financial constraints significantly influence their environmental investments and regulatory actions. Finally, we study whether the green impacts of debt restructuring are amplified by responses from the private sector. We find that listed firms in cities with higher pre-restructuring debt burdens file more green patent applications in the post-restructuring period. Taken together, our results suggest that the reduction in debt pressure improves local governments' tradeoff between economic growth and environmental protection, thereby alleviating the green costs of public debt overhang and promoting local green transition.

Our paper makes three main contributions to the literature. First, our findings shed light on the environmental implications of public debt burdens, thereby advancing the green and climate finance literature (Hong et al., 2020). In particular, we bring a public finance perspective into this field, which has traditionally focused more on the private sector and financial markets.[5] Relatedly, several studies have examined the role and strategic behaviors of governments in environmental regulation (e.g., Barwick et al., 2024b; Greenstone et al., 2022; He et al., 2020). We show that the financing constraints of local governments have important environmental implications, pointing to a policy path that combines solutions to both public debt and environmental problems (e.g., Bolton et al., 2022; Simmons et al., 2021).

Second, we add a new chapter to the study of public debt, particularly municipal financing with Chinese characteristics, by examining the restructuring of local government debt. Previous studies have primarily focused on the accumulation of local government debt, such as its crowding-out effects (Chen et al., 2023; Huang et al., 2020; Ru, 2018). Hu et al. (2022) document the unintended consequences of forced government deleveraging, where financially constrained local governments transfer their liquidity pressures to contractors via the trade credit channel. By contrast, our paper examines the restructuring of local government debt, which alleviates local governments' debt burdens. Li et al. (2024) show that the debt-to-bond swap program for local governments significantly increases banks' risk-weighted capital and reallocates credit toward more productive private firms. Departing from a purely financial perspective, we explore how a debt-relieved government can address pressing environmental challenges. Our paper also connects to the burgeoning literature on the impact of climate change and environmental preservation on municipal financing (e.g., Auh et al., 2022; Chen et al., 2024; Deng and Meng, 2025).

[5] Previous studies have examined the impact of climate and environmental risks on bond markets (for instance, see Bauer and Hann, 2010; Sharfman and Fernando, 2008), stock markets (Hong and Kacperczyk, 2009), shareholders (Tang and Zhang, 2020), institutional investors (Krueger et al., 2020), mutual funds (Riedl and Smeets, 2017), and private banks (Goss and Roberts, 2011). Kostovetsky et al. (2024) document that higher local climate attention leads to increased individual investment in ESG-focused ETFs and improved environmental performance of local firms.

Third, we provide novel empirical findings regarding the role of financial constraints in shaping governments' multitasking behavior.[6] Previous studies have largely focused on the career concerns of local officials. For instance, Chen et al. (2018b) document that local bureaucrats sacrifice GDP growth to achieve the stringent emission-reduction goal set by the central government under a target-based performance evaluation system. Cao et al. (2023) show that air quality deteriorates significantly after the minimum air quality standard has been met, particularly in cases where local governments face increased pressure to support economic development. We differ from these studies by highlighting the impact of governments' debt burdens on the economy-environment tradeoff. Our findings demonstrate that financial constraints influence governments' ability to balance competing priorities. More broadly, our findings resonate with the literature on corporate social responsibility (e.g., Hong et al., 2012) by showing that governments' financial constraints can have analogous but distinct inhibiting effects on investments in projects with positive externalities.

The remainder of our paper proceeds as follows. Section 2 introduces the background. Section 3 describes the data. Section 4 examines the impact of public debt restructuring on air quality. Section 5 discusses the energy transition mechanism. Section 6 examines the role of local governments in shaping environmental outcomes. Section 7 concludes the paper.

[6] The multitasking theory pioneered by Holmstrom and Milgrom (1991) examines the principal-agent problem with several tasks assigned to the agent. It offers a coherent framework for understanding bureaucratic constraints, such as career concerns and political incentives (Dewatripont and Tirole, 1999; Dewatripont et al., 1999; Dewatripont et al., 2000; Hellmann and Thiele, 2011), as well as the working of state-owned enterprises (Bai and Xu, 2005; Bai and Wang, 1998; Bai et al., 2006; Bai et al., 2000).

2 Institutional Background

2.1 Air Quality as a Salient Environmental Outcome

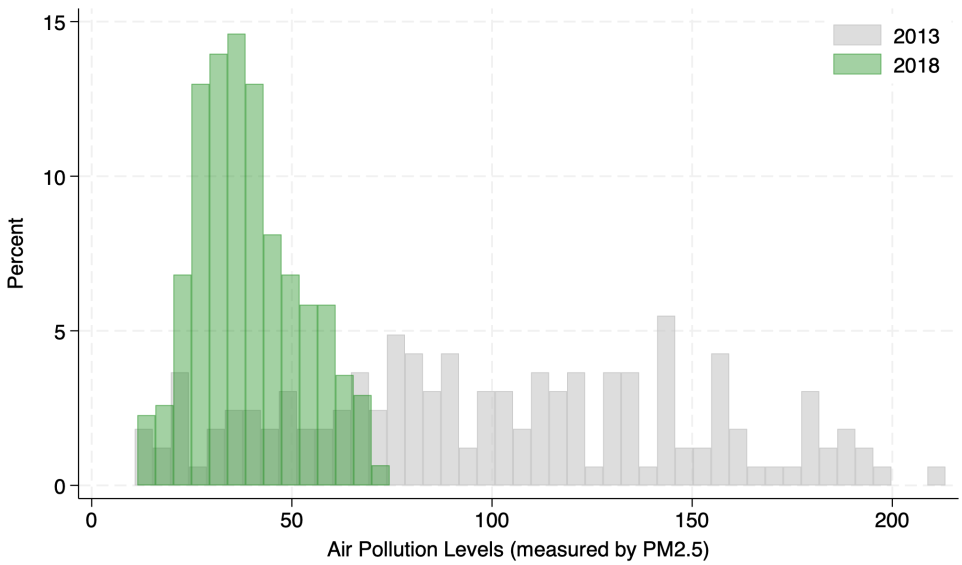
Environmental protection goals may be compromised by governments pursuing economic growth, especially those in developing countries. Nevertheless, in the early 2010s, escalating air pollution levels and increased public awareness regarding environmental issues prompted the Chinese government to address air quality problems. Between 2011 and 2013, China released a series of policies and guidelines to promote a green, low-carbon economic development model. In 2013, China introduced the Air Pollution Prevention and Control Action Plan, demonstrating a strong commitment to tackling air pollution.[7]

Furthermore, the performance evaluation mechanisms for local governments have also evolved, with green GDP emerging as a crucial metric for evaluating local officials. By moving beyond traditional metrics centered solely on economic growth, this approach seeks to strike a balance between fostering economic progress and enhancing environmental quality. The annual average concentration levels for PM2.5 and sulfur dioxide decreased by 56% and 78%, respectively, from 2013 to 2021. As shown in Figure 1, the air quality in China has substantially improved nationwide between 2013 and 2018, with the distribution of city-level PM2.5 concentration shifting toward a much lower range.

[7] China's commitment to environmental protection dates back several decades. The Environmental Protection Law of China, which was promulgated in 1989, represents the country's first comprehensive legislation on environmental protection. China joined the Kyoto Protocol, an international agreement aimed at reducing global greenhouse gas emissions to combat climate change, in 2002. In 2016, China became a formal member of the Paris Agreement, pledging to reduce greenhouse gas emissions by implementing Nationally Determined Contributions.

Figure 1: Air Quality Improvement in China, 2013-2018

This figure plots the distribution of air pollution across prefecture-level cities in China, measured by the annual average concentration level of fine particulate matter (PM2.5), a focal air quality indicator in China. A higher level of PM2.5 (in micrograms per cubic meter) means a lower level of air quality. The grey (green) bars represent the histogram of PM2.5 levels in 2013 (2018). The sample includes 164 cities with ground-monitored PM2.5 data in 2013 and 308 cities with ground-monitored PM2.5 data in 2018. Data source: CSMAR.



2.2 Debt Burdens on Local Governments in China

In the five-tier government hierarchy in China (i.e., central, provincial, prefecture-level, county-level, and village-level), local governments (primarily the prefecture-level ones) take major responsibility for managing local affairs. Under this fiscal decentralization regime, the incentives and constraints of local governments are crucial to implementing the central government's policies, including environmental protection goals. Facing mounting debt and financial obligations, local governments may tend to loosen environmental regulations to boost economic growth and generate tax revenue.

Before 2015, local governments in China lacked the ability to issue municipal bonds. In 2008, in response to the negative spillovers of the global financial crisis on China's exportdriven economy, the Chinese government launched a 4-trillion-yuan package of stimulus plans to boost domestic demand via large-scale infrastructure investments. Due to strict restrictions on municipal bond issuance, local governments, which were responsible for raising over two-thirds of the stimulus funds, extensively set up LGFVs to raise off-budget funding in the shadow banking system (e.g., Ang et al., 2018; Chen et al., 2018a; Chen et al., 2020), accumulating substantial "hidden debt" in the form of LGFVs' commercial debts.

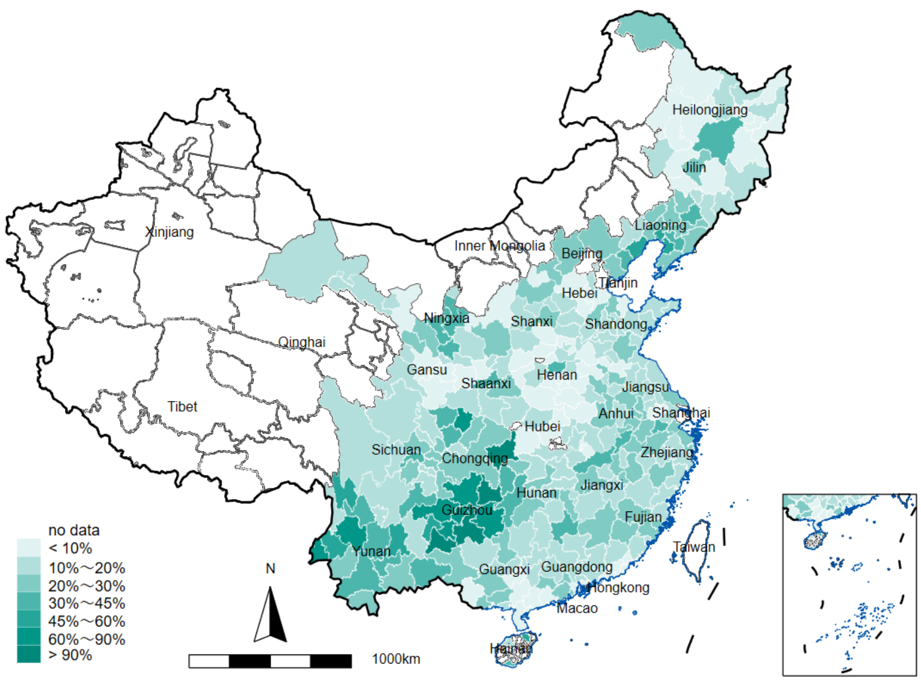
The rapid expansion of LGFV debt creates substantial fiscal burdens on local governments. Local governments' outstanding debt jumped from 5.8% of the GDP to 22% of the GDP between 2006 and 2013 (Huang et al., 2020). Figure 2 shows the spatial distribution of the outstanding local government debt balance scaled by GDP in 2014, with darker shades representing a higher level of local debt pressure. Many of these debts are characterized by high interest rates and short repayment periods, intensifying fiscal risks for local governments. Despite their weak economic and fiscal conditions, Guizhou and Yunnan Provinces in southwest China were able to accumulate substantial LGFV debt as of 2014, reflecting the financial market's expectations of an implicit guarantee from the central government.

