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Regulating Conglomerates: Evidence from an Energy Conservation Program in China†

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We study a prominent energy regulation affecting large Chinese manufacturers that are part of broader conglomerates. Using detailed firm-level data and difference-in-differences research designs, we show that regulated firms cut output and shifted some production to unregulated firms within their conglomerate instead of improving their energy efficiency. To account for conglomerate and market spillovers, we interpret these results through the lens of an industry equilibrium model featuring conglomerate production. The policy raises welfare if the per ton benefits of carbon reduction exceed $161. Alternative policies that exploit public information on business networks can increase aggregate energy savings by 10 percent. (*JEL* D22, L22, L51, L60, P28, P31, Q48)

Balancing economic growth with the negative side effects of industrialization—such as carbon emissions and pollution—is a central problem of governments in emerging economies. Nowhere is this problem more important or consequential than in China. As Figure 1 shows, energy regulation is of national and global importance

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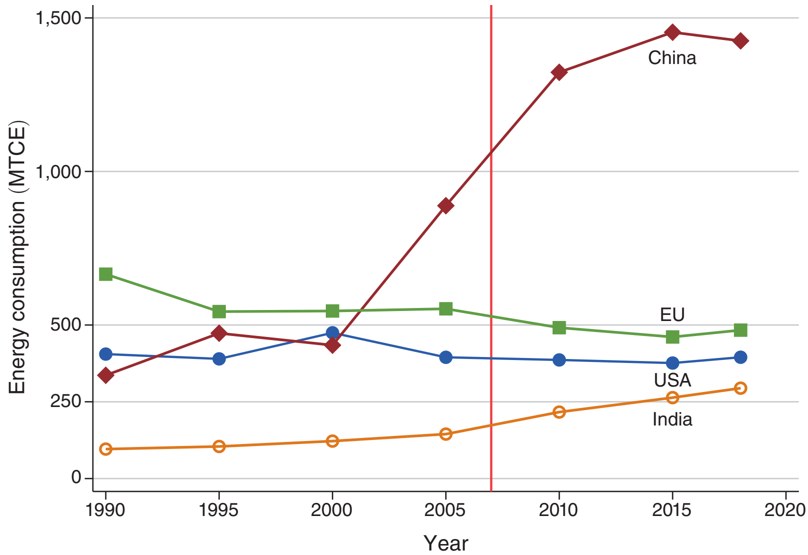

Figure 1. Cross-Country Differences in Industrial Energy Use

Notes: This figure plots aggregate industrial energy consumption in China, the United States, the EU, and India from 1990 to 2018 using units of million tons of coal equivalent (MTCE). The industrial energy consumption of China increased by more than threefold after 2000, while the industrial energy consumption of the United States and EU remained relatively stable, with a slight downward trend. The red line marks the start year of the Top 1,000 Energy Conservation Program.

Source: Authors' calculations using data from IEA (2020).

given that the industrial energy use of China overshadowed that of other leading economies in the early years of the twenty-first century.

This paper studies the effects of a large program aimed at curbing the energy use of Chinese industrial firms. The regulation that we study—the "Top 1,000" program—targeted the largest energy-consuming firms in the most energy-intensive industries. The regulation was designed following examples of "voluntary agreement" programs in developed countries that rely on the belief that firms could significantly reduce their energy use by improving their energy efficiency. The implementation of the program was adjusted to Chinese institutions and constraints, with the result that, in practice, lowering energy consumption became the main regulatory objective.

Understanding the effects of this regulation is central to broader questions of energy conservation for several reasons. First, the firms regulated by this program accounted for 47 percent of total industrial energy use in China in 2004. Additionally, as in several developing countries, industrial firms in China are often part of much larger business networks (Ramachandran, Manikandan, and Pant 2013). The sheer size of the regulated firms and their broader networks of related firms imply that a complete assessment of the effects of the regulation needs to account for within-conglomerate and market-level spillovers. Finally, the perceived success of the regulation led the Chinese government to significantly expand the program in later years.

This paper characterizes the effectiveness of the Top 1,000 program by combining difference-in-differences research designs with an industry equilibrium model featuring conglomerate production. Our difference-in-differences estimations show that, relative to unregulated firms in energy-intensive industries, Top 1,000 firms significantly decreased their energy use after the regulation. Regulated firms achieved these reductions by lowering output; we find no impact on their energy efficiency. Using detailed data on business networks and a second difference-in-differences design, we then show that unregulated firms in the same conglomerate as regulated firms increased both output and energy use. This result uncovers an important margin of adjustment that allowed Chinese conglomerates to shift 40 percent of the output decline in regulated firms to unregulated affiliates. Finally, we provide evidence of market-level spillover effects by showing that unregulated, unrelated firms in more heavily regulated industries increased their output after the regulation. These results corroborate the notion that conglomerates were not able to fully shift production across related firms.

To quantify the aggregate and welfare effects of the policy, we specify and estimate an industry equilibrium model of conglomerate production. The model accounts for conglomerate and market spillovers, matches the estimated impacts of the policy, and clarifies the interpretation of the difference-in-differences estimates in the presence of both types of spillovers.

We evaluate the welfare effects of the program and quantify that the Top 1,000 program improves welfare when the government values a per ton reduction in carbon emissions at more than $161 (e.g., from reducing emissions that contribute to global warming and from the local health benefits associated with lower pollution). Finally, we use the model to simulate the effects of expanding the program to include more firms, of relying on size-dependent and universal energy taxes, and of using public information on conglomerate networks to design conglomerate-level regulations. A conglomerate-level regulation could increase energy savings by 10 percent for the same welfare cost and presents a trade-off that is close to that of a universal energy tax.

We develop these results in three steps. We discuss the policy details and firm-level data in Section I. This section motivates our first difference-in-differences strategy, which uses firms in similar industries that were regulated in later years as control firms for the Top 1,000 firms. In Section II, we use an event-study specification to show that regulated and unregulated firms had similar trends prior to the regulation. Relative to unregulated firms, Top 1,000 firms reduced their energy use by approximately 16 percent in response to the regulation. These estimates are robust to inclusion of industry-by-year and province-by-year fixed effects as well as controls for firm characteristics. Regulated firms also saw a decline in output of approximately 20 percent; however, we do not find meaningful or statistically significant changes in energy efficiency.

Our second set of analyses leverages detailed business registration data to map the conglomerate networks of regulated firms. If regulated firms were able to circumvent the regulation by shifting production to related parties, we would expect to see an increase in both the output and energy use of firms linked to the regulated firms through ownership networks. We test this hypothesis in Section III by using a difference-in-differences strategy that compares unregulated but related firms to a matched set of unregulated and unrelated firms that share similar characteristics prior to the regulation. These analyses show that after the reform, regulated conglomerates shifted production to affiliates that were not subject to the regulation. We estimate an increase in the output of related firms of approximately 12 percent; we also find increases in energy use but no effects on energy efficiency. Importantly, we find increases in the economic activity of related firms only when their line of business coincides with the narrowly defined (four-digit) industry classification of the regulated firm. As a placebo test, we show that related firms in other industries did not see an increase in economic activity. Because related firms are smaller than regulated firms, we calculate that conglomerates were able to shift 40 percent of the output decline in regulated firms to related parties.

Conceptually, firms could respond to the Top 1,000 program in three ways: by increasing energy efficiency, by reducing output, or by shifting production to related parties. The fact that conglomerates adjusted their output allocation but did not improve their energy efficiency is informative about the costs of different margins of response to energy regulations. Our results are consistent with the notion that costly long-run investments would be required to improve the energy efficiency of regulated firms.[1] Additionally, the fact that regulated firms were not able to fully shift their production to related parties suggests there were no "low-hanging fruit" from a technological perspective (e.g., Allcott and Greenstone 2012). Consistent with the finding that conglomerates were not able to fully compensate their output loss by shifting production, we estimate market-level spillovers by showing that unregulated, unrelated firms in more heavily regulated industries increased their output as a result of the regulation. These results show that a complete assessment of the effects of the Top 1,000 program must take into account how declines in energy use at regulated firms can lead to within-conglomerate and market-level increases in energy use, otherwise known as "leakage."

In the third step, detailed in Section IV, we present an industry equilibrium model of conglomerate production that accounts for within-conglomerate spillovers to related firms as well as market spillovers. We estimate the model in Section V by matching moments of the firm size distribution and patterns of the within-conglomerate allocation of production prior to the regulation. We then use our reduced-form estimates as out-of-sample validations of the model. The fact that the model does a good job of matching the differences-in-differences estimates indicates that it correctly captures the quantitative importance of within-conglomerate and market-level spillovers. The model further decomposes our difference-in-differences estimates and shows that accounting for the effect of the program on unregulated firms lowers the effect on regulated firms from 20 percent to 14 percent. In contrast, spillovers to related firms increase the estimates from 12 percent to 19 percent. By combining the reduced-form estimates with a structural industry equilibrium model, we are able to evaluate the effects of the Top 1,000 program while taking into account spillover and equilibrium effects, which are central features of prominent energy regulations.

[1] Because coal is the main energy source for the regulated industries, meaningful improvements in energy efficiency would require firms to adopt long-lived industrial machines that rely on electricity. Firms may have been reluctant to do so given the abundance and inexpensiveness of coal in China and the government's uncertain commitment to energy-saving policies. Zhao et al. (2016) discuss a case study of a Top 1,000 firm with old, energy-inefficient capital. Even when this firm started the process of adopting new machinery in 2007, energy efficiency gains did not materialize until 2011 due to construction and installation delays. In Supplemental Appendix J.1, we extend the model by allowing for investments that can improve energy efficiency and consider how these improvements can impact the aggregate and welfare effects of the policy.

Section VI uses the model to quantify the aggregate and welfare effects of the Top 1,000 program. Accounting for market and conglomerate leakage, we calculate that the program reduced aggregate energy use by 4 percent, an annual decrease of approximately 48 million tons of coal equivalent (tce).[2] A calibration of the government's willingness to pay (GWTP) to reduce energy use shows that the program raises welfare as long as the GWTP—which includes both the social cost of carbon (SCC) and the health damages associated with local pollution—exceeds \$161 per ton of carbon.[3] Supplemental Appendix J also considers a range of extensions that allow for endogenous improvements in energy efficiency, heterogeneous preexisting differences in energy efficiency between regulated and unregulated firms, as well as a range of alternative model specifications and parameter values. Across these wide-ranging assumptions, we estimate that the GWTP that rationalizes the policy is bounded between \$114 and \$199.

The model allows us to compare the aggregate and welfare effects of incomplete regulations, such as the Top 1,000 program, to those of policies that would be preferable absent political or administrative constraints, such as a universal energy tax. First, we show that expanding the program by increasing the number of regulated firms or by tightening energy savings targets leads to similar trade-offs. A government facing administrative constraints would thus prefer to tighten the stringency of the regulation rather than increase the number of regulated firms. Second, we show that the government can increase aggregate energy savings by 10 percent for the same welfare cost by leveraging publicly available data on the ownership networks of regulated conglomerates. By targeting conglomerates instead of firms, such a regulation would avoid distorting the within-conglomerate allocation of production. Third, the model shows that a conglomerate-level regulation closely approximates the effects of a size-dependent energy tax that applies to all affiliates in conglomerates with Top 1,000 firms. Finally, we find that this size-dependent tax is only slightly inferior to a universal energy tax. These results highlight the promise of using information on the conglomerate networks of large Chinese manufacturers to improve the design of energy regulations, particularly in contexts where monitoring capacity may be limited.

This paper contributes in three ways to our understanding of whether energy regulations and interventions aimed at improving energy efficiency are effective in developing countries (e.g., Duflo et al. 2013, 2018; Greenstone and Jack 2015; Harrison et al. 2015; Ryan 2018; Ito and Zhang 2020a). First, our setting features a case of strict enforcement, which is given by the Chinese government's use of high-powered

[2] Our welfare analysis focuses on the aggregate effects of the program. However, it is possible for the program to impact welfare through heterogeneous effects across more polluted or populated areas or if it shifted production to less developed regions. Supplemental Appendix K provides an expanded welfare framework that incorporates these channels. This Supplemental Appendix also documents that the program did not significantly shift production to more polluted or populated areas and that it did not reallocate production to less developed regions in Western China. For these reasons, our model and welfare analyses abstract from spatial implications of the policy.

[3] In Supplemental Appendix I, we use estimates of pollution damages in China (World Bank 2007; Mohan et al. 2020; Ito and Zhang 2020b) to calculate that between \$4 and \$17 of the GWTP could reflect the health benefits of reducing pollution. The remaining \$144–\$157 would be attributed to the SCC. The low estimates of pollution damages per ton of carbon in China contrast with estimates from richer countries; for instance, we obtain an estimate of \$78 for the United States based on the results of Mohan et al. (2020). Using this value would imply an SCC that rationalizes the policy of \$83. For comparison, recent proposed values of the SCC range between \$51 (IWG 2021) and \$125 (Carleton and Greenstone 2021).

incentives that tie environmental performance to cadre promotion (Kahn, Li, and Zhao 2015; Jia 2017; He, Wang, and Zhang 2020). Second, the program we study represents one of the largest efforts to curb energy use in a developing country. As Auffhammer and Gong (2015) note, the Top 1,000 program and its expanded version in later years are the "most significant national programs" focusing on energy efficiency and energy conservation in China.[4] Official assessments of the program that compared the variation over time in the energy use of regulated firms concluded that the program was effective, which motivated the expansion of the program. Third, our results highlight the importance of accounting for both within-conglomerate and market-level leakage in an equilibrium framework. By using firm-level data on energy consumption and production to identify the direct effects of the program as well as aggregate effects that account for conglomerate- and market-level spillovers, our results provide a fundamental reassessment of the effectiveness of the Top 1,000 program.

Our finding that the Top 1,000 program impacted economic activity in regulated and unregulated firms contributes to the literature studying the economic costs of environmental regulations. For the United States, researchers have documented significant effects of environmental regulations on emissions and economic activity (e.g., Greenstone 2002; Greenstone, List, and Syverson 2012; Walker 2013; Shapiro and Walker 2018; Curtis 2018). He, Wang, and Zhang (2020) show that Chinese firms that face more stringent regulations experience significant decreases in productivity. In contrast, Colmer et al. (2020) find that French firms that are subject to the European Union's emissions trading scheme do not experience significant declines in production and that their declines in energy do not spill over to unregulated firms. Our paper contributes to our understanding of the economic cost of energy regulation in China, which consumes the lion's share of global industrial energy.

Researchers have also documented that regulations can have spillover effects along firm networks. For instance, Hanna (2010) finds that multinational firms respond to domestic environmental regulations by increasing their investment in foreign countries, and Gibson (2019) and Soliman (2020) find that firms may also shift economic activity to unregulated plants in counties subject to less stringent regulations. Conglomerate spillovers are particularly important in our setting because the Top 1,000 program targeted very large firms with elaborate ownership networks. Our detailed business registration data provide a unique view into how this regulation affected the production decisions of large Chinese conglomerates and how conglomerate spillovers impacted the effectiveness of the regulation. Our model leverages these spillovers to quantify the marginal cost of the regulation, using the fact that conglomerates incur a loss when they distort the within-conglomerate allocation of production (see, e.g., Anderson and Sallee 2011).

Our paper also takes into account the roles of leakage and market competition in environmental regulation. Research has shown that emissions leakage to unregulated firms can significantly alter the effects and design of environmental policies

[4] We survey prior work studying the Top 1,000 program in Supplemental Appendix B. We first discuss research on the policy details of the Top 1,000 program, the role of local government officials in achieving energy savings targets, and the difficulty involved in evaluating energy-saving measures in Supplemental Appendix B.1. Appendix B.2 then summarizes prior studies of the economic effects of the program, which have relied on time series evidence (Wang et al. 2017; Ke et al. 2012) or have mostly focused on evaluating the effects of the regulation on firm-level patenting and productivity (Shen et al. 2015; Filippini et al. 2020; Ai, Hu, and Li 2021; Xiao, Yin, and Moon 2023).

