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Winners and Losers: Firm and Labor Market Responses to China’s Coal Capacity Reduction Policy

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We examine the impact of China’s 2016 coal capacity reduction policy on the operational performance and production inputs of listed coal firms, as well as its broader effects on local labor markets and crime. The policy substantially improved the operational performance of listed coal firms—raising operating revenue and profits while reducing debt—but also reduced production inputs, including employment, total wages, and asset-related expenditures. These contractions at the firm level had wider labor market repercussions. Although overall employment in affected cities remained largely unchanged, residents’ annual incomes declined, concerns about unemployment intensified, and divorce rates increased. We further show that individuals in treated cities became less likely to work in mining and more likely to shift into wholesale and retail and real estate–related activities, helping explain why total employment did not fall despite job losses in coal-related sectors. The adverse labor market effects were most pronounced in cities with a relatively higher non-state-owned enterprise (non-SOE) share in mine closures and cutbacks. In contrast, cities with a higher SOE share experienced weaker effects, consistent with the fact that most resettlement funds were directed toward displaced SOE workers. Negative impacts were also concentrated among older and less-educated individuals. Moreover, the policy led to an increase in crime, particularly property-related offenses typically committed by individuals acting alone and resulting in relatively short prison

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sentences. Similar to the labor market effects, the rise in crime was concentrated in cities with a higher non-SOE share.
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Abstract

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1. Introduction

Throughout modern economic history, governments have repeatedly intervened to manage the decline of mature industries confronted with overcapacity, falling profitability, and intensifying global competition. During the 1970s and 1980s, advanced economies undertook extensive restructuring efforts—including the nationalization and consolidation of shipbuilding in the United Kingdom and Sweden, large-scale rationalization of the steel industry in France, the downsizing of Japan's textile sector, and substantial subsidies to support Germany's coal industry.[1] More recently, the United States has implemented large-scale interventions in the automobile industry during the 2008–2010 financial crisis and has supported coal-producing regions since 2015 amid the clean-energy transition.[2] These experiences underscore that industrial policy is not only about promoting new and strategic sectors, but also about managing decline, restructuring existing industries, and facilitating adaptation to new economic and environmental realities.

Despite the renewed interest in industrial policy, the academic literature has largely focused on supportive or developmental interventions aimed at fostering innovation or nurturing baby industries (Blonigen, 2016; Criscuolo et al., 2019; Liu, 2019; Lane, 2020; Manelici and Pantea, 2021; Choi and Levchenko, 2021; Barwick, Kalouptsidi, and Zahur, 2025; Juhász, Lane, and Rodrik, 2023; Garin and Rothbaum, 2025). In contrast, far less is known about industrial restructuring policies that manage firm exit, reduce excess capacity, or cushion the adjustment costs borne by workers and communities. Yet, as countries face mounting challenges related to decarbonization, energy transition, industrial upgrading, and digital transformation, understanding the

[1] The United Kingdom nationalized and consolidated major shipbuilding firms under the Aircraft and Shipbuilding Industries Act (1977), while Sweden created Svenska Varv AB (1977) to absorb losses in its shipbuilding sector, prompting subsequent takeovers and closures of major yards. France introduced its plan acier (1978) to restructure and partially nationalize the steel industry in response to the oil shocks and global overcapacity. Japan implemented rationalization policies through the Temporary Measures for Stabilization of Specific Depressed Industries (1978), facilitating indicative cartels and capacity reduction in sectors such as synthetic fibers, textiles, fertilizers, and shipbuilding. Beginning with the Kohlepfennig program in 1974, Germany imposed an electricity surcharge collected by energy suppliers to finance subsidies for hard coal mining.

[2] In the United States, the federal government facilitated the restructuring of General Motors and Chrysler through the 2008 Auto Industry Financing Program and later supported coal-region transition under the 2015 POWER Initiative.

consequences of such restructuring policies has become increasingly important. While much of the existing empirical work evaluates industrial policies through the lens of firm performance or product-market outcomes, relatively little attention has been paid to their labor-market implications—even though governments often justify such policies in terms of employment preservation and regional stability. In light of Rodrik's (2009) argument that "the real question about industrial policy is not whether it should be practiced, but how," assessing the broader economic and social consequences of restructuring-oriented interventions is particularly crucial as countries confront the interconnected pressures of decarbonization and technological change. This paper contributes to this gap by examining the effects of China's 2016 coal capacity reduction policy, a centrally mandated industrial restructuring initiative designed to manage firm exit and reduce outdated excess capacity.

We focus on the Chinese coal industry, which has been the world's largest since 1985 and has accounted for over 45% of global annual coal production since 2010.[3] Beginning in 2012, the sector faced weakening demand due to the slowdown in China's economic growth and the ongoing transition toward cleaner energy sources, which exacerbated the problem of overcapacity. In early 2016, the Chinese government launched a capacity reduction initiative targeting the coal sector. The policy mandated the closure of small, outdated, and heavily polluting mines, as well as those with poor safety records, during the period 2016–2018. Following its implementation, coal production declined and coal prices rose sharply (see Figures 1 and 2). In this study, we examine the broader consequences of the policy, focusing on its impact on coal firm performance, labor market outcomes, and crime in the cities most directly affected, and explores strategies to mitigate its potential adverse effects on labor markets and crime.

To assess the policy's effectiveness, we begin by analyzing firm-level data. We use information on all companies listed on the Shanghai and Shenzhen stock exchanges from 2012 to 2018. These listed firms represent the strongest and most competitive

[3] The annual coal production data for China and the world are sourced from the *Statistical Review of World Energy*. For further details, see: https://www.energyinst.org/statistical-review.

enterprises within their respective industries.[4] We define firms operating in the coal mining and washing and coal mining support activities industries as the treatment group, and those operating in industries with limited linkage to coal as the control group. Using a difference-in-differences approach, we find that listed coal firms experienced substantial increases in operating revenue and profitability after the policy, accompanied by a pronounced decline in debt—clear evidence of improved operational performance. At the same time, these firms reduced production inputs, primarily through declines in total employment, total wages, and cash expenditures on asset purchases and construction—changes that likely had significant implications for local labor markets in cities affected by the capacity reduction policy.

We then turn to the costs of the policy, focusing on its labor market and crime-related consequences. Using data from the China Family Panel Studies (CFPS, 2012, 2014, 2016, and 2018) and a city-level crime dataset (2014–2018), we implement a city-level difference-in-differences approach, defining cities with coal mines that were closed or subject to capacity reduction as the treatment group and the remaining cities as the control group. Our results show that, although the policy did not significantly affect overall employment in the treated cities, it led to a substantial decline in residents' annual income. At the same time, public perceptions of job opportunities deteriorated,

[4] We use listed firm data for several reasons. First, alternative representative firm-level datasets commonly used in China—such as the National Tax Survey of Enterprises (which covers registered tax-paying firms nationwide) and the Chinese Industrial Enterprise Database (which covers large-scale industrial firms)—do not extend beyond 2016, whereas listed firm data cover a longer time span that includes the policy period. Second, data reported by listed firms are generally more reliable because these firms are subject to strict disclosure requirements, external auditing, and market scrutiny, resulting in higher data quality. Third, a large body of research on China and other countries uses listed firm data. Examples for China include Bryson, Forth, and Zhou (2014); Wu, Gyourko, and Deng (2015); Benguria et al. (2022); Fang et al. (2023); Branstetter et al. (2023); and Li and Branstetter (2024). Studies using listed firm samples in other countries include Keller and Yeaple (2009); Guadalupe and Wulf (2010); and Autor et al. (2020). The main limitation of using listed firms is representativeness: listed firms constitute only a small share of all Chinese firms and tend to be larger and more productive. However, economic activity in China is concentrated among these firms, meaning they account for a disproportionate share of aggregate outcomes. For example, as of November 3, 2025, the total market capitalization of firms listed on the Shanghai and Shenzhen stock exchanges was 106.953 trillion RMB—equivalent to 79.3% of China's 2024 GDP. Similarly, in 2021, total R&D expenditures by non-financial listed firms reached 1.19 trillion RMB, accounting for 55.3% of total corporate R&D spending in China. In Appendix Part A, we use the 2015 National Tax Survey of Enterprises to compare listed firms with the full sample of firms along seven key dimensions: operating revenue, total profit, total liabilities, employment, total wage bill, average wage, and R&D expenditure. The comparison shows that listed firms are systematically larger and more productive, representing the upper tier of Chinese enterprises.

and divorce rates increased. We also find that the policy made residents in treated cities less likely to work in the mining sector and more likely to work in wholesale and retail as well as real estate development, leasing, sales, and related activities—patterns that may help explain why overall employment rates in these cities did not fall. The adverse labor market effects were concentrated among residents aged 35 and above and those with a senior high school education or below. Moreover, these negative impacts were most pronounced in cities with a relatively higher non-SOE share in mine closures and cutbacks, whereas the effects were muted in cities with a higher SOE share—likely because the resettlement funds provided under the policy primarily targeted SOE employees. Furthermore, the policy contributed to a rise in crime, driven mainly by property-related offenses, while violent crime remained largely unchanged. These offenses were predominantly committed by individual offenders and generally resulted in relatively short prison sentences. Consistent with the labor market patterns, the increase in crime was concentrated in cities with a relatively higher non-SOE share in mine closures and cutbacks, with no significant change observed in cities with a higher SOE share.

Our paper makes the following contributions. First, we add to the growing empirical literature on industrial policy (Blonigen, 2016; Criscuolo et al., 2019; Liu, 2019; Lane, 2020; Manelici and Pantea, 2021; Choi and Levchenko, 2021; Barwick, Kalouptsidi, and Zahur, 2025; Juhász, Lane, and Rodrik, 2023; Garin and Rothbaum, 2025). Existing studies largely examine policies designed to foster the emergence of new or high-tech industries, whereas much less is known about policies targeting mature industries struggling with structural imbalances. The literature has provided theoretical explanations for industrial overcapacity (Spence, 1977; Zhou, 2004; Lin, 2007; Lin, Wu, and Xing, 2010; Murphy, 2017; Sun, 2025), yet empirical evidence on the effectiveness and economy-wide consequences of capacity-reduction policies remains scarce.

A small set of papers evaluates particular capacity-reduction or consolidation policies (e.g., Okazaki, Onishi, and Wakamori, 2022; Rubens, 2023; Barwick, Kalouptsidi, and Zahur, 2025). Those studies investigate policies that operate through coordinated exit, entry moratoria, or preferential consolidation of selected firms. In contrast, China's 2016 coal capacity-reduction program was a large-scale, centrally mandated intervention implemented through administrative shutdowns, binding production limits, and nationwide enforcement. Because this policy differs fundamentally from the coordination-based or consolidation-oriented interventions examined in prior studies, it creates distinct adjustment incentives and empirical margins. Our analysis therefore complements earlier work by providing evidence from a policy environment with a materially different institutional design.

Our paper is most closely related to Mu, Qiu, and Yang (2025), who study the same 2016 coal program and quantify welfare changes through producer surplus, consumer surplus, and air-quality improvements. We complement their work by broadening the range of examined outcomes. In addition to firm performance and production behavior, we document key labor-market consequences—including employment and wages—as well as a salient social outcome: crime. These additional margins allow us to assess impacts that surplus-based measures do not capture.

Second, our paper contributes to the emerging literature that asks not whether industrial policy should be used, but how it should be designed. Existing empirical work evaluates industrial policies primarily through firm- or industry-level outcomes—productivity, output, profitability, and survival—and uses these outcomes to infer which policies are effective (Barwick, Kalouptsidi, and Zahur, 2025; Cherif and Hasanov, 2025; Fang, Li, and Lu, 2025). Much less attention has been paid to the labor-market spillovers generated by industrial interventions, even though the consequences for workers are central to both the political feasibility and the welfare incidence of such policies. We address this gap by evaluating the labor-market impacts of an industrial restructuring policy, documenting sizable adverse effects on employment and worker earnings. Importantly, we show that government-led complementary measures—targeted fiscal transfers and worker-placement programs—mitigate these negative effects. These results provide evidence on a key margin that is often overlooked in the design of industrial policy and help inform the broader question of how such policies should be practiced.

Third, our paper contributes to the literature on how economic restructuring (Gehrke and Weber, 2018; Mitrunen, 2025), technological adoption (Acemoglu and Restrepo, 2020; Acemoglu et al., 2022; Giuntella, Lu, and Wang, 2025), and energy transitions (Aragón, Rud, and Toews, 2018; Rud et al., 2024; Haywood, Janser, and Koch, 2024; Curtis, O'Kane, and Park, 2024) shape labor markets and individual behavior. We specifically examine the labor market effects of China's coal capacity reduction policy, a key component of the supply-side structural reforms introduced in 2015, thereby expanding the existing body of research.

Finally, our paper contributes to the literature on the effects of labor market shocks on crime. Dix-Carneiro, Soares, and Ulyssea (2018) examine how economic shifts and labor market disruptions caused by Brazil's trade liberalization in the 1990s influenced crime. Dell, Feigenberg, and Teshima (2019) explore how job losses in Mexico, driven by trade competition from China's export expansion between 2007 and 2010, affected urban crime rates. Ma, Pan, and Xu (2025) analyze how China's export slowdown after 2010 negatively impacted its labor market, leading to widespread job losses that, in turn, contributed to rising crime rates across different regions in China. Building on this literature, our study finds that the coal capacity reduction policy led to income losses, which subsequently drove an increase in crime rates in affected areas. Notably, this rise was concentrated in property crimes rather than violent crimes, offering new insights into the relationship between economic distress and crime.

The remainder of this paper is organized as follows. Section 2 provides background information. Section 3 introduces the data and key variables. Section 4 examines the impact of the coal capacity reduction policy on firms' operational performance and production input. Section 5 analyzes its effects on individual behavior, while Section 6 investigates its influence on crime rates. Finally, Section 7 concludes.

2. Background

In this section, we outline the background of the 2016 coal capacity reduction policy and show the transformations in the industry following its implementation.

2.1. Policy Background

China's coal industry has long been a cornerstone of the country's energy sector.[5] However, since 2012 it has faced mounting challenges stemming from severe overcapacity. Several factors have driven this problem. First, following China's accession to the WTO in 2001, rapid economic growth fueled a rise in coal demand (Kahrl and Roland-Holst, 2008), which in turn spurred a continuous expansion of production capacity. In addition, the Chinese government's large-scale stimulus package introduced in response to the 2008 global financial crisis further expanded investment in infrastructure, real estate, and heavy industry (Fardoust, Lin, and Luo, 2012; Deng et al., 2015; Chen et al., 2016), thereby accelerating investment in coal mining. Second, since 2010, the combination of slowing economic growth and China's steady transition toward cleaner energy has reduced coal demand (Qi et al., 2016), making the imbalance between supply and demand increasingly evident. Finally, local governments—motivated by concerns over economic growth, employment, and fiscal revenues—continued to support uncompetitive mines (Zhang et al., 2017; Wang et al., 2018), keeping them in operation and delaying necessary market adjustments. This intervention further entrenched the oversupply problem and exacerbated structural inefficiencies in the industry.

This disequilibrium created a buildup of inventories, depressed coal prices, and triggered a sharp contraction in sector-wide profitability (see Figures 2 and 3). According to news reports, by 2015 more than 90 percent of coal enterprises were operating at a loss.[6] To address the problem of overcapacity and alleviate the financial distress of firms, the State Council issued the Opinion on Resolving Overcapacity in the Coal Industry to Achieve Development Out of Predicament in February 1, 2016

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[5] For example, although the share of coal-fired power generation in China's total electricity output has been declining since 2007, coal still accounted for 61.7% of total electricity generation in 2022. Detailed data are available at: https://data.worldbank.org/indicator/eg.elc.coal.zs?end=2022&locations=CN&start=1990&view=chart&year=1990.

[6] For related news reports, see: https://m.dbw.cn/guonei/system/2016/01/25/057056062.shtml.

(hereafter referred to as *the Opinion*).[7] The Opinion set explicit targets for the subsequent three to five years. Starting in 2016, the government mandated the elimination of 0.5 billion tons of coal capacity, together with the restructuring and consolidation of an additional 0.5 billion tons. This one billion tons of capacity was equivalent to 25.8 percent of the country's average annual coal output during 2012–2015. These measures were intended to significantly curtail total production capacity, reduce the number of operating mines, alleviate the imbalance between supply and demand, and facilitate industrial upgrading and structural optimization. In parallel, major coal-producing provinces formulated their own reduction targets. For example, Shanxi Province—the largest coal-producing province in China, with an output of 967 million tons[8] in 2015—announced plans to cut 110 million tons of capacity between 2016 and 2020, including 23 million tons in 2016 alone.[9] Other key coal-producing regions, such as Inner Mongolia Autonomous Region and Shaanxi Province, introduced comparable programs involving production cuts and mine closures.[10]

The Opinion was operationalized through a multi-pronged policy framework. First, strict controls were placed on new capacity: approvals for new projects, capacity-expanding upgrades, and expansions were suspended for three years, with new mines permitted only under capacity-replacement schemes. Second, outdated capacity was eliminated through the accelerated closure of small mines with low safety standards, those located in ecologically sensitive zones, or those relying on banned technologies. Third, excess capacity was phased out in an orderly manner, targeting mines with severe geological hazards, substandard product quality, outdated technologies, or sustained financial distress, including so-called "zombie enterprises." Limited exceptions were granted to mines serving special functions, subject to strict conditions. Fourth, the policy promoted mergers and reorganizations, encouraging large enterprises to absorb smaller firms, with the aim of ensuring that all stand-alone enterprises achieved a

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[7] The full text of the policy document is available online at: https://www.gov.cn/gongbao/content/2016/content_5045944.htm.
[8] Detailed data are available at: https://tjj.shanxi.gov.cn/tjsj/tjnj/nj2016/indexch.htm.
[9] For further details, see: https://www.cnr.cn/sx/sxcj/20161201/t20161201_523298801.shtml.
[10] For further details, see: https://www.nea.gov.cn/2016-04/18/c_135289616.htm; https://www.chinanews.com/cj/2016/07-27/7953730.shtml.

production scale of at least three million tons per year. Finally, a range of supporting measures—including the revitalization of land resources, intensified enforcement against illegal construction and excess production, strengthened safety supervision, and restrictions on low-quality coal projects—reinforced the overall framework. Together, these measures established a comprehensive institutional environment for capacity reduction and restructuring in the coal sector.

In addition to the measures aimed at reducing excess capacity, the Opinion also emphasized that "worker resettlement should be treated as a top priority in addressing overcapacity." Resettlement efforts could proceed through four main channels: (1) internal adjustments within enterprises, such as wage negotiations, flexible working hours, retraining, and job transfers, to minimize layoffs; (2) voluntary early retirement for employees within five years of the statutory retirement age, with enterprises continuing to provide living allowances and social insurance contributions until the statutory retirement; (3) termination of labor contracts, in which case firms must provide statutory severance, settle wage arrears, and make full social insurance contributions; and (4) reemployment assistance, including training, job placement, public welfare positions, and the provision of unemployment insurance and social assistance for disadvantaged workers. To facilitate the implementation of these resettlement programs, in May 2016 the Chinese government established a 100 billion yuan special fund for enterprises and local governments engaged in capacity reduction. These funds were designated primarily for the reassignment of employees from SOEs, but could also be used to support the resettlement of workers from eligible non-SOEs.[11]

2.3. Descriptive Evidence of the Policy Effects

A first manifestation of the policy's impact was the sharp decline in the number of operating coal mines. We collected data from the National Energy Administration of China,[12] which documents all coal mines nationwide from September 2014 to December 2018, including their names, the cities in which they are located, their

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[11] For further details, see: https://m.mof.gov.cn/czxw/201605/t20160519_1998021.htm.
[12] For further details, see: https://www.nea.gov.cn/ztzl/mtscnlgg/scnlgg.htm.

affiliated enterprises, and their annual production capacities. Following the classification specified in the Opinion, we divided coal mines into small and large categories based on their annual production capacity.[13] We then plotted the time trends of the total number of coal mines, as well as the counts of small and large mines, in Figure 4. The figure shows that the number of operating mines decreased after the implementation of the policy (i.e., from 2016 onward) compared with the pre-policy period. The reduction was particularly pronounced among small mines, many of which were forced to exit due to more stringent safety, environmental, and technological requirements, whereas the number of large mines remained relatively stable.

