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

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Abstract

How does energy regulation affect production and energy use within conglomerates? We study the effects of a prominent program aimed at reducing the energy use of large Chinese companies. Difference-in-differences analyses show that regulated firms significantly reduced their energy consumption and output but did not increase their energy efficiency. Using detailed business registration data, we link regulated firms to non-regulated firms that are part of the same conglomerate. We estimate large spillovers on cross-owned non-regulated firms, which increased both output and energy use. We then specify and estimate a model of conglomerate production that fits our setting and the estimated effects of the regulation. The model quantifies the importance of conglomerate reallocation for aggregate outcomes, the shadow cost of the regulation, and the efficiency gains from using public information on business networks to improve the design of energy regulation.

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1 Introduction

Balancing economic growth with the negative side effects of industrialization—such as 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 given that the industrial energy use of China overshadowed that of other leading economies in the early years of the 21^{st} 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 relied on the belief that firms could significantly reduce their energy use by improving their energy efficiency. The implementation of the program was adjusted to local 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 regulation in China. This is both because the firms regulated by this program accounted for 47% of total industrial energy use in China in 2004 and because the perceived success of the regulation led the government to significantly expand the program in later years.

This paper asks three questions that characterize the effectiveness of the Top 1,000 program. Importantly, these questions account for the fact that industrial firms in China are often part of much larger business networks. First, do regulated firms comply with the program by improving energy efficiency, by reducing economic activity, or by shifting production to non-regulated firms that are part of the same conglomerate? Second, how does the ability of conglomerates to (partially) escape the regulation impact the shadow cost of regulatory programs? Finally, can governments use information on conglomerate networks to improve energy regulation?

We combine difference-in-differences research designs with a quantitative model to study the effectiveness of the Top 1,000 program. First, using a difference-in-differences strategy, we estimate that regulated firms reduced their energy use by 13%–16%. Regulated firms achieved these reductions by lowering output; we find no impact on their energy efficiency. Second, we use detailed data on business networks to study how conglomerates reallocated production across related firms. Using a second difference-in-differences design, we find 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% of the output decline in regulated firms to unregulated affiliates. Third, we specify and estimate a model of conglomerate production that matches our setting and the estimated impacts of the policy. We quantify that the ability of conglomerates to shift production lowered the shadow cost of the regulation from 11.2% of energy costs to 8.1%. Finally, we show that the government can use public information on conglomerate networks to design a conglomerate-level regulation that would achieve the same energy-use reduction at a shadow cost of 5.4% of energy costs.

Overall, we find that while the regulation reduced the energy consumption of large firms, the promise of achieving these savings through improved energy efficiency failed to materialize. Instead, regulated firms reduced their energy use by decreasing their output and by reallocating part of the lost economic activity across business networks, which significantly lowered the policy's impact on energy reduction. While the ability to shift production lowered the shadow cost for regulated conglomerates, the Top 1,000 program forced firms to shift production to less productive affiliates. Our results also show that the government can significantly improve the design of energy regulation by using publicly available data on business networks.

We develop these results in three steps. First, we implement a difference-in-differences strategy using firms in similar industries that were regulated in later years as controls. We use an event-study specification to show that Top 1,000 firms had similar trends to unregulated firms prior to the regulation. We estimate that regulated firms reduced their energy use by about 13%–16%. These estimates are robust to inclusion of industry-by-year and province-by-year fixed effects and controls for firm characteristics. Since the regulated firms consumed 670 million tons of coal equivalent in 2004, the direct reduction in energy use amounted to close to 100 million tons of coal equivalent. However, we also document that these firms saw a decline in output of between 11% and 23%, and we do not find meaningful or statistically significant changes in energy efficiency. The lack of gains in energy efficiency suggest two hypotheses. The first is that firms had limited potential to increase energy efficiency from a technological perspective—i.e., there was no "low-hanging fruit" (e.g., Allcott and Greenstone, 2012). A second hypothesis is that firms were able to escape the regulatory burden by shifting production to related parties.

Our second set of analyses leverages detailed business registration data to map the conglomerate networks of regulated firms. If regulated firms were able to escape 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 regulated firms through ownership networks. We test this hypothesis using a difference-in-differences strategy that compares non-regulated but related firms to non-regulated and non-related firms. To ensure that these two groups of firms are similar, we use a matching procedure based on pre-regulation characteristics to find a suitable set of control firms. These analyses show that after the reform, regulated conglomerates shifted production to unregulated firms. Specifically, we find an increase in firm output of 13% as well as similar increases in other measures, such as profits, sales, assets, and employment. Importantly, we only find increases in the economic activity of related firms when their line of business coincides with the narrowly defined (4-digit) industry classification of the regulated firm. As a placebo test, we show that 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% of the output decline in regulated firms to related parties. Thus, while firms were able to escape a significant fraction of the regulatory burden, the incomplete shifting of output and the null effects on the energy efficiency of regulated firms suggest that firms still faced significant costs of improving their energy efficiency. Finally, we show that following the regulation, related firms also increased their energy use.

Our last set of analyses use a model of conglomerate production to quantify the economic mechanisms underlying our reduced-form results. The model matches key facts of conglomerate production as well as the reduced-form effects of the regulation. Using the model, we show that size-based regulations such as the Top 1,000 program distort the allocation of production across related firms. The model clarifies that conglomerate-level spillovers are a distinct force from market spillovers and that ignoring this mechanism would lead to over-estimation of the impact of the policy on regulated firms and on industry-level outcomes. Our estimated model quantifies the shadow cost of the Top 1,000 program at 8.1% of energy costs. The ability of conglomerates to shift activity across related firms decreased the shadow cost from over 11.2% to 8.1% of energy costs, relative to those in a hypothetical case where regulators successfully prevented conglomerates from shifting production to related firms. Supposing instead that the government regulated the total energy use of the conglomerate would further reduce the shadow cost of the regulation by 34%. Finally, we also show that an input tax of 5.5% would yield a similar reduction in energy use and that such a policy would not distort the within-conglomerate allocation of production.

This paper contributes 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; Ryan, 2018; Ito and Zhang, 2020). In the Chinese context, the government's use of high-powered incentives that tie environmental performance to cadre promotion has been shown to provide a strong mechanism to enforce environmental policies (Kahn et al., 2015; He et al., 2020). In their discussion of recent efforts to curb energy use in China, Auffhammer and Gong (2015) note that the Top 1,000 program along with its expanded version in later years are the "most significant national programs" focusing on energy efficiency and energy conservation. Using industry-level data, Ke et al. (2012) argue that the Top 1,000 program led to significant declines in the energy intensity of regulated sectors. By using detailed firm-level data and by tracing the effects of the regulation along business ownership networks, our results provide a fundamental reassessment of the effectiveness of the Top 1,000 program.

The result that the Top 1,000 program impacted economic activity at regulated and non-regulated firms contributes to the literature studying the economic costs of regulations. In the US, researchers have documented significant effects of environmental regulations on economic activity (e.g., Greenstone, 2002; Greenstone et al., 2012; Walker, 2013; Curtis, 2018). He et al. (2020) show that Chinese firms that face more stringent regulations experience significant decreases in productivity. Our paper contributes to our understanding of the economics cost of energy regulation in China, which consumes the lion's share of global industrial energy.

Researchers have also documented that regulations can lead to spillover effects along firm networks. For instance, Hanna (2010) finds that multinational firms respond to environmental regulation by increasing investment in foreign countries and Gibson (2019) and Soliman (2020) find that firms may also shift economic activity to unregulated plants in counties that are subject to less stringent regulations. Conglomerate spillovers are particularly important in our setting since the Top 1,000 program targeted very large firms with extensive ownership networks. Our detailed business registration data therefore provide an unique view into how this regulation affected the production decisions of large Chinese conglomerates and how conglomerates 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 in productivity when they shift production to related firms (see, e.g., Anderson and Sallee, 2011).

Our paper also takes into account the role of market competition in environmental regulation. We abstract from strategic interactions between firms in a setting with monopolistic competition since we study manufacturing industries with a large number of firms that compete in national markets.[1] Accounting for market effects remains important in this setting since the regulated firms combined are responsible for a large share of industrial output. Our paper shows that conglomerate spillovers are distinct from market competition and play a quantitatively important role in the context of China.

This paper is organized as follows. Section 2 describes the policy context and the data that we use to measure firm responses to the regulation as well as the ownership networks of regulated firms. Section 3 estimates direct effects of the Top 1,000 program on regulated firms, and Section 4 estimates indirect effects on unregulated firms that belong to the business networks of regulated firms. Section 5 describes our model of conglomerate regulation, and Section 6 estimates the model parameters. Section 7 uses the model to quantify the shadow cost of the policy and to analyze distributional and aggregate effects of the regulation. Section 8 concludes.

2 Policy Background and Data

This section describes the Top 1,000 energy savings program. We also describe the different datasets that we use to measure economic activity and energy use as well as our strategy to map the ownership networks of Chinese conglomerates.

[1] Studies of energy regulation with strategic interaction often focus on concentrated industries (see, e.g., Mansur, 2007; Fowlie, 2009; Ryan, 2012; Fowlie et al., 2016).

2.1 The Top 1,000 Program

To save energy and reduce related pollution, the Chinese government's 11th Five-Year Plan (11FYP) set an ambitious goal of reducing the country's energy intensity—defined as energy consumption per unit of GDP—by 20% between 2006 and 2011 (Price et al., 2010). Since the industrial sector accounts for 70% of total energy consumption, the government designed policies that focused on nine energy-intensive industries, which accounted for 80% of the country's industrial energy use. One of these key initiatives was the Top 1,000 Energy Saving 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 nine energy-intensive industries with energy consumption above 180 thousand tons of coal equivalent in 2004. The total energy consumption of these 1,008 "super-firms" was 670 million tons of coal equivalent in 2004, accounting for 47% of China's industrial energy consumption and 33% of China's total energy consumption. Importantly, since 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 participants in the program. Moreover, the list of firms regulated by the program did not change during the five-year period. Table 1 reports the number of firms and their share of energy consumption in each of the regulated industries. Among Top 1,000 firms, firms in the iron and steel, chemical, and electric power industries accounted for around 63% of the firms and 68% of the regulated energy consumption in 2005.

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., McKinsey & Co., 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 reduce energy consumption by a total of 100 million tons of coal equivalent by 2011. Given the quick implementation of the program, many aspects of voluntary agreement programs (such as providing technological expertise or financing energy efficiency improvements) played a relatively minor role (Price et al., 2010). In practice, firms were regulated based on energy use only and not on energy efficiency.

To implement the policy, the central government assigned a target reduction in energy use to each provincial government. In turn, local officials negotiated individual quotas with each of the Top 1,000 firms. Leaders of provincial governments and state-owned enterprises were then evaluated on whether these energy saving targets were met. As a result, local government officials monitored and enforced the energy saving targets of the Top 1,000 firms very closely.[2]

[2]Under the "one-vote veto" criteria, officials would not be considered for promotions or awards if the province

This strict supervision is evident in Table A.11, where we report the results of the government's annual assessment. This table shows that the compliance rate is very high. In fact, the total energy saving target was achieved in 2008, two years ahead of schedule. At the end of the 11FYP, the government estimated energy savings of 165.49 million tons of coal equivalent, far beyond the original target of 100 million tons. Among the regulated firms that successfully achieved their reported energy saving targets, the average completion rate was over 250%.

Due to the successful experience during the 11FYP, the Top 1,000 program was expanded into the "Top 10,000" Energy Savings Program during the 12th Five-Year Plan (12FYP) in 2012. In this case, the Top 10,000 refers to 16,076 energy-intensive firms with energy consumption above 10 thousand tons of coal equivalent in 2010. These firms account for 60% 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 tons of coal equivalent during the 12FYP. Our primary analysis focuses on the Top 1,000 firms between 2001 and 2011. Since 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 in our empirical analysis.

2.2 Firm Data

Our empirical analyses combine several rich data sources. The first dataset that we use is the Annual Survey of Industrial Firms (ASIF) from the National Bureau of Statistics (2001–2009 and 2011).[3] 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 RMB (approximately 800,000 USD).

We merge these data with the lists of regulated firms using both firm name and a unique legal identifier. These lists are published by the National Development and Reform Commission. The lists of Top 1,000 and Top 10,000 firms include information on the evaluations of each regulated firm, the firm-level energy saving target, and the annual compliance rate.

We complement these data with two additional datasets. First, we 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. Second, to fill in missing data on firm investment and assets in the ASIF, we also merge data from the Annual Tax Survey (ATS) for 2009 and 2010.[4]

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or any of the local Top 1,000 firms did not achieve their targets. Similarly, the leaders of state-owned enterprises that did not meet the target did not receive annual bonuses. In this way, the Chinese setting contrasts with other developing country settings where the design of incentives for energy auditors plays a key role (e.g., Duflo et al., 2013, 2018).

[3]As is well known in the literature, data for the 2010 ASIF display a number of irregularities and are often excluded from statistical analyses.

[4]To ensure a high-quality merge, we eliminate firms where differences in investment and assets between the

Panel A of Table 2 shows the results of our data construction. Since the Top 1,000 and Top 10,000 firms are all large firms, the match rate with the ASIF is very high. We match over 99% of the Top 1,000 firms and over 97% of the Top 10,000 firms. We also have a fairly good match rate with the CESD, where we match over 80% of Top 1,000 and over 65% of Top 10,000 firms. Overall, our combined datasets capture the majority of the economic activity in the Top 1,000 and Top 10,000 firms.

Panel A of Table 2 reports summary statistics for the Top 1,000 and Top 10,000 firms in our sample. Our sample includes about 8,700 observations for Top 1,000 firms and 87,000 observations for Top 10,000 firms over a period of 10 years. Because the CESD only reports energy consumption from primary sources (e.g., coal, oil, gas), our analyses of energy use and energy efficiency exclude firms in industries that mainly rely on electricity.[5] For this reason, the sample of firms with energy consumption data is smaller.

As we show in Panel A of Table 2, Top 1,000 firms are larger, older, more likely to be state owned, and more export oriented than Top 10,000 firms. This table also shows that Top 1,000 firms are slightly less energy efficient (defined as the ratio of energy use to output) than Top 10,000 firms. However, this difference is driven mostly by industry differences, since Top 1,000 firms are more likely to be in energy-intensive heavy industries.

2.3 Mapping Conglomerate Networks

To study how conglomerates responded to the regulation, we first need to identify firms' ownership networks. Our ownership data come from China's Administrative Registration Database (CARD). These data are collected by the State Administration of Industry and Commerce and include 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 the four types of linkages displayed in Figure 3. First, we include wholly owned affiliates of regulated firms as related parties. Second, we also include firms that are at least partially owned by regulated firms. Our data allow us to identify firms that are related through multiple levels of investment. We consider firms to be related if they are owned by a regulated firm by up to two levels of investment relations. Although in practice most related firms are fully owned, we require that the regulated firm owns at least 25% of the related firm at each level of investment. Third, we include shareholders of regulated firms, and we allow up to two levels of shareholder links. Finally, we also include firms that are fully or partly

ASIF and the ATS exceed 25%.

[5]In practice, we exclude industries where electricity consumption accounts for more than 30% of the total energy consumption.

owned by the shareholders of a regulated firm. We also allow for two levels of investment, and we require ownership to be at least 25% at each level.[6] Since the government has no incentives to help firms shift production, we exclude all related firms that are only connected to regulated firms through government entities.