(e.g., Fowlie 2009; Fischer and Fox 2012; Bushnell, Chen, and Zaragoza-Watkins 2014; Baylis, Fullerton, and Karney 2014; Fowlie and Reguant 2022). This paper quantifies the aggregate and welfare effects of the Top 1,000 program by combining microdata on the operations of Chinese industrial firms, transparent research designs that identify the direct and spillover effects of a prominent energy regulation, and an industry equilibrium model that is consistent with the estimated effects of the program. The combination of these approaches accounts for market competition and leakage effects, demonstrating that conglomerate spillovers are a distinct force that plays a quantitatively important role in the context of China and that feasible conglomerate-level regulations can improve the regulation of energy.

I. Policy Background and Data

This section describes the intended design and actual implementation of the Top 1,000 Energy Conservation Program. We also describe the different datasets that we use to measure economic activity and energy use, as well as our strategy for mapping the ownership networks of Chinese conglomerates.

A. *The Top 1,000 Program*

To save energy and reduce related carbon emissions, the Chinese government's 11th Five-Year Plan (11FYP) set the ambitious goal of reducing the country's energy intensity—defined as energy consumption per unit of GDP—by 20 percent between 2006 and 2011 (Price, Wang, and Yun 2010). Because the industrial sector accounts for 70 percent of total energy consumption, the government designed policies that focused on nine energy-intensive industries that accounted for 80 percent of the country's industrial energy use (Wang et al. 2008). One of these initiatives was the Top 1,000 Energy Conservation Program, which targeted the firms with the highest energy consumption in the most energy-intensive industries.

The Top 1,000 program was first announced by the National Development and Reform Commission in April 2006, and the corresponding monitoring and assessment measures were released in 2007. The name "Top 1,000" refers to the 1,008 industrial firms in the 9 energy-intensive industries with energy consumption above 180,000 tce in 2004. The total energy consumption of these 1,008 super firms was 670 million tce in 2004, accounting for 47 percent of China's industrial energy consumption and 33 percent of its total energy consumption (Wang et al. 2008). Importantly, because the policy was announced in 2006 and selected firms based on their retrospective 2004 energy consumption, it was not possible to manipulate the list of program participants. Moreover, the list of firms regulated by the program did not change during the five-year period. Among the Top 1,000 firms, those in the iron and steel, chemical, and electric power industries accounted for approximately 63 percent of the firms and 68 percent of the regulated energy consumption in 2005 (NDRC and NBS 2007).

The Top 1,000 program was designed based on the belief that Chinese industries could significantly increase energy efficiency at a low cost (e.g., Granade et al. 2009). The program was influenced by voluntary agreement programs in developed countries and had two stated goals: to significantly increase the energy efficiency of these super firms and to save 100 million tce in energy consumption by 2011. Given the program's quick implementation, many aspects of voluntary agreement programs (such as providing technological expertise or financing energy efficiency improvements) played a relatively minor role (Price, Wang, and Yun 2010).

In the original policy design, the central government assigned an energy savings target to each provincial government. Local governments were responsible for working with firms to establish and monitor firm-level targets. Due to the difficulty of monitoring energy savings or efficiency, the practical implementation of the policy instead relied on energy use quotas. We use detailed interviews with the principal architect of the policy, government officials, and regulated companies to corroborate that in practice, firms were regulated based on energy use quotas and were not primarily evaluated on energy savings or efficiency.[5] The firms' energy quotas were based on historical energy use relative to an expected industry-level growth trajectory. For these reasons, firms would not be mechanically compliant based on secular, industry-wide improvements in energy efficiency. Regulated firms were subject to annual energy audits carried out by a third party and faced potential additional audits by the Ministry of Industry and Information Technology and the National Energy Administration. Leaders of provincial governments were evaluated on whether their targets had been met. Accordingly, local government officials monitored Top 1,000 firms very closely.

Due to this perceived success under the 11FYP, the Top 1,000 program was expanded into the "Top 10,000" Energy Conservation and Carbon Reduction Program during the 12th Five-Year Plan (12FYP) in 2012. In this case, "Top 10,000" refers to 16,078 energy-intensive firms with energy consumption above 10,000 tce in 2010. These firms account for 60 percent of China's total energy consumption. As in the Top 1,000 program, firms among the Top 10,000 were required to improve their energy efficiency with a goal of saving a total of 250 million tce during the 12FYP (NDRC 2011). Our primary analysis focuses on Top 1,000 firms between 2001 and 2011. Because the industrial firms in the Top 10,000 (but not in the Top 1,000) were also energy intensive but were not regulated during the 11FYP, they serve as useful controls for our empirical analysis.

B. *Firm Data*

Our empirical analyses combine several rich datasets that describe firm-level production and energy use. We obtain the list of firms in the Top 1,000 and Top 10,000 programs from the National Development and Reform Commission. We then collect detailed information on firm energy consumption from 2001 to 2010 from China's Environmental Statistics Database (CESD), provided by China's Ministry of Environmental Protection (CMEP 1998–2010). These data allow us to measure

[5] Supplemental Appendix A provides program details, additional descriptive facts, and detailed accounts of our interviews. Supplemental Appendix A.1 clarifies that the Top 1,000 program focused on energy conservation. Neither pollution reduction nor reallocation of economic activity across different regions was a primary goal. This Supplemental Appendix also compares the scope of the Top 1,000 program to that of other large programs around the world. In Supplemental Appendix A.2, we document that it was not feasible for either the government or the regulated firms to implement the statutory energy savings targets. Supplemental Appendix A.3 provides details on how local officials determined the individual energy use quotas of each of the Top 1,000 firms.

the effects of the regulation on the production and energy use of Top 1,000 and Top 10,000 firms. The CESD data are primarily collected by local environmental agencies and focus on polluting enterprises. These data are subject to audits by environmental protection agencies at both the local and national levels and cover the vast majority of Top 1,000 firms and a subset of Top 10,000 firms.

We complement these data with two additional datasets. First, we use data on firm characteristics from the Annual Survey of Industrial Firms (ASIF) from the National Bureau of Statistics (NBS 1998–2009, 2011–2013).[6] This dataset provides detailed information on a firm's industry, address, ownership, output, and financial information and covers all industrial firms with annual revenue above ¥5 million (approximately $604,000).[7] These data are also valuable because they cover a large number of firms related to Top 1,000 firms, which allows us to estimate the spillover effects of the program. Second, we use data from the Annual Tax Survey (ATS) for 2009 and 2010 in robustness checks (SAT 2008–2011).

Supplemental Appendix C.1 provides additional details on these firm-level datasets. This Supplemental Appendix describes how we merge the data and the steps we take to limit concerns of data manipulation.[8] Using multiple datasets allows us to cross-check our data to ensure our results are not driven by misreporting or other data quality issues. This Supplemental Appendix also discusses sample restrictions and summary statistics for our main analysis sample.[9]

C. *Mapping Conglomerate Networks*

We identify firms' ownership networks using data from China's Administrative Registration Database (CARD) (SAIC 1949–2018). These data are collected by the State Administration of Industry and Commerce and list the registration information of all firms in China starting in 1980, including firm name, registration number, date of establishment, address, ownership, registered capital, and related legal persons. Importantly, the data provide detailed shareholder information, which allows us to construct firm ownership networks at multiple levels.

We construct ownership networks using four types of linkages (see Supplemental Appendix Figure A.1 for examples). First, we include wholly owned subsidiaries of regulated firms as related parties. These affiliate linkages are analogous to the concept of plants in a multi-establishment firm in the United States. Second, we include

[6] As is well-known in the literature, data for the 2010 ASIF display a number of irregularities and are often excluded from statistical analyses. As we show in Supplemental Appendix F, our results are robust to using administrative tax data for 2009 and 2010.

[7] Throughout this paper, we rely on the ¥8.28 per dollar pegged exchange rate used by China from 1994 to July 2005 (see CRS 2013).

[8] Supplemental Appendix C also discusses government procedures to ensure data quality, including audits and penalties for misreporting.

[9] Because the CESD reports energy consumption only from primary sources (e.g., coal, oil, gas), our analyses of energy use and energy efficiency exclude firms in industries that rely mainly on electricity. In practice, we exclude industries where electricity consumption accounts for more than 30 percent of total energy consumption. As we show below, our results are robust to setting this threshold to between 25 percent and 50 percent and to including firms in all industries. We also restrict the sample to those firms with complete yearly data on coal use. After these restrictions, our estimation sample comprises 427 Top 1,000 firms, which we observe for an average of 8 years. Our results are robust to different decisions on how to construct the sample. We find similar results when we extend the sample by using administrative tax data to fill in missing values for energy use and when we restrict the sample to include firms that existed over the whole sample period.

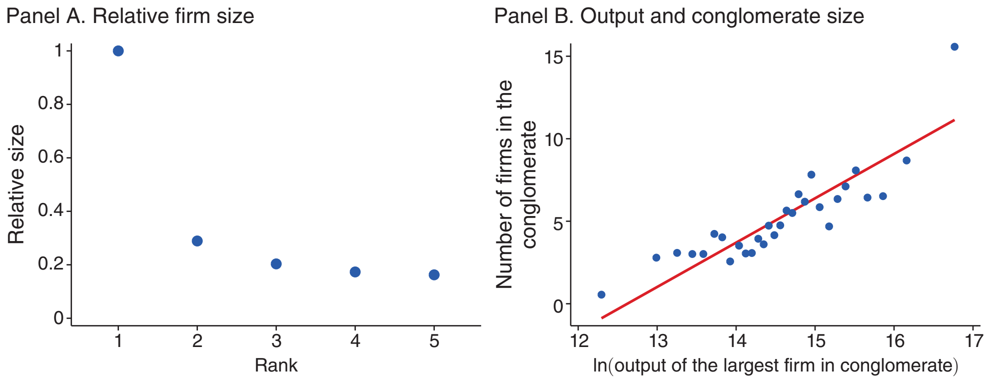

FIGURE 2. CONGLOMERATE SIZE AND PRODUCTION ALLOCATION

Notes: This figure shows stylized relationships between conglomerate size and relative firm size within conglomerates. Panel A plots the average relative size (each firm's size relative to the largest firm in the conglomerate) within a Top 1,000 conglomerate. Firms are ranked by size from the largest to the smallest, and size is measured by industrial output. This figure shows that firm size declines very quickly in a conglomerate, with the second-largest firm being only 29 percent of the size of the largest. Panel B plots the results of a regression of quantity of firms on log output of the largest firm in a Top 1,000 conglomerate. It shows that conglomerates with larger leading firms usually have more firms. See Section IC for additional discussion.

Source: Authors' calculations using ASIF and CARD data.

firms that are at least partially owned by regulated firms. Third, we include shareholders of regulated firms. Finally, we include firms that are fully or partly owned by the shareholders of a regulated firm.[10]

The merged CARD and ASIF data reveal interesting patterns. First, Top 1,000 firms have 2,466 related industrial firms in the same four-digit industry, an average of 2.45 related parties per regulated firm. Our baseline regressions examine related firms in these narrowly defined industries. Because it is likely hard to shift production to firms in other industries, we analyze firms in the same two-digit industry but outside the four-digit industry in a placebo test.

Second, because Top 1,000 firms are, in most cases, the largest firms in each industry, their related parties are smaller. On average, the output of related firms is 19.3 percent of the output of regulated firms. This implies that, while conglomerates may have had significant scope to substitute production across related firms, it is unlikely that these related parties could fully make up for production declines in Top 1,000 firms.

Third, the size distribution of firms within conglomerates tends to be very skewed. As we show in panel A of Figure 2, the second-largest firm in a conglomerate is on average only 29 percent as large as the largest firm. Interestingly, the decline in relative firm size is almost geometric, a fact that we use in our structural model. Finally, panel B of Figure 2 shows the relation between the output of the largest firm and the number of firms in a conglomerate. The fact that conglomerates with more firms

[10] We allow for up to two levels of investment for each of these relations. Although in practice most related firms are fully owned, we require ownership relations of at least 25 percent of the related firm at each level of investment. We exclude firms related only through the state-owned management committee. If firms split, the energy use targets would accompany the firms after any such separation. In addition, we do not find effects on mergers: less than 4 percent of related firms experience significant ownership changes between 2007 and 2018.

also have larger leading firms suggests that the number of firms in a conglomerate might depend on technological efficiencies shared by all firms in the conglomerate.

II. Effects of the Policy on Regulated Firms

We study the direct effects of the Top 1,000 program by comparing the activities of regulated firms relative to those of other large firms operating in energy-intensive industries. We use firms that became regulated after 2011 as part of the Top 10,000 program as controls, excluding those firms that are in the same conglomerate as Top 1,000 firms. Because control firms can be affected by market-level spillovers, the relative changes between the regulated and control firms that are identified by our difference-in-differences estimates combine the program's effects on regulated firms with its indirect effects on control firms. We interpret these effects using our model in Section VC, which allows us to separate and quantify these forces.

We provide evidence that Top 1,000 and Top 10,000 firms had similar trends prior to the implementation of this regulation using firm data from the CESD to estimate event studies of the form

$$(1) \qquad Y_{ijkt} = \sum_{\tau \neq 2006}^{2010} \beta_\tau \times Treat_i \times Year_\tau + \alpha_i + \eta_{jt} + \delta_{kt} + \varepsilon_{ijkt},$$

where Y_{ijkt} is a dependent variable for firm i in industry j, province k, and year t. $Treat_i$ is a treatment group indicator that equals 1 for Top 1,000 firms and 0 for Top 10,000 firms. The coefficients β_τ from this specification represent differences in the dependent variable between Top 1,000 and Top 10,000 firms in each year. Given that the policy evaluation began in 2007, we identify the effects of the policy relative to performance before 2006. We include firm-level fixed effects α_i and year fixed effects in all regressions, and we show that our results are robust to inclusion of (two-digit) industry-by-year fixed effects η_{jt} and province-by-year fixed effects δ_{kt}. We cluster standard errors at the firm level.

Figure 3 presents a visual implementation of our difference-in-differences estimation strategy. Panel A in Figure 3 displays the β_τ coefficients when the outcome variable is firm-level energy use (total coal consumption equivalent). This figure shows that, prior to the implementation of the regulation, our treatment and control firms had similar trends. Additionally, this figure makes clear that the policy succeeded in lowering the energy use of regulated firms relative to that of unregulated firms. Panel B of this figure compares these year-by-year effects to the overall trend in energy consumption.[11] As this figure shows, the program successfully arrested the explosive growth in the energy use of regulated firms.

We quantify the effects of the policy by estimating difference-in-differences specifications of the form

$$(2) \qquad Y_{ijkt} = \beta Treat_i \times Post_t + \mathbf{X}'_{it}\gamma + \alpha_i + \eta_{jt} + \delta_{kt} + \varepsilon_{ijkt},$$

[11] For visual clarity, panels B, D, and F in Figure 3 follow Ohrn (2018) by plotting trends for the control group that are rescaled to have the same average level in the pre-period as the treated group.

