Infrastructure, Land Prices and the Environment in Developing Economies

A thesis in fulfilment of the
requirements for the degree of
Doctor of Philosophy in Economics

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Abstract

This thesis presents contributions on the economic impacts of energy infrastructure constraints and air pollution in the developing world. I begin by investigating the impact of unreliable power supply on worker reallocation in Chinese manufacturing firms. This study contributes to the literature by highlighting the causal relationships between the quality of energy infrastructure and labour market outcomes. I find that frequent power outages significantly increase the pace at which long-term workers are reallocated. The impacts on the reallocation of temporary workers are much weaker and statistically insignificant. Evidence suggests that these impacts are driven in part by firms' decreased labour demand and the relative wages of long-term workers.

In India, to cope with the poor public electricity provision problem, many enterprises install private generators. I examine whether the adoption of such private remedial infrastructure can enhance a firm's marginal profit from production capital, and consequently, increase the investment rate. Using Indian firm-level data, the key findings suggest a heterogeneous treatment effect of private generator adoption on the investment rate. That is, firms that are the least likely to install generators however would benefit the most and have a larger impact on their investment in other production capital.

Traditional energy production and use results in air pollution, which is now recognized as an increasing concern for developing countries. To evaluate the economic impact of air pollution in China, I analyze the causal association between air pollution and urban land prices using a unique land conveyance dataset. To address the endogeneity issue of air pollution, I exploit the systematic effects of the interactions between atmospheric circulation and topographical features on the dispersion of local air pollutants. Results suggest that air pollution significantly influences land prices. Each 1% increase in average annual air pollution reduces urban land prices by approximately 1.4%. These effects vary across land types: there is a large and negative effect

on residential land, but the effects on industrial or commercial land are both small and positive.

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Chapter 1

Introduction

This thesis investigates implications arising from the weakness of energy infrastructure and the air pollution problem in the developing countries. The importance of public infrastructure on economic development and productivity growth has been widely discussed in a series of papers in the academic literature in the past two decades. Public infrastructure capital, which typically includes transportation, energy, water, and communication facilities, etc., is usually measured at a highly aggregate level (Aschauer, 1989; World Bank 1994; Demetriades and Mamuneas, 2000). However, different from the earlier literature, the first two chapters of this thesis concentrate on the quality of energy infrastructure in the developing world. I investigate the economic impacts of unreliable electricity supply in China and India, two of the largest developing countries in the world, by using firm-level data from the World Bank Enterprise Survey.

Energy infrastructure is particularly crucial for the firm's productivity and industrial development (Rud, 2012). However, because of deficient investment and technology, the poor quality of energy infrastructure is still seen as one of the obstacles that hinder the growth of developing countries. The electricity sector of many developing countries has failed to provide industrial firms with reliable power. Public grid outages hit the firms frequently, mainly due to the inadequate power generation capacity and the subsequent regulation on electricity use by the authorities.

Unfortunately, the manufacturing firms' production is highly vulnerable to the unreliable power supply. Frequent halts in production can translate into significant losses for various reasons, including lost production time, machinery breakdowns, wasted raw materials, and equipment re-start costs. Previous empirical studies have shown that poor power supply reduces the firm's performance and growth (Dollar et al., 2005; Aterido et al., 2011; Rud, 2011). However, few of them investigate the potential mechanisms of these productivity effects. One major objective of this thesis is to examine the potential mechanisms through the lens of labour reallocation and firm investment. It provides an opportunity to understand how infrastructure quality ultimately influences firm performance within the context of developing countries.

In the Chapter 2, I look into the causal effect of unreliable power supply on the worker flows in China in 2004. Assessing the causal effects of electricity constraints on worker reallocation is important because it helps to provide a better understanding of how the quality of energy infrastructure influences firm performance through labour flows. To address the well-acknowledged endogeneity problem of the power constraints at the firm level, I use temperature shocks as the instrumental variables for outages, which allows me to exploit the exogenous variation in the occurrences of blackouts. I find that frequent power outages significantly increase the pace at which long-term workers are reallocated. But the impacts of outages on the reallocation of temporary workers are much weaker and statistically insignificant. Empirical evidence suggests that frequent electricity failures considerably reduce a firm's labour demand and the wages of its long-term workers. However, outages cause the average wage of temporary workers in a firm to increase slightly. In the other words, shocks from unreliable power supply are absorbed by the flexibility of temporary workers, but long-term workers respond to shocks with increased reallocation.

In response to the unreliable electricity supply, many enterprises have installed private generators to protect against the frequent outages. However, these adjustments are not without costs, due to the cost of self-generation being much higher than purchasing electricity from the public grid, there are still questions about whether the adoption of private remedial infrastructure can substitute the unreliable power supply and enhance a firm's marginal profit of production capital, and consequently, increase the investment rate. In Chapter 3, I develop a theoretical framework to demonstrate a firm's decision in adopting a generator as well as the subsequent influence on production capital investment. I then examine the theoretical implications by applying the interval propensity score matching approach to Indian firm-level data from the World Bank Enterprise Survey Database. Empirical results suggest that a poor electricity provision significantly encourages private investment in a generator. Furthermore, there is a heterogeneous treatment effect of private generator adoption on the investment rate, specifically, firms that are the least likely to install generators however would benefit the most and have a larger impact on their investment in other production capital.

Overall, the electricity constraints in many developing countries are partly driven by their consistently growing energy demand. However, the rapid growth in economic activity and energy demand has also been accompanied by severe environmental degradation. For example, in China, coal-firing accounts for over 70% of electric power generation and 80% of the industrial fuel. The heavy reliance on coal power, with a low energy efficiency, is responsible for the high level of total suspended particulates (TSP) and sulfate concentrations (Fang et al., 2009).

With increasing concern of the continuing environmental damages and the severe consequences, the Chinese government has implemented various environmental protection policies. Improved knowledge on the economic impacts of air pollution and people's willingness to pay for air quality plays an important role in the design of pollution abatement policy. In Chapter 4, I attempt to reveal the implicit price of air quality in China by associating the air pollution with urban land prices in a hedonic framework. To address the endogeneity issue of air pollution, I exploit the systematic effects of the interactions between atmospheric circulations and topographical features on the dispersion of local air pollutants. The results from the instrumental variable approach suggest that air pollution significantly influences land prices. Each 1% increase in average annual air pollution reduces urban land prices by approximately 1.4%. The effects vary across land types: there is a large and negative effect on residential land, but the effects on industrial or commercial land are both small and positive, implying that air pollution influences land prices through different mechanisms. Finally, the random coefficient model estimates present weak evidence on heterogeneous tastes for clean air and the subsequent sorting behaviour across areas.

This thesis contributes to the existing literature in several ways. First, by using unique micro-level datasets for the empirical analyse, I am able to address the potential problems arising from the use of aggregate-level data in the previous research. Second, this thesis highlights the identification strategy design in the empirical studies. I employ rigorous econometrics methods to address the well-acknowledged endogeneity problems of infrastructure quality as well as air pollution levels. Third, and perhaps most importantly, this thesis adds to a small but growing body of evidence for the economic impacts of energy infrastructure and environmental pollution within the context of developing countries. In summary, these contributions provide new insights into issues around energy provision and its impact on the economy, whether through labour markets, investment incentives or air pollution, with the potential to inform improved policy formulation.

