Infrastructure, Technical Efficiency, or Market-Based Reforms? Paths to Improving China's Electricity Generation Sector - PRELIMINARY AND INCOMPLETE

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Abstract

I develop an approach to measure and quantify the causes of misallocation of production in a wholesale power market. Similar to Asker *et al.* (2017), this approach leverages cost data and compares observed outcomes to aggregate efficient supply curves. In turn, I use this approach along with a novel dataset to analyze the sources of inefficiency in China's coal power market. The model is able to assess many sources: poor physical transmission infrastructure, poorly planned production markets, or low average technical efficiency. I find resolving all three sources of misallocation would significantly improve the aggregate efficiency of this market. In addition, I exploit a difference-in-differences framework in the spirit of Fabrizio *et al.* (2007) and Gao & Van Biesebroeck (2014) to resolve whether major reforms in this sector in 2002 already began a transition to market-based policies.

1 Introduction

With the increased availability of firm-level data across many countries in recent years, there has been a growing interest in measuring the aggregate losses from misallocation across productive units in different economies. An industry, sector, or economy, has a set of productive units with cost and capacity distributions, and given these distributions production is not allocated to the units that result in the lowest possible aggregate cost.

This type of measurement has generally been done in two ways. As coined in Restuccia & Rogerson (2013) and Restuccia & Rogerson (2017), there is the "direct approach", which looks at evidence of misallocation arising from specific observable sources, and the "indirect approach", which identifies misallocation as coming from distortions or "wedges" from a specific model. Similar to Asker *et al.* (2017), this paper takes a hybrid approach by estimating aggregate misallocation in a specific market, and then decomposing its potential sources. My analysis focuses on misallocation based on production costs rather than total factor productivity, which can be linked to ensuing welfare losses.

This paper deviates from other Asker *et al.* (2017) by explicitly taking the planned nature of the market in question, China's wholesale coal power market, as given. Combining a model of planner behavior and institutional details, my misallocation wedges are then deviations from a model of merit-order electricity dispatch. The advantage of modeling a specific market in-depth is that I can then more specifically pinpoint several sources of misallocation: in this case a lack of transmission infrastructure, inefficient planning objectives, and inefficient production technology. Asker *et al.* (2017) use the hybrid method to examine market power, and to my knowledge no one has used it to examine any of these other sources of misallocation in a market.

I use a variant of this method in Eisenberg (2019), but that paper focuses on the dynamic consequences of the misallocation explored in this paper. This paper complements Eisenberg (2019) by extending its static misallocation model to investigate losses from limited transmission infrastructure and low plant-level efficiency. In any exercises where I reallocate production from what planners are currently doing, I exploit a richer cost structure [1] and test alternative model specifications. The regression analysis in this paper also forms the argument for treating this sector as fully planned.

China's coal power market is an especially policy-relevant venue to study this sort of question. As of 2010, 78.7% of China's power came from coal, which is almost 40% higher than the global average Liu (2013). Aggregate efficiency improvements in this market have far-reaching welfare consequences both due to its size and China's dependence on coal.

Aggregate inefficiency most notably comes from several areas: heat rates in Chinese coal fired plants are much higher than those in the US [2], transmission infrastructure is insufficient to transport electricity from coal-rich Western provinces to Eastern population centers, and pricing and production mechanisms are largely planned rather than abiding by conventional competitive principles.

My approach to measuring these competing sources starts with an explicit model of production costs and market planner behavior. This model nests a merit-order dispatch model, and distances from this model that arise from the data are the implicit wedges that reflect misallocation. In ongoing work, I plan to expand this paper using the framework developed in Asker *et al.* (2017) to gauge the role of measurement error in quantifying misallocation.

To assess the role of planner behavior given current infrastructure and technology, I can simply switch the planner behavior to merit-order dispatch while keeping marginal costs, capacity, and market sizes identical. Similarly, I can re-run a model keeping the planner's preferences intact while changing marginal costs to reflect averages in the US, in a similar exercise to Hsieh & Klenow (2009). Finally, I vary the size of the market that planners operate over (which in reality is province-level due to infrastructure restrictions) to quantify the effect of China's limited cross-country electricity transmission capability.

[1] This is limited in Eisenberg (2019) because of the computational burden of the dynamic analysis.
[2] As established by my data and seen later in the paper.

One complicating factor to this analysis is that China has undertaken serious reforms to address some of these issues, most notably with a large restructuring effort in 2002. In addition to quantifying the outstanding sources of inefficiency in this market, I a framework from Fabrizio *et al.* (2007) and a difference-in-differences specification from Gao & Van Biesebroeck (2014) to show that this market likely remains fully planned, as any efficiency gains in response to these policy changes has been limited.

Gao & Van Biesebroeck (2014) posit that state-owned firms are more exposed to these reforms and are thus a treatment group. Their analysis relies solely on financial data (and some aggregated control variables), while I can re-run their analysis using pure physical data, which would have been their "preferred" specification. As a preview of my results, I find that the purely physical version of their analysis does not.

An advantage of studying misallocation in a coal power market is that it is relatively easy to compute plant-level carbon emissions indices. While one can approximate emissions from any kind of manufacturing output, coal use has the advantage of mapping very directly to carbon emissions. It thus becomes very easy to map cross-plant efficiency differences into cross-plant emissions differences, which will be a key point of measuring emissions in any counterfactual re-allocation of resources. Choosing this industry in particular allows for a link between development-style misallocation analyses and carbon emissions that is usually made more indirectly.

This type of analysis is doubly important because China is still rapidly industrializing: China's per-capita energy consumption is still at half that of Western Europe, and a quarter of that of the United States Liu (2013). So, even with substantial conservation efforts, there may be a need to expand China's coal generating capacity, absent major intervention elsewhere in the economy. It is important to do so as efficiently and environmentally sound as possible, to the extent that it is going to happen.

