Prices vs. Production Restrictions: China's Coal Industry*

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Abstract

Regulators often address externalities with taxes or production restrictions. We develop a criterion to rank the welfare effects of these policies under mild assumptions about the external loss function. We apply the criterion to analyze a reform of China's coal industry. Using an empirical model of inter-provincial coal demand and supply, we find that relaxing the production restrictions would increase 2017 coal output by over 600 million tons. Our criterion shows that a tax could achieve higher social welfare.

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1 Introduction

Regulators often use price- and quantity-based policies to mitigate externalities. Urban planners use non-tradable rationing schemes, such as license-plate driving restrictions, as well as congestion pricing to ease road demand (Weitzman, 1977; Glaeser and Luttmer, 2003). In the financial sector, macroprudential policies use capital requirements and Pigouvian taxes on leverage to manage systemic risk (Hanson, Kashyap and Stein, 2011; Stein, 2012). In environmental policy, governments use pollution taxes and a variety of quantity instruments, such as quotas or plant closures, to reduce the external loss from pollution not internalized by the market.

The shape of the external loss function is critical to these policy choices (Weitzman, 1974). However, pinning down its parameters can be difficult. First, policymakers may face significant uncertainty about future demand, supply, or the true scale of externalities. For example, estimates of the Social Cost of Carbon vary by orders of magnitude depending on discount rates and tipping point assumptions (Pindyck, 2013). Second, researchers conducting ex-post evaluations rarely observe the objective function that guided the initial policy design, making it hard to infer whether the chosen policy was optimal.

We propose a sufficient condition for comparing the welfare effects of policy instruments. Our criterion requires estimates of economic surplus under each instrument and assumes that the external loss is monotonic in a scalar equilibrium outcome; it does not require knowing the convexity of the loss function. Consider, for instance, a loss function strictly increasing in the aggregate quantity, which may reflect emission damages. A policymaker decides between shutting down factories and imposing a pollution tax to maximize the social welfare function, which is the economic surplus minus the external loss. In this case, if a tax can deliver the same expected economic surplus as the shutdown, but the distribution of quantity under the tax is stochastically dominated, then the tax would reduce the expected external loss and raise social welfare.

We apply this criterion to China's coal industry. Policy choices in this setting are consequential. As the world's largest producer and consumer of coal, China faces acute tensions between energy security, environmental consequences, and economic stability. It has been widely reported that the reliance on coal undermines China's energy transition and global efforts to mitigate climate change (McGrath, 2019; WSJ, 2022; Bloomberg, 2022). A number of papers have documented the severe air-quality and health consequences associated with coal (Almond et al., 2009; Chen et al., 2013; Ebenstein et al., 2017). At the same time, coal mining provides significant employment opportunities and local government revenues, especially in major producing provinces dominated by state-owned enterprises (Wright, 2012;

Hervé-Mignucci et al., 2015). Policies affecting coal output therefore have large economic and distributional consequences (Clark and Zhang, 2022; Yuan et al., 2025).

We focus on a major reform of this industry launched in 2016. As part of a multi-year effort to reduce coal consumption and pollution while preserving employment and profitability of the industry, the Chinese government in April 2016 ordered small mines to close and large mines to cut output. As provinces implemented these measures, coal prices surged: our data show that the average coal price in the second half of 2016 rose by 31.0% to RMB 539 ($77.4)/ton, from RMB 411 ($60)/ton in the same period of 2015. The government continued to close mines and strictly monitor production to reduce production above the approved capacity at least through 2018.

These policies are not unique to China. Economists have long advocated for market-based price or quantity instruments, such as Pigouvian taxes (Pigou, 1920; Baumol, 1972) or cap-and-trade systems (Crocker, 1966; Dales, 1968; Montgomery, 1972), to internalize externalities efficiently. Although resource taxation is common, sophisticated cap-and-trade markets are often infeasible due to high transaction costs (Nie, 2012) or weak institutional capacity (Bell and Russell, 2002; Blackman and Harrington, 2000), especially in developing countries. In these cases, the practical policy choice is between a tax and a command-and-control restriction on production, such as factory shutdowns or moratoria on resource extraction (Blackman, Li and Liu, 2018). An important part of China's coal industry reform is such a production restriction policy.

To evaluate the reform, we first use an illustrative example to show that it is theoretically ambiguous whether a tax or a production restriction achieves higher social welfare. Similar to the efficient quota in Weitzman (1974), a production restriction can better target quantity and sometimes outperform the optimal tax when there are shocks to the economic environment. Using our criterion, we can also show that some production restrictions are worse than the optimal tax for a large class of external loss functions.

In our empirical analysis, we combine the policy intervention with a comprehensive dataset on coal production and consumption to analyze the demand and supply in the coal market. Our main data include monthly prices at the province level and shipment quantities from producers to end users both within and across provinces. We validate the shipment data with the production and consumption data reported by other sources.

We next formulate a model that incorporates key institutional features of China's massive and partially regulated coal market. First, coal procurement in the electricity and other sectors has undergone significant market reforms since 2013, essentially allowing the market to set prices that equilibrate demand with supply. Second, the shares of coal shipped from one province to another are highly stable over time, despite varying price dispersions across provinces. Third, large coal producers and buyers often operate under long-term quantity contracts. These contracts at the time often promised a delivery quantity but allowed prices to adjust based on spot market prices. In our model, the market is competitive. We specify a demand function and a supply function for each province. The local price in each province is determined by the province's demand and the total supply from different provinces. The quantity supplied by a province is determined by a weighted average of prices in provinces it sells to. The effects of the policy are modeled as province-specific shifts of the supply functions.

We estimate the demand and supply of coal across provinces. To identify demand, we construct price instruments using variations in the policy start dates and policy compliance levels across provinces that shift supply. The key identifying assumption is that the policy exclusively affects supply and is not correlated with the demand unobservables. We also consider a variety of alternative instruments. Similarly, we estimate supply using demand shifters. Our estimates suggest that the policy significantly increases aggregate marginal costs.

Given the estimated equilibrium model of coal demand and supply, we conduct a series of counterfactual simulations to quantify the effects of enforcing the production restriction. First, we find that removing the restrictions would increase the annual production by more than 600 million tons and decrease the price by more than RMB 128/ton. Using reasonable estimates of coal's environmental impact, we find that the loss of economic surplus is largely offset by the saved environmental costs.

Second, we compare the policy with an efficient quota or a cap-and-trade system. Our supply estimates suggest that the policy increases the aggregate marginal costs, especially near the approved capacity. We also find that larger, lower-cost provinces see greater cost increases. These findings suggest inefficient reductions of quantities both within- and cross-province. Holding fixed the quantity produced by each province, an alternative, efficient quota system would increase producer surplus by up to RMB 346 billion ($53 billion). Efficiently allocating quantity reductions both within and across provinces would increase the producer surplus by up to RMB 441 billion ($68 billion).

Finally, we consider whether a tax can increase the expected social welfare under a more general external loss function. To use our criterion, we assume that the loss function is a bounded increasing function of total quantity. This external loss can reflect environmental damages, but more generally captures any social costs that we do not quantify but rise with aggregate production. We establish two main results. First, when the government places equal weights on each component of the economic surplus, which includes consumer surplus, producer surplus, and tax revenues, there exists a tax that would reduce the expected economic surplus by the same amount as the observed policy but have a smaller expected external loss. Therefore, a tax would be more efficient. We also argue that institutional constraints may have led to a sub-optimal instrument in terms of social welfare. Second, when the government places a greater weight on producer surplus than on consumer surplus or tax revenues in its objective function, a tax continues to achieve a higher objective value than the observed policy until producer surplus is weighted at least 30% more. In this case, a tax is a worse instrument because the weighted loss of producer surplus under a tax can be so large that tax revenue cannot offset it, whereas production restrictions can directly increase producer surplus.

Related Literature and Contribution

In this paper, we present a novel criterion to rank policy instruments regulating externalities. A sizable theoretical literature builds on the insights of Weitzman (1974), where relative slopes of marginal benefits and costs are key determinants of the optimal policy,[1] which also has implications for attribute-based regulations (Kellogg, 2020; Borenstein and Kellogg, 2023). A number of papers use integrated assessment models (Pizer, 2002; Muller and Mendelsohn, 2009) or calibrated theoretical models (Newell and Pizer, 2003; Fell, MacKenzie and Pizer, 2012) to quantitatively assess the trade-off between a price (tax) and a quantity (cap) instrument. For these environmental applications, we show that our criterion is effective at comparing some types of quantity instruments (production restrictions) with a tax. Importantly, we do not require knowing the convexity of the external loss function, which is central to the criterion in Weitzman (1974).

Our paper is also related to the empirical literature on measuring the economic effects of environmental regulations.[2] A number of papers focus on productivity impacts (e.g., Jaffe et al., 1995; Berman and Bui, 2001; Greenstone, 2002; Greenstone, List and Syverson, 2012; He, Wang and Zhang, 2020). Using estimated equilibrium models, Ryan (2012) and Fowlie, Reguant and Ryan (2016) emphasize the roles of market power. Chen et al. (2025) study how conglomerates reallocate internal production. In this paper, we develop and estimate a new competitive equilibrium model for China's coal sector.

We also note that there have been few equilibrium analyses of China's coal industry in

[1]For a review, see, for example, Williams III (2002), Hepburn (2006), Weitzman (2020), and Stavins and Wagner (2022).

[2]More broadly, we note that there is a growing literature on the empirical evaluation of industrial policy (Kline and Moretti, 2014; Aghion et al., 2015; Alder, Shao and Zilibotti, 2016; Juhász, 2018; Kalouptsidi, 2018; Lane, 2018; Miravete, Moral and Thurk, 2018; Lashkaripour and Lugovskyy, 2018; Criscuolo et al., 2019; Rotemberg, 2019; Barwick, Kalouptsidi and Zahur, 2019; Giorcelli, 2019; Yi, Lawell and Thome, 2019; Hanlon, 2020; Bai et al., 2020; Fan and Zou, 2021; Giorcelli and Li, 2021; Guo and Xiao, 2022; Aldy, Gerarden and Sweeney, 2022).

economics despite its enormous importance to China's economy and the global environment. One reason might be the lack of granular and recent data.[3] For example, Zhou et al. (2019) study the evolution of coal mining firms' productivity, and Zheng (2024) studies the effects of buyer market power on productivity and safety, both using a production function approach based on manufacturing census data from before 2007. In our paper, we combine a detailed dataset, the institutional knowledge of the market, and the industry reform to address the endogeneity problems in the estimation of coal demand and supply in our equilibrium model. Our estimates of demand and supply elasticities may be of independent interest for other researchers studying China's coal industry.

In the rest of the paper, we first describe a general model and the ranking criterion in Section 2. We then illustrate the application of the criterion using a simple model. In the empirical application, we first describe the main institutional features of China's coal market in Section 3. Section 4 lists the various datasets used in the analysis. Sections 5 and 6 present the demand and supply models and their estimation. We use the model to analyze the reform of China's coal industry and apply the ranking tests in Section 7. Section 8 concludes.

2 Conceptual Framework

2.1 General Model

We use a vector of random variables ω to denote the state of the economy, which could represent shocks to demand, supply, or external loss. The total private benefit is denoted by a function $U(\boldsymbol{e}, \omega)$, where $\boldsymbol{e}$ is a vector of actions that could represent output or quality. We use $C(\boldsymbol{e}, \omega)$ to represent the private costs of production. The policymaker can choose a price-based policy instrument, $T(\boldsymbol{e})$, or a production restriction, which increases the private production cost to $G(C) \geq C$. For simplicity, we assume that the actions are continuous, and the vector of equilibrium actions $\boldsymbol{e}^\star$ solves a first-order condition

$$\nabla U - G' \nabla C - \nabla T + \Psi = 0, \tag{1}$$

where the equation represents the system of first-order conditions, and ∇ is the gradient operator. We use Ψ to represent the effects of potential strategic interactions, and $\Psi = 0$ in

[3] Existing studies that estimate or calibrate the coal demand or supply typically use aggregate annual data (see, for example, Burke and Liao, 2015; Shi, Rioux and Galkin, 2018; Teng, Burke and Liao, 2019). A number of papers have studied the coal-mining industry in other countries, with a focus on safety and productivity (Sider, 1983; Gowrisankaran et al., 2015), technology adoption (Rubens, 2022), labor market competition (Delabastita and Rubens, 2022; Demirer and Rubens, 2025), and the decline of the US coal industry (Watson, Lange and Linn, 2023).

a perfectly competitive market. The planner must choose a policy before the uncertainty ω is realized. The expected social welfare is

$$E_\omega \left(U\left(\boldsymbol{e}^\star, \omega\right) - G\left(C\left(\boldsymbol{e}^\star, \omega\right)\right) - \mathbb{L}\left(\boldsymbol{e}^\star, \omega\right)\right), \tag{2}$$

where $\boldsymbol{e}^\star$ is the unique equilibrium outcome[4] and $\mathbb{L}(\boldsymbol{e}, \omega)$ is the external loss function. Comparing the objective function in (2) with the first order conditions shows that optimality of a policy is often an empirical issue, which depends on the market structure, the distribution of the unobservables and the shape of the loss function. This formulation encompasses a variety of applications.

Example 1. Quota and taxes on emissions of power plants in a static competitive market (Muller and Mendelsohn, 2009). The actions in $\boldsymbol{e} = (e_1, e_2, \ldots)$ represent the emissions by different power plants, U is the aggregate power plant profits, C is the cost at given emission levels, $\mathbb{L}$ is the aggregate emission damages proportional to the sum of each firm's emissions, $\sum e_k$, and $\Psi = 0$. If the regulator correctly sets a quota level and quotas are efficiently allocated across firms, $G(C)$ represents the aggregate supply curve up to the quota and then turns to ∞. If the regulator uses a tax at rate t, then $T = t \times \sum e_k$.

Example 2. Dynamic oligopoly with emissions (Fowlie, Reguant and Ryan, 2016). The vector of actions $\boldsymbol{e}$ represents static production and dynamic investment decisions of cement producers,[5] U represents the present discounted values of present and future operating revenues, and C represents the present values of production and investment costs. The loss function accounts for the present values of emission costs of both domestic and foreign producers. The function G can represent a variety of production restrictions such as grandfathering, output-based quotas and cap-and-trade.[6] The function T represents taxes on present and future emissions. The term Ψ accounts for the wedge due to the oligopolistic competition in both production and investment.

Example 3. Data production and privacy concerns. The term U represents the firm value of data production, $\boldsymbol{e}$ represents the usage of a variety of inputs (such as internet users' private data and the amount of compute), C is the cost of production, and G reflects regulations like GDPR increasing the costs (Demirer et al., 2024). The loss in privacy can be quantified as in, for example, Acemoglu et al. (2022), and increases in the use of private data.

[4] If the equilibrium is not unique, we assume that an equilibrium choice function exists that chooses one.

[5] We can augment the equilibrium first-order conditions in (1) to allow for optimal choice probabilities of discrete decisions such as entry or exit to maximize expected private returns.

[6] We can also augment our model to allow for demand-side policies such as import taxes to affect U.

2.2 Ranking Criterion

The ranking criterion addresses an empirical question: given an existing policy, is there an alternative policy that can improve the welfare outcomes for any "reasonable" loss function? Specifically, given an observed policy (G, T), is it possible to find an alternative $\left(\tilde{G}, \tilde{T}\right)$ that can potentially improve the welfare in (2) for any $\mathbb{L}$ in some set $\mathcal{L}$? We make the following assumptions on $\mathcal{L}$:

Assumption 1.

1. *The loss function $\mathbb{L}(\boldsymbol{e}, \omega) = L(H(\boldsymbol{e}), \tilde{\omega})$, where H is a scalar function, and $\tilde{\omega}$ is a subvector of ω. Furthermore, $\tilde{\omega}$ is independent of $H(\boldsymbol{e}^{\star}(\omega))$.*

2. *The distribution of H has a bounded support $\left[0, \overline{H}\right]$ under any policy instrument.*

3. *The loss function L is differentiable, monotonic, and finite over $H \in \left[0, \overline{H}\right]$, and the direction of monotonicity is the same for any $\tilde{\omega}$.*

The first assumption restricts the external loss to be a function of an aggregate quantity H. For example, when the vector $\boldsymbol{e}$ represents production choices, H could represent a weighted sum of productions, where weights reflect different damages of actions. We also require that demand and supply shocks affect the loss only through H. For example, uncertainty about the per-unit Social Cost of Carbon does not depend on quantities demanded or supplied determined in the market. Importantly, we require the loss to be a monotonic function but do not make any assumptions on the convexity of the loss in the argument H.

The following property of stochastic dominance provides the conditions to rank the losses under different instruments:

Theorem 1. *Given random variables H_1 and H_2 and a loss function L that satisfy Assumption 1, if H_1 stochastically dominates H_2, then $E(L(H_1, \tilde{\omega})) \geq E(L(H_2, \tilde{\omega}))$ if L increases in H, and the inequality is reversed if L decreases in H.*

We provide a proof based on integration by parts in the appendix.[7] In the above, the inequality is strict if the monotonicity and stochastic dominance are both strict. Using this theorem, we can now describe the procedure to check whether an observed policy (G, T) is optimal.

1. Given U, C, G, T (from, for example, an empirically estimated model given the existing policy G and T) and the direction of monotonicity of L (from the institutional knowledge, e.g., whether H is a good or a bad), compute the corresponding expected economic surplus $S = E_{\omega}(U(\boldsymbol{e}^{\star}, \omega) - G(C(\boldsymbol{e}^{\star}, \omega)))$.

[7] The result is a variant of, for example, Theorem 1.A.8 in Shaked and Shanthikumar (1994).

2. Find a new policy $\left(\tilde{G}, \tilde{T}\right)$ that produces the same economic surplus $\tilde{S} = S$ in the new equilibrium (which can be computed from the estimated model).

3. If the distribution of the equilibrium quantity H under (G, T) stochastically dominates (is stochastically dominated by) that under $\left(\tilde{G}, \tilde{T}\right)$, and L is increasing (decreasing) in H, then by Theorem 1, the expected loss is lower under $\left(\tilde{G}, \tilde{T}\right)$ and the total welfare in (2) must be higher given the same economic surplus.

We call $\left(\tilde{G}, \tilde{T}\right)$ an SND (**s**urplus-**n**eutral tax with a **d**ominated/**d**ominating H distribution) policy for (G, T). We note that because stochastic dominance is a sufficient condition to establish a ranking, finding an SND policy shows that it can achieve higher social welfare than (G, T), but the failure to do so does not prove that (G, T) is the optimal policy.

More generally, the procedure can be adapted to compare any two given policies. For policies (G, T) and $\left(\tilde{G}, \tilde{T}\right)$, if $S \leq \tilde{S}$, the distribution of H stochastically dominates (is stochastically dominated by) that under $\left(\tilde{G}, \tilde{T}\right)$, and L is increasing (decreasing) in H, then $\left(\tilde{G}, \tilde{T}\right)$ achieves a higher expected social welfare than (G, T).

The existence of SND policies can be surprising in some contexts. For example, Weitzman (1974)'s criterion for using a tax or a quota depends on the slopes of the demand, supply and the loss function. We discuss the (non-)existence of the SND policy in an illustrative example in the next section.

2.3 An Illustrative Model

Using an illustrative model below, we show that (1) the optimal policy choice between a tax and a production restriction is theoretically ambiguous, and (2) an SND tax exists for some production restrictions.

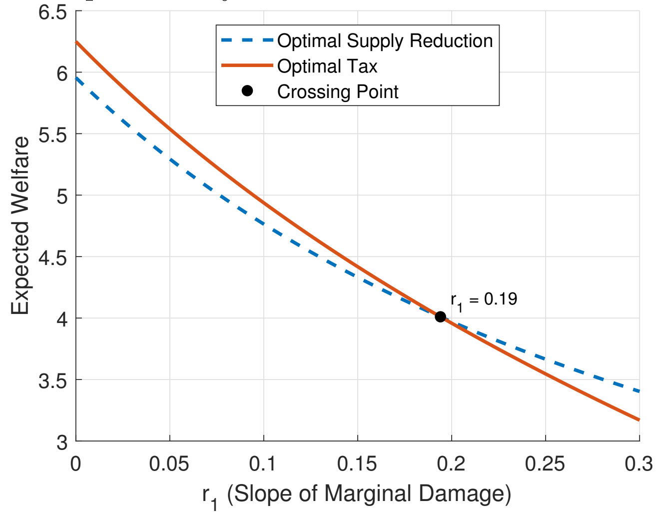
Consider a linear inverse supply function $P^S = a_0 + a_1 Q$, demand $P^D = b_0 + b_1 Q + \varepsilon$, and an external marginal loss function (such as an environmental cost not internalized by the market) $MD = r_0 + r_1 Q$, where $a_1 > 0, b_1 < 0$, and $r_0, r_1 > 0$. In this case, the loss function L is a quadratic function in Q. The shock ε has a mean-zero distribution with a variance of σ^2.

