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Essays in Applied Microeconomics on the Measurement and Determinants of Firm Efficiency and Productivity

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THOMAS JÜRG GEISSMANN
MSc ETH MTEC
ETH Zurich
born October 3rd 1986
citizen of Zurich, Switzerland

accepted on the recommendation of

Prof. Dr. Massimo Filippini
Prof. Dr. Valerie Karplus

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Abstract

This dissertation measures and analyzes the determinants of firm level efficiency and productivity using empirical parametric methods. It is composed of three essays with different contexts, for example in terms of geography, industry or methodology. Part I is set in Switzerland and estimates the transient and persistent cost efficiency of a representative sample of Swiss hydropower plants. With a share of roughly 60 percent, hydropower is Switzerland's main source of domestic electricity. However, its economic viability has suffered in recent years due to several distortions on a European level, such as an extensive subsidization of new renewables or non-internalized external costs of emissions. The scene of part II and III is set in China, where the government has two important topics on its agenda: to increase productivity and to reduce the environmental impact of its industry. Part II analyzes the effects of the national Top-1000 Energy-Consuming Enterprises Program on the productivity change of iron and steel firms. At that time, this regulation was part of the largest efforts ever made to reduce the energy intensity of the Chinese industry. Part III studies the role of management quality in explaining the productivity of Chinese manufacturing firms and the mediating properties of firm ownership.

Part I

Electricity prices on the European market have decreased significantly over the past few years, resulting in a deterioration of the competitiveness and profitability of Swiss hydro power. One option to improve the sector's economy is to increase cost efficiency. The goal of this study is to quantify the level of persistent and transient cost inefficiency of individual firms by applying the generalized true random effects (GTRE) model introduced by Colombi, Kumbhakar et al. (2014) and Filippini and Greene (2016). As the first stand-alone empirical application of this newly developed GTRE model, the level of cost inefficiency of 65 Swiss hydropower firms is analyzed for the period of 2000 to 2013 based on a total cost function. A random effects and true random effects specification is estimated as a benchmark for the persistent and transient level of cost inefficiency, respectively. Results show the presence of both, transient as well as persistent, cost inefficiencies. The GTREM predicts the aggregate level of cost inefficiency to amount to 22.3 percent on average (7.9 percent transient, 14.4 percent persistent). The two components of cost inefficiency differ in their interpretation and implication. From an individual firm's perspective, they might require a firm's management to respond with different improvement strategies. The existing level of persistent inefficiency could prevent hydropower firms from adjusting their production processes to new market environments. From a regulatory point of view, the results of this study could be used in the scope and determination of the amount of financial support given to struggling firms.

Part II The economics of environmental regulations and firm productivity have been debated in the literature for decades, however, mainly for western economies and on aggregate level. Literature on firm level is rare, especially for emerging economies like China. The industrial sector has been a major contributor to China's unprecedented economic development, where fast growth rates came hand in hand with a neglect of environmental protection. This study presents the first empirical evaluation of the effects of an environmental regulation on the total factor productivity (TFP) of Chinese industrial firms using parametric methods. Furthermore, this is the first contribution analyzing such effects with respect to TFP change subcomponents of technical change and scale efficiency change, and one of the first empirical applications estimating TFP change via a cost function. The focus is on the iron and steel industry and the national Top-1000 Energy-Consuming Enterprises Program (T1000P), which was introduced within the Eleventh Five Year Plan and spanned 2006 to 2010. The regulation aimed to reduce the energy consumption, and thereby direct and indirect emissions, of the 1000 most energy-consuming industrial firms. The iron and steel industry—still is one of the country's biggest polluters—was targeted the most by the regulation in terms of the number of treated firms. Using detailed census data on 5,340 firms for the period of 2003 to 2008, TFP is estimated to have grown on average by 6.4 percent. The iron- and steelmaking industry grew fastest, followed by the steel rolling and ferroalloy smelting industry. As one of only a few, this study provides empirical support of a positive effect of an environmental regulation on a firm's productivity: the T1000P is found to have significantly increased yearly TFP change, and thereby competitiveness of treated firms, by 3.1 percent on average. Effects on technical change and scale efficiency change are positive and statistically significant as well. They contribute about equally to the overall treatment effect. Results are robust in several dimensions, even when instrumenting for policy exposure. For China, a boost in productivity coupled with a reduction in environmental degradation are two critical factors to maintain international competitiveness and long-term growth perspectives. Our evidence suggests that environmental regulations could be supportive of both of these factors.

Part III This part probes the extent, to which management quality matters in explaining the performance of 386 industrial firms operating in the unique institutional setting of China. This is the first empirical analysis on the role of observed management quality in determining the productivity of Chinese firms. Furthermore, this is the first contribution in general that links this role to firm ownership. In China, firm ownership represents sharp distinctions among operating conditions. In contrast to the main body of literature, we apply production functions of flexible functional forms and panel model specifications. Data stems from the annual Chinese Industrial Census for the period of 2003 to 2008. Observations on managerial quality are taken from the World Management Survey. Two findings are in sharp contrast to the modern literature. First, we find the role of management practice as productive input parameter by itself to be uncorrelated with variation in output. Second, state-owned enterprises (SOEs) on average are better managed than non-SOEs. We provide first empirical evidence that the role of management could be mediated by the institutional element of firm ownership with its associated role of the government. There is indication that the adoption of modern western management practices is mostly correlated with higher output of SOEs. We explain and discuss potential factors underlying our findings.

Zusammenfassung

Diese Dissertation misst und analysiert die Einflussfaktoren auf die Effizienz und Produktivität von Firmen basierend auf empirischen parametrischen Methoden. Sie besteht aus drei Aufsätzen mit unterschiedlichem Kontext, beispielsweise bezüglich der Geographie, Industrie oder Methodik. Teil I fokussiert auf die Schweiz und schätzt die transiente sowie persistente Kosteneffizienz einer repräsentativen Stichprobe von Schweizer Wasserkraftwerken. Die Schweizer Wasserkraft ist, mit einem Anteil von rund 60 Prozent, die Hauptquelle der heimischen Stromerzeugung. Allerdings hat deren Wirtschaftlichkeit aufgrund von Marktverzerrungen auf europäischer Ebene in den letzten Jahren gelitten. Teil II und III spielen in China, wo die Regierung mit der Steigerung der Umweltfreundlichkeit und Produktivität der Industrie zwei wichtige Themen weit oben auf ihrer Agenda stehen hat. Teil II analysiert die Wirkung des nationalen „Top-1000 Energy-Consuming Enterprises Program“ auf die Produktivitätsänderung von Firmen der chinesischen Eisen- und Stahlindustrie. Diese Regulierung war Bestandteil einer bis dahin unübertroffenen Anstrengung seitens der chinesischen Regierung zur Reduzierung der Energieintensität der Industrie. Teil III studiert den Einfluss von Managementqualität auf die Produktivität von chinesischen Industrieunternehmen. Ein besonderer Fokus liegt dabei auf den Effekten der Besitzstruktur der Unternehmen.

Teil I Der Strompreis auf dem europäischen Markt ist in den letzten Jahren erheblich zurückgegangen, was zu einer Verschlechterung der Wettbewerbsfähigkeit und Rentabilität der Schweizer Wasserkraftunternehmen geführt hat. Eine Möglichkeit, die Wirtschaftlichkeit des Wasserkraftsektors zu steigern, besteht in der Erhöhung der der Kosteneffizienz. Das Ziel dieser Studie ist es, das Niveau der persistenten und transien-

ten Kostenineffizienz von Wasserkraftunternehmen mit Hilfe des Generalized True Random Effects (GTRE) Modells zu bestimmen. Dieses Modell wurde von Colombi, Kumbhakar et al. (2014) und Filippini and Greene (2016) eingeführt. In Form einer ersten eigenständigen empirischen Anwendung dieses erst kürzlich entwickelten GTRE Modells analysieren wir das Niveau der Kostenineffizienz von 65 Schweizer Wasserkraftunternehmen zwischen 2000 und 2013 basierend auf einer Gesamtkostenfunktion. Zusätzlich schätzen wir ein Random Effects und True Random Effects Modell. Die Schätzwerte dieser beiden Modelle dienen als Vergleichsgrösse für die persistente und transiente Kostenineffizienz. Die Ergebnisse zeigen, dass die Schweizer Wasserkraft sowohl von einem persistenten als auch transienten Kostenineffizienzbestandteil gekennzeichnet ist. Das GTRE Modell schätzt das durchschnittliche aggregierte Kostenineffizienzniveau auf 22.3 Prozent (7.9 Prozent transient, 14.4 Prozent persistent). Die beiden Ineffizienzbestandteile unterscheiden sich sowohl in ihrer Interpretation als auch Implikation. Aus der Sicht der Unternehmen könnten die beiden Bestandteile unterschiedliche Verbesserungsstrategien nach sich ziehen. Das beobachtete Niveau an persistenter Kostenineffizienz könnte die Wasserkraftunternehmen daran hindern, ihre Produktionsprozesse neuen Marktgegebenheiten flexibel anzupassen. Aus regulatorischer Sicht könnten die Ergebnisse dieser Studie dazu genutzt werden, um den Umfang und die Höhe der finanziellen Unterstützung für die sich in Schwierigkeiten befindenden Unternehmen zu bestimmen.

Teil II Die ökonomischen Aspekte von Umweltregulierungen sind in der Literatur seit Jahrzehnten diskutiert worden, jedoch vor allem für westliche Volkswirtschaften und auf aggregierter Ebene. Literatur auf Firmenebene ist rar, vor allem für Schwellenländer wie China. Der Industriesektor ist massgeblich an der beispiellosen wirtschaftlichen Entwicklung Chinas beteiligt gewesen, wo hohe Wachstumsraten Hand in Hand mit einer Vernachlässigung des Umweltschutzes einhergingen. Diese Studie präsentiert die erste empirische Evaluation der Effekte einer Umweltregulierung auf die totale Faktorproduktivität (TFP) von chinesischen Industriefirmen anhand parametrischer Methoden. Des Weiteren stellt dies den ersten Beitrag dar, welcher solche Effekte zusätzlich bezüglich den beiden TFP Änderungskomponenten der technischen Effizienz und Skaleneffizienz abschätzt. Als eine der ersten berechnet diese Studie TFP Änderungen mit Hilfe einer Kostenfunktion. Der Fokus der Analyse liegt auf der Eisen- und Stahlindustrie und dem nationalen „Top-1000 Energy-Consuming Enterprises Program“ (T1000P), welches im Rahmen des Elften Fünf-Jahres-Planes ins Leben gerufen wurde und sich über den Zeitraum von 2006 bis 2010 erstreckte. Es war eine von Chinas ersten gross angelegten Umweltregulierungen. Das Programm zielte darauf ab, den Energieverbrauch und damit die direkten und indirekten Emissionen der 1000 grössten industriellen Energieverbraucher zu reduzieren. Die meisten Unternehmen, welche Bestandteil des T1000P waren, gehörten der Eisen- und Stahlindustrie an. Diese Industrie ist noch immer eine der größten Umweltverschmutzer des Landes. Anhand detaillierter Daten zu 5,340 Unternehmen für den Zeitraum zwischen 2003 und 2008 wird das durchschnittliche jährliche TFP Wachstum auf 6.4 Prozent geschätzt. Bei Firmen der Eisen- und Stahlherstellung wuchs TFP am stärksten, gefolgt von den Stahlwalzfirmen und Firmen in der Eisenlegierungshüttenindustrie. Als eine von nur wenigen empirische Studien finden wir empirische Belege für einen positiven Effekt einer Umweltregulierung auf die Produktivität von Firmen: Es wird geschätzt, dass das T1000P die jährliche TFP Änderung im Schnitt um 3.1 Prozent erhöhte. Änderungen in der technischen Effizienz und der Skaleneffizienz trugen zu etwa gleich grossen Teilen zu dieser Erhöhung bei. Die Ergebnisse sind robust bezüglich mehrerer Dimensionen, unter anderem auch wenn für Teilnahme am Regulierungsprogramm instrumentiert wird. Für China stellen die Steigerung der Produktivität bei einer gleichzeitigen Minimierung der Beeinträchtigung der Umwelt zwei kritische Faktoren dar, um internationale Wettbewerbsfähigkeit und langfristige Wachstumsperspektiven zu erhalten. Unsere Resultate indizieren, dass Umweltregulierungen zur Erreichung beider Ziele dienlich sein könnten.

Teil III Dieser Teil untersucht, inwieweit die Managementqualität die Produktivität von 386 Industrieunternehmen innerhalb Chinas einzigartigem institutionellen Umfelds erklärt. Dies ist die erste empirische Analyse zur Rolle von beobachteter Managementqualität auf die Produktivität von chinesischen Unternehmen und der erste

Beitrag, welcher diese Rolle mit der Eigentümerstruktur eines Unternehmens verknüpft. In China repräsentiert die Eigentümerstruktur grosse Unterschiede in den Betriebsbedingungen. Im Gegensatz zum Grossteil der Literatur verwenden wir Produktionsfunktionen von flexibler funktionaler Form sowie Paneldatenmodelle. Die Daten stammen vom chinesischen Industriezensus und decken den Zeitraum 2003 bis 2008; Beobachtungen zur Managementqualität sind dem World Management Survey entnommen. Zwei Ergebnisse stehen im scharfen Kontrast zur modernen Literatur. Erstens finden wir keine Korrelation zwischen der Managementpraxis und der Veränderung der Produktion. Zweitens weisen staatliche Unternehmen im Durchschnitt eine höhere Managementqualität auf als nicht-staatliche Unternehmen. Wir bieten erste empirische Belege dafür, dass die Rolle der Qualität des Managements vom institutionellen Element der Eigentümerstruktur und der damit verbundenen Rolle der Regierung abhängig sein könnte. Wir finden erste Hinweise, dass staatlich kontrollierte Unternehmen am meisten von der Einführung moderner westlicher Managementpraktiken profitieren. Wir erklären und diskutieren mögliche Faktoren, die unseren Ergebnissen zugrunde liegen könnten.

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Acronyms

2SLS	Two-stage least squares
ATT	Average treatment effect on the treated
CEO	Chief Executive Officer
CES	Constant elasticity of substitution
CIC	Chinese Industrial Census
CHF	Swiss Francs
DD	Difference-in-difference
DEA	Data envelopment analysis
ED	Economies of density
ES	Economies of scale
FE	Fixed effects
FR	France
FYP	Five Year Plan
GDP	Gross domestic product
GER	Germany
GLS	Generalized least squares
GMM	Generalized method of moments
GTREM	Generalized true random effects model
GWh	Giga Watt hours
HMT	Hong-Kong, Macau or Taiwan
ID	Identifier
IV	Instrumental variable
kRMB	Thousand Chinese renminbi
ktce	Kilotons of coal equivalent
kW	Kilo Watt
kWh	Kilo Watt hours
LPM	Linear probability model

MAD	Management as a design
MAT	Management as a technology
MOPS	Management and Organizational Practices Survey
mRMB	Million Chinese renminbi
Mtce	Megatons of coal equivalent
NBS	Chinese National Bureau of Statistics
NDRC	National Development and Reform Commission
OLS	Ordinary least squares
R&D	Research and development
RE	Random effects
REM	Random effects model
RMB	Chinese renminbi
RMSE	Root mean square error
SEC	Scale efficiency change
SFA	Stochastic frontier analysis
SOE	State owned enterprise
T1000P	Top-1000 Energy-Consuming Enterprises Program
TC	Technical change
TFPC	Total factor productivity change
tce	Tons of coal equivalent
TFP	Total factor productivity
TREM	True random effects model
UK	United Kingdom
US	United States
USA	United States of America
VA	Value added
WASTA	Statistik der Wasserkraftanlagen der Schweiz
WMS	World Management Survey

Introduction

Part I: Persistent and Transient Cost Efficiency—An Application to the Swiss Hydropower Sector

Ever since Switzerland's electrification at the beginning of the 20th century, hydropower has been the country's main domestic source of electricity. Over time, Swiss hydropower firms have consolidated their position as reliable, cost effective renewable base and peak load electricity producers. However, a growing share of firms has started to incur financial losses in recent years. In the current competitive context, it is of immediate importance for them to identify strategies to increase their competitiveness by reducing production costs. The main goal of this study is to estimate the level of persistent and transient cost efficiency in the Swiss hydropower sector. For this purpose, we use a new and representative panel of detailed information on 65 Swiss hydropower firms between 2000 to 2013.

A distinction and measurement of the two components of overall cost efficiency is interesting, because it allows a firm to elicit its cost saving potential in the short- as well as the long-run. Moreover, from an economic policy perspective, a firm's level of cost efficiency, for example, might play a role under a subsidization program as it currently is under political discussion in Switzerland. Within the framework of such a program, policy makers could ask the participating firms to demonstrate a high degree of cost efficiency in order to qualify for subsidies.

The contribution of this paper to the scientific literature is threefold. First, it provides the first stand-alone empirical application of a novel approach recently introduced by Filippini and Greene (2016). Their methodology allows splitting the level of productive efficiency into a transient and a persistent part. Second, it uses a rich cost model specification explicitly controlling for technological heterogeneity in hydropower electricity generation. Third, firm-level information on the two categories of persistent and transient cost inefficiency can help the government to design an effective subsidy policy by granting financial aids only if firms meet predefined efficiency standards in both categories.

Colombi, Kumbhakar et al. (2014) and Filippini and Greene (2016) discuss how a cost inefficiency level can be split into the two parts of persistent and transient inefficiency. The persistent part captures cost inefficiencies which do not vary with time, like inefficiencies due to recurring identical management mistakes, structural problems within the electricity generation process or factor misallocations that are difficult to change over time. On the other hand, the transient component represents cost inefficiencies varying with time. Singular, non-systematic management mistakes are an example thereof. In the short- to medium-run, a firm's leverage is expected mainly to be on the improvement of the transient part of cost efficiency.

We estimate a homothetic translog frontier total cost function using three parametric model specifications. The first is the random effects model proposed by Pitt and Lee (1981) (REM hereafter). It provides an estimation of the part of productive inefficiency that does not vary over time (persistent inefficiency). The second model is the true random effects model (TREM hereafter) proposed by Greene (2005a, 2005b). This model produces values of the productive inefficiency that varies over time (transient inefficiency). The final econometric model is the generalized true random effects model (GTREM) proposed by Filippini and Greene (2016). This model offers the possibility to estimate simultaneously the transient as well the persistent component of productive inefficiency, making it our preferred model specification.

The inefficiency term of the REM captures all time invariant unobserved heterogeneity, resulting in a median cost efficiency value of 64.7 percent. This value is considerably lower than the median persistent cost efficiency estimate of 95.1 percent obtained by applying the GTREM. In contrast, the median transient efficiency of the TREM of 85.2 percent is more in line with the median transient efficiency estimate of

93.9 percent when using the GTREM specification. The correlation between the estimated efficiencies obtained with the REM and the TREM is low, pointing to the fact that they measure different sorts of cost efficiency. The correlation between the persistent and transient efficiency estimates of the GTREM is even negative. It therefore can be concluded that firms showing a high degree of persistent efficiency are not systematically exhibiting production processes of simultaneously high transient efficiency. The correlation between the REM cost efficiency and the persistent efficiency component of the GTREM is—as expected—comparatively high. The same holds for the correlation between the TREM cost efficiciency and the transient efficiency component of the GTREM. Results further confirm the existence of positive economies of density and scale for most firms.

We conclude the Swiss hydropower sector to be characterized by the presence of both, transient as well as persistent, cost inefficiency. The GTREM predicts the aggregate level of cost inefficiency to amount to 22.3 percent on average (7.9 percent transient, 14.4 percent persistent). The two components of inefficiency differ in interpretation and implication. The transient component represents cost inefficiencies varying with time, e.g., inefficiencies stemming from a wrong adaption of production processes towards changing factor prices or singular management mistakes. On the other hand, the persistent part captures cost inefficiencies not varying with time. Examples are inefficiencies due to recurring identical management mistakes, unfavorable boundary conditions of the electricity generation process or factor misallocations difficult to change over time. Therefore, the two types of cost inefficiency might require a firm's management to respond with different improvement strategies. From a regulatory point of view, the results of this study could be used in the scope and determination of the amount of subsidies to be granted to a hydropower firm. Knowledge of the level of cost inefficiency supports the government in avoiding a grant of subsidies to inefficient hydropower firms. If a hydropower firm shows a high level of cost inefficiency, the subsidy should be reduced or cancelled completely. However, the regulatory authority should also consider inertia in the short run possibilities of hydropower firms to ameliorate the level of persistent inefficiency.

Part I builds on joint work with Massimo Filippini and William Greene. A condensed version of this essay appeared in its first form in June 2016 as CER-ETH Working Paper 16/251 (Filippini, Geissmann et al., 2016). Thomas Geissmann is the primary author of this essay in all regards.

Part II: The Effects of Environmental Regulation on the Productivity of the Chinese Iron and Steel Industry

China is an emerging economy with unprecedented development, ranking second in size within only a few decades and lifting hundreds of millions of its inhabitants out of poverty. The industrial sector has been an important growth contributor for the country, which is a major exporter of energy-intensive products. Combined with a strong focus of the government to upkeep high growth rates, the rapid increase in energy demand has resulted in multiple adverse effects, for example, on the reliability and security of energy supply, human health, and environmental integrity. Being aware of these consequences, the Chinese government has started a restructuring process of the industry to reduce its environmental impact, which includes a reduction of its energy intensity. In this process, the understanding to simultaneously boost productivity while minimizing environmental degradation has gained more and more momentum. Productivity is critical for maintaining international competitiveness and sustaining high long-term growth rates. Finally, it represents a foundation of social welfare and living standards (Greenstone, List et al., 2012; Krugman, 1997).

The scientific literature differentiates between two main strands of how an environmental regulation affects productivity: the traditionalist view and Porter's hypothesis. Both views take the perspective of the firm. The traditionalist view predicts productivity of firms to be negatively affected by an environmental regulation, while Porter's hypothesis expects the opposite to be true. Most literature supports the traditionalist view, suggesting that firm heterogeneity in terms of productivity is adversely affected by environmental regulations.

The national Top-1000 Energy-Consuming Enterprises Program (T1000P) was an environmental regulation introduced by the Chinese central government within the Eleventh Five Year Plan. The regulation was effective between 2006 and 2010. At that time, the T1000P was part of the most ambitious effort ever made in China in terms of coverage and governmentally allocated resources to reduce industrial energy use. The program targeted about 1000 of the country's most energy demanding firms, i.e. the firms consuming a minimum of 180,000 tons of coal equivalent in 2004 (Price, Wang et al., 2010). Due to its high energy consumption, the highest share of firms targeted by this regulation belonged to the iron and steel industry.

This study analyzes the effects of the T1000P on firm-level total factor productivity (TFP) change. Its goals are, first, to estimate TFP change of the Chinese iron and steel industry using a parametric approach. This is one of only a few studies estimating TFP change via a cost function approach. Second, to our knowledge, this is the first study estimating the impact of an environmental regulation on the productivity of Chinese firms using parametric methods. Moreover, we are not aware of any other scientific study empirically analyzing spillover effects of an environmental regulation on the TFP change subcomponents of technical change and scale efficiency change using parametric methods. Such decomposition allows for a more detailed analysis of the effects of the regulation than what has been common practice in the literature. Third, to check for robustness of the treatment effect, this study proposes an instrument for selection into the program based on spatial firm level information.

The study uses detailed census information of an unbalanced panel of 20,076 unique observations of 5,340 firms over the period 2003 to 2008. The cost function is chosen to be of fully flexible translog parametric form. Spillover effects of the T1000P on TFP change are analyzed by applying a difference-in-difference research design. Results show that TFP on average was growing by 6.4 percent annually. The iron- and steelmaking subindustry shows the highest annual growth rates, followed by the steel rolling and ferroalloy smelting industry. The benchmark specification finds the regulation to have positively affected TFP change of treated firms by 3.1 percent on average between 2006 and 2008. The two components of technical change and scale efficiency change contributed about equally to this overall effect. Temporal, spatial, subindustry and firm-specific heterogeneities are controlled for when assessing the impact of the regulation on productivity. The average economic benefit of the program on a per firm basis is estimated to amount to 148.7 million Chinese renminbi in 1998 values, leaving the economic value of an improvement in the environmental integrity unaccounted for. Results are robust when stratifying the sample in several dimensions, when accounting for sample attrition and when instrumenting for T1000P exposure. In conclusion, a firm exposed to the regulation profited twofold. First, it profited through the direct effect of energy savings. Second, the regulation led to an increase in TFP change relative to non-treated firms, thereby increasing the competitiveness of the treated firms.

Thomas Geissmann is the primary author of this essay in all regards.

Part III: Management as Productive Input and the Role of Ownership

The studying of management has a long-standing tradition in the scientific literature, both, from an organizational theory (Barnard, 1938) as well as economic modelling perspective (Griliches, 1957). From the economic modelling perspective, the omission of management quality, which determines how efficiently and effectively the other production inputs are used, has been thought to be the most common specification error when estimating a production function (Griliches, 1957; Mefford, 1986). Management might be a factor contributing to the often observed large and persistent differences in productivity levels, not only between firms (Bartelsman and Doms, 2000; Bloom, Eifert et al., 2013; Syverson, 2011) comparable on many other observables like industry, technology, product or location (Gibbons, 2006), but also between countries (Bloom, Sadun et al., 2016). Hence, quantitative findings on the role of management in determining firm performance not only carry relevance for firms and businesses, but also for development policy and institutional design on an aggregate level. However, empirical literature, which analyses the degree to which observed management quality differentiates competitors, is surprisingly scarce. This is even more the case for studies that condition such an analysis on firm and environmental characteristics like a firm’s ownership structure.

In this paper, we probe the extent to which management quality matters in explaining the performance of 386 industrial firms operating in the unique institutional setting of China. Using data of the annual Chinese Industrial Census (CIC) for the period between 2003 and 2008, and observations on managerial quality contained in the World Management Survey, we contribute to the literature in various ways. Our first contribution is from an organizational theory point of view. This study focuses on the emerging economy of China during a period of rapid industrial growth in the mid-2000s, while previous literature analyzed the relationship between managerial quality and firm performance mainly for firms located in industrialized countries. The social and political environment of the Chinese economy is different to western economies, what might result in management quality mattering for other aspects than the ones commonly observed in the current literature. One such aspect might be the structure of firm ownership. In China, firm ownership represents sharp distinctions among operating conditions, for example, by defining a firm's degree of access to capital via lending and other means, regulatory burdens, political pressure, resources, and other intangible sources of legitimacy. We test for first empirical evidence of the institutional element of ownership mediating the relationship between observed management practices and firm performance.

Our second contribution is from an economic modelling perspective. The current empirical literature exclusively applies Cobb-Douglas production function specifications and abstracts from the question of separability of management from other productive inputs. Furthermore, apart from two recently published working papers by Bloom, Sadun et al. (2016) and Bloom, Brynjolfsson et al. (2016), it does not make use of the data's panel structure to control for time-constant firm-specific unobserved heterogeneity. Following Mefford (1986), we implement several functional forms and additionally apply panel models controlling for unobserved heterogeneity. Results of this study provide new insights into the question of the extent, to which modern western definitions of management quality matter in explaining the performance of Chinese firms.

Two of our main findings are in sharp contrast to the current literature. First, the role of management practice as productive input parameter by itself is found to be uncorrelated with the variation in firm output. Second, state-owned enterprises (SOEs) in

China on average are better managed than non-SOEs. As a third main finding, we provide first empirical evidence that the role of management in Chinese firms could be mediated by political economy elements, i.e. by the institutional element of firm ownership with its associated role of the government. There is indication that the adoption of modern western management practices is mostly correlated with higher output of SOEs.

Several hypotheses could explain why management quality by itself does not universally function as a differentiator in terms of firm productivity. Our setting is a rapidly expanding and transforming economy (Tsui, Schoonhoven et al., 2004). Here, short-run tensions between improving management practices and establishing or maintaining competitive advantages via other means could be especially acute. For a firm operating in China during a period of rapid growth, seizing the right opportunity could be as important as the effort put into seizing it (Dou, 2015). Moreover, to some degree China's past growth was investment based, similar to what was observed in other relatively underdeveloped economies in the past (Gerschenkron, 1962). According to Acemoglu, Aghion et al. (2006), for investment-based growth—in contrast to innovation-based strategies—managerial skills are not crucial. In such a setting, experienced managers and large incumbents are able to achieve larger technological improvements and productivity growth by simply copying and adopting existing technologies from the world's technological frontier (Acemoglu, Aghion et al., 2006).

Multiple elements might underlie the second and third main finding. For example, SOEs are required to develop plans, procedures and management rules in order to allow for increased state supervision (Wang, 2014). These governmentally imposed requirements might also cause, at least partially, the lower observed productivity of SOEs compared to non-SOEs. On the one hand, SOEs could be adopting better management practices (in western sense) simply to improve labor productivity and offset the generally lower total factor productivity when being state-owned. On the other hand, the Chinese government has the ability to shape market access and to deliver potentially productivity enhancing resources or domestic business connections exclusively to SOEs (Li and Xia, 2008; Nolan and Xiaoqiang, 1999; Oi, 1992). Such market opportunities might be heavily guarded, especially in some strategic industries (Bai, Lu et al., 2006; Wang, 2014). Good management practices could strengthen channels of communication and influence of SOEs with government leadership. Hence, good management practices could not only reflect requirements imposed on SOEs by the state, but also SOEs' access to privileges ("institutional rents"), which could be scaling with degree of compliance. Furthermore, there is anecdotal evidence that SOEs on average could be more technologically advanced and innovative than non-SOEs. In this case, as predicted by Acemoglu, Aghion et al. (2006) for innovative firms, management quality could be of higher importance for SOEs.

While the findings of this study are to some extent unique to China, where ownership types are perhaps more clearly delineated than elsewhere, we take liberty to propose some general insights based on our findings. Firms everywhere face varying degrees of legitimacy in their operating markets as well as in the eyes of major government and civil society stakeholders. Our results provide directional evidence of the notion of "management as a design", implying that firms use management practices in a way which fits their individual setting. Firms constrained in one dimension, in our setting by state ownership, could compensate to some extent by developing capabilities along dimensions that lie within their span of control. Such compensation could be achieved, for instance, through the development of better management practices.

Part III is partially based on a research effort with Valerie Karplus and Da Zhang and includes an extension focusing on a deeper exploration of microeconomic modelling. Thomas Geissmann is the primary author of this essay in all regards.

I Persistent and Transient Cost Efficiency—An Application to the Swiss Hydropower Sector[1]

[1] This part partially is based on the CER-ETH Working Paper 16/251 “Persistent and transient cost efficiency—An application to the Swiss hydropower sector” (Filippini, Geissmann et al., 2016). Thomas Geissmann is the primary author of this essay in all regards.

Without implication, we are grateful to the Bundesamt für Energie (BFE) for financially supporting a large study on the cost structure of Swiss hydropower firms conducted in July and August 2014.

“Um an die Quelle zu kommen, muss man gegen den Strom schwimmen.”

— Confucius

1 Introduction

Ever since Switzerland's electrification at the beginning of the 20^{th} century, hydropower has been the country's main domestic source of electricity. Over time, Swiss hydropower firms have consolidated their position as reliable, cost effective and renewable base and peak load electricity producers. Hydropower also has enabled Switzerland to play an active role on the European electricity market. The pursued business models can roughly be summarized as follows: run-of-river plants produce base load electricity while storage and pump-storage plants help covering electricity demand at peak hours, usually occurring at noon and early evening. All three technology types not only produce for the domestic market, but also are extensively involved in exporting activities to the European grid. A special role is accorded to the pump-storage plants. Their business model exploits the spread between peak and off-peak electricity prices. In addition of using natural water inflows for electricity generation, they pump water into their reservoirs during off-peak hours at favorable prices—often during nighttime—by consuming electricity directly from the high voltage grid. This electricity is partly sourced from the European electricity market, and especially from the French nuclear fleet. At peak load times, the water is turbinated again and the generated electricity is sold at comparatively high prices.

This business model was very successful until 2008. Then, the economic crisis, the low price of coal and CO_2 certificates (not reflecting the emission's external costs) and the subsidy system for renewable energies such as wind and photovoltaics have led to a significant drop in overall market prices for electricity. In addition, the spread between peak and off-peak electricity prices on the European electricity markets has decreased, or at some hours, even disappeared completely. In this context, the competitiveness of coal power plants has increased significantly. Furthermore, since 2009 the Swiss electricity market has been partially liberalized. Electricity distribution companies and large customers consuming more than 100 MWh per year now have the possibility to purchase electricity from a producer of their choice in Switzerland or other European countries or to buy electricity directly on the European spot markets. Of course, this reform has increased the level of competition among Swiss hydropower firms, resulting in a pressure to reduce production costs. In January 2015, the decoupling of the Swiss Franc from the Euro has led to an additional reduction in margins, since electricity traded on a European level is denominated in Euros. For these reasons, a growing share of hydropower plants has started to incur financial losses in recent years. In the current competitive context, it is of immediate importance for them to identify strategies to increase competitiveness by reducing production costs.

One possibility to achieve such goal is to improve the level of cost efficiency, which, as discussed in Colombi, Kumbhakar et al. (2014) and Filippini and Greene (2016), can be split into two parts: a persistent and a transient one. The persistent part captures cost inefficiencies which do not vary with time. These could be inefficiencies due to recurring identical management mistakes, structural problems within the electricity generation process or factor misallocations that are difficult to change over time. On the other hand, the transient component represents cost inefficiencies varying with time, e.g., singular, non-systematic management mistakes. In the short- to medium-run, a firm's leverage is expected to be mainly on the improvement of the transient part of cost efficiency.

Information on the level of cost efficiency is of importance not only for the firms, but also for the Swiss federal government. In fact, in 2015 the Swiss parliament decided, under some circumstances, to financially support hydropower firms in financial distress. However, the political process of specifying the details of such a subsidization system is still ongoing. From an economic policy point of view, it is important to grant such subsidies only to firms already operating at a high degree of efficiency. Hence, knowledge on the level of cost efficiency supports the government in avoiding subsidizing inefficient hydropower firms.

Despite the fact that hydropower still is the world's dominant source of renewable energy, the scientific literature only comprises a few published studies on the productive efficiency of hydropower firms.[2] Banfi and Filippini (2010) study the cost structure and level of cost efficiency of an unbalanced panel of 43 Swiss hydropower firms observed from 1995 to 2002. Using a translog variable cost function, they employ the true random effects model proposed by Greene (2005a, b), i.e. a stochastic frontier approach. The explanatory variables considered are: total amount of electricity produced, number of plants per firm, price of labor and capital stock. Furthermore, four binary indicators are added to the model controlling for different types of technology.[3] Their empirical results indicate economies of utilization as well as the presence of cost inefficiency. Using a variable cost function approach as well, Barros and Peypoch (2007) examine the cost efficiency of a balanced panel of 25 Portuguese hydropower plants, all of them belonging to the main Portuguese utility, for the years 1994 to 2004.[4] From the econometric modelling point of view, these authors also use a translog functional form and the true random effects model. Finally, Barros, Chen et al. (2013) analyze the level of cost efficiency of a relatively small panel of twelve Chinese hydropower firms for the period 2000 to 2010 using a total cost function in translog functional form. They apply a stochastic frontier latent class model to take into account possible differences in unobserved production technologies affecting costs. Estimation results indicate the presence of three distinct groups of firms. Their choice to use a latent class model is an interesting approach for the case where the firms' production technology is not directly observed.

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2 For a publication summarizing several studies on efficiency measurement in the general electricity generation sector see, e.g., Barros (2008). More recent contributions to the measurement of efficiency in the electricity generation sector were made by, e.g., Yang and Pollitt (2009) (China – coal plants – data envelopment analysis, DEA), Sueyoshi, Goto et al. (2010) (USA – coal plants – DEA), Liu, Lin et al. (2010) (Taiwan – thermal plants – DEA), Shrivastava, Sharma et al. (2012) (India – coal plants – DEA), See and Coelli (2012) (Malaysia – thermal plants – stochastic frontier analysis, SFA) and Chen, Barros et al. (2015) (China – thermal plants – Bayesian SFA).

3 The cost function specified in Banfi and Filippini (2010) was also used by Filippini and Luchsinger (2007) to quantify the economies of scale of the Swiss hydropower sector using cost share equations and the seemingly unrelated regression concept of Zellner (1962).

4 Using the same data and focusing on the period 2001 to 2004, Barros (2008) analyzes and decomposes the productivity of hydropower firms by applying a data envelopment analysis to a production function.

Most of the empirical literature so far has fallen short of a differentiation of the persistent and transient component of productive efficiency. Also the aforementioned studies only provide empirical information on the transient, but not the persistent, part of cost efficiency. This paper's main goal is to measure the level of persistent and transient cost efficiency for a sample of Swiss hydropower firms by estimating a homothetic translog stochastic frontier total cost function. We use a new and representative panel of Swiss hydropower firms. In a firm's context, the persistent part of productive inefficiency may be due a variety of factors like regulations, investments in inefficient machines or infrastructure or lasting habits of the management to waste inputs. The transient part of inefficiency on the other hand, for example, may stem from temporal behavioral aspects of the management or from a non-optimal use of some machines. Such distinction and measurement of the two components of overall cost inefficiency is interest-interesting because it allows the firms to elicit their cost saving potential in the short- as well as the long-run. Also, from a policy point of view, firms can be asked to improve their cost efficiency if they, e.g., become part of a subsidization program, as it currently is being discussed in Switzerland. Within the framework of such a program, the policy maker can ask the participating firms to improve their level of cost efficiency. Thereby, he should differentiate between persistent and transient levels of inefficiency.

The contribution of this paper to the scientific literature is threefold. Firstly, from an econometric point of view, we provide the first stand-alone empirical application of a novel approach recently introduced by Filippini and Greene (2016). Their methodology allows splitting the level of productive efficiency into a transient and a persistent part. Secondly, a rich cost model specification is used, explicitly controlling for, e.g., the technological heterogeneity between run-of-river, storage and pump-storage plants. Thirdly, firm-level information on the two categories of persistent and transient cost inefficiency can support the government in designing an effective subsidy policy by granting financial aids only if a firm meets predefined efficiency standards in both categories.

The structure of this paper is as follows: Chapter 2 contains a description and gives and overview of the data used in the empirical analysis. Chapter 3 sets out the concept of a cost function and cost efficiency. Chapter 4 describes the empirical cost model as well as the chosen functional form, and chapter 5 presents the econometric estimation methodologies. Results are summarized in chapter 6. Finally, chapter 7 concludes and discusses the findings.

2 Data

Hydropower electricity generation in Switzerland is mainly based on approximately 600 plants operated by several dozen hydropower firms[5], contributing roughly 55 to 60 percent to the total domestic electricity generation. Most of these plants (ca. 80 percent) are of run-of-river type, with storage and pump storage plants making up the remaining share (BFE, 2013). The Swiss hydropower firms are organized according to a specific structure, with the largest part of them being so-called partner firms ("Partnerwerke" in German). These firms sell the generated electricity to Swiss utilities, who in turn are mainly active in the distribution, sales and trading of electricity in Switzerland as well as on the European electricity market (see also section 4).

The econometric analysis is based on an unbalanced[6] panel data set comprising 65 hydropower firms over the time period of 2000 to 2013. The financial data was extracted from the yearly annual reports of these firms and extended by firm-specific technical information contained in the "Statistik der Wasserkraftanlagen der Schweiz" (WASTA), which is published annually by the Swiss Federal Office of Energy (BFE, 2013). By means of this technical information, hydropower firms are classified into three distinct categories to account for heterogeneities in the production processes. The three categories, representing the dominating power plant type operated by a firm, are: run-of-river,

5 A hydropower firm may have several plants under operation. A plant represents a building containing one or more turbines. Geographically, these plants usually are located in a close perimeter to each other.

6 The underlying reasons for the data to be unbalanced are, for example, firm mergers or annual reports not being obtainable anymore due to, e.g., ownership changes. None of the sample attrition was due to firms ceasing production.

storage and pump storage. Following Filippini, Banfi et al. (2001), the classification is conducted as follows: A storage firm produces at least 50 percent of its expected electricity generation by storage power plants, whereby the share of the installed pump capacity is smaller or equal to 10 percent of the total maximum possible generator capacity. A pump storage power firm produces at least 50 percent of its expected electricity generation by storage power plants, whereby the share of the installed pump capacity is larger than 10 percent of the total maximum possible generator capacity. All other firms are considered to be of type run-of-river.

A specific firm type does not imply that all plants operated by a firm are of the same kind; it rather indicates the dominating plant type. The technology of the firms classified to be of type run-of-river is relatively homogenous, i.e. most of these firms exclusively or to a large extent operate run-of-river plants. Furthermore, this firm type runs comparatively few plants, usually one or two. This is in contrast to the plants run by the storage and pump storage firms, which are more diverse in type and larger in number per firm. The average share of run-of-river type firms in our sample is 58 percent. The share of storage type firms is 19.9 percent, and 22.1 percent for pump storage type firms. Our sample of hydropower firms represents the Swiss hydropower sector quite well, especially in terms of the installed capacity and expected generation (cf. Figure I-1). For the period 2000 to 2013, we observe approximately 60 percent of the total expected generation of the Swiss hydropower plants with an installed capacity larger than 300 kW.

The power plants usually are younger than 50 years or have undergone at least once a major remodeling during the last five decades. The highest share of plants in our sample is located in Alpine cantons, corresponding to the general distribution of hydropower plants in Switzerland. For topological and hydrological reasons, the storage and pump-storage firms are mainly situated in Alpine cantons.