Because I am able to distinguish revenue and physical measures of marginal cost, this paper relates to a recent strain in the productivity literature. In Foster *et al.* (2008), much is made of the distinction between revenue-based and physical measures of productivity. While I am not directly measuring TFP, the main empirical literature on Chinese productivity thus far usually is unable to make this distinction due to data limitations (see, ie Brandt *et al.* (2014)).

As mentioned before, a prominent, recent study on the restructuring of electricity markets is Fabrizio *et al.* (2007). Studying the US, the authors find "modest medium-term efficiency benefits from replacing regulated monopoly with a market-based industry structure." In England and Wales, Newbery & Pollitt (1997) find modest increases in in efficiency as well, but very minor benefits for consumers. China's radically different market makes direct comparisons difficult, but these studies have established baseline empirical methods for studying this industry.

Some of the more negative effects of electricity restructuring–which may help to explain why China has continued its current regulatory regime–have been seen in California's electricity market. Papers like Borenstein *et al.* (2002) and Borenstein *et al.* (2008) have helped shed light on the various incentives in such a market and their consequences. These considerations are worth keeping in mind as China possibly moves toward this kind of market, but the best data available is only at the yearly level and is very coarse.

At any rate, even under reforms that would bring about more market competition, China likely intends to keep substantial central control over the industry Liu (2013).

Finally, the potential gains from infrastructure improvements in developing countries have been studied recently by Ryan (2014) in India. Due to data limitations my paper is forced to take a more abstract approach, and in future work I hope to be able to make more formal predictions about what market power in wholesale electricity could look like in China.

2 Industry Background

In this section I will discuss the most important institutional details and policies in the Chinese coal power market. Some measurement and modeling issues arise from the particular structure of the Chinese market, while others come from data limitations.

2.1 Nature of Production, Infrastructure

Electricity markets in general can be divided into generation, transmission, and distribution. This paper will focus on the first step in the chain, generation, where fuel is burned to create energy before it is sent to consumers. In China, the transmission lines are wholly owned by the government, so there is little in the way of vertical relationships to study in this market. There is a mix of state-owned, jointly owned, and purely private power plants in China's wholesale market (Liu *et al.*, 2013), though there is no obvious, systematic way that this status affects their production or pricing outcomes.

The most obvious issue with modeling this market is that, for all intents and purposes, this is a planned market. Government officials forecast demand and essentially assign production quantities and prices. Despite more recent moves toward market restructuring, such as those examined in Gao & Van Biesebroeck (2014), there is reason to think that market forces have not really begun to take hold. In April 2017, a report from Resources for the Future claimed that "China currently does not have a spot market for electricity" Ho *et al.* (2017). Later in this paper, I will examine empirically whether past reforms have done anything to mitigate this.

According to the RFF report, the guiding allocation principle is for each plant to have roughly the same number of operating hours, though this is selectively enforced and highly variable across provinces. Two major limitations are immediately apparent: this type of equitable distribution may be extremely inefficient from a cost minimizing perspective, and there is no reason to suspect that the province is the optimal region to plan over.

Provincial planning may be inefficient from a policy perspective, but it also introduces modeling complexity. To quote RFF: "given that generation planning is a decision at the provincial level, it should be expected that different provinces will dispatch generators differently, and this heterogeneity should be properly accounted for." The report claims that the rationale behind this type of allocation is "primarily distributional," though the model developed in this paper does not impose any explicit objective function on the provincial planners.

Incentives for plants to be efficient are limited in this context. If they cannot directly influence prices or quantities, it stands to reason that they will not make costly investments in streamlining their production processes. Similarly, plants with existing efficiency advantages are unable to exploit them due to this allocated production model. This motivates the analysis of Gao & Van Biesebroeck (2014), which this paper revisits with new data on physical production.

2.2 History and Reforms

China's current production model began in 1998. 1998 marked the start of a shift toward efficiency-focused reforms after decades of the government largely trying to increase capacity to meet power demands according to Xu & Chen (2006). The state no longer held a total monopoly over the power generation industry like it traditionally had, and now had "a market structure composed of diversified investors" Xu & Chen (2006). However, this by no means resulted in a smoothly-functioning market system. As Xu & Chen (2006) state: "The reform in the electricity industry was mainly on the governmental level, the old regulatory system did not change at all in the lower levels, which remained incompatible with both the power industry's market-oriented reform and diversified operating entities...influence from the central government was still very large and the governments, both central and regional, played an important role in the industry. A modern regulatory system was far from coming into being."

Put differently, the central, regional, and provincial governments all still played (sometimes conflicting) roles in a plant's operation. These actors often had differing political and economic objectives: a provincial head would likely care about maximizing province-level output or profits rather than ensuring a more efficient allocation of resources across a wider geographical areas. This is especially important in China, where coal resources are not evenly distributed across the country. As Xu & Chen (2006) put it: "Areas rich in primary energy deposits were far from power-load centers. However, market segmentation by administrative divisions exerted a tremendous impact upon resource allocation; power from cheap, clean energy sources were rarely distributed across provincial divides due to inter-political barriers." Only adding to these frictions is China's underdeveloped transmission apparatus, which adds a physical barrier to the existing political ones.

This suggests that improved transmission infrastructure could greatly minimize the costs associated with electricity production in China. Whether it can achieve more than improved planning/competition or improved technology is an empirical question. The Chinese government recognizes this and to this day is aggressively adding transmission lines across the country. For example, in July 2019, China launched a 2,065 mile transmission line from the western province of Xinhua to the eastern province of Anhui, meant to transmit 66 billion kilowatt-hours of electricity a year (Xu & Patton, 2019).

In 2002, several major reforms were enacted. They involved breaking up a major state-owned enterprise into five smaller companies and separating administrative functions at the federal level for transmission and generation. There was also a contemporaneous deregulation of the input (coal) market. Gao & Van Biesebroeck (2014) examine these reforms and found efficiency gains consistent with a transition to market-based forces.

I continue to treat the market as planned for two reasons: first, evidence from sources like the RFF report indicate that this is the case. Liu *et al.* (2013), writing in 2013, say that "power-generating companies...must sell their output at regulated prices that often do not cover costs." Massive financial issues arose around 2010, and in 2011 "the top five state-owned power generation groups lost more than $1.5 billion on their thermal power operations in the first quarter of 2011."