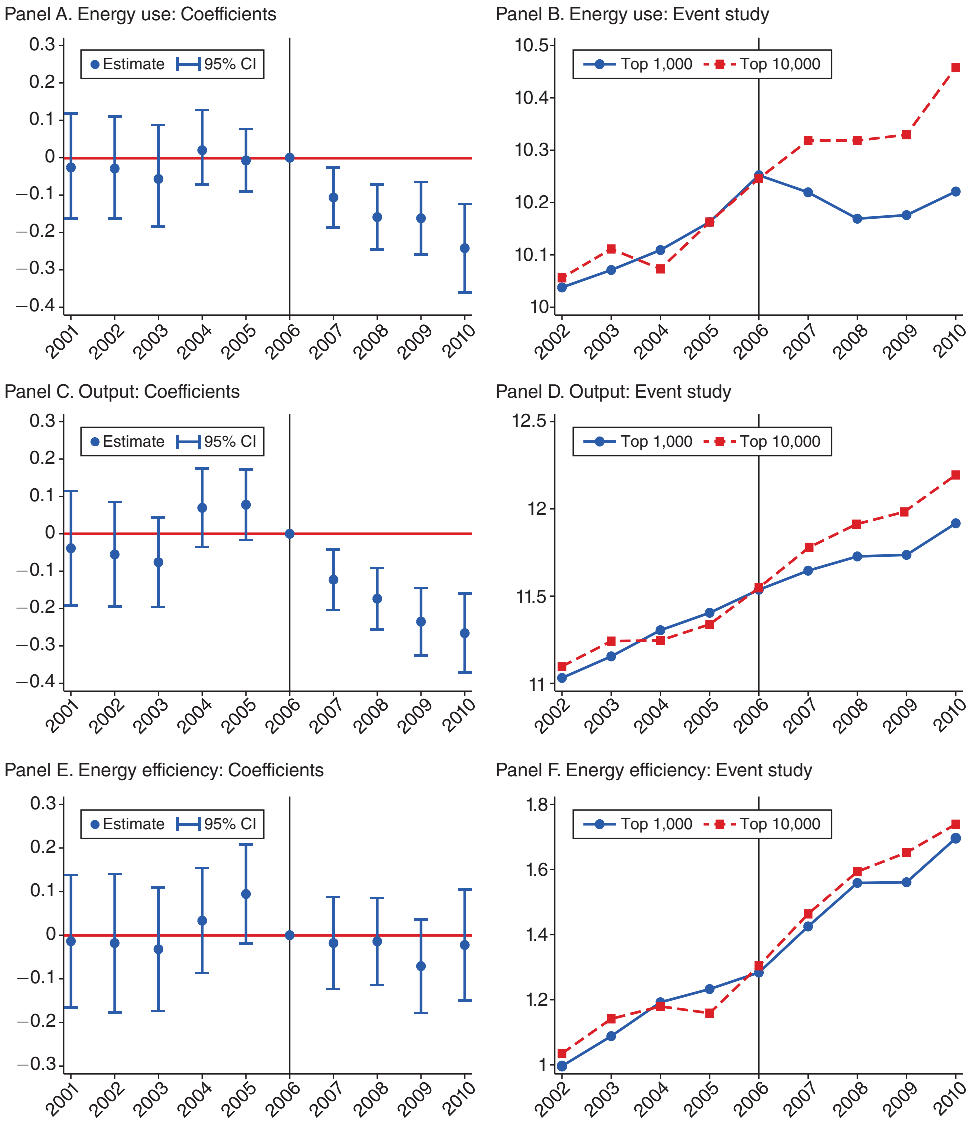

Figure 3. Effects of the Program on Regulated Firms

Notes: This figure shows estimates of equation (1) where the dependent variable is log firm energy consumption in panels A and B, log firm output in panels C and D, and log firm energy efficiency in panels E and F. Energy efficiency is defined as output per unit of energy consumption. This figure shows that regulated firms (Top 1,000 firms) decreased their energy consumption and output substantially relative to similar control firms (unrelated Top 10,000 firms) after the regulation. However, we find no improvement in energy efficiency in these regulated firms. Point estimates are displayed in Table 1. See Section II for additional discussion. Standard errors are clustered at the firm level.

Source: Authors' calculations using CESD data.

where $Post_t$ is an indicator that equals one after 2006. In addition to the different fixed effects, some specifications include controls for firm characteristics $\mathbf{X}_{it}$, which include indicators for state-owned firms and exporting firms, measures of profitability (e.g., return on assets), and firm age. Panel A of Table 1 shows that,

Table 1—Effects of the Program on Regulated Firms

Variables	ln(Energy Use)			
Panel A. Energy use				
Treat × Post	−0.125	−0.156	−0.156	−0.128
	(0.042)	(0.045)	(0.047)	(0.048)
	[0.003]	[0.001]	[0.001]	[0.008]
Observations	23,607	23,602	23,151	20,571
R^2	0.887	0.890	0.892	0.898
Variables	ln(Output)			
Panel B. Output				
Treat × Post	−0.096	−0.226	−0.204	−0.145
	(0.040)	(0.041)	(0.042)	(0.042)
	[0.017]	[0.000]	[0.000]	[0.001]
Observations	23,435	23,430	22,991	20,446
R^2	0.881	0.887	0.889	0.893
Variables	ln(Energy Efficiency)			
Panel C. Energy efficiency				
Treat × Post	0.032	−0.069	−0.049	−0.019
	(0.042)	(0.044)	(0.046)	(0.047)
	[0.451]	[0.119]	[0.290]	[0.691]
Observations	23,435	23,430	22,991	20,446
R^2	0.837	0.840	0.842	0.848
Firm fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Industry × Year fixed effects		Y	Y	Y
Province × Year fixed effects			Y	Y
Firm-level controls				Y

Notes: This table shows estimates of equation (2) where Treat × Post is an indicator for regulated firms interacted with an indicator for years after 2006 and the dependent variable is log firm energy consumption in panel A, log firm output in panel B, and log firm energy efficiency in panel C. The estimates in this table correspond to a pooled version of the regression displayed in Figure 3. The coefficient in column 4 means that regulated firms decreased energy consumption by 12.8 percent and output by 14.5 percent. However, firms did not appear to improve energy efficiency after the implementation of the policy. See Section II for additional discussion and online Appendix Table A.7 for more information about the data and variables. Standard errors clustered at the firm level are shown in parentheses, with p-values in brackets below.

Source: Authors' calculations using CESD and ASIF data.

on average, the total energy consumption of regulated firms decreased by 13–16 percent. Estimates are similar across specifications that include different levels of fixed effects and firm controls. To interpret the magnitude of this effect, recall that the regulated firms consumed 670 million tce in 2004. Taking the coefficients in Table 1 at face value therefore implies annual reductions in energy use of roughly 100 million tce, or approximately 20 percent of the total industrial energy use of the European Union.

To discern whether this reduction in energy use was driven by changes in economic activity or in energy efficiency, we now estimate the effects of the program on firm output (i.e., revenue). Panels C–D of Figure 3 show that, after the reform, firm output in regulated firms also decreased significantly. Indeed, panel B of Table 1 reports output declines of between 10 percent and 23 percent, depending on the specification. Accounting for the declines in output implies that the policy had limited impacts on energy efficiency. Panel E of Figure 3 shows that we cannot reject the null hypothesis that the policy had no impact on energy efficiency. Based on the specification with both industry- and province-by-year fixed effects in column 3 of panel C of Table 1, the 95 percent confidence interval rules out that the policy increased energy efficiency by more than 4 percent, which is significantly below the government's goal of improving energy efficiency by 20 percent. Panel F of Figure 3 shows that, while the program did not lead to relative increases in the energy efficiency of regulated firms, the average energy efficiency of both Top 1,000 and unregulated firms saw significant improvements during this time period, reflecting broad efforts to increase the energy efficiency of the Chinese economy. However, regulated firms were not able to significantly improve their energy efficiency relative to control firms during these five years.[12]

The Supplemental Appendixes explore the robustness of these results. Supplemental Appendix D.1 shows these results are robust to changing the criteria for inclusion in our analysis sample, to using tax survey data when they are available, to restricting the analysis to approximate a balanced panel, and to restricting the sample to include firms that were closer to the regulation threshold. This Supplemental Appendix also shows that regulated firms did not increase their likelihood of merging or filing a patent but decreased their likelihood of investment. We also do not find meaningful heterogeneity in the impact of the Top 1,000 program across industries or state-owned enterprises (SOEs). Supplemental Appendix D.2 further shows that our results are not sensitive to accounting for other, concurrent policies. Finally, Supplemental Appendix E explores potential margins of substitution. We do not find strong evidence that firms adjust their capital-labor ratios or their mix of energy inputs in response to the program.

The effects of the policy on regulated firms paint a picture of mixed success. On the one hand, the regulation succeeded in achieving a meaningful reduction in the energy use of energy-intensive firms. However, this reduction did not come about through a significant increase in energy efficiency, which—while not directly targeted—was one of the underlying intents of the policy. The next section studies whether conglomerates avoided the burden of the regulation by shifting economic activity to related parties.

III. Spillover Effects of the Policy through Ownership Networks

Regulated firms have strong incentives to shift production to related parties. By shifting production, conglomerates can partially offset declines in economic activity in regulated firms. Such shifting also allows conglomerates to comply with the letter of the regulation—if not with its intent—without halting output or having to invest in potentially costly improvements to energy efficiency.

[12] The lack of an effect on energy efficiency is also consistent with the extant view (e.g., Price, Wang, and Yun 2010) that other aspects of the reform (such as financing for energy efficiency improvements) played a relatively minor role in the short term. In Supplemental Appendix J.1, we consider how allowing for endogenous investments in energy efficiency impacts the aggregate outcomes and welfare effects of the policy as firms adopt energy-saving technologies over a longer period of time.

To measure the empirical importance of conglomerate spillovers, we use CARD data on the ownership networks of regulated firms to identify related firms that may have indirectly expanded as a consequence of the Top 1,000 regulation. We then use matching methods to identify control firms that were (i) not part of the Top 1,000 program, (ii) not related to a regulated firm, and (iii) in the same industry and of similar size (measured in terms of output) in the years prior to the regulation. Using these firms as controls, we then conduct event-study and difference-in-differences analyses using specifications similar to those in equations (1) and (2). In this setting, the $Treat_i$ variable is now an indicator of whether a firm is related to a Top 1,000 firm. We focus our study of spillovers on related firms in the same four-digit industry as the regulated firm, following the logic that only firms selling similar products may be able to make up for the production decline in Top 1,000 firms.

Figure 4 plots the results of these event-study analyses using ASIF data. Panel A shows that, prior to the regulation, related firms had output trends similar to those of unrelated firms. After the regulation, firms related to Top 1,000 firms saw significant increases in output that persisted for several years. The last column of panel A of Table 2 shows that related firms expanded by 13 percent on average after the regulation. This table also shows that we obtain very similar results across specifications with different levels of fixed effects and with firm-level controls.

To gauge the magnitude of these spillover effects, it is important that we account for the number of related parties of each regulated firm and for their relative sizes. On average, Top 1,000 firms have 2.45 related parties. However, because the average related firm is only 19.3 percent as large as its regulated counterpart, we calculate that conglomerates could shift only close to 41 percent of the output decline in regulated firms.[13] This result is informative for a couple of reasons. First, it shows that conglomerates were not able to fully circumvent the regulation. Second, combined with the null effect of the program on the energy efficiency of regulated firms, the result shows that firms were unable or unwilling to increase their energy efficiency in production processes.

We now show that only those related firms operating in the regulated firms' own narrowly defined industries—that is, those that could thus possibly produce substitute output—increased their economic activity. Panel B of Figure 4 and panel B of Table 2 show no impact on the output of related firms operating outside the four-digit industry of (but still in the same two-digit industry as) the regulated firm. This placebo test rules out the possibility that firms related to large conglomerates saw increases in economic activity after 2007, say, in response to the financial crisis or other shocks or trends.

The result that related firms display an increase in economic activity is robust across a number of checks described in Supplemental Appendix F. While our baseline analyses rely on one-to-one matching based on Euclidean distance in output prior to the policy, we find similar results using the entropy balancing method of Hainmueller (2012) to select control firms. This Supplemental Appendix also shows that these results are

[13] Using the 12.7 percent estimate on related firms from column 4 of panel A of Table 2, we calculate that the overall increase in related firms amounted to 6% $\left(\approx 2.45 \times 19.3\% \times 12.7\%\right)$ of the output of regulated firms. This increase is 41 percent of the comparable 14.5 percent decrease from column 4 of panel B of Table 1. Supplemental Appendix F considers the sensitivity of this calculation.

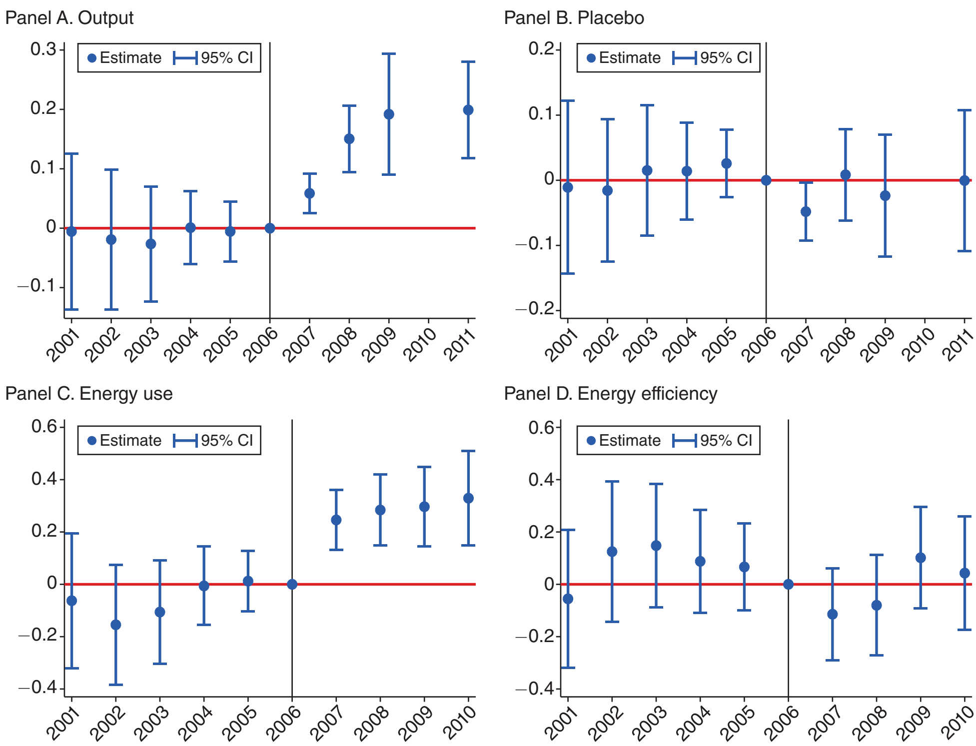

Figure 4. Spillover Effects on Related Firms

Notes: This figure shows the effects of the Top 1,000 Energy Conservation Program on the related parties of regulated firms. Panel A shows that related firms in the same four-digit industry as regulated firms increased their output significantly after the policy implementation relative to similar control firms and that this effect persisted during the policy period. See Section III for a description of the procedure used to identify the comparison firms. The point estimate for panel A is displayed in panel A of Table 2. Panel B plots the output results for placebo firms (related firms in the same two-digit industry but outside the four-digit industry of regulated firms). This graph shows that placebo firms were not affected by the regulation. The point estimate for panel B is displayed in panel B of Table 2. Panels C and D show that related firms in the same four-digit industry increased their energy consumption after the regulation but did not improve their energy efficiency relative to similar control firms. The point estimates for panels C and D are displayed in Table 2. See Section III for additional discussion. The results of robustness checks using an alternative matching method are shown in online Appendix Figure A.15. Standard errors are clustered at the firm level.

Source: Authors' calculations using ASIF and CESD data.

robust to alternative definitions of business networks, to dropping firms in the power generation industry, and to accounting for entry or exit. We do not find heterogeneous spillover effects across industries, but we document that larger related firms are more able to expand their output in response to the regulation. We also explore the possibility that the regulation shifted the location of economic activity. First, as we show in Supplemental Appendix K, the spillover effects of the regulation did not disproportionately shift production to areas with higher population density or with higher preexisting levels of industrial emissions. Additionally, Supplemental Appendix H shows that, within regulated conglomerates, the program did not lead to an increased concentration of production in more energy-efficient firms.