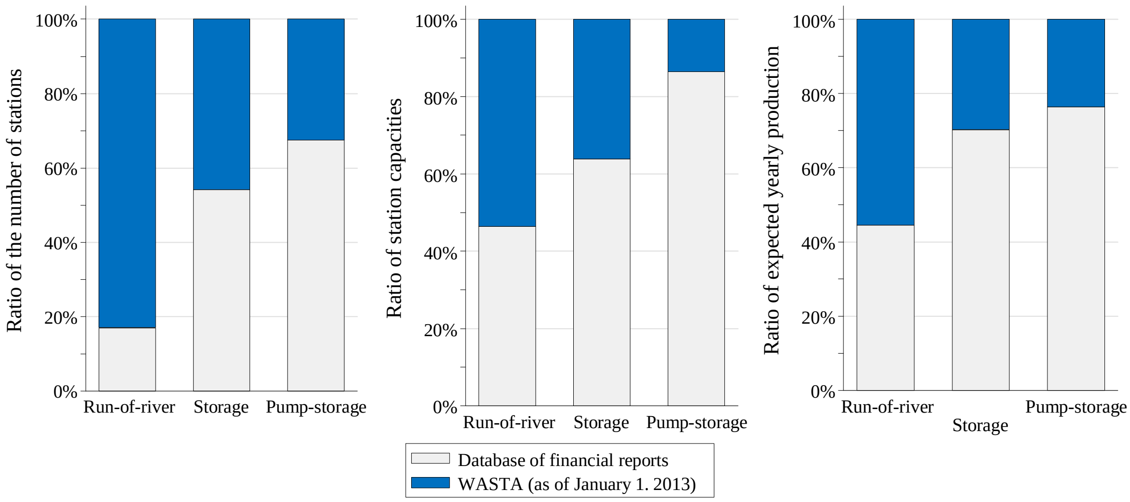

Figure I-1: *Representativeness of the sample in 2013 in terms of the number of stations, the installed capacity and the expected generation.*

Note: Figure I-1 shows the degree, to which firms of the sample are representative of the population of Swiss hydropower plants with an installed capacity of at least 300 kW. This population of plants is contained in the WASTA. For example, the right bar of the right panel indicates our sample to represent roughly 80 percent of the expected yearly generation of the population of pump-storage plants.

3 Cost Function and Cost Efficiency

Our empirical analysis of the productive efficiency and economies of scale and density is based on a cost function approach. Hence, it seems worthwhile to step aside for a moment to focus on the concept of a cost function, its properties as well as the concept of cost efficiency. A cost function reflects the cost minimizing price-output combination and is defined as

$$c(\mathbf{P},Y)=\min_{\mathbf{X}\geq 0}\left[\mathbf{P}'\mathbf{X}:\mathbf{X}\in V(Y)\right].$$

It represents the cost minimizing problem of a firm in a mathematical form as a function of a vector of strictly positive input prices **P** and a non-negative output Y. Vector **X** contains non-negative inputs and V(Y) is the input requirement set, which specifies the amounts of inputs necessary to produce a given level of output. It usually is assumed to be non-empty and closed (Chambers, 1988). Given its duality with the production function, a cost function is commonly assumed to satisfy several properties[7]:

① $c(\mathbf{P},Y)$ is non-negative and only assumes real values

② $c(\mathbf{P},Y)$ is non-decreasing in $\mathbf{P}$

③ $c(\mathbf{P},Y)$ is concave in $\mathbf{P}$

④ $c(\mathbf{P},Y)$ is continuous in $\mathbf{P}$

⑤ $c(\mathbf{P},Y)$ is positively linearly homogenous in $\mathbf{P}$

⑥ $c(\mathbf{P},Y)$ is non-decreasing in Y

In appendix A.1 it is shown, how an empirical cost function can be tested for homogeneity (property 5), monotonicity (properties 2 and 6) and quasi-concavity (property 3). The property of positive linear homogeneity

$$c(\varsigma\mathbf{P},Y) = \varsigma c(\mathbf{P},Y),\ \varsigma > 0$$

will become relevant later on, when we empirically estimate the cost function of a sample of hydropower plants. This property states that a firm bases its input allocation solely on the ratio of relative input prices; i.e. only relative prices matter with the cost minimizing demand for input i being $X_i(\varsigma\mathbf{P},Y) = X_i(\mathbf{P},Y)$, $i = \{1,...,N\}$. Monotonicity states that if $\mathbf{P}^* \geq \mathbf{P}$ and $Y^* \geq Y$, then $c(\mathbf{P}^*,Y) \geq c(\mathbf{P},Y)$ and $c(\mathbf{P},Y^*) \geq c(\mathbf{P},Y)$ (Chambers, 1988). The cost function $c: V \to \mathbb{R}$ defined on the convex set $V \subset \mathbb{R}^N$ is quasi-concave if its upper contour sets are convex sets (Mas-Colell, Whinston et al., 1995).

Two cornerstone concepts of this study are the property of homotheticity and the concept of cost efficiency. A cost function is homothetic if $c(\mathbf{P},Y) = c(\mathbf{P})h(Y)$ holds, i.e. homotheticity is sufficient for output to be separable from input prices. Homotheticity implies that inputs $\mathbf{X}$ are non-decreasing in output Y. In addition, the marginal rate

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[7] For more detailed explanations of the properties of $c(\mathbf{P},Y)$ see Chambers (1988).

of technical substitution between inputs i and j only depends on relative inputs $X_i(\mathbf{P},Y)/X_j(\mathbf{P},Y)$ (Chambers, 1988).[8] Under homotheticity, the slope of the isocost line does not change if output expands and input prices remain constant. Instead, the cost minimizing price-output combination simply expands along a vector through the origin point (cf. Figure I-2). This vector also represents the economies of scale line. Hence, the elasticities of scale and size are equivalent under a homothetic cost function (Chambers, 1988).

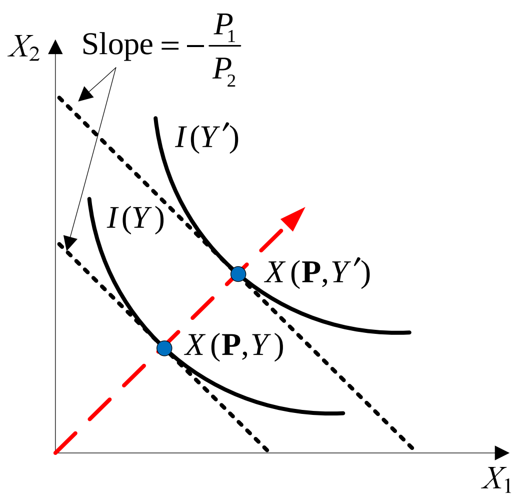

Figure I-2: *Concept of homotheticity, with Y‘ > Y (adapted from Chambers, 1988).*

[8] This property easily can be shown by applying Shephard's Lemma to $c(\mathbf{P},Y) = c(\mathbf{P})h(Y)$ with respect to inputs prices P_i and P_j. A homothetic cost function is consistent with a homothetic single aggregate input production function $Y = f(\mathbf{X})$ (Chambers, 1988). See appendix A.1 of part III for a more detailed description of the properties of a production function.

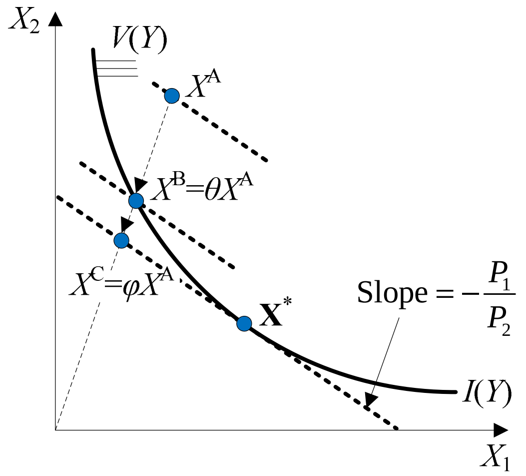

Figure I-3: *Radial measurement of technical [1 – θ] and allocative [1 – (φ – θ)] cost efficiency (adopted from Kumbhakar and Lovell, 2000).*

The concept of cost efficiency is exemplified in input space by Figure I-3. It bases on the concept of a radial measurement of efficiency with respect to the isoquant proposed by Debreu (1951) and Farrell (1957). Hence, the literature often calls this the „Debreu-Farell measure of efficiency" (Kumbhakar and Lovell, 2000). The isoquant $I(Y)$ borders the input requirement set $V(Y)$, which is assumed to be strictly convex. The isoquant represents a production technology, i.e. all possible input combination yielding the same amount of output. The cost minimizing input combination of inputs X_1 and X_2 at the tangent point of isocost and isoquant is represented by vector $\mathbf{X}^*$. The vector of input choices X^A is not cost minimizing, as we could produce an equal amount of output by reducing either input 1, or input 2, or both. Curtailing such sub-optimal choice of inputs by the ratio θ would allow the firm to reach point X^B on the isoquant and thereby achieve technical efficiency. However, while technically efficient, such input combination still is not allocatively efficient and therefore it is economically suboptimal.[9] The same amount of output could be produced at lower costs by increasing input 1 and simultaneously reducing input 2. Thereby, input combination $\mathbf{X}^*$, i.e. technical and allocative efficiency, would be achieved. A further trimming of input vector X^A by the ratio φ

9 The estimation of a production function would only allow the inference of technical efficiency. In such a case, allocative efficiency cannot be measured, as price information and therefore information on the isocost line are unobserved.

would allow the firm to reach X^{C}, which lies on the same isocost line that also defines the point of technical and allocative efficiency $\mathbf{X}^{*}$. Ratio φ represents the overall cost efficiency of a firm. Hence, technical efficiency is a measure of the degree to which inputs could be reduced equiproportionally while still producing the same amount of output. Allocative efficiency is a measure of the degree of suboptimal input choice, while keeping the level of output constant. In both cases, unit prices are assumed to stay constant.[10]

4 Empirical Specification

4.1 Parametrization of the Cost Function

The frontier total cost function represents the minimum cost a firm potentially could achieve in producing a given amount of output by using a given technology and facing given input prices. Usually, none or only a few firms are operating at the cost frontier. Failure to do so implies the existence of technical and allocative inefficiency. In what follows, a stochastic frontier total cost function is estimated using panel data. Such estimation of the frontier necessitates the specification of a parametric model, the choice of a functional form and finally, the identification of an econometric approach.

The cost of a firm operating one or more hydropower plants is influenced by several factors such as output, factor prices, size of the reservoir, production technology (storage, pump-storage or run-of-river), age or the number of plants in a firm's portfolio. Therefore, the cost function for the Swiss hydropower firms may be specified as

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[10] See, e.g., Kumbhakar and Lovell (2000), Coelli, Rao et al. (2005) or Fried, Lovell et al. (2008) for an in depth description of the concept of technical and allocative efficiency as well as overall cost efficiency.

$$C = c\left(Y, P_L, P_W, P_K, P_E, F, N, D_S, D_P, t\right), \tag{1}$$

where C are the total generation costs. Firm i and time t subscripts are dropped for notational simplicity. The single output Y is gross electricity generation in kWh. The price of labor is represented by P_L, the price of water by P_W and the residual price of capital by P_K. The price of energy used in electricity production is P_E. To capture additional heterogeneities in the production process, the cost function includes on the one hand the firm's average load factor F. This variable helps to differentiate between, e.g., a run-of-river or storage firm, as the latter usually shows a much lower load factor than the former.[11] To further control for the presence of different types of hydropower firms, technology fixed effects D_S and D_P are included into the model. These indicate whether a firm uses predominantly storage (D_S) or pump-storage (D_P) plants for electricity generation, with run-of-river representing the reference firm type.[12] With run-of-river firms bunching up in the Swiss midlands, and storage and pump storage firms being concentrated in Alpine regions, these variables in addition capture heterogeneity in terms of the production environment. Finally, the number of plants under operation, N, measures the impact on cost of jointly operating several plants. Even though electricity generation by hydropower is based on mature technologies, a time trend t is included to capture exogenous technical change. Total costs are based on an accounting approach. Hence, it is worth noting that the framing of the cost function follows a firm oriented perspective ra-

[11] Next to being inherently connected to a firm's technology, a low load factor also could indicate unplanned plant shutdowns due to, e.g., poor maintenance of machinery. A subsequent repair would result in higher costs, translating into a poorer productive efficiency. However, the annual reports indicate that shutdowns either were occurring for planned maintenance or due to adverse natural conditions. Furthermore, firms in general avoid water overflows as marginal generation costs usually are low. Therefore, and given the data's yearly aggregation and the extent of the installed capacity being defined by long-term investment cycles, the load factor can be considered to be exogenous.

[12] Another approach to capture heterogeneities in the production process would consist of an application of a latent class model, as done in, e.g., Barros et. al. (2013). However, we decided against this approach, because we observe technological heterogeneity. We are also more interested in the distinction between persistent and transient inefficiency. We believe that the latent class model is not completely appropriate for the estimation of a cost function based on a small sample and that our cost model specification and econometric approach sufficiently controls for heterogeneities in the production processes.

ther than a society oriented one, i.e. the cost function does not account for possible external costs arising from the electricity generation process.

Under the assumption of cost minimizing firms, a cost function should satisfy the properties of concavity and linear homogeneity in input prices. Furthermore, it should be non-decreasing in output and input prices. Linear homogeneity in input prices can be imposed by normalizing cost and input prices by one of the input prices. The other properties are to be verified once the translog cost function has been estimated. We argue the necessary assumption of output levels being exogenous to hold based on the monopolistic structure of the electricity market. Firms faced public service obligations for most of the years considered in the empirical analysis. Furthermore, the majority of firms contained in the sample are so called partner firms. A shareholder (usually one or several utilities that trade and sale electricity, also called mother companies) of a partner firm has the right to claim a percentage share of the electricity produced depending on the share of paid in capital. Utilities then use this electricity to partially cover domestic electricity demand as well as for export activities. The general production plan of this firm type is defined on an annual basis, instead of a daily basis depending on market conditions.

We decided to use a translog functional form (Berndt and Christensen, 1973; Christensen, Jorgenson et al., 1973) to estimate the cost function in eq. (1). In a preliminary analysis, we tried to estimate a fully flexible version of the translog functional form. However, due to the presence of highly correlated variables in the cost model, such as output, load factor or number of stations, such model specification suffered from multicollinearity. For this reason[13], we decided to estimate a homothetic version of the translog cost function, a version that is more parsimonious in the number of coeffi-

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[13] For the same reason we decided against the inclusion of Mundlak factors. The idea of Mundlak (1961, 1978) consists of including firm-specific mean values $\overline{p}_{i,X} = T_i^{-1} \sum_t p_{it,X}$, $X = \{L, W, K\}$ of a selection of cost function covariates $p_{it,X}$ into the estimated equation. Mundlak's idea was first applied to a stochastic frontier setting by Farsi, Filippini et al. (2005). T_i represents the total number of years firm *i* is observed. Mundlak factors are meant to capture all time-constant unobserved heterogeneity correlated with $p_{it,X}$, thereby separating such heterogeneity from the idiosyncratic error and inefficiency.

cients to be estimated. Based on eq. (1), the homothetic version of the translog cost function can be expressed as shown in eq. (2).

$$\begin{aligned}
c &= \alpha + \boldsymbol{\beta}'\mathbf{x} + u + v \\
&= \alpha + \beta_Y y + \sum_{Z=\{L,W,K\}} \beta_Z p_Z + \beta_F F + \beta_N n \\
&\quad + \frac{1}{2}\left(\beta_{YY} y^2 + \sum_{Z=\{L,W,K\}} \beta_{ZZ} p_Z^2 + \beta_{FF} F^2 + \beta_{NN} n^2 \right) + \sum_{Z=\{W,K\}} \beta_{LZ} p_L p_Z \\
&\quad + \beta_{WK} p_W p_K + \beta_{YF} yF + \beta_{YN} yn + \beta_{FN} Fn + \beta_{DS} D_S + \beta_{DP} D_P + \beta_t t \\
&\quad + u + v.
\end{aligned} \tag{2}$$

For notational simplicity, the unit index i as well as the time index t are omitted. Lower cases indicate values in natural logarithms, and α is the intercept. Linear homogeneity in prices is imposed by normalizing total costs and factor price variables by the price of energy. Because of its comparative robustness with regard to outliers, the variables' median value was chosen as point of approximation, i.e. the estimated coefficients represent elasticities at the sample's respective median values. As will be explained in chapter 5, the concept of the stochastic frontier analysis splits the error term ε into an inefficiency component u and the usual white noise term v, i.e. $\varepsilon = u + v$.

4.2 Variable Definitions

Total generation costs include water fees, amortization, financial expenses, profit before taxes, material and external services, personnel costs, costs for energy and grid access, other taxes and dues as well as other costs. All financial variables have been deflated to real 2010 values using the Swiss producer price index published by BFS (2014).[14] The price of labor, P_L, is defined as personnel costs divided by the number of employees. For firms with missing information on the price of labor, a year- and region-specific price proxy is constructed, thereby allowing for structural differences in salaries be-

[14] Data processing was conducted using Stata 13 (StataCorp, 2013).

tween geographic regions.[15] The price of water, P_W, is defined as the ratio of the sum of water fees and other concession fees to a firm's total installed turbine capacity. Following Friedlaender and Wang Chiang (1983), the capital price, P_K, is estimated as residual costs divided by the installed turbine capacity, which serves as a proxy for the capital stock. Residual costs are defined as total costs minus labour costs, energy costs and water costs, i.e. they include material and external service costs, allowances for depreciation, financial expenses and profits before taxes[16]. Finally, a single energy price, P_E, is assumed for all hydropower firms. In fact, energy costs are mainly composed of expenditures on electricity. The presence of a uniform European electricity market justifies the assumption of firms facing a cross-section wise constant price of energy.

Some firms activated additional capital allowances on non-depreciable investments before the opening of the electricity market to increase the level of competitiveness, especially around the beginning of the new millennium. As some of these additional allowances exceed usually observed numbers by a multiple, they cause a significant distortion of the respective firms' cost structure. To avoid the distorting effect of such special accounting measures, extraordinary allowances in one year were corrected for by adjusting the amortization rate of that year to the firm-specific average amortization rate of the other years.[17] Furthermore, if mother companies delivered pump energy free of charge, these opportunity costs were valued and subsequently added to total

[15] This labor price proxy represents the year-specific median labor price in a region. The seven geographic regions of Switzerland are defined as follows: Lake Geneva region (1), midland (2), Northwestern Switzerland (3), Zurich (4), Eastern Switzerland (5), Central Switzerland (6), Ticino (7). Furthermore, for the firms located on the German and French border, two separate regions (8 and 9) are defined.

[16] Profits before taxes are assumed to represent the equity yield rate. Unfortunately, we do not have all the information necessary to estimate a capital price based on the economic approach of opportunity costs of capital.

[17] Such amortization cost correction affected 8 firms in a total of 14 periods, i.e. ca. 1.7 percent of the observations. The amortization rate is the ratio of the amortization costs to the sum of the reported book value of fixed assets (excluding assets under construction) and realized investments. We chose the book value because not all hydropower firms publish numbers on asset acquisitions. However, the use of the book value implies a non-linear depreciation schedule, while hydropower firms usually depreciate linearly.

costs.[18] Finally, the load factor F is formed by a division of Y, the gross electricity generation, by the total installed turbine capacity, whereby the latter is multiplied by the number of hours per year. The variables' descriptive statistics are given in Table I-1.

Table I-1: *Descriptive statistics of the variables.*

	Mean	Std.dev.	Min.	Max.
Total costs C [million CHF]	24.20	30.96	0.32	195.92
Electricity generation Y [GWh]	433.38	484.06	5.82	2,695.00
Price of labor P_L [kCHF per employee]	127.80	19.10	74.90	247.15
Price of water P_W [CHF per kW]	45.41	34.64	0.54	336.98
Price of capital P_K [CHF per kW]	145.90	108.22	17.00	739.68
Load Factor F [index]	0.492	0.331	0.104	2.608
Number of stations N	2.49	2.03	1	13
Time trend t	7.46	4.02	1	14
Storage fixed effect D_S	0.199	0.400	0	1
Pump storage fixed effect D_P	0.221	0.415	0	1

Note: This table presents descriptive statistics of the variables of the cost function given in eq. (1). CHF indicates Swiss Francs. The statistics are based on the full sample of observations. Monetary values are given in real 2010 values.

5 Estimation Methodologies

In what follows, the level of cost efficiency of a sample of Swiss hydropower firms is estimated using a parametric approach, i.e. the stochastic frontier analysis (SFA).[19]

[18] This correction only affects 5 firms in a total of 39 periods, i.e. ca. 4.5 percent of the observations. The correction for non-allocated pump energy charges at a rate of 3 cents per kWh accounts for the fact that consumed pump energy is of different quality than the electricity generated by a pump storage plant: From 2000 to 2013 (our sample period), water usually was pumped at nighttime when electricity prices were low. Electricity generation, however, focused on peak load times, usually at noon and in the evening, since these periods were characterized by comparatively high prices.

[19] The literature on the measurement of a firm's productive efficiency roughly can be divided into two main methodological strands: the parametric and the non-parametric analysis. SFA represents the prevalent parametric approach, whereas the data envelopment analysis (DEA) constitutes the most prominent non-parametric approach. Non-parametric approaches do not necessitate an a priori specification of a functional form and use linear programming, while parametric approaches are based on

(*Footnote continues on next page*)

Econometric SFA models for panel data allow for an estimation of both parts of cost efficiency, i.e. of the transient and persistent part. Moreover, parametric approaches are suitable in case unobserved heterogeneity, like environmental characteristics, influences production processes.[20]

The measurement of inefficiency using SFA has a long-standing tradition in the literature. The SFA methodology dates back to the end of the 1970s when first contributions—at that time focusing exclusively on cross-sectional data—were made by Aigner, Lovell et al. (1977), Meeusen and Broeck (1977) and Battese and Corra (1977). Since then, the concept of SFA was extended significantly to the longitudinal setting by Pitt and Lee (1981), Cornwell, Schmidt et al. (1990) and Greene (2005).[21] Recently, Colombi, Martini et al. (2011) have proposed a new stochastic frontier model that simultaneously distinguishes between two parts of productive efficiency, i.e. a persistent and a transient part. However, estimation of this model resulted to be complex and cumbersome. Subsequently, Tsionas and Kumbhakar (2014), Kumbhakar, Lien et al. (2014) and Filippini and Greene (2016) proposed different econometric approaches to estimate the model proposed by Colombi, Martini et al. (2011).

In this paper, we decided to use three alternative stochastic frontier models for panel data. The first is the model proposed by Pitt and Lee (1981) (REM hereafter). It provides an estimation of the part of productive inefficiency not varying over time (persistent inefficiency). As in the basic stochastic frontier model proposed by Aigner, Lovell et al. (1977), the error term is composed of two parts. The stochastic error captures noise effects, while a one-sided non-negative disturbance represents the level of inefficiency. Following the traditional literature on panel data models, the REM

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econometric concepts, allowing them to differentiate between unobserved heterogeneity and inefficiency. Furthermore, non-parametric approaches are not able to distinguish in a satisfactory way between technical and allocative cost inefficiency, which together form the overall cost inefficiency.

[20] A more extensive discussion on methodological differences, as well as an extensive description of SFA models, can be found in, e.g., Greene (2008b), Coelli, Rao et al. (2005) or Kumbhakar and Lovell (2000).

[21] See Filippini and Greene (2015) for a review of several stochastic frontier models for panel data.

$$c_{it} = \alpha + \boldsymbol{\beta}'\mathbf{x}_{it} + u_i + v_{it} \tag{3}$$

interprets the random effects u_i as inefficiency instead of unobserved heterogeneity. Any time-invariant group-specific unobserved heterogeneity is absorbed in the inefficiency term. Hence, the REM provides an estimate of the persistent inefficiency level of firms. However, if time-constant unobserved heterogeneity is not controlled for adequately, the model might overestimate persistent inefficiency. The existence of a closed form solution for the integral of the log-likelihood function of eq. (3) (cf. p. 59 ff. in Pitt and Lee, 1981) allows the model to be estimated by maximum likelihood.

The second model is the true random effects model (TREM hereafter) proposed by Greene (2005a, 2005b). The model produces values of the productive inefficiency varying over time (transient inefficiency). The TREM

$$c_{it} = (\alpha + r_i) + \boldsymbol{\beta}'\mathbf{x}_{it} + u_{it} + v_{it} \tag{4}$$

includes group-specific random effects r_i capturing any time-invariant unobserved heterogeneity. In contrast to the REM, the random effects of the TREM are not used for the estimation of the level of productive inefficiency. The TREM hence comes with the advantage of controlling for time-constant unobserved heterogeneity. On the other side, the group-specific random effects absorb any time-invariant component of inefficiency. Therefore, the TREM tends to produce an estimate of the level of transient inefficiency. For the cost function in eq. (4), the simulated log-likelihood can be specified as

$$\begin{aligned} &\log L(\boldsymbol{\beta}, \lambda, \sigma, \sigma_r) \\ &\quad = \sum_{i=1}^{N} \log \frac{1}{Q} \sum_{q=1}^{Q} \left[\prod_{t_i=1}^{T_i} \frac{2}{\sigma} \phi\left(\frac{c - \alpha - \boldsymbol{\beta}'\mathbf{x} - \sigma_r R_{iq}}{\sigma} \right) \times \Phi\left(\frac{\lambda(c - \alpha - \boldsymbol{\beta}'\mathbf{x} - \sigma_r R_{iq})}{\sigma} \right) \right], \end{aligned}$$

where $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$ and $\lambda = \sigma_u / \sigma_v$ is the signal to noise ratio. The standard normal density is represented by $\phi(.)$ and the standard normal cumulative distribution function by $\Phi(.)$. The term $\sigma_r R_{iq}$ is the q^{th} simulated draw using Halton sequences of $\sigma_r R_i$ for firm *i*, with $R_i \sim N(0,1)$ (Greene, 2005a). For notational simplicity, unit *i* and time *t* indices are omitted for the other variables.

The final econometric specification is the generalized true random effects model (GTREM). By adding a fourth random component h_i, this model offers the possibility to simultaneously estimate the transient component u_{it} as well the persistent component h_i of productive inefficiency. As discussed previously, Colombi, Kumbhakar et al. (2014) provide a first theoretical and empirical discussion on the distinction between persistent and transient inefficiency. For this purpose, they specify the four random components model:

$$c_{it} = (\alpha + r_i + h_i) + \boldsymbol{\beta}'\mathbf{x}_{it} + u_{it} + v_{it}. \qquad (5)$$

Similar to the TREM, r_i and v_{it} capture time-constant and varying unobserved heterogeneity unrelated to cost inefficiency, respectively. By recognizing that the sum of the four random components has a closed skew-normal distribution, they apply a maximum likelihood estimation for the numerical optimization, which in practice however is highly complex and cumbersome to estimate. The coefficients are estimated using the two step procedure of Parke (1986), which gives unbiased estimates of the β-coefficients (except the intercept) in a first step and of the variances of the four random components as well as the intercept in a second step. In a final third step, the four components' posterior expected values are calculated by using the respective closed-form conditional likelihood functions.

To measure transient and persistent efficiency, Tsionas and Kumbhakar (2014) propose the estimation of a four-way error component model based on Bayesian Markov chain Monte Carlo methods. Kumbhakar, Lien et al. (2014) introduce a method of moments estimator based on OLS to simultaneously estimate persistent and transient inefficiency and test this estimator against five other panel data models. Colombi, Kumbhakar et al. (2014), however, find their approach to yield more efficient and less biased estimation results than the one of Kumbhakar, Lien et al. (2014). They also test their model against several other standard SFA models and find the four-way error component model—due to its ability to distinguish between unobserved latent heterogeneity and persistent inefficiency—to be appropriate especially if the panel is moderately long and characterized by a relatively high degree of firm heterogeneity.

Building on the theoretical platform provided by Colombi, Kumbhakar et al. (2014), Filippini and Greene (2016) suggest a practical, straightforward and transparent econometric method to estimate the GTREM. Filippini and Greene (2016) propose to estimate the two components of productive efficiency using a full information maximum simulated likelihood estimator, which for the cost function in eq. (5) can be given as

$$\log L\left(\boldsymbol{\beta},\lambda,\sigma,\sigma_r,\sigma_h\right) = \sum_{i=1}^{N}\log\frac{1}{Q}\sum_{q=1}^{Q}\left[\begin{array}{l}\prod_{t_i=1}^{T_i}\frac{2}{\sigma}\phi\left(\frac{c-\alpha-\boldsymbol{\beta}'\mathbf{x}-\left(\sigma_r R_{iq}+\sigma_h H_{iq}^{+}\right)}{\sigma}\right)\times\\ \Phi\left(\frac{\lambda\left[c-\alpha-\boldsymbol{\beta}'\mathbf{x}-\left(\sigma_r R_{iq}+\sigma_h H_{iq}^{+}\right)\right]}{\sigma}\right)\end{array}\right].$$

The term $\sigma_h H_{iq}^{+}$ is the q^{th} simulated draw using Halton sequences of $\sigma_h H_i^{+}$ for firm *i*, with $H_i^{+} \sim N^{+}\left(0,1\right)$ (Filippini and Greene, 2016). To reduce notation, unit *i* and time *t* indices are dropped for the other variables.

The highly complicated log likelihood function noted in Colombi, Kumbhakar et al. (2014) is simplified by exploiting the formulation of Butler and Moffitt (1982) in the simulation, where the log-likelihood function is computed using Hermite quadrature. The log-likelihood function then is estimated by maximum simulated likelihood using Halton sequences. Instead of using four unique disturbance terms as in Colombi et. al. (2014), Filippini and Greene (2016) propose to define a two-part disturbance term. Each part of the disturbance term is characterized by a skewed normal distribution with, in each case, one part assumed to be time-invariant and the other to be time-variant. The only difference between the TREM and GTREM setting therefore consists of the latter model containing a skewed normally instead of normally distributed time invariant disturbance term.

The conditional expectation of a firm's level of cost inefficiency of the REM and TREM is estimated using a term proposed by Jondrow et al. (1982), which is $E\left[u_{it}\middle|\varepsilon_{it}\right]=\left[\int_0^\infty u_{it}\,f_u\left(u_{it}\right)f_v\left(u_{it}-\varepsilon_{it}\right)du_{it}\right]\Big/\left[\int_0^\infty f_u\left(u_{it}\right)f_v\left(u_{it}-\varepsilon_{it}\right)du_{it}\right]$ (Greene, 2008b). The functions $f_u(.)$ and $f_v(.)$ represent the density functions of the respective variables *u* and *v*. Details on these densities are given in Table I-2. The GTREM computes a firm's transient and persistent inefficiency $E\left[h_i+u_{it}\mid\varepsilon_{it}\right]$ using eq. (17)[22] presented in Filippini and Greene (2016) on p. 192. Table I-2 summarizes the econometric specification of the three models.

Table I-2: *Distributional assumptions of the stochastic cost frontier models.*

	REM [A]	TREM	GTREM
Full random error ε_{it}	$\varepsilon_{it}=u_i+v_{it}$	$\varepsilon_{it}=r_i+u_{it}+v_{it}$	$\varepsilon_{it}=r_i+h_i+u_{it}+v_{it}$
	$u_i\sim N^+\left(0,\sigma_u^2\right)$	$u_{it}\sim N^+\left(0,\sigma_u^2\right)$	$u_{it}\sim N^+\left(0,\sigma_u^2\right)$
	$v_{it}\sim N\left(0,\sigma_v^2\right)$	$v_{it}\sim N\left(0,\sigma_v^2\right)$	$v_{it}\sim N\left(0,\sigma_v^2\right)$
		$r_i\sim N\left(0,\sigma_r^2\right)$	$r_i\sim N\left(0,\sigma_r^2\right)$
			$h_i\sim N^+\left(0,\sigma_h^2\right)$
Persistent inefficiency estimator	$E\left[u_i\middle|\varepsilon_{i1},...,\varepsilon_{iT}\right]$	None	$E\left[h_i\middle|\varepsilon_{it}\right]$
Transient inefficiency estimator	None	$E\left[u_{it}\middle|\varepsilon_{it}\right]$	$E\left[u_{it}\middle|\varepsilon_{it}\right]$

Note: This table presents the distributional assumptions of the stochastic error and inefficiency components of the REM, TREM and GTREM stochastic frontier models.
[A]: There are two mentionable variations of the REM specification according to Pitt and Lee (1981): first, Schmidt and Sickles (1984) relax the distributional assumption of u_i by applying a fixed effects instead of a random effects estimator using GLS. Second, Battese and Coelli (1988) assume a truncated normal instead of a half normal distribution for u_i.

[22] In this equation, matrix **t** has to be multiplied by –1, because we estimate a cost function instead of a production function.

6 Results

6.1 Cost Function Parameters

The estimated coefficients of the three frontier models as well as their respective standard errors are listed in Table I-3.[23] Linear homogeneity was imposed a priori by normalizing prices and output with respect to the constant electricity price. To ensure monotonicity, microeconomic theory demands the cost function to be increasing in generated electricity and input prices. Furthermore, the function is expected to be concave with respect to input prices. Such concavity implies own-price elasticities to be negative, with the Hessian matrix of second order partial derivatives of total costs with respect to prices being negative semi-definite.[24] The cost function is generally well behaved. Except for the concavity condition (one of the four eigenvalues is greater than zero), our results obey the monotonicity and concavity restrictions (cf. appendix A.1). We justify the slight violation of the concavity restriction by the estimation of a behavioral cost function: the frontier cost model builds on the implicit assumption of firms not fully minimizing costs, which contradicts the concavity condition's underlying assumption of cost minimizing firms.[25]

[23] Stochastic frontier models were estimated using NLOGIT 5 (EconometricSoftware, 2012).

[24] See appendix A.1 for a detailed description of these properties.

[25] See Bös (1989) for a discussion on behavioral cost functions.

Table I-3: *Cost function estimation results of the REM, TREM and GREM specification.*

	REM		TREM		GTREM	
	Coef.	Std.dev.	Coef.	Std.dev.	Coef.	Std.dev.
Electricity generation (β_Y)	0.543***	(0.016)	0.500***	(0.006)	0.486***	(0.006)
Labor price (β_L)	0.030	(0.032)	0.058***	(0.016)	0.082***	(0.017)
Water price (β_W)	0.189***	(0.014)	0.171***	(0.005)	0.161***	(0.005)
Residual capital price (β_K)	0.643***	(0.006)	0.629***	(0.003)	0.654***	(0.003)
Number of stations (β_N)	0.067**	(0.026)	0.309***	(0.009)	0.368***	(0.010)
Load factor (β_F)	–0.745***	(0.029)	–0.657***	(0.009)	–0.615***	(0.008)
Time trend (β_t)	0.001	(0.001)	–0.162	(0.003)	–0.140**	(0.003)
(β_{YY})	–0.112***	(0.015)	0.280***	(0.095)	0.114***	(0.106)
(β_{LL})	0.364*	(0.217)	0.057***	(0.004)	0.055	(0.004)
(β_{WW})	0.074***	(0.008)	0.212***	(0.009)	0.176***	(0.008)
(β_{KK})	0.197***	(0.013)	0.297***	(0.014)	0.421***	(0.015)
(β_{NN})	0.611***	(0.071)	0.084***	(0.003)	0.074***	(0.003)
(β_{FF})	0.124***	(0.009)	0.052***	(0.022)	0.054***	(0.020)
(β_{LW})	0.051	(0.046)	–0.065**	(0.021)	–0.030***	(0.025)
(β_{LK})	–0.055	(0.057)	–0.056***	(0.006)	–0.043	(0.005)
(β_{WK})	–0.048***	(0.008)	0.024***	(0.005)	–0.027***	(0.005)
(β_{YN})	–0.105***	(0.020)	0.197***	(0.003)	0.188***	(0.003)
(β_{YF})	0.136***	(0.011)	–0.141***	(0.007)	–0.149***	(0.007)
(β_{NF})	–0.024	(0.027)	0.263***	(0.007)	0.179***	(0.006)
Storage FE (β_{DS})	0.163**	(0.070)	0.421***	(0.008)	0.815***	(0.011)
Pump storage FE (β_{DS})	0.309***	(0.076)	0.001***	(0.000)	0.001***	(0.000)
Constant (α)	16.544***	(0.074)	16.895***	(0.010)	16.650***	(0.011)
Number of observations	873		873		873	
Unit-specific constant (r_i)			0.188***	(0.002)	0.221***	(0.003)
λ	10.077*	(5.229)	3.564***	(0.310)	4.195***	(0.406)
σ	0.573***	(0.092)	0.092***	(0.002)		
σ_r					0.096***	(0.002)
σ_h					0.816***	(0.030)
Log Likelihood	1073.54		1099.57		1084.05	

Note: This table presents the estimation results when applying the REM, TREM and GTREM to the total cost function given in eq. (2). *FE* abbreviates “fixed effect”. 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.

The estimated coefficients in general have the expected sign and many are, together with *lambda*[26], statistically significant at a level of 1 percent. The magnitude of the estimated coefficients is similar across all models. Technological progress in the hydropower sector is small; major technological components like turbines or dams can be considered as comparatively mature. Therefore, the negative coefficient estimate of the neutral technical change t is not surprising.[27]

The first order coefficients of the translog function are interpretable as elasticities at the sample median with the constant representing total costs at the approximation point. The elasticity of the generated electricity is positive and highly statistically significant. The negative and statistically significant load factor indicates higher total costs for storage and pump storage firms compared to their run-of-river counterparts, since the former technologies generally are characterized by comparatively low load factors. The firm-type fixed effects also point towards higher costs of storage and especially pump storage firms. Examples of factors contributing to these higher costs could be, next to the pump energy consumption of the latter type, relatively high investment costs for storage technologies in general, a higher complexity of operating such plants as well as their geographical remoteness.

6.2 Cost Efficiency

Table I-4 and Figure I-4 provide descriptive statistics of the estimated levels of cost efficiency. The efficiency term in the REM captures all time invariant unobserved heterogeneity. Hence, this model's median value of estimated cost efficiency of 65.3 percent is considerably lower than the median persistent cost efficiency of 85.6 percent

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[26] Lambda (λ) expresses the ratio of the standard deviation of the inefficiency term u_{it} or u_i to the standard deviation of the stochastic term v_{it}.

[27] Filippini and Luchsinger (2007) find a statistically significant effect of technical change in the Swiss hydropower sector of –0.018. They estimate a translog variable cost model using a seemingly unrelated regression and an unbalanced sample of 43 firms for the period of 1995 to 2002. In Banfi and Filippini (2010), statistically significant technical change amounts to –0.025. They estimate a translog variable cost function applying a TREM specification and use the same data as Filippini and Luchsinger (2007).

when applying the GTREM. Median transient efficiency of the TREM of 94.0 percent is relatively similar in magnitude to the median transient result of the GTREM of 92.1 percent. The dispersion of estiamted efficiencies is largest for the REM. To some extent, this could be explained by the comparatively low degree, to which this model separates further unobserved heterogeneity from inefficiency. As depicted by Figure I-5, mean efficiency estimates within the four quartiles of the yearly efficiency distributiatons are relatively constant across time, independently of the model specification. Hence, we find robust empirical evidence that Swiss hydro power firms on average neither strongly increased nor decreased their transient as well as persistent cost efficiency between 2000 and 2013.

Since the REM and TREM measure different sorts of cost efficiency, the correlation between the estimated efficiency levels of these two models is low (cf. Table I-5). In contrast, the correlation between the REM cost efficiciency and the persistent efficiency of the GTREM is, as expected, higher.[28] The same holds for the correlation between the TREM cost efficiciency and the transient efficiency of the GTREM. Accordingly, the correlation between the persistent and transient efficiency estimates of the GTREM is negative. Therefore, it can be concluded that firms showing a high degree of persistent efficiency are not systematically exhibiting production processes, which are simultaneously characterized by a high degree of transient efficiency. In conclusion, the GTREM is our preferred model specification, because it allows for a simultaneous estimation of the level of persistent as well as transient cost efficiency. The predicted aggregate level of cost inefficiency of this model amounts to 22.3 percent on average (7.9 percent transient, 14.4 percent persistent).

[28] A comparison of the Spearman correlation coefficient with the Pearson coefficient reveals this corrleation to be linear, but not monotonic.

Table I-4: *Descriptive statistics of estimated cost efficiencies.*

	REM	GTREM persistent	TREM	GTREM transient
Mean	0.653	0.856	0.940	0.921
Min	0.316	0.844	0.705	0.670
Max	0.985	0.897	0.993	0.992
Std.dev.	0.191	0.011	0.041	0.051
25% Pc.	0.527	0.851	0.928	0.907
Median	0.647	0.852	0.951	0.939
75% Pc.	0.822	0.857	0.967	0.954

Note: This table presents descriptive statistics of the cost efficiency estimates of the REM, TREM and GTREM frontier models. Statistics are based on the full sample of observations.

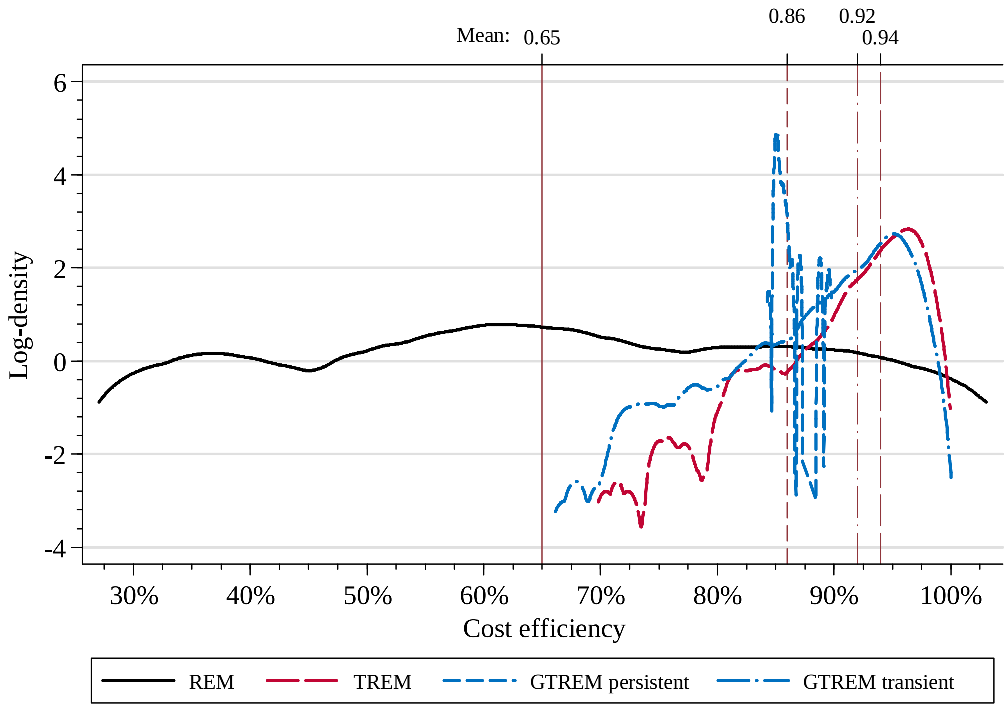

Figure I-4: *Kernel log-densities of estimated cost efficiencies.*

Note: Figure I-4 presents kernel log-densities of the REM, TREM and GTREM cost efficiency estimates. Vertical lines indicate the respective model's mean efficiency estimate. The figure is truncated at 30 percent cost efficiency to improve readability. As shown in Table I-4, such truncation is binding only for a small fraction of firms.