Second, with new physical production data I am able to largely nullify the findings in this paper. Thus, in addition to the misallocation analysis featured later, I present a series of reduced form exercises to argue this market remains planned.

2.3 Comparison to Other Countries

Electricity market reforms have been hotly debated for many years in countries like the US and the UK. Generally, "restructuring" refers to the divestiture of government-owned assets like generators and plants to private companies, who then compete in markets to supply electricity. Borenstein & Bushnell (2015) add that transmission needs to be independently overseen so the owners of power lines cannot gouge power generators.

Borenstein & Bushnell (2015) also write that prior to restructuring, the US' generation market was not run by government-owned entities but rather vertically integrated monopolies. However, the basic picture is similar to other countries post-restructuring in the US: "...assets transitioned from a cost-of-service regulation model, in which they were compensated based on average production cost, to a market-based pricing model, under which these assets earned a market price for the output they were able to produce."

While different regions in the US have different levels of government involvement, the academic literature (again largely summarized in Borenstein & Bushnell (2015)) has converged on the idea that, in theory, daily auctions with day-ahead contracting can mitigate market power and create a fairly competitive environment in electricity generation. The empirical evidence for this is "inconclusive" (Borenstein & Bushnell, 2015), with the largest success so far being found in nuclear generation (Davis & Wolfram, 2012).

Thus, while restructuring could bring competitive pressures into this market, increasing both plant-level technical efficiency and the efficiency of how production is allocated across plants, it is ambiguous how much it well help. In this paper, I start from the assumption that restructuring would be successful if implemented, and model what production would look like under such a system. The modeling of potential market power in a deregulated Chinese wholesale coal power market is a subject for other research, which I address in part in Eisenberg (2019).

The assumption that restructuring would work is in part due to data limitations. In many of the studies cited in Borenstein & Bushnell (2015), the authors have access to high frequency auction bid data as well as the terms of the forward contracts for electricity prices. In China, only annual production and cost data is available, which necessitates a coarser approach. I also only observe power plants rather than individual generators, so while this is among the first papers to have comprehensive physical cost data for this market, there are many sources of heterogeneity that may occur on a much smaller timescale than I observe.

Despite this, my data, which for all variables covers 1998 to 2007, can still help uncover which reforms would be most helpful. In addition to testing the effects of expanded transmission infrastructure and market-style mechanisms to determine production, I can assess what would happen if all the plants in China became more technically efficient by lowering their heat rates, a standard measure of efficiency, to be more like those in the US.

3 Data

The key dataset to this paper is a confidential survey of coal power plants conducted by the Chinese government. It covers, roughly, the universe of power plants from 1997-1998, 2000, and 2002-2011 [3]. Major variables include a plant's name, power generated, coal used, and nameplate capacity. The plant's name allows us to find locations and ownership status–the latter is extremely important for determining which plants were and are owned by the "big 5" state-run corporations, as well as plants that are owned partially by the state. The fullest version of the dataset contains 21,121 plant-year observations. From this data I can also derive a plant's "heat rate", a standard measure of efficiency calculated by dividing coal input by power output. This will be the main index I use to assess cross-plant physical efficiency levels, and the associated emissions from each plant's output in counterfactual scenarios.

A subset of these observations are then merged with the now-standard NBS census data from 1998-2007 to get financial information. This includes a plant's revenue, various accounting cost measures, material expenditures, location, state ownership status, capital stock, investment, and employment information. These variables are inconsistently kept across different years, so the sample varies depending on one's analysis (for an example, plants with non-missing revenue information are about 4,200). For these observations I can obtain output and input price indices, which will prove useful in distinguishing between financial measures of misallocation and physical ones.

My estimation requires using weather data as an instrument, which I get from the NOAA's land-based station data. Using geographical coordinates, weather stations are matched to the nearest county. For the observations that I am able to merge with the financial census, I can identify which county they are in, and thus I can get weather data at a sub-province level. Key weather variables I use are average temperature, average minimum temperature, dew point (for humidity), and visibility.

Finally, the US data used for comparison comes from the US Energy Information Administration, in EIA-767 and EIA-860. This provides a sample of 430 plants from 1998-2005.

[3]Thank you to Shanjun Li, Deyu Rao, and many others for preparing this data and allowing me to access it.

3.1 Summary Statistics

All variables (except N) are means. The summary statistics show that the market is growing both in terms of number of firms, average firm size, and production. Firms are also getting slowly more efficient over time. Note that input prices are only available through 2007.

Table 1: Means of Major Variables, 1998-2007

Year	Cap (MW)	Prod (MW)	Price (000 RMB/MWh)	Phys. Cost (000 RMB/MWh)	Heat Rate (tons/MWh)	N
1998	384.58	216.73	0.26	0.17	0.55	195
2000	422.75	239.15	0.28	0.17	0.60	193
2002	484.50	297.51	0.27	0.17	0.60	221
2003	491.99	328.71	0.29	0.19	0.55	232
2004	509.97	349.23	0.26	0.19	0.56	283
2005	549.39	361.71	0.29	0.23	0.56	292
2006	636.19	391.38	0.28	0.22	0.54	326
2007	693.14	416.70	0.31	0.25	0.53	351

Notes: Table depicts summary statistics for years 1998-2007. Physical variables are from confidential power plant survey, financial variables are from a combination of physical dataset and financial variables from annual NBS manufacturing census. One RMB is roughly .15 dollars, so the output price in 1998 of .26 000 RMB/MWh would equal about 40 dollars per MWh, while the 2007 output price would be more like 47 dollars. Figures are for sample where revenue and physical data is matched.

4 Descriptive Results

This section establishes the empirical basis for all three sources of misallocation examined in the paper: poor dispatch policy, poor transmission infrastructure, and poor average technical efficiency.