Panel B of Table 2 reports the results of matching our registration data with our data on firm outcomes. Under our baseline definition, we can identify 80,341 related parties of Top 1,000 firms in the CARD. Since most of these firms are small, we match 10,944 firms in the ASIF. In our baseline regressions, we require related firms to be in the same 4-digit industry as a related Top 1,000 firm.[7] Since a large number of related parties are service firms or small firms that are not recorded in the ASIF, our main sample of related firms includes 2,500 industrial firms.[8] A potential concern with CARD data is that some of the related firms may not be engaged in production and may, in fact, be holding companies. One advantage of merging the CARD data with the ASIF and the CESD is that this ensures that our results are driven by real economic activity in industrial firms. Since it is likely very hard to shift production to firms in other narrowly defined industries, we analyze firms in the same 2-digit industry but outside of 4-digit industries in a placebo test.

Panel B of Table 2 also examines the robustness of our network definitions to alternative assumptions. Allowing for up to six levels of relations does not have a large effect on our sample of related firms in the same 4-digit industry. Decreasing the ownership requirements to 20% has a small effect on the number of related firms, and the number of related parties is even somewhat stable when we increase the ownership ratio to 51%. These results suggest that within narrowly defined industries, firm ownership networks are very compact.

The merged CARD and ASIF data reveal some interesting patterns of firms that operate in the same 4-digit industry. First, we find that Top 1,000 firms have an average of 2.48 related parties in narrowly defined industries. Second, since 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 18.9% of the output of regulated firms. These facts imply that conglomerates may have significant scope to substitute production with similar technology across related firms.[9]

However, it is also unlikely that related parties can fully make up for production declines in Top 1,000 firms. Third, firms within conglomerates have an interesting relative size distribution. To produce Panel A of Figure 2, we compute each firm's size relative to the largest firm in the

[6] Figure A.11 depicts all the possible links that we consider.

[7] A related party of multiple Top 1,000 firms is classified as a same-industry related party as long as it is in the same industry as one of its related Top 1,000 firms.

[8] Omitting firms in unrelated industries is unlikely to affect our results since super-firms like Top 1,000 firms would not be able to shift production to service firms or to very small firms.

[9] In Chen et al. (2021), we show that most related parties of regulated firms are located in the same province as the regulated firm. For this reason, we do not expect that substitution of production across related parties will significantly affect the geographic distribution of energy use or related pollution.

group; we then plot the average relative size by firm rank. A striking fact of this graph is that the average relative size within a conglomerate declines sharply with firm rank: the second-largest firm in a conglomerate is only 28% as large as the largest firm, on average. Interestingly, the decline in relative firm size follows an almost geometric decline, 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 also have larger leading firms suggests that the number of firms in a conglomerate might depend on technological efficiencies that are shared by all firms in a conglomerate.

3 Effects of the Policy on Regulated Firms

As detailed in Section 2, the Top 1,000 program set energy saving targets for each regulated firm. To study the effects of the policy, we compare the effect on these firms relative to the performance of other large firms that also operate in energy-intensive industries. Specifically, we use firms that are regulated after 2011 as part of the Top 10,000 program. Because firms in the same conglomerate as a regulated Top 1,000 firm may be indirectly affected by the policy, we remove these firms from the set of control firms.

The identifying assumption of this difference-in-differences analysis is that absent the Top 1,000 regulation, the energy use and output of Top 10,000 firms would have trended similarly to that of Top 1,000 firms. To provide evidence that these firms had similar trends prior to the implementation of this regulation, we use firm data from the CESD to estimate an event-study analysis of the form:

$$Y_{ijkt} = \sum_{\tau=2002}^{2010} \beta_\tau \times Treat_i \times Year_\tau + \alpha_i + \eta_{jt} + \delta_{kt} + \varepsilon_{ijkt}, \tag{1}$$

where Y_{ijkt} is a dependent variable for firm i in industry j, province k and year t. $Treat_i$ is an indicator for the treatment group, which 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 in 2006. We include firm-level fixed effects α_i in all regressions, and we also allow for (4-digit) industry-by-year fixed effects η_{jt} as well as province-by-year fixed effects δ_{kt}. We cluster standard errors at the firm level.

Figure 4 presents a visual implementation of our difference-in-differences estimation strategy. Panel A in Figure 4 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 did indeed succeed at lowering the energy use of regulated firms relative to that of non-regulated firms.[10] 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.

To quantify the overall effects of the policy, we estimate difference-in-differences specifications of the form:

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

where $Post_t$ is an indicator that equals one after 2006. In addition to different fixed effects, some specifications control for firm characteristics 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 3 shows that on average, the total energy consumption of regulated firms decreased by 13%–16%. These estimates are stable across specifications that include different levels of fixed effects and firm controls. To understand the magnitude of this effect, recall that regulated firms consumed 670 million tons of coal equivalent in 2004. The coefficients in Table 3 therefore imply annual reductions in energy use of close to 100 million tons of coal equivalent, or about 20% of the total industrial energy use of the European Union.

To discern whether this reduction in energy use is 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 4 show that after the reform, firm output in regulated firms also decreased significantly. Indeed, Panel B of Table 3 reports declines in output between 11% and 23%, depending on the specification.[12] Accounting for the declines in output implies that the policy had limited impacts on energy efficiency. Panels E–F of Figure 4 show 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 of Panel C of Table 3, the 95% confidence interval rules out that the policy increased energy efficiency by more than 4%, which is significantly below the government's goal of improving energy efficiency by 20%.[13]

The effects of the policy on regulated firms paint a mixed picture of its success. On one hand, the regulation succeeded at achieving a meaningful reduction in the energy use of energy-

[10]One potential concern is that our results may be contaminated by mean reversion. Because firms were regulated based on their 2004 energy use, one possibility is that regulated firms had idiosyncratically large levels of energy use in 2004 that reverted to lower levels in later years. As this and other similar graphs show, the outcomes for 2004 are not significantly different from those for 2001–2003, and we also do not see large differences with the outcomes for 2005–2006.

[11]For visual clarity, Panels B, D, and F of Figure 4 follow Ohrn (2018) by plotting trends for the control group that has the same average in the pre-period as the treated group.

[12]In Table A.15 and Figure A.12 we also show that regulated firms experience a decline in the probability of investing after the regulation was enacted. Additionally, we test the Porter and van der Linde (1995) hypothesis by examining whether firms became more innovative after the regulation. Figure A.17 shows that we do not see an increase in the filing of patents related to energy efficiency in regulated firms.

[13]As we discuss in Section 2, these analyses exclude industries that primarily rely on electricity. Table A.16 shows that our results are robust to excluding more or fewer industries based on their electricity use.

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.

One concern with these results is that our difference-in-differences specifications may be contaminated by spillover effects. Indeed, as we show below, non-regulated firms that operate in more tightly regulated industries saw increases in output following the implementation of the regulation. Our results above temper the importance of this concern in two ways. First, Figure 4 shows that control firms did not grow at faster rates after the regulation was put in place. Second, our results are robust to inclusion of industry-by-year fixed effects, which may partial out some of the market-level spillover effects. In Section 6, we use our model to clarify the importance of market-level spillovers. While our model is consistent with the existence of spillovers, the estimated effects of the policy are mostly due to declines in the energy use and output of regulated firms.

The next section studies whether conglomerates avoided the burden of the regulation by shifting economic activity to related parties. While the existing literature recognizes the importance of accounting for market-level spillovers, we show that spillovers that are transmitted through ownership networks constitute a distinct margin through which conglomerates adjust to energy regulations.

4 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 the declines in economic activity in regulated firms and prevent competitors from increasing their market share. Moreover, shifting profits to related parties allows conglomerates to comply with the letter of the regulation—if not with its intent—without having to invest in potentially costly improvements in energy efficiency.

To measure the empirical importance of conglomerate spillovers, we use CARD data on the ownership networks of regulated firms to identify firms that may have indirectly expanded as a consequence of the Top 1,000 regulation. We then use matching methods to identify controls firms that were (1) not part of the Top 1,000 program, (2) not related to a regulated firm, and (3) in the same industry and of similar size (measured in 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, however, the $Treat_i$ variable is now an indicator of whether a firm is related to a Top 1,000 firm. As we discuss in Section 2, we focus our study of spillovers on firms in the same 4-digit industry as the regulated firm. This restriction follows from the logic that only firms selling similar products to those of the regulated firms may be able to make up for the decline in production of Top 1,000 firms.

Figure 5 plots the results of these event-study analyses using ASIF data. Panel A shows that prior to the regulation, related firms had similar trends in output to those of unrelated firms. After the regulation, however, firms related to Top 1,000 firms saw significant increases in output that persisted for several years. Panel A of Table 4 shows that after the regulation, related firms expanded by 13%, on average. This table also shows that we obtain very similar results across specifications with different levels of fixed effects as well as firm-level controls.

To gauge the magnitude of these spillover effects, it is important to account for the number of related parties of each regulated firm as well as for their relative size. On average, Top 1,000 firms have 2.48 related parties. However, since the average related firm is only 18.9% as large as its regulated counterpart, we calculate that conglomerates shifted close to 41% ($\approx 2.48 \times 18.9\% \times 13.3\%/15.2\%$) of the output decline in regulated firms.[14] This result is informative for a couple of reasons. First, this result 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, this result shows that firms were unable or unwilling to increase the energy efficiency of their production processes even if it meant losing profits to competitors.

While the average spillover effect allows us to gauge the magnitude of the overall spillovers, we also document interesting differences in spillovers across related firms. Panel B of Table 4 shows that related firms in higher terciles of the size distribution display larger increases in output. This result suggests that larger firms were more able to expand or, alternatively, that larger firms had excess production capacity. We also find that related firms that are more likely to be controlled by regulated firms show larger increases in output. Specifically, affiliates and firms in which regulated firms have an investment stake show larger output increases than firms related through shareholders or shareholders' investments (see Figure A.13).

The result that related firms display an increase in economic activity is robust to a number of checks. First, we show that we obtain similar results when we use one-to-one matching, three-to-one matching, or entropy balancing to find controls for related firms (see Panel A of Figure A.14 and Figure A.15). Second, Panel C of Table 4 shows that we find positive spillovers to other measures of economic activity including sales, profits, assets, fixed assets, and employment (see Figure A.14 for corresponding event studies). Third, these results are robust to dropping firms in power generation (see Table A.17 and Figure A.16). Fourth, we show that only those related

[14]Note that we obtain a smaller estimate of 30% when we instead rely on the estimate of the effect on the output of regulated firms of 21% (*i.e.*, $30\% \approx 2.48 \times 18.9\% \times 13.3\%/21\%$). We can also gauge the sensitivity of this estimate to the measurement of business networks. Supposing that regulated firms had an average of 3 related firms (a 20% increase in the number of relations), spillovers would account for 50% of the output decline in regulated firms (*i.e.*, $50\% \approx 3 \times 18.9\% \times 13.3\%/15.2\%$).

firms that operate in the regulated firms' own narrowly defined industries—and that could thus possibly produce substitute output—show an increase in economic activity. Indeed, Panel B of Figure 5 and Panel A of Table 5 show that we find no impact on the output of related firms that operate outside the 4-digit industry of the regulated firm (but that are still in the same 2-digit industry). This placebo test is important, as it 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.

Having established that conglomerates shifted output across related parties, we now explore whether these firms also saw changes in energy use and energy efficiency. Panels C and D of Figure 5 report these results using data from the CESD. Panel C shows that related firms saw an increase in energy use after the regulation. Panel B of Table 5 shows that energy use in related firms increased by 34%–38% after the regulation. However, since related firms are smaller than regulated firms, they are less likely to be included in the CESD. While the available data include firms across all affected industries, the number of observations in this panel is smaller than that in Panel A of Table 4. For this reason, caution is warranted in ascribing these increases in energy use to all related firms. Panel D of Figure 5 and Panel C of Table 5 shows 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 41% of the output reduction in regulated firms. Our structural model in the next section uses these results to quantify how the ability to shift production between related firms lowered the shadow costs of the regulation. We find larger spillover effects for larger related parties as well as firms more likely to be controlled by regulated firms. Finally, we also find suggestive evidence that related parties also increased their energy use. While we do not find significant changes in the energy efficiency of related firms, the fact that these firms are smaller suggests that they are—on average—less energy efficient than regulated firms. Therefore, it is likely that the overall spillover effect on energy use was larger than the overall output spillover, leading to compositional losses in energy efficiency.

Market-Level Spillovers

Since related parties could not make up the entire output loss of Top 1,000 firms, other firms in regulated industries may have been indirectly affected by the energy saving program due to reduced competition. To examine this indirect effect of the regulation, we estimate the following difference-in-differences specification:

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

where $spillover_j$ is the proportion of the total energy saving targets of Top 1,000 firms for industry j relative to the total energy consumption of industry j in 2006. To interpret the coefficient β as the average spillover effect, we normalize the $spillover_j$ variable by the average exposure across all industries. Since the variation in the independent variable is at the industry-year level, we do not include industry-by-year fixed effects in this regression but instead use firm fixed effects and year fixed effects only.[15] 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.

As shown in Table 6, unregulated firms in industries with stricter regulation increased their output significantly after the policy was implemented. Across all industries, we find that the average market-level spillover led to a 7%–10% increase in the output of non-regulated firms. Note that the regressions in the first two columns of this table include both regulated and unregulated industries. We find larger increases (8%–14%) when we include firms in regulated industries only. Note that in this case, the identifying variation is driven solely by differences in regulation intensity across industries.

These results yield a couple of insights. First, these findings further confirm our previous estimates that related parties were not able to make up for the full output loss of Top 1,000 firms. Second, a full accounting of the spillover effects of the regulation needs to include both within-conglomerate spillovers as well as market-level spillovers. To study the distribution and aggregate impacts of the Top 1,000 program, the next section develops a model of conglomerate production where regulations impact regulated firms, non-regulated firms that are part of the conglomerate, and unrelated competitors.

5 A Model of Conglomerates with Regulation

This section presents an industry equilibrium model of conglomerates that is consistent with cross-sectional data patterns and reduced-form responses to the policy of energy regulation. We use the model to interpret our difference-in-differences estimates, to compute the shadow cost of the regulation at the conglomerate level, and to quantitatively evaluate the aggregate and distributional impacts of the regulation.

5.1 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 CES preferences over a continuum of varieties

[15] Note also that the variation in $spillover_j$ is absorbed in our previous specifications that include industry-by-year fixed effects.

$\omega \in \Omega$:

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

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

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

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

We define a conglomerate in our model by the presence of a variety ω that can be manufactured by multiple affiliates. 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., van Biesebroeck, 2003; Fabrizio et al., 2007; Gao and Van Biesebroeck, 2014; Ryan, 2018).[16] 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, i.e., $\alpha = \alpha_k + \alpha_l < 1$. The decreasing-returns-to-scale assumption is consistent with the literature on span of control. 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 i^{th} affiliated firm is $\delta^{i-1}\phi$. This assumption can be interpreted as either a limit on the span of managerial control or as 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.

We consider the conglomerate's problem in two stages. Prior to the regulation, conglomerates observe their productivity ϕ, 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.[17] After the regulation, since capital is quasi-fixed, the conglomerate adjusts its variable inputs to maximize profits. We initially assume energy efficiency is fixed (i.e., $\nu_i = 1$ for all firms) and allow for costly investments to improve energy efficiency in an extension of the model.