Alongside the reduction in the number of coal mines, employment in the coal mining sector also declined sharply. By the end of 2013, the coal mining and washing industry employed 6.113 million workers,[14] but the number had fallen to 3.473 million by the end of 2018.[15] Although the government allocated 100 billion yuan to support the resettlement of displaced workers, it proved far from adequate. As several coal company executives observed, if the funds were evenly distributed among all laid-off workers, each would receive only about 55,000 yuan, which was inadequate.[16] In practice, many SOEs sought to reallocate workers through internal transfers to other positions within the enterprise. However, given the limited capacity of firms to absorb surplus labor, this proved highly challenging.[17] Moreover, in their fieldwork on displaced coal workers in a city in Inner Mongolia, Wang and Lo (2022) found that, compared with SOE employees, those from non-SOEs received virtually no meaningful resettlement support. According to our collected data on mine closures and capacity reductions, approximately 77% of the affected coal mines were non-SOEs.

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[13] According to the Opinion, coal mines with an annual production capacity of less than 600,000 tons in Shanxi, Inner Mongolia, Shaanxi, and Ningxia were required to exit, as were those with capacities below 300,000 tons in Hebei, Liaoning, Jilin, Heilongjiang, Jiangsu, Anhui, Shandong, Henan, Gansu, Qinghai, and Xinjiang, and those with capacities below 90,000 tons in all other regions. Accordingly, we define coal mines with annual production below the threshold specified for their respective provinces as small mines, and those above the threshold as large mines.

[14] Data source: https://www.stats.gov.cn/sj/zxfb/202302/t20230203_1898652.html.

[15] Data source: https://www.stats.gov.cn/sj/zxfb/202302/t20230203_1900526.html.

[16] For related news reports, see: https://paper.people.com.cn/zgnyb/html/2018-06/11/content_1861254.htm; https://china.huanqiu.com/article/9CaKrnJUzux.

[17] For further details, see: http://pmo9337eb.pic29.websiteonline.cn/upload/u4v9.pdf.

In terms of production, the aggregate output of the coal sector declined significantly after 2016. Figure 1 presents China's annual coal production from 2012 to 2018. Before the policy implementation, between 2012 and 2015, China produced an average of 3.88 billion tons of coal per year. After the policy was enacted, annual production averaged 3.54 billion tons from 2016 to 2018, representing a decline of approximately 8.76% relative to the pre-policy period. The decline in coal output was accompanied by a rise in coal prices. As shown in Figure 2, coal prices had been on a continuous downward trajectory from 2012 to 2015, but rebounded sharply after 2016. This suggests that supply reductions contributed to restoring balance in the coal market.

Finally, the overall operating performance of coal enterprises improved following the implementation of the policy. Figures 3 and 5 present the total profits and debt-to-asset ratio of large-scale enterprises in the coal mining and washing industry from 2012 to 2018. As shown, total profits declined steadily between 2012 and 2015 but rebounded sharply after 2016. Similarly, the debt-to-asset ratio increased continuously from 2012 to 2016 before beginning to fall thereafter. These trends indicate that the reduction of excess capacity successfully alleviated operational difficulties for coal firms.

Overall, the descriptive evidence presents a consistent picture: the 2016 policy led to a significant decline in coal sector output, reshaped the size distribution of coal mines, reversed the downward trend in market prices, and improved firm performance. At the same time, it led to the closure of many small mines, displacing a large number of workers. Inadequate resettlement measures for this labor force imposed negative shocks on the labor market. In the following sections, we analyze these patterns more systematically using econometric methods to assess the causal effects of the capacity reduction policy.

3. Data and Variables

In our paper, we use data from several sources: (1) listed firm level data, (2) individual survey data, and (3) judicial judgment record data. The sample period is restricted to 2012–2018 for the firm-level and individual survey data, and to 2014–2018 for the judicial judgment records. The reasons for this restriction are explained below. All monetary values are deflated using the CPI with 2012 as the base year.

3.1. Firm Data

We use data from A-share firms listed on the Shanghai or Shenzhen stock exchanges from 2012 to 2018 to measure firms' operational performance and production inputs.[18] The data are obtained from the CSMAR database, which is the Chinese equivalent of Compustat in the U.S. context. Previous research on firms has also utilized data from listed companies (Bryson, Forth, and Zhou, 2014; Wu, Gyourko, and Deng, 2015; Cao et al., 2019; Benguria et al., 2022; Fang et al., 2023; Branstetter et al., 2023; Kim et al., 2024; Li and Branstetter, 2024). The original sample contains 20,499 firm–year observations. Following common practice, we exclude 443 firm–year observations associated with special treatment firms that had two (ST) or three (*ST) consecutive years of net loss (Cao et al., 2019; Kim et al., 2024). Then, to minimize potential spillover effects—specifically, the influence of the capacity reduction policy on coal-related upstream and downstream industries within the control group—we draw on the *2012 China Input–Output Table* to identify industries closely linked to coal and exclude firms operating in these industries in the pre-policy period (i.e., in 2015), removing 8,480 firm–year observations in total.[19] After further dropping observations

[18] China's stock market mainly consists of A-shares and B-shares. We focus on A-share listed firms since B-share market is relatively small in scale and was originally established to attract foreign investment. In 2015, the total trading value of A-shares on the Shanghai and Shenzhen stock exchanges was 476.7 times that of B-shares (data sourced from the *Shanghai Stock Exchange Statistical Yearbook 2016* and the *Shenzhen Stock Exchange Market Statistical Yearbook 2015*).

[19] Using information from Table 4.1 of the *2012 China Input–Output Table* (covering 139 industries). First, we match the 139 industries with the sectors covered by the listed companies. Then, we calculate, for each industry in which the listed companies operate, the share of coal mining and washing products in the total value of its input materials. Industries with a share greater than 1% are excluded, as they can be regarded as downstream industries closely linked to coal mining and washing. Similarly, we calculate, for each industry, the share of its products in the total inputs of coal mining and washing. Industries with a share greater than 1% are also excluded, as they can be regarded as upstream industries closely tied to coal. Based on these criteria, the following industries are removed from the sample: other mining; paper and paper products; petroleum processing, coking, and nuclear fuel processing; chemical raw materials and chemical products; chemical fiber manufacturing; nonmetallic mineral products; ferrous metal smelting and rolling; other manufacturing; electricity and heat production and supply; gas production and supply; ecological protection and environmental management; monetary financial services; other financial services; business services; fabricated metal products; special-purpose equipment manufacturing; general-purpose equipment manufacturing; wood processing and products of wood, bamboo, rattan, palm,

with missing values for key variables, our final sample consists of 11,292 firm–year observations. The treatment group consists of firms that operated in the coal mining and washing industry as well as mining support activities in 2015, while the control group comprises firms operating in all other industries in the sample in 2015.[20]

To measure firms' operational performance, we construct the following indicators: total operating revenue, total profit, and total debt. In addition, since the capacity reduction policy may affect firms' production behavior, we construct the following indicators to capture changes in production activities: total number of employees, number of production employees, total wages, average wage per employee, cash expenditure on the purchase and construction of assets, and R&D expenditure. We use a dummy variable, *Coal*, which equals 1 if the observation belongs to the treatment group and 0 if it belongs to the control group. We also define a dummy variable, *Post*, which equals 1 for observations in the post-policy period (2016 and thereafter) and 0 for observations in the pre-policy period (2015 and earlier). Furthermore, we construct several firm-level control variables, including number of years since the firm's establishment, number of years since the firm was listed, an indicator for whether the firm was state-owned in 2015, and the amount of registered capital in 2015. Except for *Coal*, *Post*, number of years since the firm's establishment, number of years since the firm was listed, and the state-ownership indicator, all variables are winsorized at the 1st

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and straw; wholesale and retail trade; and road transport.

[20] The control group industries include: agriculture, forestry, animal husbandry, and fishery; petroleum and natural gas extraction; ferrous metal ore mining and dressing; nonferrous metal ore mining; nonmetallic mineral mining; agricultural and sideline food processing; food manufacturing; beverage, liquor, and refined tea manufacturing; tobacco products; textiles; textile and apparel manufacturing; leather, fur, feather, and related products and footwear; furniture manufacturing; printing and reproduction of recorded media; cultural, educational, arts, sports, and entertainment products manufacturing; pharmaceutical manufacturing; rubber and plastic products; nonferrous metal smelting and rolling; automobile manufacturing; railway, shipbuilding, aerospace, and other transportation equipment manufacturing; electrical machinery and equipment manufacturing; computer, communications, and other electronic equipment manufacturing; instruments and meters manufacturing; comprehensive utilization of waste resources; repair of metal products, machinery, and equipment; water production and supply; construction; railway transportation; water transportation; air transportation; pipeline transportation; loading, unloading, and transportation agency services; warehousing; postal services; accommodation and catering; information transmission, software, and information technology services; capital market services; insurance; real estate; leasing; scientific research and technical services; water conservancy management; public facility management; resident services, repair, and other services; education; health and social work; culture, sports, and entertainment; as well as firms that cannot be clearly classified into specific industries.

and 99th percentiles to mitigate the influence of extreme values. Table 1 reports descriptive statistics for the firm-level variables.

As shown in the table, the average total operating revenue in the sample is RMB 6,771.5 million, the average total profit is RMB 633.9 million, and the average debt amount to RMB 9,854.6 million. Regarding production input, the mean total number of employees is 5,991 workers, with an average of 2,901 production workers. The average cash expenditure on asset purchases and construction is RMB 500.4 million, while the mean R&D expenditure is RMB 169.6 million. Among the observations, 2.4% belong to the treatment group, and 44.8% fall in 2016 or later. On average, firms have been established for 17.6 years and listed for 10.2 years; 34.5% of sample firms were state-owned in 2015, and the average registered capital in 2015 was RMB 1,073.7 million.

3.2. Survey Data

We use data from the China Family Panel Studies (CFPS) to measure individual labor market outcomes. The CFPS is a nationwide longitudinal survey launched by Peking University in 2010. This survey covers approximately 16,000 households across 25 provinces in China.[21] The survey is conducted biennially, capturing a spectrum of information ranging from individual demographic profiles to household economic activities. We combine the 2012, 2014, 2016, and 2018 survey waves, and exclude observations with missing values in key variables. The resulting individual-level dataset contains 93,577 observations on 35,487 individuals aged 18–65 at the time of each survey wave.

To assess the impact of the capacity reduction policy on individuals in affected cities, we construct the following variables: whether the individual has a job at the time of the survey (*Has job*), the individual's annual income (*Annual income*), whether the respondent believes that society is currently facing a severe employment problem (*Perceives severe employment problem*), and whether the respondent is currently

[21] The CFPS does not cover Xinjiang, Tibet, Qinghai, Inner Mongolia, Ningxia, and Hainan provinces.

divorced (*Divorced*). We define a dummy variable, *Treat*, which equals 1 if the respondent resided in a city where coal mines were closed or subject to capacity reduction, and 0 otherwise. To identify treated cities, we collected lists of mines that were closed or experienced capacity cutbacks between 2016 and 2018 from the official websites of provincial governments, Development and Reform Commissions, Economic and Information Technology Departments, and Industry and Information Technology Departments. Using these sources, we compiled a dataset documenting which cities experienced coal mine closures or capacity reductions during this period, along with the corresponding amount of capacity withdrawn. Cities that underwent any coal mine closures or capacity reductions from 2016 to 2018 are classified as treated cities, while those that did not are classified as control cities. Figure 6 presents the geographic distribution of treated and control cities, where the treated cities are shown in blue and the control cities in white. Consistent with Section 3.1, we define a dummy variable, *Post*, which equals 1 for observations in the post-policy period (2016 and thereafter) and 0 for observations in the pre-policy period. We also include a set of control variables. At the individual level, these include age, gender, education level, and whether the respondent resides in an urban area. At the city level, the control variables are measured in the baseline year 2015, including per capita GDP, the share of secondary and tertiary industries in GDP, population density, and the ratios of government expenditure and revenue to GDP. Descriptive statistics for these variables are reported in Table 2.

As shown in Table 2, on average, 81.7% of respondents have a job, with an annual income of RMB 16,255. About 60.7% of respondents consider current employment issues in society to be quite severe. In addition, 2.2% of respondents are divorced, 47% reside in treated cities, and 45.2% of observations fall in 2016 or later. The average respondent is 42.7 years old; 49.3% are male, the mean years of education is 8, and 46.5% live in urban areas.

3.3. Judicial Judgment Record Data

The judicial judgment record data were obtained from China Judgements Online (CJO), an official website operated and supervised by the Supreme People's Court (SPC). To bolster judicial transparency and advance judicial accessibility, the SPC implemented the *Regulation on the Publication of Judgments by People's Courts on the Internet* in November 2010.[22] It mandates that different levels of courts need to publish judgments online, with some special exceptions.[23] Subsequently, CJO was officially launched in July 2013. In November 2013, the SPC issued a new version of the *Regulation of the Supreme People's Court on the Publication of Judgments by People's Courts on the Internet*, which took effect in January 2014.[24] The difference between this regulation and the one issued in 2010 lies in the fact that the new regulation mandates that judgments need to be published in CJO. As of September 2016, CJO has published more than 200 million judgments, with a total of approximately 2.2 billion visits.

We use web scraping technology to obtain the judgments from the CJO. We obtained 1,387,497 criminal cases published between January 2014 and October 2021. We use the following method to verify the representativeness of the CJO data. In Appendix Figure B1, we create a scatter plot comparing the logarithm of the annual total number of searches for crime-related keywords recorded by the Baidu Search Index (similar to Google Trends) for each city against the logarithm of the annual number of criminal offenders recorded in the CJO data for each city, both of which are limited to our sample period (2014–2018).[25] The results show a positive correlation

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[22] A Chinese version of this file can be accessed at https://tkxfy.hncourt.gov.cn/public/detail.php?id=1747.

[23] The exceptions refer to the following scenarios: (1) cases involving state secrets or personal privacy; (2) cases involving illegal activities by minors; (3) cases concluded through mediation; and (4) any other cases deemed unsuitable for public disclosure on the internet.

[24] A Chinese version of this file can be accessed at https://www.court.gov.cn/fabu/xiangqing/5867.html.

[25] The Baidu Search Index is widely used to capture public awareness of various topics in China. For example, Li et al. (2024) use this measure to assess public perceptions of air pollution and PM2.5. The crime-related keywords we used in our study include traffic accident, traffic accident crime, public safety, prostitution, dangerous driving crime, soliciting prostitution, robbery, robbery crime, child trafficking, child trafficking crime, women trafficking, intentional injury, intentional injury crime, intentional homicide, intentional homicide crime, extortion, extortion crime, drugs, public security penalty, public security administration, crime, theft, theft crime, kidnapping, kidnapping crime, social stability maintenance, fraud, fraud crime, drug trafficking, and gambling.

between the two, indicating that the perceived severity of crime reflected in search behavior (as reflected in the Baidu Search Index) is positively correlated with the number of criminals recorded in the CJO data during this period.[26] Moreover, prior studies on crime in China have also utilized this database (Ma, Pan, and Xu, 2025; Ma et al., 2026).

Judicial judgment records include detailed descriptions of the crimes, such as the occurrence time, location, number of individuals involved, and verdicts. We use the textual analysis method to obtain relevant information from the judgment records. Appendix Part C shows an example of a judgment record, and Appendix Part D describes the detailed procedure we used to obtain useful information for the analysis.

In this study, we focus on criminal crimes such as robbery, murder, theft, affray, drug-related crimes, and others that violate the Criminal Law of the People's Republic of China. When calculating the number of offenders in each city, we exclusively consider judgments issued by local courts during the initial trial phase of criminal cases and exclude those with not guilty verdicts.[27] By dividing the number of offenders by the population of each prefecture in the corresponding year (measured in millions), we construct the prefecture–year–month crime rate. Thus, the crime rate measures the number of offenders per one million residents in a given city in a given month. Following the same definition as in Section 3.2, we define *Treat* as a dummy variable equal to 1 if the city experienced coal mine closures or capacity reductions, and 0 otherwise. We also define *Post* as a dummy variable equal to 1 for observations from 2016 onward and 0 for those from 2015 or earlier. In addition, we construct a set of city-level covariates measured in 2015 to serve as control variables, including per capita GDP, the share of secondary industry in GDP, the share of tertiary industry in GDP, population density, the ratio of government expenditure to GDP, and the ratio of government revenue to GDP. Descriptive statistics for these variables are reported in

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[26] In Section 6.3, we conduct a robustness check, where we use the crime rate variable constructed from the Baidu Search Index as the dependent variable. The result from this regression is consistent with the baseline results.

[27] According to the Criminal Procedure Law of the People's Republic of China, the initial trial of criminal cases is generally handled by grassroots people's courts. We exclusively utilize judgments from these initial trials to prevent the duplication of case counts.

Table 3. On average, the city-year-month crime rate in China was 43.4 offenders per million residents. Overall, 54.7% of the observations belong to the treatment group, and 58.3% correspond to the post-2016 period.

There are two reasons for limiting the crime data to the period from January 2014 to December 2018. First, we choose January 2014 as the starting time because the regulation requiring local courts to publish judgment records in CJO took effect in January 2014. Second, the data quality of judicial judgment records began to deteriorate gradually in 2019. Therefore, we exclude data from 2019 onward.

4. Impact of the Coal Capacity Reduction Policy on Firm Performance

As shown in Section 2.3, following the implementation of the capacity reduction policy, the total profits and debt-to-asset ratio of large-scale enterprises in the coal mining and washing industry improved significantly. In this section, we employ a more rigorous causal identification strategy to analyze the impact of the policy on listed firms' operational performance and production behavior in the industry.

4.1. Event Study

We first estimate the dynamic effect of the policy using the following regression:

$$Y_{fit} = \beta_0 + \sum_t \beta_1^t Coal_i \times Dummy_t + \lambda_f + \mu_t + \eta X_{fit} + \varepsilon_{fit}, \qquad (1)$$

where t covers the years 2012–2018, with 2015 serving as the baseline year. The subscript i denotes the industry in which the firm operated in 2015;[28] f refers to the firm. Y_{fit} captures both operational performance (measured by total operating revenue, total profit, and total debt) and production behavior (measured by total number of

[28] The industry definitions in this analysis follow the *Guidelines for the Industry Classification of Listed Companies* (2012 revision), issued by the China Securities Regulatory Commission (CSRC) on October 26, 2012. Under this system, listed firms are categorized into 19 industry categories and 90 industry groups. In our analysis, the term "industry" refers to these industry groups. Examples of industry categories include agriculture, forestry, animal husbandry, and fishery; mining; manufacturing; production and supply of electricity, heat, gas, and water; construction; and wholesale and retail. Examples of industry groups include agriculture, forestry, animal husbandry, fishery, agricultural services, coal mining and washing, oil and natural gas extraction, ferrous metal ore mining, nonferrous metal ore mining, and non-metallic mineral mining. For more details, see: https://www.csrc.gov.cn/csrc/c101864/c1024632/content.shtml.

employees, number of production employees, total wages, average wage per employee, cash expenditures on the purchase and construction of assets, and R&D expenditure). All dependent variables are expressed in logarithmic form. $Coal_i$ is a dummy variable representing the treatment group, which is equal to 1 if industry i is coal-related industry, specifically those engaged in coal mining, coal washing, or coal mining support activities in 2015. $Dummy_t$ represents a series of year dummy variables. We control for firm fixed effects λ_f to absorb any time-invariant firm-level variables. We also control for year fixed effects μ_t, which could include common social and economic shocks occurring in the same period and the time trends of the outcome variables before or after the policy. Note that λ_f and μ_t absorb $Coal_i$ and $Post_t$, respectively; hence, we do not control for these two terms separately. We incorporate firm-level time-varying variables (including years since firm's establishment and years since firm was listed) as well as the interactions between linear time trends and a set of predetermined firm characteristics in X_{fit}. These predetermined characteristics include whether the firm was a state-owned enterprise and its registered capital in 2015. By including these interactions, we allow firms with different characteristics to have different linear time trends. ε_{fit} is the error term. To address the potential heteroskedasticity and serial correlation of the error term, we cluster standard errors at the industry level.