Table I-5: *Correlation coefficients of estimated cost efficiencies.*

	REM	TREM		GTREM persistent		GTREM transient	
REM	1	0.097	[0.084*]	0.121	[0.210*]	–0.013	[–0.023]
TREM		1		–0.180	[–0.071*]	0.844	[0.763*]
GTREM persistent				1		–0.647	[–0.499*]

Note: This table presents the correlation coefficients between estimated efficiencies of the REM, TREM and GTREM frontier models. Spearman correlations are given in [.] brackets. Asterisks * indicate significance at a level of 5 percent.

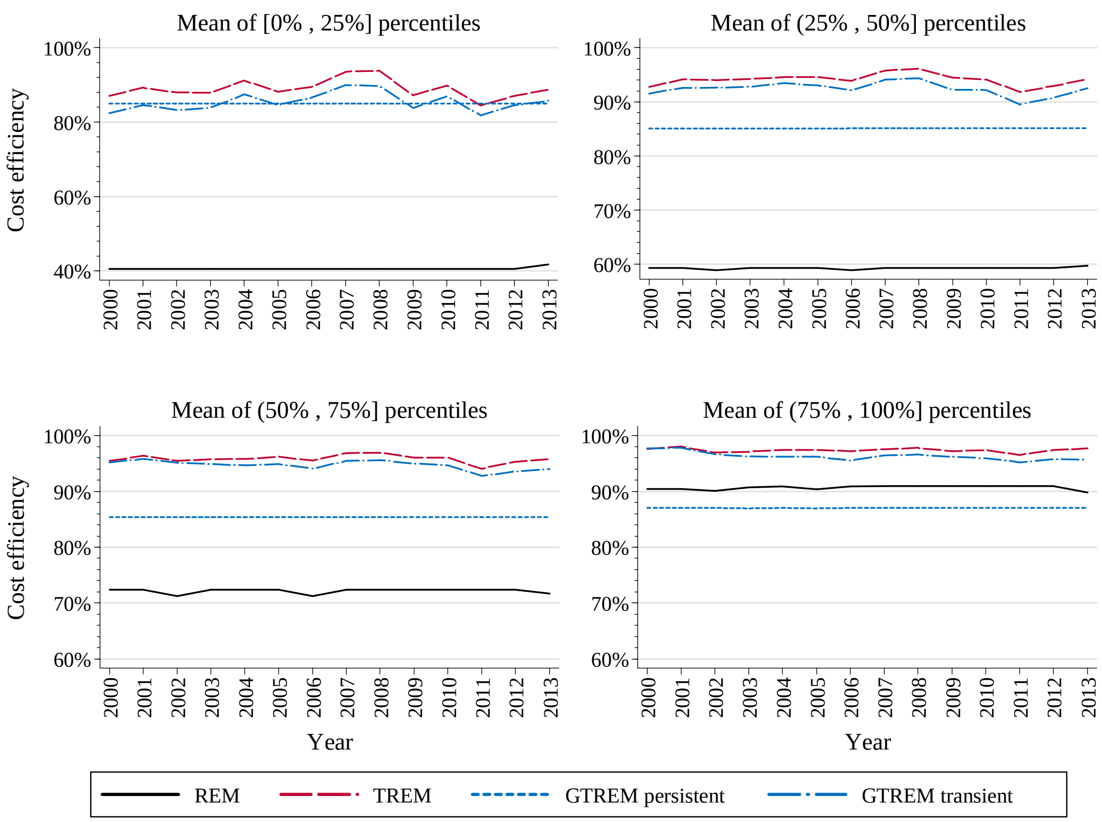

Figure I-5: *Development of estimated cost efficiencies over time.*

Note: Figure I-5 presents the development of estimated cost efficiencies under the REM, TREM and GTREM specification. For every individual year, firm level cost efficiency estimates are separated into quartiles. The figure shows the development of the yearly mean values of these quartiles.

6.3 Economies of Density and Scale

The estimated coefficients reported in Table I-3 can be used to compute the firms' level of economies of density and scale. Following the pioneering work of Caves, Christensen et al. (1981) and Caves, Christensen et al. (1984), economies of density (ED) and economies of scale (ES) are estimated as

$$ED_{it} = \frac{1}{\partial \ln C_{it} / \partial \ln Y_{it}},$$

$$ES_{it} = \frac{1}{\partial \ln C_{it} / \partial \ln Y_{it} + \partial \ln C_{it} / \partial N_{it}}.$$

Economies of scale differ to economies of density (sometimes also called economies of spatial scale) in the assumption that an increase in firm size not only raises output, but to the same proportion also the number of plants under operation (Farsi, Filippini et al., 2005). Economies of density and scale exist if the respective values of ED and ES are greater than 1. Analogously, values smaller than 1 indicate diseconomies of density or scale.

Table I-6: *Economies of density (ED) and scale (ES) of the sample.*

		REM	TREM	GREM
ED	1st quartile	1.567	1.579	1.675
	Median	1.753	2.018	2.035
	3rd quartile	2.273	2.626	2.586
ES	1st quartile	1.190	1.047	0.969
	Median	1.489	1.179	1.107
	3rd quartile	2.888	1.558	1.543

Note: This table presents the economies of density and scale when using estimates of the REM, TREM and GTREM frontier models. Statistics are based on the respective first, second and third quartile firm observation.

Table I-7: *Economies of density (ED) and scale (ES) of three typical firms.*

		REM	TREM	GREM
	Small	1.416	1.627	1.619
ED	Medium	1.843	2.002	2.061
	Large	2.392	2.565	2.694
	Small	2.303	1.433	1.398
ES	Medium	1.643	1.237	1.172
	Large	1.528	1.195	1.124

Note: This table presents the economies of density and scale when using estimates of the REM, TREM and GTREM frontier models. Statistics are based on first, second and third quartile typical firms.

Table I-6 illustrates the descriptive statistics of the economies of scale and density computed for all firms in our sample and Table I-7 presents the values for a small, medium and large hydropower firm. A small firm for instance is defined by values of Y and N that correspond to the first quartiles of the distribution of each variable. Accordingly, for the medium firm we use the median values of Y and N, and for the large firm we use the respective third quartile values. The results reported in the two tables confirm the existence of positive economies of density and scale for most firms.[29]

7 Conclusions and Discussion

The goal of this paper was to estimate the persistent and transient cost inefficiency levels in the Swiss hydropower sector applying three distinct frameworks: a random effects model (REM), true random effects model (TREM) and generalized true random effects model (GTREM). The empirical results of the GTREM implementation are promising: the estimated persistent and transient cost inefficiency levels of the GTREM

[29] The study of Filippini and Luchsinger (2007) yields similar results. They estimate the economies of scale (but not economies of density) in the Swiss hydropower sector for the period 1995 to 2002 and find scale economies to amount to 1.76 for small, 1.78 for medium, and 1.76 for large firms.

are similar in magnitude as, and also sufficiently correlated with, the respective REM and TREM results. From a methodological point of view, the GTREM model seems to be interesting because it allows to simultaneously measure both types of inefficiency, i.e. the persistent and transient one. The GTREM predicts the aggregate level of cost inefficiency to amount to 22.3 percent (7.9 percent transient, 14.4 percent persistent) on average between 2000 and 2013.

Results show that the Swiss hydropower sector is characterized by the presence of both, transient as well as persistent, cost inefficiencies. These inefficiencies are different in absolute value and the negative correlations between them indicate that they indeed measure two kinds of inefficiencies, which differ in interpretation and implication. The transient component represents cost inefficiencies varying with time, e.g., inefficiencies stemming from a wrong adaption of production processes towards changing factor prices or singular management mistakes. On the other hand, the persistent part captures cost inefficiencies which do not vary with time, like inefficiencies due to recurring identical management mistakes, unfavorable boundary conditions for electricity generation or factor misallocations difficult to change over time. The two types of cost inefficiency allow a firm to elicit its cost saving potential in the short- as well as the long-run, but they might require a firm’s management to respond with different improvement strategies. From a regulatory point of view, the results of this study could be used in the scope and determination of the amount of subsidies to be granted to a hydropower firm. Knowledge of the level of cost inefficiency supports the government in avoiding a grant of subsidies to inefficient hydropower firms. If a hydropower firm shows a high level of cost inefficiency, then the amount of the subsidy should be reduced or cancelled completely. However, the regulatory authority should differentiate between persistent and transient levels of inefficiency and consider inertia in the short run possibilities of hydropower firms to ameliorate the level of persistent inefficiency.

A Appendix

A.1 Testing for Monotonicity and Quasi-Concavity

Linear homogeneity in factor prices of the cost function given in eq. (2) implies

$$c(Y, \lambda P_L, \lambda P_W, \lambda P_K, \lambda P_E) = \lambda c(Y, P_L, P_W, P_K, P_E) \mid \lambda > 0 .$$

To reduce notation, unit *i* and time *t* subscripts are dropped. Homogeneity is imposed by dividing total costs and factor prices by the price of energy. Hence, what remains to be tested is the monotonicity and quasi-concavity of the cost function. Given the cost function of eq. (2), the estimated cost share equations are

$$\frac{\partial \ln C}{\partial \ln P_L} = \hat{S}_L = \hat{\beta}_L + \hat{\beta}_{LL} p_L + \hat{\beta}_{LW} p_W + \hat{\beta}_{LK} p_K \ ,$$
$$\frac{\partial \ln C}{\partial \ln P_W} = \hat{S}_W = \hat{\beta}_W + \hat{\beta}_{WW} p_W + \hat{\beta}_{LW} p_L + \hat{\beta}_{WK} p_K \ ,$$
$$\frac{\partial \ln C}{\partial \ln P_K} = \hat{S}_K = \hat{\beta}_K + \hat{\beta}_{KK} p_K + \hat{\beta}_{LK} p_L + \hat{\beta}_{WK} p_W \ .$$

Monotonicity is ensured if total costs are increasing in input prices as well as in output, i.e. if the following four conditions hold

$$\frac{\partial \ln C}{\partial \ln Y} = \hat{\beta}_Y + \hat{\beta}_{YY} y + \hat{\beta}_{YF} F + \hat{\beta}_{YN} n > 0 \text{ and } \hat{S}_L > 0 \text{ and } \hat{S}_W > 0 \text{ and } \hat{S}_K > 0 \ . \qquad (6)$$

Results of the evaluation of monotonicity at the sample's mean and median are shown in Table I-8. The results obey the restrictions noted in eq. (6).

Concavity is given if the Hessian matrix of second order partial derivatives is negative semidefinite. According to Binswanger (1974) p. 380, the second order partial derivatives of a cost function can be derived as L

$$\frac{\partial^2 C}{\partial P_X P_Z} = \frac{C}{P_X P_Z}\left(\beta_{XZ} + S_X \cdot S_Z\right) \text{ and } \frac{\partial^2 C}{\partial P_X^2} = \frac{C}{P_X^2}\left(\beta_{XX} + S_Z^2 - S_Z\right),$$

where $X, Z = \{L, W, K, E\}$.

Table I-8: *Monotonicity at sample mean and median.*

	REM	TREM	GTREM
		Monotonicity at sample mean	
$\hat{S}_L$	0.024	0.053	0.726
$\hat{S}_W$	0.185	0.168	0.079
$\hat{S}_K$	0.649	0.636	0.158
$\partial \ln C / \partial \ln Y$	0.721	0.753	0.659
		Monotonicity at sample median	
$\hat{S}_L$	0.030	0.058	0.675
$\hat{S}_W$	0.189	0.171	0.082
$\hat{S}_K$	0.642	0.628	0.162
$\partial \ln C / \partial \ln Y$	0.680	0.698	0.653

Note: This table presents the estimated cost shares as well as the first derivative of total costs with respect to output of the REM, TREM and GTREM frontier models evaluated at the sample mean and median.

Hence, at the approximation point[30] (the median), the Hessian matrix becomes β

$$\mathbf{G}=\begin{bmatrix} \hat\beta_{LL}+\hat\beta_L^2-\hat\beta_L & \hat\beta_{LW}+\hat\beta_L\cdot\hat\beta_W & \hat\beta_{LK}+\hat\beta_L\cdot\hat\beta_K & \hat\delta_{LE}+\hat\beta_L\cdot\hat\delta_E \\ \hat\beta_{LW}+\hat\beta_W\cdot\hat\beta_L & \hat\beta_{WW}+\hat\beta_W^2-\hat\beta_W & \hat\beta_{WK}+\hat\beta_W\cdot\hat\beta_K & \hat\delta_{WE}+\hat\beta_W\cdot\hat\delta_E \\ \hat\beta_{LK}+\hat\beta_K\cdot\hat\beta_L & \hat\beta_{WK}+\hat\beta_K\cdot\hat\beta_W & \hat\beta_{KK}+\hat\beta_K^2-\hat\beta_K & \hat\delta_{KE}+\hat\beta_K\cdot\hat\delta_E \\ \hat\delta_{LE}+\hat\delta_E\cdot\hat\beta_L & \hat\delta_{WE}+\hat\delta_E\cdot\hat\beta_W & \hat\delta_{KE}+\hat\delta_E\cdot\hat\beta_K & \hat\delta_{EE}+\hat\delta_E^2-\hat\delta_E \end{bmatrix}.$$

The δ-coefficients are not estimated directly, due to the a priori imposition of the homogeneity assumption. However, given the linear homogeneity constraints, they can be derived as

$$\begin{aligned} \hat\delta_E &= 1-\hat\beta_L-\hat\beta_W-\hat\beta_K\ , \\ \hat\delta_{LE} &= 0-\hat\beta_{LL}-\hat\beta_{LW}-\hat\beta_{LK}\ , \\ \hat\delta_{WE} &= 0-\hat\beta_{WW}-\hat\beta_{LW}-\hat\beta_{WK}\ , \\ \hat\delta_{KE} &= 0-\hat\beta_{KK}-\hat\beta_{LK}-\hat\beta_{WK}\ , \\ \hat\delta_{EE} &= 0-\hat\beta_{LE}-\hat\beta_{WE}-\hat\beta_{KE}\ . \end{aligned}$$

The vector of fitted factor shares is

$$\mathbf{s}=\begin{bmatrix} \hat S_L \\ \hat S_W \\ \hat S_K \\ \hat S_E \end{bmatrix},$$

Where $\hat S_E = 1-\hat S_L-\hat S_W-\hat S_K$. The cost function is concave if the roots of the matrix $\mathbf{H}=\mathbf{G}+\mathbf{s}\cdot\mathbf{s}'-diag(\mathbf{s})$ are non-positive, e. if $\lambda_i\le 0\ \forall i=\{1,...,4\}$ with $\det(\mathbf{H}-\lambda\cdot\mathbf{I}_4)=0$. The roots of matrix **H** evaluated at the sample's mean and median are given in Table I-9. In section 6.1, a justification is given for this slight violation of the concavity condition.

[30] At the approximation point, all second order and interaction terms of a translog function collapse to zero.

Table I-9: *Roots of matrix* **H** *at sample mean and median.*

	REM	TREM	GTREM
		Concavity at sample mean	
λ_1	*0.662*	*0.429*	*0.202*
λ_2	*0.000*	–0.000	–0.000
λ_3	–0.102	–0.159	–0.184
λ_4	–0.449	–0.406	–0.419
		Concavity at sample median	
λ_1	*0.659*	*0.426*	*0.201*
λ_2	*0.000*	*0.000*	–0.000
λ_3	–0.105	–0.162	–0.187
λ_4	–0.452	–0.409	–0.422

Note: This table presents the roots of matrix **H** of the REM, TREM and GTREM frontier models evaluated at the sample mean and median. Critical, i.e. positive values are given in *italics*.

II Environmental Regulation and Productivity Change in the Chinese Iron and Steel Industry[31]

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"Once you start thinking about productivity growth,

it is hard to think about much else."

— Robert E. Lucas Jr.

1 Introduction

China is an emerging economy with unprecedented development, ranking it second in size within only a few decades and lifting hundreds of millions of its inhabitants out of poverty. The industrial sector has been a major growth contributor and constituted 54 percent to China's gross domestic product in 2013 (NBS, 2014). The country is a leading exporter of energy-intensive products. Combined with a strong focus of the government to upkeep high growth rates, the rapid increase in the demand for energy, and accordingly fossil fuels, has resulted in multiple adverse effects on, for instance, the reliability and security of energy supply, human health and environmental integrity. The Chinese government has been aware of these drawbacks and thus is increasingly tackling environmental concerns through mandated regulations at national and provincial level (Cao, Garbaccio et al., 2009; Zhang, Aunan et al., 2011). Today, its emphasis is on environmental protection alongside economic growth. Since productivity represents a foundation of social welfare and living standards (Greenstone, List et al., 2012; Krugman, 1997), the understanding to simultaneously boost productivity when reducing environmental degradation has gained more and more momentum in this restructuring process.

The Chinese iron and steel industry has been a major source of pollution because of its high energy intensity (He, Zhang et al., 2013a; Lin, Wu et al., 2011). Consequently, it has been a main target of environmental policies. The national Top-1000 Energy-Consuming Enterprises Program (T1000P) is one of such regulation. It was introduced by the central government within the Eleventh Five Year Plan and covered the period of 2006 to 2010. The T1000P was part of the most ambitious effort ever made at that time to reduce industrial energy use in China and targeted the country's top 1000 most energy demanding firms. The T1000P belonged to the broad category of classical command-and-control regulation and aimed for a significant improvement in the targeted firms' energy intensity, i.e. in the ratio of energy used per output produced. The energy consumption reduction target was set by the government for every individual firm.

One important topic related to environmental regulations is how their introduction affects the activities and performances of firms. In this paper, we analyze the impact of the T1000P on productivity change in the Chinese iron and steel industry. The direction and magnitude of the net effects of an environmental policy instrument on firm level productivity and hence competitive advantages is controversially discussed in the literature, which can be divided into two main strands: the traditionalist view and Porter's hypothesis (also called the revisionist view).[32] Both views are from the perspective of the firm. The traditionalist view sees an environmental regulation primarily as a cost burden. It builds upon the assumption that, if an environmental regulation would increase marginal products or lower marginal costs, an optimizing firm implicitly already would have acted in compliance with the regulation beforehand. Hence, the fact that firms had to be regulated inevitably implies an increase of the firm's private costs by forcing it to either pay for its emissions, to change its production processes (technical component) and/or to amend its input choice (allocative component). Assuming that units of output produced stay constant, a firm's productivity decreases (Koźluk and Zipperer, 2013).[33]

Porter's hypothesis challenges the traditionalist view on the relation between an environmental regulation and firm performance. It was coined by Porter (1991), Porter and Van der Linde (1995a) and Porter and Van der Linde (1995b) and claims 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. Such improvements in the structure of innovation might offset compliance costs and, in form of a net effect, result in a higher productivity and thus

[32] For a presentation and discussion of these two views see, e.g., Iraldo, Testa et al. (2011) or Koźluk and Zipperer (2013).

[33] 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 output value through less environmental degradation or a more economical use of inputs through the consumption of less undesirable inputs.

competitiveness. Porter's hypothesis builds upon the insight of competitiveness primarily stemming from the dynamic factor of innovativeness under uncertainty and other frictions, and not simply from the static efficiency concept of cost minimization under perfect information (Porter and Van der Linde, 1995b).[34]

Empirical evidence on the impact of environmental policy instruments on firm level productivity is scarce, especially for China. For this reason, this study proposes an analysis of the impact of such a regulation on the performance of Chinese firms. The main goals of this study are, first, to estimate the level of total factor productivity of a sample of Chinese firms operating in the iron and steel industry, and second, to analyze empirically the impact of the T1000P on the growth rate of total factor productivity of these firms.

This study contributes to the scientific literature in multiple ways relevant for academic scholars and policymakers alike. First, to our knowledge, this is the first study analyzing the impact of an environmental regulation on TFP of Chinese firms using parametric methods, and thus is accounting for unobserved heterogeneity. Second, we estimate total factor productivity (TFP) change in the Chinese iron and steel industry on a firm level. The highest share of firms exposed to the T1000P belonged to the iron and steel industry. The empirical analysis is based on an unbalanced panel containing detailed information on 20,076 observations belonging to 5,340 firms for the time period from 2003 to 2008. Third, this is one of only a few studies eliciting TFP change via a cost function approach. Fourth, TFP change is decomposed into its subcomponents of technical change and scale efficiency change. This allows for a more detailed analysis of the effects of the environmental regulation than what has been common practice in the literature. We use a difference-in-difference approach to analyze the effect of the

[34] Porter's hypothesis relates to the assumption that, in real world, firms are not perfectly optimizing. In that sense, Porter's hypothesis also ties to the Energy Paradox literature (see, e.g., DeCanio (1993) or Allcott and Greenstone (2012), who also provide a recent review of the Energy Paradox literature). This literature finds that, despite short payback times, energy saving investments may not be carried out without an initial regulatory pressure (Porter and Van der Linde, 1995b). The propensity for such investments may also depend heavily on firm characteristics (DeCanio and Watkins, 1998). The Energy Paradox literature suggests the existence of a behavioral factor, through which firms might benefit from an environmental policy.

regulation on TFP change. Fifth, this study proposes an instrument for selection into the T1000P that is based on spatial firm level information to check the robustness of the regulation's estimated effect on firm performance.

TFP is estimated to have grown on average by 6.4 percent, with the iron- and steelmaking industry growing fastest, followed by the steel rolling and ferroalloy smelting industry. The benchmark specification finds the regulation to positively affect TFP change of firms by 3.1 percent on average between 2006 and 2008. Hence, this study provides empirical evidence for Porter's hypothesis. Effects on technical and scale efficiency change are positive and significant as well and contribute about equally to the overall effect of the policy on TFP change. Results are found to be robust in several dimensions of sample stratification, with respect to sample attrition, and also when instrumenting for policy exposure.

The structure of this study is as follows: Chapter 2 summarizes the relevant literature. Chapter 3 contains a description of the T1000P and of the Chinese Steel Industry. Chapter 4 reviews the data and chapter 5 the methodological framework applied to determine firm performance. Chapter 6 sets out the identification strategy. The effects of the environmental regulation on firm productivity are evaluated in chapter 7 and results are tested for robustness in chapter 8. Finally, chapter 9 concludes and discusses.

2 Literature Review

To our knowledge, no empirical study so far has analyzed the effects of an environmental regulation on TFP (and TFP change) of Chinese firms using parametric approaches. Hence, this literature review is divided into two sections. The first summarizes findings on the productivity of Chinese manufacturing firms with a focus on iron and steel firms. The second reviews empirical results on the effects of an environmental regulation on firm level TFP, without explicitly focusing on China. Our study combines these two strands of literature.

2.1 Productivity of Chinese Manufacturing Firms

A large body of literature has set itself to the challenge of uncovering the role of productivity in the unprecedented growth of the Chinese economy in the past few decades. Many of these studies are conducted on an aggregate level (industry, region). Tian and Yu (2012) and Wu (2011) present an extensive meta-analysis based on more than 200 primary studies on productivity in China. In general, estimated productivity varies widely, within and between studies, on aggregate as well as on firm level.[35] They explain the literature's diverging results in estimated productivities and find choices of methods and the aggregation level of the analyzed data to be main sources. Most of the studies are not considering relevant heterogeneity at the more disaggregated firm level.

A limited number of studies estimate TFP levels of the Chinese iron and steel industry.[36] They usually are built on a comparatively small sample size. The early contribution of Jefferson (1990) analyzes TFP levels of a sample of 120 firms in year 1985 by applying a translog production function with labor and capital as inputs. He controls for the investment structure of the capital stock by differentiating between productive and unproductive capital. The composition of the capital stock is found to have the largest impact on TFP levels, followed by the product mix and the level of a firm's supervision. Ma, Evans et al. (2002) estimate TFP to have grown by ca. 3 percent per year on average between 1987 and 1997. They apply non-parametric linear programming methods and use a sample containing 88 firms. Movshuk (2004) finds an average TFP change in the range of 4.4 to 6.4 percent for the economic reform and restructuring process period of 1988 to 2000. Subsequently, he decomposes TFP change into technical efficiency change and technical change. Technical change turned out as dominating contributor towards TFP growth. The analysis is based on a panel of 82 state-owned enterprises

[35] Widely varying productivity not only can be observed for China, but for other countries as well, as described in section 1 of part III.

[36] We focus on TFP change when analyzing the effect of the T1000P. Nevertheless, most studies on the estimation of TFP focus on TFP levels. Since these two concepts are closely related, we do not limit ourselves to only review literature on TFP change.

(SOEs) and uses the Battese and Coelli (1995) stochastic frontier model applied to a translog as well as Cobb-Douglas production function.

More recently, and still focusing on the Chinese iron and steel industry, Sheng and Song (2013) find TFP to have steadily increased by 2.1 percent per year between 1998 and 2007. They apply the system-GMM framework of Wooldridge (2009)[37] to a Cobb-Douglas production function framework and build on a sample of 1,654 (in 1998) to 4,929 (in 2007) firms and a total of 33,778 observations. They identify firm size, ownership and geographical location as important determinants of productivity levels. He, Zhang et al. (2013a) apply a non-parametric DEA approach, i.e. a Malmquist productivity index, to a panel of 50, mostly large, steel companies covering years 2001 to 2008. They observe technical change to contribute most to an estimated average annual TFP growth rate of 7.96 percent.

2.2 Environmental Regulation and Firm Performance

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.[38] Koźluk and Zipperer (2013) summarize empirical evidence on the effects of an environmental regulation on the productivity of firms. Their findings can be condensed to three main points: First, firm characteristics can play a role, but only a handful of studies account for such. Second, the overall effect on the treated firms' productivity is mainly found to be negative. And third, short-term effects of a regulation might be different from long-term effects. The majority of the literature analyzing the effects of an environmental regulation on productivity applies non-parametric methods, and thus abstracts from the

[37] In addition to the method of Wooldridge (2009), they used several other common methodologies to derive TFP levels via a production function in order to test for robustness of the results. These methodologies were: pooled OLS, within estimates, estimates based on first differencing and the semi-parametric methods of Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg, Caves et al. (2015).

[38] For example, Iraldo, Testa et al. (2011) or Koźluk and Zipperer (2013) present and discuss several of these studies.

existence of unobserved heterogeneity. In what follows, the focus will be on literature applying parametric methods.

Among the studies using parametric methods, Gollop and Roberts (1983) focus on sulfur dioxide emission restrictions in the US electric power industry by estimating a cost function using observations on 56 electric utilities between 1973 and 1979. 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.[39] 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 to lower TFP levels by about 2.6 percent annually, and that this effect significantly depends on a plant's technology.[40] Their case exemplifies that the overall impact of an environmental regulation might differ when accounting for technological heterogeneity.

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 period of 1972 to 1993.[41] 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

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[39] The effect of the regulation on TFP change is derived by applying the Divisia index of Gollop and Jorgenson (1980) and Shephard's Lemma.

[40] 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.

[41] 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.

the four kinds of pollution regulations separately, they found carbon monoxide regulations to support Porter's hypothesis by increasing TFP levels. 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 two-step procedure allows controlling for differences in characteristics between treated and non-treated firms.

Another evidence of Porter's hypothesis can 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 those plants being regulated to increase rapidly, whereas the productivity of the control group was decreasing. The dominant support for the traditionalist view in the literature using parametric approaches might root in empirical analyses using accounting data which reflect the firms' point of view, and leave socially undesirable productive inputs and/or outputs (e.g., pollution) unaccounted for. From this viewpoint, mandated investments in environmental improvements are considered to be wasted unproductive resources with no offsetting rise in production (Repetto, Rothman et al., 1997). Of course, we should keep in mind that an analysis from a societal point of view, which also accounts for public goods like the environment, increases the probability of observing a positive effect of an environmental regulation on TFP.[42]

[42] A number of estimation methodologies have been developed to account for socially undesirable inputs and/or outputs. However, while our study applies parametric modelling, these methodologies are all of non-parametric nature and thus cannot account of unobserved heterogeneity. In chronological order, cornerstone contributions to the non-parametric catalogue of methods were made by Norsworthy, Harper et al. (1979) (Divisia index, deduct pollution abatement capital from the capital stock), Pittman (1983) (multilateral index of Caves, Christensen et al. (1982), account for undesirable outputs based on prices extracted from abatement costs), Färe, Grosskopf et al. (1989) (data envelopment analysis (DEA), convey the idea of Pittman (1983) by using quantities of undesirable outputs instead of shadow prices), Färe, Grosskopf et al. (1993) (DEA, account for undesirable outputs based on shadow prices using output distance functions), Yaisawarng and Klein (1994) (extend the framework of Färe, Grosskopf et al. (1989) by also including undesirable inputs) and Chung, Färe et al. (1997) (DEA Malmquist-Luenberger productivity index, account for undesirable inputs and outputs). An ad-hoc measure applicabale to parametric methods could consist of taking output per unit of emissions as output variable or—as proposed in Repetto, Rothman et al. (1997), however not explicitly for the

(*Footnote continues on next page*)

We do not observe any literature on the evaluation of the impact of environmental regulations on productivity at the firm level in the context of China. This gap seems surprising, considering that China is the world's biggest environmental polluter and a government that has increasingly resorted to regulatory actions to fight pollution. A small number of studies, such as Xie (2008), conduct an environmental regulation evaluation at a macro (i.e. provincial) level for the overall Chinese industry. Thereby, they ignore firm-specific heterogeneities in their reaction towards new regulations.[43]

3 Background on the Chinese Iron and Steel Industry and the Regulation

3.1 Chinese Iron and Steel Industry

China overtook Japan in being 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

parametric case—of forming a weighted output index by subtracting the product of the quantity of emissions and their marginal damage cost from the output value. Such output value would increase with decreasing emissions. However, such procedure would necessitate information on firm-level emissions or marginal damage costs.

[43] There is a considerable body of literature focusing on China that evaluates effects of measures which could be related to the introduction of an environmental policy. However, these effects are evaluated with respect to technical performance indicators like energy efficiency or emission levels instead of economic performance indicators like total factor productivity. In this literature, due to its high energy intensity and pollution levels, the Chinese iron and steel industry is well represented, see, e.g., Zhang, Worrell et al. (2014) for a review. Newer contributions are Hasanbeigi, Jiang et al. (2014), Ma, Chen et al. (2016), Xu and Lin (2016a), Zhou and Yang (2016), Gong, Guo et al. (2016). For example, Xu and Lin (2016b) find that R&D investments into energy saving technologies could have a large potential to mitigate CO_2 emissions of the iron and steel industry. Evaluating at the firm level, but still focusing on other performance indicators than productivity, Zhang and Wang (2008) observe spending on several energy saving technologies to positively affect gross output of Chinese iron and steel firms.

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).

Of course, the iron and steel industry's high energy consumption to some extent is attributable to the intrinsic characteristics of its production processes.[44] However, compared to the iron and steel industries of developed nations, the industry is also energy inefficient (He, Zhang et al., 2013a; Ross and Feng, 1991; Zhang and Wang, 2008). He, Zhang et al. (2013a) 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.[45] Also, the industry still pays little attention to energy saving (Zhang and Wang, 2008). As a result, the iron and steel industry is one of the country's major sources of pollution (He, Zhang et al., 2013a; Lin, Wu et al., 2011). It ranks third in terms of Chinese carbon dioxide emissions (after the power generation and cement industry) by accounting for roughly 10 percent of it (Zeng, Lan et al., 2009). The high energy consumption and emissions of the Chinese industry are not only problematic in terms of global warming or environmental integrity (Davis, Caldeira et al., 2010; Piao, Ciais et al., 2010; Raupach, Marland et al., 2007; Stern, 2007). Literature also shows immediate health effects on humans (Aunan and Pan, 2004; Chen, Wang et al., 2013; Ebenstein, Fan et al., 2015; Kan, Chen et al., 2012; Shang, Sun et al., 2013; Tanaka, 2015; Xu, Gao et al., 1994) or adverse effects on the reliability and security of energy supply (Levine, Zhou et al., 2009; Yao and Chang, 2014; Yi-Chong, 2006; Zhang, Aunan et al., 2011).

From an ownership point of view, it has to be noted that in the past two decades, the share of state-owned firms has been decreasing steadily (Ma, Evans et al., 2002).

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[44] For example, Ma, Evans et al. (2002) or Zhang and Wang (2008) give an overview of the industrial structure and technological aspects of steel making in China. Zeng, Lan et al. (2009) present iron- and steelmaking processes and describe energy saving and carbon dioxide reduction potentials therein.

[45] The five largest plants hardly produced more than 30 percent of the industry's total output in the past decade (He, Zhang et al., 2013a). The industry's low degree of concentration to some extent is the result of the historic roots of China's economy with an emphasis on local self-sufficiency in iron and steel production (Ma, Evans et al., 2002). At that time, entire communities devoted themselves to the development of a system of state-owned iron and steel firms (Guo and Fu, 2010).

This is in line with the transformation of the Chinese industry and the change of the institutional structures from state to private ownership (Dougherty, Herd et al., 2007), with an increasingly higher share of joint ventures and shareholding companies (Jefferson, Rawski et al., 2000). In particular during the years 2006 and 2007, a large number of smaller iron and steel firms changed ownership, and their new owners were supposed to reduce polluting emissions or shut them down.[46]

3.2 Top-1000 Energy-Consuming Enterprises Program

China's environmental policy has increased in its scope, stringency, and enforcement since 2000. Amid growing evidence of environmental damages, the Chinese government declared the sustainable development a basic state policy in 2002 (Yuan, Kang et al., 2011). It then increasingly promulgated environmental policies and regulation to reduce the levels of energy consumption and pollution, for instance, by specifying a binding target of a 20 percent energy intensity reduction in the 2006 legislative agenda (Yuan, Kang et al., 2011).[47]

The national Top-1000 Energy-Consuming Enterprises Program (T1000P) was introduced by the central government within the Eleventh Five Year Plan (FYP). The lead agency was the National Development and Reform Commission (NDRC) (Zhou, Levine et al., 2010). Covering the period 2006 to 2010, the Eleventh FYP targeted for a reduction in the country‘s five-year energy intensity (energy use per GDP) of 20 percent (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, of nine industries (Price, Wang

[46] This was a top-down program aimed at industrial upgrading and improving environmental protection. This process is described in depth, e.g., by Zhao, Li et al. (2014) for the case of an electricity generation company, or by Zhang, Aunan et al. (2011) for the case of Shanxi province.

[47] Further milestone environmental policies that became effective after our sample period ends were, for instance, the revision of the Environmental Protection Law included in the 2011 legislative agenda (He, Zhang et al., 2013b). In 2009, the government decided to increase the level of technology used in the production processes of the iron and steel industry by supporting R&D investments and by initiating a restructuring and revitalization plan (He, Zhang et al., 2013a).

et al., 2010) to significantly improve their energy intensity, i.e. to lower the ratio of energy used to output produced. Total energy savings had to amount to 100 Mtce by 2010 (NDRC, 2006). With energy savings far exceeding 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 being achieved in 2008 when the NDRC announced savings of ca. 106 Mtce (Ke, Price et al., 2012). While Zhao, Li et al. (2016) describes firms to be likely to overestimate self-reported achievement rates, Ke, Price et al. (2012) conclude reported values to be reasonable and confirm the program’s success.[48] Of the firms evaluated in 2010 when the T1000P was terminated, only 1.7 percent of the firms were officially found as non-complying with the preset targets (NDRC, 2011).[49] 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).[50] The T1000P was extended to the Top 10,000 Enterprise Program within the Twelfth FYP (Zhao, Li et al., 2016).

At its time, the T1000P was part of the most ambitious effort of the Chinese central government ever made to decrease energy intensity of industrial firms. While the overall responsibility for the program was with the central government (and especially with the NDRC), which also registered the firm-specific abatement targets, the implementation and oversight was primarily delegated to the local, i.e. provincial and municipal governments (Price, Levine et al., 2011; Price, Wang et al., 2010; Zhao, Li et al., 2014). During the implementation process, the government provided guidance to the

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[48] 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.

[49] 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.

[50] 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)

targeted firms (Ke, Price et al., 2012; Price, Wang et al., 2010; Zhao, Li et al., 2014), whereby firms collaborated especially with the local authority (Li, Zhao et al., 2016; Zhao, Li et al., 2014). The T1000P was a command-and-control regulation only in the wider sense, as first energy intensity targets were negotiated with a long-term outlook. Subsequently, they were specified in the form of targets in a contract between the provincial government and the firm (Price, Wang et al., 2010; Zhao, Li et al., 2014). Firms had relatively large freedom in choosing 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.

Firms were selected into the program based on energy consumption, i.e. firms did not self-select into the program. Firms were allocated energy saving targets primarily based on their pre-regulation share in the energy consumption of all firms exposed to the T1000P (Zhao, Li et al., 2014, 2016). To some extent however, other factors like industry affiliation, general situation or the technological level of the firm were also taken into account when setting the targets (Price, Wang et al., 2010). Due to time constraints, this target setting process was not based on a detailed scientific bottom-up analysis of individual energy saving potentials (Price, Levine et al., 2011; Price, Wang et al., 2010). The firms self-reported their progress in saving energy directly to the Chinese National Bureau of Statistics (NBS) via a website based on predefined reporting standards (Zhou, Levine et al., 2010). Subsequently, compliance of firms was evaluated yearly by the provincial Energy Saving Offices. 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 (Li, Zhao et al., 2016; Zhao, Li et al., 2014, 2016). Fraudulent reporting could lead to criminal investigations (Zhou, Levine et al., 2010).

The literature describes various adjustment processes undertaken by the firms in response to the regulation. For example, they improved or established internal energy management and reporting capabilities, implemented incentive payments or technological retrofits (Price, Wang et al., 2010; Zhao, Li et al., 2014). Hence, firms did not simply focus on "end-of-pipe", but rather on fundamental solutions like reconfigurations of production processes. According to Porter and Van der Linde (1995b), fundamental reconfigurations increase the chance for innovativeness offsetting the costs of compliance. To incentivize firms and to reduce barriers for energy savings, local governments actively supported targeted firms in achieving their energy reduction targets. They organized not only information dissemination (e.g., energy audits) and skill building (e.g., energy data reporting skills) campaigns, but also direct funding in form of subsidies or guaranteed bank loans (Zhao, Li et al., 2014, 2016).[51] The program enjoyed substantial attention over the whole spectrum of governmental hierarchies and substantial resources flew into it (Price, Levine et al., 2011).

The program did not predefine any punishments, e.g., in financial form, in case of a firm’s non-compliance. However, provincial governments introduced individual 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 could include salary cut-offs in case of non-compliance (Zhao, Li et al., 2014). Furthermore, as part of an extensive overall catalogue[52] of performance assessment criteria, state-owned enterprises (SOEs) and local government officials were evaluated based on their achievement of the T1000P energy-saving targets (Li, Zhao et al., 2016; StateCouncil, 2007; Zhao, Li et al., 2014). This personnel appraisal system was introduced in November 2007 by the State Council and strongly incentivized government officials in supporting treated firms to reach their targets (Zhou, Levine et al., 2010).[53] Awards and

[51] The organization of information dissemination was confined to the local government. As described in Price, Levine et al. (2011), the T1000P itself did not include a framework for systematic information gathering and dissemination on a national level.

[52] 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).

[53] 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

(*Footnote continues on next page*)

promotions were given in return for regulation compliance. In case of non-compliance, firm managers and local government officials endangered their promotion and a written report was to be sent to the superior government including a specification of the time frame for rectification (Zhao, Li et al., 2014).

4 Data

The empirical evaluation of the T1000P builds on several types of data: firm level industrial census data, data on firm participation in the T1000P, data on deflators, data on intermediate input prices and data on geographic information. Accordingly, multiple steps are implemented to combine these data.[54] In a first step, firms contained in the cross-section census data are linked over time. The second step links T1000P exposure information to the census data, and the third and fourth step link the deflators and intermediate input price data. In a fifth step, information on the geographic location of the firms is added. When implementing these steps, data quality and correctness is continuously monitored. All steps and procedures are outlined in appendix A.1. In what follows, the data is described in greater detail.

4.1 Data Sources

The main data source of the analysis is the Chinese Industrial Census (CIC) of the years 2003 to 2008. This proprietary data was 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

managers. A description of such an appraisal program, for example, is given in Zhang, Aunan et al. (2011).

[54] Data processing was conducted using Stata 13 (StataCorp, 2013).

higher than 5 million Chinese renminbi (RMB), what 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). Details on the data and processes mentioned in this chapter are given in appendix A.1. All costs and output values are deflated to 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). The CIC classifies firms into several industries and subindustries. However, there were changes in the industry classification of the Chinese statistical system in 2003 and 2011. To ensure the application of the correct price deflators, the official industry mapping files of the NBS were applied (NBS (2002) and NBS (2011)). Information on firms participating in the T1000P was disclosed by the NDRC. Of these firms, 1,001 out of 1,008 (i.e. 99.3 percent) could be 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, steel, steel rolling and alloy) and province-specific annual price of material is calculated based on information on subindustry inputs and outputs obtained from 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 gives a more detailed description on the construction of the price of material.

4.2 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.[55] 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 II-1 in columns 1 to 4. The mean firm produces a gross-output value of 353.8 million RMB, employs 506.2 people, 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 observations 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.[56]

[55] The CIC is notorious to contain misreported firm information. Therefore, an extensive data screening process was implemented to detect and discard such firms. Further firms had to be dropped in the panel generation and variable adjustment processes. These processes are described in greater detail in appendix A.1. Most excluded firms were small in size. It can be hypothesized that small firms 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 II-21 in appendix A.1).

[56] 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.

Table II-1: *Descriptive statistics of firms.*

	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 5.1. *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. 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 of the one-sided unpaired t-tests.

Summary statistics differentiating between the control and treatment group are given in columns 5 to 7 of Table II-1. 148 out of 5,340 firms are observed to participate in the program, accounting for 848 observations, i.e. 3.1 percent of total observations. The average firm of the control group is considerably smaller than the average firm of the treatment group in 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 II-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 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, what partly can be attributed to state controlled firms on average being larger in size. However, it cannot be excluded that these firms were also more likely to be exposed to the T1000P, simply because they were state controlled. In fact, this even could have been an important consideration. Of course, we are aware that dispersions in important characteristics between treated and non-treated firms should be considered carefully in the empirical analysis. In addition to controlling for these heterogeneities directly in the benchmark analysis, we will implement an extensive set of robustness checks and instrument for T1000P exposure.