[16] Fabrizio et al. (2007); Gao and Van Biesebroeck (2014) adopt this assumption from van 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 being perfect complements.

[17] Conglomerates can choose $n = 0$, which we interpret as an exit decision.

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

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

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:*

$$\frac{q_i}{q_1} = \frac{k_i}{k_1} = \frac{l_i}{l_1} = \delta^{\frac{i-1}{1-\alpha}}. \tag{5}$$

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 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 $K_n = \sum_i^n k_i$, define the conglomerate's total productivity $\phi\Delta_n = \phi[\sum_{i=1}^n (\delta^{i-1})^{\frac{1}{1-\alpha}}]^{1-\alpha}$ and the constant $C_\pi = (1-\alpha\rho)\left[\left(\frac{\rho\alpha_l}{w+p_e}\right)^{\alpha_l\rho}\left(\frac{\rho\alpha_k}{r}\right)^{\alpha_k\rho}\right]^{\frac{1}{1-\alpha\rho}}$. 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 as well as the firm profits for a conglomerate of size n are then:

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

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

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

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. Since 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 non-decreasing 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*

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

Let $\pi(\phi) = \max_n \pi(\phi, n) - nfr$ be the profit for a firm of efficiency ϕ at the optimal number of affiliates. The prediction from 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.

5.3 Equilibrium

The unique equilibrium of the model is characterized by the zero profit condition and the free entry condition. Conglomerates operate whenever:

$$\pi(\phi) \geq 0 \;\Rightarrow\; \phi \geq \phi_1 = \frac{(fr)^{\frac{1-\rho\alpha}{\rho}}}{C_\pi^{\frac{1-\rho\alpha}{\rho}}}. \tag{8}$$

Equation 8 shows that only firms with $\phi > \phi_1$ choose to participate in the market.[18] With M denoting the mass of active firms, the aggregate price index is given by:

$$P = \left[\int_{\phi_1}^{\infty} p(\phi)^{1-\sigma} \frac{g(\phi)M}{1 - G(\phi_1)} d\phi\right]^{\frac{1}{1-\sigma}}. \tag{9}$$

To enter the market, an entrepreneur pays an entry cost f_e. Upon entry, the efficiency of the conglomerate ϕ is realized. Since the conglomerate operates only if $\phi > \phi_1$, the free entry condition is given by:

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

An equilibrium is given by the exit threshold ϕ_1 and the mass of active conglomerates M, such that (1) conglomerates make optimal allocation and size decisions, (2) the product market clears, and (3) the zero profit and free entry conditions (Equations 8–10) are satisfied.

[18] ϕ_1 is the minimum efficiency for a single-firm conglomerate, so that $\pi(\phi_1) = 0$.

5.4 Effects of the Top 1,000 Program

Since 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. For each conglomerate, the regulation sets a proportional input quota for its largest firm, 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 $\{l_i\}_{i=1}^n$.

To study the impact of the regulation on conglomerate production, we first substitute the result from Proposition 1 into Equation 4. We also define $\phi^* = \phi(k_1^*)^{\alpha_k}$ and let λ be the Lagrange multiplier associated with the regulatory constraint.[19] The conglomerate's first-order conditions for l_i $(1 \leq i \leq n)$ are then:

$$\frac{\partial \pi}{\partial l_i} = \underbrace{R^{1-\rho} P^{\rho}}_{\text{Market Demand}} \underbrace{\rho \left[\phi^* \sum_{i=1}^{n} \delta^{\frac{(i-1)(1-\alpha_l)}{1-\alpha}} l_i^{\alpha_l} \right]^{\rho-1}}_{\text{Residual Revenue}} \underbrace{\phi^* \delta^{\frac{(i-1)(1-\alpha_l)}{1-\alpha}} \alpha_l (l_i)^{\alpha_l - 1}}_{\text{Marginal Product}} = w + p_e + \underbrace{\lambda(\phi)\mathbb{I}[i=1]}_{\substack{\text{Shadow Cost} \\ \text{of Regulation}}}. \quad (11)$$

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 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. 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:*

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

$$\frac{l_i}{l_1} = \delta^{\frac{i-1}{1-\alpha}} \times \left[1 + \frac{\lambda(\phi)}{w + p_e}\right]^{\frac{1}{1-\alpha_l}} \quad \text{and} \quad \frac{q_i}{q_1} = \delta^{\frac{i-1}{1-\alpha}} \times \left[1 + \frac{\lambda(\phi)}{w + p_e}\right]^{\frac{\alpha_l}{1-\alpha_l}} \quad \text{for } i > 1.$$

Even though conglomerates substitute production across firms, the regulation leads to an overall reduction in the conglomerate's output. The regulation also distorts input use across conglomerates. Since only conglomerates with $\phi > \tilde{\phi}$ are part of the Top 1,000 program, the regulation increases the overall input cost of regulated conglomerates relative to unregulated conglomerates. Additionally, because conglomerates with more affiliates can shift more production

[19] Note that $k_1^* = K_n^*(\Delta_n)^{\frac{-1}{1-\alpha}}$.

to related parties, conditional on being regulated, more efficient conglomerates (higher ϕ) are subject to a smaller shadow cost $\lambda(\phi)$.

Endogenous Energy Efficiency

The analysis so far assumes that energy efficiency is fixed. Following the intent of the Top 1,000 program, we now allow for the regulation to stimulate investment in energy efficiency. We assume that the conglomerate can improve energy efficiency at firm i, ν_i, by spending $l_i c(\nu_i)$, where $c'(\nu_i) > 0$ and $c''(\nu_i) \geq 0$. The conglomerate's problem is then:

$$\pi(\phi, n) = \max_{\{l_i\}_{i=1}^n, \{\nu_i\}_{i=1}^n} \left\{ R^{1-\rho} P^{\rho} \left[\phi^* \sum_{i=1}^{n} \delta^{\frac{(i-1)(1-\alpha_l)}{1-\alpha}} l_i^{\alpha_l} \right]^{\rho} - \sum_{i=1}^{n} l_i \left(w + \frac{p_e}{\nu_i} + c(\nu_i) \right) \right\},$$

where we omit the cost of fixed capital. Absent the regulation, the conglomerate sets $c'(\nu^*)\nu^{*2} = p_e$ for all firms. This implies that the effective price of energy inclusive of investments in energy efficiency is $\frac{p_e}{\nu^*} + c(\nu^*) = c'(\nu^*)\nu^* + c(\nu^*)$. To simplify the exposition, we assume that $c(\nu) = \frac{\nu^\gamma}{1+\gamma}$, where $\gamma \geq 1$, so the effective price of energy is $(\nu^*)^\gamma$. Additionally, note that the Top 1,000 regulation does not impact the choice of ν_i for non-regulated firms. Using these results and the fact that $\nu_i = \frac{l_i}{e_i}$, we can restate the conglomerate problem as:

$$\pi(\phi, n) = \max_{\{l_i\}_{i=1}^n} \left\{ R^{1-\rho} P^{\rho} \left[\phi^* \sum_{i=1}^{n} \delta^{\frac{(i-1)(1-\alpha_l)}{1-\alpha}} l_i^{\alpha_l} \right]^{\rho} - (w + (\nu^*)^\gamma) \sum_{i=1}^{n} l_i - l_1 \left[\frac{1}{1+\gamma} \left(\frac{l_1}{\xi e_1^*} \right)^{\gamma} - (\nu^*)^\gamma \right] \right\},$$

where we substituted the regulatory constraint into the cost of energy efficiency and where we abstract away from the cost of the regulated energy.

The conglomerate's first-order conditions for l_i ($1 \leq i \leq n$), i.e., $\frac{\partial \pi}{\partial l_i}$, are then:

$$\underbrace{\underbrace{R^{1-\rho} P^{\rho}}_{\text{Market Demand}} \rho \left[\phi^* \sum_{i=1}^{n} \delta^{\frac{(i-1)(1-\alpha_l)}{1-\alpha}} l_i^{\alpha_l} \right]^{\rho-1}}_{\text{Residual Revenue}} \underbrace{\phi^* \delta^{\frac{(i-1)(1-\alpha_l)}{1-\alpha}} \alpha_l (l_i)^{\alpha_l - 1}}_{\text{Marginal Product}} = w + (\nu^*)^\gamma + \underbrace{\left[\left(\frac{l_1}{\xi e_1^*} \right)^{\gamma} \frac{1}{\xi e_1^*} - (\nu^*)^\gamma \right]}_{\substack{\text{Shadow Cost} \\ \text{of Regulation}}} \mathbb{I}[i=1].$$

Interestingly, this extension of the model yields very similar results to those in Equation 11 and Proposition 3. For the case of non-regulated firms (i.e, l_i for $i > 1$), we simply substitute p_e with the effective price of energy: $(\nu^*)^\gamma$. Similarly, the first order condition for the regulated firm implies that the shadow cost of the regulation is given by:

$$\lambda(\phi) = \left(\frac{l_1}{\xi e_1^*} \right)^{\gamma} \frac{1}{\xi e_1^*} - (\nu^*)^\gamma,$$

which is the incremental cost of improving energy efficiency in the regulated firm.[20] Finally, note that these results reveal a close link between the percentage change in the marginal product of

[20] The functional form assumption for $c(\nu)$ only simplifies the derivation. Absent this assumption, one can replace p_e in Equation 11 with the effective cost of energy $\nu^* c'(\nu^*) + c(\nu^*)$. Similarly the shadow cost would be: $\lambda(\phi) = [\nu_1 c'(\nu_1) + c(\nu_1)] \frac{1}{\xi e_1^*} - (\nu^* c'(\nu^*) + c(\nu^*))$.

inputs in the regulated firm and the change in energy efficiency:

$$\Delta \text{MP}_{l_1} = s_e \left[\frac{(1+\Delta\nu)^\gamma}{\xi e_1^*} - 1 \right],$$

where $s_e = \frac{(\nu^*)^\gamma}{w+(\nu^*)^\gamma}$ is the share of effective energy costs relative to the cost of flexible inputs. This equation shows that we can provide bounds on the parameter γ, which measures the cost of improving energy efficiency, by combining estimates of the regulation on energy efficiency and production.

This model extension yields two valuable insights. First, allowing for investment in energy efficiency does not necessarily reduce the regulation's distortion on the use of inputs across firms. Second, at the margin the conglomerate is indifferent between the cost of investing to improve energy efficiency at the regulated firm and the loss in marginal product associated with shifting production to related parties. Indeed, we can interpret the shadow cost of the regulation as an expression of the cost of improving energy efficiency to comply with the regulation.

5.5 Connecting the Model to the Empirical Results

One advantage of our model is that it allows us to quantify how conglomerate and market spillovers may impact our empirical estimates. To see how the regulation in our model connects to our difference-in-differences analysis, note that we can write conglomerate j's revenue from affiliate i as follows:

$$\ln \text{Revenue}_{ij} = \underbrace{\ln(\text{Production Share}_{ij})}_{\text{Allocation Effect}} + \underbrace{\rho \ln\left(\sum_{i\in j} q_{ij}\right)}_{\text{Residual Revenue}} + \underbrace{\ln(R^{1-\rho}P^{\rho})}_{\text{Market Demand}}, \tag{12}$$

where Production Share$_{ij} = q_{ij}/\sum_{i\in j} q_{ij}$.[21] Equation 12 clarifies the three ways in which the Top 1,000 program impacts the revenue of regulated firms. First, as we discuss above, when firm i is regulated, the conglomerate is forced to reallocate inputs to other firms, which lowers the production share in regulated firms. Second, since the marginal cost goes up at the conglomerate level, the market share of its variety decreases, which lowers the group's residual revenue as well as the revenue of the regulated firm. Finally, since all regulated firms in the industry contract, the Top 1,000 program has an equilibrium impact on the industry-level price index P, which, in turn, has a countervailing effect on the revenue of the regulated firm.

We can also use Equation 12 to characterize the impact of the regulation on the control firms in our difference-in-differences analyses in Section 3. Since these firms are not regulated or related to Top 1,000 firms, the regulation does not impact the within-conglomerate allocation of

[21] Equation 12 follows by multiplying conglomerate j's inverse residual demand by affiliate i's production.

production. Control firms see an increase in their residual and firm-level revenue as the market reallocates demand. As in the case of the regulated firms, non-regulated firms also benefit from the equilibrium impact on market demand.

This discussion clarifies the interpretation of our estimates of the impacts of the regulation on the output of Top 1,000 firms. One benefit of our difference-in-differences approach is that the common market demand effect cancels out.[22] Our estimates then capture three effects: (1) a negative allocation effect on regulated affiliates, (2) a negative residual revenue effect on regulated conglomerates, and (3) a positive residual revenue effect on control firms. To the extent that the third channel is quantitatively important, the difference-in-differences approach may overstate the negative effect of the regulation on the output of regulated firms.

A similar discussion allows us to interpret our estimates of the spillover effects of the regulation through ownership networks. First, note that the control firms have the same impact as in our estimates of the direct effects of the regulation. Second, firms related to Top 1,000 firms share the residual revenue and market demand with the regulated firms but the allocation effect increases the revenue of related parties. Since the market demand effect also cancels out in these estimations, our difference-in-differences estimates of spillover effects capture the following three mechanisms: (1) a positive allocation effect on related affiliates, (2) a negative residual revenue effect on regulated conglomerates, and (3) a positive residual revenue effect on control firms. In this case, the third channel may lead the difference-in-differences approach to understate the spillover effect on related firms.

In addition to clarifying the interpretation of the reduced-form estimates, our empirical model allows us to measure the degree to which the effects on control firms are quantitatively important. Similarly, we can use the model to produce estimates of the regulation that isolate the effects of the regulation on Top 1,000 firms as well as on non-regulated firms in the same conglomerate.

These issues arise because the regulation impacts the residual revenue terms for the control groups in our difference-in-differences analyses. Equation 12 also suggests a within-conglomerate difference-in-differences approach that avoids these issues. Specifically, the difference between the output in the Top 1,000 firm and all other related firms is such that:

$$\begin{aligned}
\ln \text{Revenue}_{\text{Top1000},jt} - \ln \text{Revenue}_{\text{Related},jt} &= \ln\left(q_{\text{Top1000},j}\right) - \ln\left(\sum_{i \neq \text{Top1000},j} q_{ij}\right) \\
&= -\frac{\alpha_l}{1-\alpha_l} \ln\left[1 + \frac{\lambda(\phi)}{w + p_e}\right] - \ln\left(\Delta_n^{\frac{1}{1-\alpha}} - 1\right).
\end{aligned}$$

The first line follows from Equation 12 and the second is implied by Proposition 3. By definition, $\lambda(\phi) = 0$ prior to the regulation and Δ_n is constant over time. Taking a time difference of this

[22] Even in the cases where the equilibrium response is industry or location specific, the market demand effect would be absorbed by industry-by-year and province-by-year fixed effects.

expression then shows that a within-conglomerate difference-in-differences approach identifies $-\frac{\alpha_l}{1-\alpha_l}\ln\left[1+\frac{\lambda(\phi)}{w+p_e}\right]$ as the allocation effect.

