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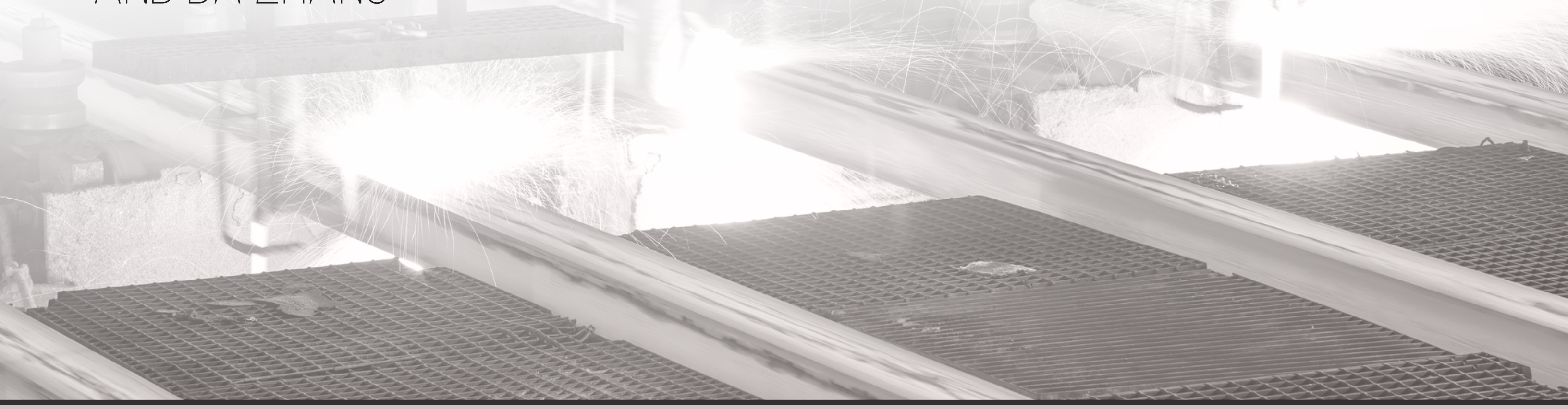

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A Green Bargain? The Impact of an Energy Saving Program on Productivity Growth in China's Iron and Steel Industry

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Abstract

The impact of environmental regulation on firm productivity has been long been debated, however, mainly for western economies and with limited firm-level evidence. We study the impact of a large-scale national energy saving program (the Top 1000 Energy-Consuming Enterprises Program, or T1000P, 2006-2010) in China on firm productivity in the iron and steel industry. The T1000P assigned targets for reducing the energy consumption of approximately 1000 most energy-consuming industrial firms. Using detailed data from the China Industrial Census on 5,340 firms for the period of 2003 to 2008, we estimate a positive effect of the T1000P on firms in the iron and steel industry. Specifically, we find T1000P firms are associated with significantly greater annualized TFP change (an increase of 3.1 percent on average), suggesting the competitiveness of treated firms increased. Effects on technical change and scale efficiency change are positive and statistically significant, and contribute about equally to the overall treatment effect. Results are robust to instrumenting for policy exposure and other alternative specifications. Private benefits to firms from the policy likely reflect the combination of incentives and targets applied under the program.

Keywords: Total factor productivity, China, Iron and steel industry, Environmental regulation, Policy evaluation

JEL classification: C23, C26, C51, D04, D22, D24, L50, L61, Q52

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1 Introduction

Rapid growth of China's industrial sector has contributed three decades of sustained economic development but has caused unprecedented degradation of the environment, prompting ever more concerted efforts to implement environmental policy (Cao, Garbaccio et al., 2009; Zhang, Aunan et al., 2011). Within the industrial sector, the Chinese iron and steel industry has been both a major engine of economic expansion and a significant source of local air pollution as well as carbon dioxide emissions due to its high direct use of coal (Lin, Wu et al., 2011; He, Zhang et al., 2013).

A central question in the design of climate mitigation policy, particularly relevant in rapidly emerging economies, is how can government policy makers incentivize firms to engage in environmentally sustainable behaviour while at the same time seeking to promote rapid economic expansion. Widespread evidence of low willingness-to-pay for the delivery of environmental goods in developing nations reveals the pervasive nature of this challenge (Greenstone and Jack, 2015). Economic analysis of policy interventions starts often from the premise that implementing protective environmental measures alter a firm's choices relative to a business-as-usual scenario. An important research question concerns the net impact of environmental measures on firms. Of particular interest is the impact of policy on productivity growth, which represents the foundation of improvements in social welfare and living standards that developing economies desire to advance (Krugman, 1997; Greenstone, List et al., 2012). Here we contribute to this research agenda by estimating the impact of an important environmental policy in place during China's Eleventh Five-Year Plan, the Top 1000 Enterprises Program, on productivity growth in China's firms.

Prior literature positing the impact of environmental policy on firms can largely be grouped into several main strands: the traditionalist view, the behavioralist view (Allcott and Mullainathan, 2010), and a view that incorporates elements of both embodied in the Porter Hypothesis (Palmer, Oates et al. (1995); Iraldo, Testa et al. (2011); Koźluk and Zipperer (2013)). The traditionalist view sees an environmental regulation as imposing costs relative to a no-policy counterfactual. It builds upon the assumption that, if an environmental regulation would increase marginal products or lower marginal costs, an optimizing firm implicitly would have already acted in compliance with the regulation. Regulation, by requiring firms to reduce emissions, necessitates deviations from cost-minimizing behavior in its production processes (technical component) and/or its input choices (allocative component). Assuming that units of output produced stay constant, a firm's productivity would decrease (Koźluk and Zipperer, 2013).[2]

The behavioral economics literature has probed the validity of the assumption of uniformly cost-optimizing agents in studies of household and firm energy management behavior (Allcott and Wozny (2014); Allcott and Greenstone (2012)). This literature has classified apparent deviations from economic behavior in the energy domain under the heading of the Energy Paradox (see, e.g., DeCanio (1993) or Allcott and Greenstone (2012)). The propensity to make energy-saving investments theoretically anticipated to be cost effective is found to depend heavily on firm characteristics, defying traditionalist predictions (DeCanio and Watkins, 1998). The Energy Paradox literature suggests the existence of a behavioral factor, through which firms might benefit from an environmental policy.

Porter's hypothesis in particular focuses on firm responses to environmental policy, suggesting that while still causing compliance costs, an environmental regulation might pressure targeted firms to increase their innovativeness or steer innovativeness into another, potentially more rewarding, direction (Porter (1991); Porter and Van der Linde (1995a); Porter and Van der Linde (1995b)). In such a situation, a firm's productivity could plausibly increase. While they do not disagree with the possibility of environmental policy imposing costs, Porter and co-authors claim that the traditionalist view is an artifact of focusing on the static efficiency concept of cost minimization and (incorrectly) assuming firms have perfect information (Porter and Van der Linde, 1995b).

Traditionalist and behavioralist theories of the impact of environmental policy on firms generally assume that environmental pressure is exogenous. However, a large po-

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[2] The analysis of an environmental regulation from a societal instead of a firm-level perspective would account for the environment's public good character. Here, an environmental regulation might as well result in an increase in societal output value by reducing costs associated with environmental degradation, for instance, public health costs.

litical economy literature hypothesizes that firms intervene to lessen policy burdens (Stigler, 1971) in proportion to the costs they would otherwise bear. This literature is sparse for developing countries, despite the fact that developmental state arguments place the government in a position of promoting the growth of firms it is simultaneously charged with regulating.

Whether or not environmental regulation helps or harms the productivity growth of targeted firms is ultimately an empirical question. Estimates of the impact of environmental policy on firm productivity are very limited. This paper provides new empirical estimates of the impact of an environmental policy—the Top 1000 Enterprises Energy-Conservation Program (here "T1000P")—on firm level productivity in China. We first estimate the level of total factor productivity of a sample of Chinese firms operating in the iron and steel industry. To maintain relative comparability of firms, we estimate the program's effects at the four-digit industry level (iron- and steelmaking, steel rolling and ferroalloy smelting). Second, we analyze empirically the impact of inclusion in the T1000P on the growth rate of total factor productivity of these firms. We use a difference-in-difference approach to analyze the effect of the regulation on TFP change. To account for potential selection bias, we re-estimate our results after instrumenting for the probability of inclusion in the program.

Our findings can be summarized as follows. We estimate that firm TFP grew by 6.4 percent on average annually in the industry as a whole, with the iron- and steelmaking sub-industry growing fastest, followed by the steel rolling and ferroalloy smelting sub-industry. The benchmark specification finds the regulation positively affects the TFP change of firms by 3.1 percent on average annually between 2006 and 2008. This surprising evidence that regulated firms benefitted is robust to a range of alternative specifications, with respect to sample stratification, sample attrition, instrumenting for policy exposure, and considering another potentially confounding policy. The results are important in their own right as empirical evidence of the net effect of environmental policy at the firm level. Our results further distinguish the contributions of technical and scale efficiency to the estimates of incremental productivity improvement in regulated firms. Technical and scale efficiency change are positive and significant, and contribute about equally to the overall effect of the policy on TFP change. Our findings beg an important question—why did firm productivity rise faster for firms targeted by the policy?

We offer two possible explanations. On the surface, our results appear to provide empirical evidence for Porter's hypothesis. It is possible that the program raised awareness of cost-effective energy saving opportunities facing firms or led managers to prioritize energy saving activities, overcoming information barriers to cost-saving investments. The policy may have also raised non-market payoffs (for instance, by improving the firm's reputation with government officials or the public) associated with investments in energy-saving opportunities that were important to firm competitiveness. Indeed, many firms in the program were state-owned enterprises charged with "social responsibility," and may have felt these pressures more acutely than private firms. However, a second explanation is consistent with the traditionalist view, and invokes political economy reasoning. In addition to setting targets for energy saving, the policy also offered participating firms sizable subsidies to partially or fully offset the cost of authorized energy-saving investments. In this context, the policy shock could be conceptualized as the outcome of bargaining between regulator and regulated firms, where the regulator is also part of national leadership that must balance environmental objectives against pressure to sustain economic growth.[3] In the absence of strong environmental policy enforcement and appetite for any initiative that would act as a brake on economic activity, inducing firms to improve energy efficiency may have required direct incentives.

The structure of this study is as follows: Section 2 provides essential background, including a review of the empirical evidence of environmental policy impact on productivity, the development of the Chinese iron and steel industry, and the T1000P. Section 3 reviews the data and Section 4 presents the empirical strategy applied to determine firm performance, including discussion of our identifying assumptions. Results are presented in Section 5, while Section 6 draws conclusions and discusses their implications.

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3 The T1000P was overseen by an office within the National Development and Reform Commission, the top economic planning organization in China.

2 Background and Empirical Setting

2.1 Impact of Environmental Regulation on Firm Productivity

There only are a few empirical studies on the impact of environmental policy instruments on firm-level TFP. These studies mainly support the traditionalist view (see for example Iraldo, Testa et al. (2011) or Koźluk and Zipperer (2013)). We summarize the studies applying parametric methods, which have an advantage over non-parametric methods in that they account for heterogeneity in firm characteristics. Gollop and Roberts (1983) focus on sulfur dioxide emissions restrictions in the US electric power industry by estimating a cost function using observations of 56 electric utilities between 1973 and 1979.[4] They find a negative effect of the regulation on TFP growth of 0.59 percentage points per year, mainly due to higher costs for low sulfur fuel. Gray and Shadbegian (2003) focus on 116 pulp and paper mills in the United States for the period of 1979 to 1990. They find higher pollution abatement operating costs in wake of the Clean Air and Clean Water Acts of the early 1970s translated into lower TFP levels by about 2.6 percent annually, and that this effect significantly depended on a plant's technology.[5] Their case suggests that indeed the overall impact of an environmental regulation might differ when accounting for technological heterogeneity.

Evidence of a positive productivity effect of environmental regulation is found only in a few studies. Greenstone, List et al. (2012) study the effect of the Clean Air Act Amendment on TFP levels of a large sample of US manufacturing plants within the pe-

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[4] Most studies, including ours, apply a two-step procedure to derive the effects of a regulation on productivity, with an estimation of productivity in the first step, followed by an evaluation with respect to the regulation in the second. However, Gollop and Roberts (1983) derive the effect of the 1970 Clean Air Act Amendment environmental regulation on TFP change within one step directly from the estimation results of a cost function. They derive the effect of the regulation on TFP change by applying the Divisia index of Gollop and Jorgenson (1980) and Shephard's Lemma.

[5] They estimate these effects by two approaches. First, via a two stage procedure, where TFP is estimated in the first stage (based on a production function using labor, capital and material as inputs). And second, via a single step procedure by including abatement costs directly into the production function.

riod of 1972 to 1993.[6] TFP levels of polluting plants located in non-attainment counties (which therefore were under more intense regulatory oversight) are found to be significantly negatively affected (in the range of 2.6 to 4.8 percent on average). However, when looking at the four kinds of pollution regulations separately, they found carbon monoxide regulations were associated with higher TFP levels.[7] Evidence for Porter's hypothesis can also be found in Berman and Bui (2001). They study the effect of air quality regulation on oil refinery productivity in the US between 1979 and 1992. They find productivity of regulated plants to increase rapidly, whereas the productivity of the control group was decreasing.

We are not aware of any literature that evaluates the impact of environmental regulations on productivity at the firm level in China. This gap is surprising, considering that China is the world's biggest energy user, most of which is coal, and has increasingly introduced policies to address pollution and climate change. A small number of studies, such as Xie (2008), evaluate the impact of environmental regulation at a macro (i.e. provincial) level for the overall Chinese industry. There are also many studies that focus on technical performance indicators such as energy efficiency or emissions levels, but studies do not focus on economic performance (see for example Hasanbeigi, Jiang et al. (2014); Ma, Chen et al. (2016); Xu and Lin (2016); Zhou and Yang (2016); Gong, Guo et al. (2016)). A large literature has considered trends and determinants of productivity growth in China (see Tian and Yu (2012) and Wu (2011) for an extensive meta-analysis).

6 This study builds on an earlier contribution of Greenstone (2002) that evaluates the impact of the Clean Air Act Amendment on manufacturing activities of US plants (in terms of the number of employees, the value of the capital stock and output) instead of TFP levels. The regulation is found to have significantly reduced manufacturing activity between 1967 and 1987.

7 Effects are measured via a two-stage procedure: first, they estimate TFP levels via a Cobb-Douglas production function and then, in a second step, regress TFP estimates on regulation and other covariates including firm fixed effects. In contrast to the methodology of Gollop and Roberts (1983), such a two-step procedure controls for differences in characteristics between treated and non-treated firms.

2.2 Iron and Steel Production in China

China overtook Japan to become the world's largest producer of primary iron and steel in 1993 (IISI, 2002). The Chinese iron and steel industry has played a central role in developing the country's economy (Guo and Fu, 2010). Between 1985 and 2013, output grew on average by 10.8 percent, and constituted 49.8 percent of the world's output in 2013 (IISI, 1986; WSA, 2014). The industry's energy consumption went up by an equally significant amount of 8.7 percent per year between 1985 and 2010 (Lin and Wang, 2014). In 2013, the iron and steel industry consumed 29 percent of total Chinese manufacturing and 23.6 percent of total industrial energy (NBS, 2014).

The iron and steel industry's high energy consumption to some extent is attributable to the intrinsic characteristics of its production processes. However, compared to the iron and steel industries of developed nations, the industry uses energy inefficiently (Ross and Feng, 1991; Zhang and Wang, 2008; He, Zhang et al., 2013). He, Zhang et al. (2013) mention several factors contributing to this low energy efficiency level. They list not only insufficient investments into R&D, but also a low labor productivity and a low degree of industrial concentration, resulting in foregone scale effects. The industry is said to pay little attention to energy saving (Zhang and Wang, 2008). It is also one of the country's major sources of pollution (Lin, Wu et al., 2011; He, Zhang et al., 2013). It ranks third among sectors as a source of carbon dioxide emissions in China (after the power generation and cement industry), accounting for roughly 10 percent (Zeng, Lan et al., 2009). The high energy consumption and emissions of the Chinese industry are problematic in terms of global warming, environmental integrity, energy security, and the human health effects of air pollution, among other impacts (Raupach, Marland et al., 2007; Stern, 2007; Davis, Caldeira et al., 2010; Piao, Ciais et al., 2010).

2.3 The Top-1000 Energy-Consuming Enterprises Program

The central government launched the national Top-1000 Energy-Consuming Enterprises Program (T1000P) at the start of the Eleventh Five-Year Plan (FYP) (Zhou, Levine et al., 2010). The Eleventh FYP (2006-2010) targeted an overall reduction in the country's energy intensity of 20 percent over the five-year period (energy use per GDP)

(StateCouncil, 2006). The T1000P became effective in April 2006. It required the country's largest 1,008 energy consuming industrial enterprises, i.e. firms consuming a minimum of 180,000 tons of coal equivalent (tce) in 2004, in nine industries (Price, Wang et al., 2010) to significantly improve their energy intensity, i.e. to lower the ratio of energy used to output produced according to a schedule of firm-specific targets. At the outset the program targeted energy savings of 100 Mtce by 2010 (NDRC, 2006b). However, as reported energy savings far exceeded the initial target—Zhao, Li et al. (2016) mention savings of 165 Mtce and Ke, Price et al. (2012) of 150 Mtce—the T1000P is widely considered as a success. Targets were already reported to have been achieved in 2008 when the NDRC announced savings of ca. 106 Mtce (Ke, Price et al., 2012). While Karplus, Shen et al. (2016) and Zhao, Li et al. (2016) describe that patterns in compliance data suggest overestimation of self-reported achievement rates, Ke, Price et al. (2012) conclude reported values were reasonable.[8] Of the firms evaluated in 2010 when the T1000P was terminated, only 1.7 percent of the firms were officially found to be out of compliance with the preset targets (NDRC, 2011).[9] The high compliance rate to some extent might be explained by the 100 Mtce saving target not being very ambitious in light of the high energy intensity of the targeted firms (Price, Levine et al., 2011).[10] The T1000P was extended to the Top 10,000 Enterprise Program in the Twelfth FYP (2011-2015) (Zhao, Li et al., 2016).

The T1000P included carrots to encourage compliance. Firms were assigned targets in a contract negotiated between the provincial government and the firm (Price, Wang et al., 2010; Zhao, Li et al., 2014). During the process of policy implementation, the local government provided guidance and financial support to the targeted firms (Price, Wang et al., 2010; Ke, Price et al., 2012; Zhao, Li et al., 2014). Firms had rela-

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8 Ke, Price et al. (2012) estimate energy savings based on overall industrial value added and energy consumption. Price, Levine et al. (2011) independently confirm that the target already was achieved as early as 2008 by estimating savings to have amounted to 124 Mtce.

9 881 firms were evaluated at the end of the T1000P in 2010 and 15 firms were found as non-compliant. The ratio of non-complying firms was 3.9, 3.1 and 1.7 percent in 2008, 2009 and 2010, respectively (NDRC, 2009, 2010, 2011). Due to, e.g., mergers and closures in years after the program announcement, some firms were excluded temporarily or permanently from the T1000P, resulting in less than 1,008 firms being evaluated every year. For more discussion see Karplus, Shen et al. (2016).

10 In 2004, targeted firms contributed 33 percent to national and 47 percent to industrial energy use (Price, Wang et al., 2010). However, the planned contribution of the T1000P to the overall Eleventh FYP energy saving target was only 15 percent (Price, Levine et al., 2011)

tively large freedom to choose appropriate measures to save energy; while the goals were clear, the approaches were flexible. According to Porter and Van der Linde (1995b), such flexible design of an environmental regulation is fundamental to foster innovation.