2.3 Top-down Government Debt Swap in 2015

To resolve risks associated with local governments' "hidden" debt, the Chinese central government has implemented a massive debt restructuring program. In August 2014, the new Budget Law of China was promulgated, making it clear that provincial governments can issue municipal bonds on behalf of prefecture-level governments to raise funding within the quota approved by the National People's Congress. To ensure a smooth transition from

Figure 2: Local Government Debt Burdens before Restructuring

This figure presents the spatial distribution of local governments' debt-to-GDP ratio in 2014. Darker shades indicate higher debt-to-GDP ratios (i.e., heavier debt burdens). The local governments' debt balance data in 2014 come from Qu et al. (2023).



LGFV debt to official municipal debt, the central government also released the Guiding Opinions on Strengthening the Management of Local Government Debt in September 2014,[8] which specified a bond issuance quota management system and announced the launch of a three-year debt-swap program beginning in 2015.

The debt restructuring program consists of two main procedures: debt identification and restructuring bond issuance. The debt identification primarily targets local governments' outstanding debts, mainly incurred through LGFVs, by the end of 2014. In 2014, the central government conducted a re-audit of public sector debt, with the Ministry of Finance (MOF) carrying out the verification and classification of local government debts in the fourth quarter.

[8]Decree No. 43 [2014] of the State Council (link).

Notably, the top-down debt restructuring program swapped high-cost LGFV debts with newly-issued municipal bonds with lower interest rates and longer maturities, which reduces the interest costs of these debt burdens and alleviates the repayment pressure of maturing debts. In 2015, the MOF announced that it would complete the local government bond swap program over a transition period of approximately three years.

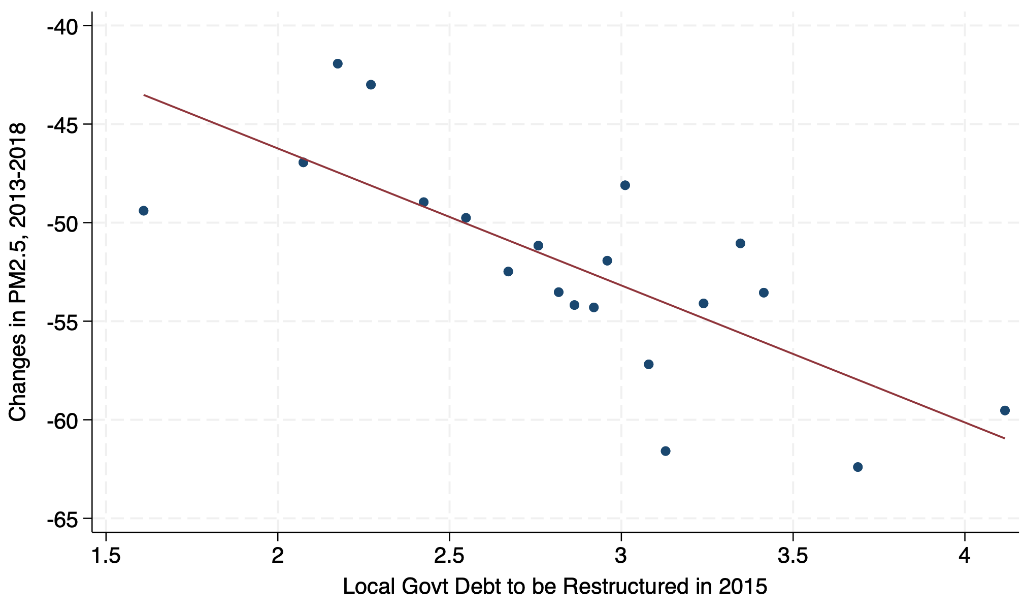
In March and June 2015, the MOF allocated 1 trillion yuan each month in debt swap quotas to local governments. In August 2015, the MOF's budget execution report indicated that the annual plan included 600 billion yuan in newly-issued municipal bonds and 3.2 trillion yuan in bond swap quotas to replace outstanding debt, which were allocated proportionally based on the debt amount. Starting in 2016, provincial governments independently reported their quotas based on debt repayment needs and market conditions. According to the MOF, China had completed an issuance of 7.2 trillion yuan of restructuring bonds by the end of September 2016, with an estimated 600 billion yuan saved in interest expenses for local governments between 2015 and 2016, which "substantially reduced the financial burden on local governments."[9]

Figure 3 provides some illustrative evidence on the potential environmental impact of public debt relief. We measure the restructuring intensity of local government debts using their pre-restructuring debt burdens. Notably, there is a negative correlation between the pre-restructuring debt-to-GDP ratios in 2014 and the changes in PM2.5 concentration levels between 2013 and 2018. This pattern indicates that previously more debt-constrained cities, which benefit more from the debt swap program starting from 2015, also experience larger reduction in local air pollution. This result is consistent with our hypothesis that the alle-

[9] Reference to official reports: https://www.gov.cn/xinwen/2016-11/04/content_5128620.htm

Figure 3: Local Government Debt Restructuring and Air Pollution Reduction

This binscatter plot shows the correlation between public debt relief and air quality improvements. We measure the intensity of the restructuring of local government debts as the natural logarithm of the local debt-to-GDP ratio in 2014, i.e., before the debt swap program. We measure air quality improvements as the changes in annual average PM2.5 concentration levels between 2013 and 2018. There are 164 cities with ground-monitored PM2.5 data in both years. The control variables include the initial level of PM2.5, the ratio of the secondary industry in GDP, GDP (log scale), and population (log scale), all in 2013 values.



viation of local governments' financial constraints improves the tradeoff between economic and environmental goals.

3 Data and Summary Statistics

3.1 Data

We combine several datasets to explore the impact and mechanism of public debt burdens on local environmental outcomes.

Air pollution. Our major outcome variable is the severity of local air pollution measured by PM2.5, i.e., the inhalable particulate matter suspended in the air with a diameter of less than 2.5 microns. We obtain grid-level data on PM2.5, PM1, and PM10 concentration between 2011 and 2018 from ChinaHighPM2.5. These air pollution data are estimated by integrating multiple data sources (e.g., ground monitors, satellite remote sensors, and meteorological data) and using decision tree methods to fill satellite data gaps for comprehensive PM2.5 concentration estimation (Wei et al., 2021).[10] The original TIF-format air pollution data are processed using a spatial latitude-longitude resolution of $0.1° \times 0.1°$, which are defined as grids (e.g., Koh et al., 2022). We then match the grid-level data with the corresponding cities based on their geographical coordinates. We also obtain grid-level precipitation data from the National Meteorological Information Center[11] to control for cleansing effect of precipitation on measured air pollution (see, e.g., Rosenfeld et al., 2007).

Local government debt. Our key explanatory variable is the debt-to-GDP ratio $DebtBurden_{j,2014}$ for city j in 2014, which captures local governments' debt burdens before the restructuring program and hence the magnitude of the debt relief. We use the outstanding debt stock of prefecture-level cities by the end of 2014, which are collected by Qu et al. (2023) by filing information disclosure applications with local governments. Other macroeconomic variables, including city-level GDP, population, and the fraction of employees in the secondary industry, come from the National Bureau of Statistics.

Utilizing the debt-to-GDP ratio rather than the absolute debt stock offers several ad-

[10]Specifically, Wei et al. (2021) employ a two-tier machine learning approach to estimate daily PM2.5 concentrations. The first tier combines the SMOTE technique with the random forest algorithm to predict high-pollution events. The second tier models the residuals between CMAQ simulations and observations to enhance prediction accuracy. Data source: http://tapdata.org.cn/?page_id=933 and https://zenodo.org/records/6398971.

[11]National Meteorological Science Data Sharing Service Platform - Daily Value Dataset of China's Surface Climate Data (V3.0). Website: https://data.cma.cn/?ref=hao.archcookie.com.

vantages. First, it provides a standardized measure of debt pressure that accounts for the size of the city's economy, enabling more meaningful comparisons across cities. Second, this approach helps assess local governments' fiscal sustainability by considering the economic base that supports debt repayment. In a robustness test, we change the denominator to local governments' fiscal revenue and find consistent results. We further alleviate the impact of extreme values on regression results by taking natural logarithms of key variables, which also enables us to interpret the estimated coefficients as elasticities.

Carbon emission and energy structure. We obtain grid-level carbon emission data from NASA.[12] Since energy production is a major contributor to local air pollution, we further examine coal-fired plants as identified by the Chinese Registration Dataset of Industrial and Commercial Enterprises, which provides entry, exit, industry, and address information of firms registered in mainland China since 1978. We also obtain data on 1,686 clean power plants in China from the Global Power Plant Database,[13] which covers over 35,000 power plants in 167 countries, with electricity generation data estimated by Yin et al. (2020).

To account for local economic activities, we also retrieve population density data from WorldPop[14] and nighttime light data from Harvard Dataverse.[15] The density of population reflects the density of residential areas and is closely related to environmental stressors, such as vehicle emissions, household energy consumption, and the generation of domestic waste. Nighttime light data reflect the level of economic development and the intensity of industrial activities, which are often used as a proxy variable for economic activities.

[12]Data source: https://disc.gsfc.nasa.gov/datasets/M2TMNXAER_5.12.4/summary.

[13]Data source: https://datasets.wri.org/dataset/globalpowerplantdatabase.

[14]Data source: https://hub.worldpop.org/.