4.1 Costs and Misallocation

It may be the case that it is difficult for plants to improve their physical efficiency in a short timeframe in China. As such, it is worth considering improvements made by prioritizing different plants and allocating them more inputs based on efficiency. Asker *et al.* (2017) undertake a similar exercise. With an eye toward quantifying aggregate misallocation measures, it is necessary to estimate a cost function that captures plant-level heterogeneity and allows for us to model this kind of efficient reallocation. First we must establish the baseline that such reallocation is possbile:

Descriptive Regressions - Heat Rate, 2000

VARIABLES	(1) Utilization	(2) Utilization	(3) Utilization	(4) Utilization	(5) Utilization
Heat Rate	-0.0401	-0.00233	-0.00122	0.0541	-0.0173
	(0.0402)	(0.0401)	(0.0404)	(0.0610)	(0.0710)
Capacity	-.000032	-.00006***	-.00006***	-.0001***	-0.0001***
	(.00002)	(.00002)	(.00002)	(.00003)	(.00003)
Entry	-0.0653***	-0.0726***	-0.0722***	-0.0988***	-0.0947***
	(0.0182)	(0.0181)	(0.0183)	(0.0257)	(0.0255)
Big 5			0.00502	0.0110	0.0107
			(0.0186)	(0.0212)	(0.0209)
Output Price				-0.0380	0.121
				(0.0610)	(0.103)
Input Price					-0.174*
					(0.0914)
Constant	0.616***	0.722***	0.719***	0.835***	0.889***
	(0.0283)	(0.0639)	(0.0653)	(0.118)	(0.120)
Observations	340	340	340	149	149
R-squared	0.044	0.311	0.312	0.580	0.593

Table shows regressions relating utilization to efficiency measures for the year 2000. Columns 2 through 4 include province fixed effects. "Big 5" represents ownership by one of the large (at the time) SOE conglomerates. Heat rate is calculated by dividing coal use by output.

Given that provinces have some level of governing authority over their electric grids, and different provinces may target different mean utilizations, it is probably appropriate to weigh specifications with the fixed effects more heavily. We can see from the above table that heat rate is never significantly related to utilization–we would expect the relationship to be highly negative and significant if it were being prioritied. Note that in Eisenberg (2019), it is established that these relationships are much stronger in the US.

The sign on the entry coefficient is unsurprising–plants that have just entered are likely to operate for less of the year than incumbents. Of interest are the two price variables (output and coal). We can see that lower input prices are associated with significantly lower utilizations–it is hard to interpret this result precisely, since there are two countervailing forces at work here: Lower input prices could reflect worse quality coal inputs, which could make operating profitably more costly and lead to lower utilizations. On the other hand, lower input costs should mean a plant is operating at a lower marginal cost, which would incentivize them to have a higher utilization than their competitors. At any rate, not a single one of these specifications indicates that lower heat rates lead to higher utilizations, controlling for many salient factors.

Descriptive Regressions - MC, 2000

VARIABLES	(1) Utilization	(2) Utilization	(3) Utilization	(4) Utilization
MC	-0.169	-0.122	-0.117	-0.373*
	(0.102)	(0.0920)	(0.0933)	(0.218)
Capacity	-6.90e-05**	-0.000112***	-0.000113***	-0.000116***
	(2.90e-05)	(2.34e-05)	(2.37e-05)	(2.37e-05)
Entry	-0.0773***	-0.0997***	-0.0994***	-0.101***
	(0.0288)	(0.0254)	(0.0255)	(0.0254)
Big 5			0.00744	0.00801
			(0.0210)	(0.0209)
Output Price				0.183
				(0.141)
Constant	0.655***	0.877***	0.877***	0.874***
	(0.0286)	(0.112)	(0.112)	(0.112)
Observations	149	149	149	149
R-squared	0.085	0.581	0.581	0.587

Again, specifications starting with column 2 include province fixed effects. The story changes somewhat when we look at pure marginal cost, which is the product of a plant's heat rate and input price. Lower marginal costs are associated with higher utilizations, so in this sense more efficient plants seem to be producing more.

Descriptive Regressions - MC, 2006

VARIABLES	(1) Utilization	(2) Utilization	(3) Utilization	(4) Utilization
MC	-0.133**	-0.168***	-0.172***	-0.434***
	(0.0605)	(0.0622)	(0.0627)	(0.161)
Capacity	-5.76e-05***	-7.63e-05***	-7.42e-05***	-7.77e-05***
	(1.35e-05)	(1.38e-05)	(1.43e-05)	(1.44e-05)
Entry	-0.131***	-0.133***	-0.134***	-0.131***
	(0.0224)	(0.0232)	(0.0232)	(0.0232)
Big 5			-0.00959	-0.00666
			(0.0164)	(0.0164)
Output Price				0.238*
				(0.135)
Constant	0.738***	0.860***	0.867***	0.847***
	(0.0205)	(0.0677)	(0.0687)	(0.0694)
Observations	334	334	334	334
R-squared	0.148	0.298	0.299	0.306

In 2006, when plants faced a **more** competitive input market, this effect has all but disappeared. This suggests that output prices and/or designated production quantities are not allowing firms to leverage cost advantages they have against each other. In fact, the regulatory regime in place before the coal market was deregulated around 2002 seems to have been ensuring a more efficient allocation of inputs based on this measure.

Capacity is highly significant in all of these regressions, and the results are highly sensitive to its inclusion, suggesting it is important to look at the size distribution of plants in China, and the relative utilizations across this distribution.

4.2 Infrastructure

Some plausible metrics to examine potential gains from transmission infrastructure before applying any kind of model would be regional input prices and heat rates. This should give us a sense of how much cheaper or more efficient the western regions actually are.

Table 2: Input Prices (000 RMB/MWh) for Representative Regional Grids

Year	Northwest	North	Northeast
1998	.211	.54	0.33
2003	.26	.34	0.38
2007	.64	.45	0.44

Notes: NW includes Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Tibet. N includes Beijing, Tianjin, Hebei, Shanxi, Shandong. NE includes Liaoning, Jilin, Heilongjiang.