Policymakers selected firms for the program based on their total energy consumption. Firms were allocated energy saving targets based primarily on their pre-regulation share in the energy consumption of all firms exposed to the T1000P (Zhao, Li et al., 2014, 2016), and without direct attention to abatement cost. To some extent, however, other factors like industry affiliation, general economic situation, or the technological level of the firm were also taken into account when setting the targets (Price, Wang et al., 2010). As the program was set up very rapidly, the target setting process was not based on a detailed or scientific bottom-up analysis of firms' individual energy saving potential (Price, Wang et al., 2010; Price, Levine et al., 2011). The covered firms self-reported their progress in saving energy directly to the Chinese National Bureau of Statistics (NBS) following predefined reporting standards (Zhou, Levine et al., 2010). Subsequently, provincial governments evaluated firm compliance on an annual basis. Assessment included short on-site inspections, but was mainly based on the firms' self-examination, due to limited resources and the complexity of the calculation of the energy saving indicator (Zhao, Li et al., 2014; Li, Zhao et al., 2016; Zhao, Li et al., 2016). Fraudulent reporting could lead to criminal investigation (Zhou, Levine et al., 2010).

The program did not specify any punishments, e.g., in financial form, in the case of a firm's non-compliance. However, some provincial governments reportedly introduced punitive measures, e.g., by increasing energy prices for non-compliant firms (Zhao, Li et al., 2014, 2016). Also, the list of firms exposed to the T1000P was made public (Price, Levine et al., 2011). Hence, a further component of the enforcement of the program was social pressure from citizens and media. Firms implemented incentive payments for their staff conditional on the achievement of energy saving targets, which also included salary cut-offs in case of non-compliance (Zhao, Li et al., 2014). Furthermore, as part of an extensive overall catalogue[11] of performance assessment criteria, state-owned enterprises (SOEs) and local government officials were evaluated based on their achievement of the T1000P energy-saving targets (StateCouncil, 2007; Zhao, Li et al., 2014; Li, Zhao et al., 2016). The energy saving achievement was included in the personnel appraisal system during the Eleventh FYP, and strongly incentivized government officials to support covered firms to reach their targets (Zhou, Levine et al., 2010).[12] Administrators gave awards and promotions in return for compliance with the regulation. In the case of non-compliance, firm managers and local government officials endangered their chances of promotion and a written report was to be sent to a superior level of government specifying the time frame for rectifying non-compliance (Zhao, Li et al., 2014).

3 Data and Empirical Strategy

3.1 Data

We rely primarily on data from the Chinese Industrial Census (CIC) from years 2003 to 2008 compiled by the NBS. The CIC represents the most extensive source of firm level information on the Chinese manufacturing sector. It contains yearly observations on the balance sheet, income statement and other non-financial information of all industrial firms registered in China with a yearly sales value higher than 5 million Chinese renminbi (RMB), which corresponds to ca. 800,000 US dollars, and all state-owned firms (independently of their sales value). Most firms are single plant firms (Brandt, Van Biesebroeck et al., 2012). The data is described in greater detail in appendix A.1.

[11] This is the cadre evaluation system appraising the overall behavior of government officials, and not just the behavior related to environmental regulation compliance. The evaluation system is described in greater detail in, e.g., (Zhang, Aunan et al., 2011).

[12] At that time, not only the national, but also provincial governments adjusted their appraisal programs to put more weight on the sustainability of development, rather than simply focusing on economic indicators. These appraisal programs then were used to evaluate local government officials and firm managers. A description of such an appraisal program, for example, is given in Zhang, Aunan et al. (2011).

All costs and output values are deflated to a reference year (1998) using four-digit industry-specific input and output deflators, which were used by Brandt, Van Biesebroeck et al. (2012) and were kindly provided by Johannes Van Biesebroeck of KU Leuven. Spatial information on the centroid longitude and latitude of 2,824 geographic clusters (counties) was obtained from a private vendor (BW, 2016). Information on the geographic borders of these clusters was obtained from of a publicly-available shape file (GADM, 2016). Information on firms participating in the T1000P originated from the NDRC. Of these firms, 1,001 out of 1,008 (i.e. 99.3 percent) were successfully matched with the CIC. While the prices of labor and capital are derived from information contained in the CIC, this is not possible for the price of material. The subindustry- (iron and steel, steel rolling, and alloy) and province-specific annual price of material is calculated based on information on subindustry inputs and outputs obtained from the NBS (2007), coal prices and electricity prices extracted from CEIC (2015) and iron ore prices from CCM (2015). These prices then are deflated using an overall price deflator constructed from NBS (2013). Appendix A.1 provides a more detailed description of the construction of the price of material.

3.2 Characteristics of Treated and Non-Treated Firms

The CIC observes a total of 13,278 firms in the iron and steel industry (or more precisely, in the ferrous metal smelting and rolling industry) over the period of 2003 to 2008. Out of this sample, 5,340 firms are considered for the empirical analysis.[13] The panel of firms is unbalanced with 2,047 observations (or 38.3 percent) forming a balanced panel. 37.3 percent of the sample was observed for five years, 18.4 percent for four years, 5.0 percent for three years and 0.9 percent for two years. Descriptive statistics of the 5,340 firms for the full sample period are given in Table 1 in columns 1 to 4. On average in each year, a firm in the sample produces a gross-output value of 353.8 million RMB,

[13] The CIC is known to contain misreported information for some firms. Therefore, an extensive data screening process was implemented to detect and discard such firms. Additional firms were dropped in the panel generation and variable adjustment processes. These processes are described in appendix A.1. Most excluded firms were small in size. Small firms may have weaker reporting standards than large firms. As a result, the sample used for the empirical analysis still is highly representative of the underlying population of firms (cf. Table 19 in appendix A.1).

employs 506.2 people, and possesses total assets of 340 million RMB and current assets of 129.4 million RMB. It utilizes intermediate inputs of 298.1 million RMB. On average, labor costs (4.1 percent) and capital costs (5.0 percent) sum to 9.1 percent of total costs, with the remaining part being attributable to material costs. On average, 9.6 percent of the firms observed exported in a given year. Firm heterogeneity with respect to several of these variables is large. For example, the 25 percentile gross output value is 7.3 times smaller than the 75 percentile value, and the ratio is 4.5 for the number of people employed. The iron- and steelmaking subindustry accounts for 18.3 percent of the observations, 64.3 percent stem from the steel rolling and 17.4 percent from the ferroalloy smelting subindustry. Furthermore, 0.6 percent of the observations are central SOEs, 9.4 percent local SOEs and 90.0 percent non-SOEs.[14]

We define a treatment group as firms included in the T1000P and initially consider the remainder of the population as a control group. Summary statistics differentiating between the control and treatment group are given in columns 5 to 7 of Table 1. 148 out of 5,340 firms are observed to participate in the program, i.e. 3.1 percent of total observations. The average firm in the control group is considerably smaller than the average firm in the treatment group in terms of all listed variables. The ratio between the treatment and control group in average gross output in the pre-regulation period amounts to 41.6. Furthermore, this ratio is 40.0 for the number of employees, 67.4 for total assets, 48.1 for current assets and 39.6 for intermediate inputs. Treated firms tend to be older and to have a higher propensity to export. Statistical tests of the differences between treated and non-treated firms are given in column 7 of Table 1. Results indicate large disparities in fundamental firm characteristics between treated and non-treated firms before the implementation of the regulation, with all differences being highly statistically

[14] Classifying Chinese firms into ownership types is not simple or straightforward. Several decades of economic reforms have resulted in varying degrees of transformation from state to private ownership across the economy. Some firms that were previously state-owned were fully privatized, while others were partially privatized or publicly listed, while retaining a state-linked controlling shareholder. Meyer and Wu (2014) give a detailed overview of ownership structures in the Chinese economy. This study defines firms as being state-owned (SOE) if they have a controlling shareholder linked to the state. The CIC dataset includes a firm-level variable designating state control. Interestingly, using this measure, state control of China’s iron and steel enterprises did not change significantly between 2003 and 2008 and even slightly increased from 8.1 to 11.2 percent, while the share of state paid-in capital in total paid-in capital diminished substantially over this period with a decrease from 5.6 to 3.3 percent.

significant. For example, larger firms were much more likely to be exposed to the regulation than smaller firms. Nevertheless, this finding is not surprising, since program participation was conditional on an energy consumption level only large firms achieve. In addition, more state controlled firms were selected for the program than their industry share would predict, which can be partly attributed to state-controlled firms on average being larger in size and shouldering more "social responsibility." We cannot exclude the possibility that some firms were also more likely to be exposed to the T1000P, simply because they were state controlled. In fact, this was likely an important consideration. Dispersions in characteristics between treated and non-treated firms are considered carefully in the design of the empirical analysis. In addition to controlling for heterogeneity directly in the benchmark analysis, we implement an extensive set of robustness checks and instrument for T1000P exposure.

Table 1: *Descriptive statistics of firms. All values are annualized.*

	Years 2003 to 2008				Years 2003 to 2005 (pre-regulation period)		
	All firms				Treatment group	Control group	Difference
	Mean	Std.dev.	Min.	Max.	Mean	Mean	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gross output (mRMB)	353.8	2,226.1	0.016	89,784.2	4,795.8	115.4	4,680.4***
Employees	506.2	3,202.1	8	120,628	9,009.8	225.0	8,784.8***
Total assets (mRMB)	340.0	3,113.6	0.324	127,167.6	5,989.5	88.9	5,900.6***
Current assets (mRMB)	129.4	1,013.2	–2.181	38,334.2	2,263.3	47.1	2,216.2***
Intermediate inputs (mRMB)	298.1	1,810.3	0.001	73,139.0	3,909.5	98.7	3,810.8***
Age	7.85	8.78	0	108	22.19	6.48	15.71***
Exporter (1 if exporting)	0.096	0.295	0	1	0.273	0.067	0.206***
Total costs C (mRMB)	335.9	2,158.5	0.482	90,363.0	4,595.1	107.3	4,487.7***
Capital price P_K (kRMB / K)	0.245	1.297	0.000	93.831	0.145	0.232	–0.087*
Labor price P_L (kRMB / L)	15.77	13.96	0.030	618.37	20.62	12.79	7.83***
Intermed. inputs price P_M (index)	156.14	38.12	68.31	313.80	133.15	137.13	–3.98***
Profitability	0.030	0.091	–2.722	2.102	0.046	0.027	0.019***
# firms / # observations	5,340 / 27,076				148 / 410	5,192 / 12,173	5,340 / 12,583
Subindustry shares in [%]: iron- and steelmaking / steel rolling / ferroalloy smelting:							
	18.3 / 64.2 / 17.4				44.9 / 45.9 / 9.3	18.2 / 64.5 / 17.3	
Share in [%] of central SOE / local SOE / non-SOE:							
	0.6 / 9.4 / 90.0				3.7 / 40.5 / 55.9	0.5 / 4.0 / 95.5	
Share in [%] of regions East / Central / West:							
	59.2 / 23.4 / 17.4				45.6 / 34.1 / 20.2	59.5 / 23.5 / 17.0	
Distribution of firm size (number of employees) in [%] of observations in intervals [0;50], (50;100], (100;500], (500;1,000], (1,000;5,000] and more than 5,000:							
	24.4 / 24.6 / 39.9 / 5.5 / 4.1 / 1.5				0.0/0.2/2.7/9.8/49.8/37.6	26.3/25.6/40.2/5.4/2.3/0.2	

Note: This table shows descriptive statistics of the overall sample (columns 1 to 4) for the period 2003 to 2008 and conditional on treatment (columns 5 and 6) for the pre-regulation period of 2003 to 2005. Data is at firm level with monetary values given in real 1998 values. *Total costs*, *capital price*, *labor price* and *material price* are described in greater detail in section 4. *Profitability* is the ratio of total profits to gross output. Column 7 shows the results of one-sided unpaired t-tests comparing the respective means of the treatment and control group. Asterisks *** indicate significance at 1 percent level, ** at 5 percent level and * at 10 percent level of the one-sided unpaired t-tests.

Spatial distribution of the firms in the complete sample

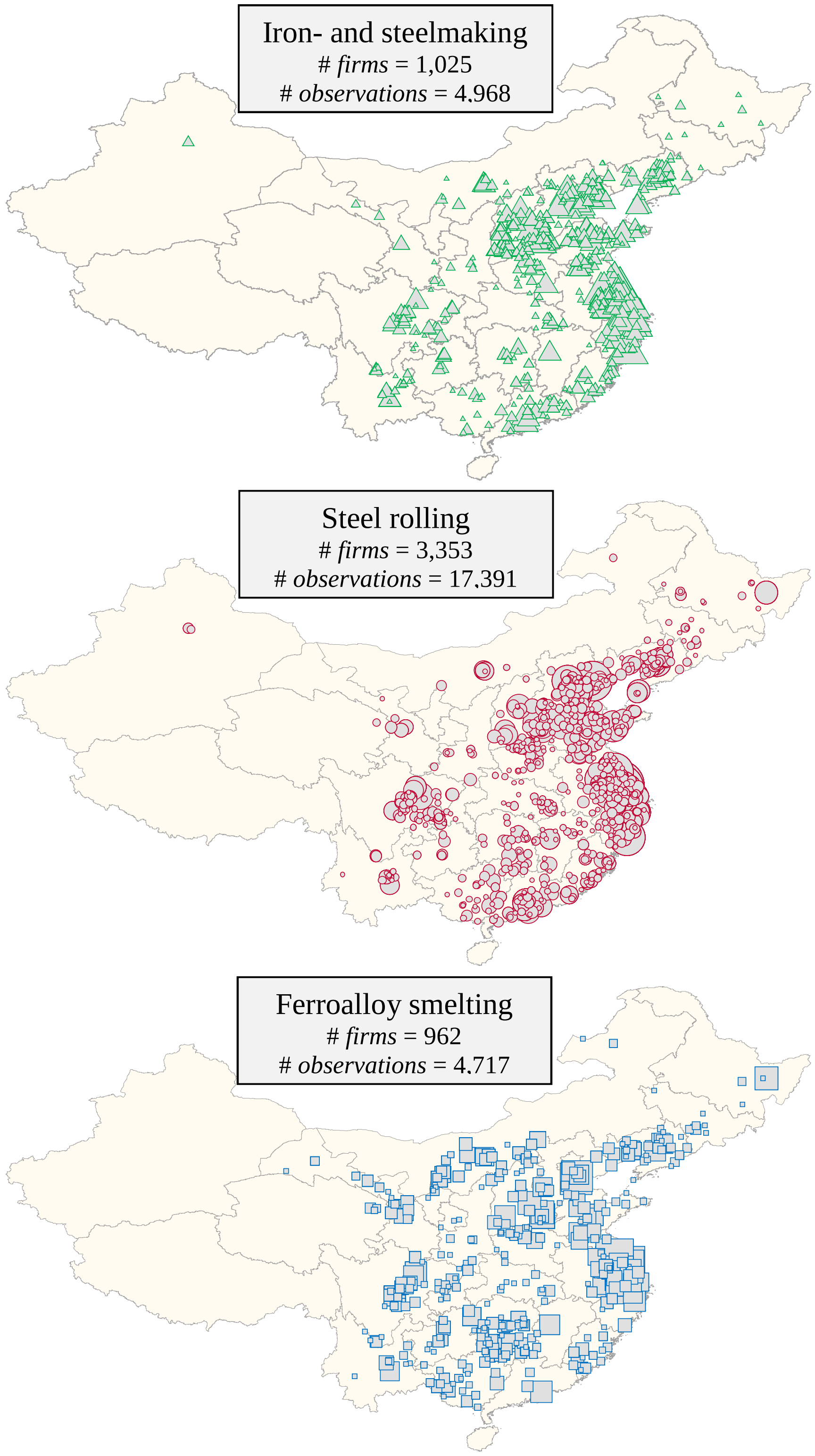

Figure 1: *Spatial distribution of the sample firms by subindustry in 2005. Marker size is relative to the number of firms observed in a county.*

Spatial distribution of the treated firms

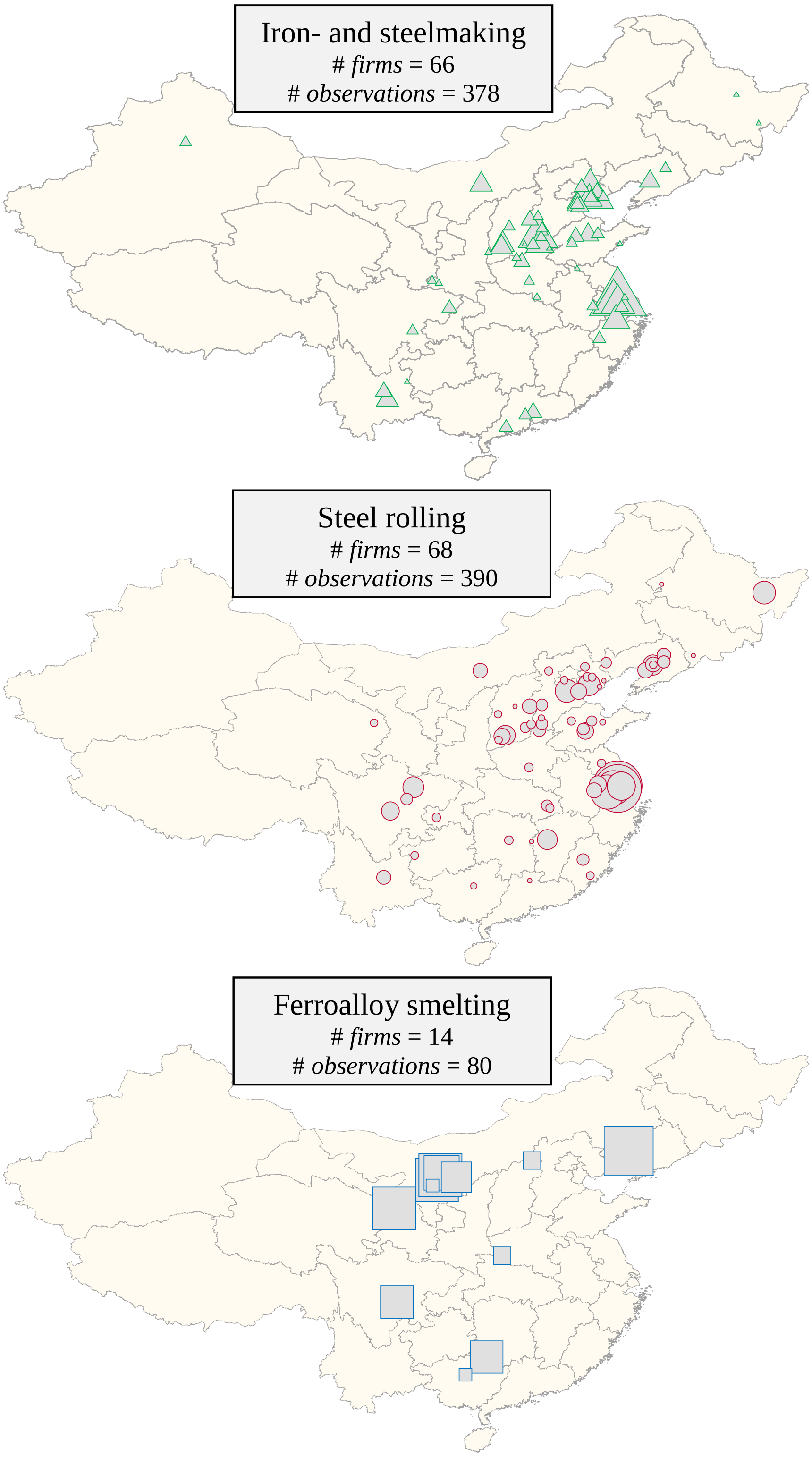

Figure 2: *Spatial distribution of the treated firms by subindustry in 2005. Marker size is relative to the number of firms observed in a county.*

Figure 1 shows the spatial distribution of the sample. In line with the general spatial distribution of economic activity in the country, most firms are located in eastern provinces, with the province of Jiangsu containing 18.2 percent and the province of Zhejiang 11.2 percent of the observations.[15] The share of Hebei, Liaoning and Shandong province is 7.3, 7.3 and 6.8 percent, respectively. Figure 2 depicts the spatial distribution of the treated firms. Consistent with the overall distribution shown in Figure 1, most treated firms, especially of the iron- and steelmaking and ferroalloy smelting subindustry, are located in eastern provinces. 18.9 percent of the treated observations are located in Hebei province and 10.6 percent each in Jiangsu and Shanxi province, respectively. In contrast, most treated firms in the ferroalloy smelting sub-industry are located in the west region. It is reassuring that we also observe a higher share of ferroalloy smelting firms located in this area, compared to the other two subindustries.