[15]An extended time-series (2000-2018) of global NPP-VIIRS-like nighttime light data - Harvard Dataverse (link: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/YGIVCD).

Environmental regulation intensity. To measure the enforcement of environmental regulations, we obtain data on the universe of administrative punishments from 2011 to 2018 imposed by local governments from PKULaw.com, a leading website that assembles laws and government regulations. Environmental penalties refer to administrative punishments on individuals or organizations that violate environmental laws and regulations, including monetary fines, production suspension orders, license revocations, and other disciplinary measures. Local government agencies (mainly local environmental protection bureaus) are responsible for enforcing environmental regulations and imposing environmental penalties.[16] Our dataset includes 118,000 environmental penalty cases from 2011 to 2018. The number of environmental penalty cases increased from 571 in 2011 to 73,537 in 2018, with more than 85% penalties imposed in the post-restructuring period.

Listed firm data. Our data on publicly listed firms in China's A-share stock market come from CSMAR, a widely used economics and financial data provider. Our firm-level data include financial data on publicly listed firms between 2011 and 2018. The patent application data come from the WIPO database and are matched to these listed companies. We define green patents based on the IPC Green List compiled by WIPO, which collates patent information related to environmentally sound technologies (ESTs) listed by the United Nations Framework Convention on Climate Change (UNFCCC) into the following sections: Alternative Energy Production, Transportation, Energy Conservation, Waste Management, Agriculture/Forest, Administrative, Regulatory or Design Aspects, and Nuclear Power Gen-

[16] A representative case (Ning-Huan-Fa-Zi [2017] No.152) involves Sinopec Nanjing Chemical Industries, which violates Article 99(2) of China's Air Pollution Prevention and Control Law by exceeding the limits of particulate emissions. The firm received a fine of 1.936 million yuan and was subject to corrective actions from the Nanjing Ecology and Environment Bureau.

eration.[17] We are particularly interested in patents related to air quality management under the Waste Management subcategory of WIPO's green innovation classification. Examples of such patents include "B01D 53/92 and F02B 75/10: Rendering exhaust gases innocuous", "C21C 5/38: Removal of waste gases or dust in steel production", "F23G 7/06: Combustion of waste gases or noxious gases", and "C09K 3/22: Dust-laying or dust-absorbing materials."

3.2 Summary Statistics

Our sample includes an annual panel of 45,823 grids in 291 prefecture-level cities,[18] which corresponds to 366,584 grid-year observations between 2011 and 2018. Table 1 provides descriptive statistics for the main variables.

Air pollution. Panel A of Table 1 shows that during our sample period between 2011 and 2018, the average annual grid-level PM2.5 concentration is 43.33 $\mu g/m^3$ (micrograms per cubic meter), with a standard deviation of 16.37. Beijing's annual average PM2.5 concentration reached 80.6 $\mu g/m^3$ in 2015, exceeding the national standard by 130%. In comparison, the European Union's annual PM2.5 limit was set at 25 $\mu g/m^3$ in 2015, far below the air pollution level in China. Cities with annual average PM2.5 concentration levels exceeding 100 $\mu g/m^3$ are predominantly located in Hebei and Henan provinces, with the highest recorded value reaching 147.2 $\mu g/m^3$. Nevertheless, as shown by the shifted air pollution distribution in Figure 1, the air quality in China has substantially improved in the past decade, with much lower PM2.5 concentrations in 2018 than in 2013.

Local government debt. Panel B of Table 1 shows that on average, the LGFV debt as

[17] Data source: https://www.wipo.int/classifications/ipc/green-inventory/home.

[18] Our sample cities include all prefecture-level cities, excluding Hong Kong, Macau, Taiwan, and four municipalities (Beijing, Shanghai, Chongqing, and Tianjin). We also exclude cities in four provincial-level autonomous regions (Xinjiang, Tibet, Qinghai, and Inner Mongolia).

Table 1: Summary Statistics

This table reports the summary statistics of the main variables used in our analysis. i indexes the grid, j indexes the city, f indexes the plant and firm, and t indexes the year between 2011 and 2018. We obtain PM1, PM2.5, and PM10 concentration data from ChinaHighPM2.5, population density data from WorldPop, precipitation data from the National Meteorological Information Center, and nighttime light data from Harvard Dataverse. City-level macroeconomic variables are obtained from China's National Bureau of Statistics via CSMAR. Data on publicly listed firms in China's A-share stock market come from CSMAR. Data on coal-fired power plants come from the Registration Records of Industrial and Commercial Enterprises. Data on clean-energy power plants come from the Global Power Plant Database. Control variables are lagged by one year.

Variables	N	Mean	SD	Min	Median	Max
Panel A: Grid-level data						
$PM2.5_{it}$ ($\mu g/m^3$)	366,584	43.33	16.37	11.49	40.27	147.20
$PM1_{it}$ ($\mu g/m^3$)	366,584	24.17	9.32	3.71	22.84	83.35
$PM10_{it}$ ($\mu g/m^3$)	366,584	78.22	31.00	27.18	70.13	297.48
$Carbon_{it}$ ($\mu g/m^3$)	366,584	6.25	3.42	0.21	6.10	39.13
$Precipitation_{it-1}$ (mm)	366,584	933.71	541.47	10.56	775.88	$3,450.41$
$Popdensity_{it-1}$ ($people/km^2$)	366,584	186.49	498.03	0.00	64.51	$23,559.99$
$Nightlight_{it-1}$ ($n\mathrm{W} \cdot \mathrm{cm}^{-2} \cdot \mathrm{sr}^{-1}$)	366,584	0.37	1.82	0.00	0.00	54.69
Panel B: City-level data						
$DebtBurden_{j,2014}$ (%)	291	22.10	22.45	2.03	17.39	294.17
$RestructuredDebt_{jt}$ (%)	2,328	1.87	4.12	0.00	0.02	78.82
$EnvExp_{jt}$ (100 million Yuan)	1,729	9.89	14.16	0.00	6.61	252.49
$Penalty_{jt}$ (%)	1,869	5.06	11.52	0.00	0.00	67.80
$Shutdown_{jt}$ (%)	1,736	3.29	11.29	0.00	0.00	200.00
GDP_{jt} (100 million Yuan)	1,886	$2,282.62$	$2,660.91$	133.75	$1,346.40$	$24,221.98$
$GDPgrowth_{jt}$(%)	1,673	9.41	4.68	-19.38	9.12	109.00
$Population_{jt-1}$ (10,000 people)	1,886	438.51	251.26	19.50	381.96	$1,435.00$
GDP_{jt-1} (100 million Yuan)	1,886	$2,088.77$	$2,432.53$	104.03	$1,246.76$	$22,490.06$
$Industry_{jt-1}$ (%)	1,886	46.07	14.18	4.46	46.50	84.40
Panel C: Power plant-level data (1,686 plants)						
$ElectricityProduction_{ft}$ (GWh)	8,430	473.33	$2,484.94$	2.10	55.39	$60,859.93$
$PlantUtilizationRate_{ft}$ ($1,000h$)	8,430	2.58	1.04	1.41	2.22	6.03
Panel D: A-share listed firms-level data (2,072 firms)						
$TotalPatent_{ft}$	13,999	4.15	28.76	0.00	0.00	$1,275.00$
$InventivePatent_{ft}$	13,999	2.82	20.77	0.00	0.00	955.00
$UtilityPatent_{ft}$	13,999	1.33	10.16	0.00	0.00	420.00
$Size_{ft-1}$ (100 million Yuan)	13,999	81.06	240.15	0.48	28.56	$11,653.47$
ROA_{ft-1} (%)	13,999	4.02	5.50	-18.39	3.78	20.67
$Leverage_{ft-1}$ (%)	13,999	42.57	22.01	4.60	41.12	97.73
$Tangible_{ft-1}$ (%)	13,999	23.08	16.87	0.00	19.69	94.80

of 2014 is equivalent to 22% of the local GDP, with a standard deviation of 0.224. Figure 2 shows a spatial distribution of China's local government debt ratio. Cities with debt ratios exceeding 50% are concentrated in Guizhou and Yunnan provinces. While the lowest debt ratio is 2%, Tongren City and Qianxinan Buyei and Miao Autonomous Prefecture in Guizhou Province record remarkably high debt ratios of 103% and 294%, respectively, highlighting severe debt burdens in less developed regions.

Environmental regulation intensity. As shown in Panel B of Table 1, an average city has 101 environmental penalty cases annually, with Zhejiang, Shandong, and Guangdong provinces recording the highest numbers. On average, 100 industrial enterprises receive an annual average of 5.06 environmental punishments (mean = 5.06%). The average number of newly-closed coal-fired power plants is 0.24 per year per city, with an average of 8.5 coal-fired power plants in operation. The average fiscal expenditure on energy conservation and environmental protection is 989 million yuan.

Clean energy and green innovation. Panels C and D of Table 1 present summary statistics of clean energy generation and green patents. On average, hydroelectric and solar power plants achieve an annual output of 473.33 GWh. The power generation time, defined as the ratio of power output (GWh) to installed capacity (MW), shows an annual average of 2,580 hours, accounting for 30% of the annual power generation time of 8,730 hours. Regarding green innovation, A-share listed firms hold an average of 3.86 green patents (standard deviation = 28.48), comprising 2.65 invention patents and 1.21 utility patents. The average number of air pollution-related green patents is 0.45 per firm, with 0.24 invention patents and 0.21 utility patents. These listed companies show an average ROA of 4%, an average leverage ratio of 43%, and an average tangible asset ratio of 23%.

4 Environmental Impact of Public Debt Burdens

4.1 Baseline DID Results

To estimate the impact of the debt restructuring program on changes in local air pollution, we use a difference-in-differences (DID) model exploiting pre-existing cross-sectional differences in local governments' debt burdens and the restructuring program in 2015. Specifically, we estimate the following regression model:

$$ln(PM2.5_{it}) = \alpha + \beta ln(DebtBurden_{j,2014}) \times Post_t + \gamma X_{it-1} + \mu_i + \eta_t + \delta_{pt} + \epsilon_{it}, \qquad (1)$$

where i denotes a grid (defined as a $0.1° \times 0.1°$ area centered around a specific latitude-longitude coordinate in city j in province p) and t denotes a calendar year. $PM2.5_{it}$ is the grid-level PM2.5 concentration levels estimated from the satellite images. $DebtBurden_{j,2014}$ is the ratio of the city's outstanding debt balance to its 2014 GDP. $Post_t$ is a dummy variable indicating the debt restructuring period, which equals 1 for years in or after 2015 and 0 for years between 2011 and 2014.