Table 3: Heat Rates (tons/MWh) for Representative Regional Grids

Year	Northwest	North	Northeast
1998	.58	.58	0.58
2003	.60	.60	0.55
2007	.51	.62	0.55

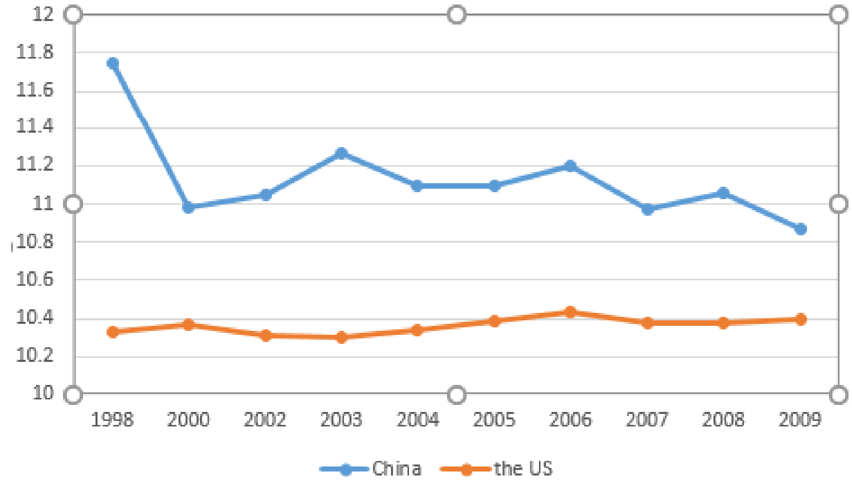
Notes: NW includes Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Tibet. N includes Beijing, Tianjin, Hebei, Shanxi, Shandong. NE includes Liaoning, Jilin, Heilongjiang.

We can see for earlier years in the sample that the western, coal rich regions are substantially cheaper, with roughly similar heat rates. By 2007 it appears that there has been a policy change that increased coal prices more in the west than it did in the east. These prices and heat rates are endogenous to how coal markets operate, so these tables do not tell the full story, but it appears that building high powered infrastructure may lead to more muted gains than the coal stores of China would initially suggest. Later in the paper I will examine this in full using plant-by-plant measures and accounting for capacity constraints.

4.3 Technical Efficiency Compared to the US

A basic comparison of US and China heat rates shows there are gains to be made in terms of pure technical efficiency:

Table 4: A Comparison of Chinese and US Heat Rates: 1998-2009



Heat rates are in MMBtu/MWh. US data comes from EIA.

This graph suggests that after 2000, there is a fairly stable relationship between US and Chinese heat rates. 2002 restructurings do not seem to have drastically improved matters, though there are many confounding factors such as entry and investment that make the story more complicated. Note that these are weighted average heat rates, so larger power plants are much more favored. The unweighted average heat rate is 14.11, compared to between 11 and 11.5 MMBtu/MWh on this graph. The largest difference, coming in 1998, suggests a potential 14% improvement in heat rates for China. Much like the other sources of misallocation, this could be substantial, but is not obviously the primary source.

5 Model

5.1 Reduced Form Efficiency Model

Gao & Van Biesebroeck (2014) borrow the cost-minimizing estimation framework from Fabrizio *et al.* (2007) to test the results of restructuring. The full derivation of their technique is available in those papers, but I will provide a basic outline of the estimation to explain my replication results.

The key identifying assumptions are that firms have a CES production function and are cost-minimizing. After some algebra, a first-order Taylor approximation, and consolidation of terms, these result in the following basic log-log models:

$$lnM_{it} = \gamma_i + \gamma_t + \gamma_1 lnQ_{it} + \varepsilon_{it}^{M} \tag{1}$$

Where M is a firm's material inputs, i indexes firms, t indexes years, and Q is a firm's output. This provides a basic regression framework to identify the effects of restructuring. The authors argue that state-owned firms were more exposed to restructuring than private ones, and thus can be thought of as a "treated" group for use in a differences-in-differences framework. While it would be ideal to combine the

DiD framework with the simple physical demand equation above, Gao & Van Biesebroeck (2014) only have access to financial data, and also have to account for missing prices:

$$lnM_{it} = \gamma_i + \gamma_t + \gamma_1 lnQ_{it} + \gamma_P X_{it} + \mu_t STATE_{0i} * Restruc_{it} + \varepsilon_{it}^M \tag{2}$$

$$lnEMP_{it} = \rho_i + \rho_t + \rho_1 lnQ_{it} + \rho_W lnWAGE_{it} + \rho_P X_{it} + \zeta_t STATE_{0i} * Restruc_{it} + \varepsilon_{it}^L \tag{3}$$

X_{it} is a set of missing price controls, including firm size, and measures like firm size interacted with province dummies. μ_t is the parameter of interest, which represents the interaction between state ownership and post-restructuring. The findings are robust to using either time fixed effects or a simple indicator variable for pre- and post- wherever time shows up in this equation, both in the original paper and my specification.

A negative sign on μ would indicate that restructuring caused firms to become more efficient. Material use would have declined in response to the policy for treated firms, holding the level of output fixed. This would represent intensive margin efficiency gains, where plants themselves became physically more efficient in response to new incentives.

This model is primarily used to assess whether the 2002 reforms were successful in deregulating the market. As explained later, I find that they were unsuccessful, and for further analysis I treat the market as planned. While this reduced form model (which is micro-founded) can help test whether plants became more efficient on the intensive margin, it does not have the structure necessary to examine how output is allocated across plants, and how much room for improvement there is in this particular measure. To do this, a measure of deviations from optimal aggregate production is necessary.

5.2 Planner Behavior Model

The bulk of the theory behind this model is derived in Eisenberg (2019), so I present an abridged version here. This model explicitly accounts for a planner's preferences and estimates their policy function for assigning production to different power plants. While this requires a strong set of assumptions, it allows me to measure how production is being allocated in China, since this particular market does not abide by any traditional competitive framework.