Having established that conglomerates shifted output across related parties, we now explore whether these related firms also saw changes in energy use and energy

Table 2—Spillover Effects on Related Firms

Variables	ln(Output)			
Panel A. Output				
Related × Post	0.152	0.147	0.118	0.127
	(0.037)	(0.037)	(0.037)	(0.035)
	[0.000]	[0.000]	[0.001]	[0.000]
Observations	18,423	18,420	18,418	17,905
R^2	0.865	0.873	0.881	0.889
Variables	ln(Output)			
Panel B. Placebo test on output				
Related × Post	−0.026	−0.025	−0.015	−0.003
	(0.040)	(0.039)	(0.039)	(0.038)
	[0.518]	[0.520]	[0.695]	[0.938]
Observations	8,923	8,921	8,905	8,730
R^2	0.898	0.903	0.911	0.919
Variables	ln(Energy Use)			
Panel C. Energy use				
Related × Post	0.322	0.320	0.302	0.318
	(0.075)	(0.073)	(0.076)	(0.094)
	[0.000]	[0.000]	[0.000]	[0.001]
Observations	3,759	3,759	3,705	2,823
R^2	0.916	0.919	0.927	0.926
Variables	ln(Energy Efficiency)			
Panel D. Energy efficiency				
Related × Post	−0.077	−0.077	−0.059	−0.087
	(0.078)	(0.077)	(0.080)	(0.099)
	[0.321]	[0.318]	[0.461]	[0.380]
Observations	3,724	3,722	3,668	2,801
R^2	0.866	0.870	0.880	0.867
Firm fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Industry × Year fixed effects		Y	Y	Y
Province × Year fixed effects			Y	Y
Firm-level controls				Y

Notes: This table shows estimates of equation (2) where Related × Post is an indicator for related firms interacted with an indicator for years after 2006. The estimates in this table correspond to a pooled version of the regression displayed in Figure 4. This table shows that related firms in the same four-digit industries increased output by 11.8–15.2 percent. We do not find output increases for related firms outside the same four-digit industry as the regulated firms (but still in the same two-digit industry). We do find increases in energy consumption of 30.2–32.2 percent after the policy implementation, but we find no effects on energy efficiency. See Section III for additional discussion. The results of robustness checks with additional matching methods are shown in online Appendix Tables A.22 and A.23. Standard errors clustered at the firm level are shown in parentheses, with p-values in brackets below.

Source: Authors' calculations using ASIF and CESD data.

efficiency. Panels C and D of Figure 4 report these results using data from the CESD. Panel C shows that related firms saw an increase in energy use after the regulation. Panel C of Table 2 shows that energy use in related firms increased by 30–32 percent after the regulation. Note that the number of observations in this panel is smaller than that in panel A of Table 2. This is because related firms are smaller overall, and only the larger related firms are included in the CESD. As a result, caution is warranted in ascribing these increases in energy use to all related firms. Panel D of Figure 4 and Panel D of Table 2 show that these firms did not experience statistically significant changes in energy efficiency.

Overall, we find robust evidence that conglomerates shifted production across related parties. On average, this shifting behavior allowed conglomerates to recover approximately 40 percent of the output reduction in regulated firms. As we show in Section VI, the ability to shift production to related firms diminished the aggregate energy savings from the regulation.

Market-Level Spillovers.—Because related parties could not compensate the entire output loss of Top 1,000 firms, other firms in regulated industries may have been indirectly affected by the energy conservation program due to reduced competition. Intuitively, we would expect larger increases in the output of unrelated and unregulated firms in industries where the Top 1,000 program covered a larger share of industrial energy use. To test this hypothesis, we create the variable $spillover_j$, which is a measure of the regulation's strictness. $spillover_j$ is defined as the ratio of total energy savings targets of Top 1,000 firms in a two-digit manufacturing industry j to the total energy consumption of that industry in 2004. We then estimate the following difference-in-differences specification:

$$Y_{ijt} = \beta spillover_j \times Post_t + \mathbf{X}'_{it}\gamma + \alpha_i + \tau_t + \varepsilon_{ijt}. \tag{3}$$

To interpret the coefficient β as the average spillover effect, we normalize the $spillover_j$ variable by the average exposure across regulated industries. Because the variation in the independent variable is at the industry–year level, we do not include industry-by-year fixed effects in this regression. We instead use firm fixed effects and year fixed effects only, and we additionally control for overall output and energy use at the industry–year level.[14] Finally, to ensure that market-level spillovers are not contaminated by ownership-network spillovers, we exclude firms related to Top 1,000 firms from this specification.

Panel A of Figure 5 shows that unregulated firms in industries with stricter regulation increased their output significantly after the policy was implemented. Panel A of Table 3 shows that, across all industries, the average market-level spillover led to a 7–8 percent increase in the output of unregulated firms. The regressions in the first two columns of this table include both regulated and unregulated industries. We find similar increases when we include only firms in regulated industries. In this case, the identifying variation is driven solely by differences in regulation intensity across industries. Supplemental Appendix F discusses robustness checks for these results.

These results yield a couple of insights. First, the findings further confirm our previous estimates that related parties were not able to offset the full output loss of Top 1,000 firms. Second, a full accounting of the spillover effects of the regulation

[14] Note that the variation in $spillover_j$ is absorbed in our previous specifications that include industry-by-year fixed effects. By controlling for industry-level aggregates, the coefficient β in equation (3) captures the impact of the regulation on the market share of unregulated firms.

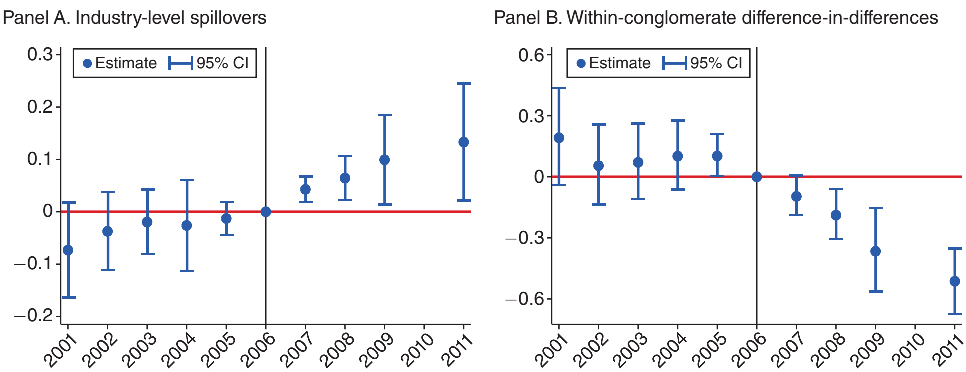

Figure 5. Industry-Level Spillovers and Within-Conglomerate Effects

Notes: Panel A of this figure shows estimates of equation (3) where the dependent variable is log firm output. Consistent with the market spillover hypothesis, we see that unregulated firms in industries with stricter regulation increased their output significantly after the policy was implemented. Coefficient estimates and robustness checks are shown in panel A of Table 3 and online Appendix Table A.31. See Section III for additional discussion. Standard errors are clustered at the industry level. Panel B of this figure plots the output change of regulated firms relative to their related firms (in the same four-digit industry) within the same conglomerate. We see a strong and persistent output reallocation following the regulation from regulated firms to their related firms. Point estimates are displayed in panel B of Table 3. See Section VC for additional discussion. Conglomerate-by-year fixed effects are included, and standard errors are clustered at the conglomerate level.

Source: Authors' calculations using ASIF data.

needs to include both within-conglomerate spillovers and market-level spillovers. Third, a potential limitation of the difference-in-differences analyses is that their interpretation depends on the strength of the conglomerate and market spillovers. The next section builds on these insights by proposing a model of conglomerate production. The model clarifies the interpretation of our reduced-form estimates in the presence of market and conglomerate spillovers, computes the aggregate effects of the Top 1,000 program, and allows us to consider the aggregate and welfare effects of alternative policies.

IV. A Model of Conglomerates with Regulation

This section presents an industry equilibrium model of conglomerate production that is consistent with the cross-sectional data patterns in Figure 2 and reduced-form responses to the energy regulation in Figures 3–5. Supplemental Appendix M provides detailed derivations of the model results.

A. *Demand and Technology*

Our industry equilibrium model draws the structure of product differentiation and monopolistic competition from Melitz (2003). We consider an individual sector with an exogenous aggregate expenditure R. The representative consumer has preferences over a continuum of varieties $\omega \in \Omega$:

$$U = \left[\int_{\omega \in \Omega} q(\omega)^{\rho} d\omega\right]^{1/\rho},$$

TABLE 3—INDUSTRY-LEVEL SPILLOVERS AND WITHIN-CONGLOMERATE EFFECTS

Variables	ln(Output)			
	All sample		Energy-intensive industries	
Panel A. Industry-level spillovers				
Spillover × Post	0.081	0.073	0.083	0.084
	(0.022)	(0.019)	(0.023)	(0.027)
	[0.001]	[0.001]	[0.006]	[0.013]
Observations	2,557,940	2,557,940	843,313	843,313
R^2	0.840	0.856	0.831	0.848
Firm fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Industry-level controls	Y	Y	Y	Y
Firm-level controls		Y		Y
Panel B. Within-conglomerate difference-in-differences				
Treat × Post	−0.343	−0.350	−0.367	−0.315
	(0.067)	(0.068)	(0.070)	(0.067)
	[0.000]	[0.000]	[0.000]	[0.000]
Observations	15,174	15,149	15,146	14,745
R^2	0.530	0.535	0.582	0.626
Treat	Y	Y	Y	Y
Conglomerate × Year fixed effects	Y	Y	Y	Y
Industry × Year fixed effects		Y	Y	Y
Province × Year fixed effects			Y	Y
Firm-level controls				Y

Notes: Panel A of this table shows estimates of equation (3) where Spillover × Post is an indicator for industry-level exposure to the Top 1,000 program interacted with an indicator for years after 2006 and the dependent variable is log firm output. Exposure to the Top 1,000 program is defined as the proportion of total energy savings targets of Top 1,000 firms relative to the total energy consumption in 2004 for each industry. The estimates in this table correspond to a pooled version of the regression displayed in panel A of Figure 5. The results show that the average market-level spillover led to a 7.3 percent–8.4 percent increase in the output of unregulated, unrelated firms. See Section III for additional discussion. Standard errors clustered at the industry level are shown in parentheses with p-values in brackets below. Panel B of this table shows the output change of regulated firms relative to that of related firms (in the same four-digit industry) within the same conglomerate. Treat × Post is an indicator for regulated firms (Top 1,000 firms) interacted with an indicator for years after 2006, and the dependent variable is log firm output. The estimates in this table correspond to a pooled version of the regression displayed in panel B of Figure 5 and show that regulated firms experienced a 31.5 percent–36.7 percent output decrease relative to the output of their related firms in the same conglomerate. See Section VC for additional discussion. Conglomerate-by-year fixed effects are included, and standard errors clustered at the conglomerate level are shown in parentheses with p-values in brackets below.

Source: Authors' calculations using ASIF data.

where $q(\omega)$ represents the consumption level of variety ω and $\sigma = 1/(1-\rho) > 1$ denotes the elasticity of substitution between varieties.[15] Utility maximization by the representative consumer yields the following residual demand curve for each variety ω:

$$q(\omega) = RP^{\sigma-1}p(\omega)^{-\sigma},$$

[15] The consumer can stand in for a downstream industry since regulated firms produce intermediate materials.

where $P = \left[\int_{\omega \in \Omega} p(\omega)^{1-\sigma} d\omega\right]^{1/(1-\sigma)}$ is the aggregate price index.[16]

We define a conglomerate in our model by the presence of a variety ω that can be manufactured by multiple affiliates.[17] Each conglomerate starts with a central producer—the model counterpart of a Top 1,000 firm. Conglomerates have heterogeneous production efficiencies ϕ, which are drawn from the distribution $G(\phi)$ with density $g(\phi)$.

Production at each affiliate i requires capital k_i, energy e_i, and variable inputs l_i. Energy and variable inputs are combined using Leontief technology $\tilde{l}_i = \min\{l_i, e_i \nu_i\}$, where ν_i is the affiliate's energy efficiency. The assumption that energy and variable inputs are perfect complements follows recent work in this area (e.g., Biesebroeck 2003; Fabrizio, Rose, and Wolfram 2007; Gao and Van Biesebroeck 2014; Ryan 2018).[18] Production at affiliate i is then $q_i = \phi_i \tilde{l}_i^{\alpha_l} k_i^{\alpha_k}$, which is subject to decreasing returns to scale, that is, $\alpha = \alpha_k + \alpha_l < 1$. Intuitively, conglomerates may operate more firms as a way to escape decreasing returns to scale and as a way to share production knowledge ϕ across firms. However, as we show in panel A of Figure 2, conglomerates are not able to replicate the same scale across related firms. To match this fact, we assume that the productivity of the ith affiliated firm is $\delta^{i-1}\phi$. This assumption can be interpreted as either a limit on the span of managerial control or a measure of imperfect knowledge sharing across firms. Finally, each manufacturing establishment incurs a fixed outlay of capital denoted by f. This assumption is motivated by the fact that conglomerates have a finite number of affiliates. Because of the fixed cost, Top 1,000 firms with larger efficiency values ϕ will also have a larger number of related firms, matching the data pattern in panel B of Figure 2.

We consider the conglomerate's problem in two stages. Prior to the regulation, conglomerates observe their productivity ϕ and optimally choose the number of affiliated firms n and the amount of capital $\{k_i\}_{i=1}^n$ and variable inputs $\{l_i\}_{i=1}^n$ for each affiliate. Conglomerates can choose $n = 0$, which we interpret as an exit decision. After the regulation, because capital is quasi-fixed, the conglomerate adjusts its variable inputs to maximize profits. We assume that energy efficiency is constant and fixed (i.e., $\nu_i = 1$ for all firms), and we consider costly investments to improve energy efficiency and heterogeneous efficiencies in Supplemental Appendixes J.1 and J.2, respectively.

B. *Profit Maximization*

The conglomerate takes the prices of energy p_e, capital r, and the variable input bundle w as given. Given the Leontief technology, the conglomerate sets $l_i = e_i$ so

[16] This market structure implicitly assumes that this industry is not characterized by dominant firms that may act strategically. This is a reasonable assumption in our setting because we study manufacturing industries that, even when narrowly defined, feature a large number of firms and that serve a national market.

[17] The assumption that outputs of related firms are perfect substitutes is motivated by the large spillover results in Table 2. Supplemental Appendix J.4 explores the robustness of our results to allowing for an imperfect degree of substitution within conglomerates.

[18] Fabrizio, Rose, and Wolfram (2007) and Gao and Van Biesebroeck (2014) adopt this assumption from Biesebroeck (2003) in the context of energy generation. Gao and Van Biesebroeck (2014) study the case of China. Ryan (2018) estimates a production function with energy using data from India and finds that energy and unskilled labor are close to perfect complements. This assumption is broadly consistent with the results we discuss in Supplemental Appendix E.

that the cost of intermediate inputs is $w + p_e$. Holding the number of affiliates n constant, the conglomerate maximizes

$$(4)\quad \pi(\phi,n) = \max_{\{l_i\}_{i=1}^n,\{k_i\}_{i=1}^n} \left\{ R^{1-\rho}P^{\rho}\left[\sum_{i=1}^{n}\phi\,\delta^{i-1}k_i^{\alpha_k}l_i^{\alpha_l}\right]^{\rho} - (w + p_e)\sum_{i=1}^{n} l_i - r\sum_{i=1}^{n} k_i \right\}.$$

For a firm i, the first-order conditions for l_i and k_i imply that $l_i = \frac{\alpha_l}{\alpha_k}\frac{r}{(w + p_e)}k_i$. Substituting this expression and comparing the first-order conditions for k_1 and k_i, we obtain the following result.

PROPOSITION 1 (Within-Conglomerate Distribution): *Absent regulation, the inputs and the output of producers in a conglomerate follow a decreasing geometric sequence given by*

$$(5)\qquad \frac{q_i}{q_1} = \frac{k_i}{k_1} = \frac{l_i}{l_1} = \frac{e_i}{e_1} = \delta^{\frac{i-1}{1-\alpha}}.$$

The within-conglomerate distribution described in Proposition 1 is broadly consistent with the empirical pattern in panel A of Figure 2, where the average output of the second-largest affiliate in a conglomerate is less than 30 percent of that of the largest one and where the output of other affiliated producers in the conglomerate decreases exponentially with their rank i. Equation (5) links this distribution to two model parameters. First, the size gap among affiliates is larger if within-group knowledge depreciation is more severe (lower δ). Second, if firms are closer to having constant-returns-to-scale production (α is closer to one), the conglomerate concentrates more activity in its top producer, which increases the dispersion of the within-group size distribution.