By estimating Equation (1), the left part of Figures 7 and 8 present the event study results for the policy's impact on firms' operational performance and production input, respectively. In Figure 7, the Panels A, B, and C report the results for the logarithm of total operating revenue, the logarithm of total profit, and the logarithm of total debt. From the left part of Panel A, we can clearly see a strong pre-trend: firms in the treatment group—those in the coal industry—were already experiencing a steady decline in total operating revenue compared to firms in the control group before the policy was implemented. Because the event study results for total operating revenue do not satisfy the parallel trends assumption required for a difference-in-differences design, and given the approximately linear pattern of pre-policy trends, we follow Dustmann et al. (2022) and Fenizia and Saggio (2024) by overlaying a linear time trend estimated from the 2012–2015 period and extrapolating it into the post-policy years (shown as the dashed black line in the left part of Panel A). To more clearly illustrate the divergence between post-policy outcomes and pre-policy trends, the right part of panel A plots the deviations of the event-study coefficients from this linear trend. The post-policy coefficients generally move in the opposite direction of the projected linear trend, yielding positive and highly statistically significant estimates for total operating revenue. This indicates that after adjusting for the pre-policy trend, the coal capacity reduction policy significantly improved the total operating revenue of coal firms.

As shown in Panel B of Figure 7, the estimates for total profit closely mirror those for total operating revenue. For total debt in Panel C, the treatment and control groups exhibited broadly parallel trends before the policy, while firms in the treatment group experienced a significant reduction in debt relative to the control group afterward. To maintain consistency with Panels A and B, we also overlay a dashed black line in the left part of Panel C, representing a linear time trend estimated from the 2012–2015 period and extrapolated into the post-policy years. The right part of Panel C then plots the deviations of the event-study coefficients from this linear trend. As can be seen, the left and right parts of Panel C are very similar.

Overall, the results in Figure 7 indicate that prior to the policy, firms in coal-related industries underperformed relative to the control group, while the capacity reduction policy substantially improved the operational performance of treated firms.

Panels A through F of Figure 8 report the results for the logarithm of total number of employees, logarithm of number of production employees, logarithm of total wages, logarithm of average wage per employee, logarithm of cash expenditure on asset purchases and construction, and logarithm of R&D expenditure, respectively. Similar to total operating revenue and total profit, the left part of Figure 8 exhibits a strong pre-trend, so we applied the same adjustment procedure as in Figure 7. After accounting for the pre-policy trend, the right part of Figure 8 shows that the coal capacity reduction policy significantly reduced both total employment and the number of production employees in treated firms, significantly decreased total wages, had no significant effect on average wage per employee, lowered cash expenditure on asset purchases and construction, and positively affected R&D expenditure.

Overall, the results in Figures 7 and 8 indicate that, once the pre-policy trend is controlled for, the policy substantially improved the operational performance of coal industry firms. At the same time, however, it led to reductions in production inputs—particularly employment and total wages—which may have adverse implications for the labor market.

4.2. Industry-Level Difference-in-Differences Results

As shown in Section 4.1, firms in the coal industry experienced a continued deterioration in both operational performance and production input relative to firms in other industries prior to 2015. To address the issue of non-parallel pre-policy trends between the treatment and control groups in the outcome variables of interest, we follow the approach of Dobkin et al. (2018) to estimate the policy's impact on treated firms.

We employ a parametric event study framework to summarize the magnitude and statistical significance of the estimated effects. Our choice of functional form is guided by the patterns documented in Section 4.1. In particular, since the pre-policy trends appear approximately linear, we adopt the following regression specification:

$$Y_{fit} = \beta_0 + \sum_{t=2016}^{2018} \beta_1^t Coal_i \times Dummy_t + \beta_2 Coal_i \times Year_t + \lambda_f + \mu_t + \eta X_{fit} + \varepsilon_{fit}, \quad (2)$$

Equation (2) includes an interaction term $Coal_i \times Year_t$ account for a linear differential pretrend between treated and control firms. The main coefficients of interest, $\sum_{t=2016}^{2018} \beta_1^t$, capture the post-policy changes in the outcome variable, net of any preexisting linear trend represented by β_2. The definitions of the other variables are the same as in Equation (1).

Tables 4 and 5 report the average annual effects from 2016 to 2018 estimated using Equation (2). Table 4 presents results for firms' operational performance, while Table 5 presents results for firms' production input. Columns (1) through (3) of Table 4 show the regression results for total operating revenue, total profit, and total debt. Columns (1) through (6) of Table 5 show the regression results for total number of employees, number of production employees, total wages, average wage per employee, cash expenditures on asset purchases and construction, and R&D expenditure, respectively. Overall, the results are broadly consistent with those in Section 4.1. Specifically, following the policy, treated firms experienced a significant increase of 28.8% in total operating revenue and 82,121.3% in total profit, along with a significant reduction of 26.7 % in total debt, indicating a substantial improvement in operational performance. Regarding production input, the policy led to significant declines of 15.5% in total number of employees, 11.8% in number of production employees, 20.9% in total wages, and 34.6% in cash expenditures on asset purchases and construction. The policy had essentially no effect on average wage per employee or R&D expenditure.

4.3. Robustness Checks

Controlling for confounding factors. If other factors influencing firms' operational performance and production inputs are correlated with $\sum_t Coal_i \times Dummy_t$ in Equations (1) or (2), then our estimation results could be biased. There are several potential confounding events that stand out. The first is the capacity reduction policy in the steel industry. On February 1, 2016, when the capacity reduction policy for the coal industry was introduced, a similar policy targeting the steel industry was also implemented. This policy aimed to eliminate outdated steel capacity that failed to meet standards regarding environmental protection, energy consumption, product quality, safety, and technology. It sought to reduce crude steel production capacity by 100–150 million tons within five years.[29] Some industries classified as part of the control group in Equations (1) or (2) may be closely linked to the steel industry and thus affected by its capacity reduction policy. To account for the potential impact of this policy, we exclude firms operating in ferrous metal ore mining and dressing industry from the

[29] For policy details, see https://www.gov.cn/zhengce/content/2016-02/04/content_5039353.htm.

control group.[30] The regression results are reported in Table 6, and they remain consistent with our baseline estimates.

The second potential confounding event is the shantytown renovation program, which continued during our sample period. This program, implemented by the Chinese government, aims to improve living conditions for urban residents in dilapidated or substandard housing by demolishing unsafe buildings and constructing new housing, as well as upgrading infrastructure and residential environments. It began before 2010 and was accelerated following the State Council's *Opinions on Accelerating Shantytown Renovation* issued on July 4, 2013.[31] The shantytown renovation program may have affected certain industries in our control group in the baseline regressions. To account for its potential influence, we exclude firms operating in the construction and real estate sectors from the control group. The estimation results, reported in Table 7, remain consistent with our baseline findings.

Redefinition of coal-related upstream and downstream industries. Recall that in Section 3.1, when constructing the regression sample, we excluded industries that are upstream or downstream of the coal industry to avoid potential spillover effects. The upstream and downstream industries of coal are defined as follows. We first calculate, for each industry, the share of coal mining and washing products in the total value of its input materials. Industries with a share greater than 1% are excluded, as they are regarded as downstream sectors closely linked to coal mining and washing. Similarly, we calculate, for each industry, the share of its products in the total inputs of the coal mining and washing industry. Industries with a share greater than 1% are also excluded, as they are considered upstream sectors closely tied to coal.

In the baseline regressions, we use 1% as the cutoff threshold. To assess the robustness of this choice, we vary the threshold to 0.5%, 0.75%, 1.25%, and 1.5% and re-estimate Equation (2) using the corresponding reconstructed samples. The results are

[30] It should be noted that the industry most closely related to the steel sector is the ferrous metal smelting and rolling industry. In our baseline regressions, this industry was already excluded because it constitutes a key downstream sector of the coal industry. Therefore, we do not consider it further in this robustness check.

[31] For policy details, see https://www.gov.cn/zwgk/2013-07/12/content_2445808.htm.

reported in Figure 9. Panels A through I present the estimates for total operating revenue, total profit, total debt, total number of employees, number of production employees, total wages, average wage per employee, cash expenditures on asset purchases and construction, and R&D expenditure, respectively. The solid line shows the estimated coefficients from the baseline regressions (i.e., the results in Tables 4 and 5), while the dashed hollow lines display the estimates obtained under the alternative thresholds. As shown in the figure, the estimated effects remain highly stable across different cutoff values, indicating that our findings are robust to the definition of coal-related upstream and downstream industries.

5. Impact of the Coal Capacity Reduction Policy on Individual Labor Market Outcomes

Thus far, we have shown that the coal capacity reduction policy significantly improved the operational performance of firms in the coal industry. However, it also led to reductions in total number of employees, number of production employees, and total wages, which may have adverse implications for the labor market. In this section, we examine how the policy affected individuals living in the affected cities.

5.1. Event Study

Based on the coal mines closure and capacity reduction data we collected, we classify cities affected by the policy as the treatment group, while the remaining cities serve as the control group. We estimate the dynamic effect of the policy using the following regression:

$$Y_{ict} = \beta_0 + \sum_t \beta_1^t Treat_c \times Dummy_t + \lambda_c + \mu_t + \eta X_{ict} + \varepsilon_{ict}, \qquad (3)$$

where the subscript i denotes the individual; c refers to the city; and t represents the survey year and takes values of 2012, 2014, 2016, and 2018. We set the year of $t = 2014$ as the baseline group. Y_{ict} denotes the outcome variable for individual i in survey year t. The outcomes include employment status at the time of the survey, annual income, perceived severity of employment conditions, and divorce status. $Treat_c$ is a dummy variable representing the treatment group, which is equal to 1 if city c implemented the coal capacity reduction policy. $Dummy_t$ represents a series of survey year dummy variables. We control for city fixed effects λ_c to absorb any time-invariant city-level variables. We also control for survey year fixed effects μ_t, which could include common social and economic shocks occurring in the same period and the time trends of the outcome variables before or after the policy. Note that λ_c and μ_t absorb $Treat_c$ and $\sum_t Dummy_t$, respectively; hence, we do not control for these terms separately. We incorporate several individual-level variables (including gender, age, educational attainment, and whether the respondent resides in an urban area) as well as the interactions between linear time trends and a set of predetermined city characteristics in X_{ict}. These characteristics include per capita GDP, the share of secondary industry in GDP, the share of tertiary industry in GDP, population density, the ratio of government expenditure to GDP, and the ratio of government revenue to GDP. By including these interactions, we allow cities with different characteristics to have different linear time trends. ε_{ict} is the error term. To address the potential heteroskedasticity and serial correlation of the error term, we cluster standard errors at the city level.

Figure 10 presents the estimates from Equation (3) along with the corresponding 95% confidence intervals for each estimated coefficient. Panels A through D display the outcome variables: whether the individual has a job at the time of the survey, annual income, whether the respondent perceives the current employment situation as severe, and whether the respondent is divorced.

These results are consistent with the parallel trends assumption, as the coefficients for the pre-policy period are close to zero and display no clear pattern. Moreover, the figure shows that the capacity reduction policy had no significant effect on employment in the affected cities but may have negatively impacted individuals' annual income, heightened their perception of unemployment problems, and increased divorce rates. Overall, the evidence suggests that the capacity reduction policy had adverse effects on individuals in the affected cities.

5.2. City-Level Difference-in-Differences Results

To more clearly illustrate the policy's impact on individuals in the affected cities, we estimate the following model:

$$Y_{ict} = \beta_0 + \beta_1 Treat_c \times Post_t + \lambda_c + \mu_t + \eta X_{ict} + \varepsilon_{ict}, \qquad (4)$$

where $Post_t$ is a dummy variable representing the post-policy period, which is equal to 1 for years after the policy. Since Figure 10 shows no evidence of non-parallel pre-policy trends between the treatment and control groups, we do not include the $Treat_c \times Year_t$ interaction terms to absorb pre-policy linear trends, as we did in Equation (2). All other variables in Equation (4) are defined in the same way as in Equation (3).

The results of the DID estimation based on Equation (4) are reported in Table 8. Columns (1) through (4) present results using, respectively, employment status at the time of the survey, annual income at the time of the survey, whether the respondent perceives the current employment situation as severe, and whether the respondent is divorced as the dependent variable. The coefficient of $Treat_c \times Post_t$ is insignificant in the first column but statistically significant at the 5% level in Columns (2) through (4). The estimated coefficients for Columns (1) to (4) are -0.003, -0.899, 0.037, and 0.004, respectively. These findings suggest that the coal capacity reduction policy had no significant effect on individual employment status. However, it substantially reduced annual income for residents in treated cities by 899 yuan, equivalent to 5.5% of the sample mean. In addition, the policy significantly increased the likelihood of residents perceiving employment problems as severe by 3.7 percentage points (6.1% of the sample mean) and raised the divorce rate by 0.4 percentage points (18.2% of the sample mean).

5.3. Robustness Checks

Different definition of Treat variable. In the baseline regressions, all cities that experienced coal capacity reductions or mine closures were classified as treated cities. However, in some of these cities, the coal industry is not a major pillar industry. As a result, the impact of coal capacity cuts or mine closures in such cities may have been relatively limited. To examine whether the definition of treated cities affects our baseline results, we redefine the *Treat* variable as follows. For each city, we calculate the ratio of the value of reduced or closed coal production capacity during 2016–2018 to the city's GDP in 2015. Based on the median value of this ratio, cities above the median are defined as the new treatment group, while those below the median are defined as the new control group. The regression results based on this alternative definition are reported in Panel A of Table 9. As shown, the estimates remain consistent with the baseline results, suggesting that our findings are robust to the definition of the treatment group.

Exclude control cities with coal mines that did not implement capacity reduction policy. In our baseline regressions, several cities in the control group also had coal mines but did not experience any production cuts or closures.[32] When coal prices rose following the implementation of the capacity reduction policy, these cities might have benefited from the price increase. To eliminate potential spillover effects arising from this channel, we exclude these control group cities from the sample. The results are reported in Panel B of Table 9. As shown, the estimation results remain consistent with the baseline findings.

Controlling for confounding factors. If other factors influencing individuals' labor market outcomes are correlated with the coal capacity reduction policy, then our estimation results may be biased. Several potential confounding events stand out. The first two are the same as those discussed in Section 4.3, namely, the capacity reduction policy in the steel industry and the shantytown renovation program. To account for the possible impact of the steel industry capacity reduction, we collected lists of steel plants that underwent capacity cuts during the sample period, along with their locations, from the official websites of provincial governments, Development and Reform Commissions, Economic and Information Technology Departments, and Industry and Information Technology Departments. Using this information, we identified cities affected by steel industry capacity reduction and constructed a dummy variable, *Steel*, which equals 1 if the city experienced steel capacity reduction and 0 otherwise. We also define *Post2016* as a dummy variable equal to 1 for observations in 2016 or later, and 0 otherwise. The interaction term *Steel* × *Post2016* is included in the regression, with results reported in Panel A of Table 10. As shown, the estimates remain consistent with the baseline results.

To account for the potential influence of the shantytown renovation program, we control for the annual ratio of completed real estate investment to GDP for each city (*Real estate GDP share*). The corresponding results are reported in Panel B of Table 10. As shown, the estimates remain consistent with the baseline results.

[32] These cities are Hohhot, Bayannur, Harbin, Fuyang, Dezhou, Heze, Zhumadian, Nanning, Yuxi, Pu'er, and Guyuan.

The third confounding event is the household registration (hukou) system reform implemented in 2014. On July 30, 2014, the State Council of the People's Republic of China issued the Opinions on Further Promoting Household Registration System Reform, officially launching a new round of hukou reform aimed at easing restrictions on obtaining local hukou.[33] This policy eased hukou requirements for migrants in cities with urban permanent populations below 5 million. To account for the potential impact of this reform, following An et al. (2024), we classify cities with urban populations under 5 million as the treatment group and define a dummy variable *Hukou*, which equals 1 for these cities and 0 otherwise. We also define a dummy variable *Reform* that equals 1 for observations after the 2014 reform. The interaction term *Hukou* × *Reform* is included in the regression, and the results are reported in Panel C of Table 10. As shown, the estimates remain consistent with the baseline results.

The fourth confounding event is the adjustment of the minimum wage. In China, when local governments set or revise the minimum wage, they must consider several factors, including the local cost of living, average wages, labor productivity, unemployment, and overall economic development (Gan, Hernandez, and Ma, 2016; Mayneris, Poncet, and Zhang, 2018). These factors may themselves be influenced by the coal capacity reduction policy, making it necessary to control for changes in the minimum wage. To account for the potential effects of minimum wage adjustments, we control for the monthly minimum wage standard in each prefecture. The results are presented in Panel D of Table 10. As shown, the estimates remain consistent with the baseline results.

5.4. Heterogeneity and Further Analysis

In the baseline regressions, we have shown that the policy worsened labor market outcomes in the treated cities. In this section, we further examine whether these effects vary across different subgroups. In addition, our baseline results indicate that the policy did not have a significant impact on overall employment in treated cities. To understand this pattern, we also investigate whether individuals adjusted by shifting into other industries, which may help explain why the policy did not lead to a substantial change in employment.

[33] A Chinese version of this file can be accessed at https://www.gov.cn/zhengce/content/2014-07/30/content_8944.htm.

Differential effects in SOE vs. non-SOE cities. As discussed in Sections 2.2 and 2.3, in May 2016 the Chinese government established a 100-billion-yuan special fund to support compensation and reemployment for workers laid off due to capacity reduction. Anecdotal evidence suggests that this fund was primarily used to assist workers in SOEs, while employees in non-SOEs received little support (Wang and Lo, 2022). To examine whether this fund mitigated the policy's negative effects for SOE workers, we conduct the following analysis. Specifically, we divide the treated cities into two groups: those where a relative larger share of the closed or downsized coal mines were owned by SOEs (denoted as *SOE cities*), and those where a relative larger share were owned by non-SOEs (denoted as *non-SOE cities*).[34] Panel A of Table 11 reports the results using the SOE cities as the treated group and the same control group as in the baseline regressions (cities without mine closures or reductions). Panel B reports the results using the non-SOE cities as the treated group, again relative to the same control group. The results show that the deterioration in labor market outcomes is concentrated in the non-SOE cities. This suggests that the 100-billion-yuan special fund mitigated the adverse labor market effects of the policy in cities where SOEs were the primary targets of capacity reduction.