A policymaker can choose a unit tax or restrict production before knowing the value of the shock. When choosing the tax rate τ, the policymaker maximizes (2), which can be written as

$$W = E\left(\int_0^{\max(Q^\star,0)} \left(P_D\left(q\right) - P_S\left(q\right) - MD\left(q\right)\right) dq\right), \tag{3}$$

where the equilibrium quantity is given by $Q^\star = \max\left(0, \dfrac{b_0 + \varepsilon - a_0 - \tau}{a_1 - b_1}\right)$, and the expec-

Figure 1: Compare Policy Instruments in an Illustrative Example



Note: We assume $a_0 = 1, a_1 = 0.2, b_0 = 5, b_1 = -0.2, r_0 = 2$, and $\sigma^2 = 1$. We vary r_1 from 0 to 0.3. Notably, the expected surplus function does not depend on the distribution of ε up to σ^2. We assume that the equilibrium quantity is strictly positive on the support of ε under either instrument.

tation is taken over ε. If the policymaker instead wishes to directly restrict production, it enacts policies that shift the supply function leftward. For simplicity, we assume that the policymaker chooses $\alpha_1 > a_1$ that shifts the supply curve to $P^S = a_0 + \alpha_1 Q$ to maximize (3). We focus on comparing a production restriction with a tax, because these two choices are the practical policies in many cases, including our empirical application. We discuss cap-and-trade at the end of the section.

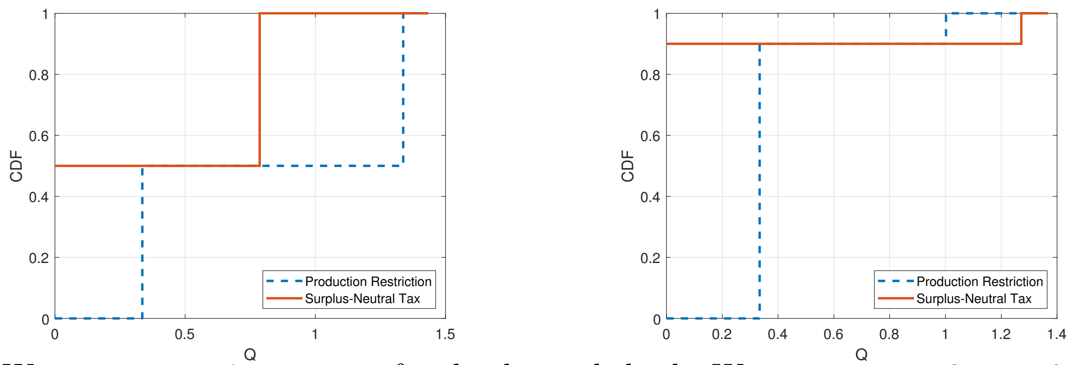
2.3.1 Optimality of Policy Instruments

We first show that the optimal instrument choice is theoretically ambiguous. The key intuition from Weitzman (1974) is that, when the external marginal loss increases sufficiently quickly in quantity, it is more efficient to regulate quantity directly as opposed to controlling it indirectly through price instruments like a tax. We illustrate this intuition in Figure 1 by plotting W under the optimal tax and production restriction policies at different values of r_1, the slope of the external marginal loss. When $r_1 = 0$, the best tax is the Pigouvian tax and it outperforms any production restriction policy. As the external damage becomes more convex, the best production restriction is better than any tax in this example.[8]

[8] We assume that the equilibrium quantity is strictly positive on the support of ε under either instrument. As the loss function becomes even more convex, a larger tax can shut down production over some support of ε, and the welfare ranking becomes less monotonic.

Figure 2: Quantity Distributions Under Production Restriction and Tax

(a) SND Tax (b) Surplus-Neutral Tax



Note: We use a two-point support for the demand shock. We assume $a_0 = 3, a_1 = 0.2, b_0 = 5, b_1 = -0.3$. In panel (a), ε takes on values of -1.5 and 0 with equal probability, the production restriction policy increases a_1 to $\alpha_1 = a_1 + 1$. The SND tax is 1.61. In panel (b), the support of ε is $\{-1.5, -0.5\}$, and the probability of $\varepsilon = -1.5$ is 0.9. The surplus-neutral tax is 0.87, but it is not SND because the CDFs cross. In both cases, we assume that the production is 0 if the tax exceeds $\varepsilon + b_0 - a_0$. The surplus neutral taxes in both cases shut down production at the low demand states.

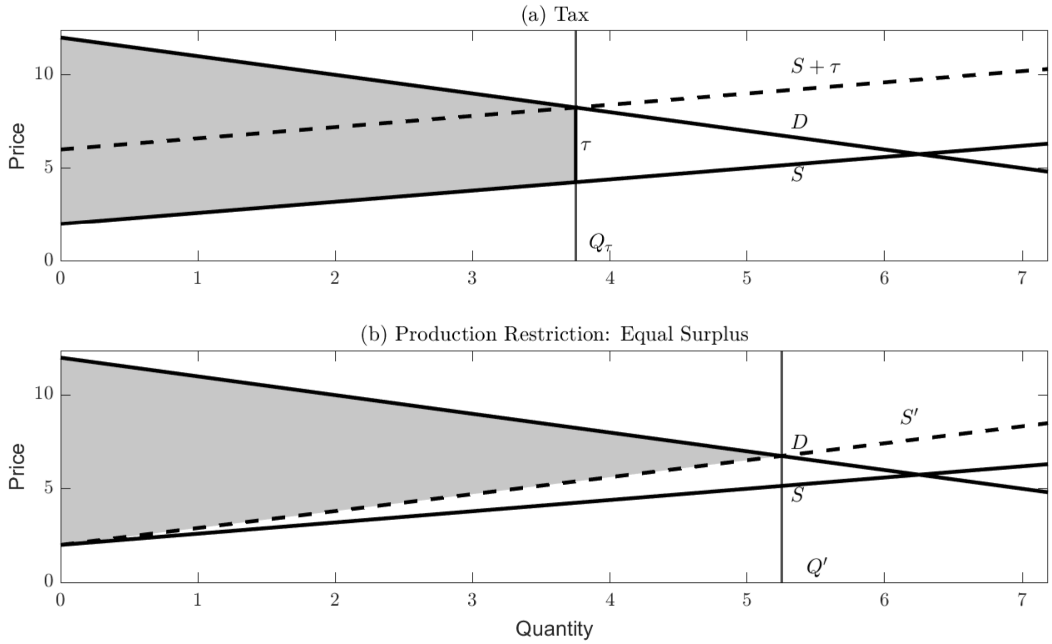
2.3.2 Applying the Criterion to Rank a Production Restriction and a Tax

We now show that there exist demand and supply functions where, for a given production restriction policy, our criterion can identify a tax that achieves higher social welfare. For simplicity, we assume that ε has a discrete distribution with two support points. In panel (a) of Figure 2, the "low" and "high" demand states occur with equal probability (0.5), and we find an SND tax that delivers the same expected economic surplus as a production restriction, but the quantity cumulative distribution function (CDF) under the tax is strictly dominated. In panel (b), the demand states are more left-skewed, where the low state occurs with probability 0.9, and the magnitude of the high state is also reduced. Given the same production restriction, we find a higher quantity under a surplus-neutral tax in the high demand state. Consequently, the quantity CDFs cross.

The key reason for the existence of an SND tax is the tax's better allocative efficiency. At the same level of output, a tax generates more economic surplus than the production restriction, which has a steeper supply. Figure 3 illustrates this idea: to generate the same surplus, the equilibrium quantity under the tax is smaller than under a rotated supply. Therefore, we typically expect quantity to be lower under a surplus-neutral tax.

The non-existence of an SND tax in this example arises when demand shocks are sufficiently left-skewed. Given low-demand shocks, the equilibrium surplus and quantity may be lower under the tax than under a production restriction policy. To see this, consider the

Figure 3: Tax Generates More Surplus than Production Restriction at the Same Quantity



Note: To generate the same surplus, the equilibrium quantity Q_τ under a tax τ is smaller than Q' under a rotated supply S'.

extreme case where $\varepsilon < \tau + a_0 - b_0$, and the tax τ shuts down production completely. In contrast, production restrictions that rotate supply inward do not lead to a complete shutdown. If low-demand states are frequent, a tax can generate significantly less surplus than a production restriction in the left tail of the demand shock distribution. To match the total expected surplus, the tax must therefore permit higher quantities in high-demand states, violating the requirement for stochastic dominance.

Relationship to Optimal Policy Instruments in Section 2.3.1 Section 2.3.1 shows that an optimal production restriction can achieve a higher social welfare W than the optimal tax if the external loss function is sufficiently convex. However, our SND ranking criterion serves a different purpose: it aims to find a tax that achieves a higher W than a given quantity policy, as opposed to the best quantity policy. If there exists a loss function where the policy coincides with a production restriction that beats the best tax (for example, the policy corresponding to the blue line to the right of the crossing point in Figure 1), our criterion yields a null result—no SND tax exists. In contrast, the criterion is useful for detecting poorly designed quantity policies.

Efficient Quota Instead of a shifted supply, production restrictions can take the form of a quota. The supply function under an efficient quota remains unchanged up to the quota level $\overline{Q}$, and then jumps to ∞. We find that no SND tax exists for a quota. To see this, note that the economic surplus in (3) is the same increasing function of quantity for a tax or a quota. If the distribution of quantity under the SND tax is stochastically dominated by that under the quota, the economic surplus under the tax must also be lower. For the same reason, an SND quota does not exist for a tax either. Therefore, for environmental applications, our approach complements the criterion in Weitzman (1974) and is useful for comparing a tax with an inefficient quantity policy (relative to an efficient quota).

3 Empirical Background

3.1 Coal Types, Quality and Mining Technology in China[9]

Over 70% of coal produced in China is bituminous coal, and 23% is anthracite.[10] High-purity bituminous coal and about half of anthracite are used for coking, which in turn produces coke for steel-making. The rest of these two types of coal are mainly used by power plants for electricity production. The main uses of lower-purity coal are for construction (cement making) and heating.

Coal purity and extraction methods vary significantly across regions. Shanxi and Inner Mongolia have the largest reserves and are the largest coal-producing provinces, accounting for over a quarter of national output.[11] Shanxi also produces the highest-quality coal, with an average heat content (defined as the total energy produced per kilogram after complete combustion) of about 6,242 kcal/kg, compared to the national average of 5,350 kcal/kg and the US average of 5,600 kcal/kg. Over 90% of mines in China are pithead mines, where coal is extracted from deep underground. The average mine depth is 456 meters. This extraction method is more costly than open-pit mining more commonly found in countries such as Australia and India, and regions such as the western US.

[9] This section is based on Nathaniel Aden, David Fridley and Nina Zheng (2009) and National Energy Report (2020).

[10] Coal is usually classified by the carbon content (by weight). The carbon content is over 86% for anthracite and between 45% and 86% for bituminous coal. The remaining coal falls into the categories with lower carbon content, such as subbituminous, lignite and brown coal (American Geosciences Institute, n.d.).

[11] Appendix Figure I.2 shows the distribution of coal reserves.

3.2 The Formation of the Coal Market

Historically, the Chinese government exercised tight control over both the supply and demand of coal through planned prices and quantities. The government partially liberalized the market in 1993 by allowing coal to be traded while maintaining special contracts that gave the large state-owned power plants the option to buy coal from mines at planned quantities and prices (Yang et al., 2018). The special contract prices were typically lower than the prevailing market prices. When contracted coal was insufficient to meet electricity demand, power plants turned to the spot market to purchase additional coal. The government further liberalized the market in a series of reforms, and fully abolished the special contracts in 2013 (State Council, 2013). These reforms also changed the procurement, operation, and investment decisions of power plants, which then started to respond to fluctuating coal prices in a manner more consistent with profit-maximizing firms (Xu and Chen, 2006; Ma, 2011; Liu, Margaritis and Zhang, 2013; Zhao and Ma, 2013; Gao and Van Biesebroeck, 2014; Eisenberg, 2019, 2024).

3.2.1 Method of Sales

Delivery Contracts During our sample period, coal buyers and producers trade via both long-term (annual or multi-year) contracts and the spot market. Major buyers include coal power plants, municipal central heating systems,[12] construction firms, steel makers, and fertilizer manufacturers. A long-term contract is signed directly between a coal producer and an end user (not a trading intermediary). Provincial governments are often involved to help firms find their matches, especially in large coal-producing provinces, which bear political responsibility to ensure coal supply to other provinces' power plants and heating systems (NDRC, 2021*b*). These contracts would nominally promise an annual delivery quantity but allow prices to adjust on a quarterly or even monthly basis, based on the spot market prices (e.g., Shanghai Securities News, 2014, 2015; ICBC, 2016). As a result, actual delivered quantities may deviate from the contractual terms (International Energy Network, 2016*a*).

Monthly Price Discovery A standard practice is for long-term contract buyers and sellers to use public monthly price indices to formulate a price. The most commonly used indices during and after our study period are average transaction prices (net of transportation costs) of coal sold to power plants in different regions (NDRC, 2016*d*, 2017*a*). Specifically, buyers

[12] Across northern China, most residential apartments, government facilities, and schools receive heating through municipal centralized systems that primarily burn coal to generate heat. This infrastructure consists of large coal-fired boilers that heat water, which is then distributed through an extensive network of insulated pipes to various buildings (Chen et al., 2013).

and sellers update their contract prices based on the signing prices (which may depend on coal quality in addition to projected supply and demand) and the average delivery prices in the past month published by coal trade associations and port authorities, which may include trades based on the contracts and in the spot market.[13]

Contract Compliance While we do not have data on contract compliance, the government has long-standing policies that penalize under-fulfillment of the long-term contracts (NDRC, 2016*b*). For example, in 2017, power plants that failed to buy at least 75% of their committed volume (by weight) in the signed contracts faced restrictions on their electricity sales (Gao, 2017). In more recent years, long-term contracts have been the main component of coal trades, consistently accounting for more than 75% of coal for electricity generation (Zhou et al., 2024). The government also prioritizes allocating rail transportation to coal sold via long-term contracts.[14] Finally, we note that power plants are usually optimized to burn coal of a specific grade and thus have incentives to procure from consistent sources. Plants that source from multiple mines may need to use a coal blending technique to maintain efficiency, which can increase operational costs (Sloss, 2014; Zhao, 2021).

3.3 Economic Policies

3.3.1 Coal Supply Reform

In the five-year plan published by the National Development and Reform Commission (NDRC, China's macroeconomic management agency) in 2016, the Chinese government outlined a plethora of goals and plans to restructure the coal-mining industry. Specifically, the government explicitly called for improving the industry's profitability, limiting coal production, and reducing the industry's environmental impact.[15] Based on this plan, the State Council, China's chief administrative body, issued orders in February 2016 to limit the number of working days for coal mines from 330 to 276 days. The order also called for the closure of

[13]International Energy Network (2016*b*) provides an example on how to reset the monthly price using the average coal prices sold to power plants (BSPI) and the average price of coal for other uses (OPI) around the gulf of Bo Hai, both published by Qinhuangdao Ocean Shipping Coal Trading Market Co. Given the contract price p, the indices p_t^{BSPI} and p_t^{OPI} in month t, and the heat content of coal h measured in kcal/kg, the new price in month $t+1$ is adjusted to $0.5p + \left(0.25p_t^{\mathrm{BSPI}} + 0.25p_t^{\mathrm{OPI}}\right)\frac{h}{5,500\mathrm{kcal/kg}}$. The government advises buyers and sellers to explicitly specify this particular form of the formula (dynamic price updates linear in average coal prices) in their long-term contracts. Contract prices, the price indices and the assigned weights could differ across firms and across years.

[14]Around 60% of coal is transported via rail (Sun, 2025).

[15]In Appendix B, we provide snapshots of the original document and its translation.

small coal mines. We refer to these orders as the **supply reduction policy** in the paper.[16]

The actual dates of implementation and compliance with the policy varied across provinces and coal mine ownership types. Shanxi, historically China's largest coal-producing province, was the first to implement the policy in April 2016. Other leading coal-producing provinces such as Shaanxi and Inner Mongolia began their implementation in May. Large state-owned coal mines were also subject to more stringent monitoring, and their output fell more (Appendix I.2). Coal prices surged in the second half of 2016 relative to the prior months in 2016 and to the same period in 2015. NDRC officially suspended the 276-working-day policy in October amid concerns over meeting the (highly inelastic) winter heating and power demand (Lai, 2016; Shi, Rioux and Galkin, 2018). Nonetheless, mine closures and strict production monitoring continued in 2017 and 2018. The policy was gradually eased in 2019 (NDRC, 2019).

3.3.2 Resource Taxation

China instituted a resource tax on coal production in 2014. The central government established a band for the coal resource tax rate of 2 to 10% on the sales revenues of the raw coal extracted,[17] within which provincial governments choose the specific rate, subject to the central government's approval (STA, 2014). Major provinces such as Shanxi set a rate at 8%, and others set lower rates (Qin, Zhang and Xie, 2020).

Policymakers did not use this tax as the main instrument in the coal industry reform two years later for several reasons. First, they designed the new tax to reduce firms' tax burden and fund provincial spending on coal-production-related environmental damage as part of a broader fiscal reform (Xinhua, 2014), which replaced a patchwork of fees on coal production with a single levy. Raising the rate to restrict output would have clashed with that political narrative. Second, fiscal reform moves slowly, while the central government saw cutting coal capacity and output as an urgent task better handled through fast, targeted administrative mandates (Li, 2016; People's Daily, 2016). Finally, the central government allows provincial governments to keep all resource tax revenues as an incentive to invest in environmental protection (Hu, 2017), making it hard to further redistribute the revenue directly to coal consumers or producers.

[16]The Chinese press often referred to this policy as "capacity reduction policy", reflecting the closure of small mines. Given that the policy also reduced the output of operating mines, we use the term "supply reduction" as a compromise.

[17]This revenue levy does not additionally distinguish between different grades of the coal, but allows for reduced rates on coal extracted in mines near depletion.

3.3.3 Other Economic Policies

We also note two other sets of significant economic policies during our sample period. First, the government expanded credit and increased infrastructure spending to counter the decline in housing and stock market prices in 2015 and 2016 (Brandt et al., 2020). Many infrastructure projects, such as the national high-speed rail system, experienced rapid expansion in subsequent years (Reuters, 2016). Second, the government started to close small or unproductive plants in other industries.[18] These closures reduced 10% of state-owned steel capacity in 2016 (Lu, 2016). However, we expect the plant closures to have a small effect on coal demand given that the output share of closed plants is likely low. Between 2016 and 2018, coal demand remained strong as the main consuming sectors—thermal power, coking, steel and cement—either expanded output or maintained historically high production levels, against the backdrop of continued economic growth.[19]

4 Data

4.1 Data Sources

Our primary dataset comes from the China Coal Transportation and Distribution Association (CCTDA), a major trade group in the coal industry. The data include monthly shipment quantities of coal between provinces from 2012 to 2016. The tonnage data combine raw coal, washed coal and other derivative products with high coal content (such as coke and briquette).[20] The shipment data include shipments within a province and to other provinces.

We then compile additional data from other sources. We collect province-level mining capacity data from 2014 to 2018 from the National Energy Administration and National Mine Safety Administration. Any capacity change is approved every 6 months.[21] We also obtain

[18]It is of separate interest that the government, as opposed to the market, needs to order the shutdown of the plants. A plausible explanation is that many plants are supported by the local governments to provide employment despite being unprofitable. To facilitate the shutdown of coal and steel plants, China's Ministry of Finance created a fund of RMB 100 billion ($15.3 billion) to provide relief to the laid-off employees (Lu, 2016).