Our major coefficient of interest is β, which captures the impact of debt restructuring on the PM2.5 concentration of the grid. We replace the outcome variables with the natural logarithm of carbon emissions, PM1, and PM10 in robustness checks. To control for time-invariant grid features and the common temporal trends, we also include the grid fixed effects μ_i, the province $\times$ year fixed effects δ_{pt}, and the year fixed effects η_t. ϵ_{it} indicates the error term. In addition, we include lagged control variables X_{it-1} in Eq. (1) to control for time-varying, grid-level features that may affect PM2.5 levels, which include precipitation,

Table 2: Government Debt Burdens and Local Air Pollution

This table reports the grid-year panel regression results on the impact of local government debt restructuring on air quality in China between 2011 and 2018. The regression equation is:

$$ln(PM2.5_{it}) = \alpha + \beta ln(DebtBurden_{j,2014}) \times Post_t + \gamma X_{it-1} + \mu_i + \mu_j + \eta_t + \delta_{pt} + \epsilon_{it}.$$

$ln(PM2.5_{it})$ is the natural logarithm of PM2.5 concentration levels in grid i (located in city j and province p) in year t. $DebtBurden_{j,2014}$ is city j's outstanding debt balances in 2014 divided by local GDP. $Post_t$ equals zero in the pre-restructuring period between 2011 and 2014 and equals one in the post-restructuring period between 2015 and 2018. X_{it-1} is a vector of grid-level control variables, including precipitation ($Precipitation_{it-1}$), population density ($Popdensity_{it-1}$), and nighttime lights ($Nightlight_{it-1}$), all in natural logarithms and lagged by one year. μ_i, μ_j, and η_t denote grid, city, and year fixed effects, respectively. We also include province-by-year fixed effects (δ_{pt}) in Columns (3) and (5). ϵ_{it} is the error term. A grid is defined as 0.1 longitude $\times$ 0.1 latitude. Our analysis focuses on grids in prefecture-level cities, excluding those in four municipalities (i.e., Beijing, Shanghai, Chongqing, and Tianjin) and some distant provinces (i.e., Tibet, Xinjiang, Inner Mongolia, and Qinghai). Standard errors are clustered at the city level and presented in parentheses. We do not report the coefficients of the constant. Asterisks denote the levels of statistical significance: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

Dependent variable:	$ln(PM2.5_{it})$				
	(1)	(2)	(3)	(4)	(5)
$ln(DebtBurden_{j,2014}) \times Post_t$	-0.017^{**}	-0.014^{**}	-0.019^{**}	-0.016^{**}	-0.018^{**}
	(0.0074)	(0.0069)	(0.0080)	(0.0071)	(0.0077)
$Precipitation_{it-1}$		-0.049^{**}	-0.051^{*}	-0.014	0.006
		(0.0248)	(0.0293)	(0.0106)	(0.0102)
$Popdensity_{it-1}$		0.040^{***}	0.039^{***}	0.047^{***}	0.016^{***}
		(0.0049)	(0.0049)	(0.0065)	(0.0052)
$Nightlight_{it-1}$		-0.008	-0.006	-0.038^{***}	-0.019^{***}
		(0.0064)	(0.0065)	(0.0064)	(0.0050)
City F.E.	Yes	Yes	Yes	No	No
Grid F.E.	No	No	No	Yes	Yes
Year F.E.	Yes	Yes	No	Yes	No
Province $\times$ Year F.E.	No	No	Yes	No	Yes
Mean of dependent variable	3.70	3.70	3.70	3.70	3.70
Adjusted R^2	0.901	0.914	0.927	0.969	0.984
N	366,584	366,584	366,584	366,584	366,584

nighttime lights, and population density.

Table 2 presents the results of our baseline regression analysis using grid-level data. As shown in Column (1), the estimated coefficient β is negative (-0.017) and statistically significant at the 5% level. Specifically, local government debt exceeding the mean by one standard deviation (0.65) is associated with a 1.2% decrease in $PM2.5_{it}$ after the restructuring program reduces local governments' debt burdens. This result remains robust when we introduce grid-level control variables associated with local air pollution in Column (2), such as $Precipitation_{it-1}$, $Popdensity_{it-1}$, and $Nightlight_{it-1}$ (all in natural logarithm) and when we include province $\times$ year fixed effect in Columns (3). These results indicate that the debt restructuring program reduces local air pollution, with more pronounced effects on cities with more substantial debt reliefs measured by pre-restructuring debt-to-GDP ratios.

4.1.1 Pretrend Analysis

One concern about interpreting β as a causal effect is the endogeneity caused by omitted variables, as cities with distinct local debt-to-GDP ratios in 2014 may be inherently different. Nonetheless, the DID approach remains valid as long as these omitted variables are not correlated with our outcome variable. We use the following dynamic specification to test whether the parallel trends assumption holds in the pre-restructuring period:

$$ln(PM2.5_{it}) = \alpha + \Sigma_{t \neq 2014} \beta_t \times ln(DebtBurden_{j,2014}) \times YearDummy_t + \gamma X_{it-1} + \mu_i + \delta_{pt} + \epsilon_{it},$$

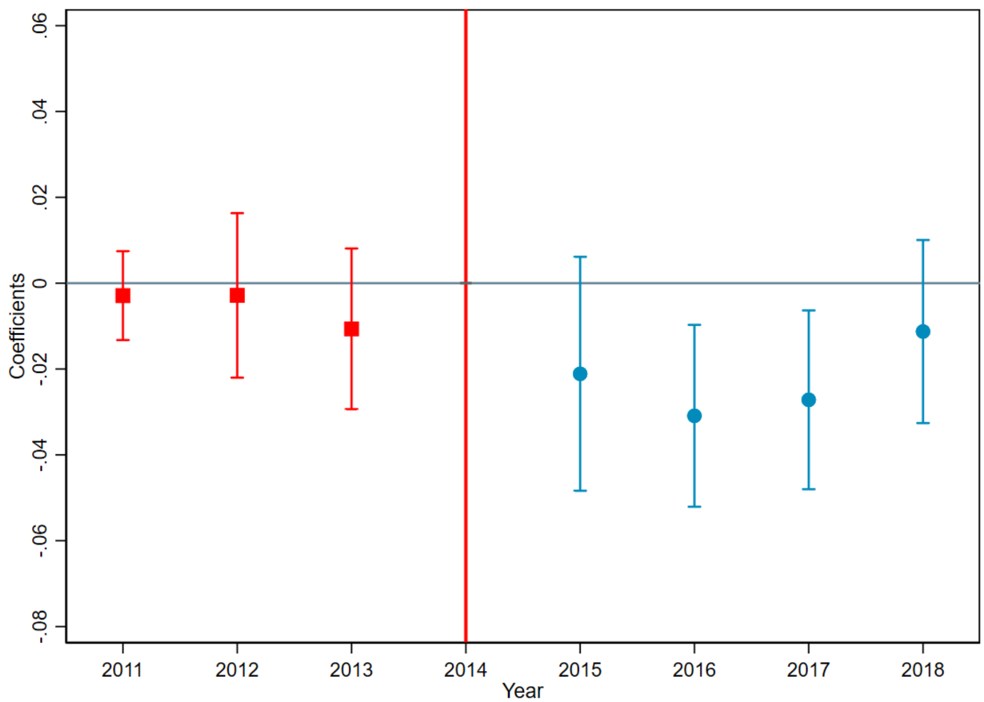
where $YearDummy_t$ equals one if t is the corresponding year and zero otherwise. We omit the dummy for 2014, which is one year before the debt restructuring, to set it as the baseline. We focus on the coefficients of the interaction terms before 2014, which should not be significantly different from zero if our assumption holds. Similar to our baseline analysis, we include grid fixed effects, μ_i, and province $\times$ year fixed effects, δ_{pt}.

Figure 4: Dynamic DID Analysis

This figure plots the estimated coefficients β and the 95% confidence intervals of the following dynamic DID regression:

$$ln(PM2.5_{it}) = \alpha + \Sigma_{t\neq 2014}\beta_t \times ln(DebtBurden_{j,2014}) \times YearDummy_t + \gamma X_{it-1} + \mu_i + \delta_{pt} + \epsilon_{it},$$

where i indexes grids (located in city j in province p) and t indexes year between 2011 and 2018. We measure air pollution by the grid-level PM2.5 concentration levels (natural log scale). $DebtBurden_{j,2014}$ is city j's outstanding debt balances as of 2014 divided by the local GDP. $YearDummy_t$ equals one if t is the corresponding year and zero otherwise. We omit the dummy for 2014 (i.e., the baseline period), which is the year before debt restructuring. X_{it-1} is a vector of grid-level control variables, including one-year-lagged natural logarithm of precipitation ($ln(Precipitation_{it-1})$), population density ($ln(Popdensity_{it-1})$), and nighttime lights ($ln(Nightlight_{it-1})$). μ_i denotes grid fixed effects. We also include province-by-year fixed effects (δ_{pt}). Standard errors are clustered at the city level.



As shown in Figure 4, the estimated coefficients of the dynamic DID analysis are close to zero and remain statistically insignificant in the pre-restructuring period. Following the local debt restructuring program in 2015, however, cities with larger benefits from the restructuring (proxied by higher existing debt burdens) experienced significantly stronger improvement in air quality. Hence, the dynamic DID analysis further indicates that local governments' debt burdens affect local environmental outcomes.

4.2 Controlling for Contemporaneous Policies

In 2016 and 2017, environmental inspections by the central government served as a critical measure to strengthen the implementation of local environmental protection. These environmental inspections involve an extensive review of cities' environmental practices to assess their compliance with national environmental standards and regulations, which play a crucial role in identifying shortcomings in environmental protection efforts and encouraging cities to implement stricter pollution control measures. Therefore, being placed on the inspection list indicates a higher level of scrutiny regarding local governments' environmental management practices and may affect local air pollution levels.

To control for the effects of environmental inspections led by the central government, we construct an inspection indicator $EnvironInspection_{pt}$ using the list of provinces subject to environmental scrutiny in each of the four rounds of environmental monitoring from the Ministry of Ecology and Environment. The dummy $EnvironInspection_{pt}$ equals one for cities in province p starting from the year of inclusion of province p in the corresponding environmental inspection list and zero otherwise. We also include $PM2.5_{j,2014} \times post_t$ as a control variable to control for trends driven by initial differences across cities in air pollution, measured by the mean of PM2.5 of all grids in city j in 2014 $PM2.5_{j,2014}$.