Heterogeneity by age and education. When facing adverse labor market shocks, older individuals and those with lower levels of education typically have fewer opportunities and lower flexibility to adjust, making them more vulnerable to negative impacts. Moreover, coal mining workers are disproportionately drawn from the less-educated labor force. To examine whether the coal capacity reduction policy had heterogeneous effects across age and education groups, we divide the treated sample into two age groups (18–34 and 35–65 at the time of survey) and two education groups (senior high school or below vs. college or above). Each treated subgroup is compared against the same control group used in the baseline regressions (i.e., respondents in cities that did not experience mine closures or production cuts). The regression results are presented in Tables 12 and 13. The findings indicate that the adverse labor market

[34] We classify SOE cities and non-SOE cities as follows. First, using the information we collected on coal mine closures and capacity reductions, combined with business registration data from Qichacha (a Chinese online platform providing comprehensive company information, available at https://www.qcc.com/), we identify whether each coal mine is owned, majority-owned, or effectively controlled by a SOE. Next, for each city, we calculate the share of closed or downsized coal mines belonging to SOEs—this share is defined as the SOE ratio. Finally, we compute the average SOE ratio across all cities; cities with an SOE ratio greater than or equal to this average are classified as SOE cities, while those below the average are defined as non-SOE cities.

effects are more pronounced among younger individuals and those with lower levels of education.

Employment Shifts Across Industries. In Section 4, our analysis of firms shows that the policy led to layoffs. However, as shown in Sections 5.1 and 5.2, overall employment in the treated cities did not change significantly. One possible explanation is that individuals who lost their jobs due to the capacity reduction policy may have reallocated to other industries. To investigate this, we use information from the CFPS data on respondents' primary industries of employment. Following the CFPS classification, we construct 15 industries: agriculture, forestry, animal husbandry, and fishery; mining; manufacturing; construction; transportation, storage, and postal services; wholesale and retail; accommodation and food services; finance; real estate development, leasing, sales, and related activities; leasing and business services; resident and other services; education; health, social security, and social welfare; public administration and social organizations; and other sectors.[35] For each industry, we construct a dummy variable indicating whether a respondent's primary job belongs to that industry. We regress these 15 dummy variables individually as dependent variables following Equation (4), and the estimated coefficients along with their 95% confidence intervals are reported in Figure 11. The findings indicate a significant decline in the probability of employment in mining and a significant increase in employment in wholesale and retail as well as in real estate development, leasing, sales, and related activities among respondents in treated cities. This suggests that employment shifts across industries may explain why overall employment in treated cities did not change significantly in the baseline regressions.

6. Impact of the Coal Capacity Reduction Policy on Crime

Thus far, we have shown that the coal capacity reduction policy had adverse effects on the income, subjective evaluations about employment issue, and marital status of residents in treated cities. In this section, we examine whether the policy also affects the crime rate in treated cities.

[35] "Other sectors" refers to industries with relatively small employment in our sample, including information transmission, computer services and software; electricity, heat, and water production and supply; scientific research, technical services, and geological exploration; water conservancy, environmental, and public facility management; and culture, sports, and entertainment.

6.1. Event Study

The estimation strategy used in this section is similar to that in Section 5. Specifically, we estimate an event-study model as follows:

$$Crime_{ct} = \beta_0 + \sum_{\tau} \beta_1^{\tau} Treat_c \times Dummy_{\tau} + \lambda_c + \mu_t + \eta X_{ct} + \varepsilon_{ct}, \qquad (5)$$

where $Crime_{ct}$ is the outcome variable, representing the crime rate in city c at year–month t, and τ ranges from −4 to 5. This specification divides the event time into 10 half-year periods: two years before the policy ($\tau = -4$, the first half of 2014), one and a half years before the policy ($\tau = -3$, the second half of 2014), …, half a year before the policy ($\tau = -1$, the second half of 2015), half a year after the policy ($\tau = 0$, the first half of 2016), …, and three years after the policy ($\tau = 5$, the second half of 2018). We set the half year of $\tau = -1$ as the baseline group. $Treat_c$ is a dummy variable equal to 1 if city c belongs to the treatment group and 0 if it belongs to the control group. $Dummy_{\tau}$ denotes a set of half-year dummy variables. λ_c and μ_t represent city fixed effects and year–month fixed effects, respectively. X_{ct} captures the interactions between linear time trends and a set of predetermined city characteristics, which include the same set of variables as in Section 5. ε_{ct} is the error term. To address the potential heteroskedasticity and serial correlation of the error term, we cluster standard errors at the city level.

Figure 12 presents the estimates from Equation (5) along with the corresponding 95% confidence intervals for each estimated coefficient. The result aligns with the parallel trends assumption: the coefficients for the periods preceding the policy are nearly zero and show no discernible trend. Additionally, the figure reveals that the estimators increase over time after the policy, suggesting that the capacity reduction policy leads to a significant increase in the crime rate in the affected cities.

6.2. City-Level Difference-in-Differences Results

Next, we estimate the following equation to obtain the effect of the capacity reduction policy on crime rates:

$$Crime_{ct} = \beta_0 + \beta_1 Treat_c \times Post_t + \lambda_c + \mu_t + \eta X_{ct} + \varepsilon_{ct}, \qquad (6)$$

where $Post_t$ is a dummy variable representing the post-policy period, which is equal to 1 for years after the policy. Since Figure 12 shows no evidence of non-parallel pre-policy trends between the treatment and control groups, we do not include the $Treat_c \times Year_t$ interaction terms to absorb pre-policy linear trends, as we did in Equation (2). All other variables in Equation (6) are defined in the same way as in Equation (5).

The results of the DID estimation based on Equation (6) are reported in Table 14. The outcome variable is the city-year-month level crime rate, which is defined as the number of offenders per million people. In Column (1), we do not control for the interactions of the linear trends and the city-level predetermined variables X_{ct}, while in Column (2), we add these interactions.

The coefficient of $Treat_{pj} \times Post_{tj}$ is 5.862 in Column (1) and significant at the 1% level. This coefficient decreases to 3.666 in Column (2). This suggests that the time trend of the outcome variable varying across prefectures with different characteristics accounts for a large proportion of the change in crime rates. However, the coefficient of the interaction term remains significant at the 1% level, showing that the coal capacity reduction policy leads to a significant increase in the crime rate in affected cities. The coefficient in Column (2) reveals that after the policy implementation, the number of offenders in the treatment group cities rose by 3.666 per million people per month, equivalent to 8.4% of the sample mean ($3.666 \div 43.396 \approx 0.084$). Given that the total population of affected prefectures in 2015 was 653.724 million in our sample, our estimate also suggests that the policy led to a total increase of 2397 offenders per month in the affected prefectures ($3.666 \times 653.724 \approx 2396.552$).

6.3. Robustness Checks

Same robustness checks as in Section 5.3. First, following the same procedure as in Section 5.3, we redefine the *Treat* variable and re-estimate Equation (6) using this new definition. The results are reported in Column (1) of Table 15.

Second, also consistent with Section 5.3, we exclude from the control group those cities that have coal mines but did not undergo capacity reduction. The corresponding results are presented in Column (2) of Table 15.

Third, again following Section 5.3, we separately control for the steel industry capacity reduction policy, the shantytown renovation program, the 2014 hukou reform, and changes in local minimum wages. These results are reported in Columns (1) through (4) of Table 16. Across all specifications, the estimates remain consistent with the baseline results.

Other robustness checks. To further justify our main results, we conduct other robustness checks. First, in the baseline regressions, the crime rate is constructed using the permanent resident population of each city in a given year as the denominator. A potential concern is that the observed increase in crime rates may be driven by population outflows from treated cities—i.e., a smaller denominator rather than a larger numerator. To address this concern, we regress the permanent resident population (for each city-year from 2014 to 2018) on Equation (6), treating population size as the dependent variable. The results are reported in Column (3) of Table 15. The estimated coefficient is not statistically significant, indicating that the increase in crime rates observed in the baseline regressions is not driven by reductions in local population.

Second, reported crimes underestimate the true (unobserved) number of crimes committed. Existing studies have addressed this problem by taking logarithms of crime rates and exploiting the panel structure of data to include fixed effects for geographical areas and time periods (Bianchi, Buonanno, and Pinotti, 2012). Following the literature, we take the logarithm of the crime rate and then estimate Equation (6) using it as the outcome variable. The results, reported in Column (4) of Table 15, show that the regression coefficients remain significant, validating the robustness of the baseline findings.

Third, to further verify that the coal capacity reduction policy indeed led to an increase in crime rates in treated cities, we use the Baidu Search Index to construct an alternative measure of crime rates. We scraped web search data from Baidu, the most frequently used search engine in China. Given the country's high internet penetration rates, search queries can effectively reflect public perceptions of crime in their surroundings. Baidu has published a search index that depicts the number of web searches for specific keywords in a given city on a given day. On this basis, we extracted web search data related to criminal behavior at the prefecture-year-month level from January 2014 to December 2018.[36] We divide this variable by the population of each city and then estimate Equation (6) using it as the outcome variable. The results, presented in Column (5) of Table 15, show that the regression coefficients remain significant, reinforcing the robustness of the baseline findings.

Fourth, one might be concerned that the coal capacity reduction policy could be accompanied by stricter law enforcement. If this were the case, the increased crime rate could be due to stricter law enforcement even if the crimes conducted did not change since we use judicial judgment record data. Another concern is that governments' expenditures on public security might have changed around the time of the policy, which could in turn affect the crime rate.

To address these concerns, we construct a variable measuring annual per capita government expenditure on public security in each city and regress this variable on Equation (6). The results, reported in Column (6) of Table 15, are not statistically significant. This suggests that the capacity reduction policy did not affect crime rates through changes in public security spending.

Moreover, local governments' efforts to maintain public safety and combat crime may be reflected not only in changes to public security expenditures but also in the language used in government documents. To verify that the policy did not significantly impact the intensity of local governments' efforts to combat crime, we follow the methodology of Chen et al. (2018) and Cao et al. (2021). We collect the annual government work reports of each prefecture in China and use text analysis to calculate the word frequencies of relevant keywords, including "illegal," "crime," "public security," "safety," "criminal," "unlawful," and "case," and then divide the word frequencies by the number of words in the corresponding report to construct an indicator of local governments' attention and support for crime prevention and enforcement efforts. We use this indicator as the dependent variable and estimate

[36] Keywords include traffic accident, traffic accident crime, public safety, prostitution, dangerous driving crime, soliciting prostitution, robbery, robbery crime, child trafficking, child trafficking crime, women trafficking, intentional injury, intentional injury crime, intentional homicide, intentional homicide crime, extortion, extortion crime, drugs, public security penalty, public security administration, crime, theft, theft crime, kidnapping, kidnapping crime, social stability maintenance, fraud, fraud crime, drug trafficking, and gambling.

Equation (6). The results are presented in Column (7) of Table 15. The regression results indicate that the policy did not lead to an increase in the ratio of these keywords in the annual government work reports of treated cities. Therefore, we can conclude that the policy did not result in treated cities placing greater emphasis on crime prevention and enforcement efforts.

6.4. Heterogeneity

Thus far, we have investigated the average impact of the policy on crime. In this section, we exploit the heterogeneous effects in different dimensions.

Differential effects in SOE vs. non-SOE cities. Consistent with the analysis in Section 5.4, we also examine whether the increase in crime differs between SOE cities and non-SOE cities. The regression results are reported in Columns (1) and (2) of Table 17. The increase in crime rates is significant only in non-SOE cities, while no significant effect is observed in SOE cities. This further suggests that the 100-billion-yuan fund helped mitigate the adverse effects of the capacity reduction policy for displaced SOE workers.

Different crime types. We classify crimes into property crimes and violent crimes following Ma, Pan, and Xu (2025). Property crimes include theft, fraud, extortion, gambling, robbery, the production of counterfeit and substandard goods, intellectual property infringement, and financial crimes. Violent crimes include offenses such as endangering public safety, rape, assault, intentional homicide, creating disturbances, terrorism, and related acts. We construct separate crime rates for these two categories at the city–year–month level and estimate Equation (6) accordingly. Columns (3) and (4) of Table 17 indicate that the coal capacity reduction policy significantly increased the incidence of property crimes only. A plausible explanation is that the policy adversely affected residents' economic conditions, thereby prompting a rise in economically motivated crimes.

Different characteristics of criminal cases. The judgment records provide detailed information about both the cases and the offenders involved. Using these data, we calculate the share of cases with specific attributes, such as whether the crime was committed by an individual acting alone, and the length of the sentence. For example, when analyzing crime rates by an individual acting alone, we compute the number of offenders acting alone per million people at the city–year–month level. These variables are then used as dependent variables in regressions based on Equation (6). The results, reported in Table 17, indicate that the increase in crime was largely driven by individual offenders rather than organized groups (Columns 5 and 6). Moreover, the sentences imposed were relatively short (Columns 7–9). Taken together, these findings suggest that the policy primarily contributed to a rise in individual crimes, with the increase concentrated in relatively minor cases.

7. Conclusion

In this paper, we investigate the impact of China's 2016 coal capacity reduction policy on individual's behavior and crime. Our findings indicate that while the policy did not significantly affect employment levels in the affected regions, it led to a substantial decline in residents' annual income. Additionally, public sentiment toward employment opportunities and social security has worsened. We also observe higher divorce rates and reduced household expenditure. Moreover, the policy appears to have contributed to a rise in crime, primarily driven by an increase in property-related offenses, whereas violent crime remains largely unchanged. These offenses are predominantly committed by unemployed individuals, first-time offenders, and single offenders, with most cases involving relatively short prison sentences.

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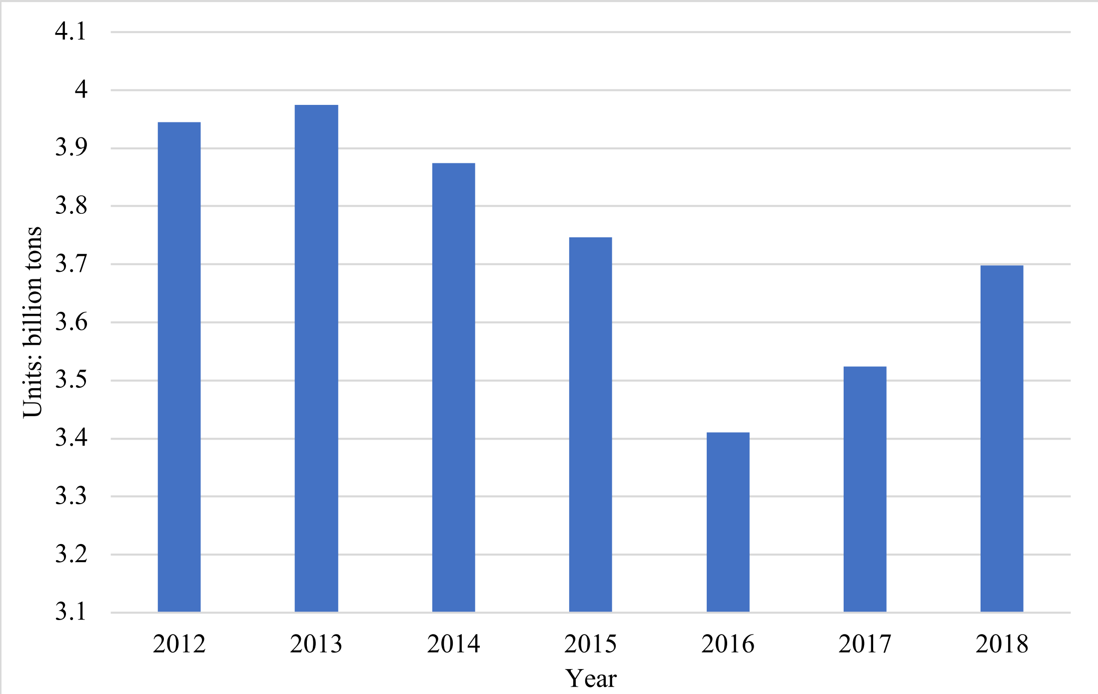
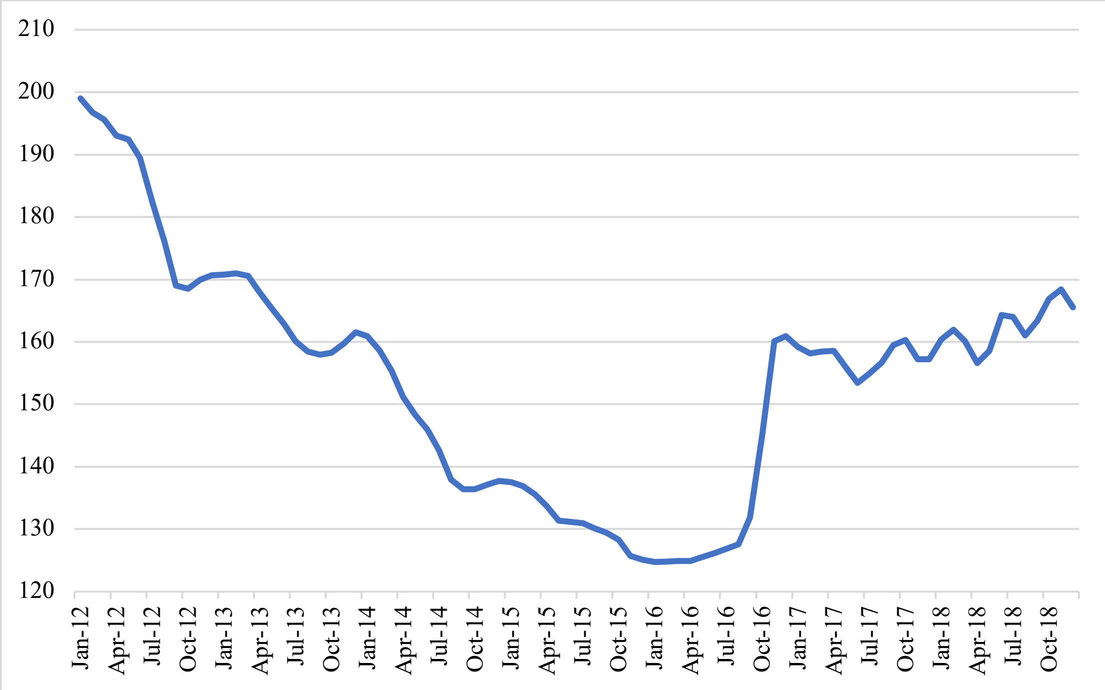
Figure 1. Annual Coal Production in China between 2012 and 2018



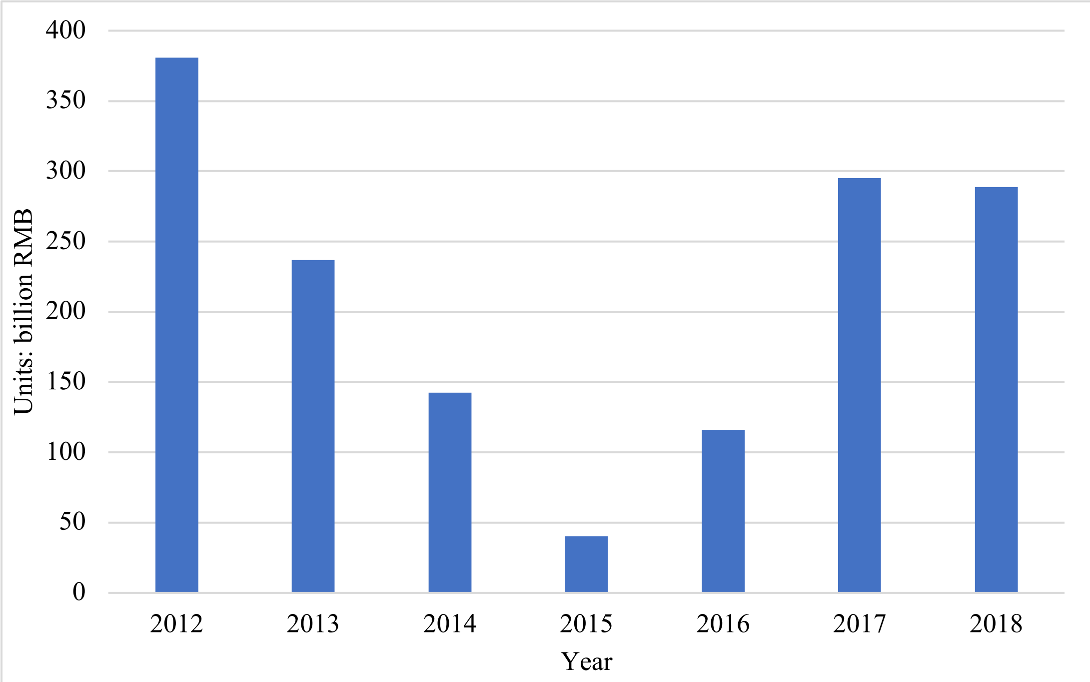
Note: This figure reports China's annual coal production from 2012 to 2018, measured in billion tons. Data for 2012 and 2013 are taken from the *China Statistical Yearbook 2015*, and data for 2014–2018 are taken from the *China Statistical Yearbook 2020*.