[19]We plot the total output in Appendix D.1.

[20]Consistent with the standard NBS practice, the data account for transportation of the tonnage of final end products from the raw coal producers to the end users. More specifically, if 1 ton of raw coal was extracted in province A, transported to province B for washing (removing impurities) with quantity reduced to $x < 1$, and burned at power plants in province C, the data would only include x in transportation from A to C and not count the $A - B$ transportation. We also note that not all raw coal needs washing, and many coal mines are integrated with washing facilities and need not transport coal to a third province for processing. Our data closely match the NBS aggregate production and consumption. See Appendix C for more details.

[21]In principle, the annual production should not exceed the approved level, and monthly production should

province-month production data in 2014–17 from CCTDA and 2018–2019 from National Bureau of Statistics (NBS). The production data reflect the total tonnage of excavated raw coal. We obtain monthly production data for key state-owned (SOE) coal mines from CCTDA, which are the largest coal mines in each province.[22] The monthly coal imports, measured in total tonnage, from outside China to each province between 2014 and 2017 are from the firm International Coal.[23] We collect monthly provincial coal prices in 2014–2019 from NDRC.[24] To study the impact of coal consumption on air pollution, we collect air quality data (hourly concentration measures of pollutants such as PM2.5 and PM10) at the monitoring station level from the Ministry of Environmental Protection.

Importantly, we do not directly have data on monthly province-level coal consumption. To construct coal consumption at the province-month level, we impute the quantities based on (1) shipment data from CCTDA, (2) monthly output of major industries using coal, and (3) annual province-level coal consumption, both from NBS. Details of this imputation are in Appendix D.

To verify the consistency of data from different sources, we compare the CCTDA's shipment data out of a province with the production data from NBS in Appendix C. Our shipment data are slightly lower (by about 4% to 8%) than the NBS statistics. At a more granular level, the same pattern holds consistently across provinces.

Data Aggregation

In the rest of the paper, we use the total weights of coal produced and consumed to analyze supply and demand. We do not further differentiate among coal types within the quantity data. Given our research questions, several potential concerns about the data may warrant discussion. Importantly, to what extent can a single demand function capture the composite demand for a variety of coal and coal products combined in our quantity data? What is the appropriate price for this composite demand? We note that in China, the demand for different coal products is likely highly correlated. The widespread use of coal blending techniques

not exceed 10% of the 1/12 of the annual level.

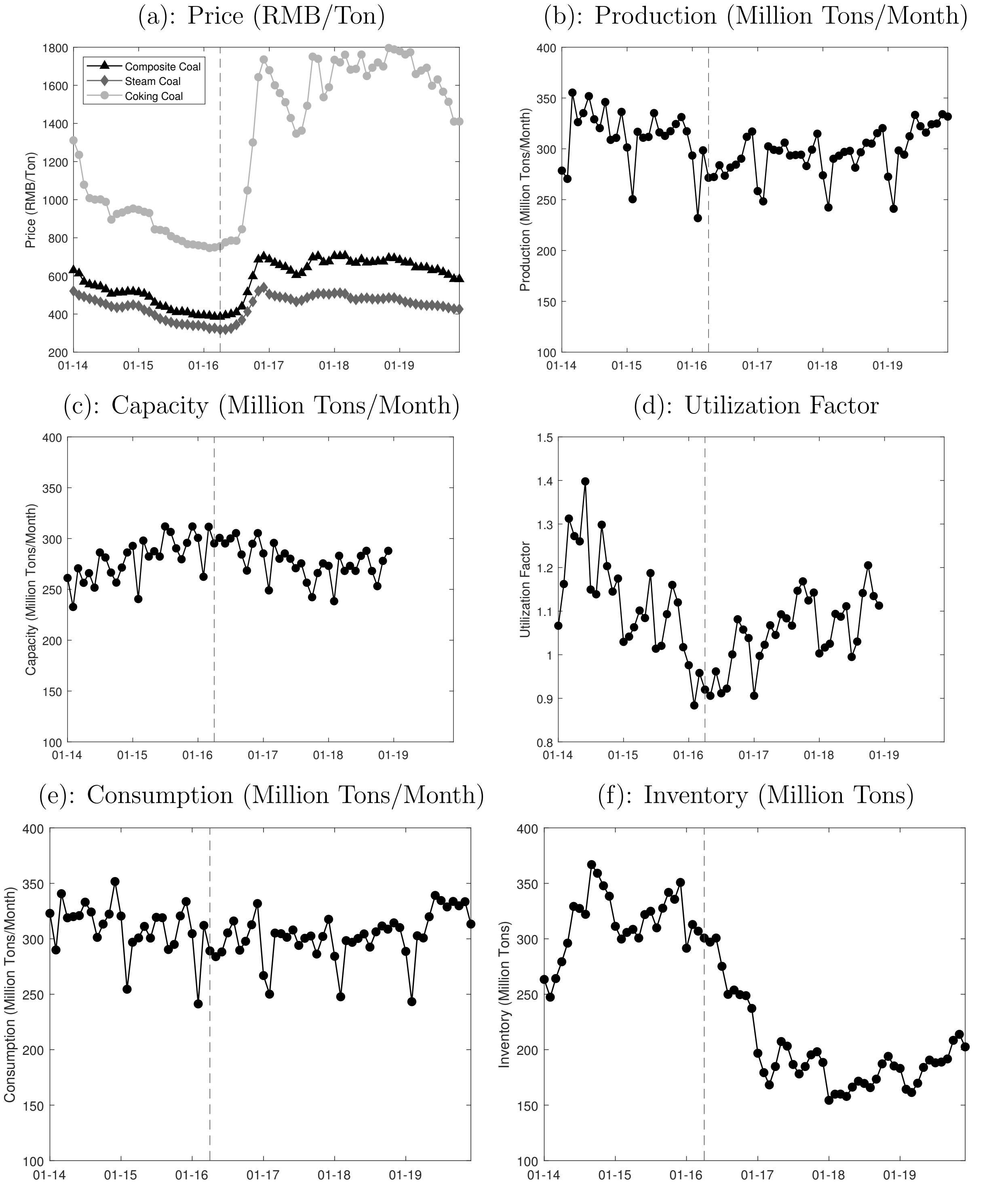
[22]NDRC designates an SOE coal mining firm as a "key SOE" based on a number of criteria, which include capacity, reserves, mining technology and coal quality (whether the coal is mainly for electricity production).

[23]The firm provides the data through the website https://mcoal.in-en.com/. We do not consider China's exports, which account for less than 0.2% of coal production during our sample period.

[24]The publicly available coal price data are based on coal used for electricity generation and heating. This type of coal, which includes a variety of coals with different heat contents and purity, is collectively referred to as "steam coal" or "thermal coal." We collect monthly province-specific prices of steam coal using the China Steam Coal Price Index from the Price Monitoring Center of NDRC. The index is based on data collected from 1,600 firms that rely on coal as the main fuel source, including major coal-fired power plants and heating facilities. Prices of coal used for coking are based on prices in Ganqimaodu in Inner Mongolia, a major hub of coking coal distribution.

enables power plants to substitute across different coal types in the event of shortages. Other end users such as heating facilities are likely even less sensitive to coal quality. As we will show next, thermal and coking coal prices are highly correlated. Therefore, we construct an average price for each province and month based on the two price series weighted by their consumption shares.

Figure 4: Time-Series Data of the Coal Market



Notes: Panel (a) plots the prices of steam coal, coking coal and the composite price, (b) plots the national monthly production, (c) plots the monthly national capacity, which is adjusted from the capacity that changes every 6 months for the number of working days in each month (our capacity data end at the end of 2018), (d) is the utilization factor, defined as national monthly production divided by capacity, (e) is the national monthly consumption, and (f) is the national inventory. The vertical line indicates the start of the supply reduction policy.

4.2 Data Summary

4.2.1 National Time Series

We plot the time series of the national coal prices, production, capacity, utilization factor, inventory and consumption in Figure 4. Coal prices shown in (a) increased significantly for both coking and steam coal as the policy started in Shanxi in April 2016. The prices remained higher throughout 2017 and 2018 and gradually decreased in 2019 after the policy pressure eased. We plot the monthly production in (b). The production in 2016 was noticeably lower than similar periods both before and after the policy.

The supply squeeze was a result of two aspects of the policy. First, the government closed coal mines and suspended new approvals, resulting in a net decrease in capacity as shown in (c). Second, the campaign to reduce over-production above approved capacity levels directly limits output. In (d), we plot the utilization factor, defined as the production-to-capacity ratio. This ratio in 2017 and 2018 (post-policy) is lower than or comparable to 2014–15, despite significantly higher prices in 2017 and 2018. The utilization factor is also lower in 2016 than in 2017–2018, reflecting more stringent enforcement in 2016 (the 276-working-day policy).

In (e) and (f), we find that the market went through a transition in 2016. The figure (e) shows that consumption has a more muted response in 2016 than production. Excess demand over production corresponds with an over 40% decrease in inventory (Figure 4.(f)) during the rapid price increase in 2016.[25] The inventory stabilized at a lower level in 2017 and 2018, when production increased above 300 million tons per month, matching the level of consumption.

[25] Monthly foreign imports also increased by about 10 million tons per month in 2016 and remained at about 20 million tons per month post-policy.

Table 1: Summary Statistics

	Mean	SD	p25	Median	p75
Panel A. Coal-Consuming Provinces					
Consumption (Million Tons/Month/Province)	10.16	7.63	4.62	7.47	13.30
Price (RMB/Ton)	532.01	133.87	430.21	523.03	615.45
Wind Generation (TWh/Month/Province)	0.53	0.73	0.06	0.29	0.70
Cooling Degree Days (°C/Month/Province)	17.77	38.16	0	0	11.12
N=1440; based on 30 coal-consuming provinces in 2014–2017					
Panel B. Coal-Producing Provinces					
Quantity (Million Tons/Month/Province)					
Supply	11.30	19.91	1.20	3.61	9.98
Capacity	11.21	17.85	1.59	5.18	12.40
N=1200; based on 25 coal-producing provinces in 2014–2017					
Panel C. Foreign Import					
Quantity (Million Tons/Month)	18.12	4.97	14.00	17.55	21.82
N=48; 2014–2017					

Notes: Panel A shows summary statistics for 30 coal-consuming provinces. The demand consists of shipments from Chinese provinces and foreign imports. Coal consumption is aggregated from consumption in all sectors using coal for each province (Appendix D). The price is the quantity-weighted average of thermal and coking coal prices plus a calibrated transportation cost (Appendix F) based on coal origins. We also use monthly wind generation and cooling degree days in the analysis. Panel B reports summary statistics for 25 coal-producing provinces. Supply is the sum of all shipments from that province each month. Capacity is aggregated from the mine-level data from NEA. Panel C reports total imports.

4.2.2 Summary Statistics

For the main analysis of the paper, we focus on the years from 2014 to 2017.[26] Table 1 summarizes our main data set. There are 30 coal-consuming provinces and 25 coal-producing provinces. All coal-producing provinces also consume coal. The reported prices include transportation costs based on coal origins, which account for approximately 17.5% of the composite price.[27]

[26] CCTDA's cross-province shipment data are available through 2016, and its production data are available through 2017. We cross-validate both datasets using NBS statistics. For subsequent years, NBS reports province-level monthly production, except for January and February.

[27] Appendix F details how we calibrate the transportation costs.

Table 2: Mean and Standard Deviation of Cross-province Shipment Shares, 2014–2016

	Inner Mongolia	Shanxi	Shandong	Hebei	Jiangsu	Shaanxi	Henan	Liaoning	Guizhou	Xinjiang
Inner Mongolia	0.392	0.011	0.049	0.017	0.064	-	0.002	0.082	-	-
	[0.014]	[0.002]	[0.008]	[0.003]	[0.010]	-	[<0.001]	[0.003]	-	-
Shanxi	0.006	0.298	0.104	0.231	0.103	0.002	0.055	0.017	-	0.001
	[0.002]	[0.013]	[0.007]	[0.029]	[0.012]	[0.001]	[0.012]	[0.002]	-	[0.001]
Shaanxi	0.004	0.148	0.086	0.039	0.101	0.411	0.059	-	0.001	-
	[0.001]	[0.020]	[0.049]	[0.010]	[0.027]	[0.070]	[0.007]	-	[0.001]	-
Guizhou	-	-	-	-	-	-	-	-	0.740	-
	-	-	-	-	-	-	-	-	[0.025]	-
Shandong	-	-	0.857	0.012	0.033	-	0.008	0.002	-	-
	-	-	[0.016]	[0.005]	[<0.001]	-	[0.001]	[<0.001]	-	-

Notes: The table reports the shipment shares of the five largest coal-producing provinces to the ten largest coal-consuming provinces, averaged over 36 months between 2014 and 2016. The share is calculated as a month's shipment from i to j divided by the total shipment from i in the month. The standard deviations are reported in square brackets.

4.2.3 Cross-province Shipment Shares Are Stable Over Time

We show that the share of a province's coal production transported to another province is highly stable over time. This important empirical fact will guide the modeling decisions in the model. In Table 2, we report the mean and standard deviation (in square brackets) of the shipment shares from province i to province j, defined as $\frac{Q_{ijt}}{Q_{it}}$, where Q_{ijt} is the tonnage of coal produced in i and transported to j, and Q_{it} is the total production in i in month t. We list the five largest coal-producing provinces on the row and the ten largest coal-consuming provinces across columns. The standard deviation for the majority of province pairs is negligible relative to the mean, indicating a high degree of stability in shipment shares over time.

There are two possible reasons for this stability despite substantial variation in coal prices over time. First, the government and railway operators allocate railway capacity when coal buyers and sellers enter into long-term contracts. The rail capacity allocations create rigidity within the duration of long-term contracts, as any significant rerouting of shipment across provinces could create cascading disruptions in the interconnected rail network. This constraint incentivizes coal buyers to switch between suppliers within a given province even when coal buyers procure coal from outside their long-term contracts. Second, although power plants can substitute across different grades of coal to some extent through coal-blending technology, they still tend to prefer similar coals when purchasing on the spot market, because coal blending can add to the plants' operating costs (Zhao, 2021). Since mines within the same province are more likely to produce similar grades of coal, they may supply to the same set of power plants, consistent with stability across multiple years.

We also find support for these structural reasons in explaining the rigidity of shipment shares. Between 2014 and 2016, the log difference between the highest and lowest coal prices across provinces varies between 0.62 and 0.94.[28] If shipment shares could change flexibly in response to price differentials, we would expect to observe strategic shipping behaviors to exploit the arbitrage opportunities, keeping price dispersion relatively constant. Instead, the observed persistence of price differentials points to a lack of such strategic behaviors. Our model below thus focuses on production decisions as opposed to shipment destination choices.

[28] The log difference of 25th–75th price levels ranges from 0.12 to 0.35.

5 Coal Demand

We specify coal consumption in province j and month t as

$$\ln q_{jt}(p_{jt}) = \alpha^D \ln p_{jt} + \beta_X X_{jt} + FE_j^{\text{demand}} + FE_{m(t)}^{\text{demand}} + \varepsilon_{jt} \tag{4}$$

where the quantity q_{jt} corresponds to the consumption of coal in province j, and p_{jt} represents the composite coal price in the province.[29] The parameter α^D has the straightforward interpretation of price elasticity. The covariates include province j's one-month lagged cooling degree days (CDD) and wind generation, which affect the local electricity residual demand for coal power plants, and an indicator for 2017 to capture any potential change in demand in response to the policy. We also include fixed effects for the province and the month of the year. The term ε_{jt} captures the unobserved demand shock.

We treat wind generation as largely exogenous to the unobserved shocks ε_{jt} for two reasons. First, wind power build-out is primarily driven by centrally planned investment that targets areas rich in wind resources (State Council, 2014). Second, NDRC directs local governments and the power grid to guarantee priority dispatch and full purchase of wind generation (NDRC, 2016*c*). Given these policies, we assume wind production to be driven by an exogenous long-term trend plus local and short-run weather conditions, which generates exogenous variations in residual demand for coal generation.

Static Demand Assumption In theory, the coal purchase decisions can be dynamic, where coal users can use existing inventory to smooth consumption when prices change (Jha, 2023). Our demand function is static, because coal consumers do not store large quantities of coal in our context. Specifically, NDRC requires coal power plants to keep enough stock for at least 7 days of operation, but explicitly caps inventories at no more than 12 days in peak seasons (NDRC, 2021*a*). A historically high value in 2024 is just 27 days (CCTV News, 2024). Major steel plants keep a similar level of coal inventory (BOCI, 2017). This practice contrasts sharply with the norm in the US, where over 90% of coal power plants keep enough coal to generate electricity for over 60 days (EIA, 2023). We also note that, although there may still be arbitrageurs with sizable capacity, such as dedicated coal traders storing coal at ports, the model in (4) focuses on coal consumption by end users instead of shipment. In our counterfactual analysis, we focus on the "steady state" of the market, where demand matches the level of consumption in the markets before 2016 or in 2017, and the inventory

[29] We note that there may exist potential differences between spot prices and the re-adjusted prices facing buyers and sellers on long-term contracts. Because we do not have contract prices or order-level prices, we use the spot prices as a first-order approximation for sales in a province.

level was roughly stable over time (Figures 4.(e) and (f)).

5.1 Identification

The equilibrium price may be correlated with the unobservable ε_{jt}. We construct shift-share instrumental variables that exploit the timing and exposure differences of provinces to the production restrictions as documented in Section 3.3.1.

Instrumental Variables (IV)

There are three potentially useful variations:

1. The policy started first in Shanxi in April 2016, followed by other provinces in May.
2. The policy imposes stricter monitoring programs on the production of state-owned enterprises (SOEs), and the share of production by SOEs differs across provinces.
3. The policy closed small coal mines, and the cutoff thresholds differ across provinces.

In each province, the variations in policy timing (first variation) and intensity (the second and third variations) shift the local supply through the largely fixed shipment shares (Section 4.2.3). Importantly, because the demand function (4) already accounts for policy effects through the 2017 indicator, our excluded instruments are based on purely supply-side variations in 2016, when the policy rolls out across provinces at different times and enforcement intensity differs from 2017 (the 276-working-day policy in 2016). Specifically, we use χ_{it} to denote whether the policy has applied to province i's supply in month t, and for each province j in month t, we define (1) a timing IV

$$Z_{jt}^{\text{Timing}} = \sum_i w_{ij}^{2012-2013} \chi_{it}, \tag{5}$$

where $w_{ij}^{2012-2013}$ is the coal shipped from i to j divided by the total shipment to j, averaged across months from 2012 and 2013 (before the estimation sample), which captures j's historical dependence on coal from i.[30] We also define (2) an SOE IV,

$$Z_{jt}^{\text{SOE}} = \sum_i o_i w_{ij}^{2012-2013} \chi_{it}, \tag{6}$$

[30] We find that the shares of shipment from a province, w_{ij}, just like the shares of shipment to a province in Section 4.2.3, are stable over time during our sample. We argue in Section 4.2.3 that structural reasons not due to changing prices are likely responsible for the rigidity.

where o_i is the output share[31] of key SOEs in province i, also averaged across months from 2012 and 2013. In the above, the interactions between o_i and $w_{ij}^{2012-2013}$ proxy the exposure differences to the supply policy shocks. Finally, we define (3) a capacity IV,

$$Z_{jt}^{\text{Capacity}} = \sum_i K_i^{\text{Small}} w_{ij}^{2012-2013} \chi_{it}, \tag{7}$$

and K_i^{Small} is province i's capacity in January 2014 below the province's cutoff thresholds for closure during the policy in 2016.[32]

IV Validity

Our IVs exploit the independence between demand shocks and the shipment shares' interaction with χ_{it} conditional on province fixed effects and month-of-the-year fixed effects, which is the key assumption for the validity of Bartik-type shift-share instruments (Goldsmith-Pinkham, Sorkin and Swift, 2020). The assumption relies on the fact that the variations in policy timing (the policy started in Shanxi first) and levels of reductions (SOEs' production is more restricted) are primarily due to policymakers targeting the largest coal mines to produce fast results (Appendix B), as opposed to correlations with demand shocks. In particular, the two largest provinces' SOEs significantly reduced their production in 2016 (Appendix I.2).