4 Empirical Strategy and Identification

We implement a two-stage approach to estimate the relationship between the T1000P and firm performance. First, firm performance is calculated using the unbalanced panel described in section 3. Second, the effects of the regulation on firm performance are analyzed using parametric models. Firm performance is expressed as total factor productivity (TFP) change and the subcomponents thereof, which are technical change and scale efficiency change.[16] Analyzing the effects on TFP change subcomponents allows

[15] We classify provinces in China in three regions: east, central and northeast, and west. The east region embraces the provinces Beijing, Fujian, Guangdong, Hainan, Hebei, Jiangsu, Shandong, Shanghai, Tianjin and Zhejiang. The central and northeast region encompasses the provinces Anhui, Henan, Hubei, Hunan, Jiangxi and Shanxi (central) and Jilin, Heilongjiang and Liaoning (northeast). The west region comprises the provinces Chongqing, Gansu, Guangxi, Guizhou, Inner Mongolia, Ningxia, Qinghai, Shaanxi, Sichuan, Xinjiang and Yunnan.

[16] This study does not focus on TFP levels. TFP change is believed to better represent the response of a firm to changes in its environment of doing business. It explicitly measures the degree of TFP relevant activity, which is less the case for the stock variable of TFP levels. TFP change is a measure that is transitive over time, while TFP levels would be transitive cross section wise. By adopting the line of argument in Ehrlich, Gallais-Hamonno et al. (1994), the evaluation of a regulation with respect to TFP

(*Footnote continues on next page*)

for more detailed insight into the effects of the policy. The concept of productivity has a clearer economic interpretation than other firm performance indicators like employment or investment because productivity speaks to the concept of how efficiently inputs are turned into outputs (Greenstone, List et al., 2012). We believe that the use of total factor productivity as performance indicator is superior to the use of partial productivity indicators such as labor productivity, as single factor productivity may be distorted (Syverson, 2011).[17] We use a parametric approach to capture firm heterogeneity, and estimate productivity by formulating a cost function.[18]

4.1 Derivation and Formulation of the Cost Function

To derive TFP change from a cost function, we follow Coelli, Estache et al. (2003). We apply the quadratic approximation lemma of Diewert (1976), as proposed by Orea (2002). Thereby, TFP change (TFPC) of firm *i* between two periods *t* and *t* – 1, consisting of the two subcomponents of technical change (TC) and scale efficiency change (SEC), can be estimated using eq. (1).

levels can be described as being inconclusive in the short-run. The compounding effect of short-run alterations in TFP change, however, might result in large differences in long-run TFP levels. In addition, Brandt, Van Biesebroeck et al. (2012) find TFP change to be more relevant than TFP levels, in the sense that between 1998 and 2007 surviving entrants in the Chinese manufacturing sector were selected based on TFP change rather than TFP levels. A multilateral measure of TFP levels proposed by Caves, Christensen et al. (1982) could be constructed by using eq. (1) and taking the year- and subindustry-specific means instead of lagged variables in the denominator.

[17] Single factor productivity measures may be distorted because they do not account for factor substitutions between inputs and therefore are affected by the intensity of use of the excluded inputs. Syverson (2011) exemplifies such a problem by two firms, which are applying the same production technology, and nevertheless are showing highly differing labor productivities, because, e.g., one firm uses much more capital relative to the other due to factors such as a favorable price of capital.

[18] The iron and steel industry employs a comparatively homogenous production process with relatively uniform output. This makes it well suited to a parametric approach. Given the large degree of heterogeneity observed in our sample, the parametric methods' ability to separate noise from signal is an essential advantage. Furthermore, the estimation of TFP change using parametric approaches allows for a decomposition of TFP change into its components.

$$
\begin{aligned}
TFPC_{it} &= \ln\left(\frac{TFP_{it}}{TFP_{it-1}}\right) \\
&= \underbrace{\frac{1}{2}\left[\left(1-e_{it}\right)+\left(1-e_{it-1}\right)\right]\cdot\left(\ln Y_{it}-\ln Y_{it-1}\right)}_{SEC_{it}} \\
&\quad \underbrace{-\frac{1}{2}\left(\frac{\partial \ln C_{it-1}}{\partial t}+\frac{\partial \ln C_{it}}{\partial t}\right)}_{TC_{it}} .
\end{aligned}
\tag{1}
$$

Total costs are represented by C and the single output is Y. Output elasticities (which are the inverse to the returns to scale elasticity) at a data point are estimated as $e_{it} = \partial \ln C_{it} / \partial \ln Y_{it}$ (Coelli, Estache et al., 2003).

A calculation of TFP change according to eq. (1) necessitates the empirical specification of a cost function for the Chinese iron and steel industry, which can be divided into the following three sub-industries s: iron- and steelmaking, steel rolling, and ferroalloy smelting. The production processes are heterogeneous across these sub-industries. Therefore, from an empirical point of view, we estimate a separate cost function for each sub-industry. This allows for coefficients specific to each sub-industry to reflect heterogeneity in production technologies, resulting in more accurate TFP change estimates compared to results derived from an overall cost function.[19] In this study, we assume a subindustry $s = \{1,2,3\}$-specific production process characterized as follows:

$$
C_{it} = c^{s}\left(Y_{it}, P_{L,it}, P_{K,it}, P_{M,srt}, t\right). \tag{2}
$$

Total costs C are defined as the sum of total intermediate input costs, labor costs and capital costs, whereby capital costs include depreciation and interest expenses and an

[19] For the sake of completeness, TFP change was estimated based on an overall cost function as well. The mean result of TFP change when applying subindustry-specific cost functions was similar in magnitude to the result obtained from an overall cost function.

assumed opportunity costs on equity of three percent.[20] The single output Y is deflated gross output. The price of labor P_L is represented by the ratio of the sum of wage and welfare payments to the number of employees. The price of capital P_K is defined as capital costs divided by the real capital stock. The calculation of the real capital stock is based on the perpetual inventory method.[21] Main materials used in the production processes of iron and steel are coal, coke, iron and electricity. The subindustry *s*- and province *r*-specific price of material P_M is derived via a Törnqvist price index of these four main material inputs.[22] A time trend t is added to the cost function in order to control for technical change. All costs and output are deflated to reference year 1998 using the respective input and output[23] deflators described in appendix A.1. Descriptive statistics of the main covariates are given in Table 1.

For the estimation of eq. (2) we decided to use a translog functional form, since this flexible functional form does not impose a priori restrictions on the technology parameters.[24] The subindustry *s*-specific cost functions are specified as

[20] Opportunity costs on equity of three percent result from the following assumptions: 20% return to capital – 12% depreciation – 5% interest rate. For an extensive overview of the returns to capital in China, see, for example, Bai, Hsieh et al. (2006).

[21] The perpetual inventory method is adopted form Brandt, Van Biesebroeck et al. (2012) and described in more detail in Brandt, Van Biesebroeck et al. (2014). See appendix A.1 for more details.

[22] While this price measure is not firm-year- but province-year-specific, it bears the benefit of being unaffected by firm-specific unobserved heterogeneity potentially also related to total costs, what would yield biased estimation results. We describe in detail how the price of material is computed in appendix A.1. Of course, we are aware that the price of each main material could have been included separately into the cost function. However, such a model specification resulted in severe multicollinearity problems when estimating a fully flexible translog cost function.

[23] A subindustry- and year-specific output price is assumed; an assumption generally made by the literature if firm-level information on output prices is unobserved. In addition, this assumption can be justified by the homogenous production process and comparatively homogenous structure of output goods in the iron and steel sector compared to other industries.

[24] See Berndt and Christensen (1973) and Christensen, Jorgenson et al. (1973) for a discussion on the properties of the translog functional form.

$$
\begin{aligned}
c_{it} &= \alpha_0^s + \alpha_i + \boldsymbol{\beta}^{s\prime}\mathbf{x}_{it} + \varepsilon_{it} \\
&= \alpha_0^s + \alpha_i + \beta_Y^s y_{it} + \sum_{Z=\{K,L\}} \beta_Z^s p_{Z,it} + \beta_M^s P_{M,srt} \\
&\quad + \frac{1}{2}\left(\beta_{YY}^s y_{it}^2 + \sum_{Z=\{K,L\}} \beta_{ZZ}^s p_{Z,it}^2 + \beta_{MM}^s P_{M,srt}^2 + \beta_{tt}^s t^2 \right) \\
&\quad + \sum_{Z=\{K,L\}} \beta_{yZ}^s y_{it} p_{Z,it} + \beta_{YM}^s y_{it} P_{M,srt} + \beta_{KL}^s p_{K,it} p_{L,it} + \sum_{Z=\{K,L\}} \beta_{ZM}^s p_{Z,it} P_{M,srt} \\
&\quad + \beta_t^s t + \beta_{Yt}^s y_{it} t + \sum_{Z=\{K,L\}} \beta_{Zt}^s p_{Z,it} t + \beta_{Mt}^s P_{M,srt} t + \varepsilon_{it} \ ,
\end{aligned}
\tag{3}
$$

with lower case letters y and p indicating output and prices in natural logarithms.[25] The panel is unbalanced (cf. section 3.2) with a firm indicator i = 1,..,N and time indicator t. Firms are observed annually over the period of $t = \{2003, ..., T_i\}$, $T_i \leq 2008$. The intercept α_0 represents total costs at the approximation point. Firm fixed effects are captured by α_i and control for firm-specific time invariant unobserved heterogeneity.[26] The error term is given by ε_{it}. Sub-industry-specific median values of the explanatory variables are chosen as approximation points of the translog cost functions. Expression (3) is estimated using a fixed effects estimator, that is, running OLS on $c_{it} - \overline{c}_i = \boldsymbol{\beta}'(\mathbf{x}_{it} - \overline{\mathbf{x}}_i) + (\varepsilon_{it} - \overline{\varepsilon}_i)$ using Huber (1967)/White (1980) cluster robust sandwich estimates at the firm level (accounting for both heteroskedasticity and serial correlation), where $\overline{c}_i = T_i^{-1}\sum_t c_{it}$. The variables $\overline{\mathbf{x}}_i$ and $\overline{\varepsilon}_i$ are constructed analogously.[27]

4.2 Identification Strategy

The effect of the T1000P on firm performance (TFPC, TC and SEC) is identified in accordance with standard assumptions required to apply a difference-in-difference (DD)

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[25] The price of material is an index and therefore already has the interpretation of an elasticity. This variable has not been transformed to log values.

[26] The fact that α_i is time-constant makes this parameter irrelevant for the estimation of TFP change.

[27] For a detailed description of the fixed effects estimator see, e.g., Greene (2008) or Cameron and Trivedi (2005).

approach.[28] This approach derives causal treatment effects by comparing the performance of treated and non-treated firms in the pre-regulation and regulation period. As described in section 2.3, the point of intervention was April 2006 for all firms participating in the program. Firms are assumed not to have anticipated the regulation and, accordingly, not to have undertaken regulation-related actions affecting firm performance beforehand.[29] Also, while firms were chosen to participate in the T1000P mainly based on energy consumption, other criteria like industry affiliation also played a role (cf. section 2.3). Firms did not actively self-select into the program. For the DD approach to yield valid results, the assumption of a parallel trend should be satisfied. This assumption implies a trend in firm performance before the introduction of the regulation that does not differ between firms in the treatment and control groups. Given that the parallel trend assumption holds, the average effect of the regulation on firm TFP change, called average treatment effect on the treated (ATT), can be identified via

$$TFPC_{it} = \alpha_0 + \alpha_i + \boldsymbol{\theta}_t + \beta_{ATT}\tau_i\,\rho_t + \boldsymbol{\gamma}'\mathbf{X}_{it} + \boldsymbol{\theta}_t\pi_i + \varepsilon_{it}\,, \tag{4}$$

where TFPC is the total factor productivity change of firm i in year t. This procedure can be followed analogously to analyze the ATT on TC and SEC by replacing TFPC with one of these other performance indicators. The intercept is α_0 and firm fixed effects α_i control for firm-specific time-constant unobserved heterogeneity affecting firm performances. Vector $\boldsymbol{\theta}_t$ captures year fixed effects and controls for year-specific shocks on firm performance common to all firms. Pre-regulation and regulation periods are captured by the binary variable ρ_t, taking the value one for all regulation periods and zero otherwise, with the year of change being 2006. The binary variable τ_i indicates wheth-

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[28]Other methodologies to evaluate the effect of the regulation would be matching or regression discontinuity. Since energy consumption is unobserved and no good proxy variable is available, we do not conduct a regression discontinuity analysis. Our study incorporates elements of the underlying idea of a matching procedure by using stratified samples to check for robustness of the results. For an extensive review of policy evaluation methods the interested reader we refer the reader to Lance, Guilkey et al. (2014) or, for a more qualitative description, Gertler, Martinez et al. (2011).

[29] We consider this assumption to be credible, as the T1000P was framed within a comparatively short time period (cf. section 2.3).

er or not a firm was part of the treatment group. The ATT is estimated by coefficient β_{ATT}. We assume a single homogenous effect of the regulation on firm performance across all regulation periods.[30] Vector $\mathbf{X}_{it}$ contains two variables to control for time-varying heterogeneity affecting firm performance. These variables are ownership structure and firm size. Size effects are controlled for by the natural logarithm of the number of employees. Ownership related effects are measured by a binary variable differentiating between SOEs and non-SOEs.[31] Province-year effects $\boldsymbol{\theta}_t \pi_i$ control for province π_i - and year θ_t-specific shocks.

A DD approach is only appropriate if the treatment conditional on time and firm effects is as good as random (Bertrand, Duflo et al., 2004). Hence, it may be important to control for α_i, $\boldsymbol{\theta}_t$ and $\mathbf{X}_{it}$. The inclusion of firm fixed effects α_i avoids biased estimation results if time-invariant unobserved firm level heterogeneity is not orthogonal with the ATT or other covariates. For instance, these effects might capture potential endogeneities in terms of an exposure to the T1000P, if the underlying firm level heterogeneity is time-constant. SOEs not changing ownership over time might have been benefiting from financial support already before the introduction of the regulation in 2006, what could allow them to become more productive also after 2006. At the same time, state ownership could have increased the probability of being exposed to the T1000P. Other time-constant conditions affecting the outcome of a firm might be geographic heterogeneity like a favorable geographic location close to iron and coal mines or ports (Greenstone, 2002), preferential political treatment, regional differences in the applica-

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[30] In principle, the estimation of year-specific ATTs would be possible as well by including $\sum_{t \geq T^*} \beta_t^{ATT} \theta_t \tau_i$ in eq. (4) instead of $\beta_{ATT} \tau_i \rho_t$. However, the observation of only three regulation periods renders the additional insights from estimating year-specific effects to be small.

[31] Note that firm size and ownership can vary over time. 17.7 percent of the observations (19.9 percent of non-treated and 5.1 percent of treated firms) change from being state controlled to being non-state controlled. A transition in the other direction is observed for 3.7 percent of the observations (3.7 percent of non-treated and 5.2 percent of treated firms). In the pre-regulation period, 14.7 percent of the observations (17.4 percent of non-treated and 6.7 percent of treated firms) change from being state controlled to being non-state controlled. A transition in the other direction is observed for 0.8 percent of the observations (0.7 percent of non-treated and 2.1 percent of treated firms). The effect of the geographic location is allowed to vary by year.

tion and enforcement of regulatory targets etc. Examples for year-specific shocks on firm performance common to all firms, captured by $\boldsymbol{\theta}_t$, are output market disruptions or political ruptures on a national level. The two-way fixed effects model (year fixed effects are included as well) is estimated as described in section 4, again by using cluster robust sandwich estimates at the firm level. By this, we are avoiding a potential downward bias in the estimated standard errors of the treatment effect due to uncontrolled positive serial correlation.[32]

A threat to the identification strategy, if unaccounted for, is time-varying unobserved heterogeneity not orthogonal to the treatment effect or other covariates. A firm's exposure was dependent to some extent on determinants other than simply an above-threshold energy consumption. Firm size and ownership are two suspect criteria. We suspect these two factors are correlated with firm performance as well, and hence are stepwise controlled for by vector $\mathbf{X}_{it}$.[33] Province- and year-specific shocks, $\boldsymbol{\theta}_t \pi_i$, are included to control for effects such as changes in a province's governance. Shocks therein potentially can be correlated not only with firm performance, but with, e.g., T1000P exposure as well.

As discussed previously, the DD analysis builds on the core assumption of TFP change (or TC or SEC) of the treatment group and its counterfactual, the control group, following a parallel trend in the pre-regulation period. The parallel trend, with the year of implementation of the regulation being indicated by T^*, is tested by the following expression:

[32] The issue and implications of serial correlation in a DD analysis are discussed in detail by Bertrand, Duflo et al. (2004).

[33] For example, Sheng and Song (2013) provide evidence of TFP levels in the Chinese iron and steel industry being dependent on ownership structure and firm size. Also Hsieh and Klenow (2009) find TFP levels in the Chinese industry being related to firm size and ownership. We cannot reject a priori such relations not to hold with respect to TFP change. The stepwise inclusion of the variables of vector $\mathbf{X}_{it}$ also serves as a robustness check. If results are robust across the different model specifications, the bias due to other, still unobserved, time varying factors only might be minor.

$$TFPC_{it} = \alpha_0 + \alpha_i + \beta_t t + \beta_t^{tr} t_i^{tr} + \boldsymbol{\gamma}' \mathbf{X}_{it} + \boldsymbol{\theta}_t \pi_i + \varepsilon_{it} \;\Big|\; t < T^*. \tag{5}$$

Expression (5) is based on an overall time trend *t* and a time trend for the treated group (indicated by "*tr*"), $t_i^{tr} = t\tau_i$, and estimated using observations of the pre-regulation period only. The parallel trend assumption is satisfied if the null hypothesis of $\hat{\beta}_t^{tr} = 0$ is not rejected. A similar test shown in eq. (6) consists in the assessment, whether there are pre-treatment effects $\theta_{i,2005}^{tr} = \tau_i \, \theta_{2005}$. Under the assumption of an exogenous treatment, no such effects are expected to exist.[34]

$$TFPC_{it} = \alpha_0 + \alpha_i + \boldsymbol{\theta}_t + \theta_{i,2005}^{tr} + \beta_{ATT} \tau_i \, \rho_t \; + \boldsymbol{\gamma}' \mathbf{X}_{it} + \boldsymbol{\theta}_t \pi_i + \varepsilon_{it} \tag{6}$$

The assumption of no pre-treatment effects holds if $\hat{\theta}_{2005}^{tr} = 0$ is not rejected.[35] In contrast to expression (5), expression (6) makes use of the full panel of information. It also includes an estimation of the, in our case overall, ATT. Firm fixed effects α_i capture the information of the covariate τ_i as well, and therefore it is not included in above three specifications. Tests for a parallel trend and pre-treatment effects in TC and SEC are conducted analogously by replacing TFPC with one of these respective variables.