Figure 2. China's Monthly Coal Price Index from 2012 to 2018



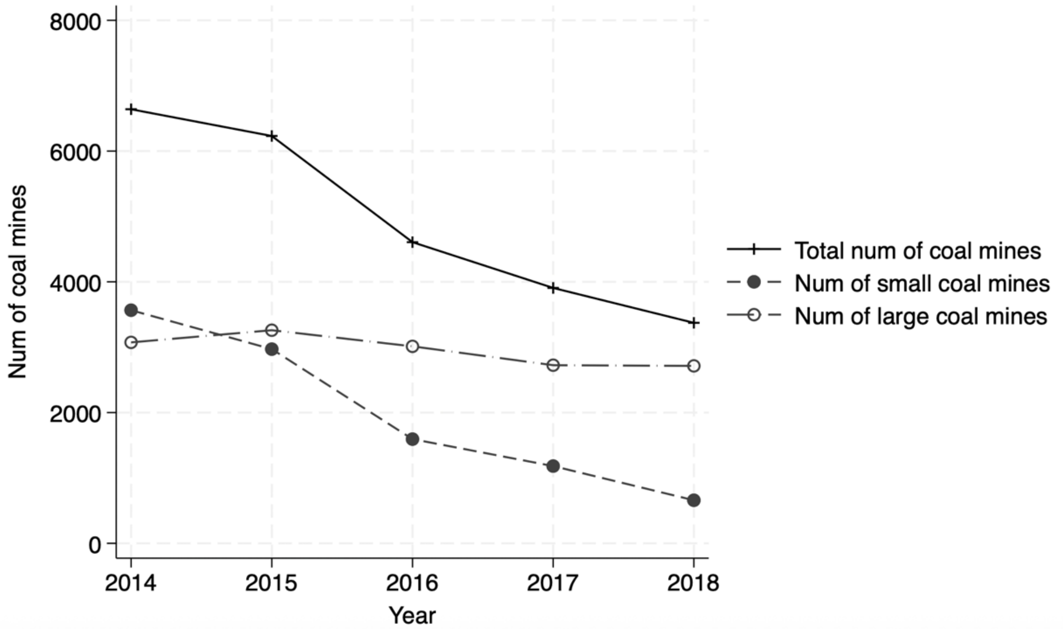
Note: This figure shows the monthly average of China's Coal Price Index from January 2012 to December 2018. The index is compiled and published by the China National Coal Association and the China Coal Transportation and Sales Association, with January 1, 2006 as the base period (=100) and a basic pricing cycle of one week. Data source: China National Coal Association (official website: https://www.coalchina.org.cn/).

Figure 3. Total Profits of Large-scale Enterprises in China's Coal Mining and Washing Industry from 2012 to 2018



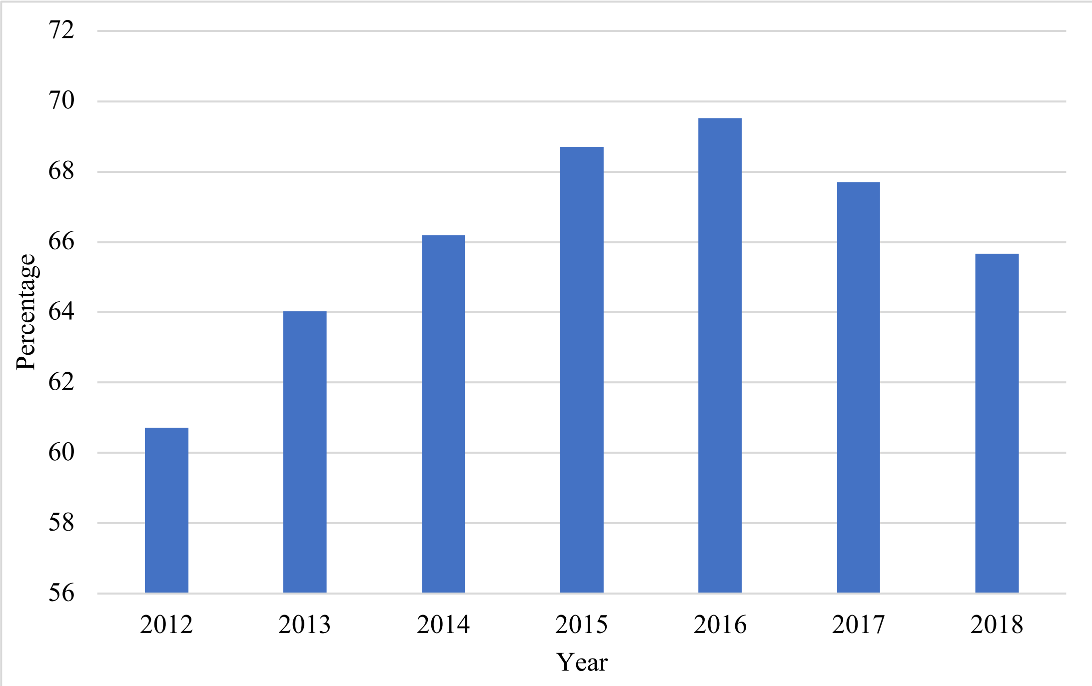
Note: This figure shows the total profits of large-scale enterprises in China's coal mining and washing industry from 2012 to 2018. The values in the figure are measured in 1 billion RMB. Each year's profit data are drawn from the China Statistical Yearbook of the following year; for example, the 2012 profit data come from the *China Statistical Yearbook 2013*.

Figure 4. The Number of Coal Mines in China, 2014–2018



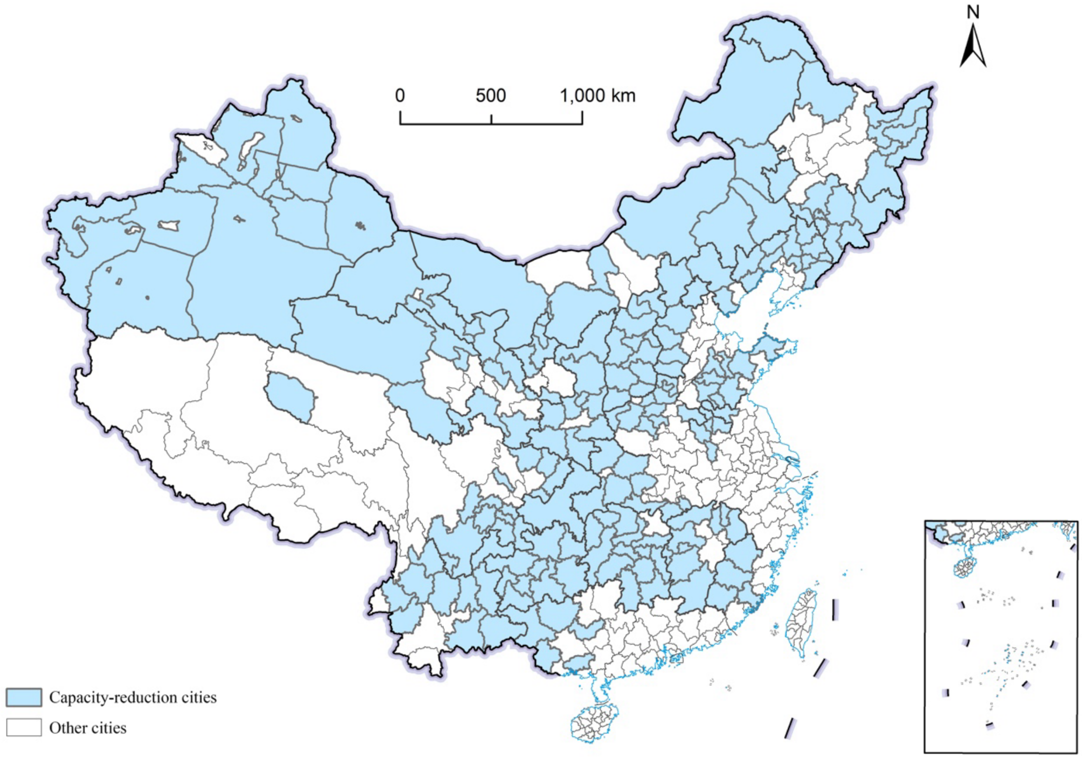
Note: This figure shows the number of coal mines in China from 2014 to 2018. The solid line at the top represents the total number of coal mines, the dashed line with hollow circles indicates the number of large coal mines, and the dashed line with solid circles represents the number of small coal mines. According to the Opinion, coal mines with an annual production capacity of less than 600,000 tons in Shanxi, Inner Mongolia, Shaanxi, and Ningxia were required to exit the market, as were those with capacities below 300,000 tons in Hebei, Liaoning, Jilin, Heilongjiang, Jiangsu, Anhui, Shandong, Henan, Gansu, Qinghai, and Xinjiang, and those with capacities below 90,000 tons in all other regions. Accordingly, we classify coal mines with annual production below the province-specific threshold as small mines, and those above the threshold as large mines. Data are sourced from the National Energy Administration of China (https://www.nea.gov.cn/ztzl/mtscnlgg/scnlgg.htm).

Figure 5. Debt-to-asset Ratio of Large-scale Enterprises in China's Coal Mining and Washing Industry from 2012 to 2018



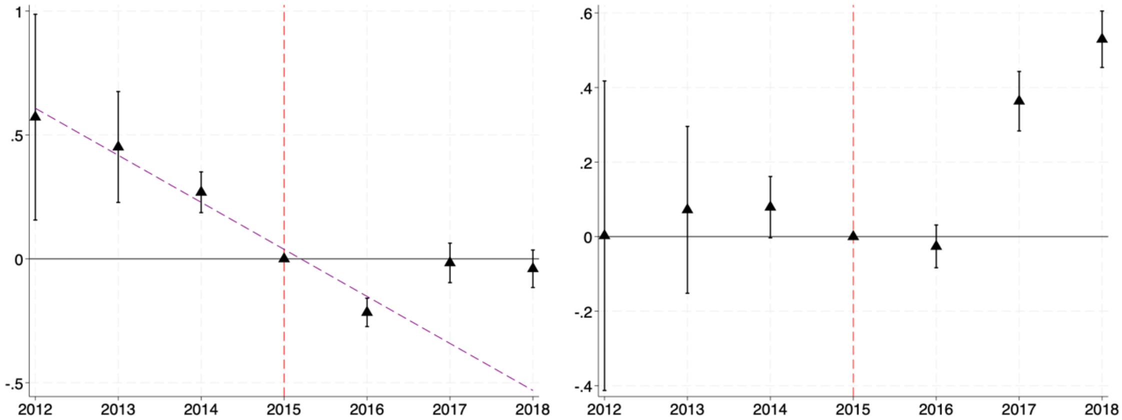
Note: This figure shows the debt-to-asset ratio of large-scale enterprises in China's coal mining and washing industry from 2012 to 2018. The values in the figure are expressed as percentages. Each year's debt-to-asset ratio is drawn from the China Statistical Yearbook of the following year; for example, the 2012 debt-to-asset ratio comes from the *China Statistical Yearbook 2013*.

Figure 6. Geographic Distribution of Treated and Control Cities

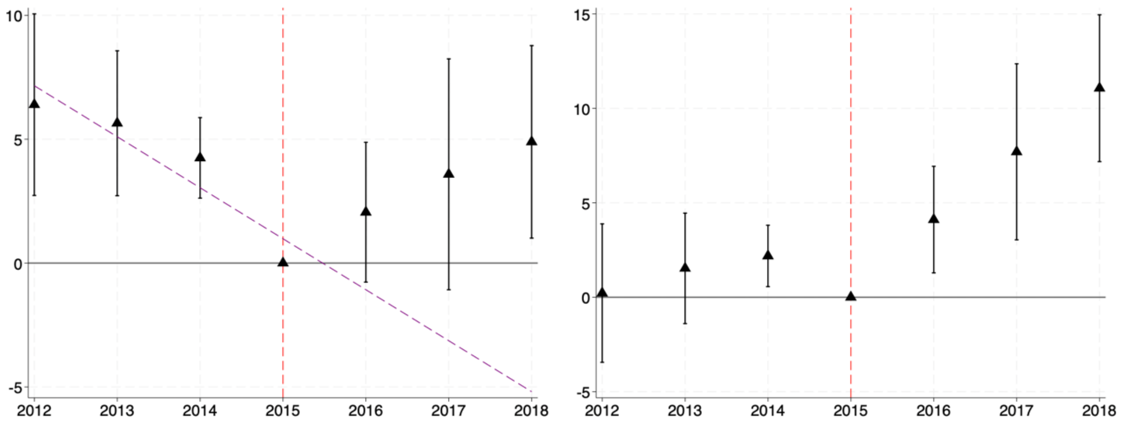


Note: This figure shows the geographic distribution of treated and control cities, where the treated cities are shown in blue and the control cities in white.

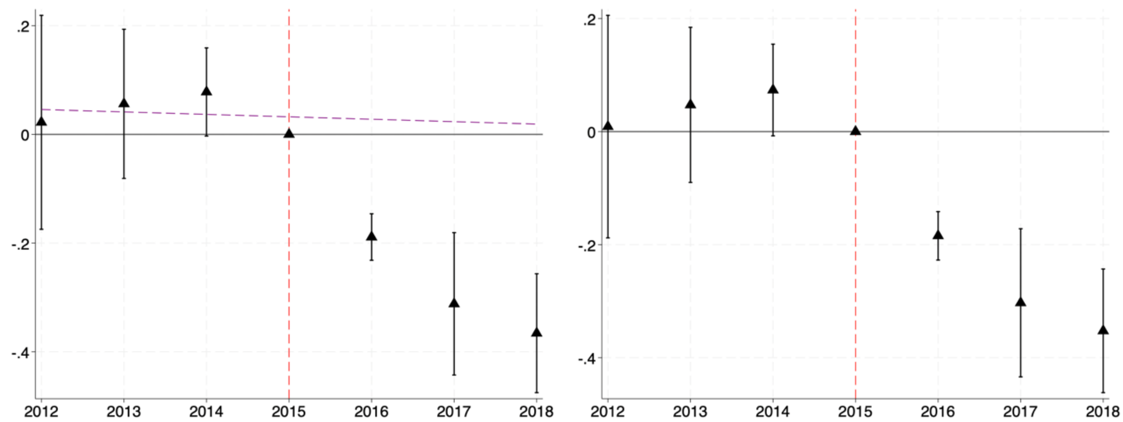
Figure 7. Event Study Results of Firm Operational Performance
Panel A. The Logarithm of Total Operating Revenue



Panel B. The Logarithm of Total Profit



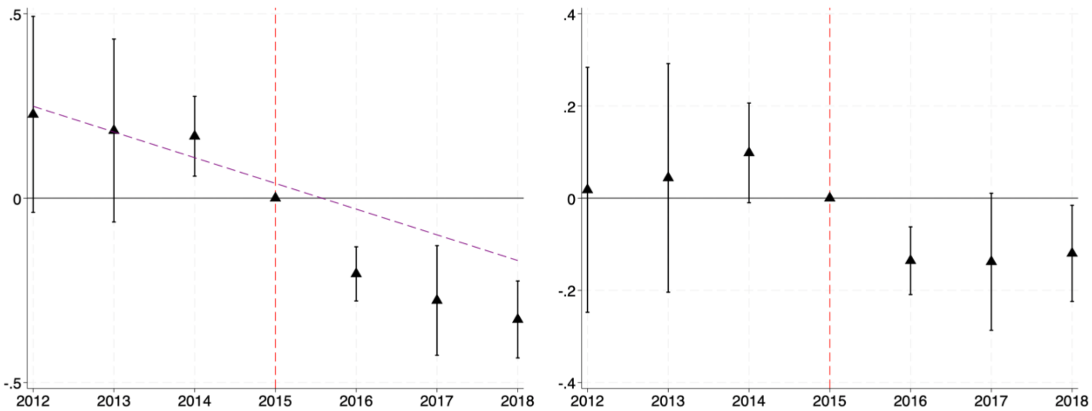
Panel C. The Logarithm of Total Debt



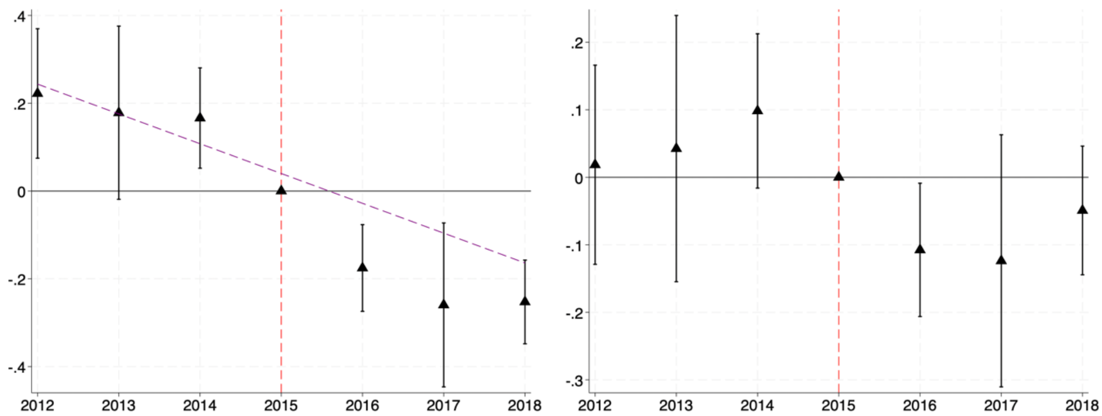
Note: The left panel of this figure presents the estimated results from Equation (1). The dashed line in the left panel represents the linear time trend estimated from the 2012–2015 period. The results in the right panel are derived by rotating all the estimated coefficients around the dashed line. Panel A shows the results for the logarithm of total operating revenue, Panel B displays the results for the logarithm of total profit, and Panel C illustrates the results for the logarithm of total debt.