Table 3 presents the results of the robustness tests. As shown in Column (1), the estimated coefficient of $DebtBurden_{j,2014} \times Post_t$ remains negative and statistically significant. The impact of local debt restructuring on air pollution remains robust when we add control

Table 3: Controlling for Environmental Inspections and Initial Pollution Levels

This table reports the robustness of our baseline results by controlling for confounding factors such as environmental inspections and trends driven by initial pollution levels. $EnvironInspection_{pt}$ equals one if year t is in or after the year of province p's inclusion in the central government's environmental inspection list and zero otherwise. $PM2.5_{j,2014}$ is the average PM2.5 concentration levels of all grids in city j in 2014. $PM2.5_{it}$ is the PM2.5 concentration levels in grid i in year t. $DebtBurden_{j,2014}$ is city j's outstanding debt balances in 2014 divided by the local GDP. $Post_t$ equals zero in the pre-restructuring period between 2011 and 2014 and equals one in the post-restructuring period between 2015 and 2018. X_{it-1} is a vector of grid-level control variables, including precipitation ($Precipitation_{it-1}$), population density ($Popdensity_{it-1}$), and nighttime lights ($Nightlight_{it-1}$), all lagged by one year and in natural logarithm of the original value (plus one for $Popdensity_{it-1}$ and $Nightlight_{it-1}$). μ_i, μ_j, and η_t denote grid, city, and year fixed effects, respectively. We also include province-by-year fixed effects (δ_{pt}) in Columns (3) and (5). ϵ_{it} is the error term. Standard errors are clustered at the city level and reported in parentheses. Asterisks denote the levels of statistical significance: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

Dependent variable:	$ln(PM2.5_{it})$				
	(1)	(2)	(3)	(4)	(5)
$ln(DebtBurden_{j,2014}) \times Post_t$	-0.024^{***}	-0.022^{***}	-0.022^{***}	-0.023^{***}	-0.021^{***}
	(0.0068)	(0.0064)	(0.0062)	(0.0066)	(0.0062)
$ln(PM2.5_{j,2014}) \times Post_t$	-0.091^{***}	-0.090^{***}	-0.142^{***}	-0.089^{***}	-0.141^{***}
	(0.0122)	(0.0124)	(0.0166)	(0.0121)	(0.0157)
$EnvironInspection_{pt}$	-0.028^{**}	-0.026^{**}		-0.027^{**}	
	(0.0124)	(0.0125)		(0.0125)	
$Precipitation_{it-1}$		-0.049^{**}	-0.052^{*}	-0.015	0.003
		(0.0248)	(0.0289)	(0.0107)	(0.0096)
$Popdensity_{it-1}$		0.039^{***}	0.039^{***}	0.035^{***}	0.007
		(0.0049)	(0.0049)	(0.0071)	(0.0045)
$Nightlight_{it-1}$		-0.006	-0.004	-0.020^{***}	-0.006^{*}
		(0.0067)	(0.0067)	(0.0055)	(0.0030)
City F.E.	Yes	Yes	Yes	No	No
Grid F.E.	No	No	No	Yes	Yes
Year F.E.	Yes	Yes	No	Yes	No
Province $\times$ Year F.E.	No	No	Yes	No	Yes
Mean of dependent variable	3.70	3.70	3.70	3.70	3.70
Adjusted R^2	0.903	0.916	0.928	0.971	0.985
N	366,584	366,584	366,584	366,584	366,584

variables and other fixed effects in Columns (2)–(4), with similar coefficient magnitudes to the baseline regression. These findings provide strong evidence that the environmental impact of public debt reliefs cannot be fully absorbed by concurrent regulatory inspections or changes induced by initial pollution levels.

4.3 Alternative Measures of Debt Burdens

As a robustness check, we construct an alternative debt burden measure by changing the denominator to the local fiscal revenue. Specifically, $DebtBurden\_alt_{j,2014}$ is defined as a city's outstanding debt balance in 2014 divided by its fiscal revenue in the same year, which aligns with China's public debt management principle that the fiscal revenue serves as the primary source for debt servicing. By focusing on fiscal sustainability, this alternative measure directly captures the financial constraints faced by local governments.

As shown in Table 4, the coefficients of the interaction term $DebtBurden\_alt_{j,2014} \times Post_t$ remain negative and statistically significant through all columns, which is consistent with our baseline findings. Column (1) presents an estimated coefficient of -0.031, which is statistically significant at 99% confidence interval. In Columns (2) and (3), the estimated coefficients are -0.029 and -0.023, which maintain their economic magnitude and statistical significance. These estimates remain robust after controlling for grid and year/province-by-year fixed effects to address spatial heterogeneity and temporal policy shocks in Columns (4) and (5), respectively. Notably, a one-standard-deviation increase in the pre-restructuring debt-to-fiscal-revenue ratio (0.55 units) corresponds to a 4.9% reduction in PM2.5 concentration ($-0.031 \times 0.55/0.35 = -4.9\%$) in the post-restructuring period, supporting the pollution-mitigation effect of public debt relief.

Table 4: Alternative Measures: Debt-to-Fiscal-Revenue Ratios

This table reports the robustness of our baseline results by changing the measure of local debt burdens:

$$ln(PM2.5_{it}) = \alpha + \beta ln(DebtBurden\_alt_{j,2014}) \times Post_t + \gamma X_{it-1} + \mu_i + \mu_j + \eta_t + \delta_{pt} + \epsilon_{it},$$

where $PM2.5_{it}$ is the PM2.5 concentration levels in grid i in year t. $DebtBurden\_alt_{j,2014}$ is city j's outstanding debt balance in 2014 divided by local governments' budget revenues. $Post_t$ equals zero in the pre-restructuring period between 2011 and 2014 and equals one in the post-restructuring period between 2015 and 2018. X_{it-1} is a vector of grid-level control variables, including precipitation ($Precipitation_{it-1}$), population density ($Popdensity_{it-1}$), and nighttime lights ($Nightlight_{it-1}$), all lagged by one year and in natural logarithm of the original value (plus one for $Popdensity_{it-1}$ and $Nightlight_{it-1}$). μ_i, μ_j, and η_t denote grid, city, and year fixed effects, respectively. We also include province-by-year fixed effects (δ_{pt}) in Columns (3) and (5). ϵ_{it} is the error term. Standard errors are clustered at the city level and reported in parentheses. Asterisks denote the levels of statistical significance: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

Dependent variable:	$ln(PM2.5_{it})$				
	(1)	(2)	(3)	(4)	(5)
$ln(DebtRatio_{j,2014}) \times Post_t$	−0.031***	−0.029***	−0.023**	−0.031***	−0.023**
	(0.0086)	(0.0085)	(0.0102)	(0.0085)	(0.0099)
$Precipitation_{it-1}$		−0.053**	−0.057*	−0.017	0.002
		(0.0264)	(0.0296)	(0.0120)	(0.0098)
$Popdensity_{it-1}$		0.047***	0.046***	0.039***	0.006
		(0.0033)	(0.0033)	(0.0066)	(0.0050)
$Nightlight_{it-1}$		−0.015***	−0.013***	−0.032***	−0.012***
		(0.0042)	(0.0043)	(0.0070)	(0.0036)
City F.E.	Yes	Yes	Yes	No	No
Grid F.E.	No	No	No	Yes	Yes
Year F.E.	Yes	Yes	No	Yes	No
Province × Year F.E.	No	No	Yes	No	Yes
Mean of dependent variable	3.70	3.70	3.70	3.70	3.70
Adjusted R^2	0.891	0.913	0.928	0.966	0.984
N	308,120	308,120	308,120	308,120	308,120

4.4 Debt Swap Progress

Next, we utilize the issuance of restructuring bonds to strengthen our argument that public debt relief leads to air quality improvements. We obtain municipal bond issuance data from the Wind database and identify restructuring bonds by their designated purposes, with some municipal bonds partially used for restructuring purposes. By retaining bonds explicitly designated for debt restructuring and summing up the fractions specifically allocated for restructuring, we construct the total volume of funds raised through restructuring bonds $Issuance_{pt}$ issued by province p in year t.

We then adopt a Bartik-IV approach to capture the magnitude of public debt relief, as the funding raised by provincial-level restructuring bonds is allocated to cities based on their pre-existing debt burdens. Specifically, we use the following formula:

$$RestructuredDebt_{jt} = \frac{Issuance_{pt} \times Debt\_Ratio_{j,2014}}{GDP_{j,2014}},$$

where $Debt\_Ratio_{j,2014}$ is the ratio of city j's existing debt burdens in the corresponding provincial aggregate debt levels before the debt restructuring. Thus, $Issuance_{pt} \times Debt\_Ratio_{j,2014}$ estimates the amount of bond issuance allocated to each city j in the post-restructuring period between 2015 and 2018. We scale this city-year-level restructuring bond issuance by the local GDP in 2014. $RestructuredDebt_{jt}$ equals zero for years in or before 2014; hence, its estimated coefficient can be interpreted as a causal impact of the debt restructuring progress.

Table 5 reruns our baseline regressions by replacing $ln(DebtBurden_{j,2014}) \times Post_t$ with $ln(RestructuredDebt_{jt})$. As shown in Columns (1)–(5), the coefficients of interest β are all negative and statistically significant, with magnitudes similar to our baseline results. Moreover, including fixed effects at different levels (city, grid, and province $\times$ year) provides a robust framework for controlling for unobserved heterogeneity that could otherwise bias our results. Translating into economic significance, these results indicate that a 1% increase in the

Table 5: Local Governments' Debt Restructuring Progress

This table shows the results of the following grid-year panel regression results:

$$ln(PM2.5_{it}) = \alpha + \beta ln(RestructuredDebt_{jt}) + \gamma X_{it-1} + \mu_i + \mu_j + \eta_t + \delta_{pt} + \epsilon_{ijt},$$

where $RestructuredDebt_{jt}$ is the estimated restructuring funds received by city j in year t, scaled by the local GDP in 2014:

$$RestructuredDebt_{jt} = \frac{Issuance_{pt} \times Debt\_Ratio_{j,2014}}{GDP_{j,2014}},$$

$Debt\_Ratio_j$ is the fraction of each city's debt in its corresponding province as of 2014. $Issuance_{pt}$ measures the annual debt restructuring quota of the province between 2015 and 2018. We use $Issuance_{pt} \times Debt\_Ratio_j$ to approximate the amount of restructured debt in each city. We set $RestructuredDebt_{jt}$ to zero in the pre-restructuring period between 2011 and 2014. X_{it-1} is a vector of grid-level control variables, including precipitation ($Precipitation_{it-1}$), population density ($Popdensity_{it-1}$), and nighttime lights ($Nightlight_{it-1}$), all lagged by one year and in natural logarithm of the original value (plus one for $Popdensity_{it-1}$ and $Nightlight_{it-1}$). μ_i, μ_j, and η_t denote grid, city, and year fixed effects, respectively. We also include province-by-year fixed effects (δ_{pt}) in Columns (3) and (5). ϵ_{it} is the error term. Standard errors are clustered at the city level and reported in parentheses. Asterisks denote the levels of statistical significance: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