To consider the choice of total capital $K_n = \sum_{i=1}^{n} k_i$, define the conglomerate's total productivity $\phi\Delta_n = \phi\left[\sum_{i=1}^{n}\left(\delta^{i-1}\right)^{\frac{1}{1-\alpha}}\right]^{1-\alpha}$ and the constant $C_\pi = (1 - \alpha\rho)\left[\left(\frac{\rho\alpha_l}{w + p_e}\right)^{\alpha_l\rho}\left(\frac{\rho\alpha_k}{r}\right)^{\alpha_k\rho}\right]^{1/(1-\alpha\rho)}$. We reformulate equation (4) using the results of Proposition 1 so the optimal choice of capital K_n solves

$$\pi(\phi,n) = \max_{K_n}\left\{\frac{R^{1-\rho}P^{\rho}C_\pi^{1-\alpha\rho}}{(1 - \alpha\rho)^{1-\alpha\rho}}\left(\frac{\rho\alpha_k}{r}\right)^{-\alpha\rho}(\phi\Delta_n)^{\rho}K_n^{\alpha\rho} - r\left(\frac{\alpha}{\alpha_k}\right)K_n\right\}.$$

The optimal capital K_n and the firm profits for a conglomerate of size n are then

$$K_n = \frac{R^{\frac{1-\rho}{1-\alpha\rho}}P^{\frac{\rho}{1-\alpha\rho}}C_\pi}{1 - \alpha\rho}\frac{\rho\alpha_k}{r}(\phi\Delta_n)^{\frac{\rho}{1-\alpha\rho}} \text{ and } \pi(\phi,n) = R^{\frac{1-\rho}{1-\alpha\rho}}P^{\frac{\rho}{1-\alpha\rho}}C_\pi(\phi\Delta_n)^{\frac{\rho}{1-\alpha\rho}}.$$

Consider now the optimal number of affiliates. The conglomerate adds an affiliate if

$$(6)\quad \pi(\phi,n + 1) - \pi(\phi,n) - fr = R^{\frac{1-\rho}{1-\alpha\rho}}P^{\frac{\rho}{1-\alpha\rho}}C_\pi \times\left[(\phi\Delta_{n+1})^{\frac{\rho}{1-\alpha\rho}} - (\phi\Delta_n)^{\frac{\rho}{1-\alpha\rho}}\right] - fr > 0.$$

Adding a new affiliate can improve the conglomerate's revenue and profit by lowering its overall marginal cost curve. On the other hand, the conglomerate incurs a fixed cost of fr when adding a new affiliate. While the marginal benefit of adding a new affiliate is increasing in ϕ, it is also decreasing in the number of existing affiliates n. Because the fixed cost is the same for all affiliates, equation (6) guarantees the existence of a cutoff value ϕ_n, where conglomerates with efficiency $\phi > \phi_n$ operate at least n affiliated producers.

PROPOSITION 2 (Optimal Conglomerate Size): *Without regulation, the optimal number of firms in a conglomerate n is nondecreasing in its fundamental efficiency ϕ. For $n > 1$, a conglomerate chooses to have n affiliated producers when $\phi_n \leq \phi < \phi_{n+1}$, where*

$$\phi_{n+1} = \frac{(fr)^{\frac{1-\rho\alpha}{\rho}}}{R^{\frac{1-\rho}{\rho}} P C_{\pi}^{\frac{1-\rho\alpha}{\rho}} \left(\Delta_{n+1}^{\frac{\rho}{1-\rho\alpha}} - \Delta_{n}^{\frac{\rho}{1-\rho\alpha}}\right)^{\frac{1-\rho\alpha}{\rho}}}. \tag{7}$$

Let $\pi(\phi) = \max_n \{\pi(\phi, n) - nfr\}$ be the profit for a conglomerate of efficiency ϕ at the optimal number of affiliates. Proposition 2 is consistent with the observation in panel B of Figure 2 that conglomerates with higher efficiency have, on average, a larger number of affiliated firms.

C. *Equilibrium and Welfare*

The unique equilibrium of the model is characterized by product-market clearing, the zero cutoff profit condition, and the free-entry condition. The aggregate price index is given by

$$P = \left[\int_{\phi_1}^{\infty} p(\phi)^{1-\sigma} \frac{g(\phi)M}{1 - G(\phi_1)} d\phi\right]^{\frac{1}{1-\sigma}}, \tag{8}$$

where M denotes the mass of active conglomerates. Conglomerates operate whenever

$$\pi(\phi) \geq 0 \Rightarrow \phi \geq \phi_1 = \frac{(fr)^{\frac{1-\rho\alpha}{\rho}}}{R^{\frac{1-\rho}{\rho}} P C_{\pi}^{\frac{1-\rho\alpha}{\rho}}}. \tag{9}$$

The minimum efficiency for a single-firm conglomerate, ϕ_1, is given by $\pi(\phi_1) = 0$. Equation (9) shows that only firms with $\phi \geq \phi_1$ choose to participate in the market.

To enter the market, an entrepreneur pays an entry cost rf_e. Upon entry, the efficiency of the conglomerate ϕ is realized. Because the conglomerate operates only if $\phi \geq \phi_1$, the free-entry condition is given by

$$\int_{\phi_1}^{\infty} \pi(\phi) g(\phi)\, d\phi - rf_e = 0. \tag{10}$$

An equilibrium is given by the exit threshold ϕ_1 and the mass of active conglomerates M such that (i) conglomerates make optimal allocation and size decisions,

(ii) the product market clears, and (iii) the zero-profit and free-entry conditions (equations (9)–(10)) are satisfied.

Welfare depends on consumption utility and on the utility costs of energy use. The CES preferences of the representative consumer imply that indirect utility is given by R/P, where R is total expenditure. Utility decreases in total carbon emissions $\beta_0 E$, where E denotes aggregate energy use and β_0 captures the carbon dioxide emitted per unit of energy, as well as in pollution $\beta_1 E$, where β_1 captures the composite effect of energy use on pollution. We assume that welfare takes the form

$$W = \left(\frac{R}{P}\right)^{1-\kappa}\left(\frac{1}{\beta_0 E}\right)^{\kappa_0}\left(\frac{1}{\beta_1 E}\right)^{\kappa_1}, \tag{11}$$

where the parameter κ_0 captures the social welfare loss from carbon emissions, κ_1 captures the welfare loss associated with pollution in China, and $\kappa = \kappa_0 + \kappa_1$.[19]

D. *Effects of the Top 1,000 Program*

We denote outcomes in the unregulated equilibrium with an asterisk to differentiate them from those in the regulated equilibrium. Because the Top 1,000 program targeted very large firms, we assume that only conglomerates with ϕ above an efficiency level $\tilde{\phi}$ are subject to the regulation. The regulation sets a proportional input quota for the largest firm in each conglomerate, which is the model counterpart of a Top 1,000 firm. Specifically, the energy use of regulated firms cannot exceed $\bar{e}_1(\phi) = \xi e_1^*(\phi)$, where $\xi < 1$ and e_1^* is the unregulated optimal energy use. At the time of the regulation, the conglomerate's capital allocations $\{k_i^*\}_{i=1}^n$ are quasi-fixed, but it can respond by adjusting its use of inputs $\{l_i, e_i\}_{i=1}^n$. Our model characterizes firm-level, conglomerate-level, and industry-wide effects of the program.

We first study how the regulation impacts firm-level production decisions. To do so, we substitute the result from Proposition 1 that $k_i = \delta^{\frac{i-1}{1-\alpha}} k_1$ into equation (4), define $\phi^* = \phi(k_1^*)^{\alpha_k}$, and let λ be the Lagrange multiplier associated with the regulatory constraint. The first-order conditions for $l_i (1 \leq i \leq n)$ are then

$$\frac{\partial \pi}{\partial l_i} = \underbrace{R^{1-\rho}P^{\rho}}_{\text{Market Demand}} \underbrace{\rho\left[\phi^* \sum_{i=1}^{n} \delta^{\frac{(i-1)(1-\alpha_l)}{1-\alpha}} l_i^{\alpha_l}\right]^{\rho-1}}_{\text{Residual Revenue}} \underbrace{\phi^* \delta^{\frac{(i-1)(1-\alpha_l)}{1-\alpha}} \alpha_l (l_i)^{\alpha_l - 1}}_{\text{Marginal Product}}$$
$$= w + p_e + \underbrace{\lambda(\phi)\mathbf{1}\{i = 1\}}_{\substack{\text{Shadow Cost} \\ \text{of Regulation}}}. \tag{12}$$

An important insight of this expression is that conglomerates internalize the marginal product of inputs across firms through the residual revenue term, which is common to all firms in the conglomerate. The impact of energy regulations on the residual

[19] See Shapiro (2016, 2021) for similar formulations of social welfare. Because we find that the regulation does not significantly shift the geographic distribution of energy use, our welfare measure does not account for the location of emissions. See Supplemental Appendix K for a discussion of our results in the context of an extended model with localized effects of emissions reductions.

revenue term is key to understanding the difference between within-conglomerate and market-level spillovers.

This equation shows that the regulation distorts the allocation of inputs within a conglomerate by adding a shadow cost $\lambda(\phi)$ to the input of the regulated firm. Because conglomerates with more affiliates can shift more production to related parties, conditional on being regulated, more efficient conglomerates (those with a higher ϕ) are subject to a smaller shadow cost $\lambda(\phi)$. Because only conglomerates with $\phi > \tilde{\phi}$ are part of the Top 1,000 program, the regulation also distorts input use across conglomerates.

The following proposition shows that the regulation leads conglomerates to allocate more inputs to the unregulated firms than in the case without the regulation.

PROPOSITION 3 (Within-Conglomerate Distribution under Regulation): *Under the Top 1,000 regulation, the inputs and the output of producers follow the sequences given by*

$$\frac{e_j}{e_2} = \frac{l_j}{l_2} = \frac{q_j}{q_2} = \delta^{\frac{j-2}{1-\alpha}} \text{ for } j > 2,$$

$$\frac{e_i}{e_1} = \frac{l_i}{l_1} = \delta^{\frac{i-1}{1-\alpha}} \times \left[1 + \frac{\lambda(\phi)}{w + p_e}\right]^{\frac{1}{1-\alpha_l}} \quad \textit{and}$$

$$\frac{q_i}{q_1} = \delta^{\frac{i-1}{1-\alpha}} \times \left[1 + \frac{\lambda(\phi)}{w + p_e}\right]^{\frac{\alpha_l}{1-\alpha_l}} \quad \text{for } i > 1.$$

Even though conglomerates substitute production across firms, the regulation leads to an overall reduction in the conglomerate's output. The following proposition describes the conglomerate-level effects of the regulation on output and energy use.

PROPOSITION 4 (Conglomerate-Level Distortions from the Regulation): *Under the Top 1,000 regulation, the energy use $e(\phi,n)$ and the output $q(\phi,n)$ of regulated conglomerates are given by*

$$\frac{e(\phi,n)}{e^*(\phi,n)} = \underbrace{\frac{\xi\left[1 + \left(\Delta_n^{\frac{1}{1-\alpha}} - 1\right)\left(1 + \frac{\lambda(\phi)}{w + p_e}\right)^{\frac{1}{1-\alpha_l}}\right]}{\Delta_n^{\frac{1}{1-\alpha}}}}_{=\xi_e(\phi)} \quad \textit{and}$$

$$\frac{q(\phi,n)}{q^*(\phi,n)} = \underbrace{\frac{\xi^{\alpha_l}\left[1 + \left(\Delta_n^{\frac{1}{1-\alpha}} - 1\right)\left(1 + \frac{\lambda(\phi)}{w + p_e}\right)^{\frac{\alpha_l}{1-\alpha_l}}\right]}{\Delta_n^{\frac{1}{1-\alpha}}}}_{=\xi_q(\phi)},$$

where $e^*(\phi,n)$ and $q^*(\phi,n)$ are the unregulated counterparts of energy use and output and $\xi_e(\phi)$ and $\xi_q(\phi)$ describe the effective input and output wedges.

The term $\xi_e(\phi)$ captures the net effect on energy use by combining the reduction in energy use in the regulated firm (ξ) with the increase in related firms, which is governed by $\lambda(\phi)$. The denominator follows from the insight of Proposition 1 that, in the unregulated case, the conglomerate-level input and output are $\Delta_n^{\frac{1}{1-\alpha}}$ times the input and output of the largest firm. The term $\xi_q(\phi)$ has a similar intuition, and it translates the effects of input changes on output through the exponent α_l.

We now characterize the equilibrium effects of the regulation.

PROPOSITION 5 (Equilibrium under Regulation): *The equilibrium price level under the Top 1,000 regulation solves the following system of nonlinear equations:*

$$\left(\frac{P}{P^*}\right)^{-\rho} = \left(1 - s_{\tilde{\phi}}\right)\left(\frac{P}{P^*}\right)^{\frac{\alpha_l \rho^2}{1-\alpha_l \rho}} + s_{\tilde{\phi}}\mathbb{E}_e\left[\xi_q(\phi)^{\rho} \,\middle|\, \phi > \tilde{\phi}\right] \tag{13}$$

$$1 + \frac{\lambda(\phi)}{w + p_e} = (\xi)^{\alpha_l - 1}\left(\frac{P}{P^*}\right)^{\rho}\xi_q(\phi)^{\rho-1}, \tag{14}$$

where $s_{\tilde{\phi}}$ is the share of energy in regulated conglomerates prior to the regulation and $\mathbb{E}_e$ denotes the expectation with respect to the energy use distribution from the unregulated equilibrium. Additionally, the aggregate change in energy use is given by

$$\frac{E}{E^*} = \left(1 - s_{\tilde{\phi}}\right)\left(\frac{P}{P^*}\right)^{\frac{\rho}{1-\alpha_l \rho}} + s_{\tilde{\phi}}\mathbb{E}_e\left[\xi_e(\phi) \,\middle|\, \phi > \tilde{\phi}\right]. \tag{15}$$

Equation (13) shows that the equilibrium price depends on two forces. First, prices increase as regulated firms reduce their output by $\xi_q(\phi)$. Second, unregulated firms respond to this price increase by increasing their output. The relative importance of these forces depends on the share of energy in regulated conglomerates $s_{\tilde{\phi}}$.

Equation (14) describes the shadow cost of the regulation in terms of the equilibrium price effect P/P^* and the conglomerate-level output wedge $\xi_q(\phi)$. This equation follows from the first-order conditions of both the regulated and unregulated cases and from the results of Proposition 3. Given P/P^*, equation (14) and Proposition 4 define an implicit function for $\lambda(\phi)$. Interestingly, as we show in Supplemental Appendix M.2, the shadow cost $\lambda(\phi)$ and the conglomerate-level wedge $\xi_q(\phi)$ are step functions that only depend on ϕ through the number of affiliates in a conglomerate n. Intuitively, this result is a consequence of the fact that the energy cap in the regulation is proportional to the firm's prior energy use, which itself depends on ϕ.

The equilibrium under the regulation is then determined by a single shadow cost for every value of n along with the equilibrium price P/P^*. This result greatly facilitates the computation of the new equilibrium. Equation (15) then shows that the equilibrium effect on energy use depends on the net change in conglomerate energy use $\xi_e(\phi)$ and the market leakage to unregulated, unrelated firms.

These results characterize the welfare effects of the program because equation (11) implies that

$$\frac{d\ln W}{1-\kappa} = -\ln\left(\frac{P}{P^*}\right) - \frac{\kappa}{1-\kappa}\ln\left(\frac{E}{E^*}\right). \tag{16}$$

This framework also allows us to study the effects of alternative policies. For instance, a universal energy tax would have $s_{\tilde{\phi}} = 1$ and a constant ξ_q for all firms. In Section VI, we compare the Top 1,000 program to a universal energy tax, a size-dependent energy tax (i.e., $s_{\tilde{\phi}} < 1$), and alternative forms of regulation, including ones that mirror the Top 10,000 program.

V. Model Estimation

This section estimates the key parameters of the model to quantitatively match the data patterns for the period prior to the regulation. We validate our estimated model by showing that it matches the untargeted difference-in-differences estimates of the effects of the Top 1,000 program.