Chapter 2

The Effects of Unreliable Power Supply on Worker Reallocation: Evidence from Chinese Manufacturing Firms

2.1 Introduction

Since the first steam-powered electric power station was established in 1882, electric power has become the backbone of industrialized countries. Making the modern energy services available and reliable in the developing world, however, can be difficult. Worldwide, approximately 1.5 billion people still lack access to electricity (Foster and Steinbuks, 2009), and there are more than 30 countries with an electrification rate under 50%.[1] Even in developing countries that have made progress in electrification, providing a reliable power supply remains highly challenging. For example, Alby et al. (2013) demonstrate that firms in South Asia experience an average of 132 electrical outages every year, followed by 61 per year in Sub-Saharan Africa, 41 per year in the

[1]Data are from the World Bank: http://data.worldbank.org/indicator/EG.ELC.ACCS.ZS

Middle East and North Africa, and 36 per year in East Asia and Pacific.[2]

The primary objective of this chapter is to investigate the causal effects of unreliable power supply on worker reallocation at the firm level in China. As an important input of production, the quality of electric power provision has been found to directly affect the firms' productivity, investment decisions and growth (Reinikka and Svensson, 2002; Dollar et al., 2005; Aterido et al., 2011; Alby et al., 2013; Rud, 2012).[3] In fact, power provision is also likely to have other impacts on labour market outcomes. On one hand, a firm constrained by electricity input tends to adjust its labour demand to maximize its profit. On the other hand, when workers' expected income is threatened by an uncertain power supply, they may voluntarily quit and search for another job. Therefore, worker reallocation, which is recognized as being closely related to firm productivity and human resources investment, may be influenced by an unreliable power supply.

Assessing the causal effects of electricity constraints on worker and job flows is important because it helps to provide a better understanding of how the quality of energy infrastructure affects firm performance through worker reallocation. Recent power shortages in China provide a good opportunity to examine the impacts of energy infrastructure. After decades of spectacular economic growth, China is hungry for electric power: the country is now the world's second largest consumer of electricity. To meet their soaring demand for power, China's energy policy calls for heavy investment in the electricity sector. For example, in 2004 and 2005, the country added nearly 117 GW of capacity. This volume of power is approximately equal to the total electrical

[2]Similar statistics on the reliability of power provision can also be found on the website of the World Bank Enterprise Survey: http://www.enterprisesurveys.org/Data/ExploreTopics/infrastructure

[3]Reinikka and Svensson (2002) find that while poor power infrastructure significantly reduces private investment, it encourages firms to invest in generators. Alby et al. (2013) take a step further and investigate how firms of different sizes and technological capabilities decide to invest in generators. Dollar et al. (2005) show that power outages are one of the most serious bottlenecks for firm productivity and profitability. Using a large set of firm-level data, Aterido et al. (2011) demonstrate the heterogeneous effects of electricity constraint on employment growth. Specifically, the authors find that a poor electricity supply tends to benefit the micro-firms and hurt the growth of small, medium, and large firms. Rud (2012) finds that electrification in India is associated with an increase in manufacturing output.

capacity of either France or Canada (IEA, 2006). Despite the significant growth of capacity, challenges remain, mainly on the electricity shortages and unreliable power supplies. In 2005, the gap between supply and demand for electricity in China was approximately 20 GW at the peak times of use.[4]

To manage energy shortages and avoid large-scale blackouts, rolling outages have been imposed by the authorities. Unfortunately, manufacturing facilities are highly vulnerable to power outages. For firms relying heavily on electric power, abrupt halts in production can translate into significant losses. These losses stem from lost production time, machinery breakdowns, wasted raw materials, and equipment re-start costs. In a 2004 investment climate survey in China, access to electrical power was ranked as the second most significant obstacle to business among 14 possible constraints.[5]

Using the conventional regression of outcome variables on the electricity outages experienced by firms is unlikely to quantify the causal impacts of unreliable power supply on worker reallocation. A large body of literature has highlighted the endogenous placement of public infrastructure.[6] Likewise, power constraints at the firm level are also subject to endogeneity problems, which are fundamentally arising from two distinct aspects. First, as the imbalanced development across different cities in China is usually associated with unequal resources of infrastructure, new start-up firms may self-select into favorable business environment. Second, even within the same location or sector, unobservable factors, including local energy policy, production technologies, and corruption, still exist. These unobservable characteristics may confound the causal effects of power failures on worker reallocation.

In this chapter, I use the instrumental variable (IV) approach as the identification strategy to correct the potential inconsistent estimation. To exploit the fact that the

[4] Data are from the State Electricity Regulatory Commission

[5] The top five business obstacles include: access to finance, electricity, workers' skills and education levels, anti-competition behaviour in other enterprises, and transport.

[6] For example, Duflo and Pande (2007) and Lipscomb et al. (2012) highlight endogeneity in constructions of dams in India and Brazil. Dinkelman (2011) and Rud (2012) emphasize the non-random placement of electrification projects in India.

electric power demand will increase in extreme weather to operate the cooling and heating system (Deschênes and Greenstone, 2011), which may trigger the blackouts because of the overloads of electrical facilities, I match the 2004 Investment Climate Survey (ICS) with detailed weather data from a weather station database. I calculate the fluctuations of numbers of days within nine different temperature categories in 2004 for all cities involved in the survey and use them as instrumental variables for the firm-reported electricity outages. Generally, firms located in cities with more extreme temperature shocks are expected to experience more blackouts. Conditional on a set of control variables, the unpredictable temperature shocks generate exogenous variation in power failures.

Empirical results show that temperature shocks strongly predict the occurrence of outages. Furthermore, IV estimates suggest that the electricity outages induce separations of long-term workers through voluntary quits and layoffs, but there is no significant effect on the hiring rates. Specifically, it is estimated that an increase of one standard deviation in outages (about 19 outages) per year can translate into an approximately 55% increase in the average annual rate of separation for long-term workers. These effect are found to be paralleled by the positive impacts on job reallocation and excess worker reallocation, which implies that the electricity constraints increase the employment volatility and yield greater reallocation of long-term workers related to match quality. However, in contrast, the impacts of outages on temporary workers are much weaker and statistically insignificant.

These findings are related to the previous research in two ways. First, the evidence of net effect on long-term worker separations is consistent with the empirical evidence for the negative effect of electricity constraints on employment growth (Aterido et al., 2011). Second, although there is no employers-employees linked data to measure the productivity of separated workers, an analysis of excess worker flows suggests that workers with higher productivity are more likely to leave when they observe the electricity constraints as a bad signal of firm performance and realize the poor matches between them and the firms. This perspective can partially explain the negative impacts of electricity outages on firm productivity (Dollar et al., 2005).

To investigate the mechanisms through which the unreliable power supply affects worker reallocation, I examine the impacts of electricity outages on a firm's labour demand and average wages. I find that the outages significantly reduce a firm's capacity utilization rate and lead to idle labour. Moreover, empirical results also show that frequent disconnections from the public grid significantly reduce the average wage of long-term workers. Specifically, every outage reduces average monthly wages by approximately 7 RMB (about 1 U.S. dollar). However, power outages have no significant effect on the average wage of temporary workers. In addition, outages also narrow the gap in wages between long-term and temporary workers within the same firm, suggesting that the wages of temporary workers probably absorb the shocks of power failures, which might otherwise be absorbed by worker reallocation.

This chapter contributes to the existing literature in several ways. First, by applying an instrumental variable approach, this study is able to address the well-acknowledged endogeneity concern on firm-level power outages.[7] Additionally, because the instrumental variables connect extreme weather shocks with unreliable power supply, it also provides important policy implications for the growth of developing countries with energy infrastructure vulnerable to global climate change. Second, and perhaps most importantly, this study adds to a growing body of evidence for the development effects of energy infrastructure by highlighting the causal relationships between the quality of energy infrastructure and labour market outcomes.[8] It provides an opportunity to understand how infrastructure quality ultimately influences firm performance within the context of developing countries.