Dependent variable:	$ln(PM2.5_{it})$				
	(1)	(2)	(3)	(4)	(5)
$ln(RestructuredDebt_{jt})$	-0.013^{***}	-0.013^{***}	-0.019^{**}	-0.013^{***}	-0.018^{**}
	(0.0043)	(0.0042)	(0.0080)	(0.0042)	(0.0077)
$Precipitation_{it-1}$		-0.050^{**}	-0.051^{*}	-0.015	0.006
		(0.0250)	(0.0293)	(0.0110)	(0.0102)
$Popdensity_{it-1}$		0.040^{***}	0.039^{***}	0.048^{***}	0.016^{***}
		(0.0048)	(0.0049)	(0.0067)	(0.0052)
$Nightlight_{it-1}$		-0.008	-0.006	-0.041^{***}	-0.019^{***}
		(0.0064)	(0.0065)	(0.0065)	(0.0050)
City F.E.	Yes	Yes	Yes	No	No
Grid F.E.	No	No	No	Yes	Yes
Year F.E.	Yes	Yes	No	Yes	No
Province × Year F.E.	No	No	Yes	No	Yes
Mean of dependent variable	3.70	3.70	3.70	3.70	3.70
Adjusted R^2	0.901	0.915	0.927	0.969	0.984
N	366,584	366,584	366,584	366,584	366,584

restructuring volume-to-GDP ratio leads to a 0.013%-0.018% reduction in the local PM2.5 concentration in the post-restructuring period. By directly regressing local air pollution on the restructuring funds allocated to each city, we gain a more straightforward understanding of the environmental impact of the local debt restructuring.

4.5 Other Measures of Air Pollution

To more comprehensively analyze the impact of debt overhang on local air quality, we replace our main outcome variable with alternative measures of air pollution, including the concentration levels of PM1 and PM10, i.e., particles smaller than 1 micron and 10 microns, respectively. These particles are of concern because they can deeply penetrate the lungs and cause health problems.

As shown in Panel A in Table 6, the coefficients of $DebtBurden_{j,2014} \times Post_t$ are significantly negative, indicating a larger reduction in PM1 levels in cities with greater debt relief from the restructuring program. Cities with local government debt exceeding the mean by one standard deviation (0.65) achieve a pollution reduction equivalent to 3.25% (= 0.65 × 0.020% / 0.40) of the one standard deviation $PM1_{it}$ through debt restructuring programs. The regressions on PM10 demonstrate consistent results, with a 1% increase in the pre-restructuring debt-to-GDP ratio leading to a 0.017% decrease in the PM10 concentration. Cities with above-average local government debt (1 standard deviation higher, approximately 0.65 units) can reduce $PM10_{it}$ by 2.9% of their standard deviation (= 0.65 × 0.017% / 0.38) through debt restructuring programs.

Panel B examines the impact of local debt restructuring on carbon emissions and local economic activities. Organic carbon, originating from both natural sources and human activities, is a main component of PM2.5 and a critical indicator of air quality due to

Table 6: Beyond PM2.5: Other Air Pollutants, Carbon Emissions, and Nighttime Lights

This table shows the impact of local government debt restructuring on different pollution indicators using grid-year panel data between 2011 and 2018:

$$Y_{it} = \alpha + \beta ln(DebtBurden_{j,2014}) \times Post_t + \gamma X_{it-1} + \mu_i + \mu_j + \eta_t + \epsilon_{it}.$$

$PM1_{it}$ ($PM10_{it}$) is PM1 (PM10) concentration levels in grid i in year t. $Carbon_{it}$ is the grid-level emission of organic carbon contents. $Nightlight_{it}$ measures the intensity of night-time light in grid i in year t. $DebtBurden_{j,2014}$ is city j's outstanding debt balances in 2014 divided by the local GDP. $Post_t$ equals zero in the pre-restructuring period between 2011 and 2014 and equals one in the post-restructuring period between 2015 and 2018. X_{it-1} is a vector of lagged control variables, including precipitation ($Precipitation_{it-1}$), population density ($Popdensity_{it-1}$), and nighttime lights ($Nightlight_{it-1}$), all in natural logarithms. μ_i, μ_j, and η_t denote grid, city, and year fixed effects, respectively. ϵ_{it} is the error term. Standard errors are clustered at the city level and presented in parentheses. Asterisks denote the levels of statistical significance: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

Panel A: Other Air Pollution Measurements				
Dependent variable:	$ln(PM1_{it})$		$ln(PM10_{it})$	
	(1)	(2)	(3)	(4)
$ln(DebtBurden_{j,2014}) \times Post_t$	-0.019^{**}	-0.020^{**}	-0.014^{**}	-0.017^{**}
	(0.0082)	(0.0083)	(0.0065)	(0.0068)
Mean of dependent variable	0.40	0.40	4.28	4.28
Adjusted R^2	0.903	0.974	0.924	0.973
N	366,584	366,584	366,584	366,584
Panel B: Carbon Emission and Nighttime Lights				
Dependent variable:	$ln(Carbon_{it})$		$ln(Nightlight_{it})$	
	(1)	(2)	(3)	(4)
$ln(DebtBurden_{j,2014}) \times Post_t$	-0.047^{***}	-0.044^{***}	-0.015	-0.004
	(0.0165)	(0.0160)	(0.0100)	(0.0069)
Mean of dependent variable	1.59	1.59	0.48	0.48
Adjusted R^2	0.919	0.979	0.766	0.953
N	366,584	366,584	366,584	366,584
All Panels:				
Grid-level controls	Yes	Yes	Yes	Yes
City F.E.	Yes	No	Yes	No
Grid F.E.	No	Yes	No	Yes
Year F.E.	Yes	Yes	Yes	Yes

its impact on both health and climate. Columns (1)–(2) indicate that cities with local government debt exceeding the mean by one standard deviation exhibit $Carbon_{it}$ reductions corresponding to 3.68% (= 0.65 × 0.047% / 0.83) of the one standard deviation $Carbon_{it}$. Columns (3)–(4) of Panel B examine the impact on grid-level nighttime lights, which do not show significant changes after the debt restructuring, suggesting that the decline in pollution is not caused by weakening economic development. Therefore, the reduction in air pollution and carbon emissions is not simply driven by reducing local economic activities.

5 Mechanisms: Energy Structure Transition

5.1 Within-City Spatial Differences

Next, we examine differences in pollution levels across grids within a city to investigate how debt restructuring influences air quality in specific geographical locations. We construct a new variable, $PM2.5_{i,2014}$, which represents grid-level PM2.5 concentration in 2014. By incorporating the three-way interaction term $ln(DebtBurden_{j,2014}) \times Post_t \times ln(PM2.5_{i,2014})$ into our analysis, we can assess the impact of debt restructuring on pollution at a more granular level and have the degree of freedom to control for time-varying trends in different cities.

As shown in Table 7, the estimated coefficients of the triple-difference term are all negative and statistically significant, indicating that within the same city, grids with higher initial air pollution levels experienced greater reductions following the debt restructuring policy. This negative impact remains robust when we progressively add fixed effects at different levels in

Table 7: Targeting Heavily Polluted Areas? Within-City Spatial Differences

This table shows the impact of local government debt restructuring on different grids within the same city between 2011 and 2018:

$$\begin{aligned} ln(PM2.5_{it}) =& \alpha + \beta ln(DebtBurden_{j,2014}) \times Post_t \times ln(PM2.5_{i,2014}) \\ &+ \textit{two-way interactions} + \gamma X_{it-1} + \mu_i + \mu_j + \eta_t + \delta_{jt} + \epsilon_{it} \end{aligned}$$

Air pollution is measured by $PM2.5_{it}$, the PM2.5 concentration levels in grid i (located in city j and province p) in year t. $DebtBurden_{j,2014}$ is city j's outstanding debt balances in 2014 divided by the local GDP. $PM2.5_{i,2014}$ is the grid-level PM2.5 concentration in 2014. $Post_t$ equals zero in the pre-restructuring period between 2011 and 2014 and equals one in the post-restructuring period between 2015 and 2018. X_{it-1} is a vector of lagged control variables, including precipitation ($Precipitation_{it-1}$), population density ($Popdensity_{it-1}$), and nighttime lights ($Nightlight_{it-1}$), all in natural logarithms. μ_i, μ_j, and η_t denote grid, city, and year fixed effects, respectively. We also include city-by-year fixed effects (δ_{jt}) in Column (4). ϵ_{it} is the error term. Standard errors are clustered at the city level and presented in parentheses. Asterisks denote the levels of statistical significance: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

Dependent variable:	$ln(PM2.5_{it})$			
	(1)	(2)	(3)	(4)
$ln(DebtBurden_{j,2014}) \times Post_t \times ln(PM2.5_{i,2014})$	-0.060^{***}	-0.063^{***}	-0.062^{***}	-0.055^{*}
	(0.0149)	(0.0150)	(0.0147)	(0.0312)
$ln(DebtBurden_{j,2014}) \times Post_t$	0.205^{***}	0.219^{***}	0.215^{***}	
	(0.0569)	(0.0574)	(0.0561)	
$ln(PM2.5_{i,2014}) \times Post_t$	0.080^{*}	0.089^{*}	0.088^{**}	0.097
	(0.0448)	(0.0452)	(0.0442)	(0.0981)
$ln(DebtBurden_{j,2014}) \times ln(PM2.5_{i,2014})$	-0.014	-0.004		
	(0.0267)	(0.0230)		
Grid-level controls	No	Yes	Yes	Yes
City F.E.	Yes	Yes	No	No
Grid F.E.	No	No	Yes	Yes
Year F.E.	Yes	Yes	Yes	No
City × Year F.E.	No	No	No	Yes
Mean of dependent variable	3.70	3.70	3.70	3.70
Adjusted R^2	0.971	0.971	0.971	0.995
N	366,584	366,584	366,584	366,584

Columns (1)–(4), even after we control for city × year fixed effects. By incorporating these high-dimensional fixed effects, we are able to absorb time-varying confounding factors at the city level, including local macroeconomic developments and changes in local environmental regulation intensity. Therefore, these results not only shed light on how the impact of debt restructuring on air pollution varies across different grids within cities but also help rule out alternative explanations. Taken together, these findings demonstrate a targeted approach by local governments towards grids with previously more severe pollution levels, which are likely to be the location of polluting firms and coal-fired power plants.