Figure 7 implements this within-conglomerate difference-in-differences approach. This figure plots results from an event-study specification similar to Equation 1, but where the control firms are non-regulated firms in the same conglomerate and where we additionally include conglomerate-by-year fixed effects. Consistent with our previous results, we find a significant decline in the output of the Top 1,000 firms relative to other firms in their same conglomerates. One drawback of this approach is that it captures a partial impact of the regulation that abstracts away from the market demand and the residual revenue terms. However, the expression above shows that the effects in Figure 7 are closely related to $\lambda(\phi)$. We use this result in our quantitative model to inform our estimate of the shadow cost of the regulation.

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 as well as equilibrium impacts on industry-level prices. In Section 6, we estimate the model parameters to fit distributional features of the data. The predictions of the estimated model match the estimated effects of the regulation on the output of regulated, related, and unrelated firms from Sections 3–4. We then use the model to decompose the importance of the different mechanisms behind our difference-in-differences estimates. Section 7 simulates the aggregate effects of the regulation and measures the shadow cost of the regulation.

6 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 then show that the model can match the observed firm-level effects of the regulation in a simulated counterpart of the Top 1,000 program.

6.1 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). We use the estimate of returns to scale of $\alpha = 0.9$ from Burnside et al. (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.[23] We then 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 we estimate: (δ, f_e, σ_m), which include the within-

[23]Conventional estimates of returns to scale range from 0.85 to 0.95, depending on aggregation and time period.

conglomerate size depreciation δ, the conglomerate-level entry cost f_e, and the dispersion of the efficiency distribution σ_m. Conditional on these parameters, the firm fixed cost f is uniquely pinned down by the equilibrium conditions (Equations 8–10) and the average sales-per-firm in the data.

We estimate the parameters $\theta = (\delta, f_e, \sigma_m)$ using the method of moments. For a candidate value of θ, we solve the model and compute the following moments: (1) the share of firms in three bins of firm revenue: 5-20 million RMB, 20-100 million RMB, and greater than 100 million; (2) the share of firm output in the same three bins; and (3) the average relative output of the second, third, and fourth largest affiliates relative to the top firm in the conglomerate. Our estimate of θ is given by:

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

where m_d are the data moments, $m(\theta)$ are the moments generated by the model, and W is the identity matrix.[24]

We estimate that $\delta = 0.908$, which means that the productivity of the second-largest firm in the conglomerate is close to 91% of that in the largest firm. Recall that Equation 5 shows that the output of affiliates depreciates in rank by the factor $\delta^{\frac{1}{1-\alpha}}$. This relation implies that the output of the second-largest firm is close to 38% of the largest firm (c.f, 29% in the data) and that of the third-largest is close to 15% (c.f., 20% in the data), which matches the pattern in Panel A of Figure 2. We also estimate that $\sigma_m = 1.23$ and that $f_e = 11$ million RMB (or about 1.7 million USD), which is reasonably commensurate with the average profit in the economy. Figure 8 shows that our model does a good job of fitting both the observed firm-size distribution and the concentration of output prior to the regulation.

6.2 Model Response to the Top 1,000 Program

We need two additional parameters to implement the Top 1,000 program in our model. As discussed in Section 5, our version of 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 $\tilde{\phi} = 6.31$, which reproduces the fact that regulated firms account for 56% of the total energy consumption in energy-intensive industries. Finally, we take the policy intensity ξ from the 11th Five-Year Plan, which targeted an energy reduction of 20%. For this reason we set $\xi = 0.8$. Panel A of Table 8 collects the model parameters.

We can then use our model to simulate the effects of the Top 1,000 program. As in Section

[24] We use the identity matrix since the sample size for the moments describing the size and output distribution is much larger than the sample size for the moments describing the relative size of firms within conglomerates. We calculate standard errors using a bootstrap covariance matrix of the moments that incorporates this information.

5.4, we assume conglomerates take the number of affiliates and capital allocation as given. We solve a new industry equilibrium by ensuring that (1) regulated conglomerates allocate variable inputs optimally (as in Equation 11), (2) unregulated firms increase output to respond to the increase in market prices, and (3) the product market clears (as in Equation 9).

Panel B of Table 8 compares our difference-in-differences estimates to simulated model analogues. This table shows that the model does a remarkable job of matching the estimated effects on firm output. This is true for regulated firms, related firms, market-level spillovers, and the within-conglomerate difference-in-differences estimate. The model prediction for the change in input use of regulated firms is just outside the 95% confidence interval of our empirical estimate but 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 4, this estimate is based on a much smaller sample and may not be representative of the overall response. Overall, these results show that our model can reproduce the effects of the regulation on the output of regulated, related, and unrelated firms. Remarkably, these are all out-of-sample predictions of the model.

We now use our model to connect the difference-in-differences estimates to the overall level effects of the program. To do so, Table 9 uses Equation 12 to decompose the total effects of the program. There are two conceptual distinctions between our estimates and the total effects of the policy. First, as we discuss in Section 5.5, our difference-in-differences estimates capture a combination of effects on regulated firms and on control firms. The second row of Panel A shows that the output of control firms increases by 3.1% due to the residual revenue effect. Second, as in any difference-in-differences estimate, market-level effects are also partialed-out. The fourth column shows that the equilibrium increase in prices would have a countervailing effect on the revenue of regulated firms of 2.1%. Undoing these effects shows that the total impact on the output of regulated firms was actually -18.4% instead of -23.6%.

Panel B conducts a similar analysis for the effects on related firms. In this case, both the residual revenue and the lack of a market effect understate the estimated effect on related firms. Accounting for these effects implies that the total effect on related firms is 17.3% instead of 12.1%. Finally, Panel C shows that the within-conglomerate difference-in-differences estimate is not contaminated by residual and market effects. However, this estimate only measures the relative allocation effect between regulated and non-regulated firms in the same conglomerate. These calculations showcase the importance of interpreting the difference-in-differences estimates through the lens of an equilibrium model.

7 Policy Simulations

This section uses our estimated model to conduct two exercises. First, we use our model to compute the aggregate effects of the policy. Second, we quantify the shadow cost of the regulation and ask whether the government can use information on business networks to improve the regulation of energy.

7.1 Aggregate Effects of the Policy

We now use the model to inspect and quantify the importance of accounting for conglomerate spillovers. Table 10 reports the effects of computing the Top 1,000 program under different assumptions. Panel A reports the impact of the policy on regulated conglomerates. The first column shows that the output of regulated conglomerates would decrease by 10.2% if the conglomerate was not able to reallocate production across related firms and absent equilibrium effects. The second column assumes that conglomerates can shift production to related affiliates holding market prices fixed. In this case, the regulation forces conglomerates to shift production to less productive affiliates. However, decreasing returns to scale and knowledge depreciation limit the degree to which it is profitable for conglomerates to make up the reduction in the output of regulated firms. Allowing conglomerates to reallocate activity would result in a smaller decline of 7.2%.

Column 3 isolates the role of market spillovers. In this case, regulated conglomerates are not able to shift production to related firms but we allow for industry prices to adjust. Competing firms face an increase in residual demand, but their output is imperfectly substitutable with that of regulated conglomerates. Allowing for prices to adjust leads to a decrease in the output of regulated conglomerates of -6.7%.

The fourth column shows the importance of accounting for both market- and conglomerate-level spillovers. Allowing for both mechanisms leads to a decrease in the output of regulated conglomerates of -4.8%. This result shows that conglomerate spillovers are not subsumed by market price adjustments. Ignoring this important margin of adjustment would overstate the predicted effects of the policy by 40%$\left(\approx \frac{6.7-4.8}{4.8}\right)$. Based on our model, we find that the within-conglomerate substitution accounts for 60% of the overall adjustment between the no-spillover case and the case with both spillovers (with the market adjustment accounting for the remaining 40%).

Panel B of Table 10 computes the aggregate impacts of the policy. The model implies smaller reductions on aggregate, as non-regulated conglomerates expand in response to the regulation. This table continues to show the importance of separately accounting for conglomerate- and market-level spillovers. Note that since this table considers the output of unregulated firms, the market-level spillovers are relatively more important than in Panel A.[25]

7.2 Shadow Cost of the Policy

We now use the model to quantify the shadow cost of the policy. This exercise allows us to measure the extent of conglomerate-specific distortions and to benchmark the cost of the program relative to that of alternative regulations.

We compute the shadow cost of the policy using Equation 11. Recall that in this equation, the shadow cost only enters the first-order condition for the regulated firm. However, the shadow cost impacts production at all related firms through the residual revenue term. In our model, firms face a lower shadow cost if they are able to substitute production away from the regulated firm. Firms that have higher efficiency ϕ and a larger number of affiliates therefore face a lower shadow cost. Additionally, the size of the shadow cost depends on our model parameters, which capture the importance of variable inputs α_l, the degree of returns to scale α, and the extent of knowledge depreciation δ.

Panel A of Figure 9 plots the implied shadow cost as a function of efficiency ϕ. The black line plots the shadow cost of our simulated Top 1,000 program. This shadow cost is zero for firms with $\phi < \tilde{\phi}$ and jumps to close to an average of 8.1% for regulated firms.[26] Since the shadow cost has the same scale as the cost of variable inputs, we can interpret this value as an equivalent tax on variable inputs. While 8.1% might seem like a small number, recall that that inputs constitute a much larger tax base, especially relative to profits.[27]

Our model allows us to consider how different model mechanisms impact the shadow cost of the program. The brown line shows that shutting down the market and conglomerate spillovers would increase the shadow cost to 15.8%. Allowing for conglomerate spillovers but holding prices fixed (green line) lowers the shadow cost to 12.33%.

The model also allows us to quantify how the ability of conglomerates to shift production to related firms lowered the shadow cost of the regulation. The pink line in Panel A of Figure 9 plots the shadow cost under the assumption that market prices adjusted but that regulated firms were not able to shift production to related parties. In this case, the shadow cost of the regulation would have been 11.2% of input costs, which is 40% larger than in the baseline case.

Finally, the model allows us to consider alternative forms of energy regulation. To make the

[25] To match the short-run nature of our empirical analysis, we have focused our discussion on the short-run effects of the policy, ignoring the entry of new conglomerates. Later changes to regulations and the overall environment would also complicate simulation of long run impacts.

[26] As we discuss in Section 5.5, the shadow cost is closely related to the within-conglomerate difference-in-differences estimate. Our model estimate of the shadow cost is then validated by the fact that we obtain a similar estimate when multiplying the within-conglomerate difference-in-differences estimate by the factor $\frac{-(1-\alpha_l)}{\alpha_l}$.

[27] Indeed, in models with constant marginal cost and with a similar value of σ, inputs are $(\sigma - 1) = 3-$times as large as profits. An equivalent profit tax would then be 24.3%.

regulations comparable, we ensure that they result in a similar energy reduction as the simulated Top 1,000 regulation. Suppose that instead of targeting the energy use of large firms, the government used information on the business networks of energy-intensive firms—which is publicly available—to design the regulation at the conglomerate level. The blue line in Panel A of Figure 9 shows that this conglomerate-level regulation would lower the shadow cost of the regulation by 34% to 5.4%. Intuitively, the Top 1,000 regulation limited output at the most productive firms. A conglomerate-level regulation is less distortionary since it allows conglomerates to equalize the marginal product of inputs across firms while reducing their overall input use.

Panel B of Figure 9 provides more detail into how this shadow cost varies by ϕ. The blue line shows that conglomerates with a higher ϕ face a lower shadow cost of the regulation and that $\lambda(\phi)$ drops discontinuously at the threshold values ϕ_n where conglomerates add additional affiliates. However, the magnitude of these differences pales in comparison to the difference in the shadow cost between regulated and non-regulated firms. Finally, this graph also plots a size-dependent energy tax that would result in the same energy reduction as the Top 1,000 program. The red dotted line shows that instead of monitoring large firms, the government could have reduced energy use by the same amount with an input tax of 5.4%. Since energy costs are close to 15% of variable input costs for Top 1,000 firms, the equivalent energy tax would be closer to 36%($\approx \frac{5.4\%}{15\%}$).

8 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 on firms that were not regulated but that are part of the same conglomerate. While the program led regulated firms to decrease energy use, this decrease was driven by a decline in production output and not by an increase in energy efficiency. We show that the program led to large increases in the output and energy use of unregulated firms that are part of the same conglomerate. By shifting production to related firms, regulated conglomerates escaped close to 40% of the regulation-driven output reduction. The facts that regulated conglomerates were unable to fully shift lost output to related firms and that we find no impacts on the energy efficiency of regulated firms imply that regulated firms found it costly to increase their energy efficiency.

We calculate the shadow cost of the regulation using a model of conglomerate production that matches our setting and the reduced-form effects of the regulation. The model shows that even with the ability to shift some production to related firms, the regulation increased the cost of conglomerate production by 8.1%. We show that this cost could be lowered by targeting the regulation at the conglomerate level or by imposing an energy use tax.

Overall, this paper shows that the economic effects and the efficacy of policies that target large firms are modulated by substitution along ownership networks. Since ownership networks are public information, the results of our paper reveal a potential avenue of improvement for existing energy regulations.

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Figures

Figure 1: Cross-Country Differences in Industrial Energy Use

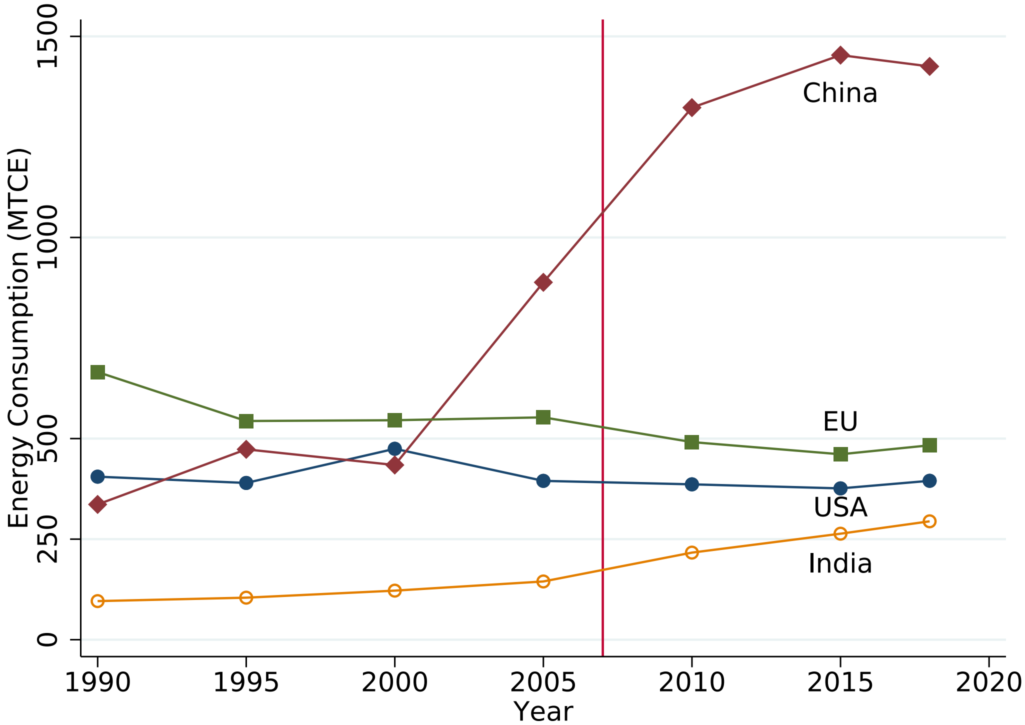
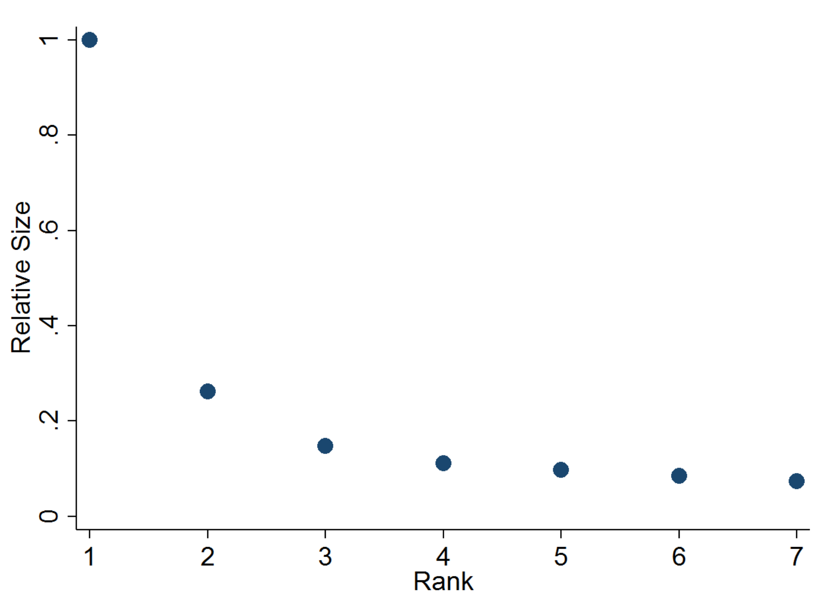