One potential concern with the exclusion restriction of the shift-share IVs is a correlation between policy start times and other economic policies. We note that the 2015-2016 economic stimulus plan is a nationwide policy that generally eases the borrowing constraints for transportation projects, such as the national network of high-speed rails (HSR). A correlation with our instruments may arise when the first province to enact the policy, Shanxi, is also a major supplier to provinces with more infrastructure projects in April that would use more coal. Appendix E lists major active infrastructure construction projects in April and May of 2016. The large volumes of concrete and steel used in these projects could generate substantial demand for coal and coke. We find no clear correlation between the locations of these projects and Shanxi's main destination provinces—Shanxi, Hebei, Shandong, and Jiangsu—which together account for over 70% of Shanxi's output (Table 2).

[31] Ideally, we should use capacity shares to construct the IV because there can be potential serial correlations in unobservables. We do not have capacity data for SOE mines. The main assumption is that any serial correlation of production between 2013 and 2016 is negligible.

[32] Following the official policy document, the capacity cutoffs for "small" coal mines to be closed are 0.3 million tons/year for major coal-producing provinces: Shanxi, Inner Mongolia, Shaanxi, and Ningxia, 0.15 million tons/year for Hebei, Liaoning, Jilin, Heilongjiang, Jiangsu, Anhui, Shandong, Henan, Gansu, Qinghai, and Xinjiang, and 0.09 million tons/year for the remaining provinces.

Another concern is that policy timing may be endogenous if coal buyers anticipated the policy and stockpiled coal in advance. Policy guidance and common industry practices discussed previously show that major end users of coal do not have significant storage capacity. National coal inventory data from NBS in Figure 4 show that the inventory actually declined before the policy, suggesting that the policy is likely a surprise.

5.2 Estimation

To understand the strengths of the IVs and the underlying variations they capture, we report the first-stage results in Table 3. Columns (1)–(3) regress the natural log of prices on each instrument in the previous section. We find that the results are intuitive. Shanxi's early policy implementation raises the prices in provinces more exposed to its supply. Similarly, prices are higher in provinces where a greater mix of supply historically comes from SOEs or small mines, and given the timing difference, particularly Shanxi's SOEs and small mines. The F statistics indicate that the timing and SOE IVs are considerably stronger.

Table 4 reports the second-stage results based on the instruments in Table 3. We use the estimated elasticity of -0.635 based on the timing and SOE IVs in column (5) as our primary specification. Notably, the stronger IVs in columns (2), (3) and (5), based on policy timing, SOEs and their combination, all imply similar demand elasticities. Although the estimate based on the weaker IV of small mine capacity (column (4)) is larger, the estimate in our primary specification is not rejected at the 95% confidence level. The IV estimates are considerably different from the positive OLS estimate in column (1). In comparison, prior work (Burke and Liao, 2015) has estimated the elasticity for coal demand to be between -0.3 and -0.7. Finally, we note that our results are robust to using the different IV estimates.

Table 3: Demand Estimation: First-Stage

	(1) Timing	(2) SOE	(3) Small-Mine Capacity	(4) Timing+SOE
Z_{jt}^{Timing}	0.075***			0.017
	(0.014)			(0.029)
Z_{jt}^{SOE}		0.147***		0.117**
		(0.023)		(0.049)
Z_{jt}^{Capacity}			0.086**	
			(0.034)	
Wind Generation (TWh)	-0.067***	-0.066***	-0.056***	-0.067***
	(0.025)	(0.025)	(0.021)	(0.025)
CDD/1000	0.260***	0.249***	0.335***	0.249***
	(0.084)	(0.085)	(0.100)	(0.085)
Province FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Kleibergen-Paap F Statistic	25.46	37.84	6.057	19.65
N	1440	1440	1440	1440

Notes: The table reports the first-stage results based on various IVs. The dependent variable is the $\ln$ price in each province and month.

Table 4: Demand Estimation

	OLS	Second-Stage Results Based on Each Set of IVs			
	(1)	(2) Timing	(3) SOE	(4) Small-Mine Capacity	(5) Timing+SOE
$\ln p_{jt}$	0.115***	-0.696***	-0.619***	-1.258***	-0.635***
	(0.031)	(0.218)	(0.201)	(0.478)	(0.203)
Wind Generation (TWh)	-0.039**	-0.081***	-0.077***	-0.110***	-0.078***
	(0.016)	(0.026)	(0.023)	(0.039)	(0.024)
CDD/1000	0.465**	0.742***	0.716***	0.934***	0.722***
	(0.219)	(0.237)	(0.229)	(0.296)	(0.231)
Province FE	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES
N	1440	1440	1440	1440	1440

Notes: The table reports OLS and IV estimates of the demand model. The dependent variable is the log of demand (shipment into a province and imports). Column (1) is the OLS result. Columns (2)-(5) are results based on various IVs.

6 Coal Supply

Our supply model incorporates two key institutional features of China's coal industry. First, the coal market is not concentrated. In Appendix I.3, we plot the combined output shares of the three largest coal-mining firms (based on the output in the key SOE production data) in each of the top five coal-producing provinces. No single firm has more than 30% of the output share in a province, and the share of the third largest firm is often below 11%. Second, as we show in Section 5.1, the share of supply from one province to another is highly stable over time.

Motivated by these two observations, we specify the aggregate marginal cost function at the province level as

$$\ln \mathrm{mc}_{it} = \alpha^S \frac{q_{it}}{K_{it}} + FE_i^{\text{supply}} + FE_{m(t)}^{\text{supply}} + \xi_{it}, \tag{8}$$

where K_{it} is the capacity in province i in month t, which is taken as given in the data, and we include fixed effects at the province and month level. We assume that, in equilibrium, the marginal cost matches the effective price $P_{it} = \sum_j s_{ij} \left(p_{jt} - \tau_{ij}\right)$, where s_{ij} is the share of coal shipped from i to j in the total shipment from i,[33] p_{jt} is the price in the destination province j, and τ_{ij} is the transportation cost calibrated following the procedure in Appendix F.[34]

Behavioral Foundation

The marginal cost function (8) implies the supply curve $\frac{Q_{it}(P_{it})}{K_{it}} = \gamma \ln P_{it} + \widetilde{FE}_i^{\text{supply}} + \widetilde{FE}_{m(t)}^{\text{supply}} + \tilde{\xi}_{it}$, where $\gamma = \dfrac{1}{\alpha^S}$, with fixed effects and shocks also appropriately transformed. The supply function can be microfounded as the aggregate decisions of many atomistic, competitive mines. Suppose each producer in province i sells a share s_{ij} to province j. The cost function is given by $c\,(q;\theta)$, where the cost parameter θ differs across mines and follows the distribution Θ_i. The total mass of the mines is $\mathcal{M}$. Slightly abusing notation, we use $a_{\theta t}$ to denote this producer's output decision, which satisfies the first-order condition $P_{it} = c'\left(a_{\theta t};\theta\right)$. Under the assumptions that the marginal cost function c' is strictly monotonic in $a_{\theta t}$ for any θ, we can then invert the production decision as $a_{\theta t} = c'^{-1}\left(P_{it};\theta\right)$. Integrating both sides with respect to $\Theta_i\left(\theta\right)$ and multiplying the total mass of the mines $\mathcal{M}$ yield an aggregate supply curve as a function of P_{it}, and appropriate choices of c and Θ_i would give the specific exponential form.

[33] We use the average shares as in Table 2, and the results are similar if we use just any one year's data to construct the shares.

[34] We also include the resource tax in the effective price.

A caveat of this microfoundation is that the effective price P_{it} would no longer be a sufficient statistic for all relevant prices if the output share s_{ij} is heterogeneous across individual mines. In the extreme case, each mine may supply coal to only one destination province, as opposed to splitting its output across provinces. Although we do not have mine-level data on output and shipment, we can rule out this extreme case based on news reports where large mines routinely supply to buyers in multiple provinces (Xinhua, 2016; China Securities Journal, 2017; Xinhua, 2018).

Static Supply Assumption

We assume that the coal output decisions are static. According to our interviews with industry practitioners, mine owners plan production based on current prices, and dynamic factors such as the amount of unexcavated coal or interest rates do not appear to be first-order drivers of their production decisions. For context, the coal reserves in China are close to 150 billion tons, while the annual production varies between 3 and 4 billion tons, with a similar amount of new reserves discovered every year.

Supply Function After Policy

Given that we observe only 25 provinces and the enforcement intensities differ in 2016 and 2017, our model of the policy effects is necessarily parametric. We consider two specifications. The first estimates the policy effects as a proportional and province-specific change in the aggregate marginal cost curve:

$$\ln \mathrm{mc}_{it} = \alpha^S \frac{q_{it}}{K_{it}} + FE_i^{\text{2016 policy}} + FE_i^{\text{2017 policy}} + FE_i^{\text{supply}} + FE_{m(t)}^{\text{supply}} + \xi_{it}. \tag{9}$$

In the above, $FE_i^{\text{2016 policy}}$ reflects the proportional reduction in output under the 276-working-day policy in 2016, and $FE_i^{\text{2017 policy}}$ reflects the adjusted enforcement intensities in the following year.

We note that the policy may raise the marginal costs significantly more when production is closer to and past the approved capacity levels. The functional form in (9) allows for this feature when the enforcement terms are positive. At the same time, we note that the policy shifts the focus from reducing all coal mines' output in 2016 to more targeted enforcement of overproduction in 2017 (NDRC, 2017*b*). Smaller and higher cost mines are subject to more intense scrutiny, which may translate to a larger increase in the aggregate marginal cost near capacity. Therefore, a potentially more flexible specification allows the policy to affect α^S (thus further tilting the marginal cost) after production reaches a certain threshold. We thus consider the following alternative specification similar to Ryan (2012), which replaces the policy effect in 2017, $FE_i^{2017 \text{ policy}}$, with a term that directly depends on quantity:

$$\ln \text{mc}_{it} = \alpha^S \frac{q_{it}}{K_{it}} + FE_i^{2016 \text{ policy}} + \alpha^{S,\text{policy}} \chi_{it}^{2017} \left(\frac{q_{it}}{K_{it}} - \nu \right)_+ + FE_i^{\text{supply}} + FE_{m(t)}^{\text{supply}} + \xi_{it}, \quad (10)$$

where χ_{it}^{2017} is an indicator for whether t is in 2017, and $(x)_+ = \max(x, 0)$. The term $\left(\frac{q_{it}}{K_{it}} - \nu\right)_+$ captures the additional effect of the policy on marginal costs when production is close to capacity through the cutoff ν, which is a parameter to be estimated. In the extreme case where β is large, the policy mimics an efficiently implemented quota within a province, and the quota level is νK_{it}. A trade-off of this specification is that we capture province-specific policy effects only up to the approved capacity K_{it}. In the counterfactual exercises later, we report results from both specifications.

6.1 Identification

The supply function and the resulting estimation equation can be written in the general form

$$\ln P_{it} = g\left(q_{it}, X_{it}^{\text{supply}}\right) + \xi_{it}, \quad (11)$$

where q_{it} is correlated with ξ_{it}, and there is a vector of exogenous covariates X_{it}^{supply} that accounts for province capacities, locations and time. A sizable literature (e.g., Newey and Powell, 2003) studies the nonparametric identification and estimation of models in this form. In addition to requiring instruments that are mean or quantile independent of the unobservables, the instruments should induce sufficient variations in q. We use demand shifters in (4) as instruments for the supply (Wright, 1928). The excluded instruments include wind generation, the one-month lagged CDD and the exponential of demand residuals, which we assume to be orthogonal to shocks to coal's production costs (MacKay and Miller, 2024; Döpper et al., 2024).[35] We additionally include their interactions with the 2017 indicator.

[35] It is sufficient to use the observed demand shifters to precisely estimate (9), and the results are similar to those in Table 5. We find that the demand residuals are essential for precisely estimating the more nonlinear model of (10).

Table 5: Supply Estimation

	(1) Proportional Policy Effect	(2) Threshold Policy Effect
α^S	1.785***	1.363***
	(0.265)	(0.484)
$\alpha^{S,\text{policy}}$		1.146**
		(0.510)
ν		0.461***
		(0.104)
Province FE	YES	YES
Month FE	YES	YES
N	1200	1200

Notes: The table reports GMM estimates of the supply model. Prices faced by domestic producers in each province are constructed as weighted averages of destination prices net of calibrated transportation costs, where the weights correspond to each destination's share in total shipments from the province. "Proportional Policy Effect" model is the supply function in (9), and the "Threshold Policy Effect" model is the supply function in (10). In both cases, standard errors are clustered at the province level.

6.2 Estimation

Column (1) of Table 5 reports the estimates of the supply function that assume proportional, province-specific policy effects in (9), and column (2) reports the estimates of the supply function (10) where the policy effects in 2017 are threshold-based. To further visualize the cost functions and the cost increases in 2017, we plot the aggregate marginal cost functions for the largest coal-producing provinces, Shanxi and Inner Mongolia, before and after the policy in Figure 5. The aggregate marginal cost increases are similar in both models when production is close to capacity.

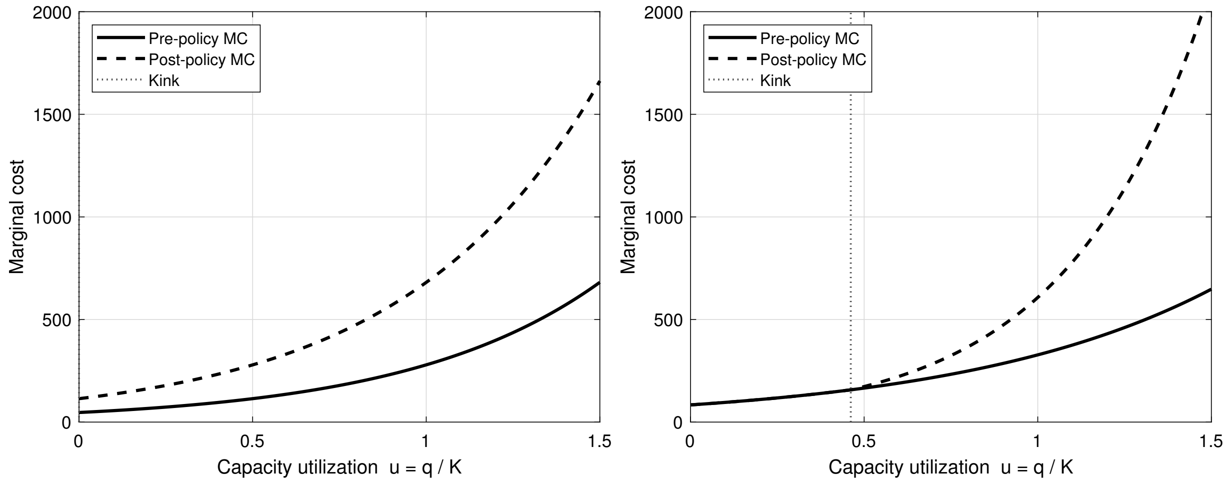
We interpret these increases as reflecting two factors. First, the policy may impose direct compliance costs, such as halting production for inspections. Second, by preventing low-cost mines from operating above capacity, the policy reallocates output toward higher-cost mines, shifting the production mix toward costlier producers and raising aggregate marginal costs for any given total quantity.

The two models also imply similar supply elasticities. In the model of proportional policy effects, the average supply elasticities at the observed quantity are 0.51 in Shanxi, 0.43 in Inner Mongolia, and 0.77 in all provinces before 2016, and 0.63 in Shanxi, 0.52 in Inner Mongolia, and 0.72 across all provinces in 2017. In the model of threshold policy effects, the average supply elasticities at the observed quantity levels are 0.67 in Shanxi, 0.56 in Inner Mongolia, and 1.01 in all provinces before 2016, and 0.45 in Shanxi, 0.37 in Inner Mongolia,

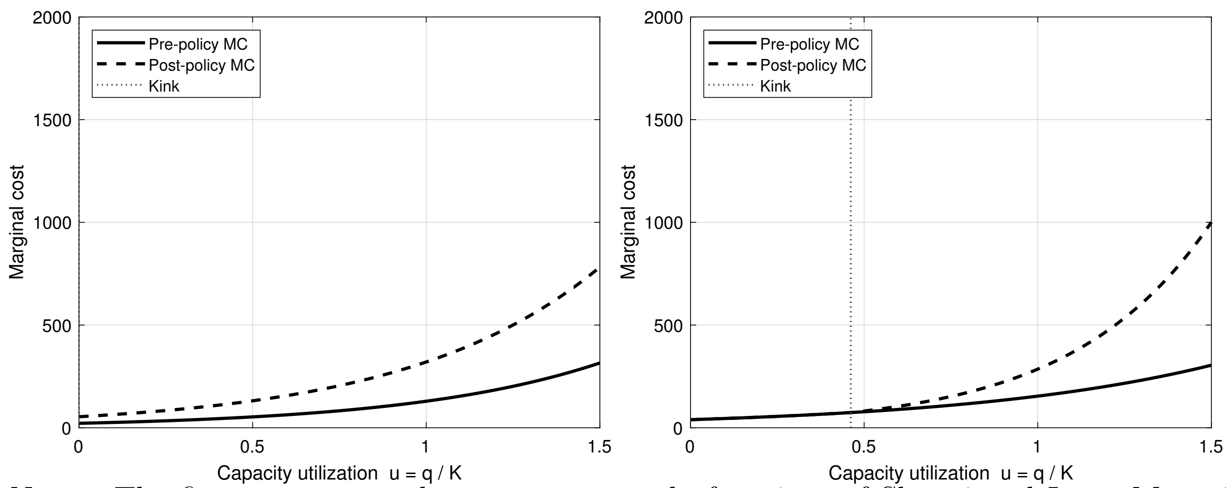
Figure 5: Estimated Aggregate Supply in the Two Largest Coal-Producing Provinces (Shanxi and Inner Mongolia)

Proportional Policy Effects Threshold Policy Effects

(a) Shanxi

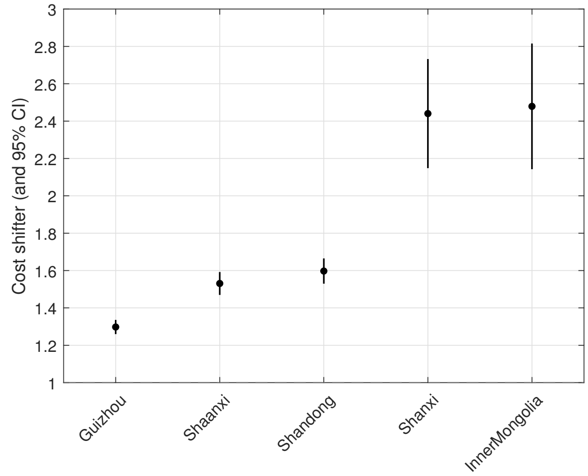


(b) Inner Mongolia



Notes: The figures compare the aggregate supply functions of Shanxi and Inner Mongolia with and without policy effects in 2017.

Figure 6: Policy Effects in the Five Largest Coal-Producing Provinces (Proportional Policy Effects)



Notes: We plot the estimated proportional increase of marginal costs, $\exp\left(FE_i^{2017\text{ policy}}\right)$, and the associated 95% confidence intervals.

and 0.55 across all provinces in 2017.

For the model of proportional policy effects, Figure 6 breaks out the estimated increase in marginal costs in 2017 (relative to pre-policy periods), $\exp\left(FE_i^{2017\text{ policy}}\right)$ for the five largest coal-producing provinces. The largest increases occur in the two largest coal-producing provinces, Shanxi and Inner Mongolia, where aggregate production costs increase by 2.5 times. Overall, policy effects are larger in lower cost provinces: the scale of cost increase is negatively correlated with the average variable costs, with a correlation coefficient of -0.386. A main reason for the greater proportional reduction in lower-cost provinces is that the policymakers wished to see fast results, emphasizing "breakthroughs" in key coal-producing provinces (Appendix B).

Finally, we compare the average variable costs with costs reported in financial statements of publicly listed coal mining firms in 2014–2016. We plot these costs in Appendix Figure I.6. The estimated and reported costs are well aligned, with a correlation coefficient of 0.557 for the proportional effect model and 0.552 for the threshold policy effect model. For example, we find that Xinjiang and Inner Mongolia have the lowest production costs, consistent with more open-pit mining in these provinces.