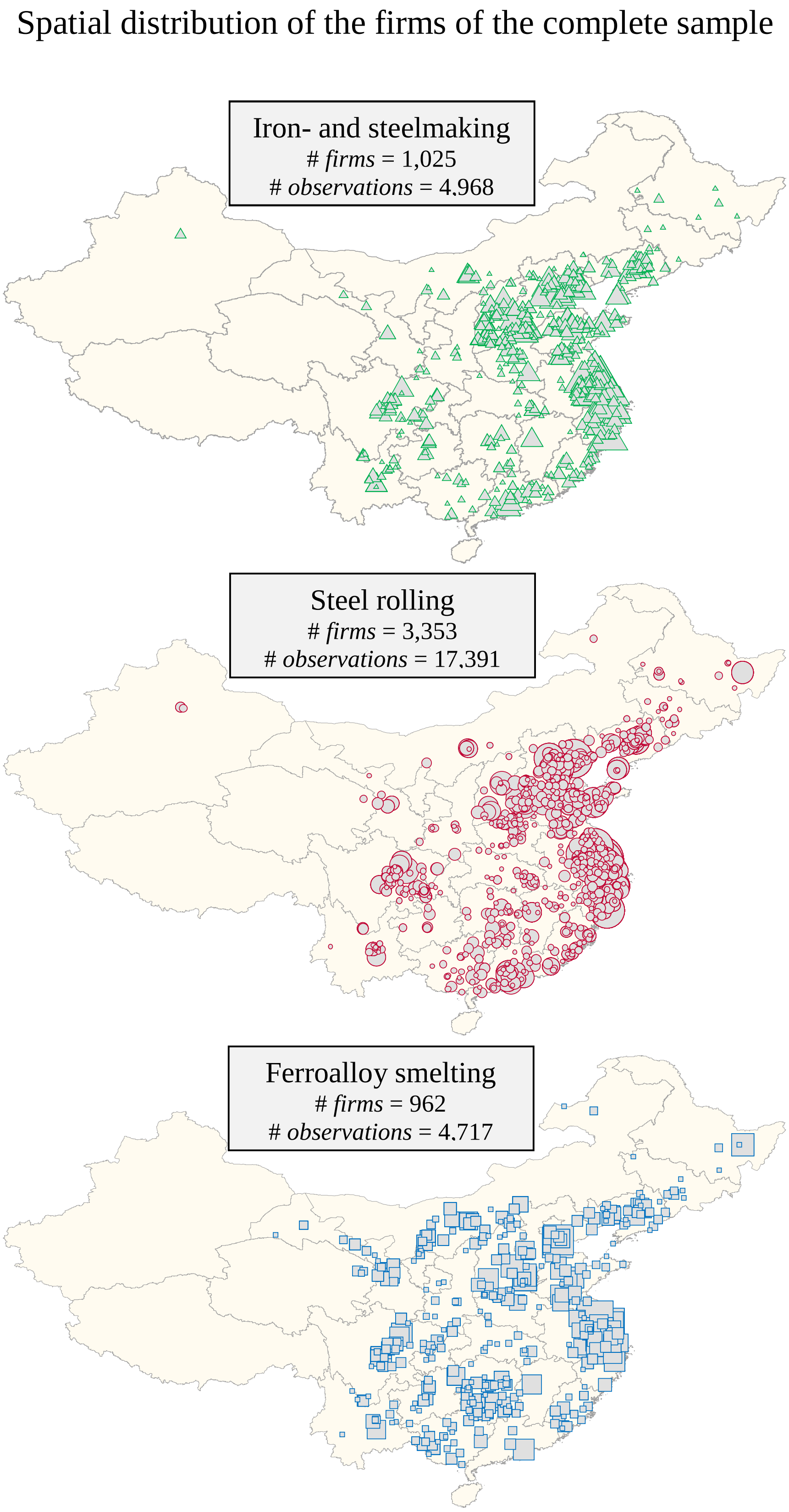

Figure II-1: *Spatial distribution of the sample firms by subindustry in 2005. Marker size is relative to the number of firms observed in a county.*

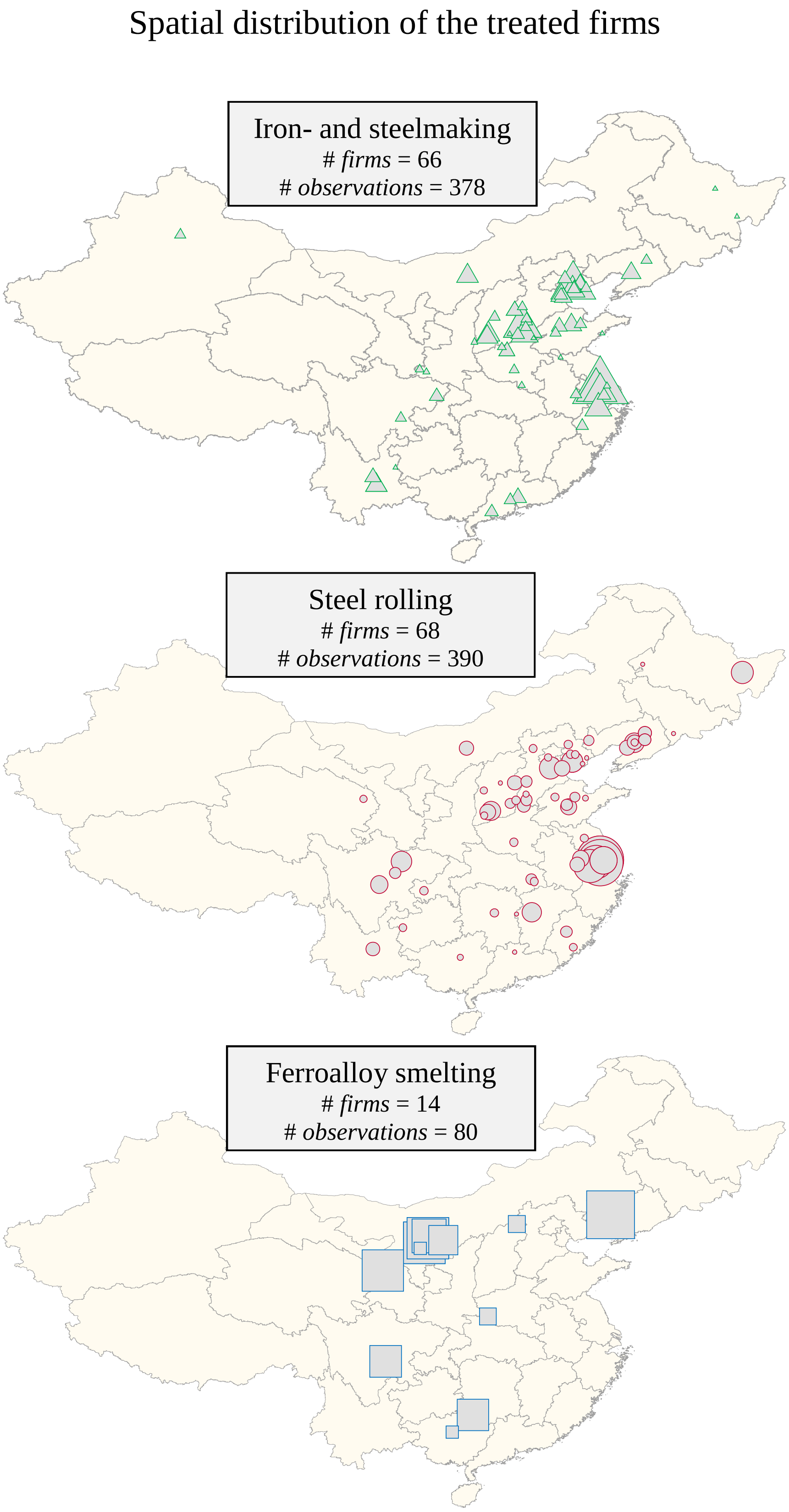

Figure II-2: *Spatial distribution of the treated firms by subindustry in 2005. Marker size is relative to the number of firms observed in a county.*

Figure II-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.[57] The share of Hebei, Liaoning and Shandong province is 7.3, 7.3 and 6.8 percent, respectively. Figure II-2 depicts the spatial distribution of the treated firms. Consistent with the overall distribution shown in Figure II-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 of the ferroalloy smelting industry are located in the west region. It is reassuring that we also observe a higher share of ferroalloy smelting firms being located in this area, compared to the other two subindustries.

5 Firm Productivity

5.1 Estimation Methodology

The relationship between the T1000P and firm performance is evaluated based on two main steps. First, firm performance is calculated using the unbalanced panel described in section 4. Second, effects of the regulation on firm performance are analyzed using parametric models. Firm performance is expressed by total factor productivity (TFP) change and the subcomponents thereof, which are technical change and scale efficiency

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[57] It is differentiated between three regions. 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.

change.[58] An analysis of the effects on TFP change subcomponents allows for more detailed insights 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 efficient 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 measures can be viewed as being distorted (Syverson, 2011).[59] This chapter describes the procedure to compute the firm performance indicators.

TFP change can be measured using three approaches, i.e. the index number approach, the parametric (including semi-parametric) approach and the non-parametric approach.[60] Index numbers construct a measure of TFP by taking the ratio of an output index to an input index. Index numbers come with the advantage of not requiring a lot of data. However, this approach does not allow decomposing TFP into its components. The parametric approach is based on the estimation of production or cost functions (or

[58] This study does not focus on TFP levels. TFP change can be considered 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 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.

[59] Single factor productivity measures are 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 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 like a favourable price of capital.

[60] For a discussion of these approaches, see, e.g., Bartelsman and Doms (2000), Coelli, Estache et al. (2003), Van Biesebroeck (2007), Eberhardt and Helmers (2010), Syverson (2011) or Van Beveren (2012). Most studies estimate TFP via a production function. For a list of common methods to derive TFP from a production function see also footnote 37.

frontiers) using econometric methods. Finally, the non-parametric approach uses linear programming methods to construct production or cost functions (or frontiers).

Parametric and non-parametric approaches have the advantages that productivity changes can be decomposed into various components such as technical change and change in the scale of production.[61] But they also differ in multiple dimensions, like whether or not they control for unobserved heterogeneity, or in their underlying economic assumptions, for example, in terms of returns to scale or separability of inputs. Non-parametric methods allow for firm-specific production functions and do not require a priori assumptions regarding the functional form. However, their deterministic nature does not explicitly control for unobserved heterogeneity. Also, they usually restrict the production technology to be of constant returns to scale. In contrast, parametric approaches based on panel data are able to account for unobserved heterogeneity, but typically assume a certain functional form.

The iron and steel industry is, compared to other industries, highly energy demanding. At the same time, it shows a comparatively homogenous production process with relatively uniform output goods.[62] This makes it an industry well suited to base a parametric framework upon. Given the, nevertheless, large degree of heterogeneity observed in our sample, the parametric methods' ability to separate noise from signal is recognized as an essential advantage. Furthermore, the estimation of TFP change using parametric approaches allows for a decomposition of TFP change into its components, which may prove to be insightful. Therefore, the empirical analysis presented in this

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[61] Some empirical studies estimate production or cost frontiers. The estimation of frontiers allows for a decomposition of productivity change into three parts: technical change, scale efficiency change and productive efficiency change. See, for instance, Bauer (1990).

[62] For example, Ma, Evans et al. (2002) (for the period of 1987 to 1997) or Sheng and Song (2013) (for the period of 1998 to 2007) describe the Chinese iron and steel industry as mainly focusing on low value-added products with a dominating (compared to other major steel producing countries) share of long products in output, relative to flat products. Further literature describing the production processes in the Chinese iron and steel industry is listed in footnote 44.

study is based on a parametric approach[63], i.e. on the estimation of a cost function[64] using econometric methods.

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).

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

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 subindustries s: iron- and steelmaking, steel rolling and ferroalloy smelting. The production processes of these subindustries are heterogeneous. Therefore, from an empirical point of view, it is interesting to estimate a separate cost function for each subindustry. This allows for subindustry-specific coefficients reflecting heterogeneity in production technologies, resulting in more accurate TFP change esti-

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[63] For comparison, a non-parametric index number method in form of the Törnqvist index was estimated alongside. Derived TFP changes were in the ballpark of the parametric estimation results.

[64] Under the assumption of exogenous input prices, a cost function is less prone to the common bias affecting estimation results of a production function if firms choose inputs based on unobserved productivity shocks. See, e.g., Eberhardt and Helmers (2010) for a description of this bias.

mates compared to results derived from an overall cost function.[65] In this study, we assume the subindustry $s = \{1,2,3\}$-specific production process to be 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 assumed opportunity costs on equity of 3 percent.[66] 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.[67] 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.[68] 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 input respectively output[69] deflators described in appendix A.1. Descriptive statistics of the main covariates are given in Table II-1.

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65 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 of an overall cost function.

66 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).

67 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.

68 While this price measure is not firm-year- but province-year-specific, it bears the benefit to be unaffected by firm-specific unobserved heterogeneity potentially also related to total costs, what would yield in biased estimation results. We describe in details 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 model specification resulted in severe multicollinearity problems when estimating a fully flexible translog cost function.

69 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 justi-

(*Footnote continues on next page*)

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.[70] The subindustry s-specific cost functions are specified as

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

with small letters y and p indicating output and prices in natural logarithms.[71] The panel is unbalanced (cf. section 4.2) with a firm being indicated by $i = 1,..,N$ and time being indicated by t. Firms are observed yearly for 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.[72] The error term is given by ε_{it}. Subindustry-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 $c_{it} - \bar{c}_i = \boldsymbol{\beta}'(\mathbf{x}_{it} - \bar{\mathbf{x}}_i) + (\varepsilon_{it} - \bar{\varepsilon}_i)$ using Huber (1967)/White (1980) cluster robust sand-

fied by the homogenous production process and comparatively homogenous structure of output goods in the iron and steel sector compared to other industries.

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

[71] 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.

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

wich 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.[73]

5.2 Results

Table II-2 presents estimated values of TFP change (TFPC) and, to gain additional information on productivity drivers, its subcomponents of technical change (TC) and scale efficiency change (SEC).[74] Results were derived using the estimated cost function coefficients reported in Table II-22 in the appendix. The cost functions of the three subindustries are well behaved, as they are found to be monotonic (Table II-24) and quasi-concave (Table II-25). 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.[75] 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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[73] For a detailed description of the fixed effects estimator see, e.g., Greene (2008a) or Cameron and Trivedi (2005).

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

[75] These findings are, in terms of sign and magnitude, in line with the general body of literature on TFP growth in the Chinese iron and steel industry cited in section 2.1.

Table II-2: *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.

The mean difference in the TFP growth rate between the 10th and 90th percentile is large; over all three subindustries it amounts to 0.199. Similar numbers are observed for the TFP change subcomponents. Given an annual mean TFP growth rate of 6.4 percent across all three subindustries, the standard deviation therein is relatively large with 10.8 percentage points. Our finding of widely varying TFP growth rates adds to the literature observing large heterogeneities in TFP levels.[76] Syverson (2011) mentions as factors contributing towards widely varying productivity levels not only heterogeneities in production processes, but also, for example, external production environments.

TFP growth is considerably lower for treated firms in the pre-regulation period (cf. Table II-2). A relatively high share of treated firms were SOEs (cf. Table II-1). Sachs and Woo (2001), for instance, note that at the time their study appeared, the consensus of scholars was a lagging productivity performance of SOEs relative to non-SOEs.[77] They hypothesize Chinese SOEs might have serious deficits in their allocative efficiency.[78] However, such inefficiency remains unmeasured in this study, as eq. (1) does not include the factor of cost efficiency change (given no stochastic frontier is estimated).

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76 Examples of this literature are Bartelsman and Doms (2000), Syverson (2011) or Hsieh and Klenow (2009). For China, Hsieh and Klenow (2009) find average dispersions in TFP levels between the 10th and 90th percentile in year 2005 of $e^{1.59} \cong 4.9$ when taking revenues as output, and of $e^{2.44} \cong 11.5$ when measuring output by an approximation of physical quantities. Hence, their measured dispersions in TFP levels are a multiple of the dispersions in TFP growth found in the study at hand.

77 Focusing on TFP levels, more recent literature like Hsieh and Klenow (2009) supports this notion by finding TFP levels of SOEs in the Chinese industry to be 40 percent lower compared to non-SOEs. For the Chinese iron and steel industry, Sheng and Song (2013) find a higher proportion of private ownership in a firm’s real capital to be positively related to TFP levels between 1998 and 2007.

78 Chinese SOEs essentially are extensions of the government and, for example, carry out functions of providing employment and social services, as well as serving as a conduit for the implementation of regulations. These functions not always possess a profit motive. For more details on differences between SOEs and non-SOEs in various dimensions see part III, especially section 2.2.

6 Identification Strategy

The effect of the T1000P on firm performance (TFPC, TC and SEC) is identified applying a difference-in-difference (DD) approach.[79] 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 3.2, 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, to have undertaken regulation related actions affecting firm performance beforehand.[80] Also, while firms were chosen to participate in the T1000P mainly based on energy consumption, also other criteria like industry affiliation played a role (cf. section 3.2). Firms did not actively self-select into the program. For the DD approach to yield valid results, the assumption of a parallel trend has to be satisfied. This assumption implies a trend in firm performance before the introduction of the regulation that does not differ between firms of the treatment and control group. Given 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

[79] The DD methodology is described in greater detail in appendix A.2. 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 restrained from conducting a regression discontinuity analysis. This study incorporates elements of the underlying idea of a matching procedure by using stratified samples to check for robustness of the results. Given that results were found to be robust, we restrained from an additional implementation of a matching procedure. For an extensive review of policy evaluation methods the interested reader might consult Lance, Guilkey et al. (2014) or, for a more qualitative description, Gertler, Martinez et al. (2011).

[80] We consider this assumption to be credible, as the T1000P was framed within a comparatively short time period (cf. section 3.2).

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 $\boldsymbol{\theta}_t$ capture 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 whether 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.[81] Vector $\mathbf{X}_{it}$ contains two variables to control for time changing 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.[82] Province-year effects $\boldsymbol{\theta}_t\pi_i$ control for province π_i - and year θ_t-specific shocks.

The appropriateness of the DD approach is only given 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

81 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.

82 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.

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 appliance and enforcement of regulation 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 5.1, 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.[83]

A threat to the identification strategy, if remained unaccounted for, is time varying unobserved heterogeneity not orthogonal to the treatment effect or other covariates. By construction of the regulation, only large energy consumers were exposed to it, i.e. the distribution of participating firms is heavily skewed towards large firms (cf. Table II-1). In addition, anecdotal evidence in the literature and observations made earlier in this study (cf. section 3.2, 4.2 and Table II-1) suggest a firm's exposure to be dependent on other determinants than simply an above threshold energy consumption. Firm size and ownership evolve as two main suspects. These two factors can be expected to be correlated with firm performance as well, and hence are stepwise controlled for by vector $\mathbf{X}_{it}$.[84] Province- and year-specific shocks, captured by $\boldsymbol{\theta}_t \pi_i$, can be thought of as being

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

[84] 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.

caused, e.g., by changes in a province's political structure. Shocks therein potentially can be correlated not only with firm performance, but with, e.g., T1000P exposure as well. Another example could be labor unions (Greenstone, 2002). These might be more prevalent in geographic locations with a high density of state controlled firms. The activism of labor unions might differ over time, with some provinces being more affected than others at some point in time.

We implement several approaches to test for robustness of the results. First, we apply the DD identification strategy to samples stratified with respect to several dimensions. Second, results are tested for robustness with respect to sample attrition. In form of a final third robustness check, T1000P exposure is instrumented for. These robustness check procedures are described in greater detail in chapter 8.

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:

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

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.[85]

[85] 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).

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

The assumption of no pre-treatment effects holds if $\hat{\theta}^{tr}_{2005} = 0$ is not rejected.[86] 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 (cf. footnote 81), ATT. Firm fixed effects α_i capture the information of the covariate τ_i as well, for which reason 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.

7 Effect of the Regulation on Total Factor Productivity Change

In this chapter, we describe the findings on the intensive margin of the T1000P on TFP change (including its subcomponents) and therefore competitiveness of treated and non-treated firms in the Chinese iron and steel industry. Before focusing on the econometric approach outlined in the previous chapter, we first conduct a deterministic evaluation of the T1000P's impact on TFP change to exemplify the underlying idea of a DD analysis. The regulation is found to positively affect TFP change and subcomponents of technical and scale efficiency change.

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

7.1 Deterministic Approach

The deterministic approach compares the differences in average TFP change before and after the introduction of the regulation in year *T** (i.e., year 2006) between the treatment group (indicated by "*tr*") and control group (indicated by "*co*"). Here, the ATT of the environmental regulation on aggregate productivity change is the differential in expected values of the differences in average TFP changes of the treatment and control group before and after the introduction of the regulation. In contrast to the econometric approach, this framework does not account for unobserved heterogeneity. The deterministic approach to computing the *ATT* can be expressed by the following formula:

$$ATT = \underbrace{E\left[TFPC_{it}^{tr}(t \geq T^*) - TFPC_{it}^{tr}(t < T^*)\right]}_{\Delta E[TFPC_{it}^{tr}]} - \underbrace{E\left[TFPC_{it}^{co}(t \geq T^*) - TFPC_{it}^{co}(t < T^*)\right]}_{\Delta E[TFPC_{it}^{co}]} .$$

Results are shown in Table II-3. The introduction of the T1000P is found to have increased TFP change of treated firms relative to the control group by, on average, 1.8 percent. The highest effect is recorded for the ferroalloy smelting industry with an increase of 2.8 percent. However, these effects might be distorted with at this point unknown direction, as other heterogeneity than T1000P exposure affecting TFP change is not accounted for.

Table II-3: *Deterministic analysis of the treatment effect of the T1000P on TFPC.*

Control group		Treatment group		Differences		Diff-in-diff
Pre-T1000P	T1000P	Pre-T1000P	T1000P	[(2) – (1)]	[(4) – (3)]	[(6) – (5)]
$E[TFPC_{it}^{co}]$ $(t < T^*)$	$E[TFPC_{it}^{co}]$ $(t \geq T^*)$	$E[TFPC_{it}^{tr}]$ $(t < T^*)$	$E[TFPC_{it}^{tr}]$ $(t \geq T^*)$	$\Delta E[TFPC_{it}^{co}]$	$\Delta E[TFPC_{it}^{tr}]$	
(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Subindustry-specific cost function (mean)				
0.088	0.055	0.026	0.011	–0.033	–0.015	0.018
(0.115)	(0.104)	(0.055)	(0.036)	(0.002)	(0.004)	(0.000)
		Iron- and steelmaking				
0.116	0.103	0.013	0.004	–0.013	–0.009	0.005
(0.132)	(0.112)	(0.069)	(0.033)	(0.004)	(0.007)	(0.000)
		Steel rolling				
0.078	0.049	0.034	0.017	–0.029	–0.017	0.012
(0.096)	(0.078)	(0.028)	(0.031)	(0.002)	(0.003)	(0.000)
		Ferroalloy smelting				
0.096	0.031	0.051	0.014	–0.065	–0.037	0.028
(0.153)	(0.153)	(0.062)	(0.058)	(0.005)	(0.015)	(0.002)

Note: In column 7 this table presents deterministic difference-in-difference results of the mean effect of the T1000P on TPFC. The treatment group contains 848 observations (148 firms) and the control group 26,228 observations (5,192 firms). The pre-regulation period covers 2003 to 2005 and the regulation period covers 2006 to 2008. Standard deviations are given in parentheses. Standard errors of columns (5) and (6) are calculated as $[(E[TFPC_{it}^{z}(t < T^*)])^2 / N^z(t < T^*) + (E[TFPC_{it}^{z}(t \geq T^*)])^2 / N^z(t \geq T^*)]^{1/2}$, $z = \{tr, co\}$, while $[(\Delta E[TFPC_{it}^{tr}])^2 / N^{tr} + (\Delta E[TFPC_{it}^{co}])^2 / N^{co})]^{1/2}$ yields the standard error of column (7). N is the number of observations in the treatment and control group, respectively. Note that this calculation of the standard errors bases on the assumption of zero correlation between $\Delta E[TFPC_{it}^{z}(t < T^*)]$ and $\Delta E[TFPC_{it}^{z}(t \geq T^*)]$ as well as between $\Delta E[TFPC_{it}^{co}]$ and $\Delta E[TFPC_{it}^{tr}]$. Given positive observed correlations, this is a conservative assumption.

7.2 Econometric Approach

The econometric approach to the DD analysis, in contrast to the methodology shown in Table II-3, allows controlling for other heterogeneity than T1000P exposure that potentially is affecting changes in productivity. The econometric approach also allows testing for a potential threat to identification of the treatment effect in form of different pre-regulation trends in the outcome variables between the control and treatment group or pre-treatment effects. The test of the parallel trend is based on eq. (5). Pre-treatment effects are tested for by using eq. (6). Results of the two tests with respect to TFP change and its subcomponents are given in Table II-4. Results are shown for the test of model specification DD–3, our, as discussed later on, preferred model.[87] With a statistically non-significant coefficient estimate of the interaction between the 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).[88] 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.

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

[88] 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.

Table II-4: *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.

Treatment effects are estimated based on expression (4), with results being shown in Table II-5.[89] For comparison purposes, as explained in chapter 6, we estimate three model versions (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 well. The T1000P was implemented and surveyed mainly on provincial level with the local governmental officials being evaluated based on the achievement of the T1000P energy-saving targets (cf. section 3.2). Hence, changes in provincial politics in the pre-regulation period could affect not only firm performance, but also the propensity of being exposed to the T1000P. Political shocks on provincial level during the regulation period could be relevant, for example, in terms of the enforcement of the regulation by affecting regulation stringency. All three models include firm fixed effects and capture political shocks on national level via year fixed effects.

Even though the respective *F*-tests reject the coefficients of the additionally included variables to be jointly equal to zero, estimated treatment effects are robust in terms of sign, magnitude and significance across all three model specifications. This increases our confidence that no significant bias is to be expected to stem from unobserved heterogeneity correlated with the additionally included variables. Given such robustness, the third model is our preferred specification nevertheless, as it most extensively controls for potential cofounding factors. In line with our deterministic findings in Table II-3, 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[90] in wake of the regulation and thereby provides

[89] We only have observations on three years where the regulation was active. However, firms are described to have started early with energy saving adjustment processes 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.

[90] 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.

(*Footnote continues on next page*)

empirical evidence of Porter's hypothesis[91]. As treated firms showed an average TFP change of 2.6 percent before the implementation of the T1000P (cf. Table II-2), the additional, 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[92]). Both subcomponents are significantly affected by the policy and, on average, contribute about equally to the overall treatment effect.[93]

In what follows, we qualitatively hypothesize on underlying factors contributing to these results. Clearly, the design of the T1000P to some extent was special. Enforcement was overseen by multiple governmental bodies and punishment in case of non-compliance was not determined a priori and explicitly. Furthermore, firms received governmental support on many levels, from information provision on provincial level, to skill building, over to government-funded loans and subsidies. We cannot exclude such financial support to some part being responsible for the significant and positive effect of the T1000P on firm performance. And, 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 of a properly designed en-

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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 mRMB(in 1998 values).

[91] Porter's hypothesis builds on the assumption that firms must comply with the regulation. As described in section 3.2, the compliance rate of the firms exposed to the T1000P was indeed very high. Our findings do not imply that the policy had no negative effects on productivity change through an increase in cost with no offsetting rise in output. We rather find evidence of a positive net effect on productivity change, i.e. of positive effects through, e.g., innovative activities outweighing negative effects.

[92] The firms of all three subindustries on average were found to exhibit positive returns to scale (cf. Table II-23 in the appendix).

[93] 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.

vironmental policy. Hence, our result of a positive net effect of the T1000P on TFP change may not be entirely surprising.

Table II-5: *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.

8 Robustness

We check the robustness of the previously presented empirical benchmark results via three approaches. The first robustness check estimates model (4) using stratified samples. Sample stratification with respect to key variables refines the counterfactual 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, subindustry affiliation and geographic region. Second, we test robustness with respect to sample attrition. And finally, 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.[94]

8.1 Sample Stratification

The following estimations are based on samples stratified with respect to firm size, ownership structure, subindustry and geographic region. Table II-6 shows every stratum to contain enough observations on treated firms for statistical inference. As a first robustness check, we re-estimate model (4) based on a sample which 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 II-23 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 the T1000P was an energy consumption of at least 180 ktce, only large firms were exposed to the regulation and, in consequence, all treated firms belong to the fourth quartile of the size distribution. The results presented in Table II-7 are in the ballpark of the benchmark results of Table II-5, with treatment effects being slightly larger for the sample only including 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,

[94] 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 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.[95] Table II-8 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. On the one hand, such finding could contradict the hypothesis of SOEs having significantly more resources available to fund the fixed costs and undertake the risks of investing in innovative and TFP increasing activities. 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 what would have allowed to carry the costs of compliance without becoming more competitive.

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 II-9. 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. Fo-

[95] See part III, especially section 2.2, for a more detailed description of the implications of ownership in the Chinese industry. It is to note that time effects are specific for a stratified sample, allowing 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 be different in their extent across firms and time, as they may have, for instance, grown stronger with the onset of the Eleventh FYP.

cusing 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.[96]

Results of the sample stratified with respect to geographic region are given in Table II-10. 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 II-1 and Figure II-2). Market oriented reforms were strongest in the east region (Sheng and Song, 2013). Hence, firms face the strongest competition on 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.

In conclusion, the results when using stratified samples are in line with the results of the benchmark specification of Table II-5. This is an indication that the dimensions of stratification are not major sources of bias, increasing our confidence in the consistency of these results.

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[96] 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.

Table II-6: *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				
4th quartile of firm sizes stratum	148	848	1,187	6,311
Stratification by ownership type				
SOE stratum	54	312	127	667
Non-SOE stratum	65	370	4,314	21,560
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. 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 II-7: *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 4th 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 II-8: *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 II-5. 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 II-9: *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 II-10: *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 57 on p. 68. 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.

8.2 Sample Attrition

Firms leaving the sample might distort the randomness of the panel and endanger its representativeness to infer about the population (Baltagi, 2008). Sample attrition could be problematic in 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 (extensive margin of the regulation on firm survival probability). Such sample attrition could result in an upward bias of estimated treatment effects. Accordingly, a downward selection bias in estimated treatment effects could result if more productive firms unexposed to the regulation were more likely to survive (intensive margin of the regulation). Robustness of our benchmark results with respect to such dynamics is tested using a balanced panel, which can be viewed as being freed from potential attrition effects.[97]

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).[98] 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. Defining the attrition free sample in this way allows us to partially keep the large number of firms entering in 2004. The re-definition of the sample necessitates a re-calculation of the approximation points of the subindustry-specific translog cost func-

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[97] 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.

[98] 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.

tions 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 II-26 and the firm performance estimates in Table II-27. 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 II-28). The evaluation of the effect of the T1000P on TFP change and its subcomponents using the sample free of attrition yields results (cf. Table II-11) staying 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 in terms of attrition bias, even though the effect of technical change TC gains slightly in importance when using the sample freed from attrition. 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 of 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 II-11: *ATTs of attrition free sample.*

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.

8.3 Instrumenting for Regulation Exposure

Firms selected into treatment were found to be highly different to firms of the control group in several key dimensions like firm size or ownership. So far, the evaluation accounted for time-constant unobserved heterogeneity as well as time varying heterogeneity with respect to size, ownership and geographic location. Then, we first tested for robustness with respect to further time varying heterogeneity and heterogeneous regulation effects by refining the counterfactuals using stratified samples. In a second step, we tested for robustness with respect to sample attrition. Finally, as explained in chapter 6, we will 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 II-3, a county is most probable to have 7 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 II-1 and Figure II-2). In can be hypothesized that such industrial clusters are inherently connected to unobserved time varying heterogeneity affecting T1000P exposure like 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 II-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 of the same cluster q. Descriptive statistics of τ_i^{IV} are given in Table II-12.

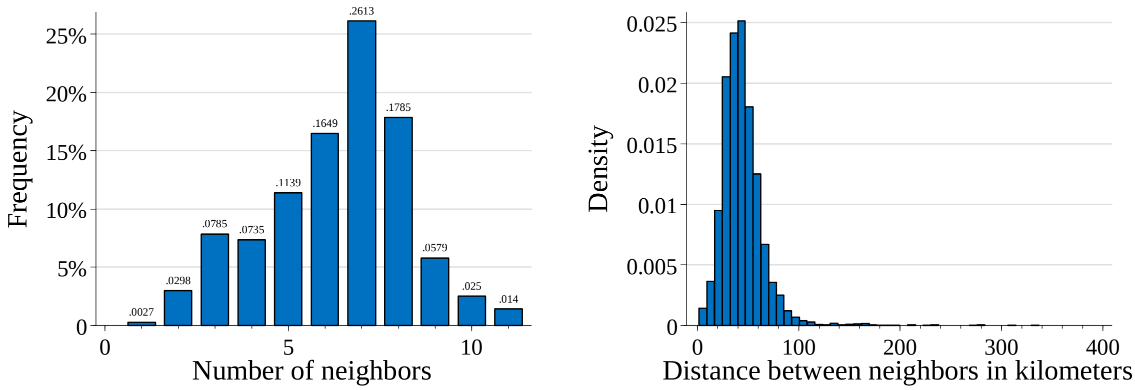

Figure II-3: *Distributions of the number of neighbors and distances between clusters.*

Table II-12: *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.[99] 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.[100] As all variables included in the first stage are of limited range, the supporting restriction of the LPM of no regressor having infinite support is satisfied.[101] 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.[102] First stage results are shown in Table II-13. Results shown in Table II-14 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 II-5). 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.

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

[100] 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 (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.

[101] 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).

[102] 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 1 percent. Hence, the instrument is found be relevant, i.e. not weak.

Table II-13: *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 II-14: *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.

9 Conclusions and Discussion

In this paper, we analyze the effects of the T1000P on TFP change of Chinese iron and steel firms from an economic point of view. The environmental regulation was introduced in April 2006 and aimed to reduce the energy intensity of roughly 1,000 firms by a significant amount. Being highly energy demanding, the iron and steel industry was the industry targeted the most by the regulation in terms of the number of treated firms.

The literature differentiates between two main strands of how an environmental regulation affects firm productivity: the traditionalist view and Porter's hypothesis. Both views are from the perspective of the firm. The traditionalist view predicts that productivity of firms is negatively affected by an environmental regulation, while Porter's hypothesis expects the opposite. Most literature suggests a firm's productivity to be adversely affected by environmental regulations, i.e. supports the traditionalist view.

This study uses a large and detailed panel of 5,340 Chinese iron and steel firms and a total of 27,076 observations between 2003 and 2008. We find a significant correlation between firm level TFP change, subcomponents thereof, and T1000P exposure. Hence, our empirical analysis yields evidence in favor of Porter's hypothesis, in the sense that positive effects of the regulation on firms' TFP change outweigh negative ones on average. 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, what is equivalent to an 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 complied with the regulation not only by changing their production processes by, e.g., installing new machinery and equipment, but also by expanding output. 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, ownership structure, industry affiliation and geographic location. Interestingly, non-SOEs on average experienced a similar positive effect of T1000P exposure on TFP change than SOEs. Furthermore, results are found to be robust with respect to sample attrition and potential endogeneity in T1000P exposure. In conclusion, a firm exposed to the regulation profited twofold: first, it profited through the direct effect of reduced costs through less expenditure on energy. Second, the regulation lead to an increase in TFP change relative to non-treated firms and hence increased the competitiveness of the treated firms.

The contributions of this study to the literature are multiple. To our knowledge, this is the first study analyzing the impact of an environmental regulation on TFP of Chinese firms and, in general, on the subcomponents of technical change and scale efficiency change using parametric methods. As done only within a few studies, we estimate TFP change via a cost function approach. Furthermore, this study proposes an instrument using spatial information to account for potential time varying endogeneity in the selection of firms into treatment.

Finally, what can we learn from a policy point of view? Certainly, with productivity representing a foundation of social welfare and a Chinese government which is increasingly resorting to environmental policies to align its industry with higher environmental sustainability, the public policy aspects of our results are multiple. First, the effects of an environmental regulation on firm productivity can be positive by incentivizing firms to use inputs in a more productive fashion through innovation, as predicted by Porter's hypothesis. Our findings oppose common wisdom of environmental regulations hurting an industry's competitiveness. Given China's need of further greening its industry, evidence in this regard is more than welcome. Clearly, the design of the T1000P to some extent was special. Enforcement was overseen by multiple governmental bodies and punishment in case of non-compliance was not determined a priori and explicitly. Firms received governmental support on many levels, from information provision on provincial level, to skill building, over to government-funded loans and subsidies. 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 of a properly designed environmental regulation. Hence, our result of a positive effect of the T1000P on

TFP change may not be entirely surprising. The analysis was conducted from the viewpoint of a firm. Additional social benefits obtained from reduced emissions remain unaccounted for and would add to the observed positive effect of the regulation.

There are diverse opportunities for future research in the field of this study. Given a future availability of high quality census data up to more recent years, it could be analyzed whether observed treatment effects persist for a prolonged period of time, how effects are changing their magnitude over time, or it could be tested for 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 a regulation 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 or ownership structure. It would be interesting to shed more light onto the role of management quality therein and to provide first empirical evidence on the link between management quality and innovativeness in response to an environmental regulation.

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 II-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*[103] and another code based on the telephone number *data_ij_by_code2*[104]. 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 II-15. 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[105] 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

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

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

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

unbalanced panel for year *i* and *k* (without observations that have the full link in *balanced_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[106]. 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 II-4.

Then, illustrated as step 3 in Figure II-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.

[106] 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.

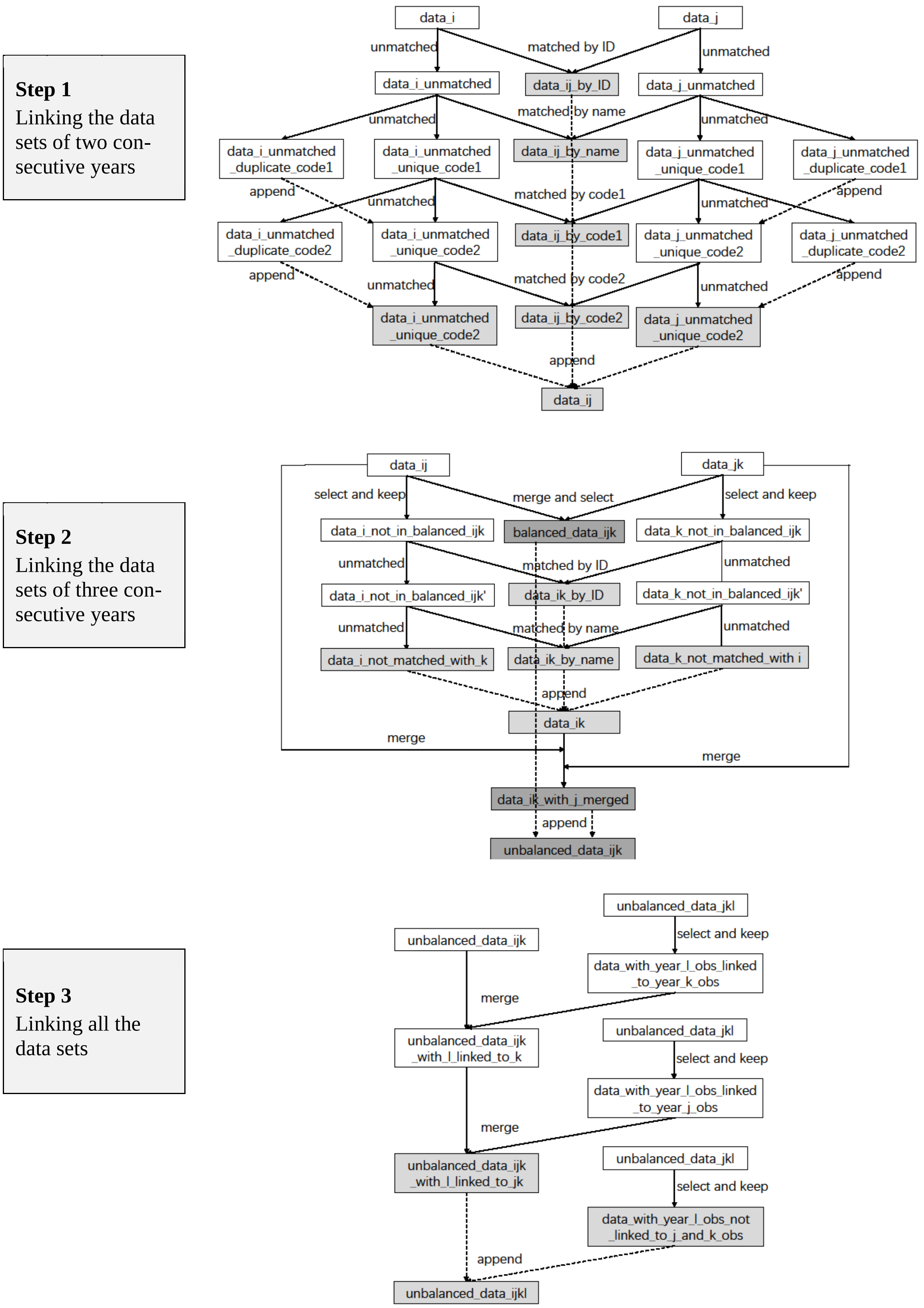

Figure II-4: *Panel construction steps.*

Table II-15: *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 II-16: *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.[107] 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 II-17), 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 II-18) 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.

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

Table II-17: *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 II-18: *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 II-19 and Table II-20. The online appendix of Brandt, Van Biesebroeck et al. (2012) describes the construction of these deflators.

Table II-19: *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 II-20: *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.[108]

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

[108] 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 II-21: *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.[109] 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

[109] 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 II-21). 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.[110] 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-

[110] 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.