Figure 2: Conglomerate Size and Production Allocation

A. Relative Firm Size



B. Output and Conglomerate Size

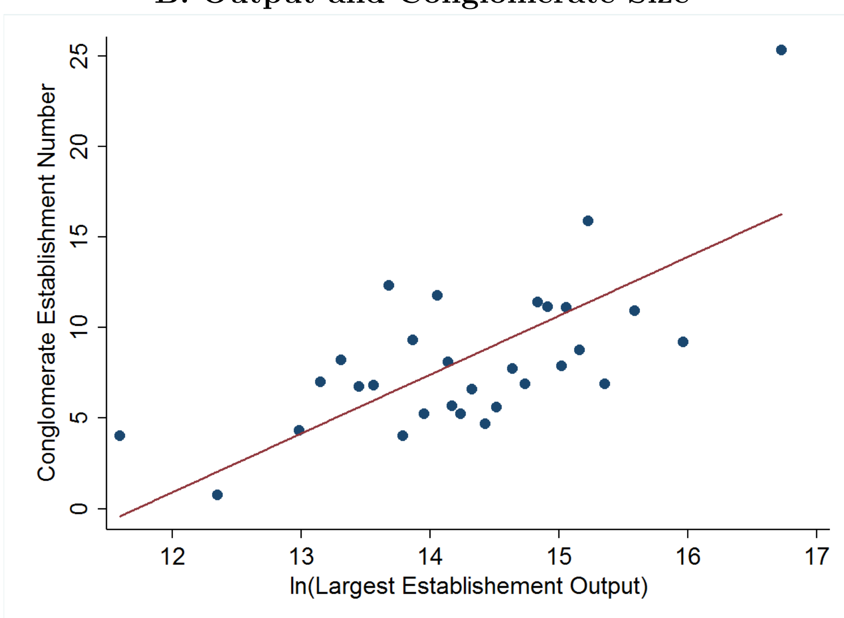


Figure 3: Examples of Firm Relations

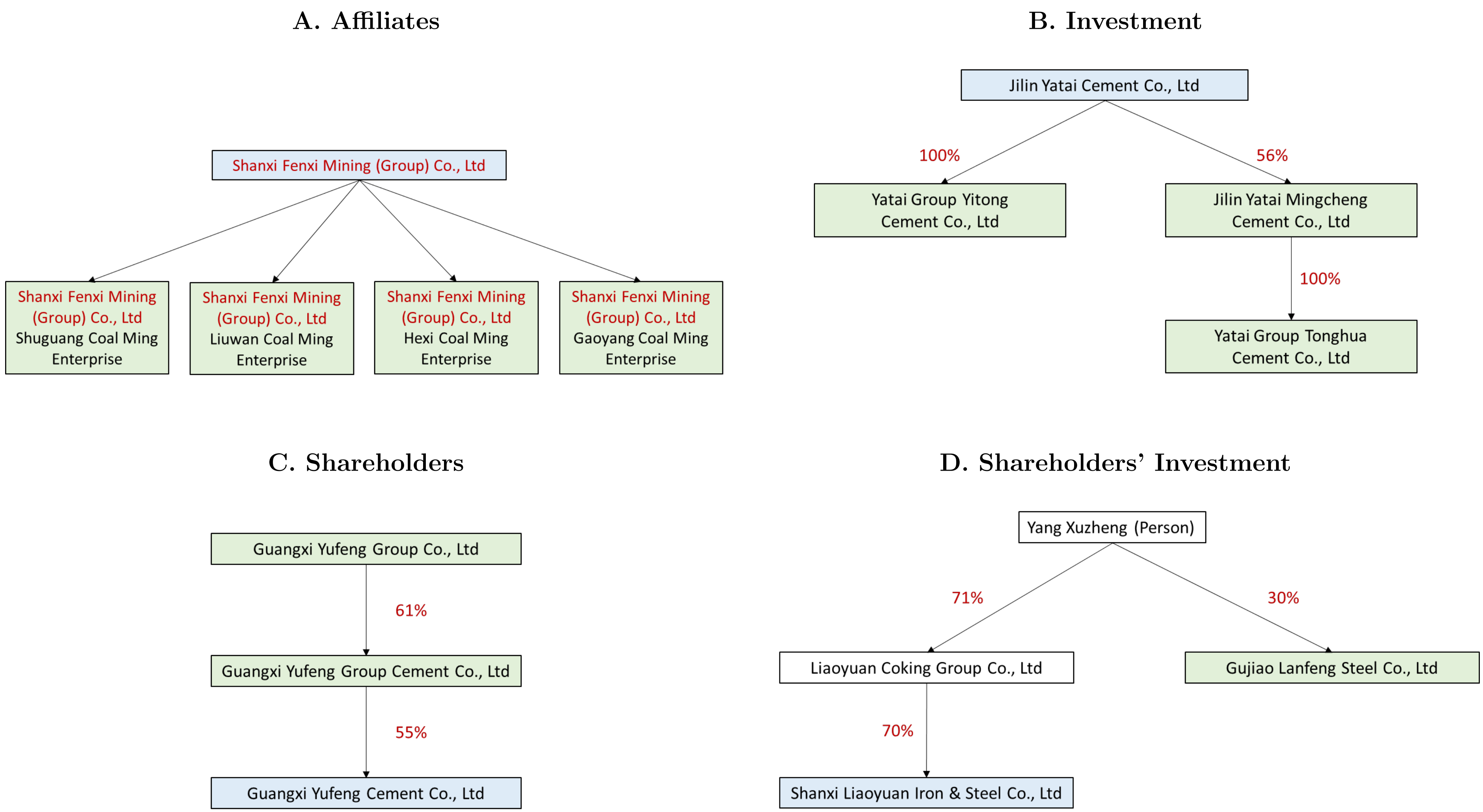


Figure 4: Effects of the Program on Regulated Firms

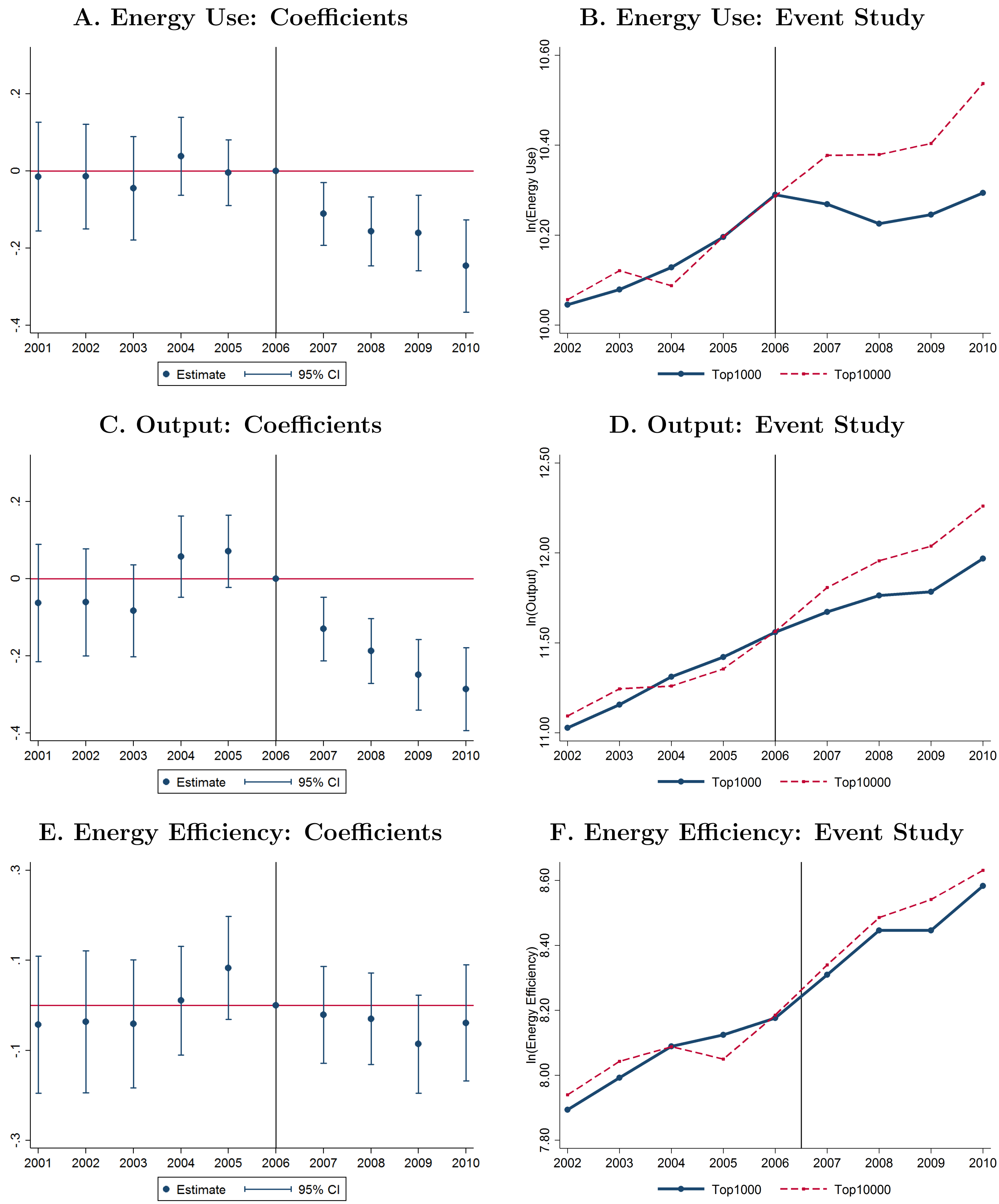


Figure 5: Spillover Effects on Related Firms

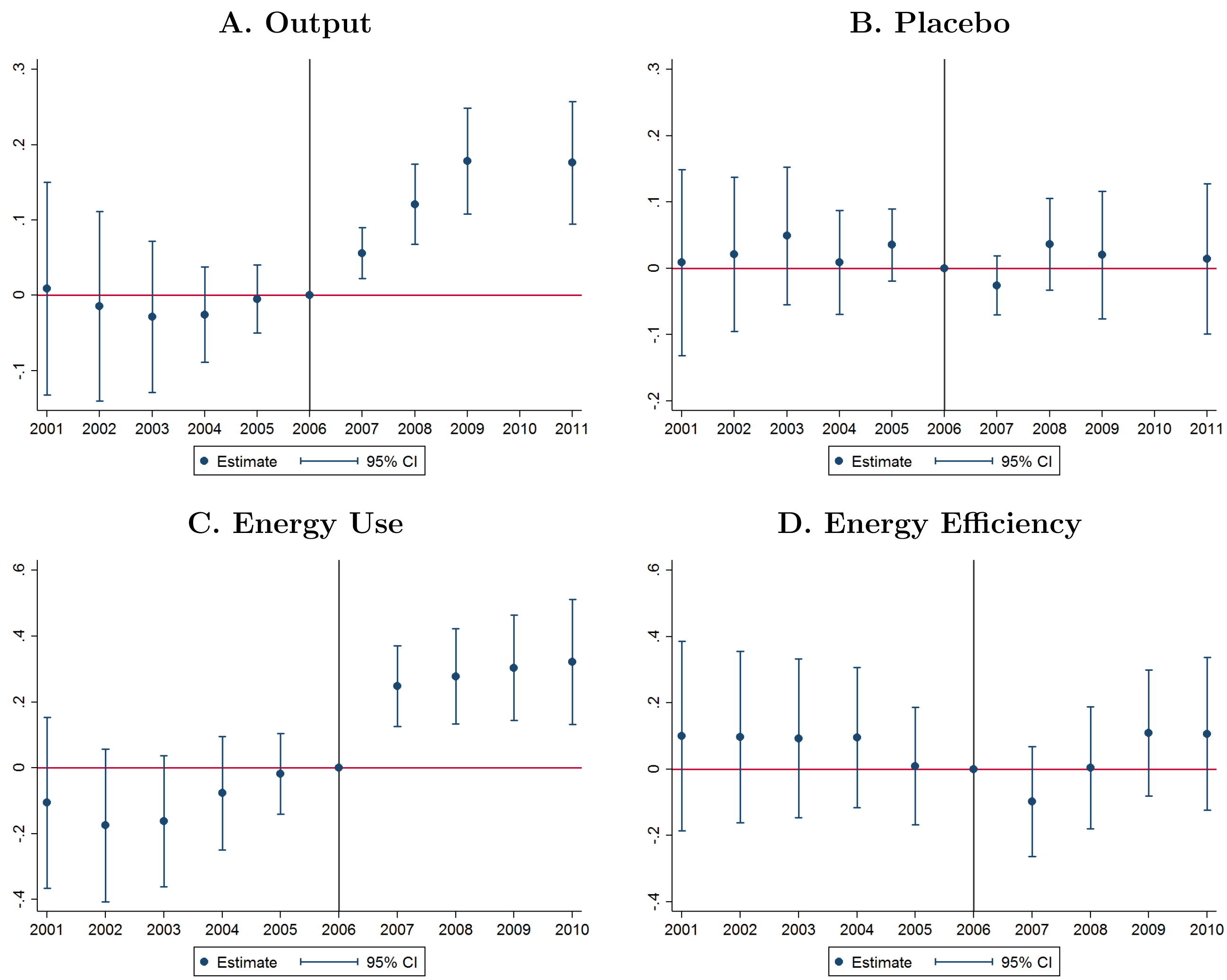


Figure 6: Industry-Level Spillovers

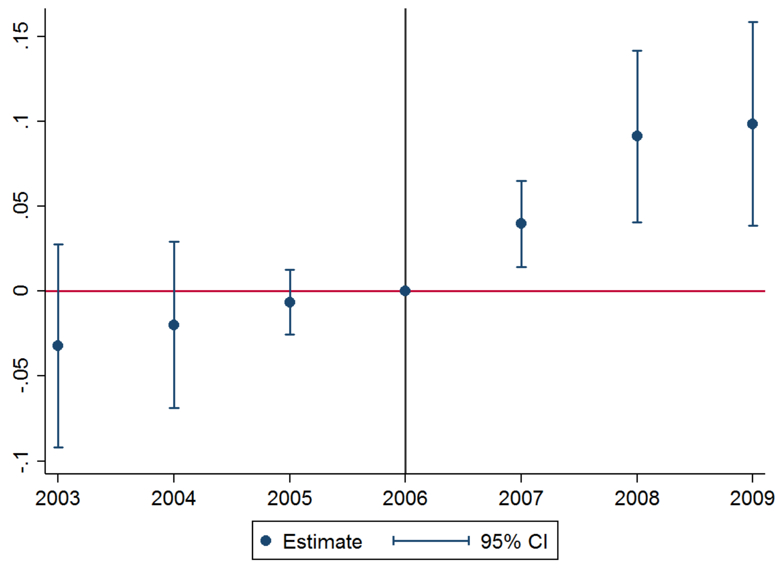


Figure 7: Within-Conglomerate Difference-in-Differences

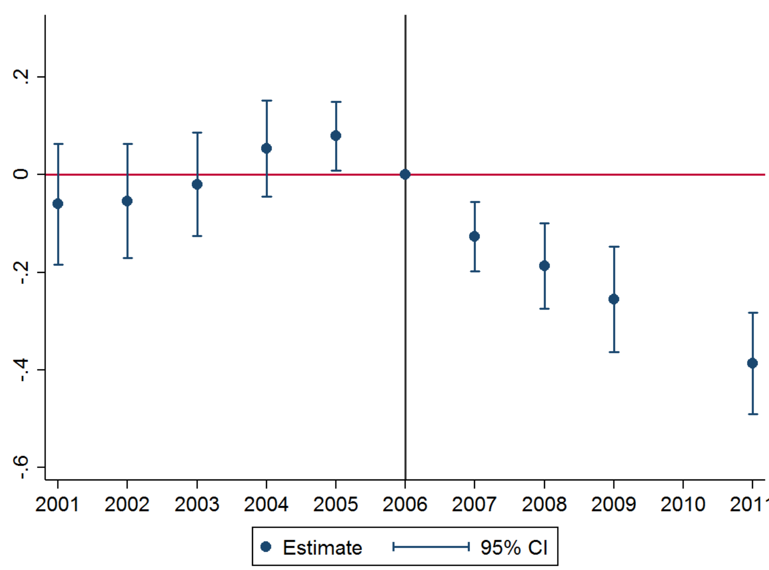
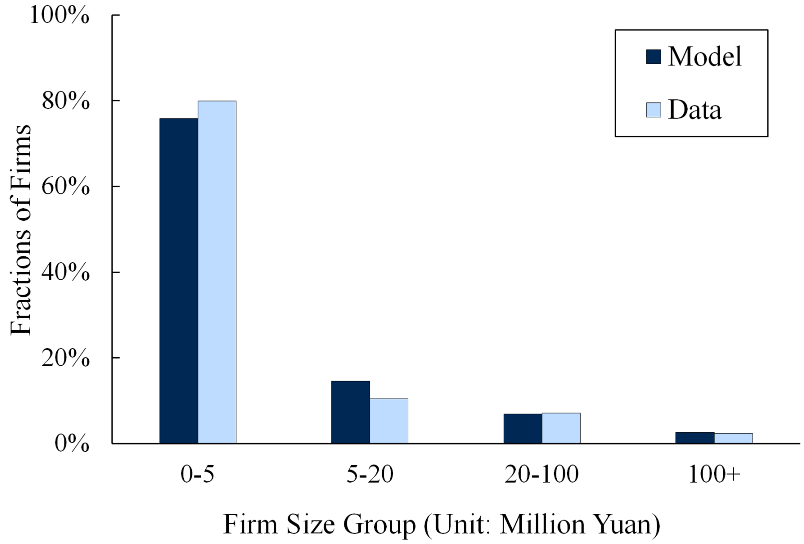


Figure 8: Distributional Moments and Structural Model Fit

A. Firm Size Distribution



B. Output Distribution

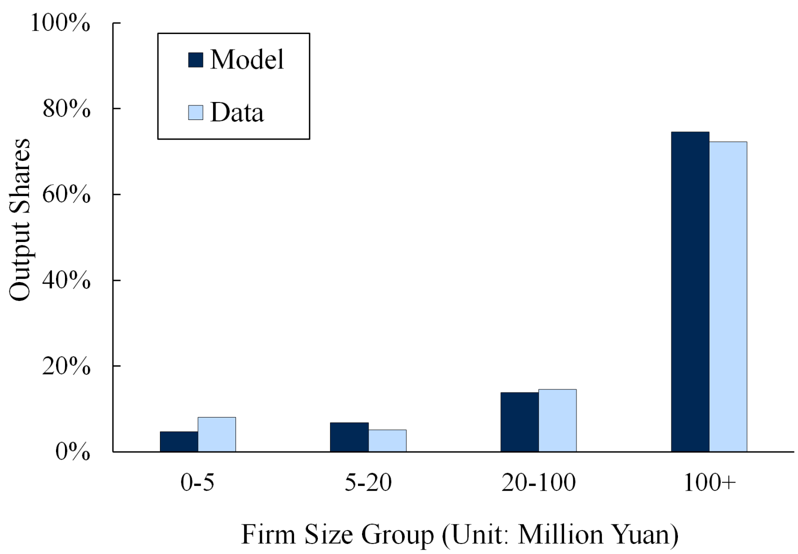
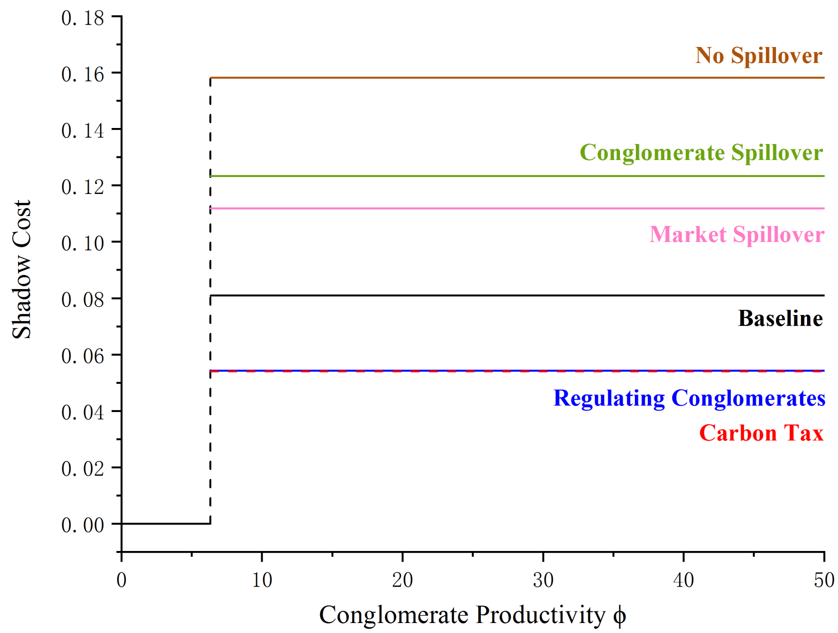
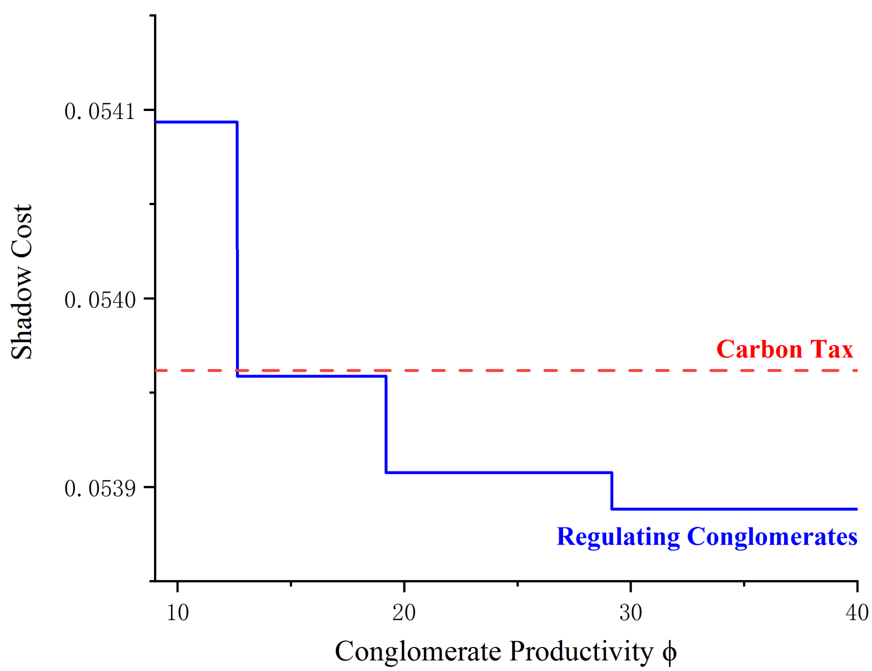


Figure 9: Model-Based Estimates of the Shadow Costs of Regulation

A. Shadow Costs of Alternative Regulations



B. Size Distortions and Equivalent Energy Tax



Tables

Table 1: Energy Consumption of Top 1,000 Firms in Different Industries

Industry	Energy Consumption 10,000 ton coal equiv.	Proportion (%)	Firm Number
Iron and Steel	22528.63	30.72	249
Electric Power	16249.64	22.16	144
Chemical	10909.29	14.88	238
Petroleum and Petrochemical	10581.76	14.43	98
Mining	5278.77	7.20	60
Nonferrous	2993.08	4.08	70
Construction Materials	2913.19	3.97	93
Pulp and Paper	961.36	1.31	24
Textile	917.57	1.25	22

Table 2: Summary Statistics

A. Firm-Level Data

Source	Variables	Top 1,000			Top 10,000 (Exclude Top 1,000)		
		Obs.	Mean	SD	Obs.	Mean	SD
ASIF	ln(Output)	8,745	14.15	1.58	87,247	12.24	1.61
	Size	8,725	14.44	1.54	87,338	12.18	1.74
	Soe	8,789	0.31	0.46	87,597	0.11	0.31
	Roa	8,557	0.05	0.10	85,402	0.08	0.16
	Age	8,775	23.04	20.32	87,449	12.63	13.82
	Export	8,789	0.34	0.47	87,597	0.25	0.43
	Variety	8,746	2.06	0.88	87,425	1.64	0.84
CESD	ln(Energy)	4,211	12.24	1.61	27,472	9.79	1.69
	ln(Coal)	3,904	12.33	1.55	25,607	9.89	1.69
	ln(Efficiency)	4,167	8.49	1.71	27,282	8.55	1.84
ASIF&ATS	Investment	4,276	0.80	0.40	47,243	0.82	0.39

B. Conglomerate Networks: Related Parties

Datasets	Six Levels	Two Levels		
	20%	20%	25%	51%
CARD	80,341	52,562	47,555	30,737
CARD&ASIF	10,944	8,447	7,811	5,358
CARD&ASIF (same 2-digit industry)	4,887	4,311	4,139	3,055
CARD&ASIF (same 4-digit industry)	2,776	2,561	2,500	2,024

Table 3: Effects of the Policy on Regulated Firms: Difference-in-Differences Results

A. Firm Energy Use

Variables	ln(Firm Energy Use)			
Treat×Post	-0.136***	-0.164***	-0.163***	-0.134***
	(0.042)	(0.045)	(0.045)	(0.047)
Observations	25,295	25,290	24,818	22,060
R^2	0.886	0.888	0.890	0.896