A. *Parameterization and Estimation*

We briefly describe the set of structural parameters of the model and how they are identified by the data. We start by setting the values of two parameters based on previous estimates. We follow the literature by calibrating the elasticity of substitution $\sigma = 4$ (Melitz and Redding 2015; i.e., $\rho = 0.75$). We use the estimate of returns to scale of $\alpha = 0.9$ from Burnside, Eirchenbaum, and Rebelo (1995), who use energy data to proxy for utilized capital, and set $\alpha_l = 0.8$ to match the cost share of variable inputs in the data.[20] Finally, we parameterize the conglomerate efficiency distribution $G(\phi)$ with a log-normal distribution with mean zero and standard deviation σ_m.

The model is characterized by the three parameters that we estimate: the within-conglomerate size depreciation δ, the conglomerate-level survival threshold ϕ_1, and the dispersion of the efficiency distribution σ_m. Given values of ϕ_1 and the market expenditure R, equations (8) and (9) pin down f. The entry cost f_e is then determined by the conglomerate free-entry condition.[21]

We estimate the parameters $\theta = (\delta, \phi_1, \sigma_m)$ using the method of moments. For a candidate value of θ, we solve the model and compute the following moments: (i) the share of firms in three bins of firm revenue (¥5–20 million, ¥20–100 million, and greater than ¥100 million); (ii) the share of firm output in the same three bins; (iii) the average output of the second-, third-, and fourth-largest affiliates relative to that of the top firm in the conglomerate; and (iv) the fraction of firms with revenue below ¥1 million. Our data moments describe the equilibrium prior to the regulation using the ASIF and industrial census data for 2004 (NBS 2004). Intuitively, the parameter σ_m is pinned down by the moments (i) and (ii), which respectively describe the firm size and firm output distributions. The parameter δ is determined

[20] Conventional estimates of returns to scale range from 0.85 to 0.95, depending on aggregation and time period. In Supplemental Appendix J.3, we show that the aggregate and welfare effects of the program are robust to reestimating the model on the basis of different values of ρ and α.

[21] To pin down f_e, first note that equations (7) and (9) imply that $\phi_{n+1} = \phi_1 \Big/ \left(\Delta_{n+1}^{\frac{\rho}{1-\rho\alpha}} - \Delta_n^{\frac{\rho}{1-\rho\alpha}}\right)^{\frac{1-\rho\alpha}{\rho}}$ and that $\pi(\phi) = \left[\left(\frac{\Delta_n \phi}{\phi_1}\right)^{\frac{\rho}{1-\rho\alpha}} - n\right] rf$. The conglomerate free-entry condition is then $f_e = \int_{\phi_1} \left[\left(\frac{\Delta_n \phi}{\phi_1}\right)^{\frac{\rho}{1-\rho\alpha}} - n\right] f g(\phi)\, d\phi$, which is determined by our fixed and estimated parameters.

Table 4—Structural Model Parameters

Parameter		Value	Target
1. Fixed values			
Elasticity of substitution	$\sigma = \frac{1}{1-\rho}$	4.00	Melitz and Redding (2015)
Returns to scale	α	0.90	Burnside et al. (1995)
Returns to scale (labor share)	α_l	0.80	Cost share of variable inputs
2. Method of moments			
Efficiency depreciation	δ	0.900	Within-conglomerate distribution
		(0.003)	
Dispersion of ln-ability ϕ	σ_m	1.239	Firm size distribution
		(0.055)	
Survival threshold	ϕ_1	0.609	Share of small firms
		(0.166)	
3. Policy parameters			
Policy threshold	$\tilde{\phi}$	9.29	Energy share of top 1,000 firms
Input quota	$1-\xi$	0.20	11th 5-year plan

Notes: This table summarizes the parameters that we set or estimate to solve the model. Standard errors are calculated by means of a bootstrapped variance-covariance matrix of data moments. See Section VA for the detailed estimation procedure.

Source: Author's calculations from the ASIF data, the CARD data, and the 2004 Economic Census.

by the within-conglomerate output distribution moments (iii). The last moment (iv) helps pin down ϕ_1. Given a weighting matrix W, our estimate of θ is given by

$$\hat{\theta} = \underset{\theta \in \Theta}{\arg\min} \left[m_d - m(\theta)\right]' W \left[m_d - m(\theta)\right],$$

where m_d are the data moments and $m(\theta)$ are the moments generated by the model.[22]

Table 4 reports the results of the estimation. We estimate that $\delta = 0.90$, which means that the productivity of the second-largest firm in the conglomerate is close to 90 percent of that in the largest firm. Recall that equation (5) shows that the output of affiliates depreciates in rank by the factor $\delta^{1/(1-\alpha)}$. This relation implies that the output of the second-largest firm is close to 35 percent of the largest firm's (compare 29 percent in the data), and that of the third-largest is close to 12 percent (compare 20 percent in the data), which match the pattern in panel A of Figure 2. We also estimate that $\sigma_m = 1.24$ and $\phi_1 = 0.61$. To interpret these estimates, note that they imply a conglomerate entry cost of $f_e =$ ¥8.9 million (approximately \$1.1 million). The per firm fixed operating cost is determined by the average sales per conglomerate in the data, which implies that $f =$ ¥44,000. Panel A of Figure 6 shows that our model does a good job of fitting both the observed firm size distribution and concentration of output prior to the regulation.

[22] We use the identity matrix because the sample size for the moments describing the size and output distributions is much larger than that for the moments describing the relative size of firms within conglomerates. Nonetheless, we calculate standard errors using a bootstrap covariance matrix of the moments that incorporates this information.

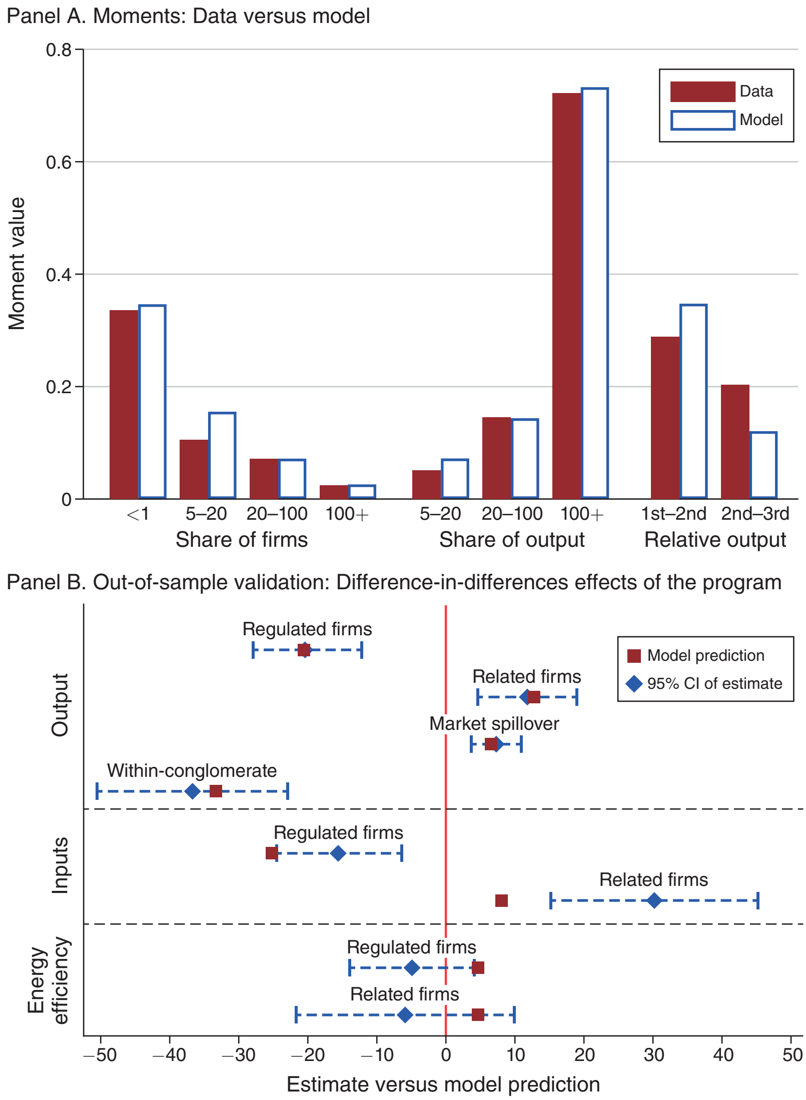

Figure 6. Structural Model Fit and Out-of-Sample Validation

Notes: This figure shows the model fit for both the firm size distribution prior to the policy and the firm response after the policy. Panel A plots the size distribution of firms predicted by our model in blue bars and the size distribution calculated from the ASIF and economic census of 2004 in red bars. It shows that our model fits the data well in terms of both the observed firm size distribution and the concentration of output prior to the regulation. Panel B plots the firm response predicted by the model in red squares and the firm response obtained from our previous difference-in-differences estimates in blue diamonds. The blue lines span the 95 percent confidence interval for our difference-in-differences estimates. This graph shows that our model does a good job of fitting the output, input, and efficiency response of firms, with almost all model-predicted values lying within the 95 percent confidence intervals. See Section VII for additional discussion.

Source: Author's calculations from the ASIF data, the CARD data, and the 2004 Economic Census.

B. *Model Response to the Top 1,000 Program*

To implement the Top 1,000 program in our model, we assume the regulation targets conglomerates with efficiency level ϕ above $\tilde{\phi}$. We choose the threshold $\tilde{\phi}$ to match the share of total energy consumed by regulated firms within energy-intensive industries. Given our estimated parameters, the model implies a value of $\tilde{\phi} = 9.29$, which reproduces the fact that regulated firms account for 56 percent of total energy consumption in energy-intensive industries. We then set the policy intensity $\xi = 0.80$ to match the 11FYP target of a 20 percent energy reduction. Table 4 collects the model parameters.

We now use our estimated model to compute the effects of the Top 1,000 program. As in Section IVD, we assume conglomerates take the number of affiliates and capital allocation as given. The new industry equilibrium ensures that (i) regulated conglomerates allocate variable inputs optimally (as in equation (12)), (ii) unregulated firms increase output to respond to the increase in market prices, and (iii) the product market clears (as in equation (8)).

Panel B of Figure 6 compares our difference-in-differences estimates to their model-simulated analogs. The model does a remarkable job of matching the estimated effects on firm output. This is true for regulated firms, related firms, and market-level spillovers. Though our model's prediction of the change in input use of regulated firms is within the 95 percent confidence interval of our empirical estimate, the model has a hard time fitting the effect on the energy use of related firms. This may reflect the fact that, as we discuss in Section III, this estimate is based on a smaller sample of larger firms and may not be representative of the overall response. However, the model does a good job of matching the effects of the program on the energy efficiency of both regulated and related firms. Overall, these results show that our model can reproduce the effects of the regulation on the output of regulated, related, and unrelated firms, which is remarkable because these are all out-of-sample predictions of the model.

C. *Using the Model to Interpret Our Difference-in-Differences Estimates*

An important force in the model is that unregulated firms are impacted by the regulation through the market spillover. This contributes to the effects of the program on the equilibrium price and aggregate energy use. We now use our model to understand how this market spillover impacts our difference-in-differences estimates.

To see how the regulation in our model connects to our difference-in-differences analysis, we multiply conglomerate *j*'s inverse residual demand by affiliate *i*'s production to write the revenue for this affiliate as follows:

$$(17)\quad \ln Revenue_{ij} = \underbrace{\ln\left(Production\ Share_{ij}\right)}_{\text{Allocation Effect}} + \underbrace{\rho \ln\left(\sum_{i\in j} q_{ij}\right)}_{\text{Residual Revenue}} + \underbrace{\ln\left(R^{1-\rho}P^{\rho}\right)}_{\text{Market Demand}},$$

where $Production\ Share_{ij} = q_{ij}/\sum_{i\in j} q_{ij}$. Equation (17) clarifies the three ways in which the Top 1,000 program impacts the revenue of regulated firms. First, when firm *i* is regulated, its conglomerate reallocates inputs to other firms, which lowers the production share in regulated firms. Panel A of Table 5 reports that, in our model, the share of production in regulated firms within a conglomerate decreases by 12.9 percent. Second, because the marginal cost goes up at the conglomerate level, the market share of the conglomerate's variety decreases, which lowers the

Table 5—Model Decomposition of Difference-in-Differences Estimates

	Allocation effect	Residual revenue effect	Market effect	Total effect
Panel A. Effect on regulated firms				
Top 1,000 firms	−0.129	−0.037	0.026	−0.140
Control firms	0	0.039	0.026	0.065
Difference-in-differences	−0.129	−0.077	0	−0.205
Panel B. Effect on related firms				
Related firms	0.205	−0.037	0.026	0.193
Control firms	0	0.039	0.026	0.065
Difference-in-differences	0.205	−0.077	0	0.128
Panel C. Within-conglomerate effect				
Difference-in-differences	−0.333	0	0	−0.333

Notes: This table reports the decomposition results for difference-in-differences estimates according to the model. Panels A, B, and C in this table correspond to panel B of Table 1, panel A of Table 2, and panel B of Table 3 by decomposing the difference-in-differences estimates first into the effects on treated and control firms and then further into allocation effects, residual revenue effects, and market effects. See Section VC for additional discussion.

Source: Author's calculations using the model developed in Section IV.

group's residual revenue. Table 5 shows that regulated conglomerates see their residual revenue decrease by 3.7 percent. Finally, the Top 1,000 program impacts the industry-level price P. This price increase has a countervailing effect on the revenue of the regulated firm and lessens the overall decline by 2.6 percent. Combining these three forces, our model implies that regulated firms decreased their output by 14 percent.

Equation (17) also characterizes the impact of the regulation on the control firms in our difference-in-differences analyses. Because these firms are neither regulated nor related to Top 1,000 firms, the regulation does not impact the within-conglomerate allocation of production. Control firms see an increase in their residual and firm-level revenue as the market reallocates demand. Table 5 shows that the residual revenue of control firms increases by 3.9 percent. As in the case of regulated firms, unregulated firms also benefit from the equilibrium impact on market demand. This analysis highlights the importance of interpreting the market-level spillovers in panel A of Table 3 as a combination of quantity and price effects.

This discussion clarifies that our difference-in-differences estimates differ from the total effect on Top 1,000 firms along two margins. First, the difference-in-differences estimator captures both within- and across-conglomerate reallocation of production. This leads to an overestimation of the effect of the program on regulated firms of 3.9 percent. Second, because the market effect cancels out, the difference-in-differences estimator does not capture the countervailing effect on the industry-level price and thus further overestimates the effect of the program by 2.6 percent. Note that the first channel arises from the impact of the regulation on the control firms. The second channel is an aggregate effect that is not identified by a difference-in-differences research design.

Similarly, our model allows us to decompose the estimates of the spillover effects of the regulation through ownership networks. Panel B of Table 5 shows that related firms have the same residual revenue and market effect terms but a positive allocation effect as their share of production within the conglomerate increases. The total effect on related firms is an output increase of 19.3 percent. The effect on control firms is the same as that in panel A. By ignoring the positive market effect and subtracting the residual revenue effect on control firms, the difference-in-differences estimator understates the spillover effect on related firms by 6.5 percent.

In addition to clarifying the interpretation of our reduced-form estimates, our model motivates an alternative approach that does not depend on the residual revenue or market effects. Specifically, consider a within-conglomerate difference-in-differences estimator where the treated firms are the regulated Top 1,000 firms and the control firms are unregulated firms in the same conglomerate. Because equation (17) shows that the residual revenue and market effects are common to a given conglomerate, this estimator captures only the allocation effects of the program. Panel B of Figure 5 implements this within-conglomerate difference-in-differences approach. This figure plots the results from an event-study specification similar to equation (1) but additionally includes conglomerate-by-year fixed effects. Consistent with our previous results, we find a significant decline in the output of Top 1,000 firms relative to that of other firms in their same conglomerates. Panel B of Table 3 reports estimates of these relative declines of between -31.5 percent and -36.7 percent. As with our previous reduced-form effects, panel B of Figure 6 shows that the model matches this within-conglomerate effect very well. Moreover, panel C of Table 5 confirms that this effect is a combination of the reallocation effects on regulated and related firms.