5.2 Air Pollution near Coal-Fired Power Plants

We further investigate the impact of public debt restructuring on grid-level air pollution near the locations of coal-fired power plants, which we identify from the registration data of industrial and commercial enterprises. Plants that were shut down prior to 2010, i.e., before our sample period, are excluded from our analysis. We then map these coal-fired power plants to corresponding grids using their geographical coordinates.

Table 8 presents the regression results using a subsample of grids near coal-fired power plants, with a neighborhood of $0.5°\times 0.5°$ centered around the coordinate of a specific coal-fired power plant in Panel A and a narrower neighborhood of $0.3°\times 0.3°$ in Panel B. We find statistically significant and negative coefficients in both panels, with magnitudes higher than our baseline results. Specifically, the estimated coefficient in Column (1) is -0.020, representing a 43% larger impact compared to the full-sample estimate (-0.014) under the same regression setting. Columns (2)–(4) use PM1, PM10, and carbon emission levels, respectively, as dependent variables and demonstrate similar effects. In Columns (2) and (3), the coefficients of PM1 and PM10 are -0.027 and -0.022, which are 35% and 29% higher than the Table 6 of -0.02 and -0.017, respectively, indicating a more pronounced pollution-reduction effect near these polluting power plants.

Table 8: Grids Near Coal-Fired Power Plants

This table reports the impact of local debt restructuring on the air quality for a subsample of grids near coal-fired power plants. We use two definitions of neighboring grids centering around the geographical coordinates of thermal power plants: within a 0.5° × 0.5° range in Panel A and within a narrower, 0.3° × 0.3° range in Panel B. $PM2.5_{it}$, $PM1_{it}$, and $PM10_{it}$ refer to the concentration levels of PM2.5, PM1, and PM10 in grid i in year t, respectively. $Carbon_{it}$ is the grid-level emission of organic carbon contents. $DebtBurden_{j,2014}$ is city j's outstanding debt balances in 2014 divided by the local GDP. $Post_t$ equals zero in the pre-restructuring period between 2011 and 2014 and equals one in the post-restructuring period between 2015 and 2018. A series of lagged control variables are added to the regression, including precipitation ($Precipitation_{it-1}$), population density ($Popdensity_{it-1}$), and nighttime lights ($Nightlight_{it-1}$), all in natural logarithms. Standard errors are clustered at the city level and presented in parentheses. Asterisks denote the levels of statistical significance: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

Panel A: Within a 0.5° × 0.5° range				
Dependent variable:	$ln(PM2.5_{it})$	$ln(PM1_{it})$	$ln(PM10_{it})$	$ln(Carbon_{it})$
	(1)	(2)	(3)	(4)
$ln(DebtBurden_{j,2014}) \times Post_t$	-0.020^{***}	-0.027^{***}	-0.022^{***}	-0.023^{***}
	(0.0061)	(0.0068)	(0.0063)	(0.0075)
Mean of dependent variable	3.85	3.29	4.37	1.91
Adjusted R^2	0.937	0.925	0.949	0.926
N	107,984	107,984	107,984	107,984
Panel B: Within a 0.3° × 0.3° range				
$ln(DebtBurden_{j,2014}) \times Post_t$	-0.020^{***}	-0.026^{***}	-0.021^{***}	-0.017^{**}
	(0.0061)	(0.0068)	(0.0068)	(0.0064)
Mean of dependent variable	3.85	3.30	4.37	1.92
Adjusted R^2	0.941	0.929	0.952	0.930
N	60,082	60,082	60,082	60,082
All Panels:				
Grid-level controls	Yes	Yes	Yes	Yes
City F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes

5.3 Electricity Production of Clean Power Plants

Next, we explore the electricity generation of clean power plants, which mainly comprise solar and hydropower plants. We obtained a sample of 1,686 clean-energy power plants in China from the Global Power Plant Database, which includes detailed information on

Table 9: Electricity Production by Clean-Energy Power Plants

This table presents the impact of local debt restructuring on the electricity production and utilization rate of clean (primarily solar and hydropower) power plants between 2013 and 2017. Given that plant-level generation data are not reported in most countries, we use the data in Yin, Byers, Valeri and Friedrich (2020), which combines statistical regressions with machine learning techniques to estimate the annual electricity generation of power plants for the Global Power Plant Database. $ElectricityProduction_{ft}$ is the estimated electricity generation of clean power plant f (located in city j) in year t. $UtilizationRate_{ft}$ measures the ratio of electricity generation (in gigawatt hours) to the plant's power capacity (in megawatts), which captures the average annual generation hours of the power plant. $DebtBurden_{j,2014}$ is city j's outstanding debt balances in 2014 divided by the local GDP. $Post_t$ equals zero in the pre-restructuring period between 2011 and 2014 and equals one in the post-restructuring period between 2015 and 2018. City-level control variables include local GDP (GDP_{jt-1}), population ($Population_{jt-1}$), and the fraction of employees in the secondary industry ($Industry_{jt-1}$), all lagged by one year. The sample is reduced due to the fact that some power plants are built in autonomous prefectures in the Yunnan-Guizhou region, and the city-level control variables in these regions are missing. Standard errors are clustered at the firm level and reported in parentheses. Asterisks denote the levels of statistical significance: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

Dependent variable:	$ln(ElectricityProduction_{ft})$			$UtilizationRate_{ft}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$ln(DebtBurden_{j,2014}) \times Post_t$	0.041***	0.008**	0.008**	0.125***	0.035***	0.035***
	(0.0032)	(0.0037)	(0.0037)	(0.0098)	(0.0121)	(0.0121)
City-level controls	No	Yes	Yes	No	Yes	Yes
Power plant F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	4.33	4.33	4.33	2.58	2.58	2.58
Adjusted R^2	0.997	0.998	0.998	0.942	0.949	0.949
N	8,430	6,657	6,657	8,430	6,657	6,657

approximately 35,000 power plants in 167 countries.[19] The energy generation data of clean power plants are estimated by Yin et al. (2020) based on a two-stage framework to balance theoretical capacity and operational heterogeneity.

Table 9 presents the firm-level regression analysis of clean power plants. Findings indicate that regions with higher debt-to-GDP ratios exhibit significant positive effects on clean energy generation following the implementation of the debt restructuring policy. In Column

[19] Data source: https://datasets.wri.org/dataset/globalpowerplantdatabase.

(1), the estimated coefficient is 0.041 and statistically significant at the 99% confidence level, suggesting that a one percentage point increase in public debt relief corresponds to a 0.041% increase in local clean energy production. Translating into economic significance, cities with pre-restructuring local debt levels one standard deviation above the average (0.65) experience an increase in clean energy production after the debt restructuring, which represents 1.8% (= 0.65 × 0.041% / 1.49) of the standard deviation of $ElectricityProduction_{ft}$. Columns (4)–(6) replace the dependent variable with the ratio of plant-level electricity production measured in gigawatt-hours (GWh) to the installed plant capacity (MW) as a measure of plant-level utilization (in 1000 hours). Cities with above-average benefits from local government debt restructuring increase the utilization time of clean-energy power plants, which accounts for 7.81% of the standard deviation of generation time variation (= 0.65 × 0.125% / 1.04). Overall, our findings indicate a significant impact of public debt relief on the local economy's transition away from "brown" electricity and toward "green" energy.

6 Further Analysis on the Role of Local Governments

In a decentralized economy, the enforcement of environmental regulations hinges on the incentives and constraints of local governments. In this section, we investigate the role of local governments by examining the impact of public debt restructuring on local governments' regulatory behaviors. While the environmental protection law has already been promulgated by the central government in China, the enforcement of the law largely falls into the purview of local governments, which may strategically loosen regulatory efforts when facing economic downturns and financing difficulties.

6.1 Closures of Coal-Fired Power Plants

Unlike clean energy power plants using renewable sources such as hydropower and solar energy, coal-fired power plants emit significant levels of pollutants during the combustion process, thereby exacerbating environmental pollution. The closure of these plants stops coal combustion and hence reduces pollutant emissions. Therefore, shutting down local coal-fired power plants can help improve environmental quality effectively (e.g., Chen et al., 2018b).

To investigate this mechanism, we compile a comprehensive dataset covering 6,219 coal-fired power plants from the registration data of industrial and commercial enterprises. Using detailed records of their establishment and closure dates, we construct a city-year measure of coal-fired power plant shutdown events, $Shutdown_{jt}$, which is defined as the ratio of the number of closed coal-fired power plants in city j in year t to the number of total coal-fired power plants in city j in the previous year. Column (3) of Panel A in Table 10 presents the results using a Poisson pseudo-maximum likelihood regression (PPML) approach. The coefficient is statistically significant at the 95% confidence level, indicating that under the stringent environmental regulations following the debt restructuring policy, the number of coal-fired power plant closures increased significantly. Notably, our results distinguish from the green-washing, strategic divestitures of pollutive plants in response to environmental pressures, where the pollution levels do not decline (Duchin et al., Forthcoming).

6.2 Intensity of Local Environmental Regulation

Environmental penalties are administrative punishments, such as fines and orders to halt production, imposed by local regulators against individuals or organizations violating envi-

Table 10: City-Level Analysis: Government Actions

Panel A of this table reports the impact of local debt restructuring on local governments' actions using a city-year panel between 2011 and 2018. $EnvExp_{jt}$ is city j's government spending on environmental protection in year t. $Penalty_{jt}$ is the ratio of environmental penalty cases initiated by the local government to the number of industrial enterprises in city j in year t. $Shutdown_{jt}$ is the number of closed coal-fired power plants in city j in year t divided by the number of operating coal-fired power plants in the previous year. $DebtBurden_{j,2014}$ is city j's outstanding debt balances in 2014 divided by the local GDP. $Post_t$ equals zero in the pre-restructuring period between 2011 and 2014 and equals one in the post-restructuring period between 2015 and 2018. City-level control variables include local GDP (GDP_{jt-1}), population ($Population_{jt-1}$), and the fraction of employees in the secondary industry ($Industry_{jt-1}$), all in natural logarithms and lagged by one year. Panel B uses cross-sectional data from 2012 to show the effectiveness of each government action in reducing air pollution in pre-restructuring periods.$\Delta \ln PM2.5_{j,2012}$ is the change in the logarithm of PM2.5 concentrations in city j in 2012 relative to 2011, i.e., the growth rate of PM2.5 levels between 2011 and 2012. We add $\ln PM2.5_{j,2011}$ to control for initial pollution levels. Standard errors are clustered at the city level and reported in parentheses. Asterisks denote the levels of statistical significance: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

Panel A: Impact on local governments' actions

Dependent variable:	$EnvExp_{jt}$	$Penalty_{jt}$	$Shutdown_{jt}$
	(1)	(2)	(3)
$ln(DebtBurden_{j,2014}) \times Post_t$	-0.012	2.266^{**}	0.615^{**}
	(0.0428)	(1.1312)	(0.2866)
Regression Model	OLS	OLS	Poisson
City-level controls	Yes	Yes	Yes
City F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Mean of dependent variable	1.84	5.06	3.29
Adjusted R^2	0.839	0.487	0.216
N	1,729	1,869	1,183

(*Continued*)

ronmental protection requirements. These penalties serve as an administrative sanctioning method for local governments to address environmental pollution issues. Greenstone and Hanna (2014) show that a higher demand for air quality leads to the effective enforcement of pollution regulations, thus contributing to a reduction in air pollution.