The basic premise of the model is that a planner who makes a continuum of small decisions about how to allocate production across each power plant can be represented by the following equation:

$$ln(\frac{q_{it}}{cap_{it}}) - ln(\frac{q_{0t}}{c_{0t}}) = \beta_0 + \mu_{it} - \beta_1 cc_{it} \tag{4}$$

Where q represents plant's allocated production, index 0 represents a normalized "fringe" firm for each (province-level) market, and cc represents a marginal cost measure for each plant. μ represents the net effect of a planner's other goals/preferences, while β_1 controls for possible unobserved cost shocks or curvature in a plant's cost function.

Capacity and production are straightforward, well defined variables in the data, but cc is slightly more complex. In Eisenberg (2019), I restrict it to be linear fuel costs, partially because this is known to account for a high portion of coal power plant costs, and partially for computational simplicity. This paper is less computationally intensive, so more complex cost measures can be use. In this model, I will explore results with just linear coal costs, coal costs and labor costs separately, and aggregate linear marginal costs (which include labor and other intermediate inputs like gas) as in Asker *et al.* (2017). Labor may be especially important in this context, as production may be misallocated partially as a way to pay high wages to workers through SOEs. The Fabrizio *et al.* (2007) and Gao & Van Biesebroeck (2014) models take labor seriously as an input, so this approach mirrors those approaches as well.

5.3 Pure Accounting Cost Model (Curvature)

The previous model requires very strict assumptions on the functional form of a plant's costs, and can only incorporate curvature through the β_1 term. In power plants and other manufacturing processes, there is often a "hockey stick" cost structure, where as plants approach their peak utilization, costs increase sharply (see, ie, Ryan (2012)).

To assess this question, I turn to the full accounting data and use a "cost of goods sold" measure, in case these hidden hockey stick costs are reflected somewhere other than pure fuel or labor costs. I specify a plant's accounting cost function the following way:

$$cost_{imt} = \phi_0 + \phi_c cap_{imt} + \phi_{1m} cc_{imt} q_{imt} + \phi_2 1(u_{imt} > \eta)(q_{imt} - \eta cap_{imt})^2 + \alpha_t + \phi_{ent} ent_{imt} + \varepsilon^a_{imt} \quad (5)$$

Observations are at the plant-year level, where i indexes a plant, m indexes a market, and t indexes a year. $cost_{imt}$ represents a firm's total operating costs, generally measured as COGS or as operating costs (the accounting system changes from year to year, and I have done my best attempt to harmonize them). ϕ_0 and $\phi_c cap_{imt}$ are meant to represent a firm's fixed costs of production. The idea is that a firm incurs some cost just to "turn on", in addition to its fuel costs. cap_{imt} represents a plant's nameplate generating capacity, and the fixed costs scale with this to account for the complexity of larger plants and units. cc_{imt}, as mentioned earlier, is a linear cost of goods sold measure.

q_{imt} is a plant's physical output, which I observe directly. Rather than setting ϕ_{1m} to 1, I estimate it. I do this for a few reasons: First, there are unobserved cost factors that, while possibly very small, may be reflected in the accounting cost measures. For the most part, these should be at least proportional to output. Second, it's possible that these costs differ by geographical location or governing authority (ie, maybe there is some unobserved transport cost in denser areas, or as you move further east). Third, letting β_1 be estimated serves as a sanity check. If it deviates too far from 1 in any province, I will know my model is likely badly misspecified.

u_{imt} is a firm's utilization, which is the ratio of their quantity produced to their nameplate capacity in mWh. It thus can take on values between 0 and 1. The ϕ_2 term is meant to represent a plant's capacity constraint, as in Ryan (2012). η represents a certain threshold beyond which a plant's total cost increases quadratically. The idea is that costs are generally linear in output, but as more and more of a plant's resources are used things become costly (like maintenance or overtime).

I include year fixed effects to capture unobserved cost trends (ie, maybe the prices of other inputs are changin). I also include an entry dummy for two reasons: First, it may be more costly to begin operations if a plant is just opening. Second, since I only observe data at the yearly level, it may be that a plant opened at some point in the middle of the year. This should lead to lower total operating costs, and this dummy helps me to capture them. It may also be the case that entrants have more advanced technology on average than incumbent firms. Thus, there is no obvious sign that the entry parameter should take.

6 Estimation

6.1 Reduced Form Efficiency Model

This model is also linear in parameters. It can be estimated using OLS or IV as well. In the original paper, the authors instrument revenues using market revenue, and I follow suit. Standard errors are also corrected for possible serial correlation.

6.2 Planner Behavior Model

As established in Eisenberg (2019), this model can be estimated using OLS or IV regression as it is linear in parameters. Which instruments are used is sensitive to the cost specification, as lags are more appropriate for some measures than others.

6.3 Accounting Costs

There are two complications here that prevent straightforward OLS. The first is that quantity decisions could easily be correlated with the error term. While TFP concerns outside of a plant's heat rate are hopefully secondary in this market, unobserved components of productivity could still hamper my estimates. Similarly, since these quantity decisions are actually made continuously throughout the year, it's possible there were some persistent shocks that plants were making their decisions with the ability to forecast in the short-term. Thus, I will resort to finding instruments to estimate this equation.

The second concern is that η is nonlinear. It cannot be estimated in a standard way, and its inference is even more complicated. To resolve this, I borrow both estimation and inference techniques from Hansen (2017). The estimation technique is fairly straightforward: pick a grid of points and run the appropriate regression model at each point, and then pick the point that minimizes the criterion function overall. If we write the regression function as a function of η, $\beta' x_t(\eta)$, the estimator can be written the following way:

$$(\hat{\beta}, \hat{\eta}) = \underset{\beta,\eta}{\arg\min} S_n(\beta, \eta) \tag{6}$$

Where S_n is the appropriate criterion function (in this case it will be a GMM estimator, discussed below).

Inference (forthcoming) is slightly more complex: "the estimates of the regression function itself are not asymptotically normal...since the regression function is a nondifferentiable function of the parameter estimates. Consequently, conventional inference methods cannot be applied to the regression function," Hansen (2017). To test for linearity and generate confidence intervals, asymptotically valid p-values can be calculated using the bootstrap to approximate the limiting distribution of the F statistic generated by comparing the models with and without the regression kink.