[7]The endogeneity of unreliable power supply has been discussed by Reinikka and Svensson(2002) and Aterido et al. (2011).

[8]For example, Dinkelman (2011) finds that household electrification raises employment by releasing women from home production and enabling microenterprises. Using a county level panel data set for Brazil, Lipscomb et al. (2012) demonstrate the positive effects of electrification on housing values and human capital development.

2.2 Background

Beginning with economic reforms in 1978, the power sector in China developed rapidly to sustain a tremendous level of continued economic growth. In the late 1980s, economic growth was hindered by severe electric power shortages. To cope with the chronic power shortages, authorities initiated the constructions of numerous power plants. It was believed that strong investment in power generation would alleviate the electricity shortages in the future. However, when the 1997 Asian Financial Crisis reduced predicted growth in GDP, the estimated growth rate of electricity demand during the period of the Tenth Five Year Plan (2001 to 2005) decreased to 5%. Consequently, many new construction projects were halted to avoid an oversupply of electric power, which in fact turned out to be short sighted. In summary, underestimating the growth of demand was partly responsible for the serious power shortages of recent years (Thomson, 2005; IEA, 2006; Bai and Qian, 2010).

The half-liberalized Chinese energy market is another factor contributing to inadequate electricity production. To date, thermal plants, which rely heavily on coal resources, still account for more than 80% of the total electric capacity in China (Bai and Qian, 2010). After many years of reform, the price of coal is now driven by the market, but the price of electricity remains strictly regulated. As a result, the half-liberalized energy market and the increasing price of coal makes thermal plants less profitable. In fact, some thermal plants refuse to produce electricity when the price of coal is high. Moreover, long-term unbalanced investment in generation capacity and the grid system have turned transmission and distribution grids into new bottlenecks in the supply of reliable power (IEA, 2006). Surplus power from the provinces with rich resources cannot be transmitted easily to the other regions due to a limited capacity for transmission. In addition, the construction of local distribution grids has lagged behind rapid urbanization and growing energy demands too.

Electricity demand has soared over the past decade. To see this clearly, Figure 2.1 shows the annual growth rate of per capita electricity consumption and GDP in

China. This figure illustrates that in most years, per capita electric power consumption is growing even faster than GDP. Generally, one important cause of increased power consumption is improved living standards that allow for the use of more electrical appliances in households (particularly air conditioners and refrigerators). For example, from 1985 to 2002, the number of refrigerators increased from 17.21 to 126.4 refrigerators per 100 urban households and from 0.06 to 14.4 refrigerators per 100 rural households, while air conditioners increased from 8.09 to 108.6 per 100 households in urban areas (Hu et al., 2005). Besides, China's rapid urbanization is creating a massive energy demands in both traditional and emerging cities. Last but not least, booming heavy industries are also experiencing remarkable increases in electricity consumption. Since the early 2000s, outputs from energy intensive industries (e.g., steel, auto manufacturing, cement, and aluminium) have increased significantly, which are mainly driven by the fast growing domestic investment (Thomson, 2005; IEA, 2006).

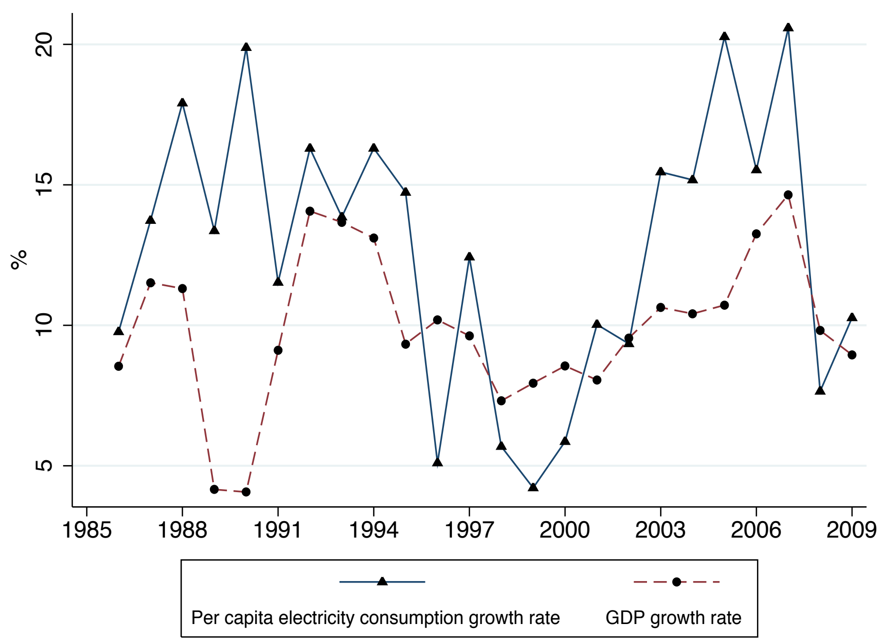


Figure 2.1: Per capita electricity consumption growth rate and GDP growth rate in China

Note: Data are from the National Bureau of Statistics in China.

The large and growing gap between power supply and demand finally resulted in an electricity crisis in the early 2000s. In response to the electricity shortages, the Chinese government has made efforts in many aspects. First, new power plants were constructed to add generating capacity, and improvements on the national grids and local distribution systems were also planned. Second, A set of demand-side management (DSM) tools, along with the ongoing step-by-step power sector reforms, were conducted by the authorities. Aiming at sustaining a more efficient economic growth and addressing power shortages, the DSM introduces mechanisms such as shifting to time-of-use pricing, adopting efficient equipment, and substituting fuels (Hu et al., 2005). Nevertheless, subject to some legal, funding, and institutional barriers, the DSM still meets a lot of difficulties.

To address immediate shortages, local authorities rely heavily on rolling blackouts. Firms are requested by the authorities to shift their work schedules. For example, many industrial firms are ordered to shut down for two days every week. It is estimated that around 70% of the peak time load reduction is achieved by this method. However, rolling outages are not without a cost. Firms that are forced to disconnect frequently from the power grid may have to turn down business opportunities and shrink the size of their business. In addition, outages also increase operational cost, particularly in industries reliant on continuous production. Finally, declines in firm performance from rolling outages may cause shifts in labour supply and demand, which subsequently influence the voluntary exit, layoff, and hiring decisions of workers and firms.

2.3 Data

The main analysis in this study uses firm-level data from the 2004 Investment Climate Survey (ICS). The 2004 ICS, which was conducted in 2005 by the National Bureau of Statistics of China, randomly selected 12,400 manufacturing firms from 120 cities and covered observations of different size, ownership and industries (see Appendix A.1

for further description of this data).[9] Compared to the other survey data, one salient advantage of this survey is that it provides rich information on different aspects of business operations, including basic firm characteristics, an evaluation of the investment climate, and labour input dynamics. More importantly, the survey data also includes a city-level location for each firm, enabling me to match this micro-level data with other data sources.

2.3.1 Unreliable power supply

Following previous studies, I use the number of electricity outages experienced by a firm as a measure of unreliable power supply. Although this approach may introduce potential measurement errors, it is still preferable to any other subjective evaluation of the quality of energy infrastructure. However, some caveats of this variable are worth to note. In the survey, firms were asked to report the average number of power outages that occurred annually over the past three years. Because there is no systematic way for firms to accurately record annual outages, the number they provide may contain noises from previous years' data as well as other measurement errors. That is, firms that experienced numerous outages in 2004 were likely to face similar electrical constraints in 2003. Therefore, the estimated impacts of outages may be biased if there are any dynamic effects of outages.