[34] For a discussion on how to test for a parallel trend or pre-treatment effects see, e.g., Lance, Guilkey et al. (2014) or Khandker, Koolwal et al. (2010). These two diagnosis tests are also listed in Bertrand, Duflo et al. (2002).

[35] In case more than one pre-regulation treatment-year fixed effects are observed, their joint insignificance can be tested via a conventional *F*-test.

Table 2: *Testing for a parallel trend and pre-treatment effects in TFPC, TC and SEC based on eq. (5) and eq. (6).*

Dependent variable:	TFPC		TC		SEC	
	Specification DD–3 [Testing based on eq. (5)]					
Time trend × Treatment (β_t^{tr})	**0.001**	**(0.012)**	**0.003**	**(0.003)**	**–0.002**	**(0.011)**
Time trend (β_t)	–0.068	(0.045)	0.001	(0.004)	–0.069	(0.044)
Size	0.063***	(0.019)	0.003	(0.002)	0.060***	(0.019)
Ownership	0.016	(0.037)	0.000	(0.008)	0.016	(0.035)
Province × Year 2005	⋮		⋮		⋮	
Constant (α_0)	–0.075	(0.130)	0.036***	(0.014)	–0.111	(0.129)
R^2	0.728		0.894		0.705	
# firms / # observations	4,708 / 7,243		4,708 / 7,243		4,708 / 7,243	
	Specification DD–3 [Testing based on eq. (6)]					
Year 2005 × Treatment (θ_{2005}^{tr})	**-0.008**	**(0.008)**	**0.003**	**(0.002)**	**–0.011**	**(0.008)**
ATT (β_{ATT})	0.026***	(0.007)	0.014***	(0.003)	0.012*	(0.007)
Year 2005 (θ_{2005})	–0.043	(0.031)	0.000	(0.003)	–0.043	(0.030)
Year 2006 (θ_{2006})	–0.046	(0.030)	0.002	(0.004)	–0.048*	(0.028)
Year 2007 (θ_{2007})	–0.055**	(0.027)	–0.002	(0.005)	–0.053**	(0.025)
Year 2008 (θ_{2008})	–0.059**	(0.028)	0.021***	(0.005)	–0.080***	(0.026)
Size	0.027***	(0.004)	–0.001	(0.001)	0.028***	(0.004)
Ownership	0.010**	(0.004)	0.003*	(0.001)	0.007*	(0.004)
Province × Year 2005	⋮		⋮		⋮	
Constant (α_0)	–0.039*	(0.020)	0.055***	(0.004)	–0.093***	(0.020)
R^2	0.399		0.749		0.324	
# firms / # observations	5,340 / 21,736		5,340 / 21,736		5,340 / 21,736	

Note: This table shows the results of the testing for a parallel trend and pre-treatment effects in TFPC, TC and SEC using the model specifications of eq. (5) and eq. (6). R^2 is unadjusted. Robust standard errors at the firm level are reported in parenthesis. Asterisks *** indicate significance at 1 percent level, ** at 5 percent level and * at 10 percent level.

We do not reject the hypothesis of parallel trends. Results of the two tests with respect to TFP change and its subcomponents are given in Table 2. Results are shown for the test of model specification DD–3, our, as discussed later on, preferred model.[36] With a statistically non-significant coefficient estimate of the interaction between the

[36] Using eq. (5), the parallel trend was tested, and found to hold, also for model specifications DD–1 and DD–2.

time indicator and the treatment, both methods—i.e., eq. (5) and eq. (6)—find their respective null hypothesis to hold for all three firm performance indicators (TFPC, TC and SEC).[37] The time trend and year 2005 fixed effect, even though statistically insignificant, suggest that TFP change on average was slightly slowing down with time in the pre-regulation period.

5 Results

Table 3 presents estimated values of TFP change (TFPC) and its subcomponents of technical change (TC) and scale efficiency change (SEC).[38] Results were derived using the estimated cost function coefficients, which are reported in Table 20 in the appendix. The cost functions of the three subindustries are monotonic and otherwise well behaved (Table 22) and quasi-concave (Table 23). TFP growth is positive for all three subindustries, suggesting continuously increasing TFP levels in the Chinese iron and steel industry on average between 2003 and 2008. TC contributes about 60 percent to average TFP change and thus is of higher importance than SEC. The iron- and steelmaking subindustry shows highest average TFP growth, followed by the steel rolling and ferroalloy smelting subindustry. Again, TC is the dominating contributor towards TFP growth in the steel rolling subindustry, while TC and SEC roughly are equally important in the ferroalloy smelting industry.

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[37] Of course, we are aware that the number of years observed before the introduction of the regulation is relatively small in order to test for a parallel trend.

[38] All estimations in this study were computed using Stata 13 (StataCorp, 2013).

Table 3: *Descriptive statistics of estimated TFPC, TC and SEC.*

	Mean	Median	Std. dev.	10% perc.	90% perc.
			Full period (2003-2008)		
All subindustries			[# firms: 5,340 / # observations: 27,076]		
TFPC	0.064	0.056	0.108	–0.028	0.171
TC	0.041	0.042	0.039	0.001	0.085
SEC	0.023	0.015	0.098	–0.053	0.110
Iron- and steelmaking			[# firms: 1,025 / # observations: 4,968]		
TFPC	0.100	0.086	0.119	–0.009	0.222
TC	0.064	0.068	0.037	0.016	0.108
SEC	0.035	0.023	0.111	–0.058	0.133
Steel rolling			[# firms: 3,353 / # observations: 17,391]		
TFPC	0.058	0.051	0.085	–0.016	0.141
TC	0.039	0.040	0.022	0.011	0.066
SEC	0.019	0.013	0.081	–0.048	0.094
Ferroalloy smelting			[# firms: 962 / # observations: 4,717]		
TFPC	0.051	0.053	0.155	–0.102	0.203
TC	0.024	0.030	0.069	–0.069	0.106
SEC	0.028	0.019	0.134	–0.073	0.149
			Pre-regulation period (2003-2005)		
Treated			[# firms: 148 / # observations: 410]		
TFPC	0.026	0.023	0.055	–0.033	0.085
TC	0.012	0.015	0.036	–0.035	0.052
SEC	0.014	0.002	0.042	–0.011	0.048
Non-treated			[# firms: 5,192 / # observations: 12,173]		
TFPC	0.088	0.073	0.115	–0.013	0.212
TC	0.051	0.051	0.030	0.019	0.085
SEC	0.037	0.023	0.108	–0.058	0.148
SOE			[# firms: 326 / # observations: 725]		
TFPC	0.048	0.036	0.083	–0.034	0.133
TC	0.034	0.033	0.038	–0.010	0.081
SEC	0.014	0.004	0.070	–0.039	0.079
Non-SOE			[# firms: 5,120 / # observations: 11,858]		
TFPC	0.088	0.073	0.116	–0.014	0.213
TC	0.051	0.051	0.031	0.018	0.085
SEC	0.037	0.024	0.108	–0.057	0.149

Note: The first four panels show the descriptive statistics of overall and subindustry-specific mean TFPC, TC and SEC values for the period of 2003 to 2008. The overall values (first panel "All subindustries") are based on all observations of the sample, i.e. the three subindustries are implicitly weighted by their number of observations. The four panels at the bottom of the table show the statistics for treated and non-treated firms for the pre-regulation period between 2003 and 2005. Firms might change ownership over time. For that reason, the number of SOEs and non-SOEs does not sum to the total number of firms.

5.1 Effect of Regulation on TFP Change

We describe the findings on the intensive margin of the T1000P on TFP change (including its subcomponents), which relates to the competitiveness of treated and non-treated firms in the Chinese iron and steel industry. The results are shown below. Treatment effects are estimated based on expression (4), with results being shown in Table 4.[39] We estimate and compare three model specifications (DD–1 to DD–3), which in a stepwise manner account for time-varying structural heterogeneity. The most parsimonious specification is the first model (DD–1). The second model (DD–2) additionally accounts for time varying heterogeneity related to ownership and size. Finally, the third model (DD–3) allows for year-specific shocks on provincial level as the local governmental officials evaluated annually on the achievement of the T1000P energy-saving targets (cf. section 2.3). Political shocks on provincial level could potentially affect the enforcement of the regulation in a particular year. All three models include firm fixed effects and capture shocks on national level via year fixed effects.

Estimated treatment effects are robust in terms of sign, magnitude and significance across all three model specifications. The third model is our preferred specification, as it most extensively controls for potential cofounding factors. TFP change of treated firms on average is positively and statistically significantly affected by the T1000P. Model specification DD–3 estimates the annual TFP growth rate to increase by 3.1 percent[40] in wake of the regulation. As treated firms showed an average annual TFP change of 2.6 percent before the implementation of the T1000P (cf. Table 3), the incre-

[39] We only have observations on three years where the regulation was active. However, firms are described to have started with energy saving adjustment processes immediately as the T1000P forced them to comply with yearly targets. Zhao, Li et al. (2014) study the behavior of a power plant and observe this plant to have addressed most of the internal energy management reforms, including retrofits, by 2007. See also Price, Wang et al. (2010) for a description of first year energy saving measures of firms exposed to the T1000P.

[40] An annual increase in TFP change of 3.1 percent corresponds to an additional, regulation induced average yearly increase in TFP levels of treated firms of $e^{0.031} - 1 \cong 0.031$ compared to non-treated firms. Treated firms showed an average gross output of 4,795.8 mRMB in 1998 values before the introduction of the regulation. Hence, on a per firm basis, a back-of-the-envelope calculation of average annual private benefits induced by the regulation through productivity gains for the period of 2006 to 2008 yields 148.7 million RMB (in 1998 values).

mental T1000P-induced increase in TFP change amounts to 0.081 percentage points. The disaggregation of TFP change into its subcomponents yields further insights in terms of whether firms responded to the regulation by adjusting technical change TC (e.g., by installing new machinery) or their scale efficiency SEC (e.g., by increasing output[41]). Both subcomponents are significantly affected by the policy and, on average, contribute about equally to the overall treatment effect.[42]

Table 4: *ATTs on TFPC, TC and SEC.*

DD version:	DD–1		DD–2		DD–3	
ATT on TFPC	0.029***	(0.004)	0.029***	(0.004)	0.031***	(0.005)
ATT on TC	0.013***	(0.002)	0.013***	(0.002)	0.012***	(0.002)
ATT on SEC	0.017***	(0.003)	0.016***	(0.004)	0.019***	(0.004)
# firms / # obs.	5,340 / 21,736		5,340 / 21,736		5,340 / 21,736	
R^2 (TFPC / TC / SEC)	0.368 / 0.685 / 0.300		0.373 / 0.686 / 0.307		0.399/ 0.749 / 0.324	
F-statistic (TFPC / TC / SEC)			22.63***/ 2.00 / 25.45***		4.70*** / 21.26*** / 3.07***	
Size	No		Yes		Yes	
Ownership	No		Yes		Yes	
Province × Year	No		No		Yes	

Note: This table shows the ATT on TFPC, TC and SEC between 2006 and 2008 using eq. (4). Only estimates of β_{ATT} are shown. For the sake of conciseness, estimates of $\boldsymbol{\theta}_t$, $\boldsymbol{\gamma}$ and province-year effects are not shown. All three model specifications (DD–1 to DD–3) control for firm fixed effects. R^2 values of the estimations with TFPC, TC or SEC as dependent variable are unadjusted. F-statistics show the joint significance of the additionally introduced size, ownership and province-year variables. Robust standard errors at the firm level are reported in parenthesis. Asterisks *** indicate significance at 1 percent level, ** at 5 percent level and * at 10 percent level.

5.2 Robustness checks

We check the robustness of the previously presented empirical benchmark results via four approaches. The first robustness check estimates model (4) using stratified samples. Sample stratification with respect to key variables refines the counterfactual

41 The firms of all three subindustries on average were found to exhibit positive returns to scale (cf. Table 21 in the appendix).

42 Due to a generally observed low industrial concentration, Price, Levine et al. (2011) described China's energy intensive industrial sector to still have large energy saving potential through mergers and acquisitions and promoting economies of scale.

groups and ensures that treated firms are compared to similar non-treated firms only. As noted by Greenstone (2002) or Meyer (1995), a comparison of treated and non-treated firms should be based on similar entities to ensure efficiency and consistency. We stratify the sample, and thereby increase similarity, in the dimensions of size, ownership, and other important characteristics. Second, we test robustness with respect to sample attrition. Third, in form of a third robustness check, we use an instrumental variable approach to account for potential time varying unobserved heterogeneity not orthogonal to T1000P exposure.[43] Finally, we test robustness considering another potentially confounding policy implemented during the same time period.

5.2.1 Sample Stratification

The following estimations are based on samples stratified with respect to firm size, ownership structure. We also stratify using subindustry and geographic region, and the results can be found in the Appendix A.3. Table 5 shows every stratum contains enough observations on treated firms for statistical inference. As a first robustness check, we re-estimate model (4) based on a sample that only includes firms of the fourth quartile of the size distribution. Larger firms, for example, might be more capable of affording investments into production processes, independently of whether or not a firm is exposed to a policy and especially in mature heavy industries like the iron and steel industry. Furthermore, positive scale effects (cf. Table 21 in the appendix) lower the adoption costs of new technologies per unit of output, while productive benefits of the new technology might be independent from the level of output. As the main selection criterion of

[43] Some firms could have been forced to reduce their energy consumption to a higher degree compared to pre-regulation levels than other firms. If such varying regulation stringency is correlated with observed covariates, estimated ATTs could be biased. While firm-specific T1000P abatement targets and achievement rates are reported, energy consumption levels remain unobserved. It therefore is not possible to explicitly account for such potentially distortionary effects. Furthermore, because we observe only three regulation periods, we also restrain from analyzing the role of general equilibrium effects. Non-treated firms, after having observed the positive effect of the regulation on treated firms, could have started to implement innovation enhancing processes as well in order to reduce energy consumption. Such general equilibrium effects could distort the estimated effect of the regulation on the performance of treated firms. It would reduce the differential in TFP change between treated and non-treated firms, and therefore could result in an underestimation of the treatment effect.

the T1000P was an energy consumption of at least 180 ktce, only large firms were exposed to the regulation and thus all treated firms belong to the fourth quartile of the size distribution. The results presented in Table 6 are in the ballpark of the benchmark results of Table 4, with treatment effects being slightly larger for the sample including only large firms.

The relationship between firm ownership and productivity of Chinese firms has been well documented (Dollar and Wei, 2007; Dougherty, Herd et al., 2007). However, the underlying mechanisms by which ownership influences productivity remain poorly understood. One difficulty inherent in relating ownership to outcomes is that ownership is not uniform in the structures, incentives, and reporting relationships it implies, and may be conditioned by a wide variety of circumstantial factors. State ownership, for instance, could imply varying degrees of direct state control and preferential access, for instance, to capital or land. Performance incentives may likewise vary widely within state-owned enterprises, conditioned by subindustry and the level of government control.[44] Table 7 reports the results of the second robustness check based on a stratified sample with respect to ownership. Models DD–2 and DD–3 are modified by excluding ownership fixed effects. The regulation is found to have a similar effect on TFP change and subcomponents thereof for SOEs and non-SOEs. Our finding is evidence that firms of both ownership types faced about an equal pressure to increase TFP. This would also contradict the hypothesis of SOEs having had weaker obligations to comply with the regulation or having faced softer constraints on the output and input markets, which would have enabled them to bear compliance costs without becoming more competitive.

In conclusion, the results using stratified samples are in line with the results of the benchmark specification of Table 4. This is an indication that the dimensions of stratifi-

[44] Time effects are specific for a stratified sample, controlling for time-varying heterogeneity on the level of stratification instead of the overall level. An example of time effects specific to firm ownership could be time-varying efforts of the government to improve the competitiveness of SOEs through programs like subsidized access to capital. Such efforts could vary across firms and time, as they may have, for instance, grown stronger with the onset of the Eleventh FYP.

cation are not major sources of bias, increasing our confidence in the consistency of these results.

Table 5: *Number of treated and non-treated firms by strata.*

	Treatment group		Control group	
	# firms	# obs.	# firms	# obs.
Total	148	848	5,192	26,228
Stratification by size				
4^{th} quartile of firm size	148	848	1,187	6,311
Stratification by ownership type				
SOE	54	312	127	667
Non-SOE	65	370	4,314	21,560

Note: This table shows the number of firms and observations conditional on treatment and sample stratification. When stratifying by ownership type, observations do no sum up to the total of 27,076, because firms changing their ownership type over time are dropped.

Table 6: *ATTs of sample stratified to contain the fourth quartile of firm sizes.*

DD version:	DD–1		DD–2		DD–3	
ATT on TFPC	0.034***	(0.005)	0.033***	(0.005)	0.035***	(0.005)
ATT on TC	0.010***	(0.002)	0.010***	(0.002)	0.010***	(0.002)
ATT on SEC	0.024***	(0.004)	0.023***	(0.004)	0.025***	(0.005)
# firms / # obs.	1,335 / 5,824		1,335 / 5,824		1,335 / 5,824	
R^2 (TFPC / TC / SEC)	0.387 / 0.624 / 0.302		0.393 / 0.624 / 0.310		0.422 / 0.687 / 0.331	
F-statistic (TFPC / TC / SEC)			6.43*** / 0.06 / 6.38***		6.32*** / 14.86*** / 2.08***	
Size	No		Yes		Yes	
Ownership	No		Yes		Yes	
Province × Year	No		No		Yes	

Note: This table shows the ATT on TFPC, TC and SEC between 2006 and 2008 using eq. (4). The allocation of firms to the 4^{th} size quartile is based on the number of people employed in 2005 (the year before the introduction of the T1000P). Only estimates of β_{ATT} are shown. For the sake of conciseness, estimates of $\boldsymbol{\theta}_t$, $\boldsymbol{\gamma}$ and province-year effects are not shown. All three model specifications (DD–1 to DD–3) control for firm fixed effects. R^2 values of the estimations with TFPC, TC or SEC as dependent variable are unadjusted. F-statistics show the joint significance of the additionally introduced size, ownership and province-year variables. Robust standard errors at the firm level are reported in parenthesis. Asterisks *** indicate significance at 1 percent level, ** at 5 percent level and * at 10 percent level.

Table 7: *ATTs of samples stratified with respect to ownership types.*

Model Version:	DD–1		DD–2owner		DD–3owner	
			SOE			
ATT on TFPC	0.020**	(0.009)	0.020**	(0.010)	0.023*	(0.012)
ATT on TC	0.010*	(0.005)	0.010**	(0.005)	0.013**	(0.005)
ATT on SEC	0.010	(0.008)	0.010	(0.009)	0.010	(0.012)
# firms / # obs.	181 / 798		181 / 798		181 / 798	
R^2 (TFPC / TC / SEC)	0.316 / 0.703 / 0.166		0.320 / 0.704 / 0.173		0.434 / 0.787 / 0.299	
F-statistic (TFPC / TC / SEC)			1.27 / 0.20 / 2.12		98.2*** / 17.9*** / 13.4***	
			Non-SOE			
ATT on TFPC	0.024***	(0.006)	0.020***	(0.006)	0.023***	(0.008)
ATT on TC	0.013***	(0.003)	0.013***	(0.003)	0.012***	(0.003)
ATT on SEC	0.011*	(0.006)	0.006	(0.006)	0.011	(0.008)
# firms / # obs.	4,379 / 17,551		4,379 / 17,551		4,379 / 17,551	
R^2 (TFPC / TC / SEC)	0.356 / 0.683 / 0.288		0.362 / 0.683 / 0.296		0.395 / 0.754 / 0.320	
F-statistic (TFPC / TC / SEC)			39.28*** / 0.45 / 44.27***		13.0*** / 36.1*** / 11.6***	
Size	No		Yes		Yes	
Province × Year	No		No		Yes	

Note: This table shows the ATT on TFPC, TC and SEC between 2006 and 2008 using eq. (4). Firms changing their ownership type over time are dropped from the analysis. For this reason, observations do no sum up to the numbers given in Table 4. Only estimates of β_{ATT} are shown. For the sake of conciseness, estimates of $\boldsymbol{\theta}_t$, $\boldsymbol{\gamma}$ and province-year effects are not shown. All three model specifications (DD–1 to DD–3) control for firm fixed effects. R^2 values of the estimations with TFPC, TC or SEC as dependent variable are unadjusted. *F*-statistics show the joint significance of the additionally introduced size, ownership and province-year variables. Robust standard errors at the firm level are reported in parenthesis. Asterisks *** indicate significance at 1 percent level, ** at 5 percent level and * at 10 percent level.