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

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

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 Methodology of Difference-in-Difference Analysis

The difference-in-difference (DD) analysis evaluates the causal effects of the T1000P on TFP change. The conceptual framework of using a counterfactual to estimate the causal effect of a treatment goes back to Rubin (1974). The following explanation of the difference-in-difference (DD) analysis follows Khandker, Koolwal et al. (2010) and Lance, Guilkey et al. (2014). Let $TFPC_{it}^{tr}$ define the TFP change of a firm *i* in period *t* that is exposed to the T1000P regulation (i.e. firm *i* belongs to the treatment group, indicated by "*tr*") and $TFPC_{it}^{tr,*}$ the performance of the *same* firm in period *t* if it would not have been exposed to the T1000P. The expected causal effect of the T1000P on the performance of the treated firms in period *t*, i.e the average treatment effect on the treated (*ATT*), can be expressed as

$$ATT_t = E\left[TFPC_{it}^{tr} - TFPC_{it}^{tr,*}\right]. \tag{8}$$

Above expression holds analogously for the computation of the average ATT over multiple periods, in which case the difference removes from the ATT any time-constant unobserved heterogeneity correlated with regulation exposure. However, potentially time varying heterogeneity of this sort remains unaccounted for. A firm commonly is assumed not to anticipate the implementation of a regulation and, hence, not to undertake any measures affecting TFP change beforehand. Under this assumption, the ATT must equal zero for the pre-regulation periods.

For demonstration purposes it now is assumed that there are several time periods before the treatment and one period after the treatment, with the treatment occurring between period $T-1$ and T. To identify the *ATT* in eq. (8), the hypothetical performance of a treated firm if it would not have been exposed to the T1000P, $E\left[TFPC_{iT}^{tr,*}\right]$, has to be estimated as it is non-observed[111]. For that means, a difference-in-difference (DD) methodology can be applied as explained in greater detail in Figure II-5. Under the assumption of a parallel trend in firm performance of the treatment group (indicated by "*tr*") and control group (indicated by "*co*") in the pre-regulation periods, the observed average trend in TFP change of the control group

$$E\left[\sum_t \Delta TFPC_{it}^{co} \middle| t \le T\right] = E\left[\sum_t (TFPC_{it}^{co} - TFPC_{i,t-1}^{co}) \middle| t \le T\right]$$

serves as counterfactual for what would have happened to the average TFP change of the treatment group $E\left[TFPC_{iT}^{tr,*}\right]$ if the T1000P would not have been implemented. It

[111] Holland (1986) calls this the "fundamental problem of causal inference".

therefore is elementary that the assumption of a parallel trend is not rejected for the DD approach to yield unbiased results. Given the parallel trend assumption holds, $E\left[TFPC_{iT}^{tr,*}\right]$ now can be expressed as

$$E\left[TFPC_{iT}^{tr,*}\right] = E\left[TFPC_{i,T-1}^{tr}(T-1) + E\left[\sum_t \Delta TFPC_{it}^{co} \middle| t \leq T\right]\right]. \tag{9}$$

Hence, by inserting eq. (9) into (8) and as shown in Figure II-5, the *ATT* can be stated based on observable variables only as

$$\begin{aligned} ATT &= E\left[TFPC_{iT}^{tr} - \left(TFPC_{i,T-1}^{tr} + E\left[\sum_t \Delta TFPC_{it}^{co} \middle| t \leq T\right]\right)\right] \\ &= E\left[\Delta TFPC_{iT}^{tr}\right] - E\left[\sum_t \Delta TFPC_{it}^{co} \middle| t \leq T\right]. \end{aligned}$$

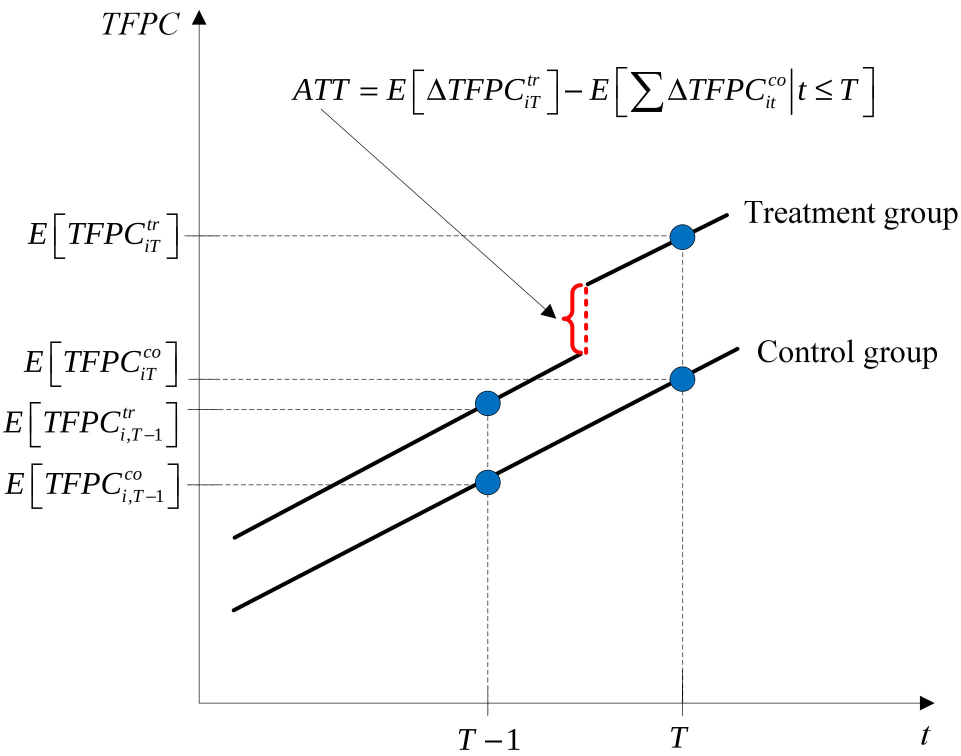

Figure II-5: *Graphic representation of the difference-in-difference approach.*

A.3 Additional Empirical Results

Estimated Coefficients of the Cost Function

Table II-22: *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 II-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 proceed analogously to section 6.3 of part I and use the estimated coefficients of Table II-22 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 II-23 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 II-23: *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 II-22.

Testing for Monotonicity and Quasi-Concavity

Testing for monotonicity and quasi-concavity of the subindustry-specific cost functions is conducted analogously to the procedure described in appendix A.1 of part I. 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

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

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

$$\mathbf{G} = \begin{bmatrix} \hat{\beta}_{KK}^s + \left(\hat{\beta}_K^s\right)^2 - \hat{\beta}_K^s & \hat{\beta}_{KL}^s + \hat{\beta}_K^s \cdot \hat{\beta}_L^s & \hat{\beta}_{KM}^s + \hat{\beta}_K^s \cdot \hat{\beta}_M^s & \hat{\delta}_{KW}^s + \hat{\beta}_K^s \cdot \hat{\delta}_W^s \\ \hat{\beta}_{KL}^s + \hat{\beta}_L^s \cdot \hat{\beta}_K^s & \hat{\beta}_{LL}^s + \left(\hat{\beta}_L^s\right)^2 - \hat{\beta}_L^s & \hat{\beta}_{LM}^s + \hat{\beta}_L^s \cdot \hat{\beta}_M^s & \hat{\delta}_{LW}^s + \hat{\beta}_L^s \cdot \hat{\delta}_W^s \\ \hat{\beta}_{KM}^s + \hat{\beta}_M^s \cdot \hat{\beta}_K^s & \hat{\beta}_{LM}^s + \hat{\beta}_M^s \cdot \hat{\beta}_L^s & \hat{\beta}_{MM}^s + \left(\hat{\beta}_M^s\right)^2 - \hat{\beta}_M^s & \hat{\delta}_{MW}^s + \hat{\beta}_M^s \cdot \hat{\delta}_W^s \\ \hat{\delta}_{KW}^s + \hat{\delta}_W^s \cdot \hat{\beta}_K^s & \hat{\delta}_{LW}^s + \hat{\delta}_W^s \cdot \hat{\beta}_L^s & \hat{\delta}_{MW}^s + \hat{\delta}_W^s \cdot \hat{\beta}_M^s & \hat{\delta}_{WW}^s + \left(\hat{\delta}_W^s\right)^2 - \hat{\delta}_W^s \end{bmatrix},$$

and the coefficients of the unobserved price p_w are estimated to

$$\begin{aligned}
\hat{\delta}_W^s &= 1 - \hat{\beta}_K^s - \hat{\beta}_K^s - \hat{\beta}_M^s \ , \\
\hat{\delta}_{KW}^s &= 0 - \hat{\beta}_{KK}^s - \hat{\beta}_{KL}^s - \hat{\beta}_{KM}^s \ , \\
\hat{\delta}_{LW}^s &= 0 - \hat{\beta}_{LL}^s - \hat{\beta}_{KL}^s - \hat{\beta}_{LM}^s \ , \\
\hat{\delta}_{MW}^s &= 0 - \hat{\beta}_{MM}^s - \hat{\beta}_{KM}^s - \hat{\beta}_{LM}^s \ , \\
\hat{\delta}_{WW}^s &= 0 - \hat{\delta}_{KW}^s - \hat{\delta}_{LW}^s - \hat{\delta}_{MW}^s \ .
\end{aligned}$$

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

$$\mathbf{q}^s = \begin{bmatrix} \hat{S}_K^s \\ \hat{S}_L^s \\ \hat{S}_M^s \\ \hat{S}_W^s \end{bmatrix},$$

where $\hat{S}_W^s = 1 - \hat{S}_K^s - \hat{S}_L^s - \hat{S}_M^s$ 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 II-24: *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 II-25: *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.

Development of TFPC and Subcomponents thereof over Time

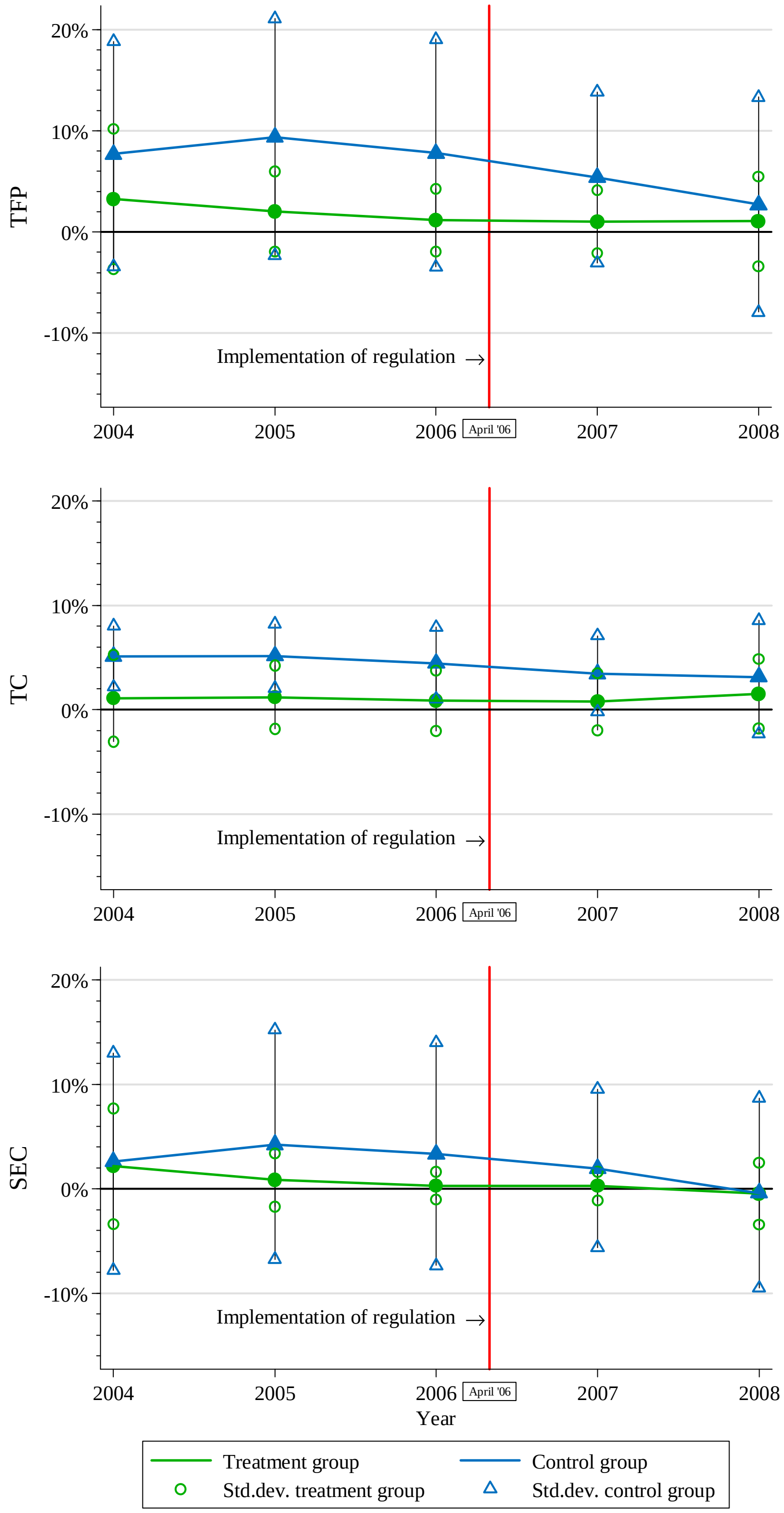

Figure II-6: *Development of TFPC, TC and SEC of treatment and control group.*

Note: Figure II-6 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 II-26: *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 section 8.2. 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 II-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 II-27: *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 section 8.2.

Table II-28: *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.

III Management as a Productive Input and the Role of Ownership[112]

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“Even a pig can fly if it stands at the center of a whirlwind.”

— Lei Jun

1 Introduction

The studying of management has a long-standing tradition in the scientific literature. Both, from an organizational theory (Barnard, 1938) as well as economic modelling perspective (Griliches, 1957). From the economic modelling perspective, the omission of management quality, which determines how efficiently and effectively the other production inputs are used, has been thought of as being the most common specification error when estimating a production function (Griliches, 1957; Mefford, 1986). Modern empirical literature combining both perspectives mainly builds on the cornerstone contribution of Bloom and Van Reenen (2007) and aims uncovering the role of management in a firm's production based on a detailed measurement of managerial quality.

The literature associates several positive outcomes with good management. For example, Mefford (1986), White, Pearson et al. (1999) or Bloom and Van Reenen (2007) find management quality to be positively related with higher productivity. Furthermore, management quality is found to be related to a reduction in product defect rates and inventory levels (Bloom, Eifert et al., 2013), improved environmental performance (Bloom, Genakos et al., 2010; Boyd and Curtis, 2014), and superior employee outcomes in terms of employment, earnings, and health (Levine and Toffel, 2010) as well as labor standard compliance (Distelhorst, Hainmueller et al., 2016). Management might be a factor contributing to the often observed large and persistent differences in productivity levels, not only between firms (Bartelsman and Doms, 2000; Bloom, Eifert et al., 2013; Syverson, 2011) comparable on many other observables like industry, technology, product or location (Gibbons, 2006), but also between countries (Bloom, Sadun et al., 2016). Given such wide variety of roles attributable to managerial quality, an understanding of how this quality determines firm performance carries relevance for development policy, institutional design and firms alike.

Reviews of the empirical literature on firm productivity (Bartelsman and Doms, 2000; Syverson, 2011) find differences in productivity not only to depend on internal factors under a firm's direct span of control like management, but also on the operating environment like firm ownership.[113] Already Jensen and Meckling (1976) describe that institutional conditions (for example, ownership structure) shape firm priorities and imply distinct agency relationships and incentives. Hence, these conditions may play an important role in explaining the origins, functions, and impacts of management practices. If the value of management, like other drivers of productivity, depends on context, there is unlikely to be one single set of productivity-enhancing practices that applies across firms, industries, geographies, and stages of development. The identification of optimal practices may not be straightforward, though, because not much is known on how these environmental characteristics interact with managerial ability (Bartelsman and Doms, 2000). Still, many firms engage professional consultants with the aim of upgrading their internal management capabilities and aligning them with growth objectives, conditional on characteristics of the firm and the operating environment. Hence, quantitative findings on such interactions are essential for projecting the effectiveness of performance-enhancing interventions.

In this paper, we probe the extent to which management quality matters in explaining firm performance for the unique institutional[114] setting of China, and thereby contribute to the literature in various ways. First, from an organizational theory point of view: previous literature mainly analyzed the relationship between managerial quality and performance of firms located in industrialized countries. This study, however, focuses on the emerging economy of China during a period of rapid industrial growth in the mid-2000s (2003 to 2008). This period falls towards the end of nearly 30 years of sustained economic expansion averaging in the double digits, and shortly follows China's entry into the World Trade Organization in 2001. Our setting offers a unique oppor-

[113] Bartelsman and Doms (2000) provide an extensive overview of firm level determinants of productivity. In addition to managerial ability, they list ownership, technology, human capital, international exposure or regulation as factors commonly found to be relevant. More recently, Syverson (2011) lists factors like managerial practice, technology, demand, market structure, competition, a firm’s organizational structure or human capital.

[114] Institutions can be seen as defining incentives and structuring political, social or economic human exchanges (North, 1990). Edquist and Johnson (1997) clarify the concept of an institution and give a qualitative overview of the role of institutions in processes and systems of innovation.

tunity to study the relationship between management practices and productivity in a rapidly expanding and transforming economy (Tsui, Schoonhoven et al., 2004). In such an environment, short-run tensions between improving management practices and establishing or maintaining competitive advantage via other means can be expected to be especially acute. Furthermore, the social and political environment of the Chinese economy is different to western economies, what might result in management quality mattering for other aspects than the ones commonly observed in the literature. One such aspect, for example, might be the structure of firm ownership. In China, the ownership structure represents sharp distinctions among operating conditions of firms by defining, e.g., a firm’s degree of access to capital via lending and other means, regulatory burdens, political pressure, resources, and other intangible sources of legitimacy. China's case is particularly interesting, because its economy encompasses a wide range of ownership forms that have proliferated since the country has begun to transition away from near-complete state ownership in the late 1970s. We test for first empirical evidence of the institutional element of ownership mediating the relationship between observed management practices and firm performance.

Our second contribution is from an economic modelling perspective: modern empirical literature exclusively applies Cobb-Douglas production function specifications and abstracts from the question of separability of management from other productive inputs. Furthermore, apart from two recently published working papers by Bloom, Sadun et al. (2016) and Bloom, Brynjolfsson et al. (2016), it does not make use of the data’s panel structure to control for time-constant firm-specific unobserved heterogeneity. Given large potential heterogeneities in production processes and environmental characteristics between firms and industries, such omission might raise the question of the robustness of results. Especially, as the literature commonly assumes a single production function for all firms. Following Mefford (1986), we implement several functional forms and, in addition, apply panel models controlling for time-constant firm-specific unobserved heterogeneity. Results of this study provide new insights into the question of the extent, to which modern western definitions of management quality matter in explaining the performance of Chinese firms.

This study uses firm level data of the annual Chinese Industrial Census (CIC) for the period of 2003 to 2008 and observations on managerial quality in Chinese firms contained in the World Management Survey. Two of our main findings are in sharp contrast to the current literature—summarized, for instance, in Bloom, Genakos et al. (2012)—even though this literature is not specifically focusing on China. First, the role of management practice as productive input parameter by itself is found to be uncorrelated with the variation in output of the firms. Second, state-owned enterprises (SOEs) in China on average are better managed than non-SOEs. In form of a third main finding, we provide first empirical evidence that the role management in Chinese firms could be mediated by political economy elements, i.e. by the institutional element of firm ownership with its associated role of the government. There is indication that SOEs, i.e. state-controlled firms with oversight at the central or provincial level, benefit most and in significant manner from the adoption of modern western management practices. We discuss potential underlying factors of these findings.

The structure of this study is as follows: Chapter 2 summarizes the relevant empirical literature on management as a productive input and on the implications of ownership for Chinese firms. Chapter 3 describes the data. Chapter 4 sets out the hypotheses and estimation methodologies. Results are given in chapter 5 and tested for robustness in chapter 6. Finally, chapter 7 concludes and discusses the findings.

2 Literature Review

2.1 Management as Productive Input

The role of managerial ability as a production factor has been subject to scientific research as early as the contribution of Walker (1887). He asks on p. 274 ff. where it comes from some employers are making profits, while others do not, and answers that this surplus

> *"[…] comes from directing force to its proper object by the simplest and shortest ways; from saving all unnecessary waste of materials and machinery; from boldly incurring the expense […] of improved processes and appliances, while closely scrutinizing outgo and practising a thousand petty economies in unessential matters; from meeting the demands of the market most aptly and instantly; and, lastly, from exercising a sound judgment as to the time of sale and the terms of payment."*

Hence, management is not simply another kind of labor input. It rather might be a further differentiator between firms making profits and prospering, and firms that merely can survive. Modern literature has focused in greater detail on the practice of management and specific channels through which management affects firm outcome, both in a quantitative as well as qualitative manner. Mintzberg (2004), for example, gives an in depth qualitative study of the structure of management practices. He describes management practices as being fundamentally "soft" and ambiguous and greatly related to traits like experience, intuition and judgement. The practice of management can be further understood as actions broadly aimed at setting in place routines, processes, and incentives that cause members of an organization to advance a set of objectives. Gibbons and Henderson (2012) note that management practices generally cannot be reduced to a set of well-defined action rules, but that they can be described as elements defining how a firm prioritizes and executes on its objectives.

When moving focus to empirical literature quantitatively testing the economic role of management quality in a production function, Griliches (1957) can be noted to have been first in studying this role in depth. Subsequently, in light of a potentially large impact on firm performance, the role of modern management in organizations has been the focus of a growing body of scholarship (Gibbons and Henderson, 2012). However, empirical literature in this field still is surprisingly scarce, even more so, when conditioning such an analysis on firm and environmental characteristics. Related literature roughly can be divided into two main strands, which differ by the degree management quality is observed. Table III-1 and Table III-2 give examples of cornerstone literature for both strands.

Table III-1: *Literature controlling for unobserved management quality in a production function.*

Management quality unobserved	Functional form	Main inputs	# firms / # obs. / # years	Countries	Method
Management measured via residual factors					
• Alvarez and Arias (2003) [A]	Translog average cost function assuming management to be non-separable	*Y*, *G*, *T*	84 / 420 / 5 (1987 – 1991)	Spain	2SLS
• Alvarez, Arias et al. (2004) [B]	Translog production frontier assuming management to be non-separable	*L*, *G*, *T*, *X*	247 / 1,482 / 6 (1993 – 1998)	Spain	MSL
Management quality measured via proxy variable					
• Mundlak (1961) [C]	Cobb-Douglas production function	*L*, *G*, *T*, *X*	66 / 330 / 5 (1954 – 1958)	Israel	OLS
• Dawson and Hubbard (1987) [D]	Translog production function assuming management to be non-separable	*K*, *L*, *G*, *X*	405 / 810 / 2 (1980 – 1981)	England/Wales	OLS/2SAE

Note: *K* represent capital, *L* labor, *M* material, *T* time, *X* other inputs and *G* is unobserved or proxied management quality. The dependent variables mentioned below refer to the benchmark model. Some studies estimate the effect of management on other firm outcomes like total factor productivity as well. Additional control variables mentioned below might not be included all at the same time in a regression. The number of firms, observations and years might differ by model specification; numbers listed in the table only give an indication of the approximate extent of the analysed sample.

[A, B, C, D]: Empirical applications focus on farms. [A, B, D]: Output is litres of milk. [C]: Output is the value of produced goods. [A]: 2SLS stands for two stage least squares instrumental variable approach. [B]: Inputs *X* are number of cows, land and feedstuffs in kilogram. MSL stands for maximum simulated likelihood. [C]: Inputs *X* are variable expenses, livestock value and amount of land irrigated. [D]: Inputs *X* are feed costs and rent. 2SAE stands for two-stage Aitken estimator.

Table III-2: *Literature controlling for observed management quality in a production function.*

Management quality observed	Functional form	Main inputs	# firms / # obs. / # years	Countries	Method
• Mefford (1986) [A]	Cobb-Douglas / CES / translog production function assuming separability of management	*K, L, G, T, X*	? / 127 / 8 (1975 – 1982)	?	OLS
• Bloom and Van Reenen (2007) [B]	Cobb-Douglas production function	*K, L, M, G, X*	709 / 5,350 / 4 (1994 – 2004)	USA, UK, FR, GER	OLS
• Bloom, Genakos et al. (2010) [C]	Cobb-Douglas production function	*K, L, M, E, G, X*	272 / 1,046 / 6 (1999 – 2004)	UK	OLS
• Bloom, Schweiger et al. (2012) [D]	Cobb-Douglas production function	*K, L, M, G, X*	717 / 974 / 1 (2009 or 2010)	10 in Central Asia	OLS
• Bloom, Sadun et al. (2016) [E]	Cobb-Douglas production function	*K, L, M, G, X*	11,383 / 12,146 / 11 (2004 – 2014)	34 on all continents	OLS/FE
• Bloom, Brynjolfsson et al. (2016) [F]	Cobb-Douglas production function	*K, L, G, X*	31,793 / 31,793 / 1 (2010)	USA	OLS/FE

Note: The question mark (?) stands for unspecified information. *K* represent capital, *L* labor, *M* material, *E* energy, *T* time, *X* other inputs and *G* is observed management quality. The dependent variables mentioned below refer to the benchmark model. Some studies estimate the effect of management on other firm outcomes like total factor productivity as well. Additional control variables mentioned below might not be included all at the same time in a regression. The number of firms, observations and years might differ by model specification; numbers listed in the table only give an indication of the approximate extent of the analysed sample.

[A]: The dependent variable is output, measured by an engineering-based and quality adjusted unit measure (with process-specific standard labor hours) to produce a certain amount of a product. This measure then is summed up over all production processes and multiplied with the units of products produced. Management quality is observed yearly. Additional control variables *X* are region fixed effects, firm size (by number of workers), technology level (by judgement) and workforce skill (by financial ratio). Firms are located in USA, Australia, Europe, Asia, Latin America and Canada.

[B]: The dependent variable is output, measured by value of sales (gross output). Additional control variables *X* are workforce and firm characteristics and WMS interview noise controls. Workforce characteristics include the workforce with a degree and the share of workforce with an MBA degree. Firm characteristics are three-digit industry and country fixed effects, average hours worked, firm age, a being listed fixed effect and a consolidated account fixed effect. Noise controls are 24 covariates connected to the interview of the firm managers.

[C]: The dependent variable is output, measured by revenues (gross output). Additional control variables *X* are workforce and firm characteristics and WMS interview noise controls. Workforce characteristics include the proportion of workers with a degree and average hours worked. Firm characteristics include three-digit industry and year and region fixed effects, firm age and a being listed fixed effect.

[D]: The dependent variable is output, measured by revenues. Additional control variables *X* are workforce and firm characteristics and WMS interview noise controls. Workforce characteristics include workers with a university degree and average weekly hours worked. Firm characteristics include firm age and whether a firm is listed on the stock market, two-digit industry, country and country-year fixed effects. 10 Central Asian countries are focused upon: Belarus, Bulgaria, Kazakhstan, Lithuania, Poland, Romania, Russia, Serbia, Ukraine and Uzbekistan. Noise controls are 9 covariates connected to the interview of the firm managers.

[E]: The dependent variable is output, measured by revenues. Additional control variables *X* are workforce and firm characteristics and WMS interview noise controls. Workforce characteristics include workers with a college degree. Firm characteristics include country and three-digit industry fixed effects. Firms are located in North and South America, Europe, Africa, Asia and Australia. FE stands for fixed effects estimation. Authors provide no information on the number of included firms and timewise length of the panel underlying the FE estimation.

[F]: The dependent variable is labor productivity, measured by value added divided by the number of employees. Additional control variables *X* are workforce and firm characteristics and MOPS interview noise controls. Workforce characteristics include the share of employees with a college degree. Firm characteristics include industry fixed effects, capital intensity, and establishment size. FE stands for fixed effects estimation.

Table III-1 summarizes the first strand of empirical literature. This strand does not observe management quality directly. Instead of simply assuming managerial quality to be omitted from the production function, it attempts to quantify the role of management via residual factors or proxy variables based on firm characteristics. A first example is Mundlak (1961), who includes firm-specific mean values of the input variables, so called Mundlak factors, into the production function. These Mundlak factors are meant to capture time-constant unobserved firm-specific heterogeneity potentially correlated with input variables. Mundlak (1961) attributes such time-constant heterogeneity to unobserved managerial ability.[115] By separating this heterogeneity from the error term, Mundlak factors are meant to reduce the bias due to unobserved management. Indeed, the underlying assumption of the role management being time invariant might seem overly restrictive. However, it is also clear that identification of time varying and firm-specific unobserved managerial ability would be more than heroic. Instead of using management fixed effects, Alvarez and Arias (2003) identify unobserved, firm-specific managerial quality via a technical efficiency term estimated by a deterministic production frontier. They apply the model of Schmidt and Sickles (1984), hence their management proxy is time-constant as well. In a second step, they include this management proxy into an average cost function. Alvarez, Arias et al. (2004) model managerial quality via a random effect correlated with observed inputs using a random coefficient stochastic frontier framework. These approaches to quantify unobserved management seem to be problematic in that estimates might be compromised by other unobserved heterogeneity, which is still part of the residual (Mefford, 1986).

The second strand of literature presented in Table III-2 includes an explicit measure of management quality into the production function. A first important contribution to this literature was made by Mefford (1986). He estimates production functions of three types of functional forms, namely the Cobb-Douglas, constant elasticity of substitution (CES) and translog functional form. These functional forms differ in their assumptions in terms of the elasticity of substitution between inputs and homotheticity,

[115] In his discussion of fixed and random effects estimators, Mundlak (1978) applies this approach to form consistent random effects estimates.

with the translog functional form being most flexible.[116] Mefford (1986) finds the inclusion of management quality to be desirable for all three functional forms, since it contributes to output in a statistically significant way. Interestingly, he does not control for material inputs. He justifies such exclusion by concerns about a potential simultaneity between output and material use and further argues management having no control over the selection and purchasing of material. However, Bloom, Genakos et al. (2010) find the ratio of material expenditure over gross output to be statistically significantly affected by management practices for a sample of UK firms. From a theoretical modelling perspective, Mefford (1986) argues material to be highly correlated with output, aggravating the well-known simultaneity bias when estimating a production function.

A growing body of more recent empirical literature directly observing managerial quality on firm level builds on the World Management Survey (WMS)[117], which was initiated by Bloom and Van Reenen (2007). These studies by and large affirm that observed levels of management matter in explaining firm performance. Bloom and Van Reenen (2007) find a positive, stable, and statistically significant link between management practice measures and firm output. Thereafter, the WMS has been continuously expanded over the years, with several studies building on it. Bloom, Schweiger et al. (2012) find management practices to be strongly linked to output for a sample of firms in ten Central Asian transition countries. Bloom, Genakos et al. (2010) find better managed manufacturing firms in the UK to be significantly less energy intensive. They also observe management quality to significantly and positively affect firm level output, to an extent similar in magnitude to findings in Bloom and Van Reenen (2007). Bloom,

[116] The translog functional form is the most flexible functional form of these three, because it does not constrain the elasticity of substitution between inputs to be constant. The Cobb-Douglas functional form even restricts this elasticity to be equal to unity, and therefore it is the most restrictive functional form of the three. In addition, the CES and Cobb-Douglas functional forms are assuming homotheticity, while the translog specification in its fully flexible form allows for non-homotheticity (Mefford, 1986).

[117] The WMS uses survey methods to elicit managerial quality on firm level. It constitutes one of the broadest (in terms of firm and country coverage) and in depth (in terms of management categories) surveys in this regard. Based on extended telephone interviews of managers in various developed and, in later waves, emerging countries, the WMS defines and empirically measures a set of management practices in firms and provides novel insights into how companies are managed across firms and countries.

Eifert et al. (2013) conduct a randomized control trial implementing management interventions within 17 Indian textile firms. They observe a strong, positive effect on firm output and other key performance indicators, thereby strengthening arguments of causality between management quality and firm performance. Bloom, Eifert et al. (2013) and Bloom, Lemos et al. (2014) find emerging countries, including China, to have a long left tail of poorly managed firms. Furthermore, Bloom, Lemos et al. (2014) observe government and founder-owned firms to be poorly managed, while stronger product market competition and higher worker skills correlate with better management practices.

At the time we have been writing this paper, two relevant working papers were published by Bloom, Sadun et al. (2016) and Bloom, Brynjolfsson et al. (2016). Bloom, Sadun et al. (2016) analyze the productive role of management for 11,383 firms in 34 countries on all five continents. They affirm management quality to be significantly linked with variation in output across all model specifications. Furthermore, they find management to account for roughly 30 percent of cross-country differences in total factor productivity relative to the US. The availability of several waves of interviews allows them—for the first time—to include a full set of firm fixed effects into the model. Moreover, they differentiate between "management as a technology" (MAT) and "management as a design" (MAD). Their notion of MAT builds on the assumption that, similar to technical progress, some types of management always are better than others in terms of increasing firm performance, independently of firm and environmental characteristics. In other words, MAT implies firm performance being strictly increasing in the quality of management. The alternative view of MAD assumes, instead, that the optimality of management practices is conditional on the environment and other firm characteristics: while a certain management practice might increase output of one firm, it might decrease output of another. They build an (as called by the authors) extremely stylized structural model of the MAT and MAD concept and find simulation results rather being supporting the notion of MAT, while only delivering partial evidence for the MAD view.

In their working paper, Bloom, Brynjolfsson et al. (2016) analyze the productive role of management for a sample of 30,000 US plants belonging to 10,000 firms. For the first time, management quality measures of the newly established US census on management practices conducted in 2010 (Management and Organizational Practices Survey, MOPS) are used for empirical estimations. The MOPS is conducted at the plant level, rather than the firm level like the WMS.[118] This allows for a first analysis of within firm differences of observed management practices, instead of exclusively focusing on between firm differences. They find that the variation of management practices within firms accounts for nearly half of the overall variation and thus is similar in extent to the variation across firms. Moreover, variation is increasing in firm size. In line with the main body of empirical literature, management quality significantly links to firm performance, which is measured by labor productivity in the benchmark specification. The authors acknowledge the issue of time-constant unobserved heterogeneity being potentially correlated with the management measurement. The availability of two management quality observations for some firms allows them to control for such heterogeneity by estimating a fixed effects model using a two period panel (year 2005 and 2010). The effect of management on labor productivity remains highly significant. For the first time, management quality within the same firm (by comparing across establishments within the same firm) is analyzed and observed to be significantly related to labor productivity.

From the econometric point of view, there are three main issues to consider when eliciting the role of managerial quality in firm production via the estimation of a production function: first, the choice of the functional form. Second, the assumption of separability of management from the other input choices. And finally, the consideration of unobserved heterogeneity.

Most empirical literature on the role of observed management quality in production applies Cobb-Douglas production functions and therefore, usually without explicit-

[118] The MOPS is similarly structured as the WMS and asks 16 questions related to management quality and differentiates between the three key practices of Monitoring, Targets and Incentives (Bloom, Brynjolfsson et al., 2016). However, in contrast to the WMS, the MOPS is a government survey, is conducted via mail or online (instead of telephone interviews) and firms are obliged to respond (instead of responding on a voluntary basis). Moreover, the WMS uses open-ended questions, while the MOPS is based on closed-ended questions (Bloom, Lemos et al., 2016).

ly stating, assumes a Hicks-neutral technical change and homotheticity, i.e. separability between managerial quality and other input factors like labor or capital.[119] Mefford (1986) and Dawson and Hubbard (1987) seem to be the only two studies allowing for non-separability between management and other input choices in their model specifications, even though they are not explicitly focusing on, or referring to, the concept of separability. Mefford (1986) notes in footnote 13 of his paper that he estimated a translog and CES production function with management entering as non-separable input. However, due to severe multicollinearity between these additional variables and the productive inputs of labor and capital, estimates were unreasonable and these additional variables were dropped from the equation. Dawson and Hubbard (1987) allow for non-separability between their management variable and other input choices in their model specification, even though they are not directly observing managerial quality but include a proxy of it based on a financial ratio. Non-separability is statistically not supported, as their results indicate a statistically insignificant interaction of management with other input choices. They mention as well the problem of multicollinearity between their explanatory variables, and hence faced similar issues as Mefford (1986) did.

To this point, empirical literature on the role of observed management quality in a production function—with the exception of the two very recent[120] working papers of Bloom, Sadun et al. (2016) and Bloom, Brynjolfsson et al. (2016)—has not made use of the data's panel structure to control for firm-specific time-constant unobserved heterogeneity. Management quality is difficult to measure (and therefore prone to measurement error)[121], since it is, as widely acknowledged, culture- and context-specific (Adler,

[119] The concept of a production function with a focus on separability is explained in appendix A.1.

[120] In fact, these papers were published while we were writing this study.

[121] Bloom and Van Reenen (2007) find, by conducting independent repeated interviews, that 25 percent of the variation in the overall management score is due to measurement error. They also note the WMS measure of management practice to only capture a subset of all practices relevant with respect to firm performance, i.e. to only provide a proxy of true management quality. Based on the MOPS (i.e. not the WMS), Bloom, Brynjolfsson et al. (2016) find measurement error to cause ca. 45 percent of the variation in management scores and thereby confirm the inherent difficulty of measuring management quality with reasonable effort. Moreover, as described in section 3.2, the implications and connotations of the language used in the WMS largely reflect western experience and may be interpreted differently in

(*Footnote continues on next page*)

1983; Hofstede, 1993). It also has been described as being rather persistent over time when using short panels (Bloom, Schweiger et al., 2012). Hence, the case of management capturing effects of time-constant unobserved heterogeneity cannot be excluded. However, panel models allow controlling for such heterogeneity.

In the study at hand, the empirical focus is on the choice of the functional form and the consideration of unobserved heterogeneity, while, for reasons explained later on, we leave the question of separability to a qualitative discussion.

When shifting the focus to China, to our knowledge, there are no econometric studies examining the relationship between directly observed managerial quality and the performance of firms. We explain this void in the literature to some extent stemming from the paucity, suspected unreliability, and difficulty of obtaining Chinese firm data. However, there is qualitative research adding richness to the understanding of what “management” means in the Chinese context. To be certain, China had well established patterns of doing business and organizing production long before the arrival of western practices in the wake of economic reforms. In applying western definitions of management to China, modern management scholarship has been accused of “inappropriate universalism” (Boyacigiller and Adler, 1991). While business education in China has rapidly expanded since the start of the country's economic opening and reform program (Tsui, Schoonhoven et al., 2004) and the number of business schools on the mainland has grown dramatically, western management practices have met with both interest and scepticism by Chinese academics, corporate leaders, and policy makers alike (Fan, 1998). Writing in the late 1980s, Lockett (1988) describes organizational structure, management skills and succession, party/management relations, operational, and motivation/labor discipline as the key challenges in managing a Chinese firm. He further identified features of Chinese culture like respect for age and hierarchy, group organization, face, and the importance of relationships as interacting with management practices in both positive and negative ways.

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the Chinese context. This might add another component to the measurement problem for the case of Chinese firms.

Two central elements when evaluating Chinese management practices are rapid and uneven market growth and firm ownership. Regarding the former, Meyer (2014) provides evidence, by using the large white-goods manufacturer Haier as a case example, that due to the rapid pace of market change and associated uncertainty, management practices may be altered or overhauled with no expectation that they will diffuse completely within the organization. Regarding the latter, Chinese firms have been characterized as having “indefinite boundaries” due to incomplete separation of firms from the state, a lack of complete post-merger integration, and partial listing of assets (Meyer and Lu, 2005). Chinese firms are frequently politically embedded, with ex-officials serving as industry leaders after leaving office (Haveman, Jia et al., 2016). In what follows, we focus in greater detail on the potentially influential factor of ownership when explaining the role of management in Chinese firms.

2.2 Management and Firm Ownership in China

China’s economy still is characterized by a relatively high share of SOEs compared to market-oriented economies of developed nations, even though in China the extent of state ownership also depends on its definition (Meyer and Wu, 2014). Nevertheless, compared to former communist times with exclusively SOEs, today’s economy is home to a wide variety of firm ownership types. Non-SOE ownership types have proliferated in the wake of China's economic SOE reform, modernization and opening program that began in the late 1970s. This program has constituted an experiment in building national champions[122] that was well advanced[123] by the first decade of the 2000s, i.e. the period

[122] A typical characteristic of the Chinese economy, rooting from its institutional past, is the dominance of large state-controlled incumbents in many sectors. These incumbents were called upon by the state to facilitate an adoption of frontier technologies in order to catch up with Western countries (Wang, 2014), similar to what was observed in other relatively underdeveloped economies in the past, as exemplified, e.g., by Gerschenkron (1962). These national champion SOEs often can be found in capital intensive, upstream sectors, and strategic sectors (Nolan and Xiaoqiang, 1999; Wang, 2014).

[123] An in depth description of the reformation process is given in, e.g., Jefferson and Rawski (1994), Nolan and Xiaoqiang (1999), Sachs and Woo (2001), Garnaut, Song et al. (2006) or Wang (2014). Before the reform period starting in 1978, Chinese state firms were operating according to predefined plans of the government, granting them only very limited autonomy but simultaneously soft budget

(*Footnote continues on next page*)

of this study. Partial privatization while retaining control rights was a strategy designed to increase the operating efficiency of SOEs by exposing them to greater competition (Meyer and Wu, 2014). Many of today's SOEs are rather successful and prosperous, which—in terms of growth or profitability—holds especially for central SOEs (Wang, 2014).

The mediating effects of ownership on the productive role of observed management quality in a firm's production, as already mentioned, can be hypothesized to be especially relevant for Chinese firms. However, we are not aware of any empirical study shedding light onto such effects. Hence, in what follows, four related strands of literature are presented. These strands partially contribute to the understanding of the linkage of observed management quality and firm ownership with firm performance.

There is a large body of literature on the theory of the firm that focuses on the implications of state and private ownership on managerial activity. Shleifer and Vishny (1994, 1997) and Shleifer (1998) not only contribute to, but also give an extensive overview of this literature. Central elements therein are agency costs, market failures, incentives to innovate, the provision of public goods and the achievement of social goals. The literature misses a clear consensus on the conditions, under which the benefits of private ownership surpass the benefits of state ownership and vice versa. Central elements of this discussion are agency conflicts and contracting theory that regulates the relationship between principals and agents. Important contributions in this regard were made by, e.g., Jensen and Meckling (1976). Related literature, for example Shleifer and Vishny (1997), studies the ties between the degree of ownership concentration and the enforceability of corporate governance.

A second strand of literature focuses on the interrelation of ownership and economic firm performance measures like productivity and profitability. This literature generally finds SOEs to show lower performances than non-SOEs. Ehrlich, Gallais-

constraints. Important reform steps were undertaken in 1983 (contract responsibility system), 1995 (policy of "Grasping the Large, Letting Go the Small (*zhua da*, *fang xiao*)" (Sachs and Woo, 2001). Between 1999 and 2001, low performers were again privatized or sold, while large, more productive SOEs were retained (Hsieh and Song, 2015).