Nevertheless, these measurement errors are not of large concern in this chapter. First, the number of outages that a firm provides should be primarily influenced by the electricity provision in 2004, not only because 2004 was the most recent year to the survey time, but also because it is acknowledged that the electricity shortage in China in 2000s is initially emerging in the mid 2003 and then became one of the most severe in history in 2004 (Thomson, 2005). Second, the IV approach applied in this study can address potential measurement error in outage by isolating the variation in

[9] There were 286 cities in China in 2004. Therefore, the ICS covers more than one third of cities in China

outages that is attributable to electricity constraints in 2003. Third, the robustness check in Section 2.5 suggests that any potential dynamic effects of power outages on outcomes in subsequent years are both statistically and economically insignificant.

The average number of electricity outages experienced by firms is approximately 11.[10] The outages are fundamentally non-random and vary widely within and between regions. To illustrate the uneven distribution of electricity outages across different regions in China, Figure 2.2 shows the average number of power outages for each survey city. In general, southern cities are more likely to suffer frequent blackouts, which is partially because of the area's lack of natural resources and limited capacity for transmitting electricity between regions. Moreover, cities in more developed regions were also more likely to experienced power outages. For example, it is evident that the average outages are higher in the Yangzi River Delta, Pearl River Delta and the Bohai Economic Region. Power failures in these regions are mainly driven by massive energy demand.

2.3.2 Worker reallocation

In the analysis, workers are divided into two different groups: long-term workers and temporary workers. Long-term workers are employees who have long-term contract with their firm. Temporary workers have either a short-term contract or no formal contract at all, and they are usually hired through temporary worker agencies (Chen and Funke, 2009).[11] In the survey, firm managers were supposed to answer questions related to the flows and wages of each worker group separately. To distinguish between different forms of worker flows, I use firm-reported quit, layoff and hiring rates to

[10] In order to eliminate the impacts of outliers on estimation results, I excluded 194 observations with reported outages exceeding 100. These observations account for approximately 1.6% of the sample.

[11] Before the China's new Labour Contract Law which became effective on 1 January 2008, hiring temporary workers were prevalent. Chinese companies often employed the temporary workers through temporary work agencies (Chen and Funke, 2009).

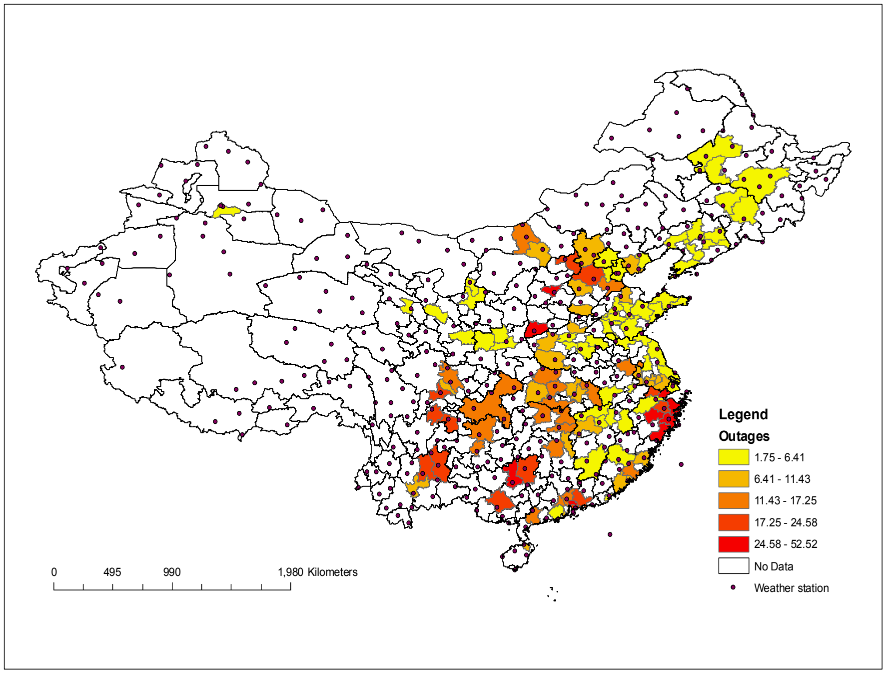


Figure 2.2: Electricity outages in China

Note: Data on the electricity outages are from the 2004 Investment Climate Survey (ICS) in China. Polygons represent different cities. Shaded area represents the 120 survey cites, where darker colour indicates more average electricity outages. 377 weather stations are projected on the map according to their coordinates provided by the Notional Oceanic and Atmospheric Administration (NOAA).

measure voluntary and involuntary worker entry and exit in a given firm i,[12] which are denoted by $quit_{ij}$, $layoff_{ij}$, and $hire_{ij}$, respectively, where j is the indicator of worker type (p for the long-term workers and t for the temporary workers).

[12] There is a translation confusion between the English questionnaire and original Chinese questionnaire on the related questions. Please see the Appendix A.2 for further details.

Variable	Description	outage < 5 (1)	$5 \leq$ outage < 10 (2)	outage ≥ 10 (3)	Total (4)
Panel A. Firms with long-term workers					
$quit_p$	quit rate of long-term workers in 2004	3.552	4.016	5.036	4.093
		(9.918)	(10.07)	(12.01)	(10.66)
$layoff_p$	layoff rate of long-term workers in 2004	2.044	2.287	2.497	2.227
		(5.507)	(6.626)	(7.541)	(6.399)
$hire_p$	hire rate of long-term workers in 2004	6.654	6.816	8.203	7.163
		(12.80)	(11.05)	(14.00)	(12.92)
$jobr_p$	job reallocation rate of long-term workers	5.696	5.838	6.831	6.073
		(12.84)	(12.37)	(15.29)	(13.58)
wr_p	worker reallocation rate of long-term workers	12.25	13.12	15.74	13.48
		(21.35)	(20.13)	(25.00)	(22.40)
ewr_p	excess worker reallocation rate of long-term workers	6.555	7.281	8.904	7.410
		(14.90)	(13.66)	(17.88)	(15.72)
pw	average wage of long-term workers in 2004	1194.5	1051.1	1012.3	1113.1
		(931.1)	(691.0)	(606.5)	(807.3)
N	number of observations	6071	2040	3649	11760
Panel B. Firms with temporary workers					
$quit_t$	quit rate of temporary workers in 2004	6.019	7.145	8.090	6.915
		(12.95)	(13.96)	(15.41)	(14.03)
$layoff_t$	layoff rate of temporary workers in 2004	2.742	3.046	3.183	2.944
		(8.421)	(8.534)	(8.675)	(8.528)
$hire_t$	hire rate of temporary workers in 2004	9.472	10.13	10.92	10.08
		(16.39)	(15.47)	(16.92)	(16.42)
$jobr_t$	job reallocation rate of temporary workers	6.679	6.587	7.274	6.862
		(14.90)	(13.69)	(15.58)	(14.93)
wr_t	worker reallocation rate of temporary workers	18.23	20.32	22.19	19.93
		(29.47)	(29.57)	(32.45)	(30.56)
ewr_t	excess worker reallocation rate of temporary workers	11.55	13.74	14.92	13.07
		(23.39)	(24.00)	(26.19)	(24.52)
tw	average wage of temporary workers in 2004	751.4	728.1	733.9	741.4
		(342.5)	(291.3)	(295.4)	(318.6)
N	number of observations	3704	1357	2555	7616

Note: Standard deviations are in parentheses. The measurement methodology for each variable is stated in the text.