5.2.2 Sample Attrition

Firms leaving the sample might distort the randomness of the panel and endanger its representativeness of the population as a whole (Baltagi, 2008). Sample attrition could be problematic along several dimensions. For example, treated firms characterized by low TFP changes unilaterally could leave the sample after the implementation of the regulation because compliance costs renders them uncompetitive. Such sample attrition could result in an upward bias of estimated treatment effects. Conversely, a downward selection bias in estimated treatment effects could result if more productive firms unexposed to the regulation were more likely to survive. We therefore tested the robustness of our benchmark results using a balanced panel.[45]

The unbalanced sample contains 5,340 firms. While a total of 1,077 firms exit the sample, only 6 out of 143 treated firms leave the sample (all of them in 2007).[46] A total of 2,047 firms (out of 5,340) are observed over the full period (2003 to 2008). As out of 2,173 firms entering the sample in 2004 only 459 firms were founded in that year, i.e. report a firm age of zero, the sample without attrition is defined by the 2,047 firms observable for the full range of years 2003 to 2008 plus the 1,354 firms entering in 2004, which have a firm age older than zero years and are subsequently observed until 2008. The re-definition of the sample necessitates a re-calculation of the approximation points of the subindustry-specific translog cost functions and a subsequent re-estimation of TFPC, TC and SEC values. The estimated coefficients of the subindustry-specific cost functions are given in the appendix in Table 24 and the firm performance estimates in Table 25. The null hypothesis of a parallel trend in firm performance before the introduction of the regulation is not rejected for the new sample (cf. Table 26). The evalua-

[45] Two other possibilities to correct for attrition bias are described for instance in Greenstone, List et al. (2012). The first approach would use a two-stage regression approach of Heckman (1979) accounting for firm survival in a first stage and including a respective correction term in the second stage. The second approach would consist of inferring the unobservable TFP change (or TC or SEC) distribution of exiting plants and subsequently using this information to correct the TFP change estimates suffering from selection bias.

[46] It is unknown whether exiting firms actually ceased production or were simply not covered by the census of 2008. 50 firms exited in 2007 and 627 firms exited 2008. Over the whole period, 2,805 firms enter the sample, with 2,173 firms entering in 2004 and 632 firms entering in 2005.

tion of the effect of the T1000P on TFP change and its subcomponents using the sample free of attrition yields results (cf. Table 8) stay in close range in terms of sign, magnitude and significance to those of the corresponding benchmark specification. Hence, we consider the benchmark estimates as being robust to attrition bias, even though the effect of technical change TC gains slightly in importance when using the balanced panel. As the ratio of exiting firms is smaller for the treatment than for the control group, this finding could support the argument of lower performing firms in the control group being more likely to exit. In such a situation, using a sample without attrition would lead to an upward bias in the estimated treatment effect on TC.

Table 8: *ATTs using the balanced panel to control for attrition bias.*

DD version:	DD–1		DD–2		DD–3	
ATT on TFPC	0.028***	(0.004)	0.028***	(0.004)	0.033***	(0.005)
ATT on TC	0.017***	(0.003)	0.017***	(0.003)	0.018***	(0.003)
ATT on SEC	0.011***	(0.004)	0.011***	(0.004)	0.015***	(0.005)
# firms / # obs.	3,401 / 15,651		3,401 / 15,651		3,401 / 15,651	
R^2 (TFPC / TC / SEC)	0.285 / 0.716 / 0.226		0.291 / 0.716 / 0.234		0.320 / 0.753 / 0.255	
F-statistic (TFPC / TC / SEC)			16.04*** / 1.22 / 17.67***		3.69*** / 18.74*** / 2.81***	
Size	No		Yes		Yes	
Ownership	No		Yes		Yes	
Province × Year	No		No		Yes	

Note: This table shows the ATT on TFPC, TC and SEC between 2006 and 2008 using eq. (4). The panel covers the period 2004 to 2008. Only estimates of β_{ATT} are shown. For the sake of conciseness, estimates of $\boldsymbol{\theta}_t$, $\boldsymbol{\gamma}$ and province-year effects are not shown. All three model specifications (DD–1 to DD–3) control for firm fixed effects. R^2 values of the estimations with TFPC, TC or SEC as dependent variable are unadjusted. *F*-statistics show the joint significance of the additionally introduced size, ownership and province-year variables. Robust standard errors at the firm level are reported in parenthesis. Asterisks *** indicate significance at 1 percent level, ** at 5 percent level and * at 10 percent level.

5.2.3 Instrumenting for Regulation Exposure

We apply an instrumental variable (IV) approach in order to check for external validity and consistency of the estimated treatment effect. For example, even though state ownership is positively correlated with firm size and firm size with energy consumption, it is unclear whether there are additional unobserved time varying factors (e.g., political preferences) that underlie the observed high share of treated SOEs and are correlated with the outcome variables.

The instrument is supposed to be orthogonal to τ_i , but not to the outcome variable. Our instrument for T1000P participation uses information on the geographic location of firms. It is based on a distance-weighted index of the ratio of the number of treated firms to the total number of firms in the geographic cluster of the firm and neighboring clusters. The geographic clusters within such a group are indexed by *h*, with an individual cluster being defined by a county *q*. As shown by Figure 3, a county is most probable to have seven neighbors. The instrument draws its validity from the roots of the Chinese economy, with clusters of iron and steel firms being dispersed across the country (cf. Figure 1 and Figure 2). In can be hypothesized that such industrial clusters are inherently connected to unobserved time varying heterogeneity affecting T1000P exposure such as social, environmental, political or institutional characteristics. Our instrument also can be assumed to satisfy the exclusion restriction with clusters—given firm fixed effects are controlled for—only having limited influence on the performance of an individual firm. The instrument τ_i^{IV} is based on year 2005 observations and for a firm *i* in county *q* can be given as

$$\tau_i^{IV} = \frac{\sum_h \frac{1}{d_{qh}} \cdot \phi_h}{\sum_h \frac{1}{d_{qh}}}, \tag{7}$$

where d_{qh} is the distance in kilometers between the firm's county *q* and neighboring counties, as summarized by Figure 3. The distance weight of a firm's own county is 1. The ratio of treated firms to the total number of firms in a cluster is ϕ_h . Note that τ_i^{IV} does not differ between firms belonging to the same cluster *q*. Descriptive statistics of τ_i^{IV} are given in Table 9.

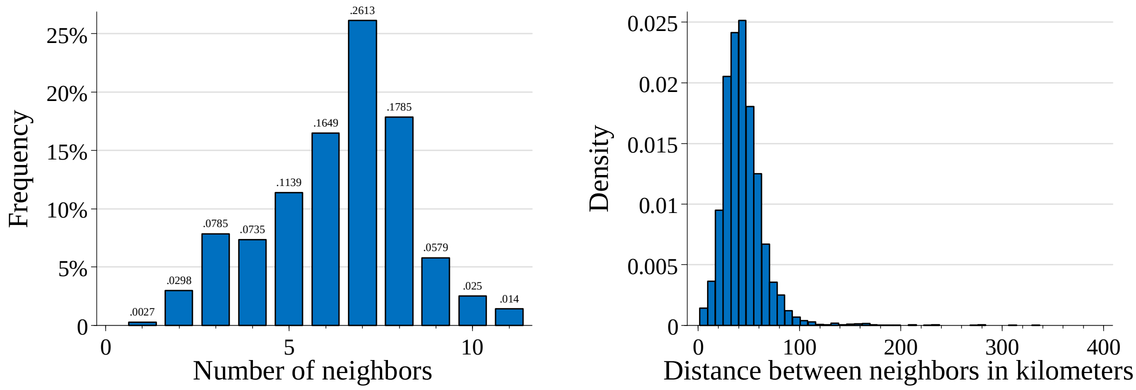

Figure 3: *Distributions of the number of neighbors and distances between clusters.*

Table 9: *Descriptive statistics of the instrument* τ^{IV}.

	Mean	Std.dev.	Min.	Max.	Corr.[A]
τ^{IV}	0.027	0.071	0	0.950	0.537
τ	0.032	0.176	0	1	

Note: This table shows descriptive statistics of the instrument τ_i^{IV} derived according to eq. (7). For comparison, descriptive statistics of the instrumented variable τ_i are given as well.

[A]: Correlation between the benchmark treatment variable τ_i and the instrumented treatment τ_i^{IV} is based on the square root of the pseudo R^2 value of a logit regression of τ_i^{IV} on τ_i .

The empirical estimation is based on a panel data two-stage least squares (2SLS) within estimator. Our approach controls for firm fixed effects and allows for a correlation of errors between the two stages. Given that τ_i is a binary variable and the outcome variable of the second stage is continuous, we decided to follow Angrist (2001) and use a linear probability model (LPM) in the first stage.[47] As noted by Angrist (2001), the estimation of a 2SLS model applying a LPM in the first stage bears the benefit of consistency, independently of whether or not the first-stage conditional expectation function is linear.[48] As all variables included in the first stage are of limited range,

[47] The implications of such a procedure are also described in Lewbel, Dong et al. (2012).

[48] Of course, we are aware of that we also could have used a logit or probit model in the first stage and, for example, adjust the standard errors of the second stage via bootstrapping. As noted by Angrist

(*Footnote continues on next page*)

the supporting restriction of the LPM of no regressor having infinite support is satisfied.[49] Equation (4) first is within transformed, thereby accounting for α_i, and then a 2SLS methodology is applied instrumenting for τ_i by τ_i^{IV} in the first stage. The methodology is described in detail in Baltagi (2008).

First, the instrument τ_i^{IV} was found to be valid.[50] First stage results are shown in Table 10. Results shown in Table 11 indicate that instrumenting for T1000P selection yields overall treatment effects, which are very similar in terms of magnitude and significance to the benchmark results of all three model specifications (cf. Table 4). TC gains in magnitude, while SEC loses significance. However, these changes do not translate into largely different overall results of the effect of the T1000P on overall TFP change.

(2001), such a procedure however would carry the drawback that, unless the first-stage conditional expectation function is correct, the second-stage estimates would be inconsistent.

49 If some regressors would show an infinite support, the first stage estimation could yield fitted probabilities of impossible magnitudes, i.e. below zero or above one (Lewbel, Dong et al., 2012).

50 The Davidson-MacKinnon test of exogeneity (Davidson and MacKinnon, 1993) rejects at a 1 percent significance level, indicating that the benchmark ATT variable indeed might be endogenous. The Kleibergen-Paap rk LM and rk Wald *F*-statistics (Kleibergen and Paap, 2006) both reject at a significance level of one percent. Hence, the instrument is found be relevant, i.e. not weak.

Table 10: *First stage results of 2SLS.*

DD version:	DD–1		DD–2		DD–3	
τ^{IV}	1.254***	(0.070)	1.257***	(0.070)	1.258***	(0.071)
Year 2005 (θ_{2005})	0.008***	(0.001)	0.008***	(0.001)	0.026**	(0.012)
Year 2006 (θ_{2006})	0.005*	(0.003)	0.007**	(0.003)	0.010	(0.031)
Year 2007 (θ_{2007})	0.006**	(0.003)	0.008***	(0.003)	0.009	(0.031)
Year 2008 (θ_{2008})	0.008***	(0.003)	0.008***	(0.003)	0.008	(0.032)
Size			0.006**	(0.002)	0.007***	(0.002)
Ownership			–0.019***	(0.005)	–0.019***	(0.006)
Province × Year	⋮		⋮		⋮	
# firms / # obs.	5,156 / 21,199		5,156 / 21,199		5,156 / 21,199	
R^2	0.275		0.277		0.280	
Size	No		Yes		Yes	
Ownership	No		Yes		Yes	
Province × Year	No		No		Yes	

Note: This table shows the first stage regression results of the 2SLS procedure. All three model specifications (DD–1 to DD–3) control for firm fixed effects. For the sake of conciseness, estimates of province-year effects are not shown. R^2 is centered. Robust standard errors at the firm level are reported in parenthesis. Asterisks *** indicate significance at 1 percent level, ** at 5 percent level and * at 10 percent level.

Table 11: *ATT on TFPC, TC and SEC when instrumenting for T1000P exposure.*

DD version:	DD–1		DD–2		DD–3	
IV-ATT on TFPC	0.032**	(0.013)	0.035***	(0.013)	0.036***	(0.014)
IV-ATT on TC	0.025***	(0.005)	0.024***	(0.005)	0.023***	(0.005)
IV-ATT on SEC	0.007	(0.012)	0.011	(0.012)	0.013	(0.012)
# firms / # obs.	5,156 / 21,199		5,156 / 21,199		5,156 / 21,199	
R^2 (TFPC / TC / SEC)	0.082 / 0.099 / 0.049		0.090 / 0.100 / 0.059		0.127 / 0.281 / 0.082	
F-statistic (TFPC / TC / SEC)			59.21*** / 5.86* / 67.10***		699*** / 3,253*** / 467***	
Size	No		Yes		Yes	
Ownership	No		Yes		Yes	
Province × Year	No		No		Yes	

Note: This table shows the second stage results of the 2SLS procedure of ATT on TFPC, TC and SEC between 2006 and 2008 using eq. (4). Only estimates of β_{ATT} are shown. For the sake of conciseness, estimates of $\boldsymbol{\theta}_t$, $\boldsymbol{\gamma}$ and province-year effects are not shown. All three model specifications (DD–1 to DD–3) control for firm fixed effects. R^2 values of the estimations with TFPC, TC or SEC as dependent variable are centered. F-statistics show the joint significance of the additionally introduced size, ownership and province-year variables. Robust standard errors at the firm level are reported in parenthesis. Asterisks *** indicate significance at 1 percent level, ** at 5 percent level and * at 10 percent level.

5.2.4 Potential Time-Varying Confounder

Our main results rely on the assumption that there are no omitted time-varying and firm-specific effects correlated with T1000P participation. We have conducted an extensive review of policies potentially affecting the iron and steel sector during the study period, and found one policy that could be a potential confounder.

Along with the goals to reduce inefficient energy use in the energy-intensive sectors via the T1000P program, the national government also implemented a program to eliminate outdated production capacity during the Eleventh FYP. The program defined production technologies that would be limited or eliminated in all sectors (NDRC, 2005a). For the iron and steel sector, outdated technologies were defined in a specific document, e.g. blast furnaces for iron smelting with a capacity less than 300 m^3 (NDRC, 2005b). Later, a detailed implementation plan was announced in 2006 (NDRC, 2006a). Though the complete list of firms that were covered by the program was not published, fortunately we were able to find a list of firms in a subset of provinces that were subject to the first phase of this program (NDRC, 2007). These firms were required to shut down or retire or update part of their production capacity.

This list included 344 firms in ten provinces, including Beijing, Hebei, Shanxi, Liaoning, Jiangsu, Zhejiang, Jiangxi, Shandong, Henan, and Xinjiang. We successfully matched 115 firms with the CIC data. Among the ten provinces, only Shanxi and Jiangsu have more than ten firms matched (47 and 40 firms respectively, in total 87 firms). Therefore, we limit the sample for this robustness check to these two provinces and remove these 87 firms to avoid any potentially confounding effect from this policy.

The results are shown in Table 12. Though significance of the treatment effects drops mildly due to a much smaller sample size, the size of the effects remains very close to the benchmark results of all three model specifications (cf. Table 4), providing the evidence that the impacts of the T1000P on the TFP change are strong even after accounting for the potentially confounding policy.

Table 12: *ATT on TFPC, TC and SEC when accounting for a potentially cofounding policy.*

DD version:	DD–1		DD–2		DD–3	
ATT on TFPC	0.030***	(0.007)	0.027***	(0.008)	0.034***	(0.010)
ATT on TC	0.014***	(0.004)	0.014***	(0.004)	0.010*	(0.005)
ATT on SEC	0.016**	(0.007)	0.013*	(0.007)	0.024***	(0.009)
# firms / # obs.	1,068 / 4,531		1,068 / 4,531		1,068 / 4,531	
R^2 (TFPC / TC / SEC)	0.355 / 0.730 / 0.267		0.358 / 0.731 / 0.274		0.362/ 0.736 / 0.279	
F-statistic (TFPC / TC / SEC)			3.94**/ 2.05 / 5.37***		2.63** / 13.81*** / 3.51***	
Size	No		Yes		Yes	
Ownership	No		Yes		Yes	
Province × Year	No		No		Yes	

Note: This table shows the ATT on TFPC, TC and SEC between 2006 and 2008 using eq. (4). Only estimates of β_{ATT} are shown. For the sake of conciseness, estimates of $\boldsymbol{\theta}_t$, $\boldsymbol{\gamma}$ and province-year effects are not shown. All three model specifications (DD–1 to DD–3) control for firm fixed effects. R^2 values of the estimations with TFPC, TC or SEC as dependent variable are unadjusted. F-statistics show the joint significance of the additionally introduced size, ownership and province-year variables. Robust standard errors at the firm level are reported in parenthesis. Asterisks *** indicate significance at 1 percent level, ** at 5 percent level and * at 10 percent level.

6 Conclusions

In this paper, we present the first analysis of the effects of the T1000P on TFP change in Chinese iron and steel firms. We find positive effects of the regulation on firms' TFP change that, on average, outweigh any negative effects. Our finding is surprising in light of the large literature pointing to net negative effects of regulation on productivity, and constitutes one of very few empirical studies that has found evidence of a positive impact of environmental regulation on an economic measure of performance. In the sense that we find evidence of enhanced innovative performance among regulated firms, our results are consistent with the Porter hypothesis.

Specifically, we find that the treatment group experienced a statistically significant increase in TFP change of 3.1 percent after the introduction of the regulation in comparison to the control group, which is equivalent to an absolute incremental increase in TFP change by 0.081 percentage points. T1000P exposure positively affected technical change and scale efficiency change to a similar extent, i.e. firms appear to have complied with the regulation not only by changing their production processes by, e.g., installing new machinery and equipment, but also by expanding output to realize efficiency gains. On average, the annual private economic benefit of the regulation for a treated firm through gains in productivity is estimated to amount to 148.7 mRMB in 1998 values. However, these are firm level benefits, and thus ignore social benefits of, e.g., cleaner air or less degradation of the environment. Results are robust in terms of sign, magnitude and significance with respect to the dimensions of firm size and ownership structure. Interestingly, non-SOEs on average experienced a similar positive effect of T1000P exposure on TFP change compared to SOEs. Furthermore, results are robust with respect to sample attrition, potential endogeneity in T1000P exposure, and another time-varying firm-specific confounder. In conclusion, a firm exposed to the regulation likely profited twofold: first, it profited through the direct effect of reduced costs through less expenditure on energy. Second, we find evidence that the regulation lead to an increase in TFP change relative to non-treated firms and hence increased the competitiveness of the treated firms.