Hamonno et al. (1994), for example, provide a theoretical model of this relationship. Empirical literature with a special focus on China[124] are, for instance Bai, Lu et al. (2009), Jefferson and Su (2006), Dong, Putterman et al. (2006) or Brandt, Van Biesebroeck et al. (2012). They all find that the conversion of SOEs to non-SOEs positively affected firm performance measures like TFP, labor productivity or profitability. Dougherty, Herd et al. (2007), Hsieh and Klenow (2009) or Brandt, Van Biesebroeck et al. (2012) find productivity advantages (both in terms of levels and changes) of non-SOEs relative to SOEs. Li, Sun et al. (2006) find a strong positive relationship between market orientation and measures of organizational performance in a survey of 274 SOEs. They also found that this relationship was mediated by institutional antecedents that relate to ownership.

Being an SOE might have direct implications on managerial quality by, for example, sheltering less successful firms and managers from competition. This would result in fewer badly managed firms to be driven out of market and in a worse match of managers with economic activities (Acemoglu, Aghion et al., 2002). A third strand of literature analyses the correlation between firm ownership and management quality, however, without linking these two elements to firm performance. On an aggregated basis of more than 10,000 interviewed firms in 20 countries, Bloom, Genakos et al. (2012) find ownership to be a factor that on average is highly related with management practices. Furthermore, they find publicly owned firms to show consistently lower management scores, even if country, industry and firm size (number of employees) are controlled for. Also Bloom, Schweiger et al. (2012), based on a sample of 1,874 firms in 10 Central Asian transition countries, find that multinational firms and firms under private ownership on average are better managed. Inter alia, they conclude that the privatization of SOEs in central Asian countries would foster better management.

[124] The effects of privatization or ownership changes on firm productivity for other countries than China are studied, e.g., by Harris and Robinson (2002) (Hungry, Romania, Russia, and Ukraine) or Brown, Earle et al. (2006) (UK). An overview and discussion of studies on the effects of privatization on firm performance in post-communist transition countries, including China, is given by Estrin, Hanousek et al. (2009).

A fourth strand of literature gives qualitative insights into the implications of state ownership for the case of China, which might directly translate into differences in the role of management. Despite the opening and privatization of its economy, China's SOEs have continued to be a primary channel through which the state balances economic stability against efficiency objectives (Bai, Lu et al., 2006; Wang, 2014). SOEs are often required to absorb excess workers and perform social planning and welfare functions (Bai, Lu et al., 2006). In addition, they increasingly possess a profit motive in the wake of economic reforms aimed at efficiency gains (Kang, Shi et al., 2008). The state is in essence responsible for both control and regulation of SOEs, with no separation among functions typical of western systems (Pargendler, 2012). The rotation of government officials in and out of SOE leadership positions helps to maintain this close connection (Haveman, Jia et al., 2016; Wang, 2014). CEOs act both as managers and government officials (Li and Xia, 2008), and are evaluated based on both performance as well as party loyalty criteria (Wang, 2012). The ability of the party to appoint the CEO of SOEs leads to performance incentives and reporting lines distinct from private firms (Wang, 2014). SOEs hold rank according to their level of oversight within China's federalized system of government, which in order of decreasing jurisdictional size includes central (national), provincial, city, county, township, and village levels.

3 Data

3.1 Chinese Industrial Census

Our empirical analysis of the role of management quality in explaining the performance of Chinese firms uses several types of data: firm level Chinese Industrial Census (CIC) data[125], firm-level data on management quality (WMS, 2015) and data on deflators (Brandt, Van Biesebroeck et al., 2012). For graphing purposes, spatial information on

[125] The CIC is a proprietary data set compiled by the Chinese National Bureau of Statistics.

the centroid longitude and latitude of geographic clusters (counties) (BW, 2016) is used. Accordingly, four main steps are implemented to combine these data.[126] The first step links the firms of the cross-section census data over time. The second step links the deflators to the relevant input and output data. The third step links the firms covered by the WMS to the census data and the fourth step links the geographic information. Step one and two are illustrated in appendix A.1 of part II. Step three and four are focused upon in greater detail in appendix A.2. The main data used for the analysis is the CIC, which is described in greater detail in section 4.1 of part II.

Descriptive statistics of key variables for the 386 firms of our sample are given in Table III-3. Firms range widely in age, with the sample including firms less than one year old and one firm having existed for 96 years. While mostly in the double digits, the median annual growth rate is varying considerably between the different industries. When excluding the electricity production industry, which is defined by a single firm only, it ranges from 3.8 percent (electric equipment) to 30.8 percent (metal smelting and rolling). The distribution of firms across industries conditional on governmental control is given in Table III-3. We define a firm as an SOE if it has a controlling shareholder linked to the state.[127] On a two-digit level, the sample contains 15 industries, with, for instance, the chemical and pharmaceutical materials industry making up for 20.3 percent of SOE and 14.8 percent of non-SOE observations. The least number of observations are made in the fuel processing and lumber, wood and furniture industry. According to Figure III-1, most firms are located along the eastern coastline, consistent with the general distribution of economic activity in China.

[126] Data processing was conducted using Stata 13 (StataCorp, 2013).

[127] Such definition of state control was used in part II (cf. footnote 56) as well.

Table III-3: *Descriptive statistics of firms.*

	Mean	Std.dev.	Min.	Max.	10% perc.	90% perc.
Gross output (mRMB)	533.8	1,467.7	4.4	18,631.9	27.2	1,104.3
Employees	884.6	1,007.3	18	16,458	238	1891
Total assets (mRMB)	487.4	2,236.9	1.1	43,742.5	20.5	916.7
Current assets (mRMB)	237.7	1,197.5	0.0	27,796.5	0.1	459.9
Intermediate inputs (mRMB)	361.1	926.2	1.5	12,718.6	18.4	780.4
Management score	2.652	0.449	1.278	3.889	2.056	3.222
Age	13.224	13.846	0	96	3	34
Exporter (1 if exporting)	0.529	0.499	0	1	0	1
Profitability	0.037	0.099	–1.053	0.611	–0.017	0.126

Share of ownership types:
The share of non-SOE observations is 79.0%. Furthermore, 3.7% of the observations are classified as central SOEs and 17.4% as local SOEs.

Distribution of firm size (number of employees):
[0;250]: 11.1% of observations. (250;500]: 32.4% of observations. (500;1,000]: 32.5% of observations. More than 1,000: 24.0% of observations.

Note: This table presents descriptive statistics of the sample. Statistics are based on 386 firms and all years of observations (2,219 observations). Monetary values given in real 1998 values. RMB indicates Chinese renminbi. Statistics on the management score are based on the year a firm was surveyed. *Profitability* is the ratio of total profits to gross output.

Table III-4: *Distribution of industries conditional on state control.*

		SOEs		Non-SOEs		Percentage	Output
		# obs.	Share	# obs.	Share	point diff.	growth
(1)	Chemical and pharmaceutical materials	92	19.7 %	255	14.6 %	5.2	9.9 %
(2)	Communications and instrument equipm.	47	10.1 %	210	12.0 %	–1.9	14.6 %
(3)	Electric equipment	40	8.6 %	110	6.3 %	2.3	3.8 %
(4)	Electricity production	6	1.3 %	—	—	—	–6.6 %
(5)	Fabricated metal products	21	4.5 %	55	3.1 %	1.4	18.9 %
(6)	Food, beverage and tabacco	28	6.0 %	122	7.0 %	–1.0	10.8 %
(7)	Fuel processing	4	0.9 %	18	1.0 %	–0.2	28.0 %
(8)	General and special equipment	81	17.3 %	140	8.0 %	9.4	14.0 %
(9)	Lumber, wood and furniture	3	0.6 %	19	1.1 %	–0.4	17.0 %
(10)	Metal smelting and rolling	5	1.1 %	69	3.9 %	–2.9	30.8 %
(11)	Non metallic mineral products	52	11.1 %	109	6.2 %	4.9	8.0 %
(12)	Other manufacturing and goods	2	0.4 %	81	4.6 %	–4.2	14.0 %
(13)	Paper and printing	18	3.9 %	59	3.4 %	0.5	6.3 %
(14)	Textiles and other	34	7.3 %	399	22.8 %	–15.5	6.6 %
(15)	Transport equipment	34	7.3 %	106	6.1 %	1.2	19.4 %

Note: This table presents the distributions of observations across industries at the two-digit level conditional on state control in terms of absolute numbers and percentages. Statistics are based on 386 firms and all years of observations (2,219 observations). *% point diff.* depicts the percentage point difference in the SOE and non-SOE percentage share. *Output growth* is the median annual growth rate in output of the firms of an industry.

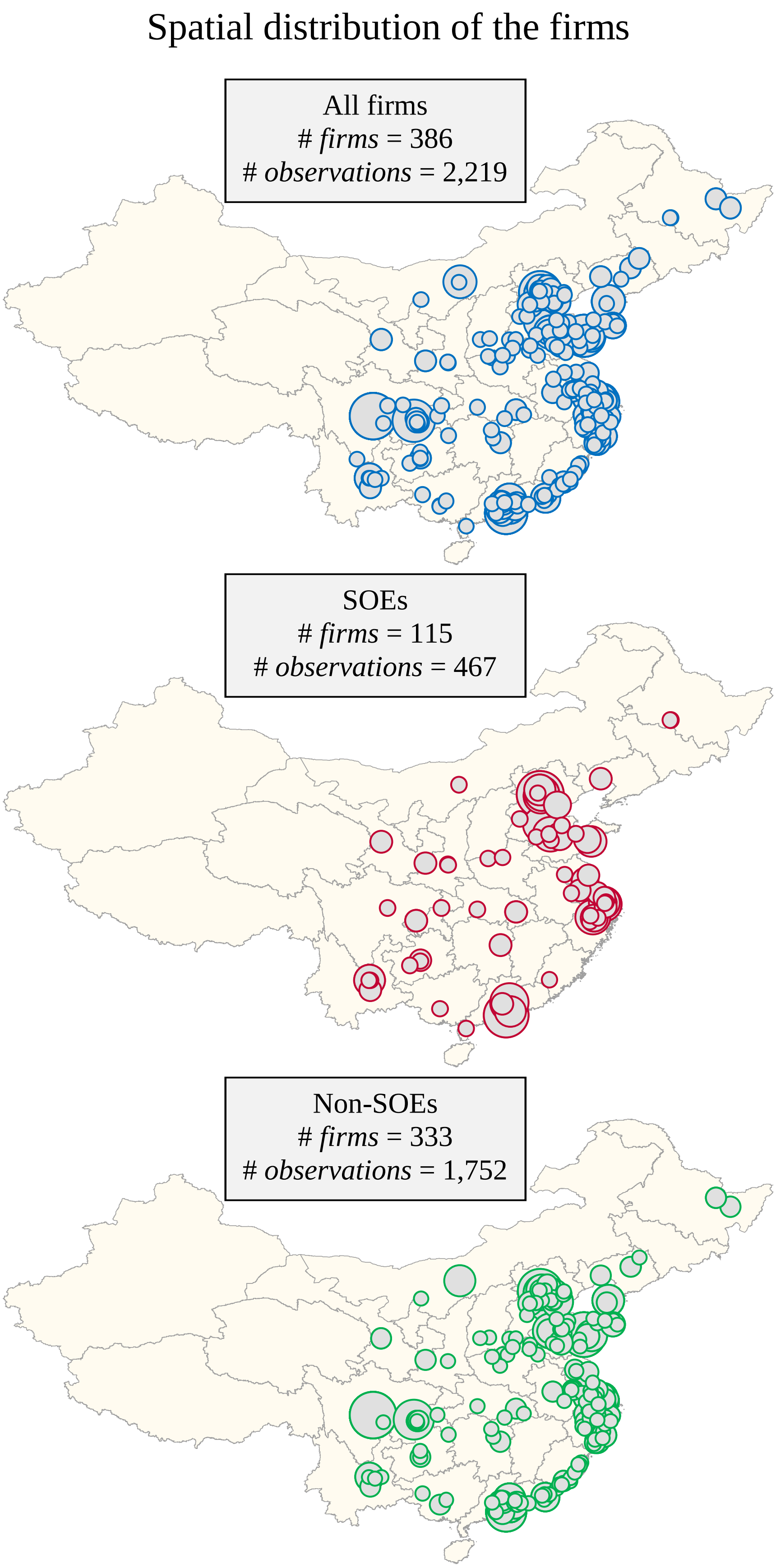

Figure III-1: *Spatial distribution of the firms, overall and by ownership.*

Note: Figure III-1 presents the spatial distribution of the firms in the sample. Firms might change ownership over time. For this reason, the number of SOEs and non-SOEs does not sum up to the total number of firms. Marker size is relative to number of firms observed in a county.

3.2 World Management Survey

The World Management Survey (WMS) data, first used in Bloom and Van Reenen (2007), was obtained with kind permission from Nicholas Bloom of Stanford University. The WMS is the most recent and comprehensive effort to document management practices across firms and countries (Bloom, Genakos et al., 2012). It captures the extent to which Chinese firms have adopted a set of management practices that were defined in consultation with a leading global management consultancy (Bloom and Van Reenen, 2007). The WMS differentiates between four management categories, which again can be differentiated into a total of 18 key practices. These 18 practices are combined into the four practice areas of Incentives (five practices), Monitoring (five practices), Operations (three practices) and Targets (five practices). Using as an example the Target category, managers were asked about the breadth of targets, their interconnection, stringency, and time horizon (Bloom and Van Reenen, 2007).

It is to note, though, that the implications and connotations of the language used in the WMS largely reflect western experience and may be interpreted differently in the Chinese context. For example, the Chinese word for management (*guanli*) carries the connotation of top-down control, either from the political hierarchy to the firm or from the firm to its employees. Targets, an important focus of the WMS, were historically used to mandate production quantities in the planned economy (and to some extent still provide guidance in some sectors).

The questions asked in the interviews were open-ended and focused on a firm's internal processes. Interviewers trained in WMS background and procedures assigned scores. The interviewer scoring (as opposed to self-scoring) methodology employed by the WMS helps to ensure a consistent measure of practices across firms. It was not declared to the managers that they were being evaluated when interviewed, with the aim of reducing subjectivity (Bloom and Van Reenen, 2007).[128] Interviewed managers were chosen to be senior enough to know the firm's management practices, while not being too senior to be detached from daily operation practices (Bloom, Sadun et al., 2016). The WMS sample was selected randomly (Bloom, Sadun et al., 2016) and to be statistically representative of the population of firms in China (Bloom, Lemos et al., 2014).

Following Bloom, Genakos et al. (2010), this study defines overall managerial quality as the unweighted average of the 18 key management practices. Information on the quality of management is only available for one year per firm. The WMS data was matched with CIC observations by applying a methodology described in greater detail in appendix A.2. By this procedure, 434 (or 80.1 percent) of the firms were successfully matched with the CIC data. Subsequently, additional adjustments and plausibility checks were implemented to exclude unqualified observations. The detailed screening process is explained in appendix A.2. The resulting final sample includes 398 firms and 2,219 observations. The pre-cleaned and final samples do not differ significantly in terms of management quality and other key covariates (cf. Table III-9 and Table III-10 in the appendix).

The distribution of overall management quality is depicted in the top panel of Figure III-2. In general, Chinese firms are found to be less well managed than firms in developed countries.[129] The overall management score for China of 2.65 (cf. Table III-5) is similar to Brazil and significantly lower than the one of US firms, which have an average score of 3.35, and Western European firms, which are generally above 3 (Bloom, Genakos et al., 2012). While the sub-categories of People, Targets and Monitoring are similarly distributed, a surprisingly high share of firms performed weak in the Operations category.

[128] Details on the survey questionnaire, the 18 key management practices and the survey method and procedure are given in, e.g., Bloom and Van Reenen (2007) and Bloom, Genakos et al. (2010).

[129] Emerging market firms in general are found to be less well managed compared to firms in developed countries (Bloom, Genakos et al., 2012; Bloom, Sadun et al., 2016).

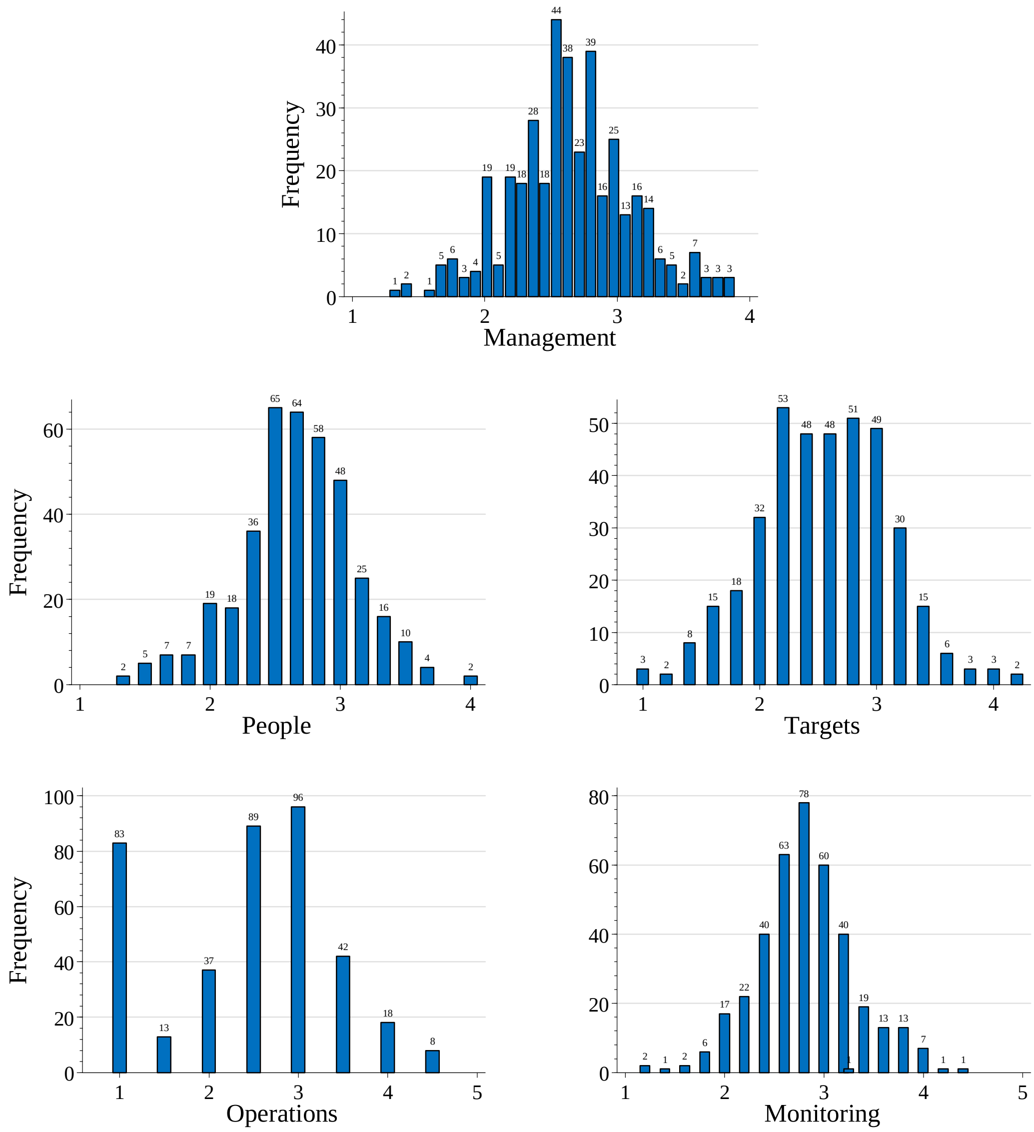

Figure III-2: *Distribution of the overall management score and subcategories.*

Note: Figure III-2 presents the frequencies of quality scores of overall management and the four practice areas, which together form the overall management score. The best score is 5. Statistics are based on 386 Chinese firms. The discreteness of the responses differs by practice area. Numbers of observations per bin are indicated at the top of a bar.

3.3 Ownership and Management Score

The five ownership categories shown in Table III-5—central and local SOE, domestic non-SOE (domestic private or collective), foreign, and HMT—represent different functional categories. In the Chinese setting, these categories translate into differences in terms of license to operate and expectations of employees, customers, government and society. For instance, SOEs carry unique societal responsibilities, such as supporting the government and allowing it to play a shaping role in the direction of economic development (Wang, 2014). For this reason, literature—for example, Sachs and Woo (2001) or Li and Xia (2008)—refers to SOEs as potentially seriously affected by allocative inefficiencies.

Chinese SOEs have been notorious for extensive wage and bonus payments, which increasingly have been paid via fringe benefits through indirect channels like the provision of housing, means of transportation or recreational facilities (Sachs and Woo, 2001). These social responsibilities and resulting allocative inefficiencies are perhaps strongest for central SOEs, who were handpicked and groomed to be national champions. As depicted in Table III-5, central SOEs' labor price is larger than the one of every other ownership type and approximately double the price faced by domestic non-SOEs and HMT firms, suggesting allocative distortions may be particularly large, although local SOEs also face a higher average labor price. Interestingly, the labor intensity (inverse of the *Y*/*L*-ratio) of SOEs is considerably lower than the one of the other ownership types (except for foreign firms). Hence, at this stage, we do not find a clear indication of SOEs absorbing more employees than they would hire if they were non-SOEs instead. Rather, SOEs seem to compensate for price distortions in the labor input by increasing the productive use of this input. Another well-documented characteristic of SOEs related to input distortions is their ability to borrow capital at low cost.[130] Table

[130] For instance, Sachs and Woo (2001) describe local governments to have lobbied local branches of state banks to grant investment loans to SOEs in order to enhance local development, with the state banks usually having granted these demands for easy money.

III-5 shows both central and local SOEs to face significantly lower costs of capital compared to their non-SOE counterparts.

Given such implications, ownership might affect the extent, to which a firm implements western management practices. For example, management practices are likely to carry a very different payoff calculation for domestic non-SOEs. The latter, for instance, do not face the same societal responsibilities and lack the legitimizing advantage of SOE connections, leading them to face greater uncertainty and exposure to resource scarcity and market volatility. Foreign and HMT firms also suffer from more limited legitimacy compared to domestic players. Hence, these firms can be expected to be more likely competing on other margins. Furthermore, foreign firms may inherit management practices from overseas parents, but may confer little domestic advantage to it. Before focusing on the econometric evaluation of the role of management in explaining the performance of Chinese industrial firms, we descriptively compare management scores across ownership categories and conduct pairwise hypothesis tests. These simple comparisons frame the empirical analysis of the following chapters.

According to Table III-5, management quality shows a high variability across ownership types. Central SOEs are found to be very well managed and rank consistently higher than local SOEs and non-SOEs in all dimensions except for talent management (People). These SOEs, which are overseen by the central government, have management capabilities statistically equivalent to China's foreign-owned enterprises, while SOEs with local (provincial and below) oversight are better managed than domestic private firms. Central SOEs clearly stand out as having management practices that, if not for the low People score, on average are equivalent to the level measured for firms in Western European countries.

Table III-5: *Management scores and other key characteristics by ownership types.*

	Mean	Std.dev.	Min.	Max.	Mean	Std.dev.	Min.	Max.
	All firms [# firms: 386]				**Domestic non-SOE [# firms: 162]**			
Management	2.65	0.45	1.28	3.89	2.52•••	0.45	1.28	3.72
People	2.66	0.44	1.33	4.00	2.60	0.46	1.50	4.00
Targets	2.55	0.56	1.00	4.20	2.41•••	0.54	1.00	3.60
Operations	2.44	0.95	1.00	4.50	2.14•••	0.94	1.00	4.00
Monitor	2.82	0.50	1.20	4.40	2.70•••	0.50	1.20	4.40
Output *Y* (mRMB)	675.2	1,839.0	4.96	16,415.9	483.4•••	1,195.5	6.76	9,432.6
Employees *L*	957.3	1,310.2	68	16,458	810.7•••	987.6	90	8,704
Capital price (kRMB)	0.19	0.48	–0.12	9.21	0.18•	0.13	–0.12	0.90
Labor price (kRMB)	25.75	22.87	4.46	177.46	18.27•••	11.67	4.46	104.35
Y/*L*-ratio (kRMB)	641.1	1,157.6	21.11	13,005.0	538.2	845.0	21.11	6,436.0
	Central SOE [# firms: 13]				**Local SOE [# firms: 69]**			
Management	2.87*	0.40	2.06	3.61	2.66○○	0.36	1.61	3.56
People	2.65	0.62	1.33	3.33	2.66	0.41	1.67	3.50
Targets	2.80*	0.49	2.00	3.80	2.59○○○	0.42	1.40	3.40
Operations	3.15***	0.59	2.50	4.50	2.54○○○	0.76	1.00	4.00
Monitor	3.08***	0.47	2.20	3.80	2.78	0.38	1.80	3.80
Output *Y* (mRMB)	2,161.8**	4,283.9	59.84	15,292.8	676.8	1,935.7	6.13	15,774.1
Employees *L*	1,775.9***	1,528.2	525	5,126	944.2	763.7	68	2,981
Capital price (kRMB)	0.13	0.06	0.06	0.23	0.15○○	0.15	–0.02	0.81
Labor price (kRMB)	45.76***	39.86	9.59	125.19	26.61○○○	22.63	5.42	132.14
Y/*L*-ratio (kRMB)	736.8	858.0	102.08	2,983.4	736.7	1,579.8	23.59	9,326.0
	Foreign [# firms: 86]				**HMT [# firms: 56]**			
Management	2.85	0.45	1.89	3.89	2.64	0.45	1.67	3.61
People	2.78	0.43	1.33	4.00	2.65	0.38	1.67	3.67
Targets	2.74	0.64	1.40	4.20	2.54	0.57	1.20	4.00
Operations	2.85	0.87	1.00	4.50	2.38	1.03	1.00	4.50
Monitor	3.03	0.49	2.00	4.20	2.82	0.52	1.60	4.00
Output *Y* (mRMB)	1,078.5^{+}	2,493.4	20.59	16,415.9	263.3	432.9	4.96	2,337.4
Employees *L*	1,265.9	2,127.0	103	16,458	733.5	719.5	90	3,709
Capital price (kRMB)	0.18	0.16	0.01	1.03	0.31	1.22	0.02	9.21
Labor price (kRMB)	38.23	31.02	8.04	177.46	22.53	16.73	5.37	89.31
Y/*L*-ratio (kRMB)	906.3	1,524.6	46.34	13,005.0	391.5	482.7	26.59	1,899.8

Note: This table shows summary statistics of management quality, overall and by ownership type. Statistics are based on the year an individual firm was surveyed by the WMS. A firm is defined as an SOE if it is under central or local governmental control. It is defined as domestic non-SOE (which are mostly private and a few collective enterprises) if it is neither a central nor local SOE and if less than 50 percent of the paid-in capital are from foreign sources or from Hong-Kong, Macau or Taiwan (HMT). A firm is defined as under foreign control if it is neither a central or local SOE and if more than 50 percent of the paid-in capital are from foreign sources excluding HMT. *Capital price* is interest and depreciation expenses and opportunity cost of equity assumed to be three percent divided by the real capital stock. *Labor price* is wages and welfare expenses divided by the number of employees. Asterisks *** indicate significance at 1 percent level, ** at 5 percent level and * at 10 percent level of one-sided unpaired *t*-tests comparing the respective means of central and local SOEs. Analogously, the following symbols represent significance levels of additional one-sided unpaired *t*-tests: pluses (+) for the comparison central SOEs vs. foreign firms, dots (●) for the comparison central SOEs vs. domestic non-SOEs and circles (○) for the comparison local SOEs vs. domestic non-SOEs.

Our finding of SOEs being significantly better managed than non-SOEs is interesting and contrary to popular wisdom. It is also contrary to the literature described in chapter 2.1, which—even though not explicitly focusing on China—found non-SOEs to be on average slightly better managed than SOEs according to the standards of the WMS. In our setting, central SOEs show the highest management quality scores on average for three out of four management subcategories. We find that even local SOEs, which are smaller than central SOEs, have more limited access to resources, and face increasing competitive pressure, do not appear to be management laggards. Local SOEs compare favourably to domestic non-SOEs on overall management scores. Here, differences in ownership appear to play a strong role, as the two groups are otherwise comparable in terms of output size and employment.

What could be underlying factors that drive Chinese SOEs to sheer off path from the traditional literature by showing higher management scores than other ownership types? SOEs had the opportunity, and often were encouraged, to adopt a wide range of management practices and behaviors in the process of the reforms, with the explicit goals of boosting competitiveness and accountability. To allow for increased state supervision, SOEs were required to put in place development strategies, medium and long-term plans, production and business operating procedures, and management rules, among other functions (Wang, 2014).[131] While these adjustments may have strengthened practices analogous to those of modern western management, it is not clear if firms adopted practices because they were required to do so or found adoption valuable. For example, an SOE might not only strengthen production processes, but also channels of communication and influence with government leadership by good management practices. To the extent that the implementation of management practices was based on such opportunities for "institutional rents" and to secure the SOE-government relationship, it may have also strengthened productivity-enhancing access to markets and other preferential treatment. In China, the government has the power to shape the competitive landscape by preferentially delivering resources and other favors available only to SOEs (Li

[131] Supervision of SOEs was further institutionalized in 2004 in response to observed unevenness of state involvement in SOE affairs (Wang, 2014).

and Xia, 2008; Nolan and Xiaoqiang, 1999; Oi, 1992). Hence, managers of SOEs not only have the possibility to maximize profits through technical innovations and an increase in productivity, but also through a “bureaucratic haggling” processes by developing good relationships with the government (Sachs and Woo, 2001).

Another factor, for example, could be firm size. The literature found larger firms to be better managed in general (Bloom, Genakos et al., 2012; Bloom, Lemos et al., 2014; Bloom, Sadun et al., 2016; Bloom, Schweiger et al., 2012), and Chinese SOEs tend to be larger in terms of output or the number of people employed.[132] We will focus more on these and other factors when discussing the empirical results of chapter 5. In the next few paragraphs, well will explore in a qualitative manner differences in management category subcomponents conditional on ownership structure and hypothesize on underlying drivers thereof.

The outranking of SOEs in the Target category could be traced back to SOEs facing broader than usual targets, which also include social alongside economic goals. Furthermore, given their ownership structure, SOEs may have incentives to report ambition, and set targets further in advance for longer time horizons, often following government plans. To the extent that target-setting practice is done to fulfil government guidance or obligations, it may also reflect the degree of closeness to market-shaping functions.[133] In other words, a well-heeled SOE, for example, may be able to access credit on more favourable terms from large state banks, or to more easily locate a buyer for its products due to its status as a government-endorsed supplier.

The good performance of SOEs in the category Operations could be explained by the government encouraging, rewarding, and even compensating SOEs for seeking training from a variety of sources to increase their operational capabilities. Indeed, many central SOEs sought the guidance of leading global management consultancies

[132] The empirical analysis of chapter 6 will shed more light onto this issue.

[133] This is perhaps most true for central SOEs, which were “hold on” by the central government during the “Holding On to the Large SOEs, and Freeing the Small SOEs (*zhua da, fang xiao*)” program formulated by the end of 1995 (cf. footnote 123) and provided with substantial resources to develop their status as national champions (Nolan and Xiaoqiang, 1999).

during the 2000s (Steinfeld, 2010). When touring SOE facilities, it is common to see red banners with slogans promoting six-sigma principles and workplace safety. While implementation is a different matter and more difficult to measure, at the very least awareness of management practices such as lean is expected to be higher among employees that have been exposed to relevant training. Given that the WMS is scored by the interviewer, scores will remove, or at least mitigate, any bias that might be expected in a self-scored evaluation.

The comparatively low People scores of central SOEs can be explained by such firms feeling less pressure to put emphasis on people (Talent) management. SOEs are expected to have no trouble attracting workers, given that SOE positions represent coveted job security and come with many non-financial forms of compensation to increase the workers welfare (Bai, Lu et al., 2006), such as improved access to housing or means of transportation (Sachs and Woo, 2001). It also might be expected that SOEs will not strongly differentiate individual workers on the basis of performance, given their egalitarian orientation. Effort devoted to attracting workers and rewarding high performance would contribute to a higher overall talent management and thereby People score.

In conclusion, we find first evidence that the role management in Chinese firms could be related to political economy elements, and especially to the institutional element of firm ownership with its associated role of the government. In the following chapters, we will shed more light onto these potential interdependencies using econometric models.

4 Model

While we do not develop a formal hypothesis, we are interested—as discussed previously—in empirically analyzing the impact of management practice and ownership on production. Moreover, in an explorative analysis, we will seek to elicit whether the impact of management practice on the level of output depends on ownership.

Our empirical analysis builds on the pioneering work of Mefford (1986) and Bloom and Van Reenen (2007) and includes a measure of management quality directly into a production function.[134] A single output Y_{it} of firm i in year t is assumed to be a function of capital K_{it}, labor L_{it}, material M_{it}, observed management quality G_i, time fixed effects contained in vector $\boldsymbol{\theta}_t$ and other covariates contained in vector $\mathbf{Z}_{it}$, i.e.

$$Y_{it} = f(K_{it}, L_{it}, M_{it}, G_i, \boldsymbol{\theta}_t, \mathbf{Z}_{it}). \tag{1}$$

Y_{it} is (inventory-adjusted) gross output. Capital inputs K_{it} are based on the real capital stock.[135] Labor L_{it} is total number of workers employed by a firm in a given year, and material use M_{it} is deflated total intermediate input costs. Material and output variables are deflated to real values using four-digit industry-specific input and output deflators.[136] Measurements of management quality G_i were extracted from the WMS. The vector of time fixed effects $\boldsymbol{\theta}_t$ captures technical change. To account for the heterogeneity in the use of production technology and to reduce the risk of estimates picking up the effect of omitted variables, further covariates are included into the production function in form of vector $\mathbf{Z}_{it}$. Based on findings in the literature on factors behind productivity patterns (cf. chapter 1 and 2, and especially Bartelsman and Doms (2000) and Syverson (2011)) and previous literature controlling for observed management quality in a production function (cf. Table III-2), we chose as such covariates industry fixed effects on two-digit industry level[137], fixed effects capturing spatial geographic information, ownership fixed effects, WMS interviewer fixed effects, firm age and mean-differenced employee compensation. The latter variable controls for workforce characteristics in form

[134] See appendix A.1 for an explanation of the concept of a production function and separability.

[135] The derivation of the real capital stock is described in appendix A.1 of part II.

[136] The reference year is 1998. The application of four-digit industry by year-specific input and output deflators assumes firms within a four-digit industry to face single yearly input and output prices. Such assumption implies competitive input and output markets, where differences in prices would be the result of market power. These relatively detailed deflators were used by Brandt, Van Biesebroeck et al. (2012) and were kindly provided by Johannes Van Biesebroeck of KU Leuven. The online appendix of Brandt, Van Biesebroeck et al. (2012) describes the construction of the deflators.

[137] Production processes can be assumed to vary widely between the different industries listed in Table III-4.

of differences in human capital.[138] The role of managerial quality conditional on firm ownership is empirically evaluated by including an interaction term of these two variables into expression (1).

Two kinds of generic parametric production functions are specified, with the first one being of Cobb-Douglas (Cobb and Douglas, 1928) and the second one of translog (Berndt and Christensen, 1973; Christensen, Jorgenson et al., 1973) functional form. The translog functional form is more flexible than the Cobb-Douglas specification, because it does not contain the implicit a priori assumption of homotheticity, i.e. identical elasticities of substitution between inputs and identical returns to scale for all firms subject to the same production function. Rather, it allows the data to indicate the actual curvature of the production function, which might differ by firm. In addition, the translog functional form would allow for the specification of a production process, where management quality is non-separable from the factor inputs of capital, labor and material. Empirical literature controlling for observed management quality implicitly assumes separability of management quality from other factor inputs (cf. section 2.1). The arguably strong implications of separability are discussed in appendix A.1. We tried to test for separability[139] of managerial quality from the productive inputs of labor, capital and material, but were facing multicollinearity issues similar as Mefford (1986) did: the high collinearity between the interaction terms of management quality with other input choices and their non-interacted counterparts yielded unreasonable estimation results. No amelioration was observed when truncating the sample to a cross-section containing only observations of the year a firm was surveyed by a WMS interviewer. Consequently, we resorted to the a priori assumption of separability of management quality with other input choices. Using modern data, the test for separability thus remains a task for future research.

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[138] The underlying assumption is that the more skilled a firm's work force is on average, the higher the firm's employee compensation per worker compared to the industry's average in a specific year. For the Chinese case, such assumption might especially hold once the type of firm ownership is controlled for. Employee compensation includes wages as well as welfare payments, and the mean is specific by two-digit industry level and year.

[139] Denny and Fuss (1977) provide an in depth description of how to test for separability when using translog production functions.

The traditional symmetric production technology in translog functional form, assuming separability of managerial quality from other productive input choices, is described in eq. (2). The variables' median value is chosen as point of approximation. Small letters indicate variables in natural logarithms.

$$
\begin{aligned}
y_{it} = \alpha_0 + \sum_{x=\{k,l,m\}} \beta_x x_{it} + \frac{1}{2} \sum_{x=\{k,l,m\}} \beta_{xx} x_{it}^2 + \sum_{x,\tilde{x}=\{k,l,m\}|x\neq\tilde{x}} \beta_{xx'} x_{it} \tilde{x}_{it} \\
+ \boldsymbol{\theta}_t + \beta_G G_i + \boldsymbol{\gamma}' \mathbf{Z}_{it} + \varepsilon_{it}
\end{aligned}
\qquad (2)
$$

The translog functional form can be converted into the Cobb-Douglas specification by setting the square and interaction terms to zero and not taking the covariates' median as point of approximation. The panel is unbalanced; firms are indicated by $i = \{1,...,N\}$ and time by *t*. Firms are observed yearly during the period $t = \{2003,...,T_i\}$, with $T_i \leq 2008$. The constant is α_0 and the error term is represented by $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$. Firms are assumed to produce with full technical efficiency, i.e. eq. (2) does not allow for an additional shift in the production function due to technical efficiency differences.

With regard to the choice of an econometric technique, the econometric literature for panel data differentiates various types of models. The three most widely used approaches are: OLS, fixed effects (FE), and random effects (RE). The OLS specification assumes a common intercept, as well as common slope coefficients across firms and time. The main difference between the OLS, RE and FE model consists in the constant term. Generally, FE and RE models are superior to OLS because they take into consideration a potential unobserved heterogeneity bias. Nevertheless, as discussed in more detail later on, OLS can be an interesting econometric approach in some situations.

In our case, the estimation of fixed effects models is not an option, as the fixed effects would absorb the management quality covariate, which is time-constant. The RE specification allows for such identification. Hence, we include random effects

$\alpha_i \sim N(\alpha, \sigma_\alpha^2)$ into eq. (2) to control for time-constant firm-specific heterogeneity that is strictly orthogonal to managerial quality, other covariates, and the error term.[140]

Following Fuller and Battese (1973, 1974), the RE version of eq. (2) is estimated by running OLS on the transformation

$$y_{it} - \theta_i \bar{y}_i = (1-\theta_i)\alpha_0 + \boldsymbol{\beta}'(\mathbf{x}_{it} - \theta_i \bar{\mathbf{x}}_i) + (1-\theta_i)\alpha_i + (\varepsilon_{it} - \theta_i \bar{\varepsilon}_i), \tag{3}$$

where $\theta_i = 1 - \sigma_\varepsilon (\sigma_\varepsilon^2 + T_i \sigma_\alpha^2)^{-1/2}$ and $\bar{y}_i = T_i^{-1} \sum_t y_{it}$ (other mean variables are constructed analogously).[141]

In comparison to OLS, the RE estimator comes with the benefit of accounting for time-constant unobserved heterogeneity. In order to choose between the OLS and RE model, we can apply, e.g., the Breusch and Pagan (1980) Lagrange multiplier test. This test rejects at the 1 percent level the null hypothesis of an absence of random effects. Nevertheless, simple OLS to identify the role of a variable *x* still might be justifiable in case of a small timewise or cross-sectional dimension of the sample and a low within unit variability of *x* relative to *y*. Under such circumstances, the RE estimate of *x* (cf. section 5.1 of part II) could be considerably different from its true value, depending in the magnitude of the estimated θ_i's. This effect is inexistent for the pooled model ($\theta_i = 0$) and most severe in case of a within effects specification ($\theta_i = 1$) (Clark and Linzer, 2015).[142] To keep in mind, the management variable is time invariant and the

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[140] Because of the strict exogeneity assumption, the inclusion of random effects does not help to control for a potential (time-constant) simultaneity bias. For an analysis of the role of firm effects in the evaluation of production functions and their relation to the problem of simultaneity see, e.g., Griliches and Mairesse (1995).

[141] Feasible GLS is applied in order to estimate the unknown variances σ_α^2 and σ_ε^2. For a detailed description of the random effects estimator see, e.g., Greene (2008a) or Cameron and Trivedi (2005).

[142] Note that the random effects model represents a weighted average between a pooled and fixed effects model. By the distributional assumption of the random effect, outlying firm effects α_i are shrunk back towards α, yielding a more stable estimate of *x* with little within variation relative to *y* compared to a fixed effects estimation. Note that the smaller T_i or σ_α^2, the smaller is the shrinkage factor θ_i, i.e. the closer is the random effects specification to the pooled model (Clark and Linzer, 2015). Assuming large asymptotics and management being uncorrelated with other variables for simplicity reasons, the variance of the estimated effect of management *G* can be given as $Var(\beta_G) \;= \sigma_\varepsilon^2 / [s_w^2(G)$

(*Footnote continues on next page*)

timewise dimension of our unbalanced sample is relatively short for some firms. Therefore, a simple OLS model extensively accounting for firm characteristics and controlling for heteroskedasticity and serial correlation at the firm level[143] can be a valid econometric approach in our case as well.

5 Results

In this chapter, we present the results of the econometric analysis. First, we focus on the results of the test whether management by itself plays a role in explaining the performance of a sample of Chinese industrial firms. We then move focus to the results, where the role of management is conditioned on firm ownership. Finally, we analyze in an explorative manner an underlying aspect of why the role of management could differ by ownership type.