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry×Year FE		Y	Y	Y
Province×Year FE			Y	Y
Firm Control				Y

B. Output

Variables	ln(Output)			
Treat×Post	-0.108***	-0.231***	-0.210***	-0.152***
	(0.040)	(0.040)	(0.041)	(0.042)
Observations	25,113	25,108	24,648	21,930
R^2	0.879	0.884	0.886	0.891
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry×Year FE		Y	Y	Y
Province×Year FE			Y	Y
Firm Control				Y

C. Energy Efficiency

Variables	ln(Firm Energy Efficiency)			
Treat×Post	0.031	-0.066	-0.048	-0.019
	(0.041)	(0.044)	(0.045)	(0.046)
Observations	25,113	25,108	24,648	21,930
R^2	0.835	0.838	0.840	0.846
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry×Year FE		Y	Y	Y
Province×Year FE			Y	Y
Firm Control				Y

Table 4: Spillover Effects on the Output of Related Firms

A. Output

Variables	ln(Output)			
Related×Post	0.138***	0.133***	0.123***	0.133***
	(0.037)	(0.036)	(0.035)	(0.034)
Observations	19,228	19,226	19,226	18,668
R^2	0.893	0.900	0.906	0.914
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry×Year FE		Y	Y	Y
Province×Year FE			Y	Y
Firm Control				Y

B. Heterogeneous Effects on Output by Firm Size

Variables	ln(Output)			
Related×Post(0%-30%)	0.103*	0.104*	0.049	0.076
	(0.056)	(0.054)	(0.054)	(0.052)
Related×Post(30%-70%)	0.142***	0.139***	0.116***	0.136***
	(0.044)	(0.042)	(0.042)	(0.039)
Related×Post(70%-100%)	0.163***	0.151***	0.168***	0.164***
	(0.052)	(0.051)	(0.049)	(0.047)
Observations	18,174	18,174	18,174	17,666
R^2	0.896	0.903	0.909	0.917
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry×Year FE		Y	Y	Y
Province×Year FE			Y	Y
Firm Control				Y

C. Additional Firm Outcomes

Variables	ln(Sale)	ln(Profit)	ln(Asset)	ln(Fixed Asset)	ln(Employment)
Related×Post	0.120***	0.209***	0.071**	0.110***	0.037*
	(0.030)	(0.065)	(0.029)	(0.035)	(0.021)
Observations	18,200	13,787	18,444	18,308	16,511
R^2	0.929	0.779	0.944	0.932	0.928
Firm FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Industry×Year FE	Y	Y	Y	Y	Y
Province×Year FE	Y	Y	Y	Y	Y
Firm Control	Y	Y	Y	Y	Y

Table 5: Spillover Effects on Related Firms: Placebo Test, Energy Use, and Energy Efficiency

A. Placebo Test on Output

Variables	ln(Output)			
Related×Post	-0.010	-0.009	-0.006	0.004
	(0.041)	(0.040)	(0.040)	(0.039)
Observations	9,391	9,389	9,379	9,169
R^2	0.894	0.899	0.907	0.916
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry×Year FE		Y	Y	Y
Province×Year FE			Y	Y
Firm Control				Y

B. Energy Use

Variables	ln(Energy)			
Related×Post	0.356***	0.355***	0.343***	0.379***
	(0.075)	(0.074)	(0.076)	(0.094)
Observations	3,906	3,906	3,852	2,886
R^2	0.912	0.914	0.933	0.921
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry×Year FE		Y	Y	Y
Province×Year FE			Y	Y
Firm Control				Y