There are at least two explanations for this observation. One is that indeed firms were induced by the policy—through a combination of carrots and sticks—to realize higher levels of productivity that ultimately benefitted them. This explanation is consistent with the traditionalist view. There are several channels through which this may have occurred. The program may have reduced or neutralized the cost of capital for new equipment or retrofits that met policy criteria, inducing firms to undertake investments with longer-term payoffs than they would otherwise have made. Substantial public resources were devoted to funding these upgrades. While firms may have benefited, our analysis says nothing about the economy-wide cost of the T1000P, especially if publicly-funded subsidies offered in connection with the program played a substantial role. In fact, public support that neutralized costs to firms, or even benefited them, may have been necessary to entice firms to participate in the program in the political bargaining process. We might expect to see similar tradeoffs embedded in bargains over environmental policy between regulators and regulated parties in other developing country contexts.

A second explanation is consistent with a behavioralist rationale. Firms in China may have been unaware of—or unwilling to pursue—savings possible from implementing energy efficient technologies and processes. Benefits from the program may have reflected a "correction" to firm behavior. Given that large public subsidies for program participants and information provision were both a core part of the policy, we cannot cleanly attribute the outcomes of the policy to one explanation or the other. More work is needed to estimate the magnitude of the original untapped energy saving opportunity, and to probe whether energy saving opportunities were not pursued by firms at the outset due to inattention, deliberate rejection, hidden costs, or for some other reason.

There are diverse opportunities for future research in the field of this study. With future availability of high-quality census data for more recent years, one could analyze whether observed treatment effects persist for a prolonged period of time, how these effects change in magnitude over time, or whether they are attenuated by general equilibrium effects. Other effects potentially worth an evaluation given longer time series could be inter-firm spillovers or the extent to which treated firms started crowding out non-treated firms in the wake of gains in competitiveness. Further examples are the implementation of a structural model to describe firm behavior in terms of investing into innovation under uncertainty in response to regulatory exposure. Such model could build, e.g., on the "real options" theory of Dixit and Pindyck (1994). For example, uncertainty not only might be related to the cost and efficacy of new abatement technologies or requirements of future regulations (Berman and Bui, 2001), but also to firm characteristics like the absorptive capacity, ownership structure, and management quality.

How generalizable are these results to other policies and national contexts? Clearly, the T1000P to some extent was special. Compliance was enforced primarily through non-financial incentives. Firms received governmental support on many levels, from information provision on a provincial level, to skill building, to government-funded loans and subsidies. We cannot exclude such support as being to some extent responsible for the significant and positive effect of the T1000P on firm performance. As we have no information on the amount of these financial supports, we cannot evaluate whether or not they exceeded the (from a firm's perspective) estimated monetary benefits of the increase in TFP change. Notably, firms were free in in their decision of how to achieve their abatement targets. According to Porter and Van der Linde (1995b), this is a key condition for environmental policy to affect innovation. Hence, our finding of a positive net effect of the T1000P on TFP change, while surprising, may not be as unlikely as it first appears.

A Appendices

A.1 Panel Construction

The following sections describe the steps undertaken to match the different data sets as well as various adjustment and plausibility checks to exclude unqualified observations. Furthermore, the definition and adjustment of several variables is described in greater detail.

Linking Firms over Time

The following methodology to construct the panel is adopted from Brandt, Van Biesebroeck et al. (2012). Due to mergers, restructuring or missing information, the unique firm identifiers given to each firm by the NBS was not sufficient to construct the full panel, i.e. to connect all identical firms over time. In order to use as much within variation as possible, an extensive procedure is implemented to connect the firms over time. First, the data sets of each year are prepared to be connected in a subsequent step. Two versions of raw data were available for year 2008. One containing a higher number of different variables but with missing information on the level of the firms' administrative authority, and another with fewer variables, e.g., with missing firm ID, but containing the “authority level” variable. Therefore, the former was used as the master data set and then sequentially merged with the latter based on firm name (399,578 of total 423,948 observations merged) and area code plus telephone number (merge of 1,606 of the remaining unmerged observations). For the data set of each year, a variable is added that indicates the prefecture city where the firm is located based on the location code information. Also, duplicate observations within a single year data set are dropped.

Panel construction is started by linking the data sets of two consecutive years (step 1, illustrated in Figure 4). For each pair of two neighboring years, the firm ID is used to merge the two single year data sets *data_i* and *data_j* ($j = i + 1$). Matched observations were kept and saved as a new data set *data_ij_by_ID*. The firm name then is used to merge the unmatched observations (by firm ID) in *data_i* and *data_j*. Again, matched observations are kept and saved as a new data set *data_ij_by_name*. Similarly, matched data sets were obtained by a code based on the CEO name *data_ij_by_code1*[51] and another code based on the telephone number *data_ij_by_code2*[52]. Then, the two-year unbalanced panel *data_ij* is generated by appending these four matched data sets to the remaining unmatched observations in *data_i* and *data_j*, which are named as *data_-i_unmatched_unique_code2* and *data_j_unmatched_unique_code2*, respectively. Matching results for two consecutive years are shown in Table 13. Only looking at the matching possibility between two neighboring years may ignore the situation that one firm may not be able to match with the previous year for some reason[53] but is able to be matched in later years. To address the problem, observations from the first year and the third year in data sets of three consecutive years that have not been indirectly linked through observations of the second year in the above step are checked for a possible match.

Next, two neighboring two-year unbalanced panels *data_ij* and *data_jk* are merged with one another, keeping the observations with the full link of year i, j and k, and subsequently saved as a new balanced panel data set *balanced_data_ijk* ($j = i + 1$, $k = j + 1$). Only observations of year i are kept that are not contained in this balanced panel data set and subsequently saved as d*ata_i_not_in_balanced_ijk*. Similarly, *data_-k_not_in_balanced_ijk* can be generated for year k. Firm ID and firm name are used sequentially to find possible matches between *data_i_not_in_balanced_ijk* and *data_k_-not_in_balanced_ijk*. Matches are saved as *data_ik_by_ID* and *data_ik_by_name*. The unmatched observations from *data_i_not_in_balanced_ijk* and *data_k_not_in_-balanced_ijk* are then appended to *data_ik_by_ID* and *data_ik_by_name* to generate the unbalanced panel for year i and k (without observations that have the full link in *bal-*

[51] Code 1 is the concatenated string of the CEO name plus the 6-digit location code plus the sector code.

[52] Code 2 is the concatenated string of the telephone number plus the 6-digit location code plus the sector code.

[53] Either because of missing observations in that year, or because of missing or inconsistent variables that are used for matching.

anced_data_ijk). Then, the variables of year *j* are brought to this panel by merging *data_ik* with *data_ij* and *data_jk* under some minor adjustments[54]. Subsequently, the resulting data set *data_ik_with_j_merged* is appended to the balanced data set *balanced_-data_ijk* to construct the unbalanced three-year panel *unbalanced_data_ijk*. With these three-year panel data sets, variables of later years finally are added to the first three-year panel year by year. This is step 2 illustrated in Figure 4.

Then, illustrated as step 3 in Figure 4, the first two neighboring three-year unbalanced panels *data_ijk* and *data_jkl* obtained from the step above (i = 2003, j = 2004, k = 2005, l = 2006) are taken. To connect the variables of year l (2006) to the first three-year panel data, observations in *data_jkl* that have observations in 2006 matched with observations in 2005 are added first to *data_ijk*. Then, observations in *data_jkl* that have observations in 2006 matched with observations in 2004 only are added. Finally, observations in *data_jkl* that have observations in 2006 not matched with observations in 2004 or 2005 are added to form the four-year unbalanced panel *unbalanced_data_ijkl*. Using this new panel and the remaining data contained in the three-year unbalanced panels, the variables from 2007 to 2008 are added analogously to construct the unbalanced six-year panel that serves as the basis of this study.

[54] Some merging conflicts were found in this step because of the inconsistency of the original raw data sets. For instance, one observation in year i can be matched with one observation in year j by firm ID, and the same observation in year i can be matched with one observation in year k by firm name with a different firm ID. However, another observation in year j, different from the year j observation above, can be matched with the observation in year k by firm ID.

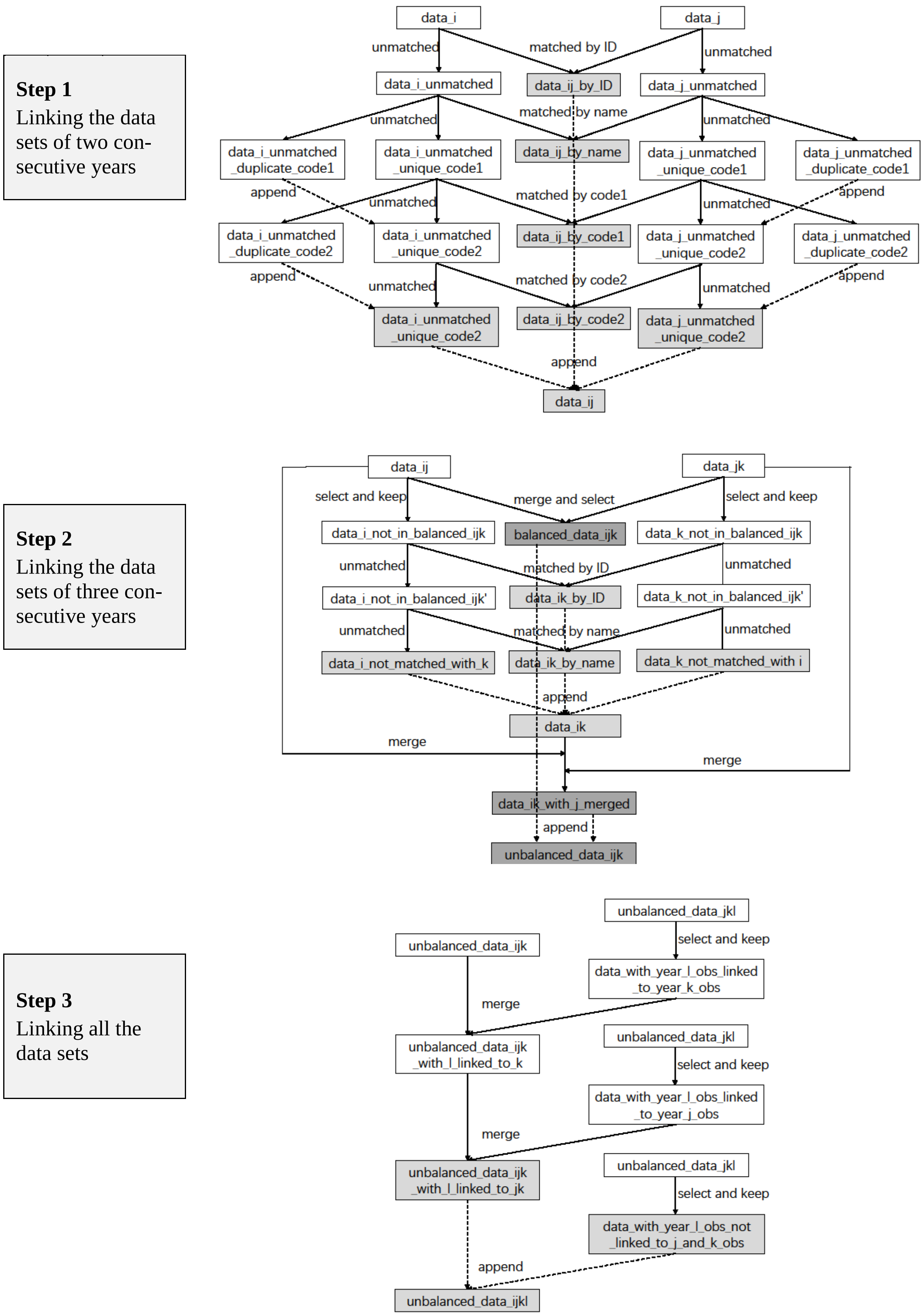

***Figure 4:** Panel construction steps.*

Table 13: *Matching results for two consecutive years.*

Year pair	Number of matched observations	Matching method	Number of matched observations by method	Number of unmatched observations former year	Number of unmatched observations latter year
2003-2004	144,337	firm ID	138,429	42,560	128,652
		firm name	555		
		code1	23		
		code2	330		
2004-2005	229,479	firm ID	225,227	43,510	35,976
		firm name	1804		
		code1	1648		
		code2	800		
2005-2006	242,617	firm ID	239,096	22,838	52,244
		firm name	1279		
		code1	1433		
		code2	809		
2006-2007	270,017	firm ID	267,122	24,844	59,455
		firm name	977		
		code1	1254		
		code2	664		
2007-2008	290,207	firm ID	279,709	39,265	113,929
		firm name	5228		
		code1	3626		
		code2	1644		

Note: This table shows the results of the matching of cross-sectional data sets of two consecutive years to a panel data set containing the information of two years.

Table 14: *Matching results for three consecutive years.*

Year pair	1st year no match	2nd year no match	3rd year no match	1st and 2nd year matched	2nd and 3rd year matched	1st and 3rd year matched	All years matched
03-04-05	38,456	31,072	33,136	12,377	96,254	2,820	133,203
04-05-06	39,135	3,594	47,907	19,225	32,325	4,332	210,304
05-06-07	21,044	4,113	57,667	20,718	48,113	1,784	221,899
06-07-08	22,494	7,379	111,557	31,840	52,052	2,333	238,187

Note: This table shows the results of the matching of two panel data sets containing the information of two consecutive years to a panel data set containing the information of three years.

Linking of T1000P Information

Most firms contained in the T1000P data set are merged with the census data based on their Chinese firm name. However, the name of some firms differed slightly between the two samples. For the subsample of the T1000P data where firm names did not match exactly with a firm in the census data a fuzzy matching process is implemented based on the Levenshtein edit distance.[55] Then, firms are checked manually for identity by means of their Chinese firm name.

Price of Material

The subindustry *s*-specific (iron, steel, steel rolling and alloy) as well as province *r*-specific price of material is calculated as follows: according the input-output table of NBS (2007) (cf. Table 15), the production process in the iron and steel industry mainly uses coal and coke (*co*), iron ore (*ir*) and electricity (*el*) as material inputs. Specifically for the period of 2003 to 2008, the relevant coal prices and electricity prices are extracted from CEIC (2015) and the iron ore prices from CCM (2015). Subsequently, these prices are deflated using an overall price deflator (constructed from NBS (2013), cf. Table 16) with respect to reference year 1998. Finally, deflated prices are aggregated to a material price index P_M by using the following Törnqvist index described in Coelli, Rao et al. (2005):

$$P_{M,srt} = \sum_{x=\{co,ir,el\}} \frac{P_{x,srt}}{P_{x,sr2003}} \cdot \rho_{x,s} \ , \quad t = \{2003,...,2008\} \, ,$$

where ρ is the subindustry-specific input-value share contained in the input-output table. Subindustries are indicated by *s* and provinces by *r*. The reference year is 2003.

[55] The calculations were done using Stata 13.0 by applying the command *strgroup*.

Table 15: *Input value shares used to calculate the price of material P_M.*

	Iron	Steel	Steel rolling	Ferroalloy
Coal input value share	0.401	0.346	0.244	0.162
Electricity input value share	0.073	0.166	0.170	0.323
Iron ore input value share	0.526	0.488	0.586	0.514

Source: NBS (2007).

Table 16: *Deflators used to adjust the price of material to reference year 1998.*

Year	2003	2004	2005	2006	2007	2008
Deflator	1.0259	1.0693	1.0392	1.0381	1.0764	1.0776

Source: NBS (2013).

Note: Deflators were constructed by taking the ratio of the nominal GDP growth rate to the real GDP growth rate.

Input and Output Deflators

It is of great importance to base the empirical analysis of production functions on a reliable and detailed measurement of input and output prices. This study uses comparatively disaggregated input and output price deflators at the four-digit industry level, which were kindly provided by Johannes Van Biesebroeck of KU Leuven. The deflators are differentiated between the three subindustries of iron and steel production, steel rolling and ferroalloy smelting, and further between inputs and outputs. Such differentiation addresses price inflation in Chinese data in a detailed manner by allowing for subindustry-specific price developments in the respective input and output markets. Furthermore, the more detailed the price deflators, the lower the risk of deflated output and input measures being contaminated by the effect of markups due to market power. The subindustry-specific input and output deflators are summarized in Table 17 and Table 18. The online appendix of Brandt, Van Biesebroeck et al. (2012) describes the construction of these deflators.

Table 17: *Output deflators (reference year = 1998).*

Year	Iron	Steel	Steel rolling	Ferroalloy smelt.
2003	1.1449	1.0059	1.0284	0.9714
2004	1.3613	1.1960	1.2227	1.1550
2005	1.4246	1.2517	1.2796	1.2087
2006	1.3676	1.2016	1.2284	1.1604
2007	1.4757	1.2965	1.3254	1.2521
2008	1.7670	1.5524	1.5870	1.4993
Average annual inflation rate				
	9.44%	9.44%	9.44%	9.44%

Source: Brandt, Van Biesebroeck et al. (2012).

Table 18: *Input deflators (reference year = 1998).*

Year	Iron	Steel	Steel rolling	Ferroalloy smelt.
2003	1.0203	1.0042	1.0106	1.0074
2004	1.1305	1.0856	1.0947	1.0927
2005	1.1854	1.1278	1.1386	1.1395
2006	1.2075	1.1404	1.1591	1.1541
2007	1.2753	1.1865	1.2110	1.2027
2008	1.5341	1.3779	1.4284	1.3520
Average annual inflation rate				
	8.69%	6.66%	7.31%	6.13%

Source: Brandt, Van Biesebroeck et al. (2012).

Geographical Information

Spatial geographic information on centroid longitude and latitude information for 2,824 counties is obtained from a commercial source (BW, 2016) and merged with the census data by using information on county names in Chinese. This merge is successful for 5,132 out of 5,274 firms, i.e. 637 observations cannot be allocated longitude and latitude information.

The construction of the instrument necessitates not only information on longitudes and latitudes, but also on the neighboring counties of a county. The information on the borders of a county is extracted from a shape file obtained from (GADM, 2016). The shape file contains border and centroid longitude and latitude information of 2,408 geographic identities of China. However, the centroids of these counties do not exactly match the geographic information that was matched to the census beforehand. Therefore, the centroid information of the firms is matched to the shape file based on the shortest geodetic distance to a centroid of the shape file. Subsequently, the neighbors of every centroid are defined and the geodetic ellipsoidal distances between the individual centroids are calculated based on longitude and latitude information.[56]

Data Screening Process

Often present when working with Chinese firm level data is the issue of misreported data. The CIC, given its sheer extent by containing all industrial firms with a yearly sales value of more than 5 million RMB, is prone to measurement errors and unrealistic outlier values (Nie, Jiang et al., 2012). As described in the following paragraphs, several plausibility checks are conducted to ensure the sample does not include misreported data.