Figure 8. Event Study Results of Firm Production Inputs

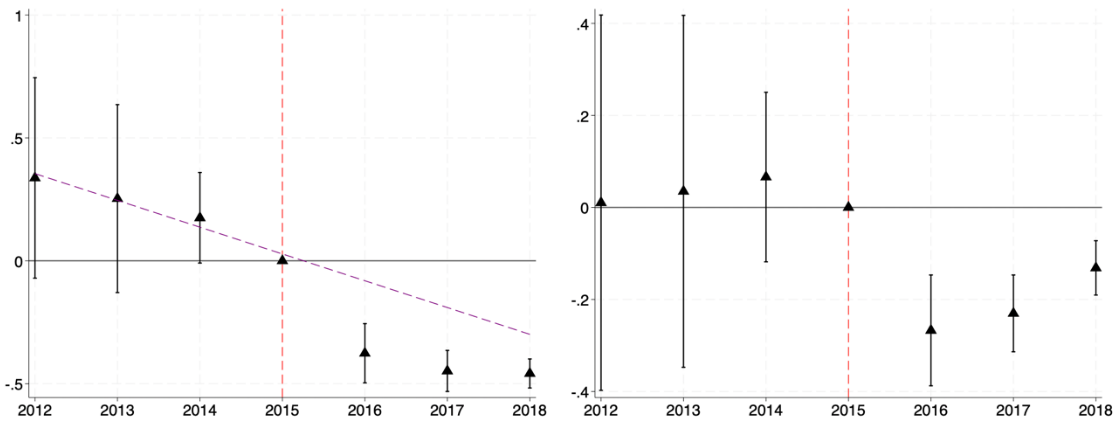
Panel A. The Logarithm of Total Number of Employees



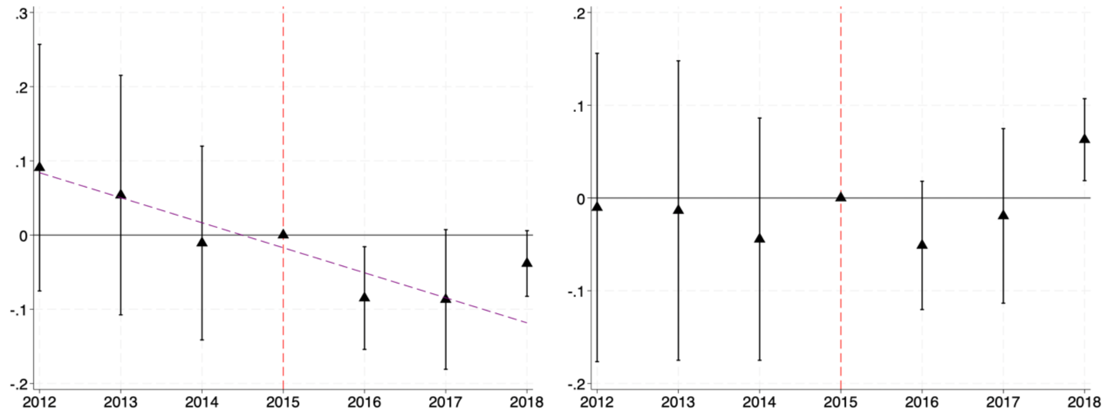
Panel B. The Logarithm of Number of Production Employees



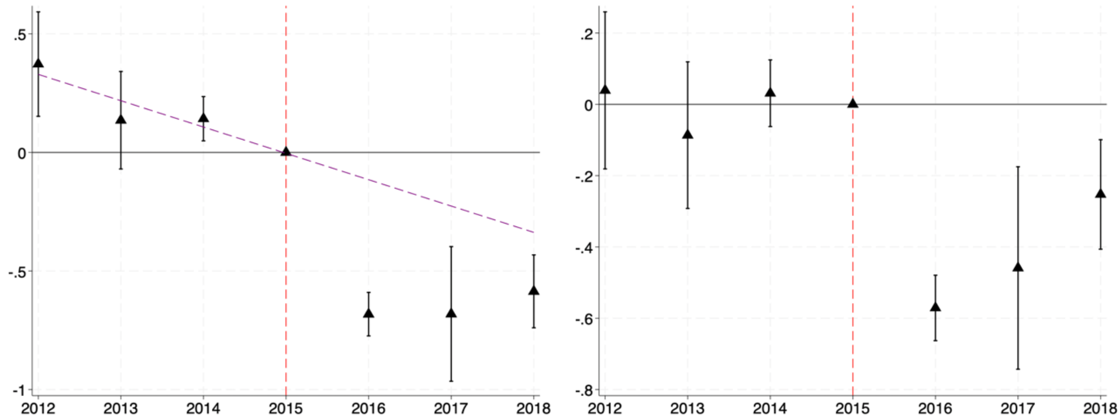
Panel C. The Logarithm of Total Wages



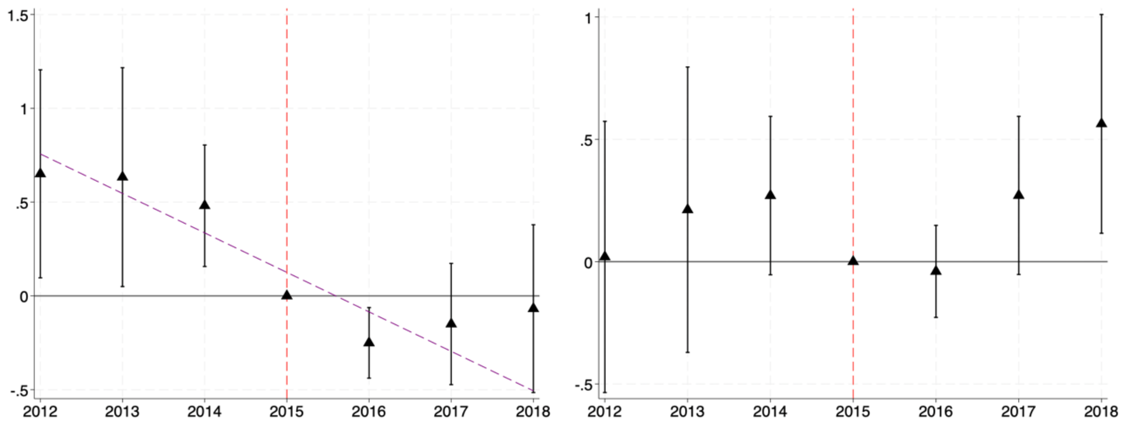
Panel D. The Logarithm of Average Wage per Employee



Panel E. The Logarithm of Cash Expenditure on Assets

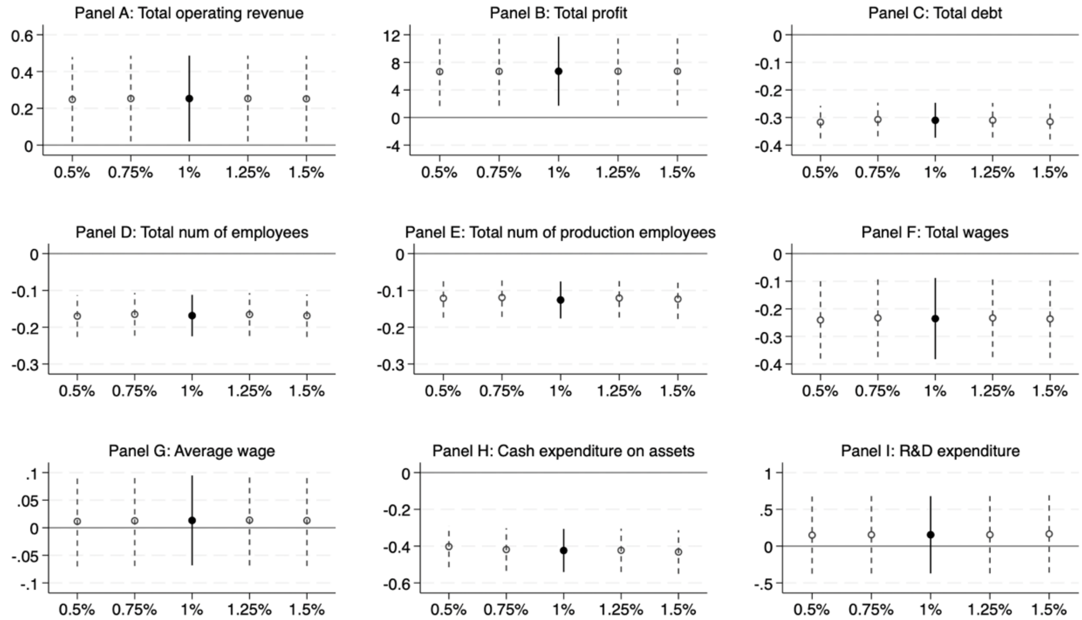


Panel F. The Logarithm of R&D Expenditure



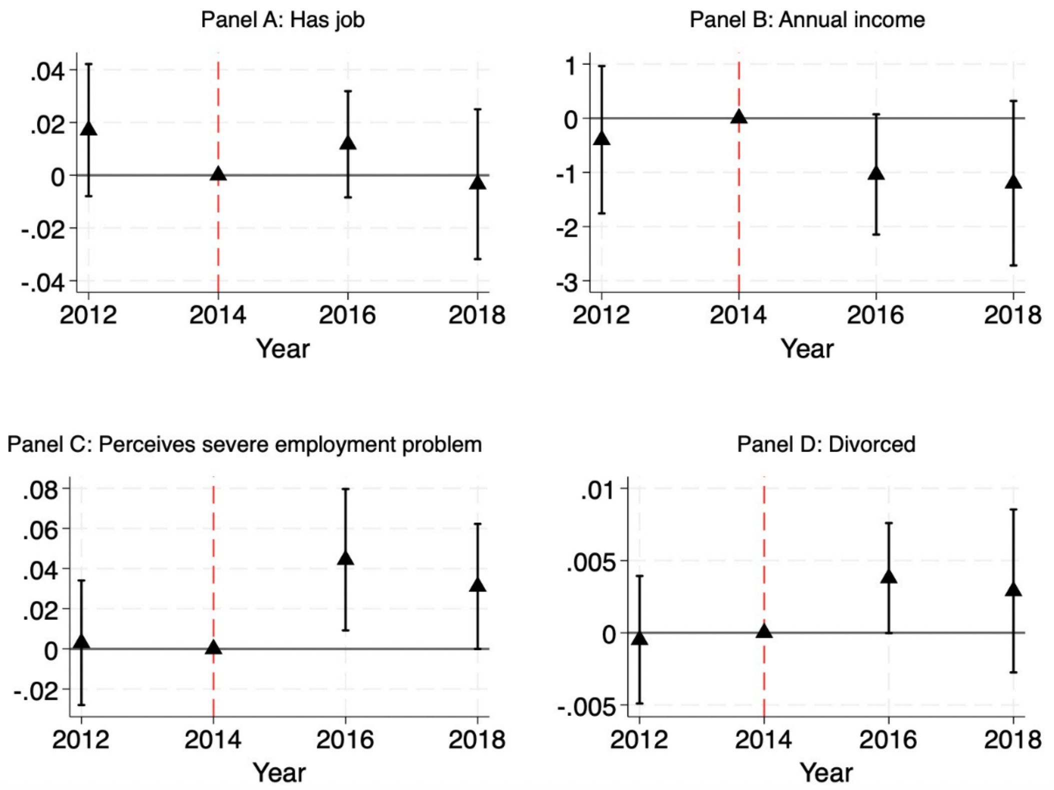
Note: The left panel of this figure presents the estimated results from Equation (1). The dashed line in the left panel represents the linear time trend estimated from the 2012–2015 period. The results in the right panel are derived by rotating all the estimated coefficients around the dashed line. Panel A reports the results for the logarithm of total employment, Panel B for the logarithm of the number of production employees, Panel C for the logarithm of total wages, Panel D for the logarithm of average wage, Panel E for the logarithm of cash expenditures on asset purchases and construction, and Panel F for the logarithm of R&D expenditure.

Figure 9. Adjust the Composition of Coal-related Upstream and Downstream Industries



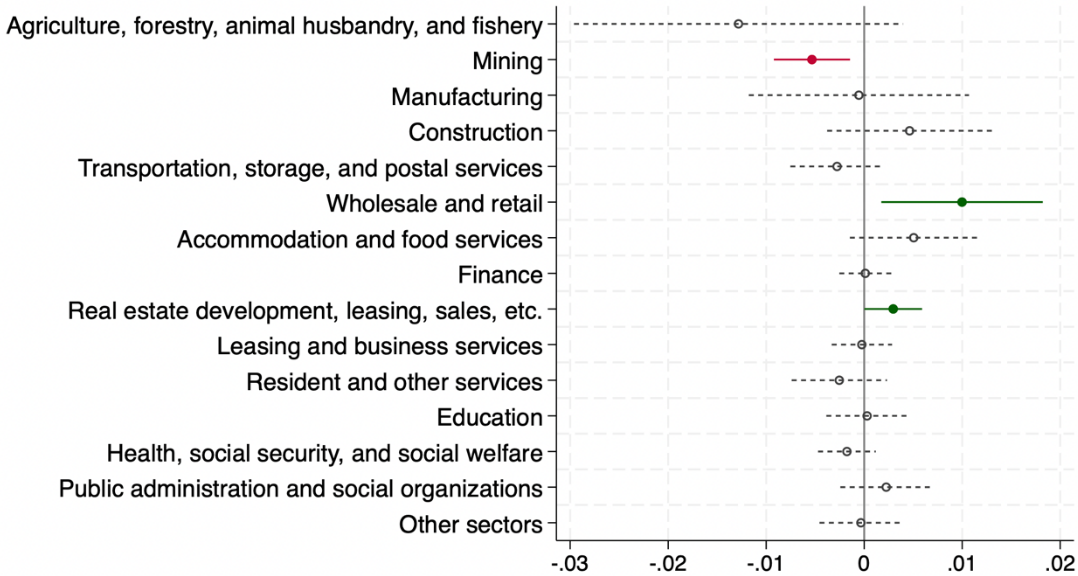
Note: This figure examines the robustness of our results to alternative definitions of coal-related upstream and downstream industries. In the baseline analysis, industries are classified as coal-linked and excluded if either (i) coal mining and washing products account for more than 1% of their total input value (downstream linkages), or (ii) their products account for more than 1% of total inputs used in coal mining and washing (upstream linkages). Here, we vary this cutoff to 0.5%, 0.75%, 1.25%, and 1.5% and re-estimate Equation (2) using the resulting samples. Panels A–I report the coefficients for total operating revenue, total profit, total debt, total number of employees, number of production employees, total wages, average wage per employee, cash expenditures on asset purchases and construction, and R&D expenditure, respectively. The solid line corresponds to the baseline results (1% cutoff), while the dashed hollow lines show estimates under alternative thresholds.

Figure 10. Event Study Results of Labor Market Outcomes



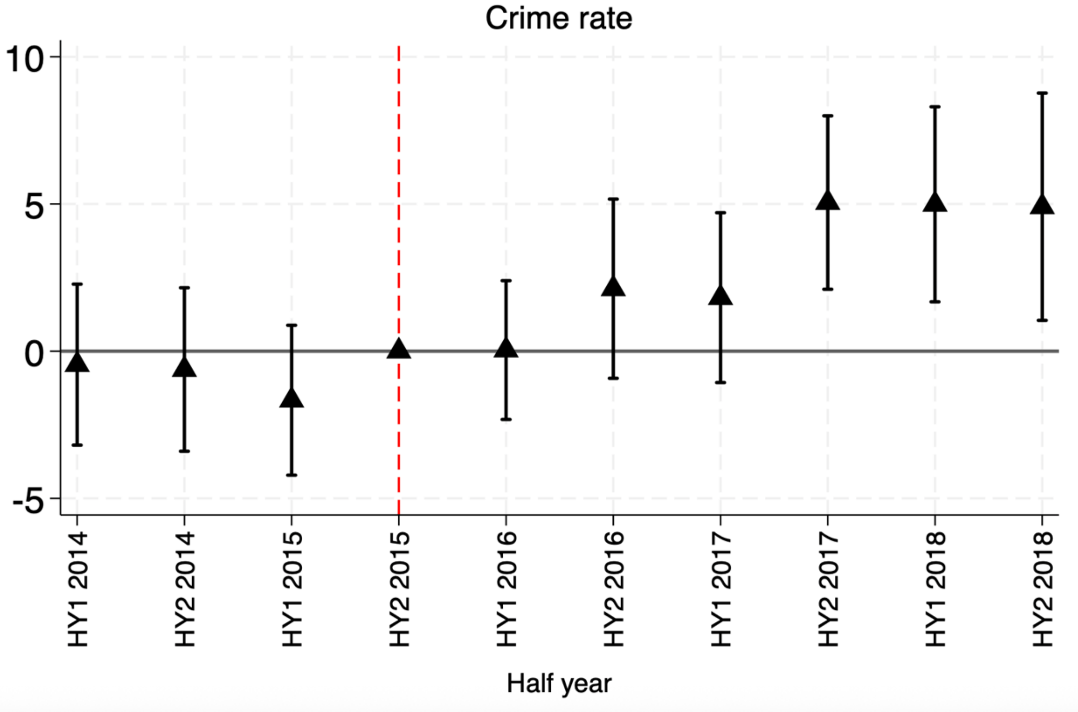
Note: This figure presents the estimated results from Equation (3). The figure reports the estimated coefficients along with their 95% confidence intervals. Panel A reports the results for whether the respondent was employed at the time of the survey, Panel B shows annual income, Panel C reports whether the respondent perceived employment issues as serious, and Panel D shows whether the respondent was divorced.

Figure 11. Changes in Employment Industry



Note: This figure illustrates the impact of the coal capacity reduction policy on the distribution of employment across industries in treated cities. The regressions are based on CFPS data, and the plotted estimated coefficients with 95% confidence intervals correspond to the results from Equation (4). In each case, the dependent variable is an indicator for whether the respondent was employed in a given industry at the time of the survey (e.g., whether the individual was working in the mining sector).

Figure 12. Event Study Results of Crime Outcome



Note: This figure presents the estimated results of Equation (5). The figure reports the estimated coefficients along with their 95% confidence intervals.

Table 1. Variable Definitions and Sample Statistics for the Listed Firm Data

Variable	Definition	N	Mean	SD	Min	Max
Total operating revenue	Total operating revenue (unit: million RMB).	11,292	7,029.858	21,047.55	46.417	166,888.784
Total profit	Total profit (unit: million RMB).	11,292	613.927	1,957.996	-1,357.639	15,125.593
Total debt	Total debt (unit: million RMB).	11,292	9,670.838	34,361.197	34.005	278,186.063
Total number of employees	Total number of employees (in thousands).	11,287	5.937	13.312	0.070	94.598
Number of production employees	Number of production employees (in thousands).	9,390	2.930	6.341	0.000	44.342
Total wages	Total wages (unit: million RMB).	11,292	685.988	1,889.365	8.633	14,781.255
Average wage per employee	Average wage per employee (unit: thousand RMB).	11,287	112.624	76.731	31.883	517.144
Cash expenditure on assets	Cash expenditure on purchase and construction of assets (unit: million RMB).	11,283	495.692	1,506.492	0.443	12,064.187
R&D expenditure	R&D expenditure (unit: million RMB).	9,136	168.146	424.654	0.571	3,300.909
Coal	A dummy variable equal to 1 if the firm's industry in 2015 is coal mining and washing or mining support activities, and 0 otherwise.	11,292	0.023	0.149	0.000	1.000
Post	Whether the time of the observation falls after the policy implementation (i.e., 2016 or later), yes=1, no=0.	11,292	0.451	0.498	0.000	1.000
Years since establishment	Number of years the firm has been in operation since its establishment.	11,292	17.716	5.916	3	64
Years since listing	Number of years since the firm was listed.	11,292	10.383	7.022	0	28

SOE	Whether the firm was state-owned in 2015, =1 if it was a state-owned enterprise, =0 if it was not.	11,292	0.350	0.477	0	1
Register Capital	The firm's registered capital in 2015 (unit: million RMB).	11,292	1,086.768	1,978.724	75.401	14,002.587

Note: All variables are at the firm-year level. The definitions, means, standard deviations, minimums, and maximums are reported. The data sources are described in Section 3.