C. Energy Efficiency

Variables	ln(Energy Efficiency)			
Related×Post	-0.031	-0.030	-0.042	-0.008
	(0.079)	(0.078)	(0.080)	(0.099)
Observations	3,836	3,836	3,794	2,829
R^2	0.842	0.848	0.861	0.856
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry×Year FE		Y	Y	Y
Province×Year FE			Y	Y
Firm Control				Y

Table 6: Industry-Level Spillovers

Variables	ln(Output)			
	All Sample		Energy-Intensive Industries	
Spillover	0.100***	0.067***	0.140***	0.082***
	(0.036)	(0.015)	(0.051)	(0.019)
Observations	2,026,061	1,979,314	680,826	663,995
R^2	0.837	0.856	0.846	0.865
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm Control		Y		Y

Table 7: Within-Conglomerate Difference-in-Differences

Variables	ln(Output)			
Top1000×Post	-0.328***	-0.335***	-0.358***	-0.283***
	(0.069)	(0.070)	(0.072)	(0.070)
Observations	14,935	14,909	14,905	14,493
R^2	0.543	0.548	0.595	0.634
Conglomerate×Year FE	Y	Y	Y	Y
Industry×Year FE		Y	Y	Y
Province×Year FE			Y	Y
Firm Control				Y

Table 8: Model Parameters and Fit

A. Model Parameters

Parameter		Value	Target
1. Fixed Values			
Elasticity of substitution	$\sigma = \frac{1}{1-\rho}$	4.00	Melitz and Redding (2015)
Return to scale	α	0.90	Burnside et al. (1995)
Return to scale (Labor Share)	α_l	0.80	Cost share of variable inputs
2. Simulated Model			
Efficiency depreciation	$\delta^{\frac{1}{1-\alpha}}$	0.38	
Dispersion of ln-ability ϕ	σ_m	1.23	Firm size distribution
Entry cost	f_e	1.17×10^7(Yuan)	
Fixed energy cost	f	3.18×10^4(Yuan)	
4. Match Policy			
Policy threshold	$\tilde{\phi}$	6.31	Energy share of Top1000 firms
Input quota	$1-\xi$	0.20	11th Five Year Plan

B. Model Fit

	Model Prediction	Empirical Result	95% CI
Output Response			
Regulated-Other	-23.6%	-21.0%	(-29.1%,-12.9%)
Related-Other	12.1%	12.3%	(5.4%,19.3%)
Other	5.2%	6.7%	(3.7%,9.7%)
Regulated-Related	-35.7%	-35.8%	(-50.2%,-21.4%)
Input Response			
Regulated-Other	-27.5%	-16.3%	(-25.2%,-7.4%)
Related-Other	11.4%	34.3%	(19.3%,49.3%)

Table 9: Model Decomposition of Difference-in-Differences Estimates

	Allocation Effect	Residual Revenue Effect	Market Effect	Total Effect
A. Effect on Regulated Firms				
Top 1,000 Firms	-0.150	-0.055	0.021	-0.184
Control Firms	0	0.031	0.021	0.052
Difference-in-Differences	-0.150	-0.086	0	-0.236
B. Effect on Related Firms				
Related Firms	0.207	-0.055	0.021	0.173
Control Firms	0	0.031	0.021	0.052
Difference-in-Differences	0.207	-0.086	0	0.121
C. Within-Conglomerate Effect				
Difference-in-Differences	-0.357	0	0	-0.357

Table 10: Effects of Simulated Counterfactuals

A. Regulated Conglomerate Response

	No Spillover	Conglomerate Spillover	Market Spillover	Conglomerate & Market Spillover
Input	-12.41%	-8.71%	-8.02%	-5.61%
Output	-10.18%	-7.24%	-6.69%	-4.81%

B. Aggregate Impact

	No Spillover	Conglomerate Spillover	Market Spillover	Conglomerate & Market Spillover
Input	-11.6%	-8.12%	-6.73%	-4.87%
Output	-9.51%	-6.75%	-5.70%	-2.74%

Online Appendix: Not For Publication

This appendix contains multiple additional analyses.