Starting with 13,278 firms (43,357 observations), therein 190 treated firms, 324 firms (1,263 observations) are deleted because of missing observations. 6,750 firms (10,843 observations) are deleted because none of their observations overlap with the regulation period of 2006 to 2008. It is checked whether all firms exist for at least 2 years, no firm is dropped. Following Nie, Jiang et al. (2012), 96 firms (398 observations) are dropped because their mean sales value over the years is lower than 5 million RMB. Following Brandt, Van Biesebroeck et al. (2012), 132 firms (595 observations) are dropped because their number of employees is less than 8, and therefore fall under a different legal regime. Such number is also too low to qualify as an above scale firm. Then, following Cai and Liu (2009), several plausibility checks are conducted: 2 firms (12 observations) are dropped because the difference of total assets minus liquid assets is negative. It is checked that the difference of total assets minus fixed assets is positive and no firm is dropped. 13 firms (71 observations) are dropped because the difference

[56] The calculations were done using Stata 13.0, with geodetic ellipsoidal distances being calculated based on the method of Vincenty (1975) by applying the command *geodist*.

of total assets minus net value of average fixed assets is negative. 22 firms (125 observations) are dropped because the difference of accumulated depreciation minus current depreciation is negative. 83 firms (398 observations) are dropped because paid-in capital is smaller or equal to zero. 27 firms (137 observations) are dropped because their cost of sales is smaller or equal to zero. 7 firms (32 observations) are dropped because their expenses for wages are smaller or equal to zero. 8 firms (45 observations) are dropped because their welfare payments are smaller than zero. 8 firms (45 observations) are dropped because their depreciation expenses are smaller than zero. 16 firms (77 observations) are dropped because fixed assets in original prices are smaller or equal to zero. Fixed assets in original prices are used to calculate the amortization rate, which is the ratio of depreciation expenses in a year and the value of this type of assets in the previous year. It then is checked whether the amortization rate of the firms is smaller, larger or equal to zero and all firms obey this condition. 1 firm (6 observations) is dropped because in one year it showed an amortization rate greater than one. It is checked if welfare expenses of some firms are smaller than zero in a certain year and no firm is dropped. However, 13 firms (64 observations) are dropped because intermediate input values are smaller or equal to zero. It is checked for duplicate firms in terms of identical financial values and no firm is dropped. 14 firms (70 observations) are dropped because the dominating sector code is not part of the iron and steel industry. The dominating sector code is defined as the industry sector (subindustry) the firm belongs to for more than 50 percent of its observations (firms might change their subindustry over time). If the dominating sector code is different to 3210 (ironmaking), 3220 (steelmaking), 3230 (steel rolling) or 3240 (ferroalloy smelting), the firm is dropped.

Table 19: *Representativeness of the sample.*

Variable	Mean values: Non-excluded	Mean values: Excluded	*t*-Test	Share (non-excluded/total)
		Overall		
Output (mRMB)	353.8	131.9	***	81.71%
Employees	506.2	248.9	***	77.21%
Age	7.85	6.12	***	
# observations	27,076	16,254	—	
		Year 2003		
Output (mRMB)	287.8	128.9	***	73.80%
Employees	710.2	396.3	***	69.33%
Age	8.48	9.16	**	
# observations	2,535	2,009	—	
		Year 2004		
Output (mRMB)	244.1	105.2	***	80.40%
Employees	468.5	235.0	***	77.90%
Age	6.44	6.77	*	
# observations	4,708	2,662	—	
		Year 2005		
Output (mRMB)	279.5	135.8	***	86.56%
Employees	454.4	303.2	**	82.43%
Age	6.76	7.06		
# observations	5,340	1,706	—	
		Year 2006		
Output (mRMB)	346.9	125.4	***	86.91%
Employees	467.4	252.8	***	81.60%
Age	7.75	5.58	***	
# observations	5,340	2,226	—	
		Year 2007		
Output (mRMB)	447.5	141.9	***	83.37%
Employees	509.9	216.1	***	78.95%
Age	8.75	4.95	***	
# observations	4,890	3,077	—	
		Year 2008		
Output (mRMB)	508.7	143.7	***	76.74%
Employees	535.9	192.1	***	72.22%
Age	9.48	5.12	***	
# observations	4,263	4,574	—	

Note: This table presents differences in variable mean values of non-excluded and excluded firms. Asterisks *** indicate significance at 1 percent level, ** at 5 percent level and * at 10 percent level of one-sided unpaired *t*-tests. The ratio of the cumulative sum of the respective variable between the non-excluded and all iron and steel firms contained in the CIC is given in the right column.

Due to inconsistencies in the different yearly cross sections of the CIC, some important variables might be missing in one or several years and have to be determined. Given the availability of panel data, there are three possibilities to derive values of variables which are missing in some years. First, by using accounting rules and observed information on other variables for the year of missing information. Second, by using econometric estimation techniques, or third, via a deterministic calculation based on ratios. The latter two approaches are based on information of other years than the year of missing information and then use this information to derive the missing value of a variable. This study applied all three techniques. In terms of the second and third technique, it was found that the predictive power of ratios was higher in years where there was information on the value of a variable with missing information in another year.[57] Key missing variables were gross output in 2004, intermediate input cost in 2008 and depreciation expenses in 2008. Gross output was approximated by the sum of main business revenue, outside business revenue and the increase in inventory of finished goods in 2004. The firm-specific mean value of the share of intermediate input cost in total cost of sales in other years than 2008 and total cost of sales in the missing year are used to estimate intermediate input cost. The mean value of a firm's amortization rate in other years than 2008, multiplied with the fixed assets in original prices, yields an estimate of the depreciation cost in the missing year.

Finally, 24 firms (125 observations) were dropped because it was not possible to assign these firms to a dominating sector code. However, such code is needed to merge observations on material prices to these firms. Then, 34 firms (147 observations) are dropped because they have missing material price information. Furthermore, it was checked whether variables of the cost function given in eq. (3) are unreasonable in terms of size in some years they are observed, i.e. whether they are smaller or equal to zero. For Y these are 16 firms (84 observations), for K 212 firms (1098 observations), for L no firm, for M no firm, for P_K 134 firms (634 observations), for P_L no firm and for

[57] The regression approach for prediction of a variable with missing information in a certain year included as covariates a linear and quadratic time trend as well as variables closely related to the missing variable. For example, the variables included in the OLS regression to predict intermediate inputs in 2004 were cost of sales, a time trend and a quadratic time trend.

P_M no firm. Then, the capital structure is checked for reasonable values, i.e. whether paid-in capital of several categories is larger or equal to zero. For state capital 1 firm (6 observations) did not obey this restriction and for private capital 1 firm (6 observations). Observations of collective, corporate, Hong Kong/Macau/Taiwan and foreign capital were found to satisfy this restriction. It is to note that this screening process over-proportionally reduced the number of non-treated firms; 7,896 non-treated firms were dismissed from the analysis, while this was the case for only 42 treated firms. A reason for this ratio might be that treated firms on average were much larger with implied higher reporting standards. As a result, the sample used for the empirical analysis is still highly representative of the underlying population of firms (cf. Table 19). In conclusion, 5,340 firms, therein 148 treated firms, and 27,076 observations are used for the empirical analysis.

Real Capital Stock

The calculation method of the real capital stock is adopted from Brandt, Van Biesebroeck et al. (2012) and Brandt, Van Biesebroeck et al. (2014). Following their recommendation, we calculate the firm-level real capital stock to acquire a more accurate measurement of a firm's capital input. The estimation extends their method, which is described in detail in Brandt, Van Biesebroeck et al. (2014), with slight adjustments we believe to be important to improve the results.[58] The real capital stock K_{iT}^{Real} of firm i of subindustry s in province r in year T' a firm is first observed (2003 or later) is estimated using the "original fixed assets" value $K_{iT'}^{Orig}$ observed in the CIC, which is the sum of past investments at historical prices. Similar to Brandt, Van Biesebroeck et al. (2012) and Brandt, Van Biesebroeck et al. (2014), we assume the annual investment growth rate before year T' to be constant and approximate it by the two-digit industry- and province-specific average nominal capital stock growth rate γ_{sr} between the years 1993 and 1998. The price deflator for investments in year t (using 1998 price as a refer-

[58] For example, we change the year for the real capital stock extension from 1998 to the first year that a firm actually is observed in the dataset.

ence) is represented by ϕ_t. A constant discount rate δ (9%) is assumed for all years. In form of a simplifying assumption, T_0 is defined either by the firm's founding year or the year 19 years prior to T', depending on which year is later. Such simplifying assumption can be justified with only a limited number of years prior to T' being relevant when accounting for past investments due to depreciation and potential growth in investments. The real capital stock of a firm in year T' it is first observed can be shown to amount to the expression given below.

$$K_{iT'}^{Real} = \sum_{t=T_0}^{T'} \frac{K_{iT'}^{Orig}}{\sum_{t=T_0}^{T'} (1+\gamma_{sr})^{t-T'}} \left(\frac{1-\delta}{1+\gamma_{sr}}\right)^{T'-t} \frac{\phi_{1998}}{\phi_t}$$

$$= K_{iT'}^{Orig} \sum_{t=T_0}^{T'} \frac{\left(\frac{1-\delta}{1+\gamma_{sr}}\right)^{T'-t}}{\sum_{t=T_0}^{T'} (1+\gamma_{sr})^{t-T'}} \frac{\phi_{1998}}{\phi_t} \ .$$

For later years t $\left(T' < t \leq T \middle| T \leq 2008\right)$, the observed change in the firm's "original fixed assets" is used as an estimate of nominal fixed investment I_{it}. The real capital stock now can be given as

$$K_{it}^{Real} = K_{i,t-1}^{Real}(1-\delta) + \frac{I_{it}}{\phi_t} .$$

A.2 Additional Empirical Results

Estimated Coefficients of the Cost Function

Table 20: *Estimated coefficients of the subindustry-specific cost functions.*

Subindustry:	Iron & steel making		Steel rolling		Ferroalloy smelting	
	Coef.	Std.dev.	Coef.	Std.dev.	Coef.	Std.dev.
Output (β_Y)	0.825***	(0.014)	0.869***	(0.010)	0.851***	(0.037)
Price of capital (β_K)	0.051**	(0.020)	0.023**	(0.011)	0.058***	(0.022)
Price of labor (β_L)	0.080***	(0.026)	0.052***	(0.016)	0.150***	(0.046)
Price of material (β_M)	0.344***	(0.092)	0.436***	(0.056)	0.742***	(0.151)
(β_{YY})	0.033***	(0.009)	0.031**	(0.012)	0.079***	(0.017)
(β_{KK})	0.002	(0.007)	–0.006*	(0.003)	–0.003	(0.006)
(β_{LL})	0.006	(0.009)	0.001	(0.007)	–0.012	(0.021)
(β_{MM})	–0.093	(0.162)	–0.149*	(0.089)	–0.677***	(0.202)
(β_{YK})	–0.005	(0.005)	0.003	(0.003)	–0.007	(0.006)
(β_{YL})	–0.013**	(0.006)	–0.015***	(0.004)	–0.048***	(0.014)
(β_{YM})	–0.003	(0.015)	–0.003	(0.008)	0.002	(0.039)
(β_{KL})	–0.007	(0.010)	0.002	(0.006)	0.000	(0.010)
(β_{KM})	–0.030	(0.029)	–0.023	(0.015)	–0.059**	(0.027)
(β_{LM})	–0.013	(0.039)	–0.011	(0.024)	–0.134**	(0.053)
Time trend (β_t)	0.018	(0.057)	0.021	(0.031)	–0.281***	(0.076)
(β_{tt})	–0.020	(0.138)	0.035	(0.062)	–0.012	(0.121)
(β_{Yt})	0.020	(0.012)	0.001	(0.009)	–0.017	(0.021)
(β_{Kt})	0.009	(0.024)	0.016	(0.012)	0.032*	(0.019)
(β_{Lt})	0.000	(0.027)	0.027	(0.018)	0.092***	(0.033)
(β_{Mt})	–0.069	(0.139)	–0.093	(0.064)	0.263**	(0.124)
Constant (α_0)	10.517***	(0.043)	10.231***	(0.026)	9.858***	(0.066)
R^2	0.977		0.978		0.951	
ρ	0.658		0.519		0.429	
# firms / # obs.	1,025 / 4,968		3,353 / 17,391		962 / 4,717	

Note: This table presents the estimation results of the subindustry-specific total cost functions given in eq. (3). Robust standard errors at the firm level are reported in parenthesis. Given that intermediate inputs make up the dominant share in total costs (cf. Table 1), the coefficient of the price of material is highest in magnitude. R^2 is unadjusted. *Rho* (ρ) indicates the ratio of the variance of the fixed effects to the variance of the idiosyncratic error. Asterisks *** indicate significance at 1 percent level, ** at 5 percent level and * at 10 percent level.

Economies of Scale

We use the estimated coefficients of Table 20 to compute the economies of scale (ES) of firm *i* in year *t* of subindustry *s* as follows:

$$ES_{it}^{s} = \frac{1}{\partial \ln C_{it} / \partial \ln Y_{it}} = \frac{1}{\hat{\beta}_{Y}^{s} + \hat{\beta}_{YY}^{s} y_{it} + \hat{\beta}_{YK}^{s} p_{K,it} + \hat{\beta}_{YL}^{s} p_{L,it} + \hat{\beta}_{YM}^{s} P_{M,srt} + \hat{\beta}_{Yt}^{s} t}.$$

Economies of scale exist if ES is greater than 1. A subindustry would be characterized by diseconomies of scale if ES is smaller than 1, and by constant returns to scale of ES equals 1. Table 21 illustrates the descriptive statistics of the economies of scale differentiated by subindustry. The results confirm the existence of positive economies of scale for most firms.

Table 21: *Economies of scale (ES) in the three subindustries.*

	Mean	Std.dev.	Min.	Max.	25% perc.	50% perc.	75% perc.
Iron & steel making	1.186	0.075	0.933	1.579	1.137	1.191	1.242
Steel rolling	1.148	0.060	0.930	1.575	1.110	1.154	1.193
Ferroalloy smelting	1.201	0.132	0.831	3.913	1.119	1.197	1.276

Note: This table presents the economies of scale using estimates of the subindustry-specific cost functions given in Table 20.

Testing for Monotonicity and Quasi-Concavity

Testing for monotonicity and quasi-concavity of the subindustry-specific cost functions is conducted as follows. The estimated share equations for subindustry $s = \{1,2,3\}$ are

$$\frac{\partial \ln C}{\partial \ln P_K} = \hat{S}_{K}^{s} = \hat{\beta}_{K}^{s} + \hat{\beta}_{KK}^{s} p_K + \hat{\beta}_{YK}^{s} y + \hat{\beta}_{KL}^{s} p_L + \hat{\beta}_{KM}^{s} P_M + \hat{\beta}_{Kt}^{s} t \ ,$$

$$\frac{\partial \ln C}{\partial \ln P_L} = \hat{S}_{L}^{s} = \hat{\beta}_{L}^{s} + \hat{\beta}_{LL}^{s} p_L + \hat{\beta}_{YL}^{s} y + \hat{\beta}_{KL}^{s} p_K + \hat{\beta}_{LM}^{s} P_M + \hat{\beta}_{Lt}^{s} t \ ,$$

$$\frac{\partial \ln C}{\partial P_M} = \hat{S}_{M}^{s} = \hat{\beta}_{M}^{s} + \hat{\beta}_{MM}^{s} P_M + \hat{\beta}_{YM}^{s} y + \hat{\beta}_{KM}^{s} p_K + \hat{\beta}_{LM}^{s} p_L + \hat{\beta}_{Mt}^{s} t \ .$$

To reduce notation, unit i and time t subscripts are dropped. Small letters y and p indicate output and prices in natural logarithms. The derivation of total costs with respect to output yields

$$\frac{\partial \ln C}{\partial \ln Y} = \hat{\beta}^s_Y + \hat{\beta}^s_{YY} y + \sum_{Z=\{K,L\}} \hat{\beta}^s_{YZ} y p_Z + \hat{\beta}^s_{YM} y P_M + \hat{\beta}^s_{Yt} t \quad .$$

At the approximation point, the Hessian matrix **G** becomes

$$\mathbf{G} = \begin{bmatrix} \hat{\beta}^s_{KK} + \left(\hat{\beta}^s_K\right)^2 - \hat{\beta}^s_K & \hat{\beta}^s_{KL} + \hat{\beta}^s_K \cdot \hat{\beta}^s_L & \hat{\beta}^s_{KM} + \hat{\beta}^s_K \cdot \hat{\beta}^s_M & \hat{\delta}^s_{KW} + \hat{\beta}^s_K \cdot \hat{\delta}^s_W \\ \hat{\beta}^s_{KL} + \hat{\beta}^s_L \cdot \hat{\beta}^s_K & \hat{\beta}^s_{LL} + \left(\hat{\beta}^s_L\right)^2 - \hat{\beta}^s_L & \hat{\beta}^s_{LM} + \hat{\beta}^s_L \cdot \hat{\beta}^s_M & \hat{\delta}^s_{LW} + \hat{\beta}^s_L \cdot \hat{\delta}^s_W \\ \hat{\beta}^s_{KM} + \hat{\beta}^s_M \cdot \hat{\beta}^s_K & \hat{\beta}^s_{LM} + \hat{\beta}^s_M \cdot \hat{\beta}^s_L & \hat{\beta}^s_{MM} + \left(\hat{\beta}^s_M\right)^2 - \hat{\beta}^s_M & \hat{\delta}^s_{MW} + \hat{\beta}^s_M \cdot \hat{\delta}^s_W \\ \hat{\delta}^s_{KW} + \hat{\delta}^s_W \cdot \hat{\beta}^s_K & \hat{\delta}^s_{LW} + \hat{\delta}^s_W \cdot \hat{\beta}^s_L & \hat{\delta}^s_{MW} + \hat{\delta}^s_W \cdot \hat{\beta}^s_M & \hat{\delta}^s_{WW} + \left(\hat{\delta}^s_W\right)^2 - \hat{\delta}^s_W \end{bmatrix},$$

and the coefficients of the unobserved price p_w are estimated to

$$\begin{aligned} \hat{\delta}^s_W &= 1 - \hat{\beta}^s_K - \hat{\beta}^s_K - \hat{\beta}^s_M \quad , \\ \hat{\delta}^s_{KW} &= 0 - \hat{\beta}^s_{KK} - \hat{\beta}^s_{KL} - \hat{\beta}^s_{KM} \quad , \\ \hat{\delta}^s_{LW} &= 0 - \hat{\beta}^s_{LL} - \hat{\beta}^s_{KL} - \hat{\beta}^s_{LM} \quad , \\ \hat{\delta}^s_{MW} &= 0 - \hat{\beta}^s_{MM} - \hat{\beta}^s_{KM} - \hat{\beta}^s_{LM} \quad , \\ \hat{\delta}^s_{WW} &= 0 - \hat{\delta}^s_{KW} - \hat{\delta}^s_{LW} - \hat{\delta}^s_{MW} \quad . \end{aligned}$$

The vector of fitted factor shares **q** is

$$\mathbf{q}^s = \begin{bmatrix} \hat{S}^s_K \\ \hat{S}^s_L \\ \hat{S}^s_M \\ \hat{S}^s_W \end{bmatrix},$$

where $\hat{S}^s_W = 1 - \hat{S}^s_K - \hat{S}^s_L - \hat{S}^s_M$ and matrix $\mathbf{H} = \mathbf{G} + \mathbf{s} \cdot \mathbf{s}' - diag(\mathbf{s})$. Results show that all three cost functions generally are well behaved.

Table 22: *Monotonicity at sample mean and median for the three subindustries.*

	Iron & steel making	Steel rolling	Ferroalloy smelting
	Monotonicity at sample mean		
$\hat{S}_K$	0.026	0.015	0.024
$\hat{S}_L$	0.064	0.063	0.086
$\hat{S}_M$	0.184	0.196	0.279
$\partial \ln C / \partial \ln Y$	0.847	0.872	0.852
	Monotonicity at sample median		
$\hat{S}_K$	0.029	0.016	0.030
$\hat{S}_L$	0.067	0.068	0.108
$\hat{S}_M$	0.183	0.194	0.327
$\partial \ln C / \partial \ln Y$	0.842	0.867	0.836

Note: This table presents the estimated cost shares as well as the first derivative of total costs with respect to output of the three subindustries evaluated at the sample mean and median.

Table 23: *Roots of matrix* **H** *at sample mean and median for the three subindustries.*

	Iron & steel making	Steel rolling	Ferroalloy smelting
	Concavity at sample mean		
λ_1	–0.000	*0.000*	–0.000
λ_2	–0.083	–0.054	–0.104
λ_3	–0.201	–0.161	–0.310
λ_4	–1.019	–1.153	–2.318
	Concavity at sample median		
λ_1	*0.000*	–0.000	*0.000*
λ_2	–0.086	–0.056	–0.112
λ_3	–0.205	–0.168	–0.338
λ_4	–1.019	–1.152	–2.336

Note: This table presents the roots of matrix **H** for the three subindustries evaluated at the sample mean and median. Critical, i.e. positive values are given in *italics*. However, none of these critical values is larger than 1.724e–16.