7 Counterfactual Simulation

We begin by defining the equilibrium given a set of shocks. Let $\mathcal{J}$ denote the set of coal-consuming provinces, $\mathcal{I}$ for the coal-producing provinces and τ_{ij} for the transportation costs.

Definition. In period t, an equilibrium consists of a set of delivery prices $\{p_{jt}\}_{j\in\mathcal{J}}$ and production quantities $\{Q_{it}\}_{i\in\mathcal{I}}$ that satisfy (4) and (11), where a province j's demand is given by $q_{jt} = \sum_{i\in\mathcal{I}} s_{ij}Q_{it}$, and the price facing producers in province i is $P_{it} = \sum_j s_{ij}(p_{jt} - \tau_{ij})$.[36]

The supply reduction policy of the reform has two main effects: (1) it reduces capacity by closing small mines and halting new entry, and (2) it tightens enforcement by closely monitoring remaining mines to prevent production above approved capacity. Because we lack mine-level data on entry and exit, we take capacity as given and focus on the enforcement effects—how stricter enforcement reduces production conditional on capacity. Our estimates of economic surplus should be interpreted as the sum of consumer surplus and variable profits, which do not account for investment or fixed costs. In all simulations, we allow foreign imports to respond endogenously, following an estimated import supply function.[37]

7.1 Enforcement Effects

Our first simulation quantifies the enforcement effects of the policy. We remove the estimated shifts in supply and re-compute the expected equilibrium outcomes. For the supply model (9) of proportional policy effects, we set the $FE^{2017\text{ policy}} = 0$, and for the model (10) of threshold policy effects, we set $\alpha^{S,\text{policy}} = 0$. We assume that the demand and supply shocks at the province level follow an AR(1) process, and we also simulate forward the processes of CDD and wind generation.[38] We report the 2.5%–97.5% range and the average of market outcomes based on 300 simulation paths.

Figure 7 compares the average equilibrium prices and production under the no-policy simulation with observed outcomes under the policy, holding fixed the capacity as observed in the data. The simulations align closely with the data before the policy. We further show in Appendix I.5 that either supply model can match province-level production despite the parsimonious specifications. We find that, absent the policy, prices would have been about RMB 550/ton in December 2016 as opposed to nearly RMB 700/ton in the data. The quantity would have been nearly 50% higher.

[36]We can establish the equilibrium existence by first constructing closed intervals of prices and quantities on which the equilibrium conditions map the extrema of the intervals back into the intervals using the monotonicity of the demand and supply functions and the fact that their range is $(0, \infty)$. Then an application of Brouwer's fixed point theorem shows existence. For uniqueness, we do not find multiple equilibria in our simulations.

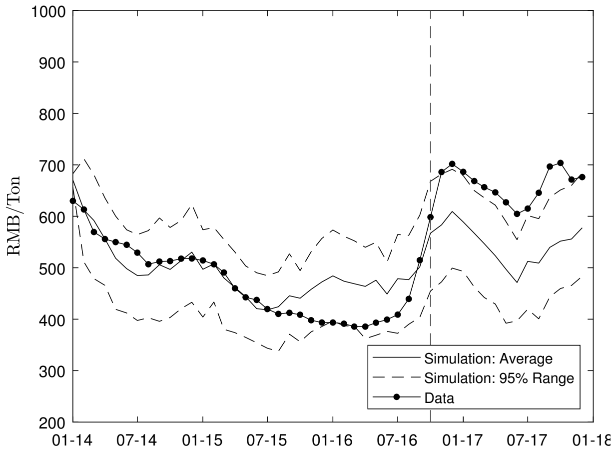
[37]Our shipment data show that the share of imports to each province is also stable over time and allows us to construct a similar effective price for imports. We estimate the import supply elasticity in a log-log specification. An OLS regression based on data from 2014 to 2017 (48 months) yields an estimate of 1.35, with a robust standard error of 0.15. A corresponding IV estimation produces nearly identical results.

[38]Appendix G reports the estimates of these processes.

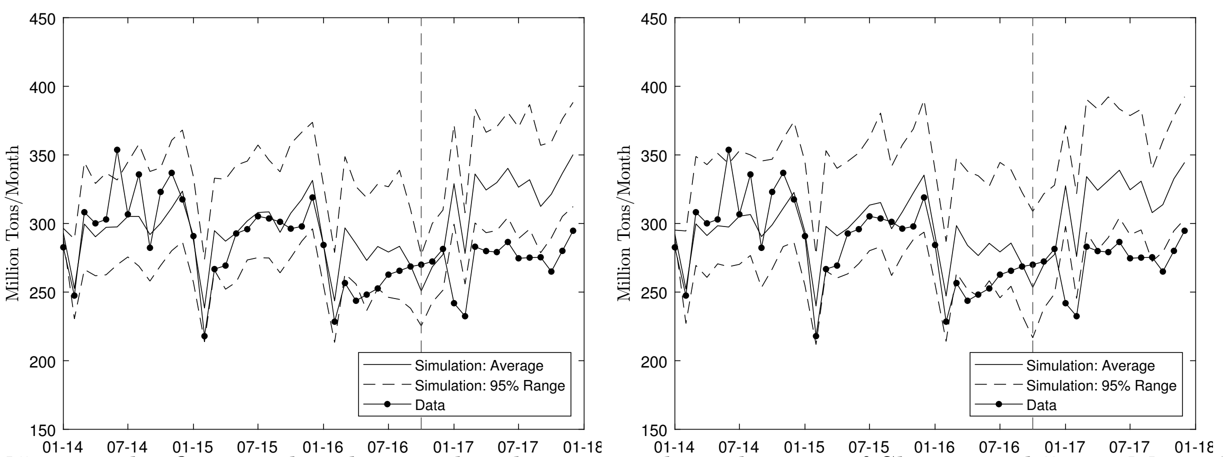
Figure 7: Prices and Production With and Without the Policy

Proportional Policy Effects Threshold Policy Effects

(a) Average Price



(b) Production



Notes: The figures plot the simulated prices and production of Shanxi and Inner Mongolia from 300 simulations in a no-policy counterfactual. We plot the simulated 2.5%–97.5% range, the average and the data paths (with policy). The vertical lines indicate the start of the policy.

Welfare Effects

Table 6 presents the welfare effects of the policy in 2017 relative to a no-policy counterfactual. We focus on 2017 because inventory adjustment was unusually large in 2016: between April and December 2016, a substantial inventory drawdown contributed to the consumption by coal's end users. By 2017, inventory levels had largely stabilized, so consumption more closely tracked production. This makes 2017 the appropriate period to apply our equilibrium framework, in which demand reflects consumption and supply maps production to consumption without a sizable inventory-change component. We simulate the market outcomes with and without the policy effects using the estimated time-series processes for shocks and other covariates conditional on their values in the last month of 2016.[39]

Column (1) estimates the loss of economic surplus and saved environmental costs from restricting production based on the supply model of proportional policy effects. The total loss in economic surplus amounts to RMB 479 billion, which is 0.6% of China's GDP in 2017. At the same time, producer surplus increases by RMB 39.5 billion, consistent with the policy objective of improving the profitability of the coal industry. The changes in resource tax revenues are relatively small because of the low tax rates. Saved environmental costs, including reduced air pollution, water depletion and costs of carbon almost completely offset the economic cost of the policy. The resulting total welfare loss is just 5% of the economic surplus loss.

Column (2) reports the results based on the supply model of threshold policy effects. The estimates imply a greater increase in producer surplus due to the policy. This is not surprising, because we estimate smaller increases of inframarginal costs, and the policy effects are more similar to a quota compared with the supply model of proportional effects. The estimates show that the net effect of the policy is positive, after taking into account the policy's environmental impact.[40]

[39]It is possible that the time-series processes before and after the policy may differ. We find that all of our results are qualitatively robust to using the processes estimated based on 2017 data alone.

[40]Appendix Figure I.9 breaks down the surplus changes at the province level. We see that both models predict similar consumer surplus losses for most provinces. For the producer surplus, some provinces see decreases because of increased costs based on the proportional effect model, whereas the model of threshold effects generally predicts producer surplus increases.

Table 6: Enforcement Effects of the Policy in 2017

	(1) Supply Model of Proportional Effects	(2) Supply Model of Threshold Effects
Δ Delivery price (RMB/Ton)	142.26	160.65
	[128.08, 155.89]	[146.84, 175.90]
Δ Domestic coal production (Million Tons/Year)	-620.98	-692.62
	[-636.77, -602.92]	[-763.82, -626.93]
Δ Coal consumption (Million Tons/Year)	-569.43	-642.20
	[-587.31, -551.51]	[-710.59, -580.09]
Δ Economic Surplus and Environmental Costs (RMB bn.)		
Economic Surplus	-478.90	-299.94
	[-528.58, -429.31]	[-342.91, -262.39]
Consumer	-530.45	-607.16
	[-582.84, -481.98]	[-682.74, -539.24]
Producer	39.48	292.71
	[29.49, 51.44]	[264.42, 322.67]
Resource Tax	12.08	14.51
	[10.80, 13.16]	[12.72, 16.42]
Saved Environmental Cost	453.42	516.36
	[444.17, 459.22]	[472.33, 559.70]
Air Pollution	203.28	234.92
	[196.20, 208.93]	[219.79, 250.25]
Social Cost of Carbon	167.54	188.94
	[162.26, 172.80]	[170.67, 209.07]
Water Depletion	82.60	92.49
	[80.37, 84.82]	[83.68, 102.12]
Total Surplus	-25.48	216.42
	[-75.31, 22.86]	[187.32, 256.93]

Notes: The table reports the average market outcomes and the 2.5%–97.5% range (square brackets) across simulations in 2017 at the estimated parameters. We simulate forward the equilibrium based on the shocks in the last month of 2016. We report the changes relative to the observed policy. The air pollution is calculated in Appendix H. The social cost of carbon is set at the income-adjusted level of 162 RMB/ton for China (Ricke et al., 2018), and we assume that one ton of consumed coal generates 1.886 tons of CO_2. We account for the environmental costs of water depletion at RMB 86.6 per ton of coal (Gu and Li, 2017).

Allocative Inefficiency

We next quantify the policy's inefficiency relative to an efficiently implemented quota. We note two types of inefficiencies. First, our estimates suggest that the policy raises inframarginal costs, which is similar to the supply rotations in the illustrative model in Section 2.3 and leads to within-province allocative inefficiency. Second, our estimates indicate greater production restrictions in larger, lower-cost provinces such as Inner Mongolia, indicating cross-province inefficiency. Although cap-and-trade, or a productivity-based production restriction, is likely infeasible given the institutional constraints, understanding these inefficiencies not only sheds light on the welfare costs of the policy, but also enables us to apply the ranking criterion in Section 2 to compare the policy with a hypothetical tax.

Table 7 quantifies the two inefficiencies. We first decompose the inefficiencies caused by the supply function shift in each province. Holding the 2017 equilibrium quantity fixed in each simulation path, we re-compute producer surplus using the pre-policy supply curve integrated up to that quantity. Columns (1) and (3) report the increase in producer surplus under the two supply models relative to the observed policy. The within-province inefficiency is large, estimated to be at least RMB 156 billion (model of threshold effects) and up to RMB 346 billion (model of proportional effects).

Next, we measure the total inefficiency. An efficient quota allocation across provinces requires the marginal surplus loss from an additional unit of reduction to be equalized across provinces. Therefore, holding fixed a time series of simulated shocks in 2017, for any total reduction ΔQ, the efficient allocation is the one implied by a uniform tax that achieves the same total reduction. We use the following procedure to find the efficient allocation: in each simulation based on the post-policy supply function, we (i) solve for the tax that delivers the same aggregate reduction in equilibrium, (ii) fix the quantities produced in each province under this tax, and (iii) compute economic surplus by integrating demand and the pre-policy supply functions up to those efficient quantities. Column (2) and (4) report the increase in producer surplus under the two supply models relative to the observed policy. We note that the within-province inefficiency accounts for 78.4% and 63.3% of the total inefficiency in the two models.

7.2 Is Tax More Efficient?

In Section 3.3.2, we discussed the political reasons why production restrictions, as opposed to a tax, are used to implement the reform. Yet, the economic question remains: is it more efficient to use a tax? If the external loss function is linear in quantity, the optimal policy is a Pigouvian tax. However, the loss function may be nonlinear if we account for

Table 7: Policy Inefficiency Relative to Efficient Quotas

	Supply Model of Proportional Effects		Supply Model of Threshold Effects	
	Within-Province (1)	Total (2)	Within-Province (3)	Total (4)
Δ Producer Surplus (RMB bn.)	345.57	441.46	155.97	246.35

Notes: The table reports the average increase in producer surplus when we correct the within-province and total inefficiencies of the policy relative to efficient quotas under the two models. The increases of the total economic surplus are RMB 394.57 billion under the supply model of proportional effects and RMB 202.76 billion under the supply model of threshold effects.

the benefits of energy transition or the costs of coal mining accidents. Section 2.3 shows that, under a nonlinear external loss function, the welfare ranking between a production restriction and a tax is theoretically ambiguous. Therefore, the production restriction vs. tax comparison shows whether the institutional constraint leads to a sub-optimal policy choice in our empirical context.

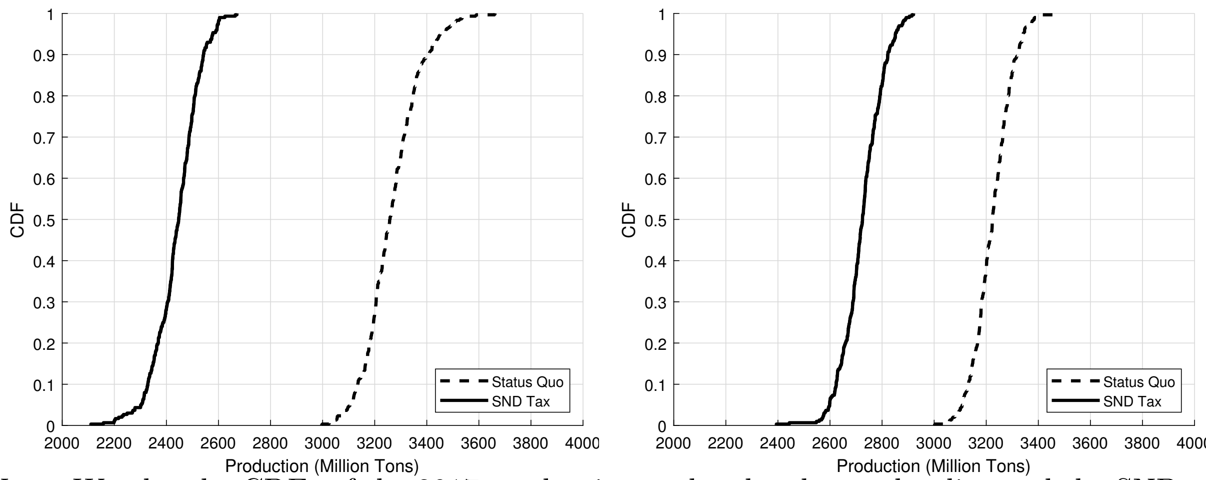
Our criterion can rank these policy instruments while being agnostic about the nature or the convexity of a general loss function that captures environmental impacts and other social costs of coal production. Consistent with Assumption 1, we assume that the external loss function increases in the aggregate production quantity.[41] This assumption aligns with most of the central government's guidelines which target a national total capacity or output. For example, the 5-year planning document (NDRC, 2016*a*) explicitly calls for an annual production target of 3.9 billion tons of coal by 2020. Furthermore, aggregate coal output is a reasonable sufficient statistic for many policy-relevant social costs, including air pollution, carbon emissions, mine-site ecological damage and mining accidents (holding capacity fixed). Finally, our results are similar if we use total consumption, due to the limited effects of imports.

To identify an SND tax, we solve for the unit tax rate that produces the same expected economic surplus as the policy. The surplus under the tax is calculated as the sum of the expected producer surplus, consumer surplus and tax revenues based on the estimated AR(1) processes of the demand and marginal cost shocks. Panel (a) of Figure 8 shows that at an SND tax level of RMB 653/ton, the CDF of the total quantity is stochastically dominated

[41] Leakage is an externality that we do not explicitly account for. Next to coal (65%), hydro (20%) had the second largest share in the power generation mix in 2016, followed by wind (4%) and nuclear (4%). Natural gas accounted for 3% of the generation mix (Göß and Niggemeier, 2017). In the long run, reduced coal consumption, especially in electricity generation, is likely to be offset by both the growth of renewable generations and increased natural gas use (EIA, 2022). Generations from these sources typically have lower local pollution intensities and carbon emissions than coal. Therefore, such substitution would still be expected to reduce the overall external loss when coal consumption falls.

Figure 8: Quantity CDFs: Production Reduction and SND Tax

(a) Supply Model of Proportional Effects (b) Supply Model of Threshold Effects



Note: We plot the CDFs of the 2017 production under the observed policy and the SND tax based on the two supply models.

by that under the observed policy given the supply model of proportional policy effects.[42] Panel (b) based on the supply model of threshold policy effects identifies a lower SND tax (RMB 487/ton). Our criterion thus suggests that a tax can increase the expected social welfare relative to the observed policy. The high SND tax is also consistent with the large economic surplus loss identified in the previous section.

Anticipation of the Demand and Supply Shocks An assumption in the application of the criterion above is that the unobservables in the demand and supply functions are also unknown to the market participants or policymakers. This assumption is important for correctly defining expected welfare, but our qualitative results on the efficiency of the tax are likely robust to weaker information assumptions. In the extreme case where the unobservables are fully known to buyers, sellers and the government, a tax would generate less allocative inefficiency and would be unambiguously more efficient than a production restriction for the same quantity target.[43]

[42] There are several ways to formally test the stochastic dominance. First, for a simple but formal statistical test, we test an even stronger condition, which is that the quantity under the SND tax based on the estimated parameters is statistically smaller than under the policy for each simulated path of shocks. More generally, given sufficiently many simulation draws, we can ignore the simulation errors and compute the maximal difference between the two CDFs over their support. The 95% confidence interval of this difference can be simulated using the asymptotic distribution of the estimated parameters.

[43] On the other hand, an optimally chosen production restriction can sometimes outperform even an optimally chosen tax given uncertainties, as we show in Section 2.3.1.

Government Weighs Producer Surplus More

Our analysis above focuses on a social welfare function where consumer surplus, producer surplus and tax revenue are weighted equally. Yet, one of the policy objectives is to raise the profitability of the coal industry, which suggests that in the government objective function, producer surplus may be valued more than consumer surplus. Furthermore, as discussed in Section 3.3.2, one reason that a tax was not chosen for the reform is the challenge of redistributing the tax revenue, which decreases the value of the tax if the government wishes to use it to compensate the coal producers. Therefore, it is reasonable to consider the following government objective function

$$\underbrace{\text{consumer surplus} + \mu \cdot \text{producer surplus} + \text{tax revenue}}_{S_\mu} - \text{external loss}$$

for a weight $\mu > 1$. We can adapt our method to rank policy instruments based on this objective function by looking for a tax that matches the re-weighted economic surplus S_μ.

At higher values of μ, restricting production becomes a more attractive policy than a tax. To see this, we note that when μ is sufficiently large, no tax can generate sufficient revenues to offset the loss of producer surplus weighted by μ. We find SND taxes for values of $\mu \leq 1.95$ under the proportional effect supply model or $\mu \leq 1.3$ under the threshold effect supply model. In other words, for the government to prefer the observed production restriction to taxation, it must value one dollar of producer surplus at least 30% more than a dollar of consumer surplus or tax revenue.

8 Conclusion

Conceptually, the paper studies the instrument-choice problem with minimal assumptions on the economic impact of externalities. We propose a criterion to rank policy instruments and apply it to China's 2016 coal supply-reduction reform. Empirically, we find that the policy tightened production conditional on capacity and shifted surplus from consumers to producers. Our criterion shows that a tax could raise social welfare and reduce total output, even though the fiscal reform required to implement such a tax can be challenging. We also show that a tax may no longer be the optimal policy if the government values producer surplus more than consumer surplus or tax revenue.

The results also underscore the challenges of transitioning to a low-carbon economy given the institutional constraints. Consistent with this observation, China has made massive investments in renewable energy. In 2024, for the first time, the share of coal in electricity generation fell below 60%, primarily driven by the growth of low-cost electricity production from renewable sources, as opposed to reduced coal consumption (Howe, 2024).