These insights highlight the importance of interpreting quasi-random estimates through the lens of a model that accounts for within- and across-conglomerate reallocation of production and equilibrium impacts on industry-level prices.

VI. Policy Analysis

This section uses our estimated model to capture the aggregate effects of the Top 1,000 program on prices and energy use and the implied welfare trade-off for the government. We then consider the effects of alternative policies, including program expansions, and show that the government can improve energy regulation by using public information on business networks.

A. *Aggregate and Welfare Effects of the Top 1,000 Program*

We now evaluate the aggregate and welfare effects of the Top 1,000 policy by considering the social welfare function of a government concerned with both decreases in energy-use-related emissions and the impact of production distortions on consumption.[23]

We compute the aggregate effects of the program by solving the equilibrium conditions in Proposition 5. Panel A of Figure 7 plots the effects of the Top 1,000 program in the space of price increase and energy reduction. The red diamond in this figure shows that the Top 1,000 program led to a price increase

[23] As in our empirical analysis, we study the short-run effects of the policy, ignoring entry of new conglomerates.

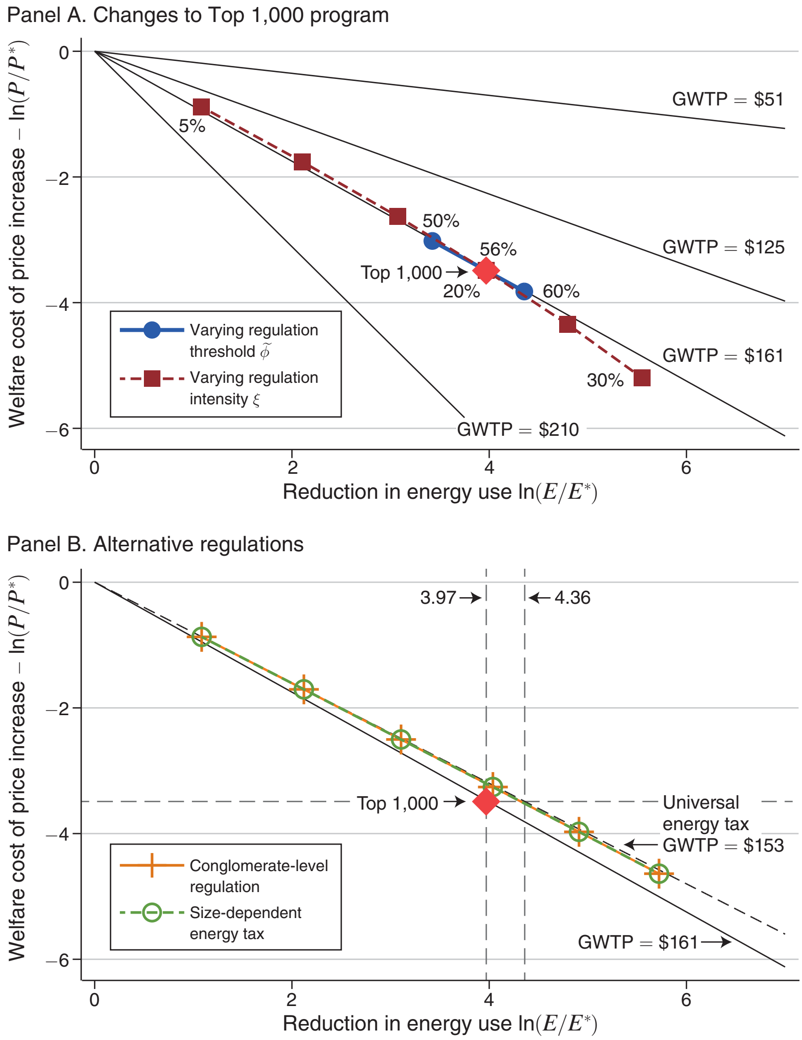

Figure 7. Welfare Effects of Alternative Regulations

Notes: This figure shows the welfare effects of different regulations measured by the trade-off between reductions in energy use and the welfare cost of price increases. Panel A shows the welfare effects of the Top 1,000 program. The black lines are indifference curves for different GWTPs. The red diamond shows that the Top 1,000 program led to an aggregate energy consumption reduction of close to 4 percent and a price level increase of approximately 3.5 percent, which can be rationalized with a GWTP = \$161. The navy line indicates that expanding or contracting policy coverage to cover between 50 percent and 60 percent of an industry's energy use does not change the fundamental trade-off between reductions in energy consumption and price increases. The dashed crimson line indicates that increasing the input reduction quota from 5 percent to 30 percent makes this trade-off slightly worse. See Section VIA for additional discussion. Panel B shows the welfare effects under alternative types of regulations. Regulating conglomerates and imposing a size-dependent energy tax show a similar trade-off at a GWTP = \$154, which corresponds to a better performance than that of the original policy. A universal energy tax performs even better, with a GWTP = \$153. See Section VIB for additional discussion.

Source: Author's calculations using the model developed in Section IV.

of approximately 3.5 percent and an aggregate energy use reduction of close to 4 percent. Equation (15) helps us understand how we obtain a 4 percent aggregate reduction in energy use. First, we find that—including within-conglomerate reallocation—regulated conglomerates reduced their energy use by $1 - \mathbb{E}_e\left[\xi_e(\phi) \,\middle|\, \phi > \tilde{\phi}\right] = 5.8\%$. Second, unregulated conglomerates increased their energy use by close to 6.5 percent. Finally, the aggregate 4 percent decline follows from the fact that the share of energy in regulated conglomerates is $s_{\tilde{\phi}} = 86\%$.[24] Thus, even though we find in Section II that Top 1,000 firms reduced their energy use by close to 100 million tce, the annual aggregate reduction—including conglomerate and market leakage—was closer to 48 million tce.

To determine whether the program increased welfare, we compare its effects on energy reduction and output losses. Using the Cobb–Douglas structure of the welfare function, we can relate $\kappa = \kappa_1 + \kappa_0$ to the shares of aggregate income that the government would like to spend on reducing carbon emissions (κ_0) and pollution (κ_1):

$$\kappa_0 = \frac{\text{Social Cost of Carbon} \times \text{Carbon Emissions}}{\text{Aggregate Income} \times 0.8} \text{ and}$$

$$\kappa_1 = \frac{\text{Total Pollution Damages}}{\text{Aggregate Income} \times 0.8}.$$

In both cases, the adjustment factor 0.8 comes from the fact that the Chinese government's 11FYP recognized its underspending in reducing energy and adopted a goal to reduce energy use by 20 percent. We first consider the combined effect of these two motives to estimate the government's total willingness to pay (GWTP) to reduce emissions:[25]

$$\kappa = \frac{\text{GWTP} \times \text{Carbon Emissions}}{\text{Aggregate Income} \times 0.8}.$$

According to equation (16), welfare increases when the aggregate price-to-energy-use elasticity (i.e., $\frac{-\ln(P/P^*)}{\ln(E/E^*)}$) is smaller than $\kappa/(1 - \kappa)$. Given our aggregate estimates of the effects of the Top 1,000 program, we find that the program raises welfare as long as κ is greater than the threshold value $\bar{\kappa}$, given by the condition $\bar{\kappa}/(1 - \bar{\kappa}) = 0.875$, which implies that $\bar{\kappa} = 0.47$. That is, the Top 1,000 program raises welfare as long as the government is willing to accept a 0.875 percent output loss for every 1 percent reduction in energy use. We obtain an estimate of the GWTP based on this threshold value $\bar{\kappa}$. Using 2006 data on overall emissions in China (6.38 billion tons of carbon; Ritchie, Roser, and Rosado 2020) and gross domestic product (\$2.752 trillion; World Bank 2022), we calculate a GWTP value of \$161.

Figure 7 visualizes the government's trade-off between energy reduction and output losses by plotting black indifference curves that correspond to different

[24] The energy increase for unregulated firms is given by $(P/P^*)^{\frac{\rho}{1-\alpha_l \rho}} = (1.035)^{\frac{0.75}{1-0.8\times 0.75}} \approx 1.067$. Recall that regulated firms account for 56 percent of energy use; accounting for related firms in the same conglomerate raises this fraction to 86 percent. The aggregate effect is then $-4\% = \ln(1.06 \times 0.14 + 0.942 \times 0.86)$.

[25] This expression follows by considering the pollution damage per ton of carbon, so that $\kappa = \kappa_0 + \kappa_1 = \frac{(\text{Social Cost of Carbon (SCC)} + \text{Pollution Damage Per Ton of Carbon}) \times \text{Carbon Emissions}}{\text{Aggregate Income} \times 0.8} = \frac{(\text{GWTP}) \times \text{Carbon Emissions}}{\text{Aggregate Income} \times 0.8}$, where the GWTP includes both the SCC and the pollution damages associated with a ton of carbon.

hypothetical GWTP values. For a given GWTP value, these lines plot combinations of price and energy use changes that yield the same effect on welfare. The red diamond in this figure shows that the Top 1,000 program lies on the indifference curve that corresponds to a GWTP of $161.

We study the robustness of the welfare effects of the Top 1,000 program in Supplemental Appendix J. We first extend our model to allow for firms to invest in energy efficiency improvements (Supplemental Appendix J.1). We then allow for unregulated and unrelated firms to have preexisting differences in energy efficiency (Supplemental Appendix J.2). Supplemental Appendix J.3 discusses results for different values of calibrated parameters (e.g., α, ρ). This Supplemental Appendix also discusses extensions that allow for firms to adjust their capital in response to the regulation and for imperfect substitution of output within conglomerates. As we show in Supplemental Appendix Figure A.2, the value of the GWTP that rationalizes the policies ranges between $114 and $199 across these different model extensions.

We now estimate the social cost of carbon implied by the Top 1,000 program by subtracting the pollution damages associated with a ton of carbon emissions from the GWTP. We rely on four estimates of pollution damages from the World Bank (2007); Mohan et al. (2020); and Ito and Zhang (2020b), which encompass varied methodologies spanning calculations of gross external damages, willingness-to-pay analyses, and adjusted human capital approaches. Across these methodologies, we estimate that the pollution damages associated with a ton of carbon can be valued at between $4 and $17.[26] Relative to our estimated GWTP of $161, these estimates imply that the policy would increase welfare if the SCC exceeded the $144–$157 range.[27]

Our estimates of the health benefits of reducing pollution may contrast with intuition derived from the context of high-income countries. In Supplemental Appendix I, we show that the gross external damages estimate of Mohan et al. (2020) implies a $78 cost of pollution damages per ton of carbon. If the Chinese government used this valuation, the SCC that would justify the policy would then be $83, which is comparable to SCC values used in high-income countries. For instance, in the United States, the Biden administration has recently proposed an SCC value of $51 (IWG 2021), and researchers have recently argued for a higher value of $125 (Carleton and Greenstone 2021).

[26] The gross external damages (GED) approach of Mohan et al. (2020) implies total pollution damages in China of $108 billion. Relative to carbon emissions in 2006, the pollution damage per ton of carbon is valued at $17. The World Bank (2007) produces two independent estimates of air pollution damages. The first uses a willingness-to-pay methodology and yields a value of pollution damage per ton of carbon of $13. The second estimate uses an adjusted human capital approach, which implies a value of pollution damage per ton of carbon of $4. Finally, Ito and Zhang (2020b) use a willingness-to-pay approach for reducing exposure to air particulates that relies on quasi-experimental variation in pollution exposure due to the Huai River policy. Combined with estimates of the mortality effects of pollution (e.g., Ebenstein et al. 2017), the estimates in Ito and Zhang (2020b) imply a value of pollution damage per ton of carbon of $6. To be more conservative, our analyses rely on the GED and willingness-to-pay measures. See Supplemental Appendix I for details.

[27] In practice, the health benefits of reducing firms' energy use could be larger than average if these firms rely on dirtier energy sources. In Supplemental Appendix I, we obtain an upper bound on the health benefits from reducing emissions by assuming that all of the air pollution in China is generated by coal, the main source of energy of Top 1,000 firms. The estimates of the value of health benefits increase to between $5 and $22, which imply a range of values of the SCC that rationalizes the policy of between $139 and $156.

B. *Alternative Policies*

We now use the model to consider alternative policies. We first explore different ways in which the Top 1,000 program could be expanded or contracted. This exercise is motivated by the fact that the Chinese government expanded the program to include more than 16,000 firms in the Top 10,000 program in 2012. We then explore the effects of alternative regulations and energy taxes to examine the degree to which the government can improve the regulation of energy.

We explore two ways to change the scope of the Top 1,000 program. First, we consider the effect of varying the regulation threshold $\tilde{\phi}$, which changes the number of firms affected by the program. The blue dots in panel A of Figure 7 show the effects of changing the size threshold $\tilde{\phi}$. The first blue dot (to the left of the red diamond) considers the effect of decreasing the number of regulated firms to cover only 50 percent of the energy use in the regulated industry (relative to the current 56 percent). The second blue dot lowers $\tilde{\phi}$ so that the regulation instead covers 60 percent of the industry's energy use.[28] As expected, we find larger energy decreases when the program covers a larger fraction of overall energy use. However, Figure 7 shows that expanding or contracting the number of firms in the program does not alter the fundamental trade-off that the government faces between price increases and reductions in energy use.

An alternative way to change the scope of the Top 1,000 program is to increase or decrease the energy use quota ξ. The maroon squares in panel A of Figure 7 plot the effects of policies where $1 - \xi$ varies in 5 percent increments between 5 percent and 30 percent. Larger values of $1 - \xi$ lead to both larger price increases and larger energy reductions. Taking both changes into account, we find that the implied GWTP increases with the required energy reduction and equals \$167 when $1 - \xi = 30\%$. This result is valuable because the government may be concerned about the administrative costs of regulating a larger number of firms. Because increasing ξ and lowering $\tilde{\phi}$ have similar welfare effects, it may be desirable to place stricter energy use limits on fewer firms if the government lacks the capacity or the funds to conduct additional energy audits.

We now consider the effects of an alternative policy that targets the energy use of all firms in a given conglomerate.[29] The orange crosses in panel B of Figure 7 plot the effects of this type of regulation at different values of ξ. These policies have the benefit of not distorting the within-conglomerate distribution of production, thus lowering the shadow cost of the policy (see panel A of Supplemental Appendix Figure A.3). Such a policy is preferable to the Top 1,000 program from a welfare perspective because it can achieve larger energy use reductions for a given price increase. As we show in panel B of Figure 7, this type of regulation can yield a

[28] This alternative regulation mirrors that of the Top 10,000 program by increasing the program's coverage. We study the empirical effects of the Top 10,000 program in Supplemental Appendix L. As with our simulation, we find that a more complete regulation reduces the scope for within-conglomerate and market leakage.

[29] We derive equilibrium conditions under these alternative regulations in Supplemental Appendix N. To make this case comparable, we model the effects of a regulation that limits the conglomerate-level energy use to the levels under the Top 1,000 program. While conglomerate-level regulations may face political pressure from business groups, such policies have been used in other countries, where, for example, subsidy eligibility criteria may depend on conglomerate-level characteristics (see, e.g., the UK's R&D tax credit for small and medium-sized enterprises in the study by Dechezleprêtre et al. 2023).

4.36 percent reduction in aggregate energy use for the same price increase as the Top 1,000 program. This is a 10 percent increase from the energy reduction under the Top 1,000 program, corresponding to additional energy savings of 5 million tce. This policy improves welfare as long as the GWTP $\geq$ \$154. While this program would involve monitoring additional firms, the number of firms related to Top 1,000 firms is less than 20 percent of the number of firms in the Top 10,000 program. These results show that the government can improve the regulation of energy by using publicly available data on business networks to target conglomerates, and that doing so would be more effective than regulating additional unrelated firms, as with the Top 10,000 program.