Table 2.1: Descriptive statistics: worker reallocation and wage

Table 2.1 provides summary statistics for the flows rates of two worker groups. Because 4,493 firms reported having no temporary workers in their labour force, the sample size for firms with temporary workers is substantially smaller than the sample size of firms with long-term workers. In the data, long-term workers have an average quit rate of 4.09%, an average layoff rate of 2.23%, and an average hiring rate of 7.16%, which are relatively smaller than the corresponding statistics for temporary workers (6.92%, 2.94% and 10.08%, respectively). The higher flow rates of temporary workers partially reflect the fact that with a much lower human capital investment, training and firing cost, the temporary positions are typically less secure and they are of higher volatility. Additionally, the flow rates identified in this study are slightly lower than those observed in previous research on the U.S. economy (Lane et al., 1996) and a number of transition economies (Davis and Haltiwanger, 1999; Haltiwanger and Vodopivec, 2003).

To describe the rough correlation between unreliable power supply and labour outcomes, I divide the number of power outages into 3 different ranges and then summarize the flow rates in these ranges separately (see column 1 to 3 in Table 2.1). Interestingly, it is evident that firms experiencing more outages also have higher worker flow rates for both long-term and temporary workers. However, without a rigorous analysis, a causal relationship between outages and worker flows has yet to be established.

Following Haltiwanger and Vodopivec (2003), I next construct the measures of worker reallocation, job reallocation and excess worker reallocation. The first important index is the job reallocation rate. Every year, many businesses expand and others contract, changing the number of jobs available at each individual firms. This process is driven by forces such as technological and institutional change, the cost of hiring, training, and firing workers, and the general business environment. In this chapter, given the quit, layoff, and hiring rates in 2004, it is straightforward to construct the employment growth rate for worker type j in firm i is $hire_{ij} - quit_{ij} - layoff_{ij}$. A positive employment growth rate implies job creation, whereas a negative employment growth rate implies job destruction. Based on the employment growth rate, the job reallocation rate is defined as:

$$jobr_{ij} = |hire_{ij} - quit_{ij} - layoff_{ij}| \tag{2.1}$$

which measures the employment volatility of worker type j firm i. Job reallocation among firms requires workers to switch employers and employment status. Therefore, a larger worker adjustment is conducted to accommodate the job reallocation. The worker reallocation rate is simply the sum of the worker exit and entry rates, given by:

$$wr_{ij} = hire_{ij} + quit_{ij} + layoff_{ij} \tag{2.2}$$

It is important to note that the ongoing matching and sorting process of worker flows always exceed the job flows, this is because a worker may separate due to a position being terminated or because of a poor employer-employee match. In order to isolate the component of worker reallocation that is largely relevant to matching quality, the excess worker reallocation rate is constructed as:

$$ewr_{ij} = hire_{ij} + quit_{ij} + layoff_{ij} - jobr_{ij} \tag{2.3}$$

Table 2.1 presents summary statistics for job reallocation, worker reallocation and excess worker reallocation rates. Consistent with the findings on worker separations and accessions, the average worker reallocation rate of long-term workers is substantially lower than that of temporary workers. Moreover, as a measure of worker flows related to the quality of firm-worker matches, the excess worker reallocation accounts for approximately 54% of long-term worker flows. This percentage is even larger for temporary workers. Finally, it appears that job reallocation, worker reallocation and excess worker reallocation all increase as electricity constraints become more severe.

2.3.3 Firm characteristics

Table 2.2 describes an additional set of firm- and city-specific characteristics, including firm age, size, capacity utilization rate, percentage of long-term employees, ownership, workers' education level, city population, number of employees in manufacturing sector in the city, and the city's average wage.[13] Column 1, 2 and 3 present summary statistics for these variables by the severity of power failures.

There are clear monotonic trends in the mean values of several firm-specific characteristics. First, average age and size appear to decline with the number of outages: younger and smaller firms tend to face more severe power constraints. Second, as a proxy for production technology, workers' education levels are negatively related to the frequency of outages. Moreover, blackouts seem to vary with enterprise ownership. Firms that share a large proportion of private capital are more likely to face challenges in accessing a reliable power supply. In summary, all the evidence above points to the same direction that the electricity failures are evidently non-random.

One limitation of these data is the lack of information on the ownership of private generators. This deficiency may compromise the interpretation of final results because back-up generators can help to alleviate the impacts of power failures. However, using a data set from 1999 to 2004, Fisher-Vanden et al (2012) finds that only 7% of the firms in China self generate electricity. This small proportion is not expected to significantly influence the overall effects of electricity outages. The second reason is coming from an econometrics consideration, which is named 'bad control problem' by Angrist and Pischke (2009). Specifically, because generator ownership tends to be a consequence of blackouts rather than a cause of them, it is inappropriate to control for generator ownership when examining the causal impacts of electricity outages is of major interests in this chapter.

[13]Data of city population and number of employees in manufacturing sector are from China Data Online (http://chinadataonline.org/). The city's average wage is measured by the average wage of long-term workers in the same city, using data from 2004 ICS.

Variable	Description	outage < 5 (1)	$5 \leq$ outage < 10 (2)	outage ≥ 10 (3)	Total (4)
cu	capacity utilization rate in 2004	83.15	81.93	82.61	82.80
		(18.27)	(18.37)	(17.57)	(18.05)
outage	average number of electricity outages	1.691	5.953	23.12	10.92
		(1.369)	(1.228)	(17.56)	(19.92)
age	firm age	13.54	12.67	11.45	12.72
		(14.58)	(13.44)	(11.98)	(13.61)
size	firm size (measured by the number of workers in 2003)	1016.2	670.2	613.8	842.1
		(3018.2)	(2319.0)	(1483.6)	(2644.3)
percentp	% of workers are long-term workers	79.73	76.12	75.53	77.83
		(27.66)	(30.04)	(30.08)	(28.88)
steown	% owned by state capital	15.99	12.90	9.609	13.42
		(33.85)	(31.14)	(27.29)	(31.55)
colown	% owned by collective capital	9.576	7.754	7.446	8.534
		(27.37)	(24.38)	(23.84)	(25.75)
priown	% owned by private capital	34.07	41.84	43.52	38.43
		(43.38)	(45.58)	(45.45)	(44.66)
forown	% owned by foreign capital	15.08	14.12	14.18	14.61
		(31.81)	(31.40)	(31.67)	(31.69)
*educ*04	% of workers have college degree	20.44	17.72	15.46	18.35
		(18.72)	(17.31)	(16.15)	(17.79)
potn_city	population of the city (million)	5.881	5.977	5.873	5.884
		(3.681)	(4.679)	(4.808)	(4.223)
manuee_city	number of employees in manufacturing sector (million)	0.233	0.201	0.196	0.215
		(0.262)	(0.227)	(0.195)	(0.237)
N	number of observations	6268	2105	3802	12175

Table 2.2: Descriptive statistics: other variables

2.4 Identification Strategy

To examine the effects of unreliable power supply on a set of labour-related outcomes, consider the following regression:

$$y_i = \beta_0 + \beta_1 \cdot outage_i + \beta_2 \cdot X_i + \beta_3 \cdot C_i + \varepsilon_i \tag{2.4}$$

where X_i denotes a vector of firm-specific control variables and C_i represents the city-level controls. A major concern in this regression model is the omitted variable bias. That is, some unobservable firm characteristics are likely to correlate with blackout frequency, job flows, and worker flows simultaneously, making the OLS regression estimates to be inconsistent.