Because I am using instrumental variables, the criterion function will not be straightforward OLS. Determining this function will obviously require specifying which exact instruments I am using. To start, both $MC_{imt}q_{imt}$ and u_{imt} will be endogenous, so at least two instruments are necessary. Additionally, β_{1m} varies by market, so key instruments will also need to be interacted with province indicators.

To start, I am using weather variables from the NOAA as instruments. I can match them at the county level to many of my observations that are in the financial census, and the panel covers all the years necessary. The relationship between weather demand and electricity, while reasonably well understood, is not straightforward. For example. according to Hor *et al.* (2005), there is clearly a seasonal pattern in electricity demand that relates to temperature, but there is a "nonlinear dependence of demand on temperature at the hot and cold temperature extremes." They also find that including variables related to humidity in their model greatly improves their forecasts.

As a result, I choose four variables from the NOAA data: average temperature, average minimum temperature, visibility, and a humidity index (which I calculate by subtracting the dew point from the average temperature). For now I just include linear terms for all four, and I also interact each of them with province indicators. The model is thus overidentified. Eventually, I plan to do some kind of more thorough model selection procedure (maybe LASSO) to figure out the best possible functional form.

7 Parameter Results

7.1 Reduced Form Efficiency Model

7.1.1 Replication with Financial Variables

The contemporaneous revenue variable may have endoegneity issues, so I instrument it with province-level production. The results are also robust to using twice-lagged revenue, though the first stage F statistic is less than 12 in the materials equation, suggesting this is not a strong enough instrument.

Province-level production results in a first-stage F of about 20. All first-stage F's are well above 12 for the labor equations.

Table 5: Gao and von Biesebroeck Specification Using Revenues

	(1)	(2)
VARIABLES	Log Coal	Log Employment
Log Revenue	0.074	-0.2
	(0.084)	(0.13)
Log Employment	0.086	
	(0.20)	
Age	0.0002	0.0001
	(0.0002)	(0.0001)
Restruc	0.44***	-0.01
	(0.0650)	(0.0599)
Restruc x SOE	-0.207***	-0.111**
	(0.0654)	(0.0542)
Log Wage		-0.529
		(0.380)
Constant	10.01***	6.919***
	(0.935)	(1.128)
N	2,634	1,822
Plants	731	654

Notes: Revenues are instrumented using market revenues. Regressions include province fixed effects interacted with log employment and individual fixed effects.

Both the material and labor equations show that the effects of restructuring are significant. This aligns with the finding in the original paper, which means that my sample and calculations do not obviously bias any further analysis I do against this result.

7.1.2 Physical Data Regressions

The physical data allows me to do the original regressions intended in Gao & Van Biesebroeck (2014) without the confounding missing prices. While they have made efforts to control for this issue, it is entirely plausible that X_{it} did not adequately control for missing prices, and the coefficients in these regressions may still be biased.

Table 6: Gao and van Biesebroeck Specification Using Physical Data

VARIABLES	(1) Log Coal	(2) Log Emp
Log Output	0.84***	0.70**
	(0.16)	(0.29)
Restruc	0.092	-0.22***
	(0.060)	(0.074)
Restruc x SOE	-0.0054	0.077
	(0.045)	(0.079)
Log Capacity		-0.53*
		(0.28)
Constant	3.46*	4.80***
	(1.79)	(0.50)
N	2,879	2,634
Plants	739	731

Notes: Output is instrumented using market revenues. Includes plant fixed effects, but not employment interacted with province-level ones since prices no longer confound the data.

In these new regressions, there is no significant result in either equation. The point estimate for the labor equation is even moderately positive. While these are not extremely precise 0's and we cannot categorically rule out the results from the financial regressions, this casts serious doubt on the effects of restructuring. Even according to the analysis of Gao & Van Biesebroeck (2014), the physical regressions are the preferred specification.

7.1.3 Pricing Regressions

Table 7: Naive Pricing Regressions Using G+vB Independent Variables

VARIABLES	(1) Log Price	(2) Log Price	(3) Log Input Price	(4) Log Input Price
Log Output	1.18***	8.94	.496***	1.42***
	(0.19)	(6.11)	(.103)	(.38)
Restruc	-.40***	-1.89	-.158**	-.28***
	(0..36)	(1.42)	(.054)	(.11)
Restruc x SOE	.36***	1.39	.181***	.27***
	(0.087)	(0.99)	(.052)	(.09)
Log Capacity		-8.2		-1.34***
		(5.6)		(.35)
Constant	-12.8***	-.60	-6.87***	-.57
	(1.79)	(3.62)	(1.21)	(.69)
N	2,621	2,597	1,957	1,946
Plants	560	559	503	503

Notes: Output is instrumented using market revenues. Includes plant fixed effects, but not employment interacted with province-level ones since prices no longer confound the data.

These pricing regressions get at why the physical and revenue-based assessments of restructuring differ: input and (possibly separately or in turn) output prices are varying with the restructuring and treatment variables. This may be for several reasons: the restructuring policies themselves may have lead to these pricing changes, or separate deregulation in input markets merely make it look like the reforms were successful.

7.1.4 Robustness Checks

Gao & Van Biesebroeck (2014) do a large number of robustness checks to support their findings, and get consistent results across almost all of them. Given that this paper is focused on additional analysis, I have chosen only to run the physical counterparts for a select few.

As mentioned before, my results hold (as in, no significantly negative coefficients) using provincial output, lagged output, and twice-lagged output as instruments. Importantly for my analysis, they are also robust to only looking at plants that have full price data, which significantly decreases the available observations. OLS versions of the physical regressions also fail to replicate the financial efficiency findings, as does restricting the restructuring dummy to 2004 or later instead of 2002.

It is possible that a detailed event study or a similar analysis could reveal a common reason that invalidates both the original and my analyses. At any rate, the new regressions show that the case for restructuring leading to plant-level efficiency gains is ambiguous at best.