Finally, we consider the effects of energy taxes. We first model the effects of a size-dependent energy tax that affects all firms in conglomerates with Top 1,000 firms (i.e., with $\phi > \tilde{\phi}$). The green circles in panel B of Figure 7 show that the effects of this size-dependent energy tax are very close to those of the conglomerate-level regulation.[30] We further consider the effects of a universal energy tax that impacts all firms in the economy. We model this tax by setting $s_{\tilde{\phi}} = 100\%$ instead of 86 percent. Panel B of Figure 7 shows that, while a universal energy tax yields a slight improvement over the size-dependent tax (GWTP $=$ \$153), both the size-dependent tax and the conglomerate-level regulations imply very similar welfare trade-offs.

The results in this section are informative about the efficacy and design of a prominent real-world policy that regulates quantities and has incomplete coverage. While the preferred policy solution for most economists on the regulation of carbon emissions related to energy use is a universal carbon tax, this policy may not be feasible given legal, administrative, or political constraints. We find that the government could achieve similar aggregate effects by either expanding the program through stricter regulations for current firms or increasing the number of firms in the program. While the former option has narrower coverage and generates larger inequities between regulated and unregulated firms, the latter may require an increase in administration costs. We also find that the government can improve the regulation of energy by targeting the ownership networks of regulated firms. This policy increases aggregate energy savings by 10 percent without increasing welfare costs. Moreover, this policy can be implemented with publicly available data, has a lower administrative cost than the Top 10,000 program, and implies a welfare trade-off close to that under a universal energy tax.

VII. Conclusion

This paper studies the effects of a prominent energy conservation program in China. We combine detailed data on energy use and business networks to study the effects of the regulation on both regulated firms and unregulated firms within the same conglomerate. While the program led regulated firms to decrease their energy use, this decrease was driven by a decline in production output and not by

[30] It is worth noting that our quantification lacks two features that often motivate the use of taxes over regulation. First, in our calculations, the revenue from the tax is not rebated to consumers; this calculation ignores potential "double dividend" effects. Second, firms in our setting have homogeneous abatement costs; in a setting with heterogeneous abatement costs, a tax would additionally reallocate production to "cleaner" firms.

an increase in energy efficiency. We show that the program led to large increases in the output and energy use of unregulated firms in the same conglomerate. The facts that regulated conglomerates were unable to fully shift lost output to related firms and that we find no impact on the energy efficiency of regulated firms imply that regulated firms found it costly to increase their energy efficiency.

A welfare analysis of the aggregate effects of the policy on consumption and energy use characterizes the government's willingness to pay to reduce carbon emissions that would be required for the Top 1,000 program to raise welfare. Importantly, the GWTP includes both global externalities from reducing carbon emissions and local health benefits from reducing pollution. Our results suggest that the program increases welfare as long as the government is willing to pay at least \$161 to reduce a ton of carbon emissions. In additional analyses in Supplemental Appendix J, we characterize the uncertainty in this estimate by exploring a number of alternative model specifications and parameter values. Across these wide-ranging assumptions, we find that the GWTP value that rationalizes the policy lies between \$114 and \$199.

Our analysis of the Top 1,000 program improves our understanding of the trade-offs involved in reducing energy use and related emissions in an important context. Indeed, the firms regulated by this program are some of the largest emitting firms in the world, and understanding their behavior is crucial for the global control of carbon emissions. Moreover, the economic mechanisms we highlight—such as the importance of leakage within conglomerates—may also be important in other settings.

REFERENCES

Ai, Hongshan, Yang Hu, and Ke Li. 2021. "Impacts of Environmental Regulation on Firm Productivity: Evidence from China's Top 1000 Energy-Consuming Enterprises Program." *Applied Economics* 53 (7): 830–44.

Allcott, Hunt, and Michael Greenstone. 2012. "Is There an Energy Efficiency Gap?" *Journal of Economic Perspectives* 26 (1): 3–28.

Anderson, Soren T., and James M. Sallee. 2011. "Using Loopholes to Reveal the Marginal Cost of Regulation: The Case of Fuel-Economy Standards." *American Economic Review* 101 (4): 1375–1409.

Auffhammer, Maximilian, and Yazhen Gong. 2015. "China's Carbon Emissions from Fossil Fuels and Market-Based Opportunities for Control." *Annual Review of Resource Economics* 7 (1): 11–34.

Baylis, Kathy, Don Fullerton, and Daniel H. Karney. 2014. "Negative Leakage." *Journal of the Association of Environmental and Resource Economists* 1 (1-2): 51–73.

Biesebroeck, Johannes Van. 2003. "Productivity Dynamics with Technology Choice: An Application to Automobile Assembly." *Review of Economic Studies* 70 (1): 167–98.

Burnside, Craig, Martin Eichenbaum, and Sergio Rebelo. 1995. "Capacity Utilization and Returns to Scale." *NBER Macroeconomics Annual* 10: 67–110.

Bushnell, James, Yihsu Chen, and Matthew Zaragoza-Watkins. 2014. "Downstream Regulation of CO2 Emissions in California's Electricity Sector." *Energy Policy* 64: 313–23.

Carleton, Tamma, and Michael Greenstone. 2021. "Updating the United States Government's Social Cost of Carbon." Unpublished.

Chen, Qiaoyi, Zhao Chen, Zhikuo Liu, Juan Carlos Suárez Serrato and Daniel Yi Xu. 2025. "*Data and Code for: Regulating Conglomerates: Evidence from an Energy Conservation Program in China.*" Nashville, TN: American Economic Association; distributed by Inter-university Consortium for Political and Social Research, Ann Arbor, MI. https://doi.org/10.3886/E196012V1.

CMEP. 1998–2010. *Chinese Environmental Statistics Database.* Chinese Ministry of Environmental Protection.

Colmer, Jonathan, Ralf Martin, Mirabelle Muûls, and Ulrich J. Wagner. 2020. "Does Pricing Carbon Mitigate Climate Change? Firm-Level Evidence from the European Union Emissions Trading Scheme." Unpublished.

CRS. 2013. *China's Currency Policy: An Analysis of the Economic Issues*. Washington, DC: Congressional Research Service.
Curtis, E. Mark. 2018. "Who Loses under Cap-and-Trade Programs? The Labor Market Effects of the NOx Budget Trading Program." *Review of Economics and Statistics* 100 (1): 151–66.
Dechezleprêtre, Antoine, Elias Einiö, Ralf Martin, Kieu-Trang Nguyen, and John Van Reenen. 2023. "Do Tax Incentives Increase Firm Innovation? An RD Design for R&D, Patents, and Spillovers." *American Economic Journal: Economic Policy* 15 (4): 486–521.
Duflo, Esther, Michael Greenstone, Rohini Pande, and Nicholas Ryan. 2013. "Truth-telling by Third-party Auditors and the Response of Polluting Firms: Experimental Evidence from India." *Quarterly Journal of Economics* 128 (4): 1499–1545.
Duflo, Esther, Michael Greenstone, Rohini Pande, and Nicholas Ryan. 2018. "The Value of Regulatory Discretion: Estimates from Environmental Inspections in India." *Econometrica* 86 (6): 2123–60.
Ebenstein, Avraham, Maoyong Fan, Michael Greenstone, Guojun He, and Maigeng Zhou. 2017. "New Evidence on the Impact of Sustained Exposure to Air Pollution on Life Expectancy from China's Huai River Policy." *Proceedings of the National Academy of Sciences* 114 (39): 10384–89.
Fabrizio, Kira R., Nancy L. Rose, and Catherine D. Wolfram. 2007. "Do Markets Reduce Costs? Assessing the Impact of Regulatory Restructuring on US Electric Generation Efficiency." *American Economic Review* 97 (4): 1250–77.
Filippini, Massimo, Thomas Geissmann, Valerie J. Karplus, and Da Zhang. 2020. "The Productivity Impacts of Energy Efficiency Programs in Developing Countries: Evidence from Iron and Steel Firms in China." *China Economic Review* 59: 101364.
Fischer, Carolyn, and Alan K. Fox. 2012. "Comparing Policies to Combat Emissions Leakage: Border Carbon Adjustments versus Rebates." *Journal of Environmental Economics and Management* 64 (2): 199–216.
Fowlie, Meredith L. 2009. "Incomplete Environmental Regulation, Imperfect Competition, and Emissions Leakage." *American Economic Journal: Economic Policy* 1 (2): 72–112.
Fowlie, Meredith L., and Mar Reguant. 2022. "Mitigating Emissions Leakage in Incomplete Carbon Markets." *Journal of the Association of Environmental and Resource Economists* 9 (2): 307–43.
Gao, Hang, and Johannes Van Biesebroeck. 2014. "Effects of Deregulation and Vertical Unbundling on the Performance of China's Electricity Generation Sector." *Journal of Industrial Economics* 62 (1): 41–76.
Gibson, Matthew. 2019. "Regulation-Induced Pollution Substitution." *Review of Economics and Statistics* 101 (5): 827–40.
Granade, Hannah Choi, Jon Creyts, Anton Derkach, Philip Farese, Scott Nyquist, and Ken Ostrowski. 2009. *Unlocking Energy Efficiency in the US Economy*. Milton, Vermont: Villanti and Sons.
Greenstone, Michael. 2002. "The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufactures." *Journal of Political Economy* 110 (6): 1175–1219.
Greenstone, Michael, and B. Kelsey Jack. 2015. "Envirodevonomics: A Research Agenda for an Emerging Field." *Journal of Economic Literature* 53 (1): 5–42.
Greenstone, Michael, John A. List, and Chad Syverson. 2012. "The Effects of Environmental Regulation on the Competitiveness of U.S. Manufacturing." NBER Working Paper 18392.
Hainmueller, Jens. 2012. "Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies." *Political Analysis* 20 (1): 25–46.
Hanna, Rema. 2010. "US Environmental Regulation and FDI: Evidence from a Panel of US-Based Multinational Firms." *American Economic Journal: Applied Economics* 2 (3): 158–89.
Harrison, Ann, Benjamin Hyman, Leslie Martin, and Shanthi Nataraj. 2015. "When Do Firms Go Green? Comparing Command and Control Regulations with Price Incentives in India." NBER Working Paper 21763.
He, Guojun, Shaoda Wang, and Bing Zhang. 2020. "Watering Down Environmental Regulation in China." *Quarterly Journal of Economics* 135 (4): 2135–85.
IEA. 2020. *World Energy Balances.* https://www.iea.org/data-and-statistics/data-sets (accessed November 24, 2020).
Ito, Koichiro, and Shuang Zhang. 2020a. "Reforming Inefficient Energy Pricing: Evidence from China." NBER Working Paper 26853.
Ito, Koichiro, and Shuang Zhang. 2020b. "Willingness to Pay for Clean Air: Evidence from Air Purifier Markets in China." *Journal of Political Economy* 128 (5): 1627–72.
IWG. 2021. *Technical Support Document: Social Cost of Carbon, Methane, and Nitrous Oxide Interim Estimates under Executive Order 13990*. Washington, DC: Interagency Working Group on Social Cost of Greenhouse Gases.
Jia, Ruixue. 2017. "Pollution for Promotion." Unpublished.

Kahn, Matthew E., Pei Li, and Daxuan Zhao. 2015. "Water Pollution Progress at Borders: The Role of Changes in China's Political Promotion Incentives." *American Economic Journal: Economic Policy* 7 (4): 223–42.
Ke, Jing, Lynn Price, Stephanie Ohshita, David Fridley, Nina Zheng Khanna, Nan Zhou, and Mark Levine. 2012. "China's Industrial Energy Consumption Trends and Impacts of the Top-1000 Enterprises Energy-Saving Program and the Ten Key Energy-Saving Projects." *Energy Policy* 50: 562–69.
Melitz, Marc J. 2003. "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity." *Econometrica* 71 (6): 1695–1725.
Melitz, Marc J., and Stephen J. Redding. 2015. "New Trade Models, New Welfare Implications." *American Economic Review* 105 (3): 1105–46.
Mohan, Aniruddh, Nicholas Z. Muller, Akshay Thyagarajan, Randall V. Martin, Melanie S. Hammer, and Aaron van Donkelaar. 2020. "The Growth of Nations Revisited: Global Environmental Accounting from 1998 to 2018." NBER Working Paper 27398.
NBS. 1998–2009, 2011–2013. *Annual Survey on Industrial Firms.* National Bureau of Statistics.
NBS. 2004. *China's National Economic Census.* Enterprise Survey Dataset.
NDRC. 2011. *Announcement of the Implementation of the Top 10,000 Energy Conservation and Carbon Reduction Program*. Beijing: National Development and Reform Commission.
NDRC and NBS. 2007. *Bulletin on Energy Use of Top 1,000 Firms.* Beijing: National Development and Reform Commission, National Bureau of Statistics.
Ohrn, Eric. 2018. "The Effect of Corporate Taxation on Investment and Financial Policy: Evidence from the DPAD." *American Economic Journal: Economic Policy* 10 (2): 272–301.
Price, Lynn, Xuejun Wang, and Jiang Yun. 2010. "The Challenge of Reducing Energy Consumption of the Top-1000 Largest Industrial Enterprises in China." *Energy Policy* 38 (11): 6485–98.
Ramachandran, J., K. S. Manikandan, and Anirvan Pant. 2013. "Why Conglomerates Thrive (Outside the US)." *Harvard Business Review,* December. https://hbr.org/2013/12/why-conglomerates-thrive-outside-the-us.
Ritchie, Hannah, Max Roser, and Pablo Rosado. 2020. *China: CO2 Country Profile.* OurWorldInData, https://ourworldindata.org/co2/country/china.
Ryan, Nicholas. 2018. "Energy Productivity and Energy Demand: Experimental Evidence from Indian Manufacturing Plants." NBER Working Paper 24619.
SAIC. 1949–2018. *Chinese Administrative Registration Database.* State Administration of Industry and Commerce.
SAT. 2008–2011. *Enterprise Tax Survey Dataset*. Chinese State Administration of Tax.
Shapiro, Joseph S. 2016. "Trade Costs, CO2, and the Environment." *American Economic Journal: Economic Policy* 8 (4): 220–54.
Shapiro, Joseph S. 2021. "The Environmental Bias of Trade Policy." *Quarterly Journal of Economics* 136 (2): 831–86.
Shapiro, Joseph S., and Reed Walker. 2018. "Why Is Pollution from US Manufacturing Declining? The Roles of Environmental Regulation, Productivity, and Trade." *American Economic Review* 108 (12): 3814–54.
Shen, Meng, Yanping Zeng, and Ruxiao Qu. 2015. "Environmental Regulation and Exportation: Micro Evidence from China's Top–1000 Policy." *Journal of International Trade* (*In Chinese*) 8: 43–50.
Soliman, Felix Samy. 2020. "Intrafirm Leakage." Unpublished.
Walker, W. Reed. 2013. "The Transitional Costs of Sectoral Reallocation: Evidence from the Clean Air Act and the Workforce." *Quarterly Journal of Economics* 128 (4): 1787–1835.
Wang, Xuejun, Zhihua Fu, Wei Zhang, and Youbin Ye. 2008. "5. Top1000 Energy Conservation Program and the 20% Energy Saving Target Achievement in the 11th Five Year Plan." In *A Study of Approaches and Methods to Meet China's 20% Energy Efficient Target for 2010.* China Sustainable Energy Project.
Wang, Yufei, Huimin Li, Qijiao Song, and Ye Qi. 2017. "The Consequence of Energy Policies in China: A Case Study of the Iron and Steel Sector." *Resources, Conservation and Recycling* 117: 66–73.
World Bank. 2007. *"4," in "Cost of Pollution in China: Economic Estimates of Physical Damages* (English)." World Bank Group.
World Bank. 2022. *GDP* (*Current US$*) *- China.* https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=CNs (accessed December 16, 2023).
Xiao, Yuxian, Haitao Yin, and Jon J. Moon. 2023. "Coping with Externally Imposed Energy Constraints: Competitiveness and Operational Impact of China's Top-1000 Energy-Consuming Enterprises Program." *Energy Journal* 44 (2): 103–38.
Zhao, Xiaofan, Huimin Li, Liang Wu, and Ye Qi. 2016. "Enterprise-Level Amount of Energy Saved Targets in China: Weaknesses and a Way Forward." *Journal of Cleaner Production* 129: 75–87.