The identification strategy of this chapter relies on the vulnerability of power infrastructure to extreme temperatures events. Conditional on a set of covariates, the extreme temperature shocks in 2004, which are independent of the omitted variables in Equation (2.4), can provide exogenous variation in the frequency of outages and thus lead to a consistent estimates of outages' causal effects.

The electrical supply system is a complex system which typically includes power plants, transmission stations, grid lines, distribution stations, and end users. The system generally works at a balance of supply and demand. However, the reliability of power infrastructure declines significantly with extreme temperatures. The reason is that because the transformers in the transmission and distribution substations are usually designed to operate during periods of relatively stable weather and loading patterns, increased loads during periods of extreme temperatures can lead to problems with overheating: blackouts will eventually occur if transformers are unable to cool off efficiently (Kezunovic et al., 2008). If the weather in a given year is outside of the range of predicted temperatures for a designed timescale, the local power distribution system may not be able to adapt sufficiently. This was particularly true for China in the early 2000s, as the grid system was still lagged far behind rapid urban development and could not respond successfully to temperature shocks.

Therefore, it is the temperature shocks, rather than the average temperatures, trigger failures of power infrastructure. To exploit this exogenous variation in electricity outages, I construct measures of temperature shocks in 2004. First, daily temperature data are taken from the U.S. National Oceanic and Atmospheric Administration. The data covers 377 weather stations in China and provide detailed temperature data from 1995 to 2004.[14] Figure 2.2 shows station locations. The stations cover the entire area of the enterprise survey, reaching from the south (10.38 °N) to north (52.13 °N), east (75.98 °E) to west (132.96 °E), which deviate a lot in temperature distributions and hence enable this chapter to include the impacts of both extreme hot and cold weather shocks on power systems.

The key variable in the data is the maximum daily temperature. Maximum daily temperature is usually recorded by weather stations at 2 pm, which is also when peak electricity loads occur. Since the heavy snowfall on extremely cold days may interrupt the availability of other infrastructure, thereby influencing the dependent variables through other potential channels. Therefore, I exclude days with snow depth exceeding two inches. These days account for less than 1% of total observations.

Following Deschênes and Greenstone (2011), daily temperatures are divided into 9 categories as follows: $\leq 10\,°\mathrm{F}$, $(10\,°\mathrm{F}\ \ 20\,°\mathrm{F}]$, $(20\,°\mathrm{F}\ \ 30\,°\mathrm{F}]$, $(30\,°\mathrm{F}\ \ 40\,°\mathrm{F}]$, $(40\,°\mathrm{F}\ \ 50\,°\mathrm{F}]$, $(70\,°\mathrm{F}\ \ 80\,°\mathrm{F}]$, $(80\,°\mathrm{F}\ \ 90\,°\mathrm{F}]$, $(90\,°\mathrm{F}\ \ 100\,°\mathrm{F}]$, and $> 100\,°\mathrm{F}$.[15] To avoid the multicollinearity problem, categories between 50 °F and 70 °F are dropped. The annual number of days within each category from 1995 to 2003 is counted separately. Temperature shocks in 2004 are calculated as:

$$fluc_{2004}(T) = days_{2004}(T) - \sum_{k=1995}^{2003} days_k(T)/9 \tag{2.5}$$

where $days_k(T)$ denotes the number of days in the Tth temperature category in

[14] Please see the Appendix A.3 for a description of the data

[15] For example, $(10\,°\mathrm{F}\ \ 20\,°\mathrm{F}]$ indicates that $10\,°\mathrm{F} < Temperature \leq 20\,°\mathrm{F}$.

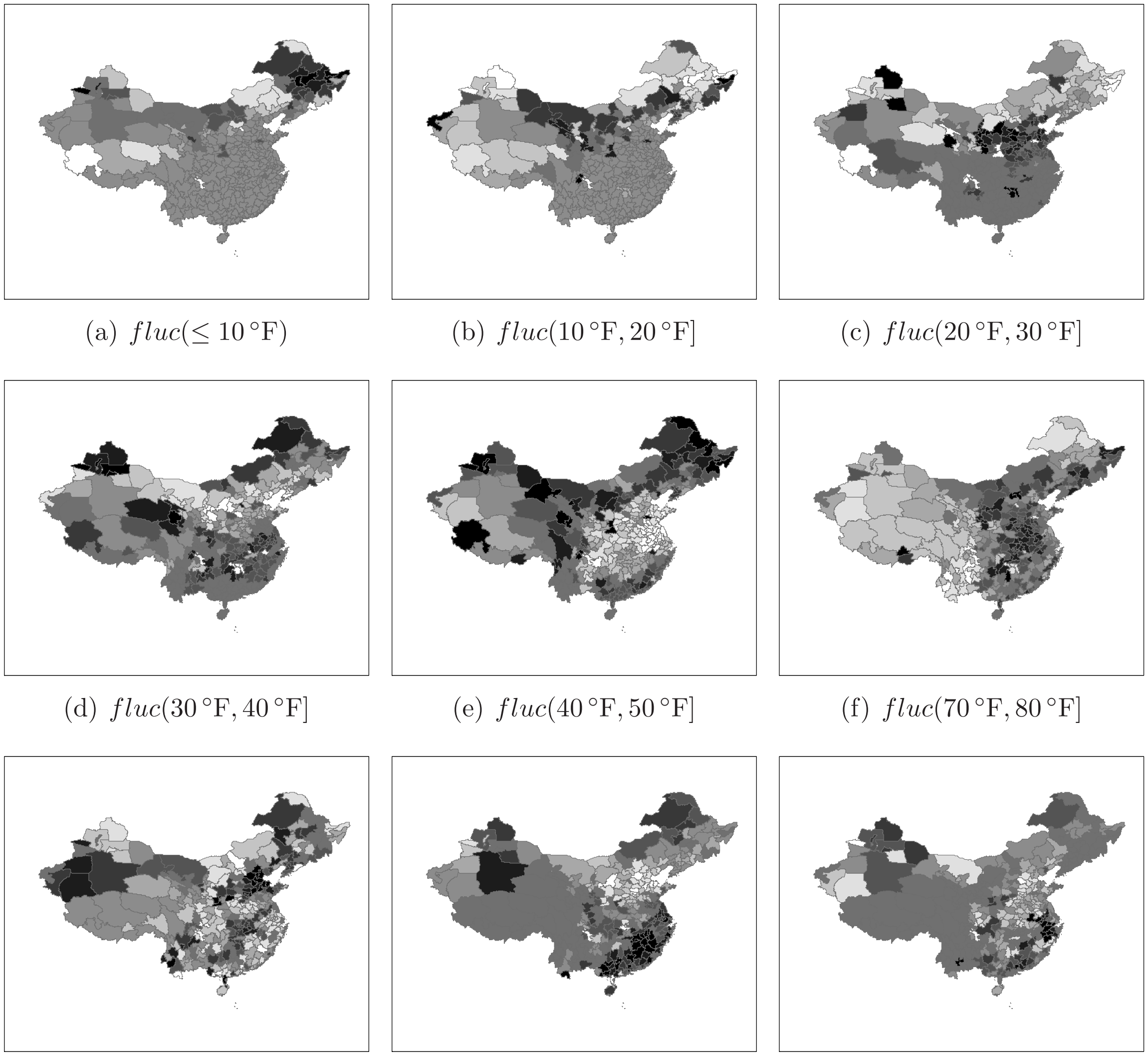
year k. Comparing to setting thresholds to define cold and hot weather (e.g., below 40 °F and above 90 °F), the advantage of calculating shocks in different temperature bins and using them as instrumental variables is clear. Because marginal effects of shocks in different temperature categories on blackouts are likely to be nonlinear, for example, the likelihood of a blackout on a 10 °F day is higher than the likelihood on a 40 °F day. dividing temperatures into bins can help capture these heterogeneous marginal effects.