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A Proof of Theorem (1)

We prove the result for the case of a strictly increasing L. Use F_{H_1} and F_{H_2} to denote the CDFs of H_1 and H_2. Consider the difference of the expectation in Lebesgue integrals:

$$E\left(L\left(H_1\right)\right) - E\left(L\left(H_2\right)\right) = \int_0^{\overline{H}} L\left(h\right)\left(dF_{H_1}\left(h\right) - dF_{H_2}\left(h\right)\right)$$

Apply integration by parts. The difference above becomes

$$\begin{aligned} & L\left(\overline{H}\right)\left(F_{H_1}\left(\overline{H}\right) - F_{H_2}\left(\overline{H}\right)\right) - L\left(0\right)\left(F_{H_1}\left(0\right) - F_{H_2}\left(0\right)\right) \\ & - \int_0^{\overline{H}} \left(F_{H_1}\left(h\right) - F_{H_2}\left(h\right)\right) dL\left(h\right). \end{aligned}$$

Because $F_{H_1}\left(\overline{H}\right) = F_{H_2}\left(\overline{H}\right) = 1$ and $F_{H_1}\left(0\right) = F_{H_2}\left(0\right) = 0$, the difference simplifies to

$$- \int_0^{\overline{H}} \left(F_{H_1}\left(h\right) - F_{H_2}\left(h\right)\right) dL\left(h\right).$$

The monotonicity of L implies that $L' \geq 0$. Given the dominance relationship, we have

$$E\left(L\left(H_1\right)\right) - E\left(L\left(H_2\right)\right) = \int_0^{\overline{H}} \left(F_{H_2}(h) - F_{H_1}(h)\right) L'(h)\, dh \geq 0.$$

B Policy Documents

Figure B.1 provides a snapshot of the original government document for the supply reduction policy. We provide an English translation of this document in this section.

In order to implement the *"Opinions of the State Council on Resolving Overcapacity in the Coal Industry and Achieving Sustainable Development"* (Guo Fa [2016] No. 7, hereinafter referred to as the "Opinions"), and to further regulate and improve the coal production and management order, effectively resolve overcapacity, and promote the sustainable development of coal enterprises, the following notice is issued regarding related issues:

1. **Fully understand the importance of standardizing and improving the order of coal production and operation**

   Currently, the coal industry is in a serious predicament. Especially since last year, some coal enterprises have resorted to measures such as overcapacity production, compensating for price through volume, and low-price dumping to maintain production operations in an effort to seize market share. These actions have not only severely disrupted the normal order of coal production and operation but have also exacerbated the imbalance between supply and demand in the market, intensifying the difficulties faced by the industry. If these issues are not promptly curbed, the national goals and tasks related to the development of the coal industry will be difficult to achieve. All regions and enterprises must adopt a strategic perspective that promotes supply-side structural reform and effectively addresses capacity reduction tasks. It is essential to enhance overall awareness and fully recognize the importance of standardizing and improving the order of coal production and operation for facilitating the recovery and development of the coal industry. This requires unifying thought and action with the spirit of the "Opinions", taking effective measures to ensure the implementation of regulations concerning the control of overcapacity production, reduction of production volume, suspension of production during holidays, and maintenance of fair competition.

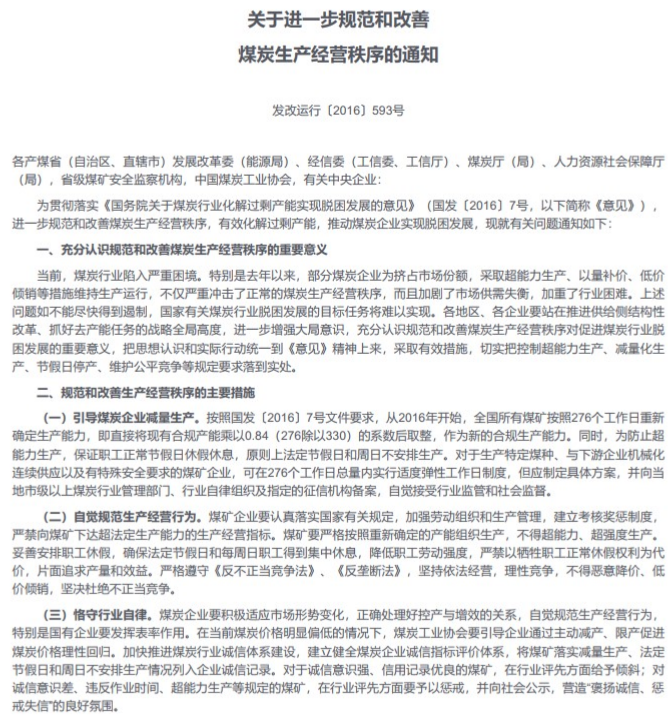
2. **Main Measures to Standardize and Improve Production and Operation Order**

   (a) **Guiding Coal Enterprises to Reduce Production Volume:** In accordance with the requirements of the State Council Document [2016] No. 7, starting from 2016, all coal mines nationwide are to re-determine their production capacity based on 276 working days. This means directly multiplying the existing compliant capacity by a coefficient of 0.84 (276 divided by 330) and rounding to the nearest whole number to establish the new compliant production capacity. Additionally, to prevent overcapacity production and ensure employees can take their normal holidays, no production should be scheduled on statutory holidays and Sundays. For coal mines producing specific coal types, providing mechanized continuous supply to downstream enterprises, or with special safety requirements, a moderately flexible working day system may be implemented within the total of 276 working days, provided that a specific plan is developed and filed with local coal industry management departments at or above the municipal level, industry self-regulatory organizations, and designated credit institutions, and that these enterprises consciously accept industry regulation and social supervision.

(b) **Consciously Standardizing Production and Operation Behavior:** Coal mines must earnestly implement national regulations, strengthen labor organization and production management, and establish a performance assessment and reward-punishment system. It is strictly prohibited to set production and operation targets that exceed the legal production capacity for coal mines. Production must be organized strictly according to the re-determined capacity, and overcapacity or excessively intense production is not allowed. Employee leave must be properly arranged to ensure that staff can rest during statutory holidays and every Sunday, thereby reducing labor intensity. It is forbidden to sacrifice employees' normal leave rights in order to pursue output and efficiency. Coal mines must strictly adhere to the "Anti-Unfair Competition Law" and the "Anti-Monopoly Law," operate in accordance with the law, engage in rational competition, refrain from malicious price cuts, and eliminate unfair competition.

(c) **Upholding Industry Self-Regulation:** Coal enterprises must actively adapt to changes in market conditions, correctly balance production control and efficiency enhancement, and consciously regulate their production and operation behavior, especially state-owned enterprises which should set a leading example. In the current context of notably low coal prices, the coal industry association should guide enterprises to promote rational price recovery through proactive production reduction and output limitations. The construction of an integrity system in the coal industry should be accelerated, establishing and improving an integrity index evaluation system for coal enterprises. Compliance with production reduction, as well as not scheduling production on statutory holidays and Sundays, should be included in the integrity records of enterprises. Coal mines with strong integrity awareness and good credit records should receive favorable treatment in industry evaluations, while those with poor integrity awareness, violations of operational hours, and overcapacity production should face penalties in industry evaluations and be publicly disclosed to create a positive atmosphere of "rewarding integrity and punishing dishonesty."

Figure B.1: Policy Document: Supply Reduction Policy



关于进一步规范和改善
煤炭生产经营秩序的通知

发改运行〔2016〕593号

各产煤省（自治区、直辖市）发展改革委（能源局）、经信委（工信委、工信厅）、煤炭厅（局）、人力资源社会保障厅（局），省级煤矿安全监察机构，中国煤炭工业协会，有关中央企业：

为贯彻落实《国务院关于煤炭行业化解过剩产能实现脱困发展的意见》（国发〔2016〕7号，以下简称《意见》），进一步规范和改善煤炭生产经营秩序，有效化解过剩产能，推动煤炭企业实现脱困发展，现就有关问题通知如下：

一、充分认识规范和改善煤炭生产经营秩序的重要意义

当前，煤炭行业陷入严重困境。特别是去年以来，部分煤炭企业为挤占市场份额，采取超能力生产、以量补价、低价倾销等措施维持生产运行，不仅严重冲击了正常的煤炭生产经营秩序，而且加剧了市场供需失衡，加重了行业困难。上述问题如不能尽快得到遏制，国家有关煤炭行业脱困发展的目标任务将难以实现。各地区、各企业要站在推进供给侧结构性改革、抓好去产能任务的战略全局高度，进一步增强大局意识，充分认识规范和改善煤炭生产经营秩序对促进煤炭行业脱困发展的重要意义，把思想认识和实际行动统一到《意见》精神上来，采取有效措施，切实把控制超能力生产、减量化生产、节假日停产、维护公平竞争等规定要求落到实处。

二、规范和改善生产经营秩序的主要措施

（一）引导煤炭企业减量生产。按照国发〔2016〕7号文件要求，从2016年开始，全国所有煤矿按照276个工作日重新确定生产能力，即直接将现有合规产能乘以0.84（276除以330）的系数后取整，作为新的合规生产能力。同时，为防止超能力生产，保证职工正常节假日休假休息，原则上法定节假日和周日不安排生产。对于生产特定煤种、与下游企业机械化连续供应以及有特殊安全要求的煤矿企业，可在276个工作日总量内实行适度弹性工作日制度，但应制定具体方案，并向当地市级以上煤炭行业管理部门、行业自律组织及指定的征信机构备案，自觉接受行业监管和社会监督。

（二）自觉规范生产经营行为。煤矿企业要认真落实国家有关规定，加强劳动组织和生产管理，建立考核奖惩制度，严禁向煤矿下达超法定生产能力的生产经营指标。煤矿要严格按照重新确定的产能组织生产，不得超能力、超强度生产。妥善安排职工休假，确保法定节假日和每周日职工得到集中休息，降低职工劳动强度，严禁以牺牲职工正常休假权利为代价，片面追求产量和效益。严格遵守《反不正当竞争法》、《反垄断法》，坚持依法经营，理性竞争，不得恶意降价、低价倾销，坚决杜绝不正当竞争。

（三）恪守行业自律。煤炭企业要积极适应市场形势变化，正确处理好控产与增效的关系，自觉规范生产经营行为，特别是国有企业要发挥表率作用。在当前煤炭价格明显偏低的情况下，煤炭工业协会要引导企业通过主动减产、限产促进煤炭价格理性回归。加快推进煤炭行业诚信体系建设，建立健全煤炭企业诚信指标评价体系，将煤矿落实减量生产、法定节假日和周日不安排生产情况列入企业诚信记录。对于诚信意识强、信用记录优良的煤矿，在行业评先方面给予倾斜；对诚信意识差、违反作业时间、超能力生产等规定的煤矿，在行业评先方面要予以惩戒，并向社会公示，营造"褒扬诚信、惩戒失信"的良好氛围。

C Data Comparison

To validate the provincial and monthly production and consumption data we compiled from various sources, we compare the statistics based on our data and those from the National Bureau of Statistics of China in Table C.1. The first column displays the national values aggregated from our data based on coal transportation, the second column is derived from the NBS Coal Balance Table for all provinces, and the third column represents the national statistics in the NBS National Coal Balance Table.

Overall, the national statistics derived from our transportation data are reasonably close to those in NBS. For instance, both datasets show declining output and consumption between 2014 and 2016, and a decrease in imports in 2015 followed by a rebound in 2016.

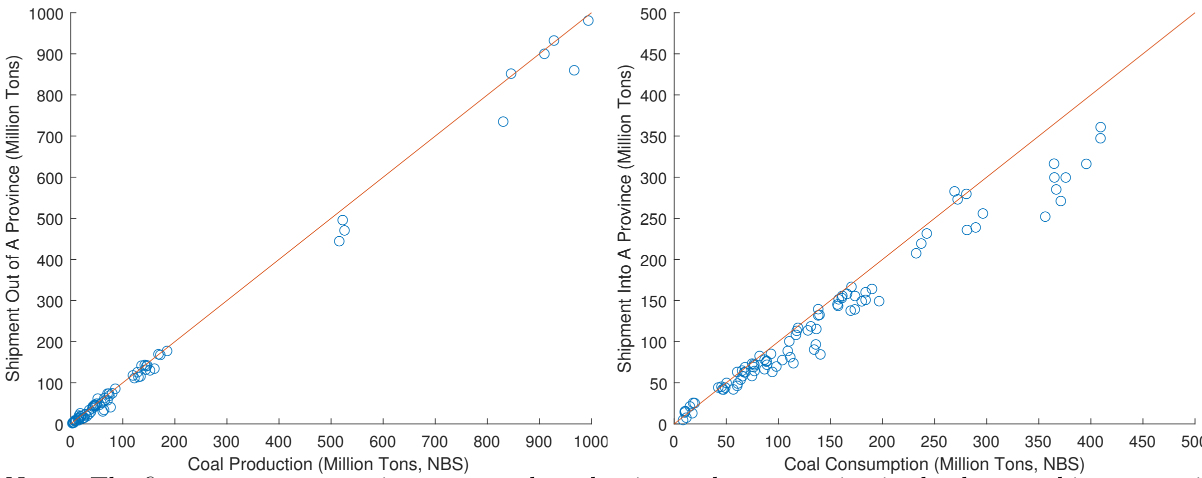
Table C.1: Data Comparison of Coal Output and Consumption (million tons)

	2014			2015			2016		
	Main	NBS (Prov)	NBS (Nat)	Main	NBS (Prov)	NBS (Nat)	Main	NBS (Prov)	NBS (Nat)
Output	3703	3876	3874	3457	3747	3747	3135	3411	3411
Consumption	3860	4317	4136	3662	4255	3998	3574	4249	3888
Thermal power	1974	1823	1895	1872	1792	1796	1908	1818	1827
Heating supply	181	306	224	204	323	241	222	345	266
Coking Coal	563	667	639	530	625	609	536	626	606

Notes: The table compares the transportation data used in the empirical analysis (under main columns) with the annual numbers reported by the National Bureau of Statistics of China. The column of NBS (Prov) contains data collected from province coal balances tables and aggregated to national numbers, and the column NBS (Nat) uses statistics reported in the national coal balance tables. The sum of coal consumption across provinces exceeds the national total because of the potential double counting according to the official Q&A from China NBS (See `https://www.stats.gov.cn/hd/cjwtjd/202302/t20230207_1902276.html`). Under the main column, the output is calculated as total shipment, and the monthly consumption is constructed in Appendix D. We then aggregate province-month production and consumption to the national level.

Figure C.1: Data Comparison of Shipment, Coal Output and Consumption at Province Levels (Million Tons)

(A) Shipment Out of a Province vs Production (B) Shipment into a Province vs Consumption



Notes: The figure compares province-year coal production and consumption in the data used in our empirical analysis with those reported by province coal balance tables. One dot in the figures represents one province-year pair. The y-axis is calculated by aggregating monthly total shipment out of and into a province within a year.

We also validate our data at the province-year level. Figure C.1 compares the shipment out of and into a province in each year with the annual coal production and consumption data by province in the provincial coal balance tables from NBS. Overall, they align closely, with the imputed consumption data being slightly lower than those reported by the NBS. This difference is expected because NBS data explicitly state that they do not remove certain instances of double-counting at the province level.[44]

D Coal Consumption

We collect monthly coal consumption data from 2014 to 2016 across seven sectors: electricity, coking, construction, heating supply, steel-making, chemistry, and others. Table D.1 displays annual consumption in these sectors. Electricity is the largest coal consumer, accounting for over 50% of total consumption. Other major users include coking and cement plants, each accounting for 15%. The consumption breakdown is stable during our sample period. The "others" sector, which mainly includes residential demand and small-scale industrial processes, accounted for 7% in 2014 and declined to 3% in 2016. We plot the national time series of the downstream output in Figure D.1.

[44] For example, coal transported to province A for washing and burned at power plants in B are both counted as consumption in provinces A and B. Our shipment data only count the final consumption in B.

Table D.1: Consumption Shares by Sectors

Year	2014	2015	2016
Electricity	0.51	0.51	0.53
Coking	0.15	0.14	0.15
Construction	0.15	0.15	0.14
Heating Supply	0.05	0.06	0.06
Steel-making (steam coal only)	0.04	0.04	0.04
Chemistry	0.04	0.04	0.04
Others	0.07	0.06	0.03

Note: The table shows annual coal consumption shares by sector. We collected monthly coal consumption by sector from China Coal Resource, and then aggregated them annually to calculate those shares.

To allocate coal consumption by sector across provinces, we further collect the monthly output of primary products in each sector by province from the NBS and convert it into coal consumption. For the electricity sector, we use thermal electricity output as the main product. Although thermal electricity generation includes both coal and natural gas, natural gas contributes to only about 4.5% of total thermal generation, making its impact negligible.[45] We use cement as the representative product for the construction sector, as it accounts for 83.7% of coal consumption there. In the chemistry sector, fertilizers serve as the primary product.

Provincial coal balance tables provide annual coal consumption for thermal electricity generation and coking. We aggregate thermal and coke output to the province-year level and calculate coal consumption per 1 MWh of electricity and per ton of coke for each province and year. We assume that these ratios remain constant across months within a province and year, converting thermal electricity generation and coke into coal consumption for the electricity and coking sectors. For cement, steel, and fertilizers, we aggregate their output by month across provinces and calculate the coal-to-output ratio. Assuming this ratio is constant across provinces within a month, we compute coal consumption in the construction, steel, and chemistry sectors based on their province-month output. Table D.2 shows that producing 1 MWh of electricity uses less coal over time, reflecting the gradual improvement in power plant energy efficiency. The conversion ratios are also consistent with engineering estimates by industry experts.[46]

[45] `https://chinaenergyportal.org/en/2016-detailed-electricity-statistics-updated/`

[46] For example, producing 1 ton of cement requires 0.11 ton of standard coal, equivalent to a conversion ratio of 0.15 between coal and cement, given that 1 ton of raw coal equals 0.7143 ton of standard coal. See `https://www.chinanews.com.cn/cj/2011/05-03/3011403.shtml`.

Table D.2: Coal-to-End Product Output Ratio by Sectors

Year	2014	2015	2016
Electricity (Ton of coal/MWh)	0.47	0.44	0.43
Cement (Ton of coal/Ton)	0.23	0.24	0.21
Steel (Ton of coal/Ton)	0.14	0.12	0.13
Coke (Ton of coal/Ton)	1.18	1.19	1.20
Fertilizer (Ton of coal/Ton)	2.01	1.85	2.00

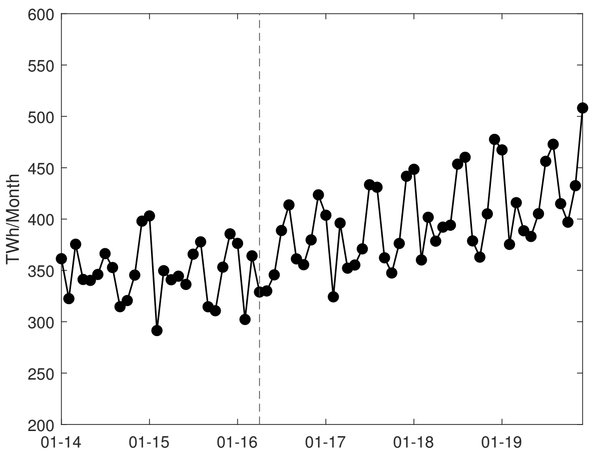
Note: The table reports the conversion ratios used to estimate coal consumption for the production of key downstream products in each sector. Monthly data on the output of thermal electricity, cement, steel, coke, and fertilizers by province is collected from the NBS. The provincial coal balance tables provide annual coal consumption for thermal electricity generation and coking. We aggregate thermal and coke output to the province-year level to calculate the coal consumption per 1 MWh of electricity and per ton of coke. The table shows the average across provinces for each year. For cement, steel, and fertilizers, we calculate national output annually and match it with coal consumption data for the construction, steel (steam coal only), and chemical sectors from China Coal Resource, resulting in an annual conversion rate applied uniformly across all provinces.

For the heating sector and the "other" sector, which lack representative products, we collect annual coal consumption for heating supply from provincial coal balance tables. We then compute annual consumption in the "other" sector as the residual of total coal consumption after accounting for electricity generation, heating supply, industry, and construction. Using these data, we first calculate province-specific annual coal consumption shares by sector and then allocate monthly consumption across sectors according to these shares.