To examine the impact of government debt restructuring policies on the intensity of environmental regulation, we collect data on the number of environmental penalty cases across

Table 10—*Continued*

Panel B: Previous effectiveness in air pollution reduction

Dependent variable:	$\Delta \ln PM2.5_{j,2012}$		
	(1)	(2)	(3)
$EnvExp_{j,2012}$	0.002		
	(0.0025)		
$Penalty_{j,2012}$		-0.009^{***}	
		(0.0022)	
$Shutdown_{j,2012}$			-0.0002^{***}
			(0.0001)
$\ln PM2.5_{j,2011}$	0.058^{***}	0.061^{***}	0.075^{***}
	(0.0119)	(0.0108)	(0.0095)
Mean of dependent variable	-0.04	-0.04	-0.04
Adjusted R^2	0.163	0.193	0.270
N	246	266	241

various cities between 2011 and 2018 from PKUlaw.com, a widely-used website compiling legal and administrative documents. Our dataset contains 118,000 environmental penalties between 2011 and 2018. The variable $Penalty_{jt}$ denotes the number of environmental penalty cases scaled by the number of industrial enterprises in city j in year t. An increase in environmental penalty cases relative to the number of local firms thus reflects more strict punishments imposed by local governments against environmental violations. As shown in Column (2) of Panel A in Table 10, the estimated coefficient is positive and statistically significant at the 95% confidence level. That is, cities with larger debt relief increase the enforcement of environmental penalties by a greater magnitude.

Somewhat surprisingly, we find no statistically significant association between local governments' pre-swap debt burdens and their subsequent total green spending, as shown in Column (1) of Panel A. This null result suggests that the observed environmental improvements may primarily stem from a structural shift in the allocation of green spending—such as reallocating resources toward low-tax-revenue investments—rather than an overall increase in the amount of green spending.

Panel B of Table 10 further demonstrates the effectiveness of power plant shutdowns in reducing local air pollution. Our empirical analysis employs cross-sectional data in 2012, where $\Delta \ln PM25_{j,2012}$ captures the annual percentage change in PM2.5 concentrations from 2011 to 2012. $EnvExp_{j,2012}$ measures the logarithm of city j's government spending on environmental protection in 2012. $Penalty_{j,2012}$ is the ratio of the number of environmental penalty cases to the number of industrial enterprises in 2012. $Shutdown_{j,2012}$ is the number of closed coal-fired power plants in city j in 2012 divided by the number of operating coal-fired power plants in 2011. To account for initial pollution levels, we incorporate $\ln PM25_{j,2011}$ to control for the city's initial PM2.5 levels. Interestingly, local governments' direct environmental spending does not have a significant impact on the change in pollution, as shown in Column (1) of Panel B. Columns (2) and (3) of Panel B present evidence that penalty and shutdown reduce air pollution in a statistically significant manner. These results suggest that local governments rationally choose to close down polluting power plants and intensify environmental regulation to achieve immediate pollution reduction.

6.3 Green Innovations by Listed Firms

How do firms respond to the tightened regulation enforcement by local governments with relieved debt burdens? This section focuses on firms' investment in green innovation, proxied by the number of green patent applications filed by local firms. We obtain green patent application data from WIPO for A-share listed companies in China between 2011 and

Table 11: Green Innovations by Publicly Listed Firms

This table reports the impact of local debt restructuring on green patent applications of A-share listed companies in China. $TotalPatent_{ft}$ is the total number of green patents filed by firm f (with office address in city j) in year t in Panel A and the total number of green patents related to air quality management in Panel B. We further classify these patents into green inventive patents $InventivePatent_{ft}$ and green utility patents $UtilityPatents_{ft}$. We use Poisson pseudo-maximum likelihood estimations as many firm-year cells show zero green patents. $DebtBurden_{j,2014}$ is city j's outstanding debt balances in 2014 divided by the local GDP. Firm-level control variables include firm size ($Size_{ft-1}$, natural log scale), leverage ratio ($Leverage_{ft-1}$), ROA (ROA_{ft-1}), fixed asset ratio ($Tangible_{ft-1}$), all lagged by one year. Standard errors are clustered at the city level and presented in parentheses. Asterisks denote the levels of statistical significance: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

Panel A: Green Patents						
Dependent variable:	$TotalPatent_{ft}$		$InventivePatent_{ft}$		$UtilityPatents_{ft}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$ln(DebtBurden_{j,2014}) \times Post_t$	0.234***	0.345***	0.252***	0.395***	0.192***	0.263***
	(0.0386)	(0.0367)	(0.0432)	(0.0435)	(0.0455)	(0.0441)
Pseudo R^2	0.810	0.819	0.800	0.811	0.710	0.722
N	6,885	6,858	5,958	5,938	5,334	5,303
Panel B: Green Patents Addressing Air Pollution						
$ln(DebtBurden_{j,2014}) \times Post_t$	0.339***	0.472***	0.376***	0.598***	0.290**	0.311**
	(0.1162)	(0.1274)	(0.1298)	(0.1498)	(0.1161)	(0.1247)
Pseudo R^2	0.681	0.702	0.600	0.635	0.644	0.668
N	3,252	3,194	2,422	2,370	2,585	2,506
All Panels:						
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	No	Yes	No	Yes	No
Province × Year F.E.	No	Yes	No	Yes	No	Yes

2018, as defined by the WIPO green patent catalog in Section 3. Several recent studies have also examined other forms of firm-level commitment to environmental protection, including newly commercialized green products (Chiu et al., 2025).

Table 11 presents the PPML regression results on all green patents in Panel A and air-quality-related green patents in Panel B. As shown in Columns (1) and (2), the estimated coefficients of $TotalPatent_{ft}$ are positive and statistically significant, meaning that firms located in cities with greater benefits from the public debt relief increase their green patent applications by a larger magnitude. Columns (3) and (4) focus on inventive green patents, which are regarded as the most innovative type of patents, while Columns (5) and (6) examine utility green patent applications. These regression results all demonstrate statistically positive coefficients, indicating that local firms invest more in cleaner technologies to cope with tightened environmental regulations. This firm-level analysis reveals that local debt restructuring stimulates corporate green innovation, which brings a persistent impact on air pollution reduction in longer terms.

6.4 Impact on Local Economic Growth

Is the improved air quality achieved by compromising local economic growth? To address this concern, we utilize data on GDP and GDP growth as measures of regional economic development to examine the impact on the local economy. As shown in Table 12, we do not find statistically significant results, meaning that the local debt restructuring does not significantly affect GDP growth. This result is different from the case where the benefits of reduced air pollution are achieved by economically disruptive approaches (e.g., Chen et al., 2018b). Since the debt restructuring aims at reducing financial burdens on local governments by lowering interest payments and extending repayment horizons, local governments now have more fiscal and financial space to stimulate the economy, which may help alleviate the side effects of environmental protection. These findings underscore the potential for debt restructuring policies to effectively balance economic growth and environmental protection.

Table 12: Impact on Economic Growth

This table presents the impact of local debt restructuring on economic outcomes using city-year panel data between 2011 and 2018. GDP_{jt} represents the gross domestic product of city j in year t. $GDPgrowth_{jt}$ denotes the annual growth rate of GDP. $DebtBurden_{j,2014}$ is city j's outstanding debt balance in 2014 divided by the local GDP. $Post_t$ equals zero in the pre-restructuring period between 2011 and 2014 and equals one in the post-restructuring period between 2015 and 2018. City-level control variables include local GDP (GDP_{jt-1}), population ($Population_{jt-1}$), and the fraction of employees in the secondary industry ($Industry_{jt-1}$), all lagged by one year. The sample is reduced due to the fact that some power plants are built in autonomous prefectures in the Yunnan-Guizhou region, and the city-level control variables in these regions are missing. Standard errors are clustered at the city level and presented in parentheses. Asterisks denote the levels of statistical significance: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.1$.

Dependent variable:	$\ln GDP_{jt}$		$GDPgrowth_{jt}$	
	(1)	(2)	(3)	(4)
$ln(DebtBurden_{j,2014}) \times Post_t$	0.021	-0.004	-0.078	0.029
	(0.0223)	(0.0061)	(0.4310)	(0.4972)
City-level controls	No	Yes	No	Yes
City F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Mean of dependent variable	16.51	16.51	9.41	9.41
Adjusted R^2	0.987	0.997	0.400	0.401
N	1,886	1,886	1,673	1,673

7 Conclusion

In recent years, debt and climate crises have become increasingly interconnected, especially in developing countries. Does public debt burden affect governments' capacity to tackle environmental challenges? This paper empirically examines how public debt burdens affect environmental outcomes. Our analysis exploits China's large-scale debt restructuring program in 2015, which provided fiscal relief to local governments by allowing them to issue low-interest municipal bonds to replace high-interest LGFV bonds. We find that cities deriving greater benefits from the restructuring program, proxied by higher pre-restructuring debt-to-GDP ratios, exhibit larger improvements in air quality. These results cannot be explained by top-down environmental inspections or pre-existing pollution trends.

The pollution-reduction effect is stronger in areas with higher initial pollution levels or proximity to coal-fired power plants. In the post-restructuring period, local governments that benefit more from the debt relief exhibit larger increases in environmental penalties imposed on polluting firms, more closures of coal-fired power plants, and higher utilization of clean power plants. Moreover, listed firms in these cities show a greater increase in green patent applications. Importantly, we do not find adverse effects on local economic development, indicating the critical role of financial constraints in shaping local governments' trade-offs between economic and environmental objectives. Our findings underscore the environmental benefits of public debt restructuring and provide novel empirical evidence on the nexus between fiscal and environmental sustainability.

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