Finally, temperature shocks detected by different weather stations are matched with the survey data, according to geographic location.[16] Figure 2.3 shows the distribution of temperature shocks across the 9 different temperature categories. Extremely cold weather shocks are primarily concentrated in northern China whereas extremely hot weather shocks predominantly appear in southern China.[17] However, negative and positive shocks within different temperature bins are observed at the same latitudes. Overall, the distribution of shocks is considered random and is not representative of a region's development.

A potential threat to the validity of IV estimation is the possibility of unobservable adaptive behaviour by firms and power infrastructure. Specifically, because only temperature shocks in 2004 are used as instruments in this study, it is plausible that cities exposed to the volatile temperature were actually more likely to have experienced large shocks in 2004. Shocks in a single year, therefore, partially capture the volatility of the local climate. In fact, both infrastructure and firms can adapt to the local climate. For example, cities experiencing more pronounced fluctuations between extreme temperatures may upgrade transmission and distribution systems more frequently or may install transformers with larger load capacities. Similarly, firms can also adopt adaptive technique based on the prior experience. To avoid the potential inconsistent estimation

[16] ArcGIS was used to match weather stations and cities, see the Appendix A.3 for details on matching methodology.

[17] This is because the maximum temperature in northern China rarely exceeds 100 °F, and the minimum temperature in southern China does not reach 40 °F.



(a) $fluc(\leq 10\,°\mathrm{F})$ (b) $fluc(10\,°\mathrm{F}, 20\,°\mathrm{F}]$ (c) $fluc(20\,°\mathrm{F}, 30\,°\mathrm{F}]$

(d) $fluc(30\,°\mathrm{F}, 40\,°\mathrm{F}]$ (e) $fluc(40\,°\mathrm{F}, 50\,°\mathrm{F}]$ (f) $fluc(70\,°\mathrm{F}, 80\,°\mathrm{F}]$

(g) $fluc(80\,°\mathrm{F}, 90\,°\mathrm{F}]$ (h) $fluc(90\,°\mathrm{F}, 100\,°\mathrm{F}]$ (i) $fluc(> 100\,°\mathrm{F})$

Figure 2.3: Temperature fluctuations in 2004 in China

Note: Data are from Notional Oceanic and Atmospheric Administration (NOAA). Temperature shocks in every category is calculated by Equation (2.5) and depicted in different panel above: positive shocks are shaded dark, negative shocks are shaded white, magnitude of shocks changes gradually with colour.

arising from the unobservable adaptive behaviour, I control for the standard deviation of days in each temperature bin to capture the volatility of the weather. Finally, the first stage regression specification is:

$$outages_i = \beta_0 + \sum_{T=1}^{9} \beta_T \cdot fluc_{2004}(T) + \beta_{10} \cdot X_i + \beta_{11} \cdot C_i + \sum_{T=1}^{9} \beta_{11+T} \cdot S.D_{2004}(T) + \nu_i \quad (2.6)$$

where $S.D_{2004}(T)$ denotes the standard deviations in the Tth temperature category. Conditional on a set of firm- and city-level covariates, the exclusion restriction is that the temperature shocks do not impact worker flows or job flows except through their impacts on the supply of electricity.

2.5 Results

2.5.1 Power outages occurrences

Table 2.3 presents the first stage regression results. The substantial change in results between column 1 and 2 suggests that the inclusion of standard deviation of days within each weather bins is important. Empirical findings indicate that partial effects of extreme temperature shocks are generally smaller after controlling for historical weather volatility. Across column 2 to column 4, the magnitude and significant level of the coefficients of temperature shocks do not vary considerably with the inclusion of other firm characteristics and city controls.

In the last column of Table 2.3, conditional on a full set of covariates, there is a monotonic trend of the coefficient magnitudes from $fluc(< 10\,°\mathrm{F})$ to $fluc(40\,°\mathrm{F}, 50\,°\mathrm{F}]$, indicating that cold weather shocks lead to more blackouts. Although the marginal effects of high temperature shocks do not display a similar monotonic trend, shocks above $100\,°\mathrm{F}$ still show a significant positive effect on the occurrence of blackouts. Overall, these results are consistent with the hypothesis that reliability of power infrastructure declines with extreme temperature shocks.

The coefficients of a number of other control variables are also worth noting. Interestingly, the estimated parameter on the percentage of a firm that is owned by state capital is negative, implying that state-owned enterprises have better access to reliable power. In contrast, the positive coefficient of the percentage of private capital suggests that private firms have less access to reliable electricity. Additionally, a firm's technology level is likely to affect the number of blackouts that the firm experienced. Specifically, firms that adopt the advanced technology, which is represented by a higher worker education level, have a lower likelihood of being disconnected from the public grid. This finding is reasonable because some rolling blackouts planned by local authorities explicitly target firms with lower technological level and energy efficiency.

2.5.2 Effects of outages on quit, layoff, and hiring rates

This analysis begins by examining how public power failures have affected worker flows in terms of quit, layoff, and hiring rates. Panel A and B in Table 2.4 present estimates of impacts on long-term and temporary workers, respectively. Despite the instrumental variables have shown a strong predictive power on electricity outages in the first stage regressions, the Conditional Likelihood Ratio (CLR) test, which is robust to weak instruments in over-identified models (Andrews and Stock, 2007), is also provided for IV regressions. Both the standard test and the CLR test suggest similar inference results in each regression.

In Panel A, a first observation is that without accounting for the endogeneity of electricity outages, OLS estimates substantially underestimate the impacts of outages on the quit rates and layoff rates of long-term workers. Moreover, results from 2SLS regressions suggest that outages have significant positive effects on the separations of long-term workers through quits and layoffs, but there is no significant effect on the hiring of new workers. Specifically, ceteris paribus, every additional outage increases the separation rate of long-term workers by approximately 0.175%. In other words, given that average quit and layoff rates for long-term workers are 4.093% and 2.227%, respectively, an increase of one standard deviation in outages can translate into an approximately 55% increase in the average separation rate of long-term workers. The