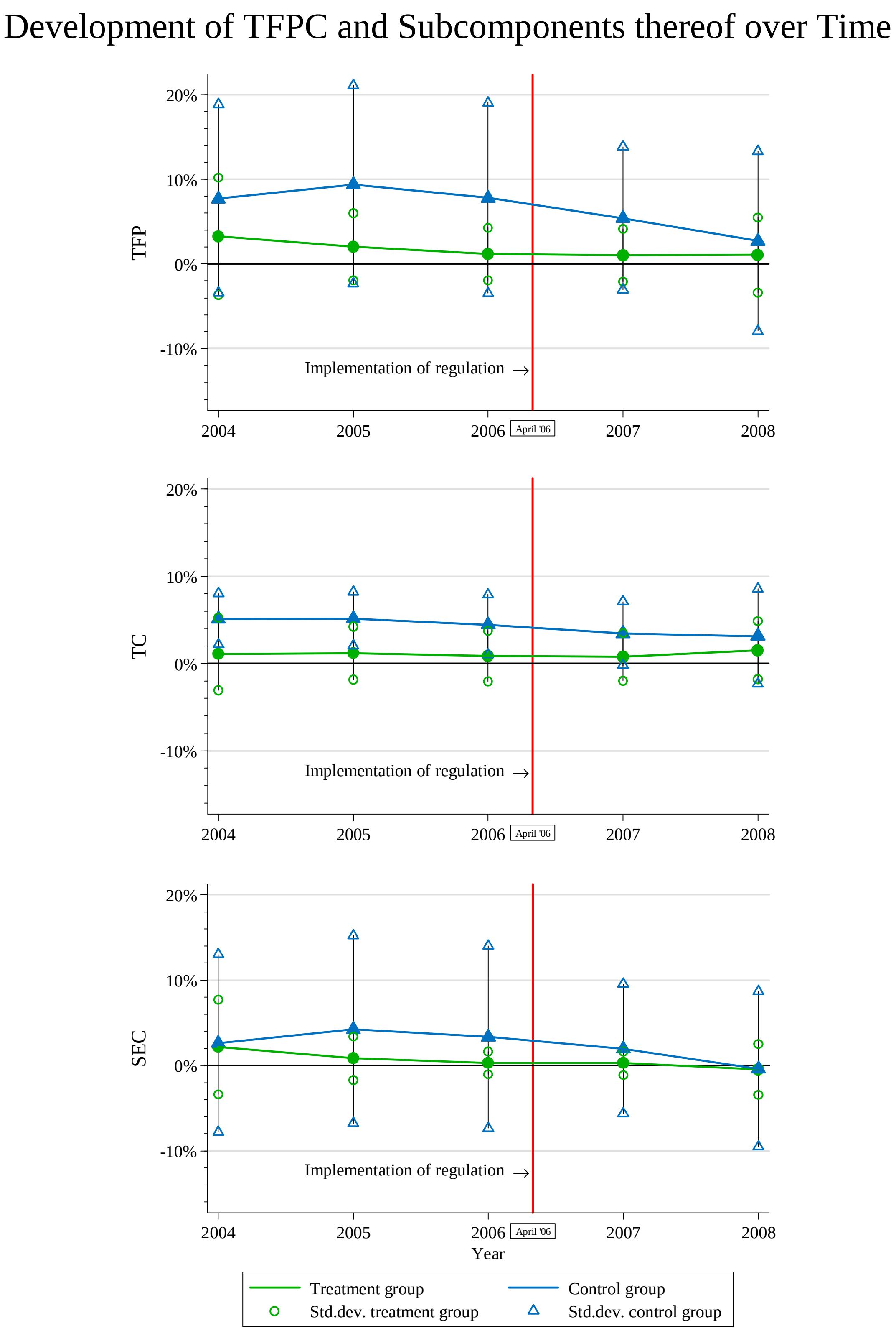

Figure 5: *Development of TFPC, TC and SEC of treatment and control group.*

Note: Figure 5 presents yearly TFPC, TC and SEC values for the treatment and control group. The distance between the spikes indicates the range of the standard deviation of the individual performances for the treatment and control group.

Estimation Results without Sample Attrition

Table 24: *Estimated coefficients of the subindustry-specific cost functions without sample attrition.*

Subindustry:	Iron & steel making		Steel rolling		Ferroalloy smelting	
	Coef.	Std.dev.	Coef.	Std.dev.	Coef.	Std.dev.
Output (β_Y)	0.816***	(0.019)	0.854***	(0.013)	0.849***	(0.037)
Price of capital (β_K)	0.061**	(0.027)	0.026**	(0.012)	0.060**	(0.029)
Price of labor (β_L)	0.111***	(0.033)	0.055***	(0.018)	0.098*	(0.052)
Price of material (β_M)	0.273**	(0.109)	0.445***	(0.063)	0.787***	(0.189)
(β_{YY})	0.032***	(0.009)	0.038**	(0.015)	0.064***	(0.019)
(β_{KK})	0.011	(0.011)	–0.005	(0.003)	0.000	(0.009)
(β_{LL})	0.007	(0.009)	0.004	(0.009)	–0.020	(0.026)
(β_{MM})	–0.095	(0.201)	–0.245**	(0.105)	–0.676***	(0.244)
(β_{YK})	–0.004	(0.007)	0.005	(0.003)	0.001	(0.008)
(β_{YL})	–0.020***	(0.006)	–0.016***	(0.005)	–0.060***	(0.020)
(β_{YM})	0.010	(0.017)	0.003	(0.008)	–0.035	(0.032)
(β_{KL})	–0.004	(0.011)	0.002	(0.006)	0.008	(0.016)
(β_{KM})	0.001	(0.043)	–0.033*	(0.018)	–0.071*	(0.037)
(β_{LM})	–0.056	(0.049)	–0.021	(0.028)	–0.076**	(0.065)
Time trend (β_t)	0.084	(0.067)	0.061*	(0.035)	–0.176*	(0.092)
(β_{tt})	–0.140	(0.173)	–0.090	(0.072)	–0.099	(0.133)
(β_{Yt})	0.013	(0.014)	–0.005	(0.011)	0.018	(0.022)
(β_{Kt})	–0.031	(0.032)	0.023	(0.015)	0.039*	(0.024)
(β_{Lt})	0.010	(0.032)	0.033	(0.021)	0.087**	(0.044)
(β_{Mt})	–0.005	(0.178)	–0.007	(0.075)	0.231*	(0.135)
Constant (α_0)	10.823***	(0.054)	10.274***	(0.029)	9.999***	(0.084)
R^2	0.979		0.979		0.953	
ρ	0.698		0.557		0.496	
# firms / # obs.	547 / 3,073		2,359 / 13,225		495 / 2,754	

Note: This table presents the estimation results of the subindustry-specific total cost function given in eq. (3). The panel is defined as described in appendix A.1. Robust standard errors at the firm level are reported in parenthesis. Given that intermediate inputs make up the dominant share in total costs (cf. Table 1), the coefficient of the price of material is highest in magnitude. R^2 is unadjusted. *Rho* (ρ) indicates the ratio of the variance of the fixed effects to the variance of the idiosyncratic error. Asterisks *** indicate significance at 1 percent level, ** at 5 percent level and * at 10 percent level.

Table 25: *Descriptive statistics of estimated TFP change and subcomponents thereof for sample free of attrition.*

	Mean	Median	Std. dev.	10% perc.	90% perc.
Mean of all industries			[# firms: 3,401 / # observations: 19,052]		
TFPC	0.052	0.049	0.098	–0.044	0.152
TC	0.031	0.030	0.045	–0.022	0.084
SEC	0.021	0.014	0.089	–0.054	0.104
Iron- and steelmaking			[# firms: 547 / # observations: 3,073]		
TFPC	0.077	0.074	0.105	–0.035	0.195
TC	0.046	0.047	0.055	–0.026	0.118
SEC	0.031	0.022	0.096	–0.054	0.123
Steel rolling			[# firms: 2,359 / # observations: 13,225]		
TFPC	0.046	0.045	0.085	–0.035	0.126
TC	0.028	0.029	0.033	–0.015	0.070
SEC	0.017	0.012	0.081	–0.050	0.091
Ferroalloy smelting			[# firms: 495 / # observations: 2,754]		
TFPC	0.050	0.042	0.136	–0.087	0.201
TC	0.024	0.026	0.070	–0.068	0.111
SEC	0.026	0.020	0.114	–0.070	0.135

Note: This table shows the descriptive statistics of mean TFPC, TC and SEC for the period of 2003 to 2008. The panel is defined as described in appendix A.1.

Table 26: *Testing for a parallel trend and pre-treatment effects in TFPC, TC and SEC based on eq.(5) and eq. (6) for sample without attrition.*

Dependent variable:	TFPC		TC		SEC	
			Specification DD–3 [Testing based on eq. (5)]			
Time trend × Treatment (β_t^{tr})	0.003	(0.014)	0.006	(0.004)	–0.003	(0.014)
Time trend (β_t)	–0.063	(0.053)	0.019***	(0.004)	–0.082	(0.052)
Size	0.073***	(0.023)	0.004	(0.003)	0.069***	(0.023)
Ownership	0.030	(0.039)	0.004	(0.008)	0.025	(0.036)
Province × Year 2005	⋮		⋮		⋮	
Constant (α_0)	–0.203	(0.156)	–0.067***	(0.017)	–0.135	(0.155)
R^2	0.651		0.893		0.610	
# firms / # observations	3,401 / 5,448		3,401 / 5,448		3,401 / 5,448	
			Specification DD–3 [Testing based on eq. (6)]			
Year 2005 × Treatment (θ_{2005}^{tr})	–0.006	(0.009)	0.006**	(0.003)	–0.012	(0.009)
ATT (β_{ATT})	0.029***	(0.008)	0.022***	(0.004)	0.008	(0.008)
Year 2005 (θ_{2005})	–0.046	(0.036)	0.017***	(0.004)	–0.063*	(0.036)
Year 2006 (θ_{2006})	0.003	(0.035)	0.041***	(0.004)	–0.038	(0.034)
Year 2007 (θ_{2007})	0.010	(0.030)	0.063***	(0.005)	–0.052*	(0.029)
Year 2008 (θ_{2008})	0.009	(0.033)	0.087***	(0.006)	–0.078**	(0.031)
Size	0.026***	(0.005)	0.000	(0.001)	0.026***	(0.005)
Ownership	0.011***	(0.005)	0.003	(0.002)	0.008*	(0.004)
Province × Year 2005	⋮		⋮		⋮	
Constant (α_0)	–0.097***	(0.025)	–0.004	(0.006)	–0.093***	(0.024)
R^2	0.320		0.753		0.255	
# firms / # observations	3,401 / 15,651		3,401 / 15,651		3,401 / 15,651	

Note: This table shows the results of the testing for a parallel trend and pre-treatment effects in TFPC, TC and SEC using the model specifications of eq. (5) and eq. (6). R^2 is unadjusted. Robust standard errors at the firm level are reported in parenthesis. Asterisks *** indicate significance at 1 percent level, ** at 5 percent level and * at 10 percent level.

A.3 Additional Robustness Checks for Sample Stratification

In addition to size and ownership, we also test whether stratification with respect to subindustry affiliation and geographic region change our results. shows every stratum to contain enough observations on treated firms for statistical inference.

Sample stratification with respect to subindustry allows controlling for factors like time varying industry concentration. A higher market concentration might increase incentives to innovate and become more productive (Schumpeter, 1942). Results are shown in Table 28. Modell DD–3 has not been estimated, because in several provinces the iron- and steelmaking and the ferroalloy smelting industry are represented by a few firms only. Results are found to be in the ballpark of the benchmark specifications. Focusing on model DD–2, the T1000P is found to have the highest impact on TFP change in the ferroalloy smelting industry. TFP change of the iron- and steelmaking and steel rolling industry was affected to a lesser degree. An underlying factor of this finding, for example, could be abatement targets varying in unobserved stringency between the different industries.[59]

Results of the sample stratified with respect to geographic region are given in Table 29. Time varying heterogeneity connected to the geographic region could have numerous implications on the treatment effect. Potential factors range from the quality of infrastructure over population density to local input market characteristics. TFP change of firms in the central and northeast region was most affected by the T1000P, followed by the west and central regions. Most firms, treated as well as untreated, are located in the east region (cf. Figure 1 and Figure 2). Market oriented reforms were strongest in the east region (Sheng and Song, 2013). Hence, firms face the strongest competition on

[59] According to our data, the average yearly abatement target was 0.133 Mtce for a firm of the iron- and steelmaking subindustry, 0.300 Mtce for the steel rolling subindustry and 0.037 Mtce for the ferroalloy smelting subindustry. Data shows achievement rates at the end of 2008—the program lasted until 2010—to amount to 168 percent, 125 percent and 88 percent in the respective industries. The comparatively low achievement rate of the ferroalloy smelting industry, despite relatively low yearly targets on average, could indicate that this industry faced greater challenges in complying with the policy.

output and input markets in this region. The eastern industry on average can be considered to be more developed than the one of the other regions. Hence, firms in the east region might start from a higher productivity level at the time the regulation became effective, what could render incremental TFP increases more difficult to achieve and expensive, compared to the hypothetically less developed firms of the other regions.

Table 27: *Number of treated and non-treated firms by strata.*

	Treatment group		Control group	
	# firms	# obs.	# firms	# obs.
Stratification by subindustry				
Iron- & steelmaking stratum	66	378	959	4,590
Steel rolling stratum	68	390	3,285	17,001
Ferroalloy smelting stratum	14	80	948	4,637
Stratification by region				
East region stratum	68	387	3,054	15,646
Central and northeast region stratum	51	292	1,219	6,046
West region stratum	29	169	920	4,536

Note: This table shows the number of firms and observations conditional on treatment and sample stratification.

Table 28: *ATTs of samples stratified with respect to subindustries.*

Model Version:	DD–1		DD–2	
		Iron- & steelmaking		
ATT on TFPC	0.020**	(0.008)	0.019**	(0.009)
ATT on TC	–0.002	(0.002)	–0.001	(0.002)
ATT on SEC	0.022***	(0.007)	0.020**	(0.008)
# firms / # obs.	1,025 / 3,943		1,025 / 3,943	
R^2 (TFPC / TC / SEC)	0.363 / 0.946 / 0.299		0.368 / 0.949 / 0.307	
F-statistic (TFPC / TC / SEC)			7.05*** / 35.41*** / 9.29***	
		Steel rolling		
ATT on TFPC	0.020***	(0.004)	0.020***	(0.004)
ATT on TC	0.002	(0.002)	0.002	(0.002)
ATT on SEC	0.018***	(0.003)	0.018***	(0.003)
# firms / # obs.	3,353 / 14,038		3,353 / 14,038	
R^2 (TFPC/TC/SEC)	0.350 / 0.825 / 0.298		0.354 / 0.825 / 0.304	
F-statistic (TFPC/TC/SEC)			10.50*** / 5.37*** / 11.55***	
		Ferroalloy smelting		
ATT on TFPC	0.059***	(0.011)	0.065***	(0.013)
ATT on TC	0.021***	(0.005)	0.022***	(0.005)
ATT on SEC	0.038***	(0.010)	0.043***	(0.012)
# firms / # obs.	962 / 3,755		962 / 3,755	
R^2 (TFPC / TC / SEC)	0.438 / 0.831 / 0.303		0.450 / 0.832 / 0.314	
F-statistic (TFPC / TC / SEC)			9.68*** / 6.41*** / 6.99***	
Size	No		Yes	
Ownership	No		Yes	
Province × Year	No		No	

Note: This table shows the ATT on TFPC, TC and SEC between 2006 and 2008 using eq. (4). Industry affiliation is based on the dominating sector code (defined as described in appendix A.1). Only estimates of β_{ATT} are shown. For the sake of conciseness, estimates of $\boldsymbol{\theta}_t$, $\boldsymbol{\gamma}$ and province-year effects are not shown. All two model specifications (DD–1 and DD–2) control for firm fixed effects. R^2 values of the estimations with TFPC, TC or SEC as dependent variable are unadjusted. F-statistics show the joint significance of the additionally introduced size, ownership and province-year variables. Robust standard errors at the firm level are reported in parenthesis. Asterisks *** indicate significance at 1 percent level, ** at 5 percent level and * at 10 percent level.

Table 29: *ATTs of samples stratified with respect to regions.*

Model Version:	DD–1		DD–2		DD–3	
			East region			
ATT on TFPC	0.029***	(0.004)	0.026***	(0.005)	0.032***	(0.006)
ATT on TC	0.013***	(0.002)	0.013***	(0.002)	0.014***	(0.002)
ATT on SEC	0.016***	(0.003)	0.013***	(0.004)	0.018***	(0.005)
# firms / # obs.	3,122 / 12,912		3,122 / 12,912		3,122 / 12,912	
R^2 (TFPC / TC / SEC)	0.381 / 0.776 / 0.309		0.386 / 0.777 / 0.315		0.397 / 0.789 / 0.327	
F-statistic (TFPC / TC / SEC)			9.91*** / 7.04*** / 10.98***		3.63*** / 14.99*** / 3.83***	
			Central and northeast region			
ATT on TFPC	0.037***	(0.009)	0.040***	(0.009)	0.036***	(0.010)
ATT on TC	0.017***	(0.004)	0.017***	(0.004)	0.011***	(0.004)
ATT on SEC	0.020**	(0.008)	0.024***	(0.008)	0.025***	(0.009)
# firms / # obs.	1,270 / 5,068		1,270 / 5,068		1,270 / 5,068	
R^2 (TFPC / TC / SEC)	0.333 / 0.661 / 0.264		0.336 / 0.661 / 0.269		0.359 / 0.715 / 0.285	
F-statistic (TFPC / TC / SEC)			3.75** / 0.66 / 5.12***		3.31*** / 11.72*** / 2.18***	
			West region			
ATT on TFPC	0.033***	(0.008)	0.033***	(0.009)	0.021**	(0.011)
ATT on TC	0.013**	(0.006)	0.013**	(0.006)	0.012*	(0.007)
ATT on SEC	0.020***	(0.007)	0.020**	(0.009)	0.009	(0.010)
# firms / # obs.	949 / 3,756		949 / 3,756		949 / 3,756	
R^2 (TFPC / TC / SEC)	0.396 / 0.692 / 0.323		0.410 / 0.693 / 0.338		0.434 / 0.734 / 0.356	
F-statistic (TFPC / TC / SEC)			12.67*** / 1.10 / 11.74***		4.29*** / 25.49*** / 2.81***	
Size	No		Yes		Yes	
Ownership	No		Yes		Yes	
Province × Year	No		No		Yes	

Note: This table shows the ATT on TFPC, TC and SEC between 2006 and 2008 using eq. (4). The assignment of the different provinces to the three regions is described in footnote 15 on p. 13. Only estimates of β_{ATT} are shown. For the sake of conciseness, estimates of $\boldsymbol{\theta}_t$, $\boldsymbol{\gamma}$ and province-year effects are not shown. All three model specifications (DD–1 to DD–3) control for firm fixed effects. R^2 values of the estimations with TFPC, TC or SEC as dependent variable are unadjusted. *F*-statistics show the joint significance of the additionally introduced size, ownership and province-year variables. Robust standard errors at the firm level are reported in parenthesis. Asterisks *** indicate significance at 1 percent level, ** at 5 percent level and * at 10 percent level.

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