Table 2. Variable Definitions and Sample Statistics for the CFPS Individual Data

Variable	Definition	N	Mean	SD	Min	Max
Has job	Whether the respondent is in employment status at the time of the survey, in employment status=1, otherwise=0.	85,041	0.817	0.386	0	1
Annual income	Annual income (unit: 1,000 RMB).	79,249	16.255	21.172	0.000	138.556
Perceives severe employment problem	Whether the respondent believes that society is currently facing a severe employment problem, yes=1, no=0.	85,279	0.607	0.488	0	1
Divorced	Whether the respondent is currently divorced, yes=1, no=0.	77,923	0.022	0.146	0	1
Treat	Whether the respondent is currently in a city where coal mines were closed or subject to capacity reduction, yes=1, no=0.	93,577	0.470	0.499	0	1
Post	Whether the survey time of the observation falls after the policy implementation (i.e., 2016 or later), yes=1, no=0.	93,577	0.452	0.498	0	1
Age	Respondent’s age.	93,577	42.718	13.411	18	65
Male	Whether the respondent is male, yes=1, no=0.	93,577	0.493	0.500	0	1
Education	Years of schooling.	93,577	7.981	4.639	0	22
Urban	Whether the respondent’s current residence is in an urban area, yes=1, no=0.	93,577	0.465	0.499	0	1
Per capita GDP	The per capita GDP (1,000 RMB) in 2015 in the city where the respondent resides.	93,577	47.100	28.396	10.210	127.546
Secondary industry share	The proportion of the secondary industry’s added value in GDP (%) in 2015 in the city where the respondent resides.	93,577	43.647	9.522	19.740	64.880
Tertiary industry share	The proportion of the tertiary industry’s added value in GDP (%) in 2015 in the city where the respondent resides.	93,577	44.246	10.087	26.340	79.650
Population density	The population density (thousand people per square kilometer) of the city in 2015 where the respondent resides.	93,577	4.409	2.867	0.454	15.055
Fiscal expenditure share	The proportion of the fiscal expenditure in GDP (%) in 2015 in the city where the respondent resides.	93,577	9.071	4.313	3.067	21.970

Fiscal revenue share	The proportion of the fiscal revenue in GDP (%) in 2015 in the city where the respondent resides.	93,577	22.204	11.988	6.591	64.888

Note: All variables are at the individual-wave level. The definitions, means, standard deviations, minimums, and maximums are reported. The data sources are described in Section 3.

Table 3. Variable Definitions and Sample Statistics for the Crime Data

Variable	Definition	N	Mean	SD	Min	Max
Crime rate	Number of offenders per million population at the city–year–month level.	17,220	43.396	25.143	0.000	448.122
Treat	Whether the observation belongs to a city where coal mines were closed or subject to capacity reduction, yes=1, no=0.	17,220	0.547	0.498	0	1
Post	Whether the time of the observation falls after the policy implementation (i.e., February 2016 or later), yes=1, no=0.	17,220	0.583	0.493	0	1
Per capita GDP	The per capita GDP (1,000 RMB) in 2015 in the city.	17,220	48.037	26.812	10.210	156.162
Secondary industry share	The proportion of the secondary industry's added value in GDP (%) in 2015 in the city.	17,220	46.607	9.568	15.170	71.450
Tertiary industry share	The proportion of the tertiary industry's added value in GDP (%) in 2015 in the city.	17,220	41.044	8.756	24.170	79.650
Population density	The population density (thousand people per square kilometer) of the city in 2015.	17,220	3.696	2.531	0.454	15.055
Fiscal expenditure share	The proportion of the fiscal expenditure in GDP (%) in 2015 in the city.	17,220	21.346	13.383	6.591	169.900
Fiscal revenue share	The proportion of the fiscal revenue in GDP (%) in 2015 in the city.	17,220	8.374	3.122	3.067	23.632

Note: All variables are at the monthly city level. The definitions, means, standard deviations, minimums, and maximums are reported. The data sources are described in Section 3.

Table 4. Impact of the Coal Capacity Reduction Policy on Firm Operational Performance

Variable	(1) Ln(total operating revenue)	(2) Ln(total profit)	(3) Ln(total debt)
Average effect	0.253*	6.712**	-0.310***
	(0.142)	(3.040)	(0.038)
Observations	11,292	11,292	11,292
Firm control	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Mean of dep. var.	8.201	4.758	7.958

Note: (1) Firm control represents years since establishment and listing and the time linear trends of firm-level control variables, including whether the firm was a state-owned enterprise and its registered capital in 2015.
(3) Standard errors in parentheses are calculated by clustering over industries. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5. Impact of the Coal Capacity Reduction Policy on Firm Production Inputs

Variable	(1) Ln(total number of employees)	(2) Ln(number of Production employees)	(3) Ln(total wages)	(4) Ln(average wage per employee)	(5) Ln(cash expenditure on assets)	(6) Ln(R&D expenditure)
Average effect	-0.168***	-0.126***	-0.235**	0.013	-0.424***	0.154
	(0.034)	(0.031)	(0.089)	(0.050)	(0.071)	(0.319)
Observations	11,287	9,390	11,292	11,287	11,283	9,136
Firm control	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Mean of dep. var.	1.669	1.117	6.054	5.261	5.291	4.656

Note: (1) Firm control represents years since establishment and listing and the time linear trends of firm-level control variables, including whether the firm was a state-owned enterprise and its registered capital in 2015.
(3) Standard errors in parentheses are calculated by clustering over industries. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Account for the Steel Capacity Reduction Policy

	(1)	(2)	(3)
Variable	Ln(total operating revenue)	Ln(total profit)	Ln(total debt)
Average effect	0.255*	6.724**	-0.309***
	(0.142)	(3.041)	(0.038)
Observations	11,244	11,244	11,244
Firm control	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Mean of dep. var.	8.205	4.775	7.987

	(4)	(5)	(6)	(7)	(8)	(9)
Variable	Ln(total number of employees)	Ln(number of Production employees)	Ln(total wages)	Ln(average wage per employee)	Ln(cash expenditure on assets)	Ln(R&D expenditure)
Average effect	-0.169***	-0.128***	-0.236**	0.012	-0.421***	0.154
	(0.034)	(0.031)	(0.089)	(0.049)	(0.071)	(0.319)
Observations	11,239	9,345	11,244	11,239	11,237	9,120
Firm control	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Mean of dep. var.	1.671	1.117	6.048	5.261	5.291	4.657

Note: (1) Firm control represents years since establishment and listing and the time linear trends of firm-level control variables, including whether the firm was a state-owned enterprise and its registered capital in 2015.
(3) Standard errors in parentheses are calculated by clustering over industries. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7. Account for the Shantytown Renovation Program

Variable	(1) Ln(total operating revenue)	(2) Ln(total profit)	(3) Ln(total debt)
Average effect	0.262*	6.844**	-0.311***
	(0.142)	(3.041)	(0.044)
Observations	9,919	9,919	9,919
Firm control	YES	YES	YES
Firm FE	YES	YES	YES
Year FE	YES	YES	YES
Mean of dep. var.	8.138	4.656	7.779

Variable	(4) Ln(total number of employees)	(5) Ln(number of Production employees)	(6) Ln(total wages)	(7) Ln(average wage per employee)	(8) Ln(cash expenditure on assets)	(9) Ln(R&D expenditure)
Average effect	-0.160***	-0.117***	-0.221**	0.016	-0.365***	0.159
	(0.034)	(0.030)	(0.088)	(0.050)	(0.065)	(0.317)
Observations	9,914	8,504	9,919	9,914	9,911	8,567
Firm control	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Mean of dep. var.	1.703	1.155	6.056	5.214	5.41	4.654

Note: (1) Firm control represents years since establishment and listing and the time linear trends of firm-level control variables, including whether the firm was a state-owned enterprise and its registered capital in 2015.

(3) Standard errors in parentheses are calculated by clustering over industries. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8. Impact of the Coal Capacity Reduction Policy on Individual Behavior

	(1)	(2)	(3)	(4)
Variable	Has job	Annual income	Perceives severe employment problem	Divorced
Treat × Post	-0.003	-0.899**	0.037**	0.004**
	(0.012)	(0.449)	(0.015)	(0.002)
Observations	85,041	79,249	85,279	77,923
R-squared	0.106	0.219	0.072	0.016
City control × year	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES
Mean of dep. var.	0.817	16.255	0.607	0.022

Note: (1) We control for gender, age, education level, and whether the respondent's current residence is in an urban area.

(2) City control × year represents the time linear trends of city-level control variables, including the share of the secondary industry in GDP, the share of the tertiary industry in GDP, the population density, the ratios of fiscal revenue and fiscal expenditure to GDP, and GDP per capita.

(3) Standard errors in parentheses are calculated by clustering over cities. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9. Robustness Checks for Labor Market Outcomes

	(1)	(2)	(3)	(4)
Variable	Has job	Annual income	Perceives severe employment problem	Divorced
Panel A: different definition of Treat variable				
Treat × Post	0.001	-0.865*	0.038**	0.004**
	(0.012)	(0.445)	(0.015)	(0.002)
Observations	85,041	79,249	85,279	77,923
R-squared	0.106	0.219	0.072	0.016
Mean of dep. var.	0.817	16.255	0.607	0.022
Panel B: exclude control cities with coal mines that did not implement capacity reduction policy				
Treat × Post	-0.002	-0.919*	0.040**	0.004**
	(0.012)	(0.466)	(0.016)	(0.002)
Observations	82,019	76,498	82,280	75,090
R-squared	0.107	0.221	0.072	0.015
Mean of dep. var.	0.816	16.358	0.608	0.0214
City control × year	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES

Note: (1) We control for gender, age, education level, and whether the respondent's current residence is in an urban area.

(2) City control × year represents the time linear trends of city-level control variables, including the share of the secondary industry in GDP, the share of the tertiary industry in GDP, the population density, the ratios of fiscal revenue and fiscal expenditure to GDP, and GDP per capita.

(3) Standard errors in parentheses are calculated by clustering over cities. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10. Control for Confounding Events

	(1)	(2)	(3)	(4)
Variable	Has job	Annual income	Perceives severe employment problem	Divorced
Panel A: control for the capacity reduction policy in the steel industry				
Treat × Post	-0.002	-0.916**	0.037**	0.004*
	(0.012)	(0.449)	(0.015)	(0.002)
Steel × Post2016	-0.017*	0.541	0.022	0.001
	(0.009)	(0.493)	(0.014)	(0.002)
Observations	85,041	79,249	85,279	77,923
R-squared	0.106	0.219	0.072	0.016
Mean of dep. var.	0.817	16.255	0.607	0.022
Panel B: control for the shantytown renovation program				
Treat × Post	-0.004	-0.859*	0.033**	0.003*
	(0.012)	(0.436)	(0.014)	(0.002)
Real estate GDP share	-0.002*	0.035	-0.004***	-0.000
	(0.001)	(0.032)	(0.001)	(0.000)
Observations	85,041	79,249	85,279	77,923
R-squared	0.106	0.219	0.073	0.016
Mean of dep. var.	0.817	16.255	0.607	0.022
Panel C: control for the 2014 hukou reform				
Treat × Post	-0.002	-0.859**	0.037**	0.004*
	(0.012)	(0.428)	(0.015)	(0.002)
Hukou × Reform	0.005	3.089**	0.015	-0.001
	(0.018)	(1.254)	(0.018)	(0.004)
Observations	85,041	79,249	85,279	77,923
R-squared	0.106	0.220	0.072	0.016
Mean of dep. var.	0.817	16.255	0.607	0.022
Panel D: control for changes in the minimum wage				
Treat × Post	-0.003	-0.867*	0.036**	0.003*
	(0.012)	(0.457)	(0.015)	(0.002)
Minimum wage	-0.004	0.158	-0.005	-0.001*
	(0.003)	(0.155)	(0.005)	(0.001)
Observations	85,041	79,249	85,279	77,923
R-squared	0.106	0.219	0.072	0.016
Mean of dep. var.	0.817	16.255	0.607	0.022
City control × year	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES

Note: (1) We control for gender, age, education level, and whether the respondent's current residence is in an urban area.

(2) City control × year represents the time linear trends of city-level control variables, including the share of the secondary industry in GDP, the share of the tertiary industry in GDP, the population density, the ratios of fiscal revenue and fiscal expenditure to GDP, and GDP per capita.

(3) Standard errors in parentheses are calculated by clustering over cities. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11. Heterogeneity Analysis Results by SOE and non-SOE Cities

Variable	(1) Has job	(2) Annual income	(3) Perceives severe employment problem	(4) Divorced
Panel A: SOE cities				
Treat × Post	-0.012	-0.783	0.025*	0.001
	(0.015)	(0.556)	(0.014)	(0.003)
Observations	63,051	59,105	63,220	57,476
R-squared	0.102	0.229	0.068	0.015
Mean of dep. var.	0.815	17.057	0.608	0.020
Panel B: non-SOE cities				
Treat × Post	-0.001	-0.951*	0.043**	0.006***
	(0.012)	(0.533)	(0.018)	(0.002)
Observations	67,021	61,947	66,860	61,457
R-squared	0.108	0.222	0.071	0.017
Mean of dep. var.	0.819	16.882	0.595	0.023
City control × year	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES

Note: (1) We control for gender, age, education level, and whether the respondent's current residence is in an urban area.
(2) City control × year represents the time linear trends of city-level control variables, including the share of the secondary industry in GDP, the share of the tertiary industry in GDP, the population density, the ratios of fiscal revenue and fiscal expenditure to GDP, and GDP per capita.
(3) Standard errors in parentheses are calculated by clustering over cities. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 12. Heterogeneity Analysis Results by Age

	(1)	(2)	(3)	(4)
Variable	Has job	Annual income	Perceives severe employment problem	Divorced
Panel A: aged 18–34 at the time of the survey				
Treat × Post	0.009	0.667	0.027*	0.009**
	(0.014)	(0.574)	(0.016)	(0.004)
Observations	55,855	53,732	56,628	49,184
R-squared	0.103	0.215	0.074	0.016
Mean of dep. var.	0.813	17.837	0.618	0.021
Panel B: aged 35–65 at the time of the survey				
Treat × Post	-0.008	-1.662***	0.040***	0.002
	(0.012)	(0.455)	(0.015)	(0.002)
Observations	74,217	67,320	73,452	69,749
R-squared	0.122	0.242	0.066	0.017
Mean of dep. var.	0.820	16.273	0.589	0.022
City control × year	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES

Note: (1) We control for gender, age, education level, and whether the respondent's current residence is in an urban area.
(2) City control × year represents the time linear trends of city-level control variables, including the share of the secondary industry in GDP, the share of the tertiary industry in GDP, the population density, the ratios of fiscal revenue and fiscal expenditure to GDP, and GDP per capita.
(3) Standard errors in parentheses are calculated by clustering over cities. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 13. Heterogeneity Analysis Results by Education

	(1)	(2)	(3)	(4)
Variable	Has job	Annual income	Perceives severe employment problem	Divorced
Panel A: individuals with senior high school education and below				
Treat × Post	-0.003	-1.212**	0.039**	0.004**
	(0.012)	(0.463)	(0.015)	(0.002)
Observations	81,069	74,773	80,755	74,954
R-squared	0.112	0.223	0.064	0.017
Mean of dep. var.	0.815	15.660	0.595	0.022
Panel B: individuals with college education or above				
Treat × Post	-0.017	0.973	0.013	-0.001
	(0.016)	(0.728)	(0.014)	(0.005)
Observations	49,003	46,279	49,325	43,979
R-squared	0.100	0.229	0.079	0.018
Mean of dep. var.	0.821	19.081	0.612	0.021
City control × year	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Wave FE	YES	YES	YES	YES

Note: (1) We control for gender, age, education level, and whether the respondent's current residence is in an urban area.

(2) City control × year represents the time linear trends of city-level control variables, including the share of the secondary industry in GDP, the share of the tertiary industry in GDP, the population density, the ratios of fiscal revenue and fiscal expenditure to GDP, and GDP per capita.

(3) Standard errors in parentheses are calculated by clustering over cities. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 14. Impact of the Coal Capacity Reduction Policy on Crime

Variable	(1) Crime rate	(2) Crime rate
Treat × Post	5.862***	3.666***
	(1.550)	(1.287)
Observations	17,220	17,220
R-squared	0.723	0.732
City control × Time	NO	YES
City FE	YES	YES
Time FE	YES	YES
Mean of dep. var.	43.396	43.396

Note: (1) City Control × Time represents the time linear trends of city-level control variables, including the share of the secondary industry in GDP, the share of the tertiary industry in GDP, the population density, the ratios of fiscal revenue and fiscal expenditure to GDP, and GDP per capita.
(2) Standard errors in parentheses are calculated by clustering over prefectures. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 15. Robustness Checks for Crime

Variable	(1) Crime rate	(2) Crime rate	(3) Population	(4) Ln(crime rate)	(5) Baidu index	(6) Public security	(7) Ratio of words
Treat × Post	3.569***	4.158***	-0.015	0.063***	0.175**	-0.080	0.012
	(1.228)	(1.363)	(0.025)	(0.024)	(0.087)	(0.122)	(0.069)
Observations	17,220	16,560	1,435	17,220	17,220	1,395	1,433
R-squared	0.732	0.734	0.999	0.761	0.920	0.931	0.486
City control × Time	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES
Mean of dep. var.	43.396	43.655	4.496	4.319	3.437	5.086	1.496

Note: (1) City Control × Time represents the time linear trends of city-level control variables, including the share of the secondary industry in GDP, the share of the tertiary industry in GDP, the population density, the ratios of fiscal revenue and fiscal expenditure to GDP, and GDP per capita.
(2) Standard errors in parentheses are calculated by clustering over prefectures. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 16. Control for Confounding Events

Variable	(1) Crime rate	(2) Crime rate	(3) Crime rate	(4) Crime rate
Treat × Post	3.672***	3.452***	3.666***	3.651***
	(1.289)	(1.278)	(1.287)	(1.286)
Steel × Post2016	0.769			
	(1.442)			
Real estate GDP share		-0.206		
		(0.165)		
Hukou × Reform			-3.681	
			(3.559)	
Minimum wage				-0.305
				(0.387)
Observations	17,220	17,220	17,220	17,220
R-squared	0.732	0.733	0.733	0.732
City control × Time	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Mean of dep. var.	43.396	43.396	43.396	43.396

Note: (1) City Control × Time represents the time linear trends of city-level control variables, including the share of the secondary industry in GDP, the share of the tertiary industry in GDP, the population density, the ratios of fiscal revenue and fiscal expenditure to GDP, and GDP per capita.

(2) Standard errors in parentheses are calculated by clustering over prefectures. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 17. Heterogeneity Analysis

	(1)	(2)	(3)	(4)	
	SOE cities	Non-SOE cities			
Variable	Crime rate	Crime rate	Property crime rate	Violent crime rate	
Treat × Post	1.646	4.265***	1.331***	0.099	
	(1.704)	(1.331)	(0.421)	(0.305)	
Observations	10,980	14,040	17,220	17,220	
R-squared	0.733	0.736	0.729	0.456	
City control × Time	YES	YES	YES	YES	
City FE	YES	YES	YES	YES	
Time FE	YES	YES	YES	YES	
Mean of dep. var.	45.674	44.161	15.211	9.025	
	(5)	(6)	(7)	(8)	(9)
	Act in a Group		Imprisonment		
Variable	YES	NO	0-1 year	1-5 years	>5 years
Treat × Post	1.389	2.354***	3.788***	0.036	0.029
	(1.045)	(0.744)	(1.076)	(0.294)	(0.089)
Observations	17,220	17,220	17,220	17,220	17,220
R-squared	0.546	0.766	0.714	0.582	0.391
City control × Time	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES
Mean of dep. var.	21.699	21.697	30.196	11.069	2.102

Note: (1) City Control × Time represents the time linear trends of city-level control variables, including the share of the secondary industry in GDP, the share of the tertiary industry in GDP, the population density, the ratios of fiscal revenue and fiscal expenditure to GDP, and GDP per capita.