Appendix Figures

Figure A.10: Map of Top 1,000 Firms

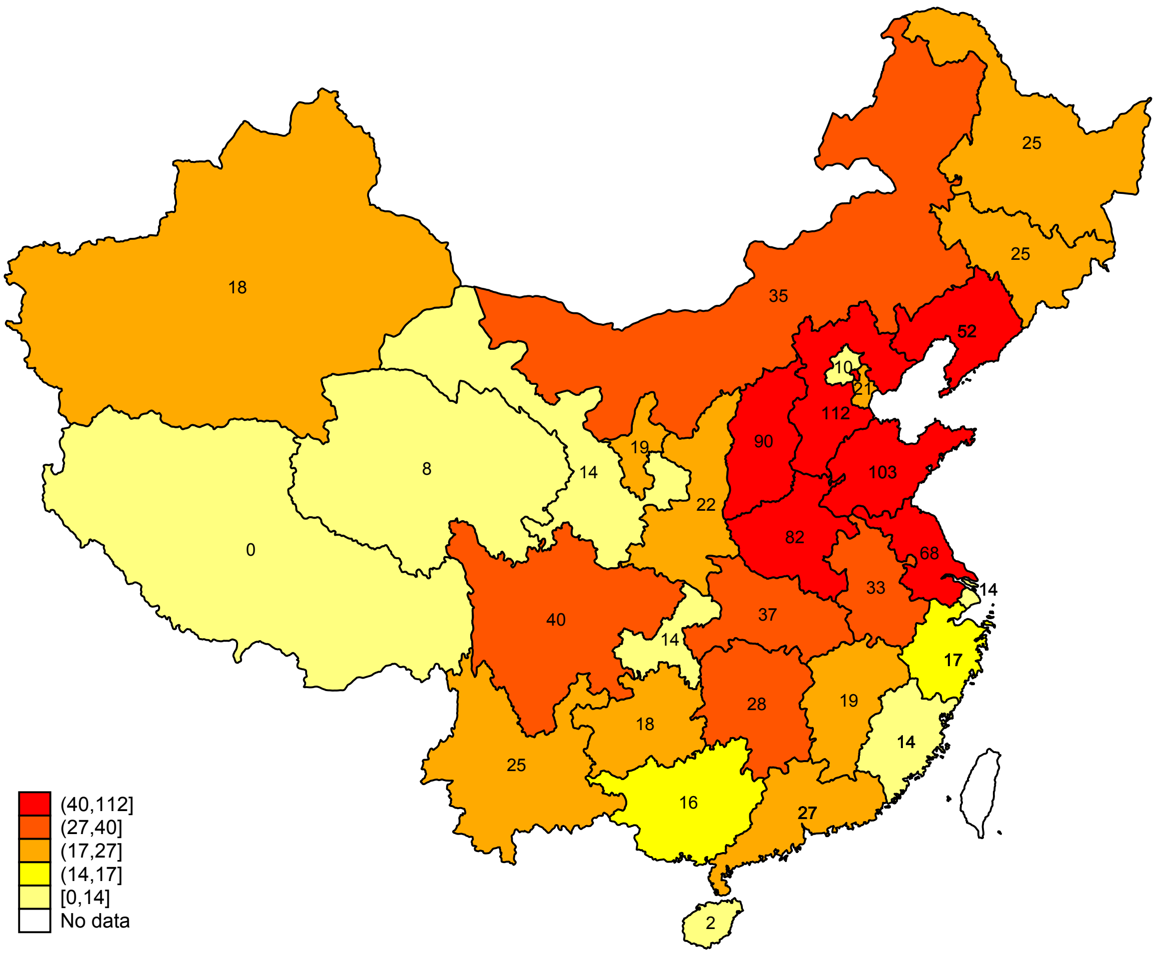


Figure A.11: Types of Related Parties

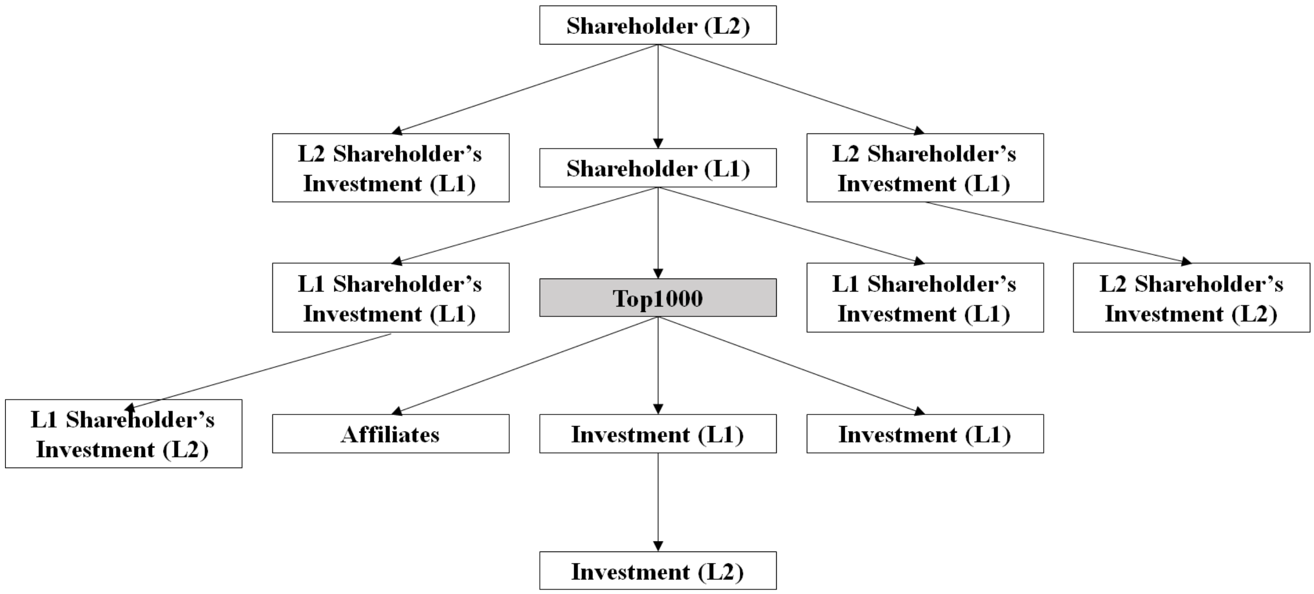


Figure A.12: Effects of Policy on the Investment of Regulated Firms

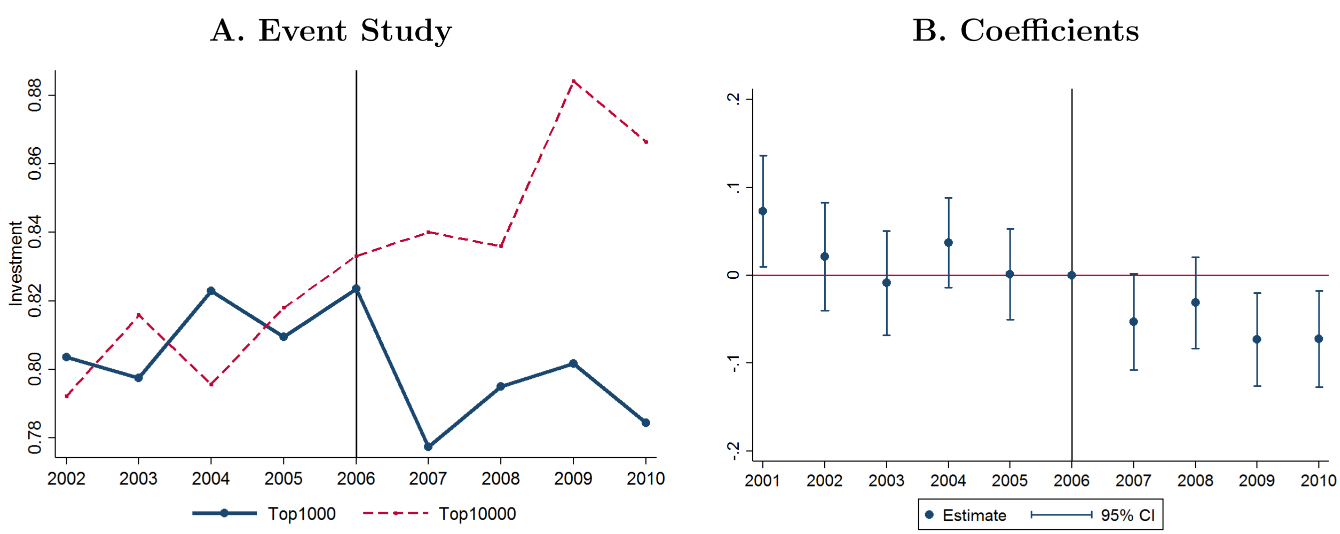


Figure A.13: Spillover Effects on Output by Firm Relation

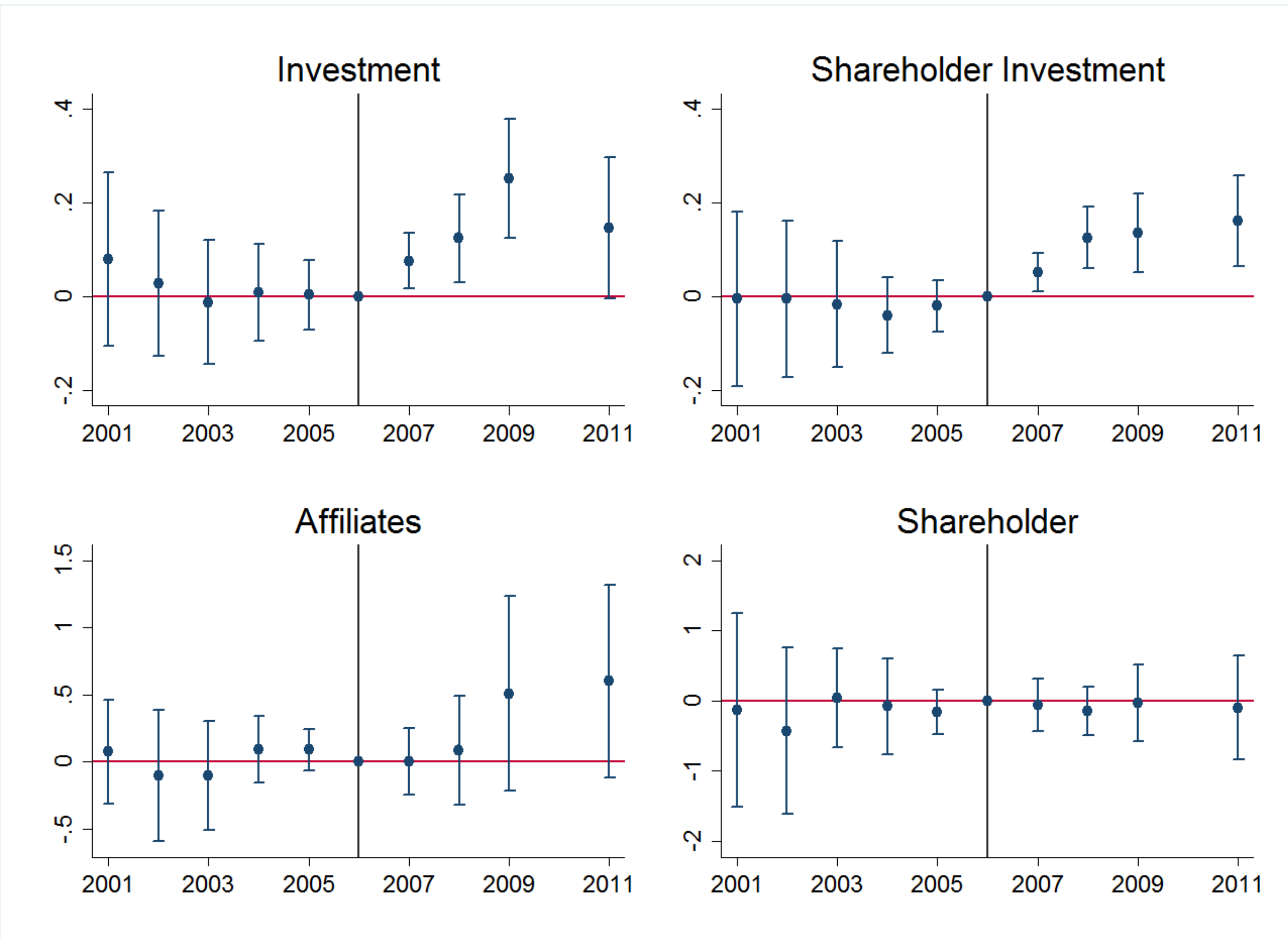
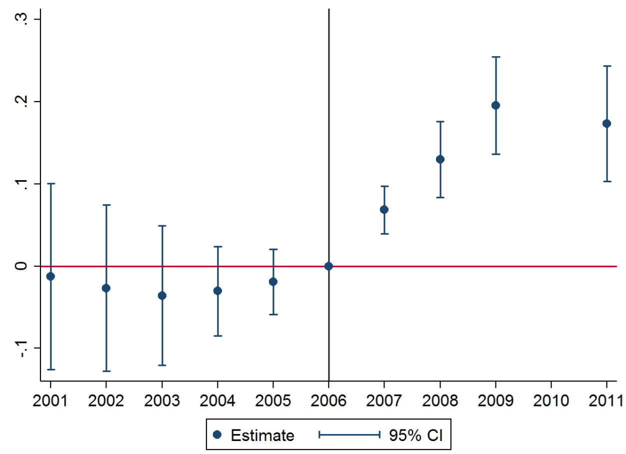
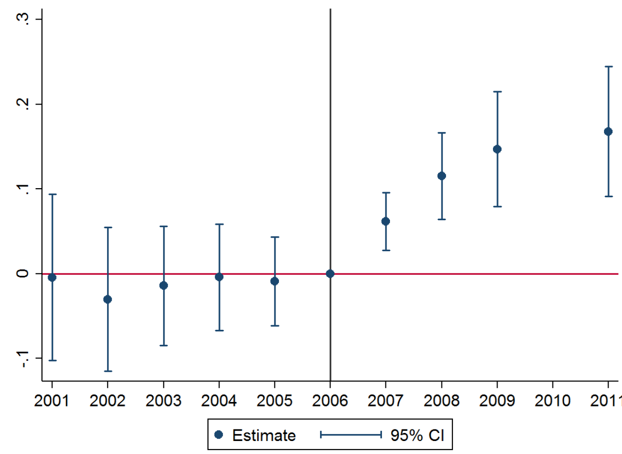


Figure A.14: Additional Spillover Effects of the Program

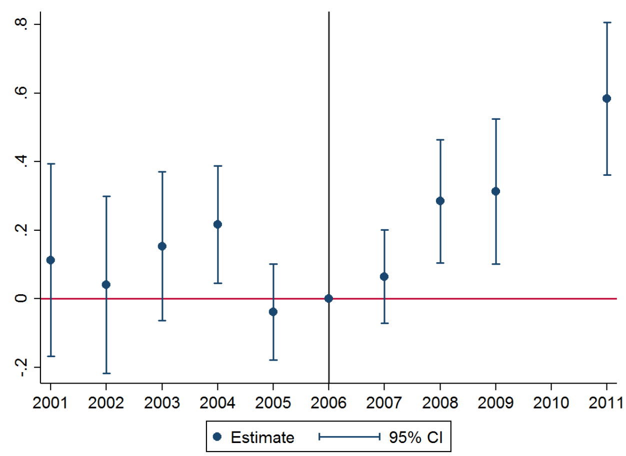
A. Output (Robustness to 3:1 Matching)



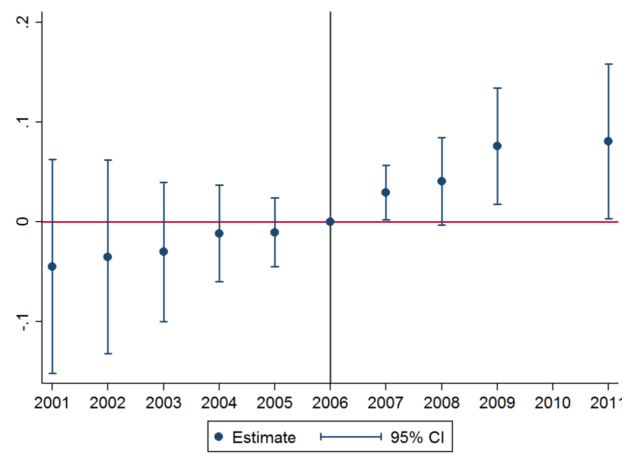
B. Sales



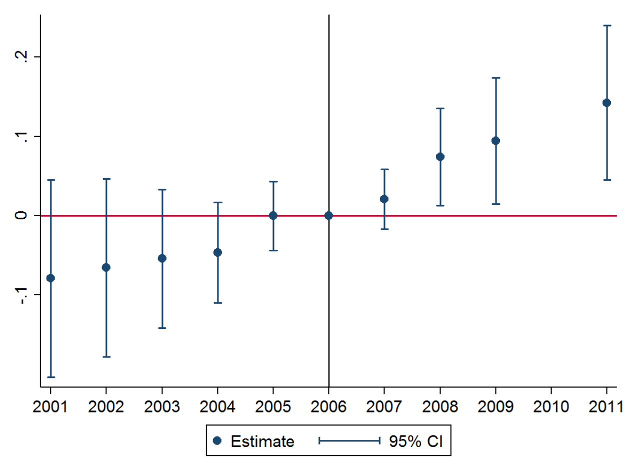
C. Profit



D. Assets



E. Fixed Assets



F. Employment

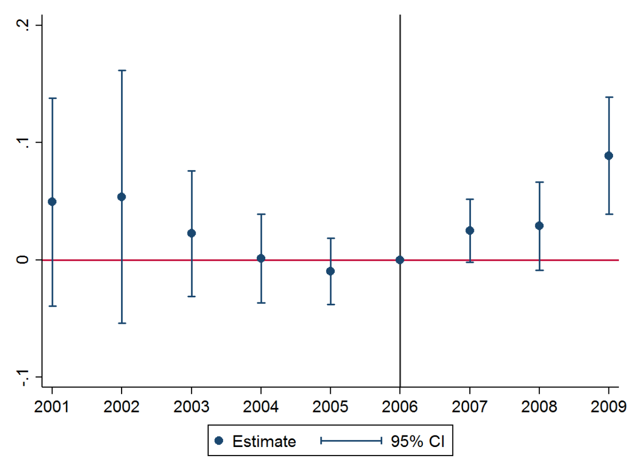
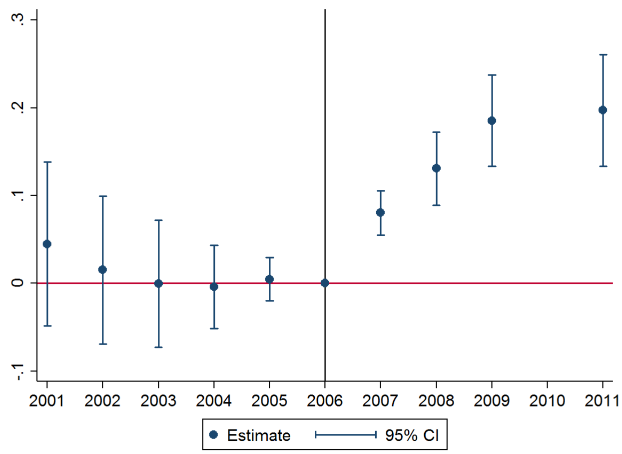
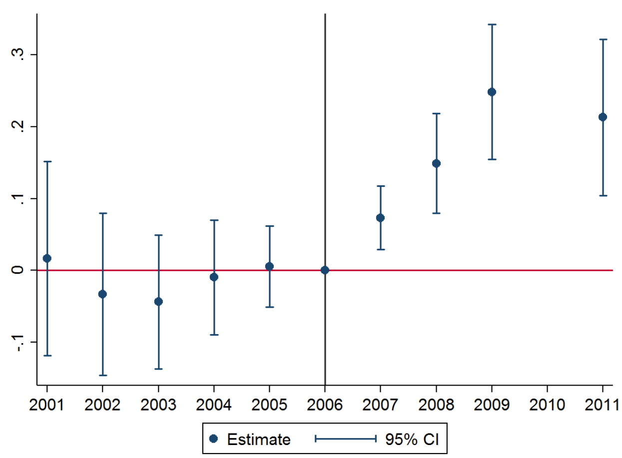


Figure A.15: Robustness for Related Spillover: Entropy Matching 2004-2006



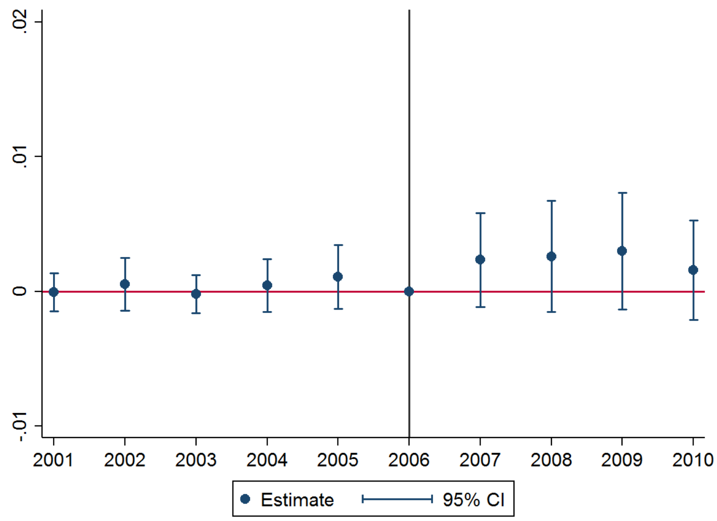
Notes: This figure shows spillover effects for 4-digit industry related firms using entropy matching on 2004-2006 firm output (3 years before policy) and 4-digit industry.

Figure A.16: Robustness to Dropping Electric Power Generation and Supply



Notes: This figure shows spillover effects (output dynamics) for 4-digit industry related firms of Top1000 in industries other than electric power.

Figure A.17: Innovation of Top 1,000 Firms: Energy-Saving Patent Applications



Appendix Tables

Table A.11: Policy Compliance

Type	Orig.list	Evaluation			
Year		2007	2008	2009	2010
Firm number	1008	953	922	901	881
Non-compliant firms	-	74	36	28	15
Non-compliant rate	-	7.76%	3.90%	3.11%	1.70%

Table A.12: Dataset Matching

Datasets	Top 1,000		Top 10,000	
	Number	Ratio	Number	Ratio
List	1008	-	14639	-
ASIF	1001	99.31%	14300	97.68%
CESD	818	81.15%	10723	73.25%
ASIF & CESD	809	80.26%	9482	64.77%
ASIF & ATS	447	44.35%	6623	45.24%

Table A.13: Determinants of Overfulfillment

Variables	Overfulfill			
	All Top 1,000 Firms		Completion Rate < 200%	
ln(related num.)	0.0467***	0.0635***	0.0732***	0.0909***
	(0.0148)	(0.0178)	(0.0215)	(0.0258)
ln(complement num.)		-0.0307*		-0.0354
		(0.0180)		(0.0287)
Observations	512	512	318	318
R^2	0.167	0.172	0.228	0.232
Firm Control	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Province FE	Y	Y	Y	Y

Table A.14: Conglomerate Groups

Number of Top 1,000 Firms in Group	Number of Groups
1	341
2	44
3	26
4	5
5	3
6	4
7	2
9	1
10	1

Table A.15: Effects of Policy on the Investment of Regulated Firms

Variables	If Firm Invests			
Treat×Post	-0.057***	-0.071***	-0.072***	-0.071***
	(0.013)	(0.014)	(0.014)	(0.014)
Observations	50,987	50,967	50,967	49,346
R^2	0.191	0.200	0.208	0.212
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry×Year FE		Y	Y	Y
Province×Year FE			Y	Y
Firm Control				Y

Table A.16: Robustness to Dropping Electricity-Intensive Industries

	ln(Energy)	ln(Coal)	ln(Output)	ln(Efficiency)
Electricity<15%	-0.135***	-0.149***	-0.217***	-0.080*
	(0.048)	(0.048)	(0.045)	(0.047)
Electricity<20%	-0.142***	-0.149***	-0.187***	-0.044
	(0.049)	(0.050)	(0.044)	(0.049)
Electricity<25%	-0.154***	-0.163***	-0.202***	-0.047
	(0.047)	(0.047)	(0.042)	(0.046)
Electricity<30%	-0.163***	-0.169***	-0.210***	-0.048
	(0.045)	(0.046)	(0.041)	(0.045)
Electricity<35%	-0.173***	-0.180***	-0.207***	-0.036
	(0.045)	(0.045)	(0.040)	(0.044)
Electricity<40%	-0.171***	-0.178***	-0.204***	-0.034
	(0.044)	(0.045)	(0.040)	(0.044)
Electricity<45%	-0.172***	-0.180***	-0.205***	-0.035
	(0.044)	(0.045)	(0.040)	(0.044)
Electricity<50%	-0.177***	-0.183***	-0.241***	-0.065
	(0.042)	(0.043)	(0.041)	(0.044)
Firm Fixed Effects	Yes	Yes	Yes	Yes
Industry × Year Fixed Effects	Yes	Yes	Yes	Yes
Province × Year Fixed Effects	Yes	Yes	Yes	Yes

Notes: This table shows the robustness result of our baseline regression to dropping electricity-intensive industries. Our data cleaning process for CESD includes: (1) drop electricity-intensive industries (30% in our baseline regression), (2) drop firm sample that do not report coal consumption data yearly, (3) drop firm sample in fire power industry (CESD doesn't have records for fire power firms after 2006). And this table shows that relax or tighten the first condition will not change our belief in the baseline results.

Table A.17: Robustness to Dropping Electric Power Generation and Supply

Variables	ln(Output)			
Related×Post	0.172***	0.164***	0.166***	0.173***
	(0.040)	(0.038)	(0.037)	(0.035)
Observations	11,652	11,650	11,642	11,377
R^2	0.881	0.891	0.899	0.909
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry×Year FE		Y	Y	Y
Province×Year FE			Y	Y
Firm Control				Y

Notes: This table shows spillover effects for 4-digit industry related firms of Top1000 in industries other than electric power. It suggests that the spillover effects of Top1000 firms in other industries is larger than that in electric power generation and supply industry. This is quite intuitive as Top1000 firms in electric power generation and supply industry have much more related firms than in other industries, thus the average spillover effects should be smaller.