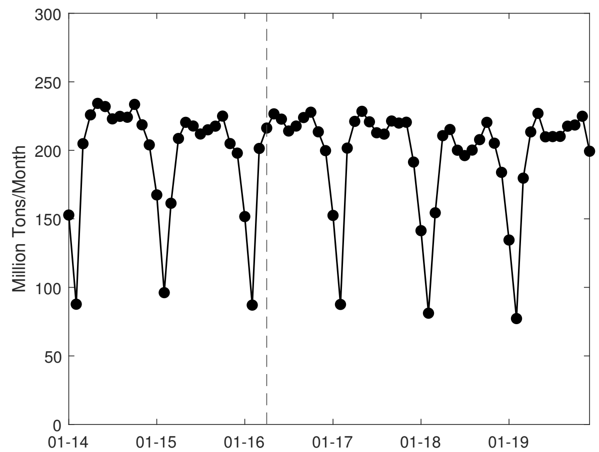
We extrapolate these data to 2017. Our monthly, sector-level consumption data and cross-province shipment data end in 2016. For 2017, we impute the consumption data using the province-level monthly production data from NBS. Specifically, we allocate each province's production to destination provinces using shipment shares observed in 2016. We note that the shipment quantity is slightly lower than NBS's production data in prior years, likely due to a double-counting issue with the NBS data as discussed in Appendix C. Therefore, the allocated production is scaled down by 0.936, the average production-to-shipment ratio observed in 2014-15. We assume that the total production allocated to a province is its consumption, which is a reasonable assumption given that coal inventory has stabilized in 2017 (Figure 4).

Figure D.1: Output in Major Downstream Sectors

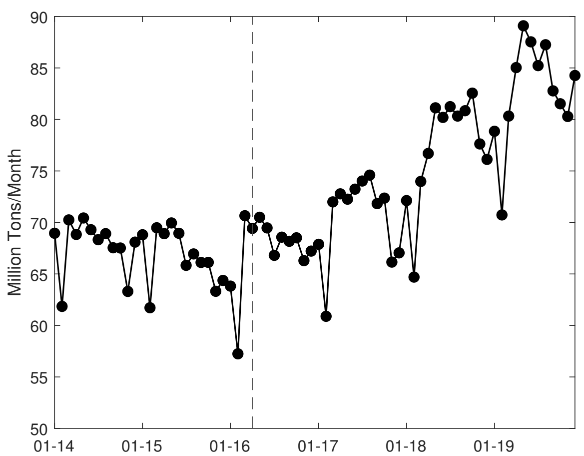
(a): Thermal Electricity



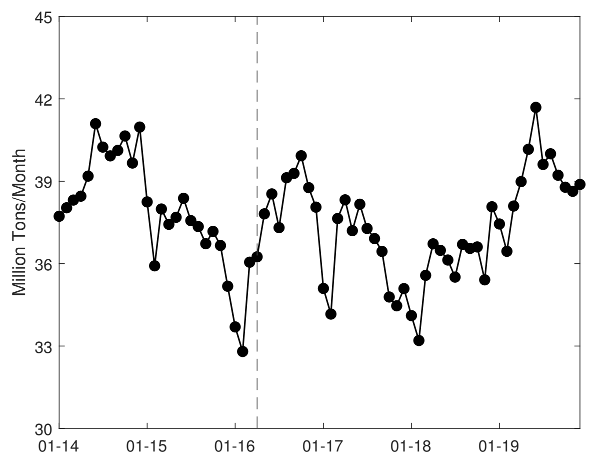
(b): Cement



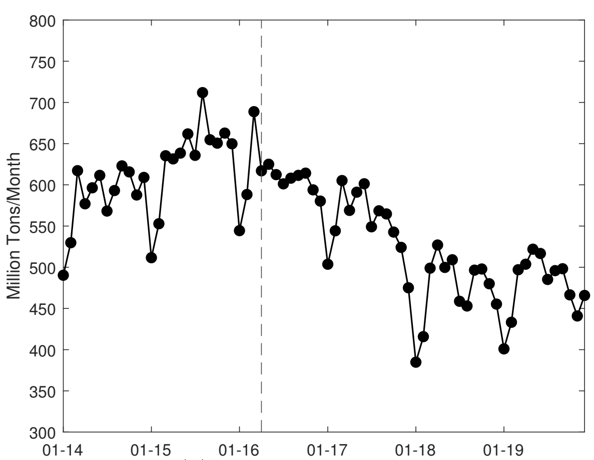
(c): Steel



(d): Coke



(e): Fertilizer



Notes: Panel (a) plots the national thermal electricity generation, (b) plots the national cement production, (c) plots the national steel production, (d) plots the national coke production, (e) plots the national fertilizer production.

E China's Major Infrastructure Development in April and May of 2016

The list below represents our best-effort search for major active infrastructure projects (with a cost over RMB 50 billion) in April and May of 2016, based on NDRC announcements, Xinhua News, China Daily and other news sources. We focus on projects that are extremely material-intensive, thus requiring significant use of coal and coke for concrete and steel. We exclude the Guangzhou–Shenzhen–Hong Kong Express Rail Link (Hong Kong section), which meets the RMB 50 billion cost threshold, but the scale (26km of railway) was far smaller than the other projects.

New Projects

1. Yuxi–Mohan Railway (China-Laos Railway) in Yunnan (southwest of China). Full-scale construction began on April 19, 2016, following earlier preparatory works that started in September 2015. The project's total cost is about RMB 51.6 billion.[47]

2. Beijing–Zhangjiakou High-Speed Railway (HSR) in Beijing and Hebei (central China). The construction started on April 29th, 2016 (Wang, 2021), with a total investment of RMB 58.4 billion.[48]

3. Tianfu International Airport in Chengdu (southwest of China). The construction started in May 2016, with a total investment of RMB 72 billion.[49]

Ongoing Projects

1. Haoji Railway between Shanxi and Inner Mongolia (northwest-central China). The construction started in 2015 and was completed in 2019, with a cost more than RMB 193 billion.[50]

2. Daxing International Airport in Beijing and Hebei (central China). The construction started in 2014 and was completed in 2019, with a cost of RMB 80 billion.[51]

[47] https://global.chinadaily.com.cn/a/202007/03/WS5efe84baa310834817256ef1.html

[48] https://www.reuters.com/article/sports/china-approves-9-2-billion-winter-olympics-high-speed-rail-line-local-government-idUSKCN0SS04F/

[49] https://aviationweek.com/air-transport/chinas-new-chengdu-airport-facilitates-massive-air-travel-growth

[50] https://global.chinadaily.com.cn/a/201910/05/WS5d97d87fa310cf3e3556ecde.html

[51] https://www.chinadaily.com.cn/business/2014-12/26/content_19177195.htm

3. Beijing–Shenyang HSR in Beijing, Hebei and Liaoning (central-north China). The construction began in 2014 and was completed in 2021, with a cost of RMB 123.5 billion.[52]

4. Hong Kong–Zhuhai–Macau Bridge in Guangdong, Hong Kong and Macau (south China). The construction began in 2009 and was completed in 2018, with a cost of RMB 127 billion.[53]

5. Wudongde Hydropower Station in Sichuan and Yunnan (southwest of China). The construction started in 2015 and was completed in 2021, with a cost of RMB 120 billion.[54]

6. Lianghekou Hydropower Station in Sichuan (southwest of China). The construction started in 2014 and was completed in 2022, with a cost of RMB 66.5 billion.[55]

F Coal Transportation

An integrated railroad and coastal marine shipping system is the primary mode of coal transportation in China, accounting for 65.2% of total coal transport in 2017.[56] The transportation costs typically include the direct expenses associated with freight charges, which are influenced by the distance to be traveled, the mode of transportation (such as rail, truck, or barge), and the specific logistics involved. While shipping fares for waterway transport are influenced by market forces, railroad transportation fares are typically regulated.[57] Additionally, loading and unloading fees, terminal charges, and any necessary handling costs contribute to the total transportation expenditure. Other factors, such as fuel prices, maintenance of transportation vehicles, and labor costs, also play a significant role in shaping these costs.

Due to the limited variation in transportation shares, directly estimating transportation costs through shipping choices via a behavioral model is challenging. Instead, we manually collected estimated transportation costs between major coal producers and consumers from an authoritative industry report (Cao and Feng, 2017) published by China Bond Rating Co.,

[52]https://usa.chinadaily.com.cn/china/2013-12/30/content_17205381.htm

[53]https://web.archive.org/web/20190327195326/http://www.xinhuanet.com/english/2018-10/23/c_137553194.htm

[54]https://www.reuters.com/business/energy/chinas-giant-wudongde-hydro-project-put-into-full-operation-2021-06-16/

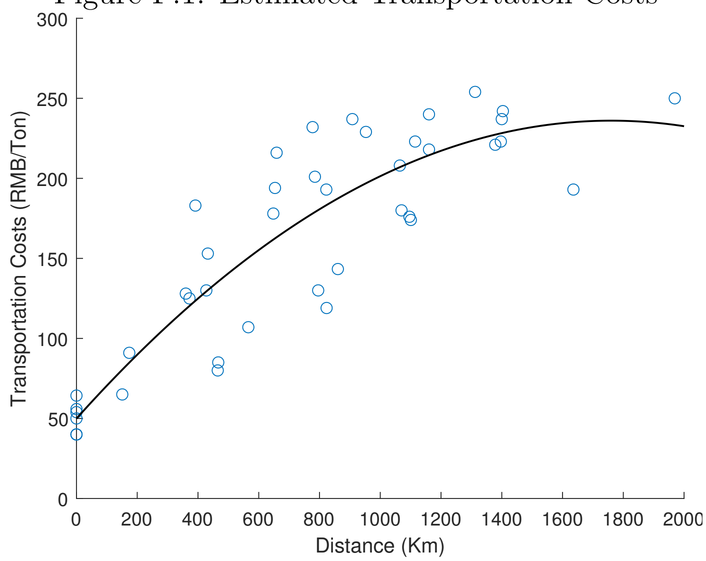
[55]https://www.chinadailyhk.com/hk/article/264174

[56]See `http://pdf.dfcfw.com/pdf/H3_AP201811151246522585_1.PDF`.

[57]For more details about the composition of regulated fares for transporting coal by railroad, please refer to `http://www.gov.cn/xinwen/2017-12/26/5250421/files/5a71188c4fd34d1d9f05ef5e16690d2e.pdf`.

Ltd., a leading agency that investigates and collects industry information to assess default risks of bonds across various sectors, including coal. Then we fit a quadratic relationship between the transportation costs and the distance between any two provinces, imposing the restriction that transportation costs increase with distance up to the maximum distance between any two provinces in China. Figure F.1 shows the transportation costs of province pairs estimated by the industry report, along with the estimated relationship between inter-provincial distance and transportation costs. The intercept represents the costs of transporting coal within a province, estimated to be RMB 60.9/ton. The estimates also indicate slight distance discounts.

Figure F.1: Estimated Transportation Costs



Notes: The figure shows transportation costs (RMB/ton) between major coal-producing and coal-consuming provinces, plotted against the distance between their capital cities (km), based on an industry report (Cao and Feng, 2017) published by China Bond Rating Co., Ltd. We then approximate the relationship between transportation costs and distance using a quadratic function (black curve).

G Simulation of Demand and Supply Shocks

We estimate the following AR(1) processes for demand shocks ε_{jt} and supply shocks ξ_{it}:

$$\varepsilon_{jt} = \delta_0^D + \delta_1^D \varepsilon_{jt-1} + \omega_{jt}^D$$

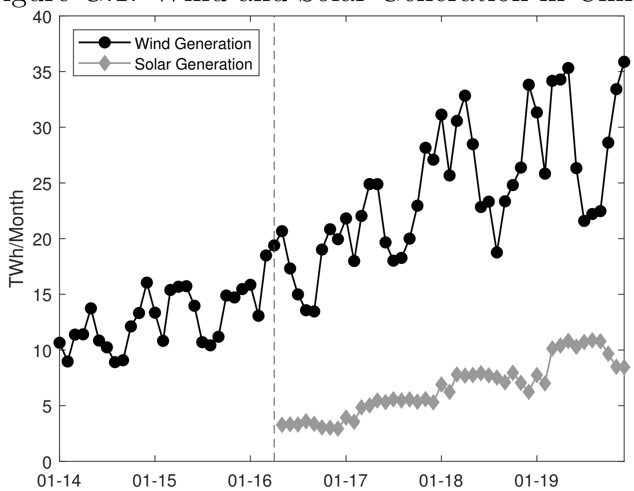
$$\xi_{it} = \delta_0^S + \delta_1^S \xi_{it-1} + \omega_{it}^S,$$

Table G.1 reports the estimated AR(1) coefficients, showing that demand shocks exhibit greater persistence than cost shocks.

	Demand	Domestic Supply
δ_1	0.805	0.494
	(0.025)	(0.066)
N	1020	850

Table G.1: Estimated AR(1) Process for Demand and Cost Shocks

Figure G.1: Wind and Solar Generation in China



Note: We plot the total monthly wind and solar generation in China. The solar generation data are available after April 2016, and their levels are considerably lower than the wind's.

To forecast future demand, we additionally model the evolution of wind generation and cooling degree days (CDD). Motivated by the growth pattern of the total wind generation at the national (Figure G.1) and province level, we model the generation as a province-specific linear time trend with province-month-of-the-year fixed effects and shocks:

$$X_{jt}^{\text{Wind}} = \delta_{jm(t)}^{\text{Wind}} + \delta_{j1}^{\text{Wind}} t + \omega_{jt}^{\text{Wind}},$$

which is estimated separately for each province. We assume that $\omega_{jt}^{D}, \omega_{it}^{S}, \omega_{jt}^{\text{Wind}}$ are mutually independent in the forward simulation. We re-sample historical CDDs by year, under the assumption that cross-year climate variation over the sample period is stable.

H Coal Consumption and Air Pollution

To quantify the environmental impact of reducing coal production, we additionally model air pollution as a function of coal consumption and health benefits from changes in pollution levels.

H.1 Air Pollution

We specify a mapping from coal consumption to monthly PM2.5 and PM10 concentrations within a province,[58] which are the primary predictors of health costs in the literature we use later. We estimate the following model for the concentration of pollutant $\ell \in \{\text{PM2.5, PM10}\}$ in province j and month t (where the coefficients are ℓ-specific):

$$\ln \ell_{jt} = \psi_C \ln \tilde{C}_{jt} + \psi_X X_{jt} + FE_j^{\text{pollution}} + FE_{m(t)}^{\text{pollution}} + \omega_{jt}. \tag{H.1}$$

In the above, to account for spillover effects (Fu, Viard and Zhang, 2022), we define the variable $\tilde{C}_{jt}$ as the total coal consumption in province j and all of its neighboring provinces in period t.[59] The variable X_{jt} includes meteorological conditions, including temperature, dew point temperature, sea level pressure, wind speed, sky condition total coverage code, precipitation duration and depth. Additionally, we control for fixed effects at the province and month-of-the-year levels.

Coal consumption and the unobservable ω_{jt} may be correlated. Specifically, the coal consumption could be correlated with other economic activities that also contribute to pollution, but also correlated with heightened monitoring and regulation that reduces pollution. We therefore use the same IVs as the demand estimation for coal consumption.[60]

Table H.2 indicates that a 1% increase in coal consumption in a province and its neighbors raises local PM2.5 concentration by about 1.4%. The effect is similar when we use PM10 concentration as the outcome variable.[61]

[58] We use the average of all monitoring stations' concentration readings in a province.

[59] We do not further normalize the variables by the province's size because both the pollution measure and the consumption are logged, and we control for province fixed effects.

[60] We construct instruments for $\tilde{C}$ by summing the instruments across neighboring provinces.

[61] Ito and Zhang (2020) estimate the elasticity of PM10 concentration with respect to coal usage to be 0.5 using a regression discontinuity design exploiting the Huai-River heating policy. This is similar to the OLS estimates from our province-month panel data, but smaller than the IV estimates.

Table H.2: The Effects of Coal Consumption on Air Pollutants

	(1) ln(PM2.5) OLS	(2) ln(PM10) OLS	(3) ln(PM2.5) IV	(4) ln(PM10) IV
$\ln \tilde{C}_{jt}$	0.416***	0.386***	1.438***	1.284***
	(0.115)	(0.096)	(0.332)	(0.314)
Province FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
Meteorological Controls	YES	YES	YES	YES
Observations	1,440	1,440	1,440	1,440
Adjusted R^2	0.654	0.605	0.554	0.490
Kleibergen-Paap F Statistic			35.13	35.13

Notes: The table reports estimates of the effects of coal consumption on PM2.5 and PM10 concentrations by OLS and IV. All estimates control for meteorological conditions, including air temperature, dew point, sea level pressure, wind speed, sky condition coverage, and liquid precipitation duration and depth. The instruments used are the same as those in estimating demand. Standard errors are clustered at the province level.

H.2 Health Effects

We monetize morbidity and mortality costs associated with changes in ambient pollutant concentrations following Barwick et al. (2021).[62] Specifically, they estimate that a 10 $\mu g/m^3$ reduction in daily PM2.5 generates \$9.2 billion in annual morbidity benefits. They also quantify mortality costs using a back-of-the-envelope calculation based on the mortality estimates in Ebenstein et al. (2017) (with data from 2004 to 2012). This calculation implies mortality costs of approximately \$13.4 billion per year associated with a 10 $\mu g/m^3$ increase in PM10. We convert all estimates to a per-person per-month basis and express them in 2016 RMB.[63] In the simulation, we first predict the percentage changes of concentrations of both pollutants from coal consumption changes based on the marginal effects of coal consumption estimated using IV, and then translate the level changes to the total morbidity and mortality health costs per capita. The total changes are calculated by weighting the changes by the

[62] An alternative is based on the approach in Ito and Zhang (2020) that estimate a household's willingness-to-pay of 1.34 dollars per year for 1 $\mu g/m^3$ of decrease in PM10 based on data from 2006 to 2014. They also derive an income-dependent willingness to pay based on their estimates of a random-coefficient logit model for air purifiers. This measure leads to a slightly lower monetary value for reducing air pollution.

[63] The health cost estimates reported in Barwick et al. (2021) are expressed in 2015 U.S. dollars. We convert these estimates to RMB using an exchange rate of RMB 6.5 per USD. To obtain per-capita values and express them in real 2016 terms, we use a national population of 1.375 billion and consumer price indices (CPI) of 615.2 in 2015 and 637.5 in 2016. Finally, we divide the resulting annual per-capita values by 12 to obtain monthly measures.

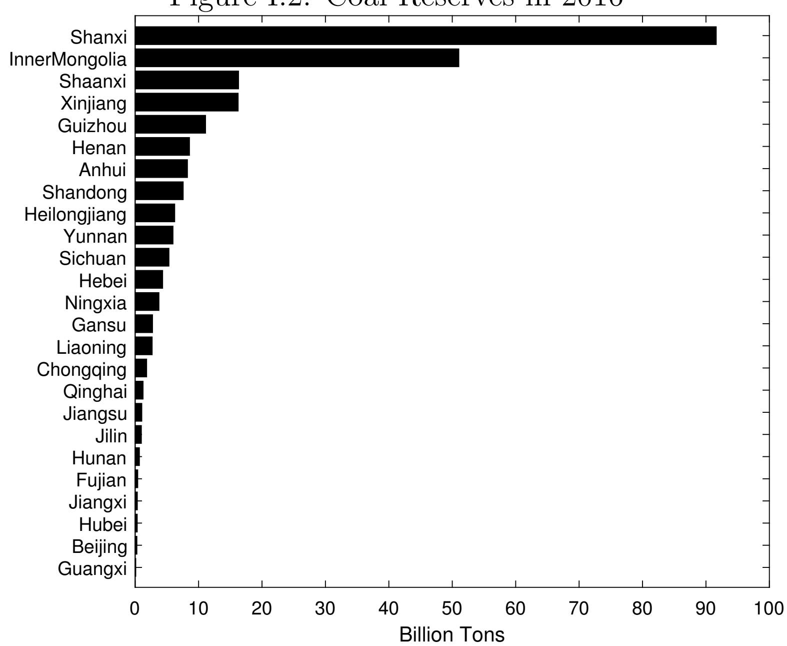
population for each province and then summing across provinces.