5.1 Management as Productive Input

Table III-6 presents the results obtained by estimating different versions of expression (2).[144] Models 1 to 3 are based on the use of a Cobb-Douglas functional form, whereas models 3 to 9 use the translog functional form. Further, models 1, 4 and 7 do not in-

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$+(1-\theta)s_b^2(G)]$, where s_w^2 and s_b^2 is the within and between variance, respectively. Hence, if $\theta > 0$ and σ_ε^2 is assumed to remain constant, then $Var_{OLS}(\beta_G) < Var_{RE}(\beta_G)$. Also Griliches and Hausman (1986) mention within estimates often to be unsatisfactory, in the sense that they are too low and insignificant. Furthermore, it would aggravate the (in case of a positive coefficient) negative attenuation bias due to a potential measurement error (Griliches and Mairesse, 1995).

[143] Heteroskedasticity and serial correlation is controlled for by using Huber (1967)/White (1980) cluster robust sandwich estimates. Potential cross-sectional correlation in ε_{it} that is constant for every cross-sectional pair of firms is controlled for by the time fixed effects (Hoechle, 2007). We do not further account for cross-sectional correlation via, e.g., the approaches of Driscoll and Kraay (1998) and Hoechle (2007), since these estimators rely on large T asymptotics, while our panel obeys large N asymptotics.

[144] All estimations were computed using Stata 13 (StataCorp, 2013).

clude managerial quality as explanatory variable, whereas the other models do. Finally, models 3, 6 and 9 additionally account for ownership structure and further firm and WMS interview characteristics in form of general and interview controls. Such stepwise refining of the model allows eliciting the effects the newly added variables not only on output, but also on the estimates of the other covariates. If these estimates remain in the ballpark of each other in terms of magnitude and significance, only a minor bias can be expected to evolve from an omission of the additionally included variables. From an econometric point of view, models 1 to 6 are estimated using OLS, while models 7 to 9 apply a RE specification. The latter model has the advantage of accounting for unobserved heterogeneity. However, the identification of the true coefficients of variables which do not vary over time, such as management quality, could be difficult (cf. chapter 4).

The results reported in Table III-6 indicate that, independently of the model specification, we do not find statistically significant evidence of management explaining variation in firm productivity.[145] While model specifications 1 to 3 assume input substitution elasticities to be equal to unity, homotheticity, and returns to scale that remain constant, model specifications 4 to 9 drop all of these assumptions. The application of a more flexible functional form or a control of unobserved heterogeneity via random effects does not change significance of the effect of observed management quality. *F*-tests reject the additional control variables to be jointly equal to zero, indicating that general and interview controls capture heterogeneity which otherwise would have remained unaccounted for. This heterogeneity is correlated with management quality and, once we accounted for it, the effect of management is negligible not only in a statistical sense, but also in terms of its magnitude.

[145] Since the production function includes the full range of inputs of capital, labor and material, the estimated coefficient of management quality in the production function can be interpreted as effect on total factor productivity (Bloom, Genakos et al., 2010; Gray and Shadbegian, 2003). Given the assumption of separability, the coefficient of management represents the *ceteris paribus* effect on output, i.e. the effect of management if the inputs of capital, labor and material, as well as all other covariates are kept constant. Output conditional on these covariates (except management) is equivalent to the residual, which commonly is interpreted as TFP.

Given the statistical significance of the additional controls and the ownership fixed effect, model 9 could seem as the preferred specification. However, considering insights from Clark and Linzer (2015) discussed in chapter 4, OLS can be a valid estimation procedure if key covariates only vary little over time relative to the dependent variable, the panel dimension for some observations is very short and heterogeneity is extensively controlled for.[146] Our preferred models are specifications 6 and 9, given the flexible form of their underlying production function and the abundance of controls, which are jointly (and also mostly individually) statistically significant.

In general, estimated magnitudes of the effect of management practices are considerably lower than what was found in previous literature on the effects of WMS measures of management quality on output. For example, Bloom and Van Reenen (2007) found—even though for developed countries—magnitudes between 0.032 and 0.075. The most abundant model specification of Bloom, Schweiger et al. (2012) yielded a magnitude of 0.050 for ten Central Asian transition countries. Bloom, Sadun et al. (2016) observed magnitudes of 0.035 for a worldwide sample.

It is reassuring to observe that, independently of the model specification, magnitudes and significance levels of estimated first order coefficients of capital, labor and material stay in relatively close range. The low values of the coefficients on capital use are an issue commonly observed when estimating a production function using panel methods (Griliches and Mairesse, 1995). SOE status is significantly negatively correlated with production to a similar extent across all models. Translog results clearly indicate that the value of economies of scale varies with size. Hence, for the Chinese setting, the Cobb-Douglas functional form does not describe the underlying production technology of the firms to the full extent. It seems questionable, whether this would be the case for the samples used by the empirical literature, which generally bases its estimates on Cobb-Douglas production functions (cf. chapter 2.1). Results indicate a mostly positive technical change in the Chinese industrial sector over time.

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[146] All model specifications extensively control for firm, time, industry and spatial characteristics. Once available management quality scores are characterized by a within variation and panel dimensions remain large enough, the use of panel models without doubt should be the preferred option.

In conclusion, managerial quality by itself is not a relevant input factor to control for unobserved heterogeneity and to explain variation in output of our sample of industrial firms in rapidly growing China. Given the literature on the role of observed management quality in explaining firm output described in section 2.1, our prior was the existence of a positive and significant relationship between modern management practices and firm performance. Hence, our results are in sharp contrast to the literature, which consistently found a positive and significant relationship. This literature mainly uses Cobb-Douglas production functions and does not apply panel models to account for unobserved firm effects. Nevertheless, we find the role of management to remain insignificant even when applying model specifications closely related to the ones commonly found in the literature (models 1 to 3 in Table III-6). In chapter 7, we will discuss potential underlying factors which could explain our finding that—according to western standards—better management by itself does not universally function as a differentiator in terms of the productivity of Chinese firms.

***Table III-6:** Effect of management quality on firm output.*

Estimation method	Cobb-Douglas OLS			Translog OLS			Translog RE		
Model number	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Management		**0.019 (0.019)**	**0.003 (0.019)**		**0.017 (0.018)**	**–0.002 (0.018)**		**0.028 (0.019)**	**0.011 (0.020)**
Capital (β_k)	0.028*** (0.008)	0.027*** (0.008)	0.018** (0.008)	0.034*** (0.008)	0.033*** (0.008)	0.024*** (0.008)	0.039*** (0.009)	0.038*** (0.009)	0.033*** (0.008)
Labor (β_l)	0.048*** (0.018)	0.047*** (0.018)	0.086*** (0.021)	0.061*** (0.018)	0.060*** (0.018)	0.105*** (0.019)	0.063*** (0.016)	0.062*** (0.016)	0.097*** (0.017)
Material (β_m)	0.923*** (0.016)	0.922*** (0.016)	0.896*** (0.017)	0.912*** (0.014)	0.911*** (0.014)	0.883*** (0.014)	0.895*** (0.013)	0.893*** (0.014)	0.873*** (0.014)
SOE			–0.034 (0.021)			–0.044** (0.020)			–0.050*** (0.019)
Year 2004 fixed effect	–0.001 (0.014)	–0.002 (0.014)	–0.005 (0.015)	–0.005 (0.014)	–0.005 (0.014)	–0.007 (0.014)	–0.003 (0.014)	–0.003 (0.014)	–0.005 (0.014)
Year 2005 fixed effect	0.073*** (0.013)	0.073*** (0.013)	0.069*** (0.013)	0.076*** (0.013)	0.076*** (0.013)	0.073*** (0.013)	0.078*** (0.012)	0.078*** (0.012)	0.074*** (0.012)
Year 2006 fixed effect	0.100*** (0.014)	0.100*** (0.014)	0.102*** (0.015)	0.103*** (0.014)	0.103*** (0.014)	0.107*** (0.015)	0.106*** (0.013)	0.107*** (0.013)	0.107*** (0.014)
Year 2007 fixed effect	0.122*** (0.015)	0.122*** (0.015)	0.123*** (0.016)	0.132*** (0.016)	0.133*** (0.016)	0.134*** (0.016)	0.134*** (0.014)	0.135*** (0.015)	0.132*** (0.015)
Year 2008 fixed effect	0.113*** (0.018)	0.113*** (0.018)	0.116*** (0.019)	0.128*** (0.018)	0.128*** (0.018)	0.133*** (0.019)	0.130*** (0.017)	0.131*** (0.017)	0.130*** (0.018)
(β_{kk})				–0.002 (0.007)	–0.003 (0.007)	–0.005 (0.006)	0.005 (0.007)	0.004 (0.007)	0.004 (0.007)
(β_{ll})				0.090*** (0.034)	0.088*** (0.034)	0.079** (0.031)	0.056* (0.031)	0.054* (0.031)	0.053* (0.030)
(β_{mm})				0.029* (0.017)	0.029* (0.017)	0.037** (0.016)	0.017 (0.016)	0.017 (0.016)	0.028* (0.014)
(β_{kl})				0.016 (0.010)	0.016* (0.010)	0.033*** (0.009)	0.013 (0.011)	0.013 (0.011)	0.029*** (0.011)
(β_{km})				0.010 (0.008)	0.011 (0.008)	0.006 (0.007)	–0.000 (0.009)	0.000 (0.009)	–0.004 (0.008)
(β_{lm})				–0.080*** (0.024)	–0.080*** (0.024)	–0.093*** (0.023)	–0.047** (0.021)	–0.047** (0.021)	–0.065*** (0.020)
Constant (α_0)	0.498*** (0.112)	0.474*** (0.112)	0.615*** (0.195)	11.709*** (0.055)	11.664*** (0.070)	11.648*** (0.142)	11.743*** (0.064)	11.667*** (0.076)	11.666*** (0.152)
R^2	0.978	0.978	0.980	0.980	0.980	0.981	0.979	0.979	0.981
ρ							0.379	0.379	0.339
θ							0.537	0.537	0.505
F-statistic			5.61***			5.70***			48.33***
Controls: general / interview	No / No	No / No	Yes / Yes	No / No	No / No	Yes / Yes	No / No	No / No	Yes / Yes
# firms / # observations	386 / 2,219	386 / 2,219	383 / 2,177	386 / 2,219	386 / 2,219	383 / 2,177	386 / 2,219	386 / 2,219	383 / 2,177

Note: This table presents the estimates of the effect of management on firm production under the assumption of separability between management and other productive inputs. The approximation point of the trans-log function was chosen to be the sample's median. The dependent variable is *gross output* in logs for all models. Management is assumed to be constant for a firm over time as management practices are plausibly sticky. All regressions include *two-digit industry fixed effects* and *province fixed effects*. General controls include *firm age* and *mean-differenced employee compensation* in logs, whereby the mean is taken on two-digit industry level. Interview controls include 6 interviewer fixed effects, the reliability of the interview and the duration of the interview in logs. Due to space constraints, estimates of industry and province fixed effects, general and interview controls are not shown. *F*-statistics show the joint significance of the additionally introduced general and interview controls. *Rho* (ρ) indicates the ratio of the variance of the RE to the variance of the idiosyncratic error. 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 Management and the Role of Ownership

In what follows, the role of managerial quality in explaining firm performance is conditioned on a firm's ownership structure, whereby we differentiate between SOEs and non-SOEs. Estimations are based on the model specifications presented in Table III-6, with the exception of one additional term being included, namely the interaction of managerial quality with ownership. Results are shown in Table III-7. Models SOE–1 to SOE–3 are based on a Cobb-Douglas functional form and on OLS, and therefore are in line with the kind of models commonly estimated by the modern literature (cf. Table III-2). Models SOE–4 to SOE–6 use OLS and a more flexible functional form, whereas models SOE–7 to SOE–9 are estimated using random effects.

Analogously to observations made in section 5.1, it is reassuring that the first order coefficients of capital, labor and material inputs are robust across the different model specifications. In line with findings presented in Table III-6, the role of management in explaining firm performance by itself is statistically insignificant. However, in some models, the coefficient of the interaction of management and ownership is significant and positive. This implies that, at least in these models, managerial quality plays a role in SOEs. Statistical significance disappears and magnitudes of the conditional effects of management decrease once the RE model specifications SOE–7 to SOE–9 are applied.[147] As explained before, these models are interesting from an econometric point of view, as they extensively control for time-constant firm-specific unobserved heterogeneity.[148] However, as discussed in chapter 4, we think that OLS under some circumstances can be considered to be a valid model specification as well. As in the previous

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[147] Similar to the results shown in section 5.1, the θ_i's on average are estimated to lie in range between 0.537 (model 7) and 0.500 (model 9), i.e. the within effects component of eq. (3) is weighted to a degree of roughly 50 percent. As explained in chapter 4, the RE specifications could cause the estimate of variables with a low degree of within variation to be far off their true value. The SOE variable has a small within variation, as a few firms change ownership over time, while the within variation of management is zero.

[148] Breusch-Pagan Lagrange multiplier tests for random effects (Breusch and Pagan, 1980) again reject at the 1 percent level the null hypothesis of an absence of random effects for models SOE–7 to SOE–9.

section, our preferred model specifications are SOE–6 and SOE–9, due to their flexible functional form and extensive control for firm heterogeneity.

Model SOE–6 indicates that, once the management score is interacted with SOE status, the effect of management becomes significantly positive and larger in magnitude relative to the results shown in Table III-6. If managerial quality is increased from the 10^{th} to the 90^{th} percentile by 1.166 (cf. Table III-3), output of SOEs is predicted to growth, ceteris paribus, by ca. 11.2 percent more than the output of non-SOEs (11.2 percent = $\exp(0.096 \cdot 1.166))$. Analogously, a 10 percent rise in managerial quality leads to an increase in the production of SOEs relative to non-SOEs of 0.9 percent. A comparison of the models SOE–1 to SOE–6 reveals that the control for firm characteristics has a major effect on the significance and magnitude of the effect of management. The additional control for interview characteristics again slightly increases the conditioned effect's magnitude, while the overall (i.e., unconditioned) effect further decreases in magnitude.[149] Furthermore, the estimated ownership effects indicate that being an SOE has a strong negative effect on firm productivity.[150] Managerial skills could help to narrow this consistently negative effect of being state controlled on productivity, but—given the distribution of managerial quality as shown in Table III-5—hardly to overcome it completely.[151]

[149] For example, Bloom and Van Reenen (2007) and Bloom, Genakos et al. (2010) observe changes in the magnitude of the effect of management as well when adding controls for firm characteristics, although they did not link management quality to ownership.

[150] In case of model SOE–6, SOEs are predicted to be roughly 30 percent less productive. For the period of 1998 to 2005, Hsieh and Klenow (2009) likewise find SOEs to be 41 percent less productive.

[151] For example, in case of model SOE–6, the management score of SOEs had to be—on average—about three points higher than the one of non-SOEs in order to overcome the productivity gap.

Table III-7: *Effect of management quality on output conditional on ownership.*

Estimation method	Cobb-Douglas OLS			Translog OLS			Translog RE		
Model number	(SOE–1)	(SOE–2)	(SOE–3)	(SOE–4)	(SOE–5)	(SOE–6)	(SOE–7)	(SOE–8)	(SOE–9)
Management	**0.008 (0.019)**	**–0.005 (0.018)**	**–0.012 (0.019)**	**0.006 (0.018)**	**–0.009 (0.017)**	**–0.017 (0.019)**	**0.024 (0.019)**	**0.012 (0.019)**	**0.004 (0.020)**
SOE × Management	**0.071 (0.050)**	**0.091** (0.043)**	**0.100** (0.044)**	**0.067 (0.048)**	**0.093** (0.042)**	**0.096** (0.043)**	**0.023 (0.049)**	**0.041 (0.047)**	**0.044 (0.048)**
SOE	**–0.206 (0.134)**	**–0.280** (0.116)**	**–0.304** (0.120)**	**–0.203 (0.130)**	**–0.298*** (0.112)**	**–0.303*** (0.115)**	**–0.096 (0.129)**	**–0.160 (0.123)**	**–0.168 (0.126)**
Capital (β_k)	0.029*** (0.008)	0.019** (0.008)	0.019** (0.008)	0.034*** (0.008)	0.026*** (0.008)	0.025*** (0.008)	0.039*** (0.009)	0.034*** (0.008)	0.033*** (0.008)
Labor (β_l)	0.047*** (0.018)	0.083*** (0.020)	0.086*** (0.021)	0.061*** (0.018)	0.099*** (0.018)	0.104*** (0.019)	0.063*** (0.016)	0.093*** (0.016)	0.097*** (0.017)
Material (β_m)	0.922*** (0.016)	0.894*** (0.017)	0.895*** (0.017)	0.910*** (0.014)	0.880*** (0.014)	0.883*** (0.014)	0.893*** (0.014)	0.870*** (0.013)	0.873*** (0.014)
Year 2004 fixed effect	–0.002 (0.014)	–0.004 (0.015)	–0.005 (0.015)	–0.006 (0.014)	–0.007 (0.014)	–0.007 (0.014)	–0.003 (0.014)	–0.005 (0.014)	–0.005 (0.014)
Year 2005 fixed effect	0.072*** (0.013)	0.070*** (0.013)	0.069*** (0.013)	0.075*** (0.013)	0.074*** (0.013)	0.073*** (0.013)	0.077*** (0.012)	0.075*** (0.012)	0.074*** (0.012)
Year 2006 fixed effect	0.101*** (0.014)	0.105*** (0.015)	0.104*** (0.015)	0.104*** (0.014)	0.110*** (0.014)	0.109*** (0.015)	0.107*** (0.013)	0.109*** (0.014)	0.108*** (0.014)
Year 2007 fixed effect	0.123*** (0.015)	0.127*** (0.016)	0.124*** (0.016)	0.133*** (0.016)	0.137*** (0.016)	0.135*** (0.016)	0.135*** (0.015)	0.135*** (0.015)	0.133*** (0.015)
Year 2008 fixed effect	0.113*** (0.018)	0.117*** (0.019)	0.117*** (0.019)	0.129*** (0.018)	0.133*** (0.019)	0.133*** (0.019)	0.131*** (0.017)	0.131*** (0.018)	0.131*** (0.018)
(β_{kk})				–0.002 (0.007)	–0.002 (0.006)	–0.004 (0.006)	0.005 (0.007)	0.006 (0.006)	0.003 (0.007)
(β_{ll})				0.090*** (0.034)	0.091*** (0.031)	0.081*** (0.031)	0.054* (0.031)	0.062** (0.029)	0.054* (0.030)
(β_{mm})				0.030* (0.017)	0.040** (0.016)	0.039** (0.016)	0.018 (0.016)	0.031** (0.014)	0.028** (0.014)
(β_{kl})				0.016 (0.010)	0.025*** (0.009)	0.031*** (0.009)	0.014 (0.011)	0.024*** (0.009)	0.029*** (0.011)
(β_{km})				0.010 (0.008)	0.003 (0.008)	0.005 (0.007)	–0.001 (0.009)	–0.007 (0.009)	–0.004 (0.009)
(β_{lm})				–0.081*** (0.024)	–0.088*** (0.022)	–0.093*** (0.023)	–0.047** (0.021)	–0.062*** (0.019)	–0.066*** (0.020)
Constant (α_0)	0.505*** (0.111)	0.774*** (0.119)	0.680*** (0.192)	11.703*** (0.072)	11.766*** (0.068)	11.706*** (0.138)	11.694*** (0.078)	11.722*** (0.074)	11.690*** (0.151)
R^2	0.978	0.980	0.980	0.980	0.981	0.981	0.979	0.981	0.981
ρ							0.379	0.335	0.333
θ							0.537	0.501	0.500
F-statistic		20.31***	5.89***		25.22***	5.98***		47.32***	48.92***
Controls: general / interview	No / No	Yes / No	Yes / Yes	No / No	Yes / No	Yes / Yes	No / No	Yes / No	Yes / Yes
# firms / # observations	386 / 2,219	386 / 2,194	383 / 2,177	386 / 2,219	386 / 2,194	383 / 2,177	386 / 2,194	386 / 2,219	383 / 2,177

Note: This table presents the estimates of the effect of management on firm production conditional on ownership under the assumption of separability between management and other productive inputs. A firm is defined as state-owned if it is under central or local governmental control. The approximation point of the translog function was chosen to be the sample's median. The dependent variable is *gross output* in logs for all models. Management is assumed to be constant for a firm over time as management practices are plausibly sticky. All regressions include *two-digit industry fixed effects* and *province fixed effects*. General controls and interview controls are defined as in Table III-6. Due to space constraints, estimates of industry and province fixed effects, general and interview controls are not shown. *F*-statistics show the joint significance of the additionally introduced general and interview controls. *Rho* (ρ) indicates the ratio of the variance of the RE to the variance of the idiosyncratic error. 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.

In conclusion, our empirical analysis yields some evidence—at least when applying OLS—that the impact of management on output could depend on firm ownership. Hence, our results contradict the notion of "management as a technology" supported by Bloom, Sadun et al. (2016) from two sides. First, management by itself is not significantly correlated with firm performance. And second, the role of management could depend on firm characteristics like ownership structure. Hence, we provide empirical evidence for the hypothesis of "management as a design", in that firms use management practices in a way which fits their individual setting. Better management, as defined by the WMS, does not seem to uniformly increase firm productivity. Rather, SOEs seem to adopt management practices which prove highly efficient in increasing productivity for their individual setting.

Multiple factors might explain why, for the Chinese setting, the role of management could depend on firm ownership. They range from governmental requirements to allow for state supervision, over to the securement of "institutional rents" (cf. section 2.2). Moreover, in an effort to up with their more agile competitors in a period of breakneck growth and growing competition, SOEs could mimetically implement good management practices to deal with challenges unique to being state controlled. For example, our results indicate a consistently negative effect of being state controlled on firm productivity (cf. Table III-6 and Table III-7). Allocative distortions in inputs are a well-known challenge to Chinese SOEs. As described in section 3.3 using descriptive statistics, SOEs seem to compensate for price distortions in the labor input by increasing the productive use of this input. In an explorative manner, we henceforth look at this aspect empirically by testing, whether management quality is correlated with labor productivity.

In order to analyze the interdependencies between management quality and labor productivity, we regress labor productivity against management quality, ownership and a variable that links the role of management to ownership (models L–SOE–1 and L–SOE–3). Models L–SOE–2 and L–SOE–4 further control for the intensities in the use of capital and material.[152] The first two model specifications are based on OLS, while the latter two use random effects.

Table III-8: *Effect of management quality on labor productivity conditional on ownership.*

Estimation method	Cobb-Douglas OLS				Cobb-Douglas RE			
Model number	(L–SOE–1)		(L–SOE–2)		(L–SOE–3)		(L–SOE–4)	
Management	**0.216****	**(0.100)**	**–0.012**	**(0.019)**	**0.376*****	**(0.112)**	**0.006**	**(0.020)**
SOE × Management	**0.169**	**(0.200)**	**0.091****	**(0.044)**	**–0.122**	**(0.118)**	**0.012**	**(0.048)**
SOE	**–0.742**	**(0.566)**	**–0.284****	**(0.120)**	**0.225**	**(0.326)**	**–0.083**	**(0.126)**
ln(K/L)			0.017**	(0.008)			0.026***	(0.008)
ln(M/L)			0.904***	(0.017)			0.901***	(0.014)
Constant	6.664***	(0.815)	0.649***	(0.188)	5.458***	(1.022)	0.516***	(0.182)
R^2	0.558		0.968		0.473		0.967	
ρ					0.739		0.385	
F-statistic	26.11***		5.24***		173.72***		62.52***	
Controls: general / interview	Yes / Yes		Yes / Yes		Yes / Yes		Yes / Yes	
# firms / # observations	386 / 2,177		383 / 2,177		383 / 2,177		383 / 2,177	

Note: This table presents the estimates of the effect of management on labor productivity conditional on ownership under the assumption of separability between management and other covariates. *Labor productivity* is the natural logarithm of the ratio of output to the total number of employees. A firm is defined as state-owned if it is under central or local governmental control. Management is assumed to be constant for a firm over time as management practices are plausibly sticky. All regressions include *year fixed effects*, *two-digit industry fixed effects* and *province fixed effects*. General controls and interview controls are defined as in Table III-6. *F*-statistics show the joint significance of the additionally introduced general and interview controls. *Rho* (ρ) indicates the ratio of the variance of the RE to the variance of the idiosyncratic error. 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.

Results presented in Table III-8 are consistent with the mimetic hypothesis, that is, firms could be upgrading management structures because these are correlated with an improvement in labor productivity.[153] The adoption process is different between the two ownership characteristics, once capital and material use are controlled for. The loss in significance under the RE specification could be explained by the factors mentioned before (cf. section 4). Interestingly, SOE status is negatively correlated with labor productivity. This could be explained by a well-known challenge and imperative unique to

[152] Constant returns to scale were tested and found to hold for model SOE–3, from which models L–SOE–2 and L–SOE–4 are derived by dividing by the input of labor.

[153] At this point it should be noted that we are well aware of the issue of reverse causality, common to most empirical literature in this field (cf. section 2.1). As noted by Bloom, Schweiger et al. (2012) and Bloom, Genakos et al. (2010), such estimated effects of management are not necessarily causal. Hence, we would like to emphasize that our results first and foremost imply correlation, and not causality.

SOEs, which is the accommodation of excess labor, especially during a period of consolidation in many industries and an increase in private sector competition. For SOEs, the improvement of labor productivity through better management could be undertaken to counteract potential allocative distortions due to their extraordinary high price of labor, labor over-allocations and their generally lower total factor productivity.

6 Robustness

This section probes the robustness of the benchmark results presented in chapter 5 in several dimensions: first, we test robustness in terms of the assumption of the stickiness of management quality. Then, we move focus and test, whether there is evidence of a monotonic effect of management, or whether results could be subject to a sample attrition bias. Furthermore, we address the issues of simultaneity and output market power and test for firm size being another channel that potentially could be driving results. In case of a truncation of the original benchmark sample used in chapter 5, the approximation point of the translog function is re-calculated. Estimation results supporting the statements on robustness made in the following paragraphs are listed in appendix A.3.

Stickiness of Management Quality

The benchmark analysis of the implications of management quality on firm outcome assumed management quality to be constant for a firm over time by arguing such practices to be plausibly sticky. Also Bloom, Schweiger et al. (2012) note that the literature found observed management practices not to change rapidly when using short panels. All firms of our sample were interviewed in the period of 2006 to 2008.[154] To test for the assumption of management quality being sticky over time, the period of analysis is stratified into two sections, one covering 2003 to 2005 and one covering 2006 to 2008.

[154] 14 firms (accounting for 81 observations) were interviewed in 2006, 294 firms (accounting for 1,689 observations) in 2007 and 78 firms (accounting for 449 observations) in 2008.

Subsequently, benchmark estimates are analyzed for robustness using the truncated sample covering 2006 to 2008. Results shown in Table III-11 and Table III-12 indicate both benchmark specifications in Table III-6 and Table III-7 to be robust in terms of sign, magnitude and significance with respect to the assumption of management quality being sticky for the whole period spanning 2003 to 2008.[155]

Sample Attrition

Ideally, our empirical analysis would account for the effect of entering and exiting firms. For instance, if badly managed firms leave the sample, because output is insufficient to cover costs, the estimated coefficient of management could be upward biased. However, only 12 firms (out of 386) are observed to exit the sample between 2003 and 2008, with all of them exiting in 2008.[156] It is unclear, whether these firms ceased operation in that year, or whether they just were not covered anymore by the CIC.[157] Robustness with respect to sample attrition is tested by re-estimating the benchmark results using a sample freed from attrition. Differences in results between the benchmark specification and the sample without attrition could be an indication of benchmark results being affected by attrition bias. As only 8 out of 73 firms entering the sample in 2004 were also founded in that year, i.e. report a firm age of zero, the sample without attrition is defined by the 362 firms that cover at least the years 2004 to 2008 and are older than

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[155] The timewise dimension of only three years was considered to be too short for the estimation of a random effects model. To further test for robustness of the results with respect to the assumption of stickiness of management quality, all models were re-estimated by limiting firms to enter the sample only in the year when they participated in the WMS survey. Such truncation of the sample discards all within variation and only 386 observations remain for estimation. Benchmark results of the OLS Cobb-Douglas and translog specification of Table III-6 again were found to be robust with respect to such cross-sectional specification, in that management was found to be statistically insignificant while similar in magnitude. The availability of a single cross-section observation per firm did not allow for the estimation of a random effects model. Given the extensive control for cofounding factors and the loss of all within variation, the effects of management conditional on ownership became insignificant across all models as well, while the magnitude stayed in close range to the benchmark specification in Table III-7.

[156] A total of 86 firms enter the sample: 73 firms in 2004, 1 firm in 2005, 2 firms in 2006 and 1 firm in 2007, respectively.

[157] No firm exited because it failed to meet the size threshold of 5 million RMB to be included in the CIC.

zero years in 2004. Based on Table III-13 and Table III-14, benchmark results are found to be robust. Estimated coefficients using the sample free of attrition remain within range of those of the corresponding benchmark specification in terms of magnitude, sign and significance.

Simultaneity

Estimation results of a production function are prone to a simultaneity bias if input and outputs are chosen contemporaneously (Griliches and Hausman, 1986; Griliches and Mairesse, 1995). This situation would correspond to eq. (2) containing an unobserved, non-predetermined and time varying decision component ϕ_{it} that is related to input choices. This bias will persist even if random effects are controlled for, and might propagate into the estimate of any covariate.[158] Especially material use, which by cost share is the primary input, is likely to be adjustable in the short term to productivity shocks.[159] China's flexible supply chain offering many options of suppliers and the possibility to change orders on very short notice may increase the propensity for such bias to exist with respect to material use. On the other hand, the difficulty to fire non-performers in many industries would make labor less subject to the bias.

[158] The RE model assumes the time-constant unobserved heterogeneity α_i to be strictly exogenous. The inclusion of Mundlak factors $\overline{x}_i^* = T_i^{-1} \sum_t x_{it}^*$ —following the idea of Mundlak (1961, 1978)—of the first order terms x_{it}^* of labor, capital and material into eq. (2) would control for heterogeneity correlated with input choices of labor, capital and material. Mundlak (1978) shows that the combination of random effects and Mundlak factors to some extent has the interpretation of a fixed effects model, while still allowing for an estimation of the effect of management quality. Results including Mundlak factors are robust and nearly identical in terms of magnitude and significance to the benchmark estimates. However, such a correction does not help to account for productivity shocks, i.e. the time varying part of the decision component ϕ_{it}.

[159] We restrained from the estimation of value added (VA) production functions to account for a potential simultaneity between material use and output (potentially simultaneous material inputs are not part of a value added production function). As noted by Bartelsman and Doms (2000), VA production functions might be useful when making statements about welfare, but are less useful to understand sources of productivity. This, because VA production functions neglect from the possibility of substitution between material and the other inputs of labor and capital. VA production functions are based on the two polar assumptions of either an infinite elasticity of substitution or an elasticity of substitution of zero between intermediate inputs and the VA-component $f(L, K)$ of a production function (Ringstad, 1978).

Robustness with respect to potentially unobserved heterogeneity related to contemporaneous output and input choices is tested for by applying the GMM estimator of Wooldridge (2009).[160] This approach assumes the unobserved productivity shock π_{it} to be of form $\pi_{it} = \phi_{it} - E\left[\phi_{it} \middle| \phi_{i,t-1}\right]$, i.e. to follow a random walk. The model assumes a Cobb-Douglas functional form, $\phi_{it} = g\left(k_{it}, m_{it}\right)$ and $E\left[\phi_{it} \middle| \phi_{i,t-1}\right] = f\left[g\left(k_{i,t-1}, m_{i,t-1}\right)\right]$. The function $g(.)$ contains any polynomial, up to the order of three, or less. The coefficients are identified based on the simultaneous GMM estimation of the following two equations:

$$\begin{aligned} y_{it} &= \alpha_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + g(k_{it}, m_{it}) \\ &\quad + \boldsymbol{\theta}_t + \beta_G G_i + \boldsymbol{\gamma}'\mathbf{Z}_{it} + \varepsilon_{it},\ t = \{2003, ..., T_i\},\ T_i \leq 2008, \end{aligned} \tag{4}$$

$$\begin{aligned} y_{it} &= \alpha_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + f\left[g\left(k_{i,t-1}, m_{i,t-1}\right)\right] \\ &\quad + \boldsymbol{\theta}_t + \beta_G G_i + \boldsymbol{\gamma}'\mathbf{Z}_{it} + \pi_{it} + \varepsilon_{it},\ t = \{2004, ..., T_i\},\ T_i \leq 2008. \end{aligned} \tag{5}$$

Given the orthogonality conditions $E\left[\varepsilon_{it} \middle| k_{it}, l_{it}, m_{it}, k_{i,t-1}, l_{i,t-1}, m_{i,t-1}, ..., k_{i1}, l_{i1}, m_{i1}\right] = 0$, $t = \{2003, ..., T_i\}$, and $E\left[\pi_{it} + \varepsilon_{it} \middle| k_{it}, k_{i,t-1}, l_{i,t-1}, m_{i,t-1}, ..., k_{i1}, l_{i1}, m_{i1}\right]$, $t = \{2004, ..., T_i\}$, $T_i \leq 2008$, any polynomial of $\left(k_{it}, l_{it}, g(m_{it})\right)$, lags, and polynomials of these lags can be

[160] Related literature controls for simultaneity in the estimation of a production function via the method proposed by Olley and Pakes (1996). Examples are Bloom and Van Reenen (2007), Bloom, Genakos et al. (2010) or Bloom, Sadun et al. (2016). The complicated two-step semi parametric approach of Olley and Pakes (1996) allows to control for the selection bias in a first step (less productive firms have a higher propensity to exit). Their proposed correction method necessitates information on non-negative investments. However, investments of an extended amount of firms in our sample are observed to be negative, whereby investments are derived from changes in the real capital stock. (The ratio of negative investment is also high when using changes in the book values of capital.) For this reason, we cannot apply such procedure. However, as shown before, results were found to be robust with respect to sample attrition. Hence, the benefit of the Olley and Pakes (1996) procedure of controlling for firm selection in a first step is not relevant for our case. We therefore feel confident in applying the methodology proposed by Wooldridge (2009), who shows that the moment conditions of the complicated two-step semi-parametric approach of Olley and Pakes (1996) to control for the simultaneity bias and the modification to it proposed by Levinsohn and Petrin (2003) can be implemented in a GMM framework yielding more efficient estimates amongst other advantages, see Wooldridge (2009).

used as instruments for eq. (4). As instruments for eq. (5) we can use the terms $\left(k_{it}, l_{i,t-1}, g(k_{i,t-1}, m_{i,t-1})\right)$ and polynomials of $g(k_{i,t-1}, m_{i,t-1})$, whereby lags of more than one period also would be allowed.[161] Results are given in Table III-15. Signs of the coefficients on management quality are robust when estimating the GMM model specifications.

Firm Size

We already described that SOEs in our sample on average are much larger than non-SOEs, while the literature based on the WMS observed larger firms in general to exert better management practices (cf. section 3.3). Independently of ownership type, larger firms could have more resources available to implement good management practices. And of course, there remains the question of reverse causality in the sense that firms are larger because they implemented better management practices beforehand. While the second factor of reverse causality is difficult to control for, we test for the possibility of the effect of management conditional on ownership to be primarily driven by firm size effects. We re-estimate models SOE–l to SOE–9 by additionally conditioning the role of management on firm size categories.[162] Results shown in Table II-16 assert that firm size is not the primary channel for the significant relationship between management quality and firm productivity conditional on ownership, what increases our credence in the benchmark results.

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[161] To avoid the loss of too many time periods, we only use one-period lags. Our instruments are found to be valid. The Kleibergen-Paap rk LM and rk Wald *F*-statistics (Kleibergen and Paap, 2006) reject the equation to be underidentified respectively weakly identified at a level of 1 percent. Hansen's *J*-statistic (Hansen, 1982) does not reject at a 10 percent level.

[162] The four size categories are shown in Table III-3. The number of (SOE/non-SOE) observations in the four categories are, starting with the smallest category: (34/212), (110/609), (155/566) and (168/365). Hence, most SOEs are observed in the largest category (firms with more than 1,000 employees). We restrained from interacting managerial quality directly with the number of people employed, due to multicollinearity issues with the labor input.

Market Power

Market power of SOEs could result in an overestimation of the impact of management on output when conditioning on ownership structure. The use of deflated revenues as a proxy for output quantities assumes a competitive output market environment.[163] If markets would not be competitive, deflated outputs would not represent output quantities, but rather quantities plus mark-ups, whereby such mark-ups differ with the degree of a firm's market power.[164] We found SOEs on average to be larger than non-SOEs, both in terms of sales (763 vs. 473 million Chinese renminbi, mRMB) and value added (271 vs. 112 mRMB), and also slightly in terms of number of people employed (1,111 vs. 824). Their size and political backup could accord SOEs market power, allowing them to charge a price surplus on the output market. In that case, the benchmark results could overestimate the true effect of management linked to ownership on output. This, because SOEs could have been facing higher market prices than the prices that were used to deflate output, resulting in inflated output quantities. If such mark-up is constant over time and ownership category, it already would be controlled for by the ownership fixed effect. As a robustness check, the effect of ownership on output is allowed to vary over time, thereby controlling for a potential time varying effect of SOE-related market power on output constant across firms.[165] Results of Table III-17 are in line with the benchmark results.

[163] Griliches and Mairesse (1995) give a concise summary of the problem of unobserved markups when using deflated revenues as output.

[164] Market power of SOEs might not only affect output, but also input measures. The close relationship with the government may help SOEs to source intermediate inputs at favourable prices, e.g., from other SOEs. In that case, the deflated intermediate inputs as a proxy for material use would underestimate real input quantities of SOEs due to unobserved mark-downs.

[165] We are aware that such procedure does not control for market power varying across firms and time. Our procedure of using period fixed effects is similar to a measure proposed by Griliches and Mairesse (1995) to control for demand shifters and aggregate industry prices affecting the relative price of a firm's own products.

7 Conclusions and Discussion

This study contributes to the literature on the role of management as a production factor by shedding light onto the question of whether management matters in explaining output of Chinese firms. In sharp contrast to the modern literature—even though this literature does not specifically focus on China and mainly does not apply panel models—we find the role of management practice as productive input parameter by itself to be uncorrelated with the variation in output. Hence, the question can be raised why managerial quality by itself does not contribute towards the performance of Chinese firms?

Several hypotheses could serve as underlying explanations. Our setting is a rapidly expanding and transforming economy (Tsui, Schoonhoven et al., 2004). Here, short-run tensions between improving management practices and establishing or maintaining competitive advantage via other means could be especially acute. Lei Jun, founder of China's to-date wildly successful smartphone manufacturer *Xiaomi*, is quoted as saying *"Even a pig can fly if it stands at the center of a whirlwind"*, which is interpreted to mean that for a firm operating in China during a period of rapid growth, seizing the right opportunity could be as important as the effort put into seizing it (Dou, 2015). In other words, if catching a "whirlwind" is all that is required, a firm may find little near-term value in upgrading its management practices. Another line of argument is provided by Acemoglu, Aghion et al. (2006), who note that for investment-based growth—in contrast to innovation-based strategies—managerial skills are not crucial: experienced managers and large incumbents are able to achieve larger technological improvements and productivity growth by simply copying and adopting existing technologies from the world's technological frontier. To some degree China's past growth was investment based, similar to what was observed in other relatively underdeveloped economies in the past (Gerschenkron, 1962).

In a second step, the role of management quality is conditioned on a political economy element, i.e. on the institutional element of firm ownership with its associated role of the government. First, and again in sharp contrast to the modern literature, we find state-owned firms to be better managed than non-state owned firms. We then provide first empirical evidence that the role management in defining the performance of Chinese firms could be mediated by ownership. There is indication that SOEs, i.e. state-controlled firms with oversight at the central or provincial level, benefit most and in significant manner from the adoption of modern western management practices.

Multiple elements might underlie the second and third main finding. For example, SOEs are required to develop plans, procedures and management rules in order to allow for increased state supervision (Wang, 2014). These governmentally imposed requirements might also cause, at least partially, the lower observed productivity of SOEs compared to non-SOEs. On the one hand, SOEs could be adopting better management practices (in western sense) simply to improve labor productivity and offset the generally lower total factor productivity when being state-owned. On the other hand, the Chinese government has the ability to shape market access and to deliver potentially productivity enhancing resources or domestic business connections exclusively to SOEs (Li and Xia, 2008; Nolan and Xiaoqiang, 1999; Oi, 1992). Such market opportunities might be heavily guarded, especially in some strategic industries (Bai, Lu et al., 2006; Wang, 2014). Good management practices could strengthen channels of communication and influence of SOEs with government leadership. Hence, good management practices could not only reflect requirements imposed on SOEs by the state, but also SOEs' access to privileges ("institutional rents"), which could be scaling with degree of compliance.

Finally, SOEs on average could be more technologically advanced and innovative than non-SOEs and thus, as predicted by Acemoglu, Aghion et al. (2006), management quality is of higher importance for them. This hypothesis could be supported by the privatization reform of "Holding On to the Large SOEs, and Freeing the Small SOEs" in the 1990s, where low performers where privatized and large, more productive SOEs were retained (Hsieh and Song, 2015). SOEs can be expected to rather undertake long term investments and to innovate compared to non-SOEs, as they are less affected by legal protection risks. In addition, the government has actively promoted SOEs to become active in this regard (Li and Xia, 2008).

While the findings of this study to some extent are unique to China, where ownership types are perhaps more clearly delineated than elsewhere, we take liberty to propose some general insights based on our findings. Firms everywhere face varying degrees of legitimacy in their operating markets as well as in the eyes of major government and civil society stakeholders. Our results provide directional evidence that firms constrained on one dimension, in our setting by state ownership, could compensate to some extent by developing capabilities along dimensions that lie within their span of control. Such compensation could be achieved through, for instance, the development of better management practices.

Our results set the stage for further research to understand when management practices add value. Even if they do not uniformly enable greater productivity, management practices could be instrumental in achieving other (potentially highly desirable) goals such as coping with regulatory oversight and increasing market complexity. They may also represent strategies for firms looking to minimize the impact of burdensome external requirements eroding competitive advantage like, e.g., state ownership or environmental policies. Figuring out why firms do not adopt "best practice" and characterizing drivers of variation in "best practice" are important components of this research agenda. Moreover, modern empirical literature is missing an analysis if, or under what circumstances, management can be assumed to be separable from other inputs. Certainly, it also would be interesting to replicate previous literature by using models accounting for firm effects and analyze, whether statistical significance of the role of management persists. The relationship between the pace of economic (industry) growth and a firm's investments in management deserves further attention as well. Then, in the background of diverse cultural contexts, the accurateness of a measurement of managerial quality based on western definitions should be studied in greater depth. Finally, our results first and foremost imply correlation, and not causality. There might be issues of reverse causality in that, for example, more productive, better managed firms were kept as SOEs and others were privatized. Future work could control for such aspects via, e.g., the point in time a firm was privatized. The hypothesis could be that less well managed firms were privatized at an earlier point in time. In addition, future work could strengthen arguments of causality via, e.g., field experiments.