7.2 Planner Behavior Model

Current results utilize lagged cost and total investment for the five largest firms in a plant's market as instruments:

Table 8: Allocation Model Estimates of $1/\sigma$

	(1)	(2)
Estimate	1.61***	.235***
SE	(.594)	(.094)
Individual FEs	Yes	No
Year FEs	Yes	Yes
Province FEs	No	Yes
First Stage F	18.01	567
J Stat p-value	.30	.07
N	1501	1501

Notes: σ is variance of unobserved cost shocks, or the coefficient on marginal cost. $1/\sigma - - > 0$ would imply perfect merit-order dispatch. Dependent variable is log utilization minus log fringe utilization.

An estimate for σ of around .62 implies a substantial role for unobserved cost shocks. Given an average marginal cost of around .19, intra-annual demand considerations are clearly a large factor in determining which plants get allocated production. This will bear out significantly in the results comparing predictions from this model to the structural model of planner behavior.

7.2.1 Relation to Restructuring

With these estimates of planner "preferences," μ, it is possible to examine whether this residual production changed in response to restructuring. The following borrows the same DiD specification from before:

Table 9: Planner Wedge Regressions

VARIABLES	OLS	OLS	OLS	IV
Linear Marginal Cost	-.21***	-.55***	-.30*	-1.2**
	(.07)	(0.11)	(.17)	(.51)
MC x Restructuring			-.34*	
			(.18)	
Restructuring	-.02	.13***	.19***	.16***
	(.02)	(0.03)	(.04)	(.03)
Restruc x SOE	.05**	-.1**	-.10**	-.05
	(.03)	(0.04)	(.04)	(0.05)
Constant	.09***	.08***	.03	.21**
	(.02)	(.03)	(.04)	(.09)
Fixed Effects	None	Plant	Plant	Plant
N	2,090	2,090	2,090	1,498
Plants	526	526	526	428

Notes: Dependent variable is residual allocated production from planner behavioral model. Instruments include lagged marginal cost and investment behavior of largest firms in each province.

These regressions shed some light on why restructuring may not have resulted in large efficiency improvements: with plant-level fixed effects included, there is no evidence that, controlling for marginal costs, SOE plants experienced more favorable draws from regulators. If anything, 3 of the 4 specifications indicate that things may have gotten worse for them. Regressions of marginal cost on SOE and restructuring status suggest that SOE's actually improved their costs at a slower rate in response to restructuring. Thus, by available physical measures they did not become more efficient than private plants, and a better return on marginal costs may have actually hurt them. The point estimate on restructuring alone is positive, however, suggesting there was not overall cost savings in response.

8 Analysis and Counterfactuals

8.1 Reallocation via Planner Behavior Model

Overall, the cost savings per unit across the plants included in the sample is about 2.8% when considering only linear fuel costs. This is much lower than preliminary estimates from accounting-cost based measures presented later in this section, which suggests unobserved cost shocks and heterogeneity may be playing a significant role in how planners behave in China.

8.2 Reallocation via Pure Accounting Costs

Before and after restructuring, if a social planner were allowed to reshuffle inputs to meet the same production quota while minimizing costs, there would be national cost savings of at least 9% (and some years up to 15%). This is significantly larger then with the planner behavior model, suggesting unobserved shocks (or possibly regulatory preferences) may play a major role in these estimates.

8.3 Changing Market Size

If a social planner is allowed to reshuffle within regional grids, these figures jump to nearly 20%. This signals the urgent need for improved transmission infrastructure in China, and sheds light on the possible role that province-level local protectionism may be playing in this market. Merging this work with the planner behavior model is ongoing.

8.4 Improving Technology to US Levels

Like other counterfactuals, this work is ongoing.

9 Conclusion

This paper provides a first step in documenting and diagnosing the misallocation in the Chinese coal power industry. This manifests in several ways, with firms producing far from their optimums based on first-order conditions, to prices being set in such a way that aggregate production would be drastically different if they were allowed to. Optimally producing firms, by my estimates, would cause output to fall by over 50% in 2000, and rise by roughly 20% in 2005 keeping prices fixed. That many plants would like to optimally shut down in both years just accentuates how inefficient cross-plant allocation of resources were at this time. It seems clear that whatever regulatory regime was in place, both before and after restructuring, was not geared toward getting plants to produce at efficient levels, even if these estimates are also picking up many unobserved frictions.

These plant-level distortions result in aggregate inefficiency: both before and after restructuring, if a social planner were allowed to reshuffle inputs to meet the same production quota while minimizing costs, there would be national cost savings of at least 9% (and sometimes up to 15%). If a social planner is allowed to reshuffle within regional grids, these figures jump to nearly 20%. This signals the urgent need for improved transmission infrastructure in China, and sheds light on the possible role that province-level local protectionism may be playing in this market.

These results are starkly contradicted when a structural model of planner behavior that includes unobserved cost shocks is applied. Using this approach, aggregate gains from efficient reallocation fall closer to 3%. Given the conservative nature of this approach, it is likely that the actual amount falls somewhere between my two estimates.

The environmental implications of these findings are small compared to the absolute financial figures coming in to play, but savings from emissions reach almost $1 billion under some counterfactual scenarios, and up to $2.4 billion under some stronger assumptions when using only accounting costs. If we extrapolate these to the capacity growth that has happened since 2007, it is possible that these numbers are now dramatically larger.

While there are competing explanations for many of the findings in this paper (frictions, lack of enforcement, local protectionism, measurement error), it establishes a firm baseline result that the 2002 restructuring did not cause any fundamental improvements in how resources are allocated across power-plants, even if there was a general move toward lower heat rates at the time. This is in line with the many qualitative papers that suggest these reforms did not quite "take", and that many institutional changes need to be made before China would have a chance of benefitting from a Western-style deregulation [4]. So, while current policies appear to be leading to large-scale misallocation and economic losses, China's skepticism in this regard is likely warranted.

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[4] Especially given that it is unclear how much Western economies benefitted from these changes.

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