This approach likely understates the health benefits from reducing coal production by focusing solely on air pollution attributed to the resulting decrease in coal consumption. Other environmental damages associated with coal production (Chu et al., 2023), transportation, and storage of coal (Jha and Muller, 2018), such as air pollution from the excavation process, water contamination and land degradation, are not quantified here. We account for the environmental costs of water depletion at RMB 86.6 per ton of coal (Gu and Li, 2017). Nevertheless, addressing air pollution from coal consumption likely would have the greatest welfare impact given the large affected population and would be a high priority goal of the supply reduction policy (Feng et al., 2019).

I Additional Figures and Tables

I.1 Distribution of Coal Reserves

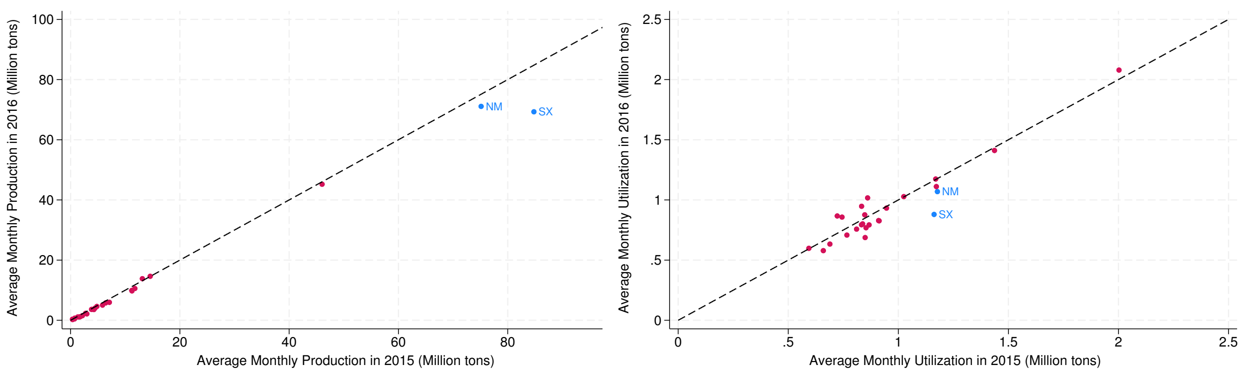
Figure I.2: Coal Reserves in 2016



Notes: Reserves are coal resources that have been surveyed and are feasible for excavation based on data from Qianzhan Industrial Research Institute.

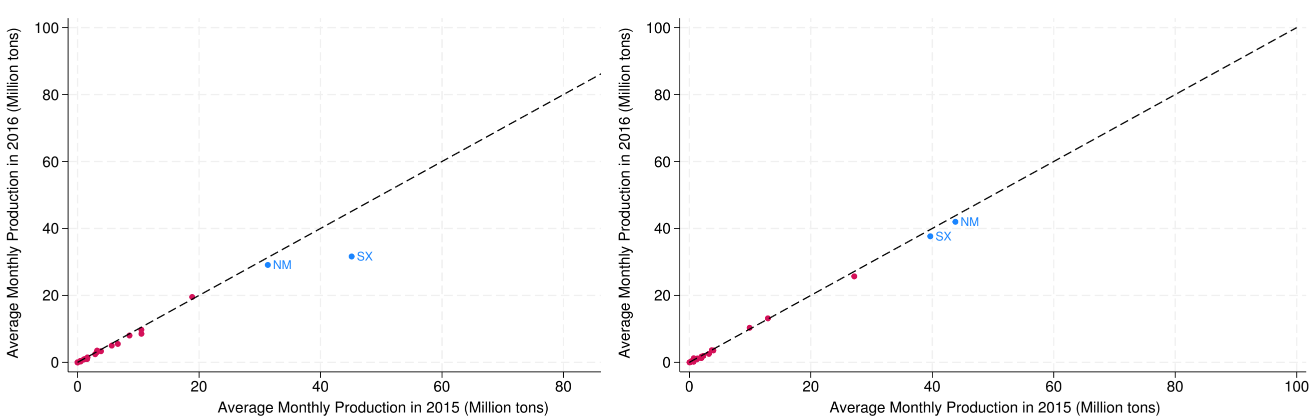
I.2 Policy Effects on Each Province and SOEs

Figure I.3: Shanxi and Inner Mongolia Reduce Production More in 2016
(a): Year-to-Year Production (b): Year-to-Year Utilization Factor



Notes: In panel (a), each dot represents a combination of 2015 (horizontal) and 2016 (vertical) average monthly production of a province. A location below the 45 degree line indicates that the 2016 production is lower. In panel (b), each dot represents a combination of average monthly utilization factors, defined as production over capacity (both normalized to the monthly level), of a province. A location below the 45 degree line indicates that the 2016 utilization factor is lower.

Figure I.4: SOE Reduces Production More in 2016
(a): Year-to-Year SOE Production (b): Year-to-Year Non-SOE Production



Notes: In panel (a), each dot represents a combination of 2015 (horizontal) and 2016 (vertical) average monthly production of a province's state-owned enterprises (SOE). A location below the 45 degree line indicates that the 2016 production is lower. In panel (b), each dot represents a combination of average monthly production by a province's non-SOE.

I.3 Concentration of Top State-owned Coal Companies

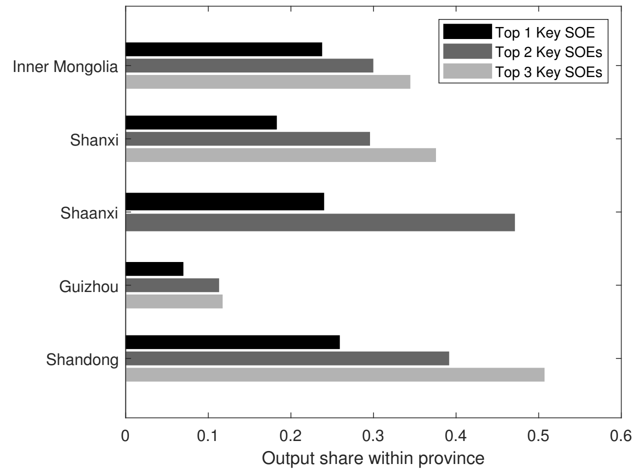
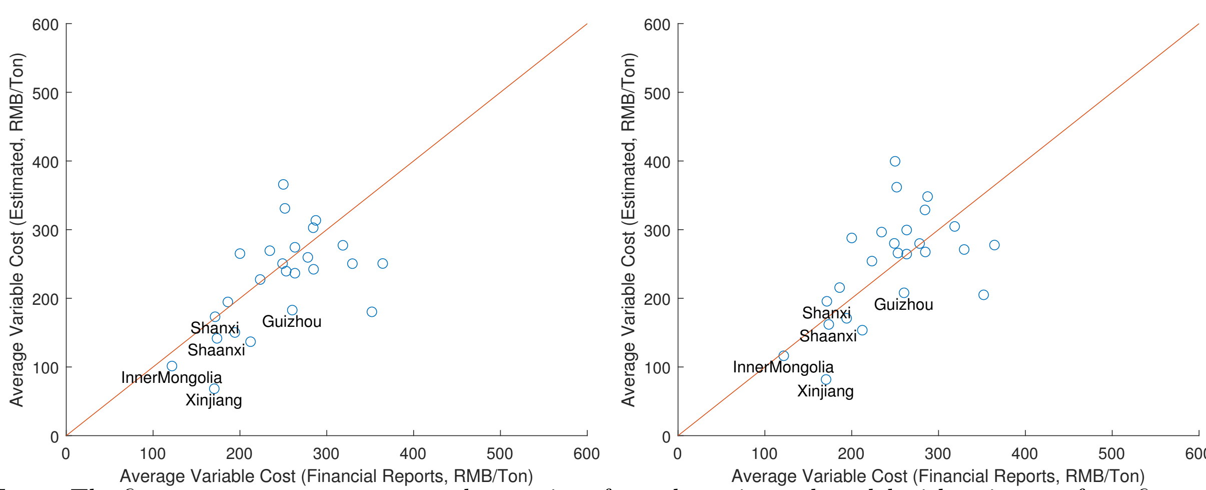


Figure I.5: Market Shares of Major SOE Coal Producers in Key Provinces

I.4 Comparison between Estimated Average Costs and Unit Costs from Financial Reports

Figure I.6: Compare Estimated Average Costs with Unit Costs from Financial Reports

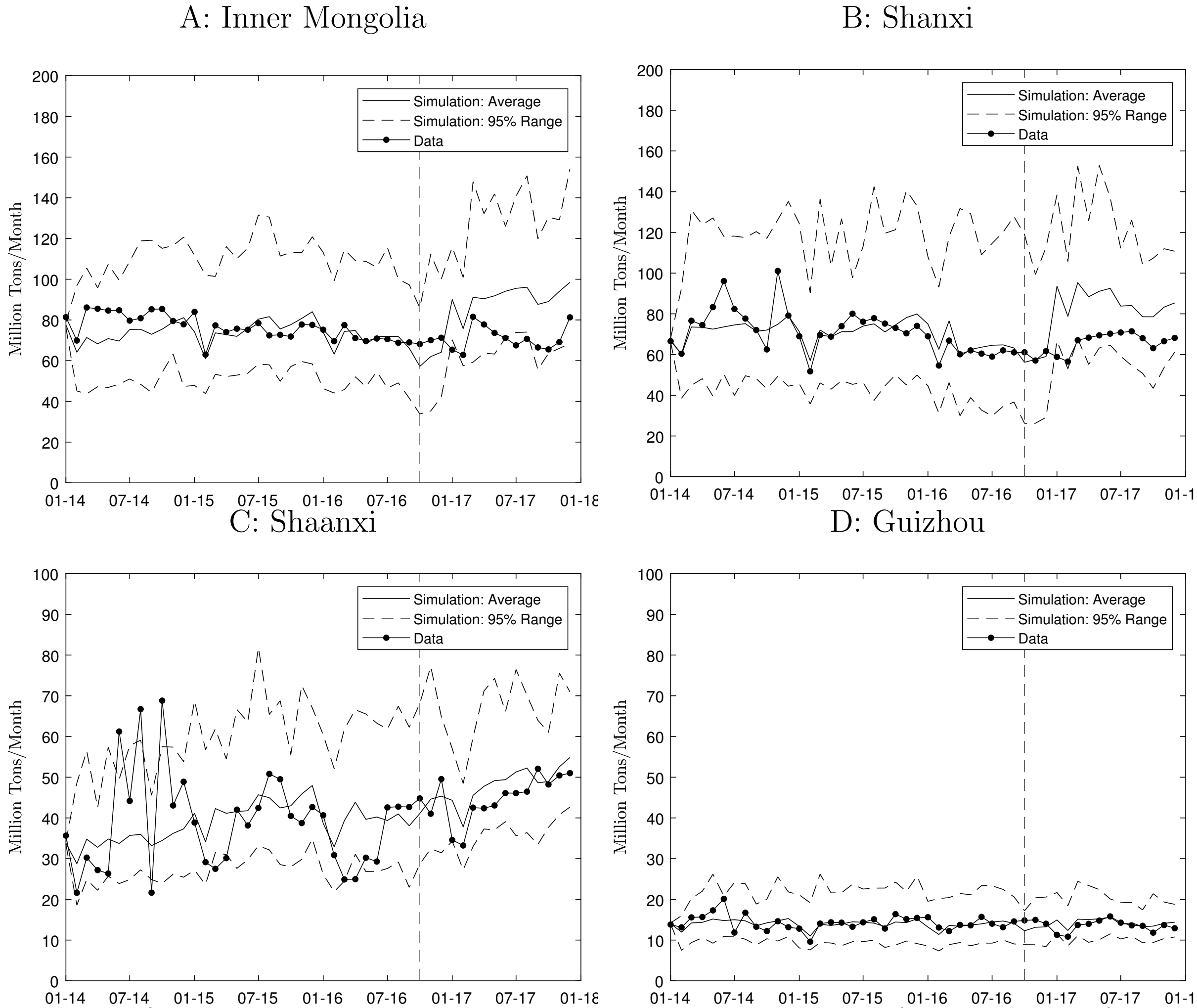
(A) Supply Model of Proportional Effects (B) Supply Model of Threshold Effects



Notes: The figure compares average costs by province from the estimated model with unit costs from financial reports. The model's estimated average costs are calculated at the observed quantity and averaged between 2014 and 2016. The unit costs are collected from financial reports and bond prospectuses of major coal companies in each province, then averaged across all companies over three years in the sample.

I.5 Model Fit by Provinces

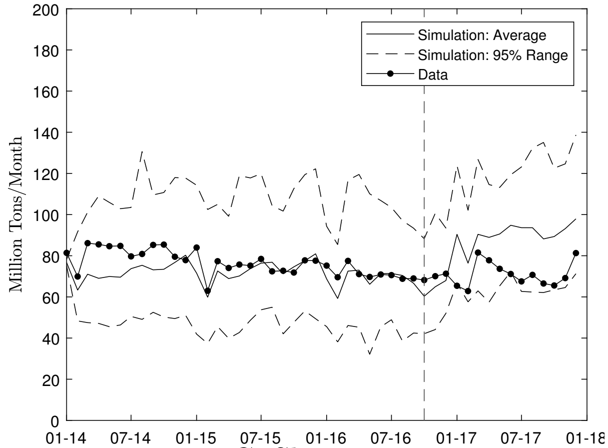
Figure I.7: Simulations: Output by Provinces (Supply Model of Proportional Effects)



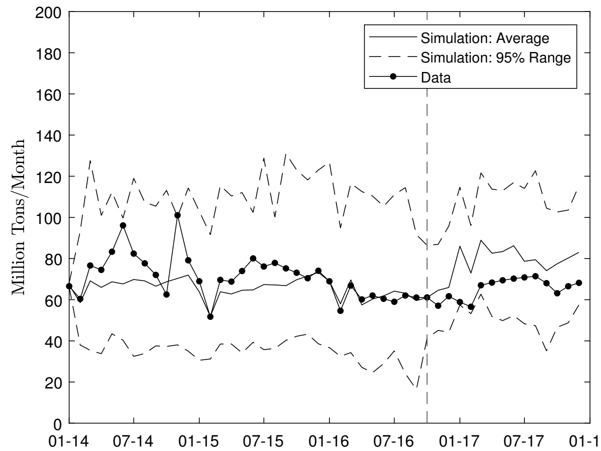
Notes: The figures plot the mean and 2.5%–97.5% range across all simulations for output in the four largest coal-producing provinces: Inner Mongolia, Shanxi, Shaanxi and Guizhou.

Figure I.8: Simulations: Output by Provinces (Supply Model of Threshold Effects)

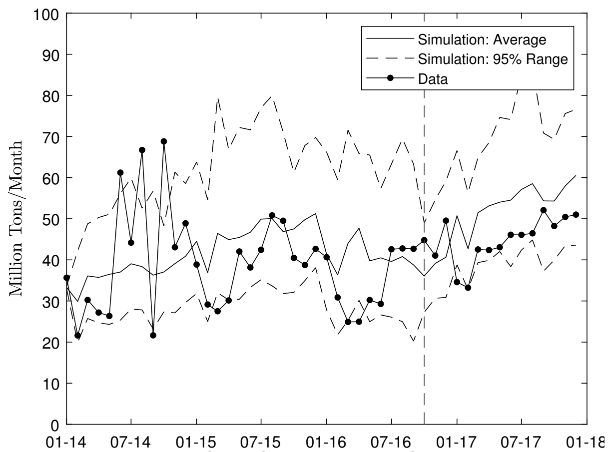
A: Inner Mongolia



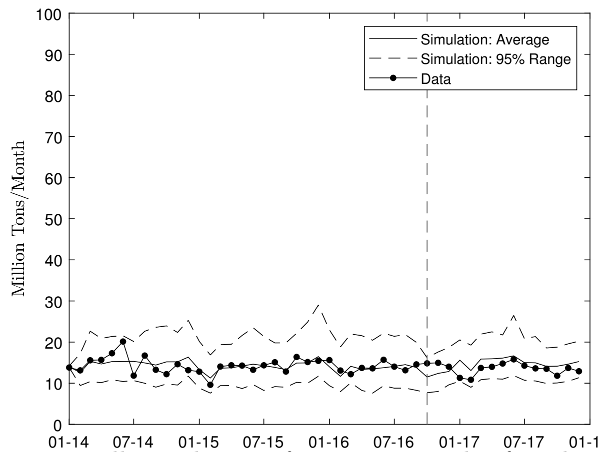
B: Shanxi



C: Shaanxi



D: Guizhou



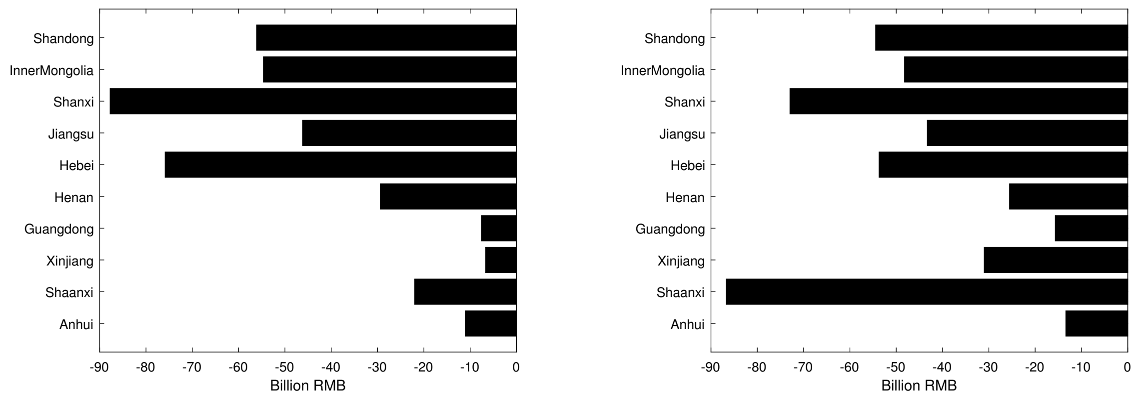
Notes: Figures plot the mean and 2.5%–97.5% range across all simulations for output in the four largest coal-producing provinces: Inner Mongolia, Shanxi, Shaanxi and Guizhou.

I.6 Distribution of Economic Surplus by Top 10 Provinces

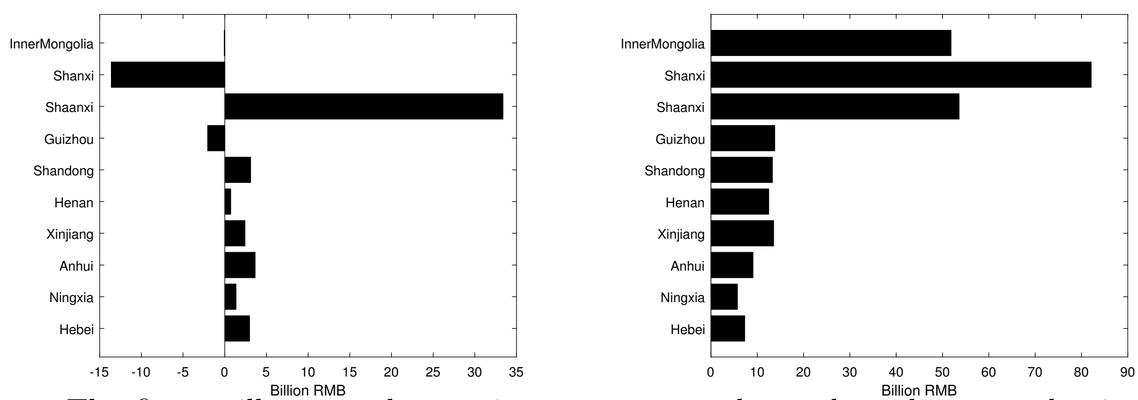
Figure I.9: Policy Effects on Economic Surpluses in Major Provinces

Proportional Policy Effects | Threshold Policy Effects

(a) Δ Consumer Surplus (RMB bn.)



(b) Δ Producer Surplus (RMB bn.)



Notes: The figures illustrate changes in consumer surplus and producer surplus in 2017 relative to a no-policy counterfactual. Changes in consumer surplus are ordered by provinces' average pre-policy consumption, while changes in producer surplus are ordered by provinces' average pre-policy production.