A Appendices

A.1 Production Function and Concept of Separability

According to Chambers (1988), a production function $f(.)$ is a mathematical representation of how a non-negative, economically scarce and controllable vector of inputs $\mathbf{X}$ is processed into a non-negative output Y.[166] It can be defined as

$$Y = f(\mathbf{X})$$

The production function is assumed to yield a single valued maximum output given an arbitrary vector of inputs, i.e. it is abstracted from the existence of any sort of technical inefficiency in the production processes. A production function is commonly assumed to satisfy several properties (Chambers, 1988):

① $f(\mathbf{X})$ is monotone or strictly monotone
② $V(Y)$ is a (strictly) convex set[167] and $f(\mathbf{X})$ (strictly) quasi-concave
③ Inputs $\mathbf{X}$ are weakly (or strictly) essential
④ $V(Y)$ is closed and nonempty for all $Y > 0$
⑤ $f(\mathbf{X})$ is finite, nonnegative, real and single valued for all nonnegative and finite inputs $\mathbf{X}$
⑥ $f(\mathbf{X})$ is everywhere continuous and twice continuously differentiable

As described in Chambers (1988), separability in a production function can be defined as marginal rates of technical substitution being independent of other inputs. Assuming

[166] Production functions also can be specified for the multiple output case. However, this study focuses on single output production functions only.

[167] For a description of the input requirement set $V(Y)$ see chapter 3 of part I.

a twice separable production function $f(\mathbf{X})$ using three inputs combined in input vector $\mathbf{X}$, inputs X_1 and X_2 are separable from input X_3 if

$$\frac{\partial}{\partial X_3}\frac{\partial f/\partial X_1}{\partial f/\partial X_2}=0. \tag{6}$$

Or, in another way said, X_1 and X_2 are separable from input X_3 if a change in X_3 does not change the rate at which inputs X_1 and X_2 substitute for each other in producing output Y. This property is depicted in Figure III-3. There, an non-separability of inputs X_1 and X_2 from X_3 would tilt the isoquant in response to a change in X_3 towards X_3'. Inputs are usually assumed to be non-separable from themselves (Chambers, 1988).[168] From the empirical point of view, the use of a Cobb-Douglas functional form in the estimation of a production function implies separability, whereas the use of a translog functional form does not.

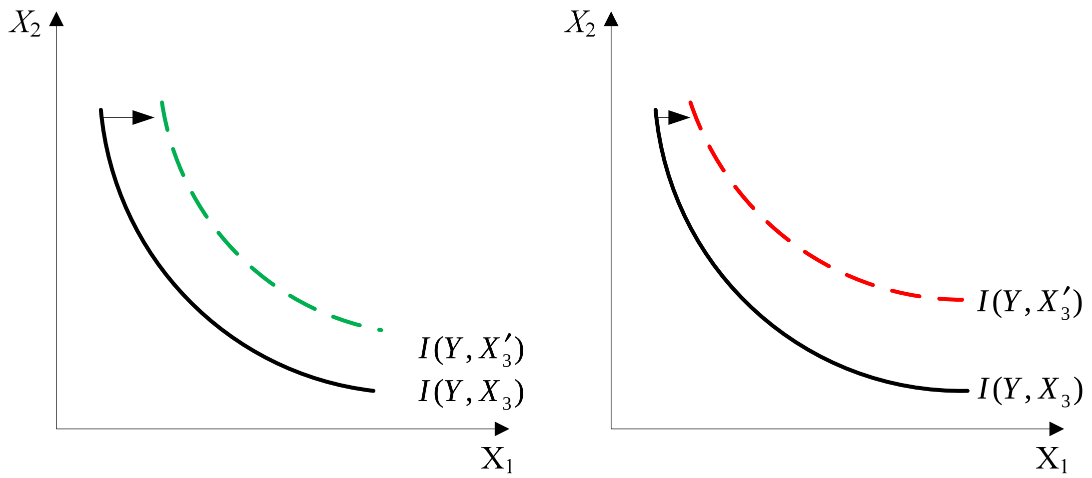

Figure III-3: *The concept of separability (adopted from Chambers, 1988).*

Note: Figure III-3 presents the concept of separability in a production function using three inputs. The left panel shows a production function where inputs X_1 and X_2 are separable from input X_3. The panel to the right shows a production function where the assumption of such separability does not hold.

[168] It further can be differentiated between a weak and strong separability. The interested reader might refer to Chambers (1988) p. 43 ff. for a description thereof.

A.2 Panel Construction

The processes of linking firms over time and to geographic information are exposed in appendix A.1 of part II. In what follows, the matching of the WMS observations to the CIC and the data screening process are described in greater detail.

Matching WMS Data to Census Data

Firms contained in the WMS data set were merged with the CIC data based on their firm id. Following the approach taken in Bloom, Genakos et al. (2010), the probability of a successful match is found to be, in a statistical sense, independent of the quality of management (in terms of the overall score as well as sub-scores) and also of the number of people employed (cf. Table III-9).

Table III-9: *Descriptive statistics comparing matched and unmatched firms.*

	Mean values		
Variable	Unmatched	Matched	*t*-Test
Management	2.636	2.649	
People	2.662	2.667	
Targets	2.489	2.545	
Operations	2.509	2.448	
Monitor	2.804	2.810	
Number of employees	962.35	1138.16	*
Number of observations	108	434	

Note: This table presents differences in variable mean values of matched and unmatched firms. The number of employees of the unmatched firms is the approximate value given in the WMS. Asterisks *** indicate significance at 1 percent level, ** at 5 percent level and * at 10 percent level of one-sided unpaired *t*-tests.

Matching Geographical Information

Spatial geographic information on centroid longitude and latitude information for 2,824 counties was obtained from a commercial source (BW, 2016) and merged with the CIC using information on county names in Chinese. This merge was successful for 380 out of 386 firms, i.e. 6 observations could not be allocated longitude and latitude information.

Data Screening Process

The detailed data screening process proceeds as follows: starting with 434 firms (2,475 observations), first, 2 firms (12 observations) are dropped as they do not belong to sectors covered by the price deflators described in footnote 136. Then, 6 firms (28 observations) are dropped because of missing observations. It is checked whether all firms exist for at least 2 years and 3 firms (3 observations) are dropped. Following Nie, Jiang et al. (2012), it is checked if the mean sales value of the firms over the years is lower than 5 million RMB and no firm is dropped. Following Brandt, Van Biesebroeck et al. (2012), 2 firms (11 observations) are dropped because they employ less than 8 people, and therefore fall under a different legal regime. Such number is also too low to quality as an above scale firm, which is the requirement for non-SOE firms to be included in the CIC. Then, following Cai and Liu (2009), several plausibility checks for unreasonable values are conducted: It is checked whether the difference in total assets minus liquid assets is negative, whether the difference of total assets minus fixed assets is positive and whether the difference of total assets minus net value of average fixed assets is negative and no firm is dropped. 9 firms (52 observations) are dropped because the difference of accumulated depreciation minus current depreciation is negative. 1 firm (6 observations) is dropped because its cost of sales is smaller or equal to zero. It is checked for duplicate firms in terms of identical financial values and no firm is dropped. Furthermore, it is checked whether variables of the cost function given in eq. (2) are reasonable in terms of size in all years they are observed, i.e. whether they are strictly positive. 13 firms (77 observations) are dropped because they show a negative real capital stock in at least one year. All other variables (Y, L, and M) are found to obey the restriction of being strictly positive. Then, the capital structure is checked for reasonable values, i.e. whether paid-in capital of several categories (state, collective, corporate, Hong Kong/Macau/Taiwan and foreign capital) is larger or equal to zero. Again, all firms are found to satisfy this restriction. Finally, following Bloom, Genakos et al. (2010), 12 firms (67 observations) are dropped that show a change in the ratio of variable costs to gross output of more than 200 percent in a year. Variable costs consist of expenses for labor and intermediate inputs. In conclusion, 386 firms and 2,219 observations are used in the empirical analysis.

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. As described in appendix A.1 of part II, there are three possible approaches to derive cross-sectionally missing values of variables when using panel data and that the predictive power of the approach based on ratios was found to be highest. Key missing variables were gross output in 2004 and intermediate inputs in 2008. Gross output was approximated by the sum of main business revenue, outside business revenue and the increase in inventory of finished goods. The multiplication of the firm-specific mean value of the share of intermediate input cost in total cost of sales in other years than 2008 with total cost of sales in 2008 yields the estimate for intermediate input cost in 2008.

Table III-10 shows the probability of a firm being excluded from the analysis to be independent of a firm's management quality (in terms of the overall score as well as sub-scores). However, smaller firms (in terms of output) and older firms are more likely to be excluded. A reason might be that smaller firms on average have weaker reporting standards, what increases their propensity of being excluded.

Table III-10: *Descriptive statistics comparing non-excluded and excluded firms.*

	Mean values		
Variable	Non-excluded	Excluded	*t*-Test
Management	2.649	2.647	
People	2.661	2.712	
Targets	2.549	2.513	
Operations	2.440	2.510	
Monitor	2.816	2.758	
Output (mRMB)	533.59	283.03	***
Number of employees	884.57	804.86	
Age	13.22	15.70	***
Number of observations	386	48	

Note: This table presents differences in variable mean values of matched and unmatched firms. Asterisks *** indicate significance at 1 percent level, ** at 5 percent level and * at 10 percent level of one-sided unpaired *t*-tests. Tests of equality between management quality variables are based on the WMS year of survey only (434 observations). Tests of equality between output, number of employees and age are based on the full sample (2,463 observations).

A.3 Empirical Results of Robustness Checks

The following tables list the results of empirical analyses to check robustness of the benchmark results given in Table III-6 and Table III-7. Robustness in checked with respect to the following dimensions: assumption of stickiness of management quality (Table III-11and Table III-12), sample attrition (Table III-13 and Table III-14), simultaneity in input choices (Table III-15), firm size (Table II-16) and market power (Table III-17). The approximation point of the translog production function was recalculated in case of a truncation of the original sample.

Table III-11: *Effect of management quality on output for years 2006 to 2008.*

Estimation method	Cobb-Douglas OLS				Translog OLS			
Model number	(R1–1)		(R1–2)		(R1–3)		(R1–4)	
Management	**0.017**	**(0.021)**	**0.002**	**(0.023)**	**0.020**	**(0.021)**	**–0.001**	**(0.023)**
Capital (β_k)	0.024**	(0.010)	0.017*	(0.010)	0.027***	(0.010)	0.023**	(0.009)
Labor (β_l)	0.066***	(0.021)	0.102***	(0.023)	0.070***	(0.019)	0.114***	(0.019)
Material (β_m)	0.910***	(0.017)	0.883***	(0.019)	0.901***	(0.015)	0.870***	(0.015)
SOE			–0.018	(0.031)			–0.035	(0.025)
Year 2007 fixed effect	0.024**	(0.009)	0.023**	(0.010)	0.030***	(0.009)	0.028***	(0.010)
Year 2008 fixed effect	0.014	(0.012)	0.016	(0.012)	0.025**	(0.012)	0.027**	(0.012)
(β_{kk})					–0.008	(0.009)	–0.011	(0.008)
(β_{ll})					0.072*	(0.039)	0.070**	(0.035)
(β_{mm})					0.031*	(0.018)	0.042***	(0.015)
(β_{kl})					0.013	(0.012)	0.039***	(0.011)
(β_{km})					0.015	(0.010)	0.008	(0.008)
(β_{lm})					–0.072***	(0.025)	–0.095***	(0.022)
Constant (α_0)	0.582***	(0.141)	0.658***	(0.241)	11.813***	(0.087)	11.729***	(0.173)
R^2	0.981		0.982		0.982		0.984	
Controls: general / interview	No / No		Yes / Yes		No / No		Yes / Yes	
# firms / # observations	386 / 1,145		383 / 1,133		386 / 1,145		383 / 1,133	

Note: This table presents the estimates of the effect of management on firm production under the assumption of separability between management and other productive inputs. The sample is truncated to contain only observations of the years 2006 to 2008. The approximation point of the translog function was chosen to be the sample's median. The dependent variable is *gross output* in logs for all models. Management is assumed to be constant for a firm over time as management practices are plausibly sticky. All regressions include *two-digit industry fixed effects* and *province fixed effects*. General controls and interview controls are defined as in Table III-6. 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 III-12: *Effect of management quality on output conditional on ownership for years 2006 to 2008.*

Estimation method	Cobb-Douglas OLS						Translog OLS					
Model number	(R1–SOE–1)		(R1–SOE–2)		(R1–SOE–3)		(R1–SOE–4)		(R1–SOE–5)		(R1–SOE–6)	
Management	**0.009**	**(0.022)**	**–0.003**	**(0.021)**	**–0.012**	**(0.023)**	**0.011**	**(0.022)**	**–0.005**	**(0.021)**	**–0.016**	**(0.024)**
SOE × Management	**0.059**	**(0.057)**	**0.088***	**(0.051)**	**0.108****	**(0.053)**	**0.062**	**(0.055)**	**0.102****	**(0.049)**	**0.112****	**(0.051)**
SOE	**–0.158**	**(0.154)**	**–0.249***	**(0.138)**	**–0.307****	**(0.144)**	**–0.179**	**(0.148)**	**–0.307****	**(0.132)**	**–0.335****	**(0.137)**
Capital (β_k)	0.024**	(0.010)	0.018*	(0.010)	0.017*	(0.010)	0.027***	(0.010)	0.025***	(0.009)	0.022**	(0.009)
Labor (β_l)	0.065***	(0.020)	0.096***	(0.021)	0.102***	(0.023)	0.070***	(0.019)	0.105***	(0.017)	0.114***	(0.019)
Material (β_m)	0.910***	(0.017)	0.882***	(0.019)	0.883***	(0.019)	0.901***	(0.015)	0.868***	(0.015)	0.870***	(0.015)
Year 2007 fixed effect	0.023**	(0.009)	0.023**	(0.010)	0.022**	(0.010)	0.030***	(0.009)	0.028***	(0.009)	0.028***	(0.010)
Year 2008 fixed effect	0.014	(0.012)	0.014	(0.012)	0.015	(0.012)	0.024**	(0.012)	0.024**	(0.012)	0.026**	(0.012)
(β_{kk})							–0.008	(0.009)	–0.008	(0.008)	–0.011	(0.008)
(β_{ll})							0.074*	(0.040)	0.090***	(0.035)	0.074**	(0.035)
(β_{mm})							0.033*	(0.018)	0.047***	(0.015)	0.044***	(0.015)
(β_{kl})							0.013	(0.012)	0.030***	(0.010)	0.038***	(0.011)
(β_{km})							0.014	(0.010)	0.004	(0.008)	0.007	(0.008)
(β_{lm})							–0.073***	(0.025)	–0.090***	(0.021)	–0.096***	(0.022)
Constant (α_0)	0.607***	(0.142)	0.877***	(0.158)	0.716***	(0.239)	11.842***	(0.091)	11.923***	(0.087)	11.781***	(0.168)
R^2	0.981		0.982		0.982		0.982		0.984		0.984	
Controls: general / interview	No / No		Yes / No		Yes / Yes		No / No		Yes / No		Yes / Yes	
# firms / # observations	386 / 1,145		386 / 1,141		383 / 1,133		386 / 1,145		386 / 1,141		383 / 1,133	

Note: This table presents the estimates of the effect of management on firm production conditional on ownership under the assumption of separability between management and other productive inputs. The sample is truncated to contain only observations of the years 2006 to 2008. A firm is defined as state-owned if it is under central or local governmental control. The approximation point of the translog function was chosen to be the sample's median. The dependent variable is *gross output* in logs for all models. Management is assumed to be constant for a firm over time as management practices are plausibly sticky. All regressions include *two-digit industry fixed effects* and *province fixed effects*. General controls and interview controls are defined as in Table III-6. 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 III-13: *Effect of management quality on output without sample attrition.*

Estimation method	Cobb-Douglas OLS		Translog OLS		Translog RE	
Model number	(R2–1)	(R2–2)	(R2–3)	(R2–4)	(R2–5)	(R2–6)
Management	**0.020 (0.019)**	**0.003 (0.019)**	**0.015 (0.018)**	**–0.002 (0.018)**	**0.028 (0.019)**	**0.011 (0.020)**
Capital (β_k)	0.028*** (0.008)	0.018** (0.008)	0.033*** (0.008)	0.023*** (0.008)	0.039*** (0.008)	0.032*** (0.009)
Labor (β_l)	0.052*** (0.019)	0.095*** (0.022)	0.062*** (0.018)	0.105*** (0.019)	0.068*** (0.016)	0.096*** (0.018)
Material (β_m)	0.920*** (0.017)	0.892*** (0.018)	0.909*** (0.015)	0.884*** (0.015)	0.888*** (0.014)	0.874*** (0.015)
SOE		–0.036* (0.022)		–0.040** (0.020)		–0.048** (0.020)
Year 2004 fixed effect	0.003 (0.014)	-0.005 (0.015)	0.001 (0.014)	–0.006 (0.015)	0.002 (0.014)	–0.004 (0.014)
Year 2005 fixed effect	0.072*** (0.013)	0.069*** (0.013)	0.076*** (0.013)	0.074*** (0.013)	0.078*** (0.012)	0.072*** (0.012)
Year 2006 fixed effect	0.101*** (0.014)	0.102*** (0.015)	0.107*** (0.014)	0.109*** (0.015)	0.110*** (0.013)	0.106*** (0.014)
Year 2007 fixed effect	0.124*** (0.016)	0.124*** (0.017)	0.135*** (0.016)	0.135*** (0.017)	0.138*** (0.015)	0.132*** (0.016)
Year 2008 fixed effect	0.117*** (0.018)	0.121*** (0.020)	0.132*** (0.019)	0.136*** (0.020)	0.133*** (0.017)	0.129*** (0.019)
(β_{kk})			–0.001 (0.007)	–0.006 (0.006)	0.007 (0.007)	0.002 (0.007)
(β_{ll})			0.093** (0.039)	0.072** (0.034)	0.055* (0.033)	0.044 (0.033)
(β_{mm})			0.034* (0.019)	0.034* (0.018)	0.022 (0.016)	0.022 (0.016)
(β_{kl})			0.017 (0.011)	0.031*** (0.010)	0.018* (0.010)	0.027** (0.012)
(β_{km})			0.009 (0.008)	0.008 (0.008)	–0.004 (0.009)	–0.001 (0.009)
(β_{lm})			–0.086*** (0.028)	–0.090*** (0.027)	–0.051** (0.022)	–0.059** (0.023)
Constant (α_0)	0.448*** (0.114)	0.575*** (0.212)	11.681*** (0.070)	11.655*** (0.153)	11.677*** (0.078)	11.683*** (0.166)
R^2	0.978	0.980	0.980	0.981	0.979	0.981
ρ					0.390	0.339
Controls: general / interview	No / No	Yes / Yes	No / No	Yes / Yes	No / No	Yes / Yes
# firms / # observations	362 / 2,110	359 / 2,079	362 / 2,110	359 / 2,079	362 / 2,110	359 / 2,079

Note: This table presents the estimates of the effect of management on firm production under the assumption of separability between management and other productive inputs. The sample is truncated to contain only observations of the years 2003 to 2008 that form a balanced panel and observations entering the sample in 2004 with a firm age older than zero years. The approximation point of the translog function was chosen to be the sample's median. The dependent variable is *gross output* in logs for all models. Management is assumed to be constant for a firm over time as management practices are plausibly sticky. All regressions include *two-digit industry fixed effects* and *province fixed effects*. General controls and interview controls are defined as in Table III-6. Due to space constraints, estimates of industry and province fixed effects, general and interview controls are not shown. *Rho* (ρ) indicates the ratio of the variance of the RE to the variance of the idiosyncratic error. 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 III-14: *Effect of management quality on output conditional on ownership without sample attrition.*

Estimation method	Cobb-Douglas OLS			Translog OLS			Translog RE		
Model number	(R2–SOE–1)	(R2–SOE–2)	(R2–SOE–3)	(R2–SOE–4)	(R2–SOE–5)	(R2–SOE–6)	(R2–SOE–7)	(R2–SOE–8)	(R2–SOE–9)
Management	**0.007 (0.020)**	**–0.004 (0.018)**	**–0.013 (0.020)**	**0.002 (0.018)**	**–0.008 (0.017)**	**–0.017 (0.019)**	**0.023 (0.020)**	**0.014 (0.019)**	**0.004 (0.020)**
SOE × Management	**0.078 (0.050)**	**0.095** (0.043)**	**0.103** (0.044)**	**0.077 (0.049)**	**0.095** (0.041)**	**0.097** (0.042)**	**0.026 (0.050)**	**0.039 (0.047)**	**0.043 (0.048)**
SOE	**–0.225* (0.135)**	**–0.293** (0.115)**	**–0.315*** (0.120)**	**–0.229* (0.132)**	**–0.297*** (0.111)**	**–0.304*** (0.114)**	**–0.105 (0.132)**	**–0.153 (0.123)**	**–0.163 (0.127)**
Capital (β_k)	0.030*** (0.008)	0.019** (0.008)	0.019** (0.008)	0.035*** (0.008)	0.024*** (0.008)	0.023*** (0.008)	0.041*** (0.008)	0.033*** (0.008)	0.032*** (0.009)
Labor (β_l)	0.052*** (0.019)	0.091*** (0.020)	0.094*** (0.022)	0.062*** (0.018)	0.099*** (0.018)	0.105*** (0.019)	0.069*** (0.016)	0.092*** (0.017)	0.096*** (0.018)
Material (β_m)	0.919*** (0.017)	0.890*** (0.018)	0.891*** (0.018)	0.908*** (0.015)	0.881*** (0.015)	0.884*** (0.015)	0.887*** (0.014)	0.871*** (0.014)	0.875*** (0.015)
Year 2004 fixed effect	0.002 (0.015)	–0.004 (0.015)	–0.005 (0.015)	–0.000 (0.014)	–0.006 (0.015)	–0.006 (0.015)	0.001 (0.014)	–0.004 (0.014)	–0.005 (0.014)
Year 2005 fixed effect	0.071*** (0.013)	0.071*** (0.013)	0.069*** (0.013)	0.075*** (0.013)	0.074*** (0.013)	0.074*** (0.013)	0.076*** (0.012)	0.073*** (0.012)	0.072*** (0.012)
Year 2006 fixed effect	0.103*** (0.014)	0.106*** (0.015)	0.104*** (0.015)	0.108*** (0.014)	0.111*** (0.015)	0.110*** (0.015)	0.110*** (0.013)	0.108*** (0.014)	0.107*** (0.014)
Year 2007 fixed effect	0.125*** (0.016)	0.128*** (0.017)	0.125*** (0.017)	0.135*** (0.016)	0.137*** (0.017)	0.136*** (0.017)	0.138*** (0.015)	0.134*** (0.015)	0.132*** (0.016)
Year 2008 fixed effect	0.118*** (0.018)	0.123*** (0.020)	0.122*** (0.020)	0.132*** (0.019)	0.136*** (0.020)	0.137*** (0.020)	0.133*** (0.017)	0.130*** (0.018)	0.130*** (0.019)
(β_{kk})				–0.000 (0.007)	–0.003 (0.006)	–0.005 (0.006)	0.007 (0.007)	0.005 (0.006)	0.002 (0.007)
(β_{ll})				0.095** (0.039)	0.083** (0.036)	0.074** (0.034)	0.056* (0.033)	0.053 (0.033)	0.046 (0.033)
(β_{mm})				0.036* (0.019)	0.037** (0.018)	0.036** (0.018)	0.023 (0.016)	0.024 (0.016)	0.022 (0.016)
(β_{kl})				0.017 (0.011)	0.022** (0.010)	0.029*** (0.010)	0.019* (0.010)	0.021** (0.010)	0.026** (0.011)
(β_{km})				0.008 (0.008)	0.005 (0.008)	0.007 (0.008)	–0.005 (0.009)	–0.004 (0.009)	–0.001 (0.009)
(β_{lm})				–0.086*** (0.028)	–0.083*** (0.026)	–0.090*** (0.027)	–0.052** (0.022)	–0.055** (0.022)	–0.060*** (0.023)
Constant (α_0)	0.481*** (0.113)	0.753*** (0.123)	0.648*** (0.209)	11.723*** (0.073)	11.783*** (0.068)	11.718*** (0.148)	11.706*** (0.081)	11.730*** (0.075)	11.709*** (0.164)
R^2	0.978	0.980	0.980	0.980	0.981	0.981	0.979	0.981	0.981
ρ							0.390	0.335	0.331
Controls: general / interview	No / No	Yes / No	Yes / Yes	No / No	Yes / No	Yes / Yes	No / No	Yes / No	Yes / Yes
# firms / # observations	362 / 2,110	362 / 2,096	359 / 2,079	362 / 2,110	362 / 2,096	359 / 2,079	362 / 2,110	362 / 2,096	359 / 2,079

Note: This table presents the estimates of the effect of management on firm production conditional on ownership under the assumption of separability between management and other productive inputs. A firm is defined as state-owned if it is under central or local governmental control. The approximation point of the translog function was chosen to be the sample's median. The dependent variable is *gross output* in logs for all models. Management is assumed to be constant for a firm over time as management practices are plausibly sticky. All regressions include *two-digit industry fixed effects* and *province fixed effects*. General controls and interview controls are defined as in Table III-6. Due to space constraints, estimates of industry and province fixed effects, general and interview controls are not shown. *Rho* (ρ) indicates the ratio of the variance of the RE to the variance of the idiosyncratic error. 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 III-15: *Effect of management quality on output accounting for potential simultaneity in inputs.*

	Cobb-Douglas GMM					
Model number	(R3–1)		(R3–2)		(R3–3)	
Management	**0.020**	**(0.013)**	**0.009**	**(0.012)**	**0.004**	**(0.014)**
Capital (β_k)	0.024**	(0.011)	0.020*	(0.011)	0.019*	(0.011)
Labor (β_l)	0.027**	(0.011)	0.058***	(0.012)	0.063***	(0.013)
Material (β_m)	0.943***	(0.009)	0.922***	(0.009)	0.922***	(0.009)
SOE					–0.020	(0.016)
Constant (α_0)	–0.304	(0.401)	–0.430	(0.408)	–0.454	(0.421)
R^2	0.979		0.980		0.980	
Management	**0.009**	**(0.013)**	**–0.005**	**(0.013)**	**–0.010**	**(0.014)**
SOE × Management	**0.068****	**(0.032)**	**0.089*****	**(0.029)**	**0.098*****	**(0.030)**
SOE	**–0.187****	**(0.086)**	**–0.259*****	**(0.078)**	**–0.285*****	**(0.080)**
Capital (β_k)	0.024**	(0.011)	0.020*	(0.011)	0.019*	(0.011)
Labor (β_l)	0.026**	(0.011)	0.058***	(0.012)	0.062***	(0.013)
Material (β_m)	0.944***	(0.009)	0.922***	(0.009)	0.923***	(0.009)
Constant (α_0)	–0.213	(0.402)	–0.278	(0.402)	–0.323	(0.417)
R^2	0.979		0.980		0.980	
Controls: general / interview	No / No		Yes / No		Yes / Yes	
# observations	1,833		1,824		1,810	

Note: This table presents the estimates of the effect of management on firm production conditional on ownership under the assumption of separability between management and other productive inputs. A firm is defined as state-owned if it is under central or local governmental control. The dependent variable is *gross output* in logs for all models. Management is assumed to be constant for a firm over time as management practices are plausibly sticky. All regressions include *two-digit industry fixed effects* and *province fixed effects*. General controls and interview controls are defined as in Table III-6. 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 III-16: *Effect of management quality on output conditional on ownership and firm size.*

Estimation method	Cobb-Douglas OLS			Translog OLS			Translog RE		
Model number	(R4–SOE–1)	(R4–SOE–2)	(R4–SOE–3)	(R4–SOE–4)	(R4–SOE–5)	(R4–SOE–6)	(R4–SOE–7)	(R4–SOE–8)	(R4–SOE–9)
Management	**–0.001 (0.023)**	**–0.011 (0.021)**	**–0.016 (0.023)**	**–0.010 (0.023)**	**–0.023 (0.021)**	**–0.025 (0.023)**	**0.020 (0.023)**	**0.007 (0.023)**	**0.002 (0.025)**
SOE × Management	**0.065 (0.051)**	**0.087** (0.044)**	**0.096** (0.046)**	**0.060 (0.049)**	**0.088** (0.042)**	**0.093** (0.043)**	**0.020 (0.050)**	**0.039 (0.047)**	**0.042 (0.048)**
SOE	**–0.194 (0.138)**	**–0.271** (0.119)**	**–0.296** (0.124)**	**–0.188 (0.132)**	**–0.286** (0.113)**	**–0.297** (0.116)**	**–0.089 (0.130)**	**–0.154 (0.124)**	**–0.163 (0.127)**
Size2 × Management	–0.002 (0.011)	–0.005 (0.010)	–0.005 (0.010)	0.010 (0.011)	0.010 (0.011)	0.005 (0.010)	0.001 (0.009)	0.003 (0.009)	0.001 (0.010)
Size3 × Management	0.006 (0.014)	0.003 (0.013)	0.002 (0.013)	0.020 (0.015)	0.020 (0.014)	0.012 (0.015)	0.000 (0.014)	0.004 (0.013)	–0.001 (0.015)
Size4 × Management	0.023 (0.020)	0.018 (0.019)	0.015 (0.019)	0.032 (0.020)	0.027 (0.019)	0.018 (0.019)	0.011 (0.018)	0.011 (0.018)	0.005 (0.019)
Capital (β_k)	0.029*** (0.008)	0.019** (0.008)	0.019** (0.008)	0.035*** (0.008)	0.026*** (0.008)	0.025*** (0.008)	0.039*** (0.009)	0.034*** (0.008)	0.033*** (0.008)
Labor (β_l)	0.021 (0.023)	0.061** (0.026)	0.067** (0.026)	0.030 (0.025)	0.072*** (0.025)	0.086*** (0.026)	0.053** (0.022)	0.083*** (0.022)	0.092*** (0.024)
Material (β_m)	0.921*** (0.016)	0.893*** (0.017)	0.894*** (0.017)	0.909*** (0.014)	0.880*** (0.014)	0.883*** (0.014)	0.893*** (0.014)	0.870*** (0.013)	0.873*** (0.014)
Year 2004 fixed effect	–0.002 (0.015)	–0.004 (0.015)	–0.005 (0.015)	–0.005 (0.014)	–0.006 (0.014)	–0.007 (0.014)	–0.003 (0.014)	–0.005 (0.014)	–0.005 (0.014)
Year 2005 fixed effect	0.071*** (0.013)	0.070*** (0.013)	0.068*** (0.013)	0.075*** (0.013)	0.074*** (0.013)	0.073*** (0.013)	0.076*** (0.012)	0.074*** (0.012)	0.073*** (0.012)
Year 2006 fixed effect	0.100*** (0.014)	0.104*** (0.014)	0.102*** (0.014)	0.104*** (0.014)	0.110*** (0.014)	0.109*** (0.015)	0.107*** (0.013)	0.109*** (0.013)	0.107*** (0.014)
Year 2007 fixed effect	0.121*** (0.015)	0.124*** (0.016)	0.122*** (0.016)	0.133*** (0.015)	0.138*** (0.016)	0.135*** (0.016)	0.135*** (0.014)	0.135*** (0.015)	0.132*** (0.015)
Year 2008 fixed effect	0.110*** (0.017)	0.114*** (0.018)	0.114*** (0.019)	0.128*** (0.018)	0.133*** (0.019)	0.133*** (0.019)	0.130*** (0.017)	0.130*** (0.018)	0.130*** (0.018)
(β_{kk})				–0.002 (0.007)	–0.002 (0.006)	–0.004 (0.006)	0.005 (0.007)	0.006 (0.006)	0.004 (0.007)
(β_{ll})				0.092*** (0.035)	0.096*** (0.032)	0.083*** (0.032)	0.049 (0.033)	0.060* (0.031)	0.051 (0.033)
(β_{mm})				0.030* (0.017)	0.040** (0.016)	0.039** (0.016)	0.018 (0.016)	0.031** (0.014)	0.028* (0.014)
(β_{kl})				0.017* (0.010)	0.026*** (0.009)	0.031*** (0.009)	0.014 (0.011)	0.024*** (0.009)	0.029*** (0.011)
(β_{km})				0.010 (0.008)	0.003 (0.007)	0.005 (0.007)	–0.001 (0.009)	–0.007 (0.008)	–0.004 (0.009)
(β_{lm})				–0.080*** (0.024)	–0.088*** (0.022)	–0.092*** (0.023)	–0.047** (0.021)	–0.062*** (0.019)	–0.066*** (0.020)
Constant (α_0)	0.694*** (0.143)	0.933*** (0.151)	0.816*** (0.206)	11.705*** (0.071)	11.766*** (0.067)	11.703*** (0.138)	11.702*** (0.078)	11.726*** (0.074)	11.699*** (0.152)
R^2	0.978	0.980	0.980	0.980	0.981	0.981	0.979	0.981	0.981
ρ							0.380	0.335	0.334
Controls: general / interview	No / No	Yes / No	Yes / Yes	No / No	Yes / No	Yes / Yes	No / No	Yes / No	Yes / Yes
# firms / # observations	386 / 2,219	386 / 2,194	383 / 2,177	386 / 2,219	386 / 2,194	383 / 2,177	386 / 2,219	386 / 2,194	383 / 2,177

Note: This table presents the estimates of the effect of management on firm production conditional on ownership under the assumption of separability between management and other productive inputs. A firm is defined as state-owned if it is under central or local governmental control. Firm size binary variables span the following range of employees: *Size2* (250;500], *Size3* (500;1,000] and *Size4* more than 1,000. The approximation point of the translog function was chosen to be the sample's median. The dependent variable is *gross output* in logs for all models. *Size* is a fixed effect indicating whether a firm had at least 500 people employed on average. Management is assumed to be constant for a firm over time as management practices are plausibly sticky. All regressions include *two-digit industry fixed effects* and *province fixed effects*. General controls and interview controls are defined as in Table III-6. Due to space constraints, estimates of industry and province fixed effects, general and interview controls factors are not shown. *Rho* (ρ) indicates the ratio of the variance of the RE to the variance of the idiosyncratic error. 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 III-17: *Effect of management quality on output conditional on ownership controlling for time varying market power – First part of table.*

Estimation method	Cobb-Douglas OLS						Translog OLS						Translog RE					
Model number	(R5–SOE–1)		(R5–SOE–2)		(R5–SOE–3)		(R5–SOE–4)		(R5–SOE–5)		(R5–SOE–6)		(R5–SOE–7)		(R5–SOE–8)		(R5–SOE–9)	
Management	**0.007**	**(0.019)**	**–0.006**	**(0.018)**	**–0.013**	**(0.019)**	**0.005**	**(0.018)**	**–0.009**	**(0.017)**	**–0.018**	**(0.019)**	**0.023**	**(0.019)**	**0.011**	**(0.019)**	**0.002**	**(0.020)**
SOE × Management	**0.072**	**(0.050)**	**0.093****	**(0.043)**	**0.102****	**(0.045)**	**0.067**	**(0.048)**	**0.094****	**(0.042)**	**0.097****	**(0.043)**	**0.023**	**(0.049)**	**0.042**	**(0.047)**	**0.045**	**(0.048)**
SOE	**–0.250***	**(0.135)**	**–0.334*****	**(0.118)**	**–0.358*****	**(0.123)**	**–0.245***	**(0.132)**	**–0.352*****	**(0.116)**	**–0.361*****	**(0.119)**	**–0.117**	**(0.131)**	**–0.194**	**(0.126)**	**–0.207**	**(0.130)**
SOE × Year 2004	0.089**	(0.038)	0.088**	(0.038)	0.086**	(0.038)	0.096**	(0.037)	0.097**	(0.038)	0.097**	(0.038)	0.078**	(0.036)	0.078**	(0.037)	0.081**	(0.037)
SOE × Year 2005	–0.004	(0.027)	0.003	(0.028)	0.001	(0.028)	0.003	(0.028)	0.012	(0.028)	0.013	(0.028)	–0.006	(0.026)	–0.002	(0.027)	0.002	(0.027)
SOE × Year 2006	0.031	(0.033)	0.046	(0.033)	0.048	(0.034)	0.022	(0.030)	0.044	(0.030)	0.048	(0.030)	0.003	(0.029)	0.020	(0.029)	0.025	(0.029)
SOE × Year 2007	0.043	(0.034)	0.057*	(0.034)	0.059*	(0.034)	0.042	(0.032)	0.058*	(0.032)	0.062*	(0.032)	0.018	(0.030)	0.029	(0.031)	0.036	(0.031)
SOE × Year 2008	0.085*	(0.044)	0.092**	(0.044)	0.090**	(0.045)	0.082**	(0.040)	0.092**	(0.041)	0.094**	(0.041)	0.054	(0.039)	0.062	(0.039)	0.067*	(0.040)
Controls: General / Interview	No / No		Yes / No		Yes / Yes		No / No		Yes / No		Yes / Yes		No / No		Yes / No		Yes / Yes	

Effect of management quality on output conditional on ownership controlling for time varying market power – Second part of table.

Estimation method	Cobb-Douglas OLS			Translog OLS			Translog RE		
Model number	(R5–SOE–1)	(R5–SOE–2)	(R5–SOE–3)	(R5–SOE–4)	(R5–SOE–5)	(R5–SOE–6)	(R5–SOE–7)	(R5–SOE–8)	(R5–SOE–9)
Capital (β_k)	0.029*** (0.008)	0.019** (0.008)	0.019** (0.008)	0.035*** (0.008)	0.026*** (0.008)	0.025*** (0.008)	0.040*** (0.009)	0.034*** (0.008)	0.034*** (0.008)
Labor (β_l)	0.047*** (0.018)	0.083*** (0.020)	0.086*** (0.021)	0.061*** (0.018)	0.100*** (0.017)	0.105*** (0.018)	0.063*** (0.016)	0.094*** (0.016)	0.098*** (0.017)
Material (β_m)	0.921*** (0.016)	0.894*** (0.017)	0.895*** (0.017)	0.909*** (0.014)	0.880*** (0.014)	0.883*** (0.014)	0.892*** (0.014)	0.870*** (0.013)	0.873*** (0.014)
Year 2004 fixed effect	–0.021 (0.016)	–0.024 (0.016)	–0.024 (0.016)	–0.026* (0.016)	–0.028* (0.016)	–0.028* (0.016)	–0.020 (0.016)	–0.022 (0.016)	–0.023 (0.016)
Year 2005 fixed effect	0.070*** (0.015)	0.067*** (0.015)	0.066*** (0.015)	0.072*** (0.015)	0.068*** (0.015)	0.068*** (0.015)	0.077*** (0.014)	0.073*** (0.014)	0.071*** (0.014)
Year 2006 fixed effect	0.094*** (0.015)	0.094*** (0.016)	0.092*** (0.016)	0.099*** (0.015)	0.099*** (0.016)	0.097*** (0.016)	0.107*** (0.015)	0.104*** (0.016)	0.102*** (0.016)
Year 2007 fixed effect	0.113*** (0.017)	0.113*** (0.017)	0.110*** (0.018)	0.123*** (0.017)	0.123*** (0.018)	0.121*** (0.018)	0.131*** (0.017)	0.128*** (0.018)	0.124*** (0.018)
Year 2008 fixed effect	0.095*** (0.019)	0.096*** (0.020)	0.096*** (0.020)	0.110*** (0.020)	0.112*** (0.020)	0.112*** (0.021)	0.119*** (0.019)	0.117*** (0.020)	0.116*** (0.020)
(β_{kk})				–0.002 (0.007)	–0.002 (0.006)	–0.004 (0.006)	0.006 (0.007)	0.006 (0.006)	0.004 (0.007)
(β_{ll})				0.090*** (0.034)	0.091*** (0.031)	0.081*** (0.030)	0.055* (0.031)	0.063** (0.029)	0.055* (0.030)
(β_{mm})				0.031* (0.017)	0.040*** (0.016)	0.039** (0.016)	0.018 (0.016)	0.031** (0.014)	0.029** (0.014)
(β_{kl})				0.017* (0.010)	0.026*** (0.009)	0.032*** (0.009)	0.014 (0.011)	0.024*** (0.009)	0.029*** (0.011)
(β_{km})				0.009 (0.008)	0.002 (0.008)	0.005 (0.007)	–0.001 (0.009)	–0.007 (0.009)	–0.005 (0.009)
(β_{lm})				–0.081*** (0.024)	–0.088*** (0.022)	–0.093*** (0.023)	–0.048** (0.021)	–0.063*** (0.019)	–0.067*** (0.020)
Constant (α_0)	0.510*** (0.111)	0.780*** (0.119)	0.683*** (0.193)	11.712*** (0.072)	11.778*** (0.068)	11.716*** (0.137)	11.698*** (0.078)	11.730*** (0.074)	11.697*** (0.151)
R^2	0.978	0.980	0.980	0.980	0.981	0.981	0.979	0.981	0.981
ρ							0.373	0.325	0.325
Controls: general / interview	No / No	Yes / No	Yes / Yes	No / No	Yes / No	Yes / Yes	No / No	Yes / No	Yes / Yes
# firms / # observations	386 / 2,219	386 / 2,194	383 / 2,177	386 / 2,219	386 / 2,194	383 / 2,177	386 / 2,219	386 / 2,194	383 / 2,177

Note: This table presents the estimates of the effect of management on firm production conditional on ownership under the assumption of separability between management and other productive inputs. A firm is defined as state-owned if it is under central or local governmental control. The approximation point of the translog function was chosen to be the sample's median. The dependent variable is *gross output* in logs for all models. Management is assumed to be constant for a firm over time as management practices are plausibly sticky. All regressions include *two-digit industry fixed effects* and *province fixed effects*. General controls and interview controls are defined as in Table III-6. Due to space constraints, estimates of industry and province fixed effects, general and interview controls are not shown. *Rho* (ρ) indicates the ratio of the variance of the RE to the variance of the idiosyncratic error. 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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