(2) Standard errors in parentheses are calculated by clustering over prefectures. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Online Appendix to:

Winners and Losers: Firm and Labor Market Responses to China's Coal Capacity Reduction Policy

Run Ge, Jialin Huang, Xinzheng Shi, and Wanqing Xu*

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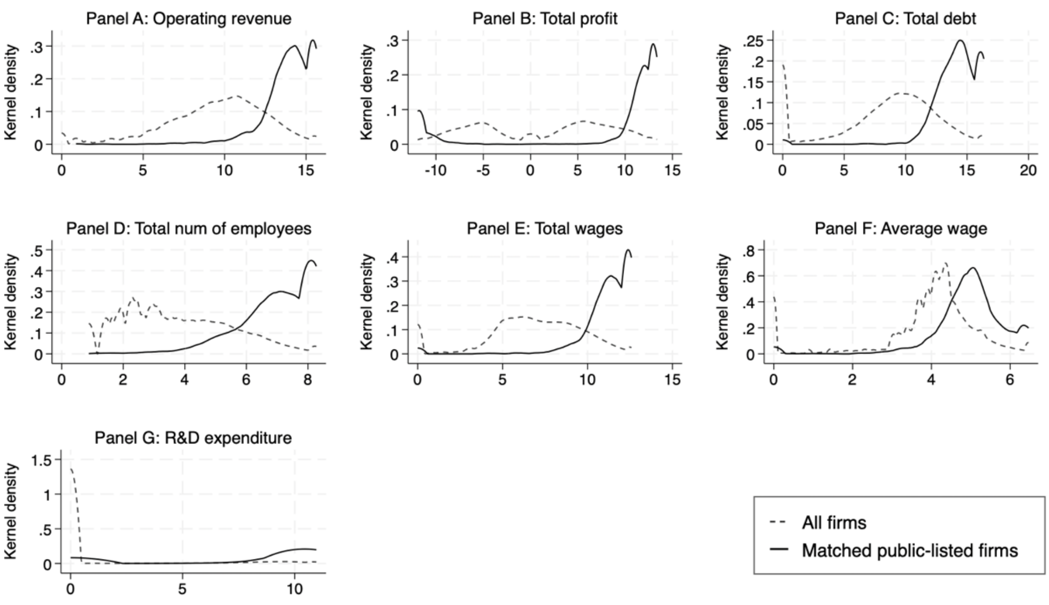
Part A. Comparison Between Chinese Listed Firms and the Full Population of Chinese Firms

To compare listed firms with the broader population of Chinese firms, we use the 2015 National Tax Survey of Enterprises and identify the listed firms within it. In this dataset, there are 1,797 listed firms, accounting for 63.521% of all listed firms in operation in 2015 and 0.348% of all firms covered in the survey. We focus on differences between listed and all sample firms across seven key indicators: operating revenue, total profit, total debt, total number of employees, total wages, average wage, and R&D expenditure. Figure A1 plots the distributions of these indicators, where Panels A–G correspond to the seven variables. In each panel, the dashed line represents the full sample of firms in the tax survey, while the solid line represents the 1,797 listed firms.

Figure A1. Distributions of Key Indicators for Listed Firms and All Firms

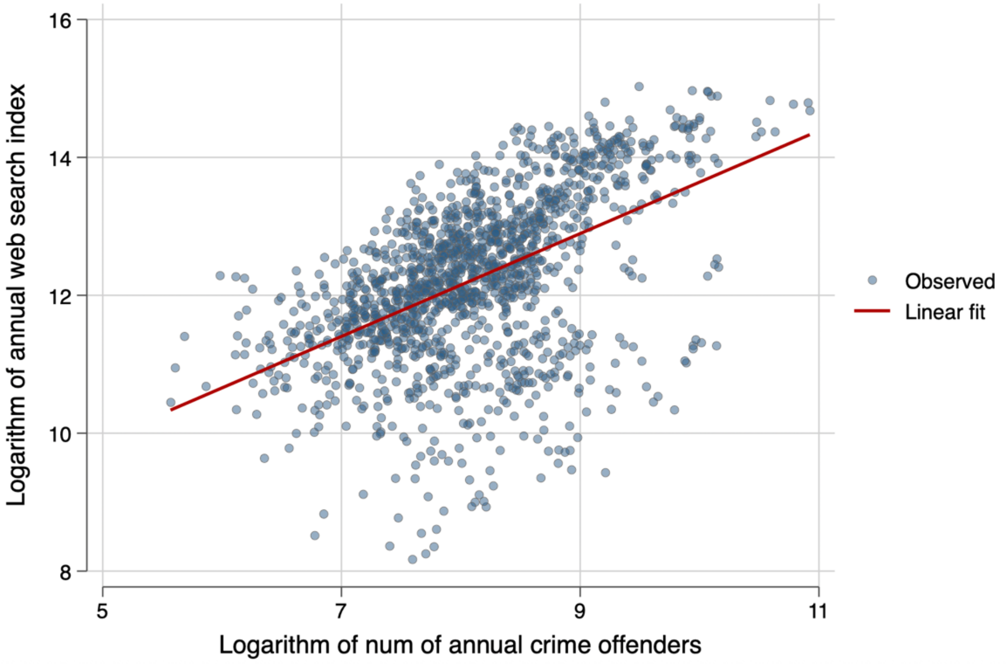


Note: This figure presents the distributions of seven key indicators—operating revenue, total profit, total debt, total number of employees, total wages, average wage, and R&D expenditure—comparing listed firms with all firms in China. The data are drawn from the 2015 National Tax Survey of Enterprises. In the figure, the dashed lines represent all firms in the database, while the solid lines represent the 1,797 listed firms included in the survey.

We also calculate the aggregate shares of these listed firms relative to all surveyed firms. The listed firms account for 3.250% of total operating revenue, 5.323% of total profit, 3.558% of total debt, 2.921% of total employment, 3.534% of the total wages, and 8.593% of total R&D expenditure. Overall, these 1,797 firms represent the most competitive segment of the firm distribution in the dataset, consistent with the notion that listed firms are generally larger, more productive, and more R&D-intensive than the average Chinese firm.

Part B. Representativeness of the CJO Data

Figure B1. Correlation between the CJO Data and the Baidu Search Index



Note: The scatter plot compares the log of the annual total number of searches for crime-related keywords (including traffic accident, traffic accident crime, public safety, prostitution, dangerous driving crime, soliciting prostitution, robbery, robbery crime, child trafficking, child trafficking crime, women trafficking, intentional injury, intentional injury crime, intentional homicide, intentional homicide crime, extortion, extortion crime, drugs, public security penalty, public security administration, crime, theft, theft crime, kidnapping, kidnapping crime, social stability maintenance, fraud, fraud crime, drug trafficking, and gambling) recorded by the Baidu Search Index (similar to Google Trends) for each city against the log of the number of annual crime offenders recorded in the CJO data for each city, both of which are limited to our sample period (2014–2018).

Part C. Example of a Judgment Record

To provide a clearer understanding of our data and the extraction process, Figure C1 presents a screenshot of a judgment record obtained from China Judgements Online. This screenshot visually represents the typical legal documents we scraped.

Figure C1. Screenshot of a Judgment Record

Source:
https://wenshu.court.gov.cn/website/wenshu/181107ANFZ0BXSK4/index.html?docId=8PAXKtUruF0vlyQX54CxHHpTVKiKiHjDcSu2NnEdqaJ6Wny3TYsz9JO3qNaLMqsJ1HIoA3946LWGXI+9llIO/e1StXN009oBif75qfqTGRBhVz/pl0G03YtOat7wjCCT. Registration and login are needed.

We also include the full content of this judgment in Chinese below. This text contains all relevant details, such as the case number, court name, defendant's information, charges, and the court's decision. Following the full content, we provide an English translation of the judgment, ensuring that the key elements are clearly conveyed. This allows for a better understanding of the case content and the information we used for further analysis.

陕西省宝鸡市渭滨区人民法院

刑事判决书

公诉机关宝鸡市渭滨区人民检察院。

被告人王小鹏，男，出生于陕西省宝鸡市，汉族，高中文化，捕前租住宝鸡市渭滨区高家镇。2012 年 9 月 23 日被抓获，次日因涉嫌犯盗窃罪被刑事拘留，同年 10 月 25 日被逮捕，现羁押于宝鸡市渭滨区看守所。

辩护人黄侃祥，陕西西虢律师事务所律师。

被告人张晓利，女，36 岁，出生于陕西省宝鸡市，汉族，高中文化，住宝鸡市金台区。2013 年 1 月 11 日因涉嫌犯掩饰、隐瞒犯罪所得罪被取保候审。

宝鸡市渭滨区人民检察院以宝渭检刑诉字（2013）第 08 号起诉书指控被告人王小鹏犯盗窃罪、被告人张晓利犯掩饰、隐瞒犯罪所得罪，于 2013 年 1 月 23 日向本院提起公诉。本院依法适用简易程序，实行独任审判，公开开庭审理了本案。被告人王小鹏及其辩护人黄侃祥、被告人张晓利到庭参加诉讼。现已审理终结。

公诉机关指控，2012 年 9 月 5 日 10 时许，被告人王小鹏在其与王利萍（在逃）租住的宝鸡市渭滨区高家镇三合村二组出租屋院内窃取隔壁邻居张凤房门钥匙一串，当时下午，被告人王小鹏趁无人之机，用该钥匙打开张凤房门，窃取其高仿诺基亚 N99 手机一部（鉴定价值 270 元）、大显牌手机一部（鉴定价值 680 元）、悠迪斯 HD160T 型数码摄像机一台（鉴定价值 1100 元）、现金 321.5 元。后将窃得高仿诺基亚 N99 手机藏于其与王利萍的红色行李箱内，将大显手机和悠迪斯 HD160T 型数码摄像机交予王利萍，由王利萍到宝鸡市文化路北段诚信通讯店（被告人张晓利经营）以 10 元价格卖与被告人张晓利。几日后的一天 10 时许，被告人王小鹏再次以同样的方式进入被害人张凤房内，窃取其房间内乔丹运动女鞋一双（鉴定价值 52 元）、黑色女式皮鞋一双（鉴定价值 25 元）、白色女士皮鞋一双（鉴定价值 15 元）、女士马甲一件（鉴定价值 16 元）、女士长袖 T 恤一件（鉴定价值 7 元）、钱包一个（鉴定价值 10 元），其中一双运动鞋被其丢弃，其余物品由王利萍持有。

据此，公诉机关依据《中华人民共和国刑法》第二百六十四条、第三百一十二条之规定，指控被告人王小鹏犯盗窃罪、被告人张晓利犯掩饰、隐瞒犯罪所得罪，提请本院依法惩处。

上述事实，被告人王小鹏、张晓利在开庭审理过程中亦无异议，并有公诉机关提供的被害人张凤陈述，接受刑事案件登记表、报案材料、抓获经过、到案经

过、扣押及发还物品清单、户籍材料等书证，证人王利萍、王亚军证言，宝鸡市渭滨区价格认证中心价格鉴定结论书，辨认笔录、搜查笔录、追赃笔录及照片，被告人王小鹏、张晓利供述等证据予以证明，足以认定。

本院认为，被告人王小鹏以非法占有为目的，秘密窃取他人财物，其行为已构成盗窃罪，被告人张晓利明知是盗窃所得而予以收购，其行为已构成掩饰、隐瞒犯罪所得罪，公诉机关指控罪名成立。二被告人到案后均如实供述犯罪事实，依法对其均予从轻处罚。依据《中华人民共和国刑法》第二百六十四条、第三百一十二条、第六十七条第三款、第三十八条、第四十一条、第四十二条、第四十四条、第五十二条、第五十三条之规定，判决如下：

被告人王小鹏犯盗窃罪，判处拘役五个月，并处罚金人民币 1000 元。

（有期徒刑的刑期从判决执行之日起计算，判决执行前先行羁押一日折抵刑期一日，即自二 0 一二年九月二十三日起至二 0 一三年二月二十二日止。罚金已交纳。）

被告人张晓利犯掩饰、隐瞒犯罪所得罪，判处管制一年，并处罚金人民币2000元。

（管制的刑期从判决执行之日起计算。罚金已交纳。）

如不服本判决，可在接到判决书的第二日起十日内，通过本院或直接上诉于陕西省宝鸡市中级人民法院。书面上诉时，应交上诉状正本一份、副本两份。

审判员　　宫雪

二〇一三年一月三十一日

书记员　　巴黎

Weibin District People’s Court of Baoji City, Shaanxi Province

Criminal Judgment

The prosecuting authority is the Weibin District People’s Procuratorate of Baoji City.

Defendant Wang Xiaopeng, male, born in Baoji City, Shaanxi Province, of Han ethnicity, has a high school education and resided in Gaojia Town, Weibin District, Baoji City prior to his arrest. He was apprehended on September 23, 2012, and subsequently detained the following day on suspicion of theft. He was formally arrested on October 25, 2012, and is currently held at the Weibin District Detention Center.

The defendant's counsel is Huang Kanxiang, an attorney from the Xi Guo Law Firm in Shaanxi.

Defendant Zhang Xiaoli, female, 36 years old, born in Baoji City, Shaanxi Province, of Han ethnicity, has a high school education and resides in Jintai District, Baoji City. She was released on bail on January 11, 2013, for suspicion of concealing and hiding criminal proceeds.

The Weijin District People's Procuratorate has filed a public prosecution against Wang Xiaopeng for theft and Zhang Xiaoli for concealing and hiding criminal proceeds, as per indictment number (2013) No. 08. The case was brought to this court on January 23, 2013. This court has adopted a simplified procedure for the trial, which was conducted publicly with a sole judge. Both defendants and their counsel were present in court. The trial has concluded.

According to the prosecution, on September 5, 2012, at approximately 10 AM, defendant Wang Xiaopeng, while renting a property in Sanhe Village, Gaojia Town, Weibin District, where he was residing with Wang Liping (who is at large), stole a set of keys belonging to neighbor Zhang Feng. Later that afternoon, taking advantage of the absence of others, Wang used the stolen keys to unlock Zhang Feng's door and stole a counterfeit Nokia N99 mobile phone (valued at 270 yuan), a Daxian brand mobile phone (valued at 680 yuan), a Yudis HD160T digital camera (valued at 1,100 yuan), and 321.5 yuan in cash. He hid the stolen counterfeit Nokia N99 phone in a red suitcase shared with Wang Liping and gave the Daxian phone and Yudis camera to Wang Liping, who sold them to Zhang Xiaoli at the Xingxin Communications Store for 10 yuan. A few days later, at approximately 10 AM, Wang Xiaopeng again unlawfully entered Zhang Feng's home and stole a pair of women's Qiaodan brand sneakers (valued at 52 yuan), a pair of black women's shoes (valued at 25 yuan), a pair of white women's shoes (valued at 15 yuan), a women's vest (valued at 16 yuan), a long-sleeve women's T-shirt (valued at 7 yuan), and a wallet (valued at 10 yuan). One pair of sneakers was discarded, while the remaining items were held by Wang Liping.

On the basis of these facts, the prosecution charges Wang Xiaopeng with theft and Zhang Xiaoli with concealing and hiding criminal proceeds, in accordance with Articles

264 and 312 of the Criminal Law of the People’s Republic of China, and requests that the court impose legal penalties.

The aforementioned facts were not disputed by the defendants Wang Xiaopeng and Zhang Xiaoli during the trial. The evidence provided by the prosecution included statements from victim Zhang Feng, a criminal case registration form, report materials, details of the arrest, lists of seized and returned items, household registration documents, testimonies from witnesses Wang Liping and Wang Yajun, the price evaluation report from the Baoji City Weibin District Price Certification Center, identification records, search records, recovery records, and photographs, along with confessions from both defendants, all of which sufficiently establish the case.

The court finds that defendant Wang Xiaopeng, with the intention of illegal possession, secretly stole another’s property, constituting theft; Defendant Zhang Xiaoli knowingly purchased stolen goods, thereby constituting the crime of concealing and hiding criminal proceeds, as charged by the prosecution. Both defendants provided truthful accounts of their criminal acts after their arrest and are thus eligible for leniency in sentencing. Based on Articles 264, 312, 67(3), 38, 41, 42, 44, 52, and 53 of the Criminal Law of the People’s Republic of China, the court sentences are as follows:

Defendant Wang Xiaopeng is sentenced to five months of detention and fined 1,000 yuan. (The term of imprisonment begins from the execution of the judgment, with one day of presentence detention credited against the term, from September 23, 2012, to February 22, 2013. The fine has been paid.)

Defendant Zhang Xiaoli is sentenced to one year of public surveillance and fined 2,000 yuan. (The term of public surveillance starts from the execution of the judgment. The fine has been paid.)

Should there be any dissatisfaction with this judgment, an appeal may be filed within ten days from the second day of receipt of the judgment document, either through this court or directly to the Intermediate People’s Court of Baoji City, Shaanxi Province. A written appeal must include one original and two copies of the appeal document.

Judge: Gong Xue

January 31, 2013

Clerk: Ba Li

Part D. Procedure for Extracting Information

To analyze the text data, we implemented a multistep procedure to extract key variables related to the defendants. The process was as follows:

1. **Defendant Name Extraction:**

   We first extracted the names of defendants using the keywords such as “被告人” (defendant) combined with an exhaustive list of common Chinese surnames. This allowed us to accurately identify and capture all defendants’ names within each case and count the number of individuals involved.

2. **Handling Multiple Defendants:**

   In cases where multiple defendants were involved, we matched each defendant to the relevant descriptions in the judgment by tracking the occurrence of their name in each sentence. This allowed us to correctly associate specific details, such as charges and sentencing, with the corresponding defendant in multiple defendant cases.

3. **Extraction of Key Details:**

   Once the defendants were identified, we extracted key demographic details, case details and sentencing information on the basis of specific keywords:

   - Birthplace: Keywords such as “出生于” (born in [province] [city]) were used to extract the defendant’s place of birth.
   - Sex: Sex was extracted by searching for the keywords “男” (male) or “女” (female) in the descriptive sections related to each defendant.
   - Date of Offense: We identified the offense date by locating keywords such as “公诉机关指控” (indictment by the public prosecutor) and capturing the first date that appeared after this phrase, marking it as the date of the crime.
   - Prior Convictions: We used keywords such as “累犯” (repeat offender) to determine if the defendant had a prior criminal record. If such terms appeared, we recorded the defendant as having a prior conviction.
   - Sentencing and Fines: We extracted the sentencing duration by identifying terms following “判处” (sentenced to) and extracted fine amounts by

detecting amounts following “处罚金人民币” (fine in RMB). This allowed us to record both imprisonment terms and monetary fines where applicable.

- Location: In China, criminal cases are typically handled by the court in the jurisdiction where the crime was committed, as stipulated by law. Therefore, we used the location of the People’s Court named in the title of each judgment to identify the crime’s location accurately.

This process allowed us to systematically extract key variables such as names, birthplaces, sex for each defendant, date of offense, location, number of individuals involved, and verdicts, ensuring that the data were clean and organized for further analysis.