	(1) outage	(2) outage	(3) outage	(4) outage
$fluc(\leq 10\,°\mathrm{F})$	0.281*	1.193***	1.253***	1.214***
	(0.151)	(0.196)	(0.196)	(0.196)
$fluc(10\,°\mathrm{F}, 20\,°\mathrm{F}]$	1.070***	1.184***	1.111***	1.058***
	(0.114)	(0.125)	(0.125)	(0.130)
$fluc(20\,°\mathrm{F}, 30\,°\mathrm{F}]$	0.853***	0.527***	0.525***	0.519***
	(0.062)	(0.079)	(0.079)	(0.083)
$fluc(30\,°\mathrm{F}, 40\,°\mathrm{F}]$	0.679***	0.550***	0.572***	0.577***
	(0.033)	(0.048)	(0.048)	(0.050)
$fluc(40\,°\mathrm{F}, 50\,°\mathrm{F}]$	0.408***	0.460***	0.492***	0.497***
	(0.019)	(0.026)	(0.027)	(0.028)
$fluc(70\,°\mathrm{F}, 80\,°\mathrm{F}]$	0.065***	0.177***	0.175***	0.180***
	(0.018)	(0.021)	(0.021)	(0.021)
$fluc(80\,°\mathrm{F}, 90\,°\mathrm{F}]$	0.067***	-0.031	0.011	0.029
	(0.024)	(0.026)	(0.026)	(0.027)
$fluc(90\,°\mathrm{F}, 100\,°\mathrm{F}]$	-0.032	-0.255***	-0.243***	-0.229***
	(0.020)	(0.025)	(0.025)	(0.025)
$fluc(> 100\,°\mathrm{F})$	0.684***	0.244***	0.277***	0.337***
	(0.062)	(0.077)	(0.077)	(0.081)
age			-0.009	-0.008
			(0.010)	(0.010)
$worker03$			-0.000***	-0.000***
			(0.000)	(0.000)
$steown$			-0.015***	-0.016***
			(0.005)	(0.005)
$colown$			-0.001	-0.001
			(0.005)	(0.005)
$priown$			0.010***	0.009***
			(0.003)	(0.003)
$forown$			-0.008*	-0.007
			(0.005)	(0.005)
$educ04$			-0.055***	-0.053***
			(0.007)	(0.007)
$percentp$			-0.006	-0.005
			(0.004)	(0.004)
$potn\_city$				0.031
				(0.039)
$manuee\_city$				-0.142
				(1.184)
$wage\_city$				-0.001
				(0.001)
S.D of the temperature categories?	N	Y	Y	Y
N	12175	12175	12175	12175
R^2	0.079	0.111	0.137	0.137
F-statistic on weather fluctuations	115.30	55.33	56.88	53.22

Standard errors in parentheses
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 2.3: First stage regression

asymmetric effects of outages on worker separations and accessions subsequently result in a net destruction of long-term positions.

In contrast, results in Panel B yield different conclusions for temporary workers.

	Quit rate		Layoff rate		Hire rate	
	IV	OLS	IV	OLS	IV	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Long-term workers						
outage	0.120**	0.023***	0.055***	0.014***	0.031	0.035***
	(0.049)	(0.007)	(0.021)	(0.005)	(0.053)	(0.009)
CLR test p-value	0.000	-	0.104	-	0.801	-
S.D of the temperature categories?	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls?	Yes	Yes	Yes	Yes	Yes	Yes
City controls?	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic on IVs in first stage	52.09	-	52.09	-	52.09	-
Hansen J statistics p value	0.49	-	0.09	-	0.42	-
N	11760	11760	11760	11760	11760	11760
Panel B. Temporary workers						
outage	0.022	0.038***	-0.001	0.024**	-0.065	0.026*
	(0.085)	(0.014)	(0.037)	(0.009)	(0.077)	(0.013)
CLR test p-value	0.397	-	0.496	-	0.166	-
S.D. of the temperature categories?	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls?	Yes	Yes	Yes	Yes	Yes	Yes
City controls?	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic on IVs in first stage	33.00	-	33.00	-	33.00	-
Hansen J statistics p value	0.27	-	0.15	-	0.36	-
N	7616	7616	7616	7616	7616	7616

[1] Note: Robust standard errors clustered at city level are in parentheses. The Conditional Likelihood Ratio (CLR) test, which is robust to weak instrument in the over-identified models, is provided for the inference of endogenous variable.
[2] * Significant at the 10% level.
[3] ** Significant at the 5% level.
[2] *** Significant at the 1% level.

Table 2.4: Effects of power outages on worker flows

The point estimates in OLS specifications show positive effects of outages on separations and accessions of temporary workers. However, after correcting for endogeneity by IV estimations, the impacts of outages on temporary workers become weaker and statistically insignificant. In summary, there are heterogeneous effects of electricity constraints on the employment of long-term and temporary workers.

2.5.3 Effects of outages on worker reallocation

I now turn to an investigation of the relationship between electrical outages and worker reallocation. Based on the information of quit, layoff, and hiring rates at the firm level, the worker reallocation rate is computed by Equation (2.2), and it is then decomposed into two categories: the job reallocation rate and the excess worker reallocation rate.

Whereas the job reallocation rate represents the volatility of total employment, and the excess worker reallocation rate is primarily related to the quality of employee-firm match. Because these two rates are fundamentally different but move simultaneously, regressions using these indicators can help us understand how electricity constraints influence decisions of firms and workers.

	Job reallocation		Worker reallocation		Excess worker reallocation	
	IV	OLS	IV	OLS	IV	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Long-term workers						
outage	0.100*	0.030***	0.206**	0.072***	0.106	0.042***
	(0.056)	(0.009)	(0.090)	(0.016)	(0.066)	(0.014)
CLR test p-value	0.046	-	0.008	-	0.021	-
S.D of the temperature categories?	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls?	Yes	Yes	Yes	Yes	Yes	Yes
City controls?	Yes	Yes	Yes	Yes	Yes	Yes
Hansen J statistics p value	0.46	-	0.38	-	0.43	-
N	11760	11760	11760	11760	11760	11760
Panel B. Temporary workers						
outage	0.034	0.034**	-0.088	0.092***	-0.121	0.058***
	(0.073)	(0.014)	(0.176)	(0.027)	(0.149)	(0.020)
CLR test p-value	0.635	-	0.239	-	0.273	-
S.D of the temperature categories?	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls?	Yes	Yes	Yes	Yes	Yes	Yes
City controls?	Yes	Yes	Yes	Yes	Yes	Yes
Hansen J statistics p value	0.48	-	0.39	-	0.14	-
N	7616	7616	7616	7616	7616	7616

[1] Note: Robust standard errors clustered at city level are in parentheses. The measurement of dependent variables is defined in the text.
[2] * Significant at the 10% level.
[3] ** Significant at the 5% level.
[2] *** Significant at the 1% level.

Table 2.5: Effects of power outages on worker reallocation

Table 2.5 reports estimation results. In Panel A, as expected, the worker reallocation rate for long-term workers positively correlates with the number of electricity outages. Holding other factors constant, on average, each electrical outage results in the reallocation of about 0.2% of long-term workers. Additionally, the coefficient of *outage* in column 1 suggests that outages increase firms' employment volatility. In other words, firms adjust their total labour input in response to electricity constraints. The results of the excess worker reallocation rate regression are of particular interest here. As a measure of the reallocation that is closely tied to match-quality, the excess worker reallocation rate is found to be positively influenced by a firm's electricity constraints. Although the p-value for the standard inference from 2SLS regression is slightly higher than 0.1, the robust CLR test shows a significant effect. In summary, in the presence of observable electricity outages, a remarkable fraction of the long-term workers separate and are replaced by other workers.

The effects of blackouts on job reallocation, worker reallocation and excess worker reallocation of temporary workers are all statistically insignificant. However, despite the imprecise estimation of these impacts, the magnitudes and signs of coefficients of *outage* in different regressions are still worth noting. First, in the job reallocation rate regression, it is found that the impacts of outages on employment volatility for temporary workers are smaller than volatility impacts for long-term workers. Second, the sign of coefficient of *outage* in the excess worker reallocation rate regression is negative, implying that outages may reduce the match-quality related reallocation of temporary workers.

The evidence of outage impacts on worker reallocation in this chapter can be related to the previous literature. Dollar et al. (2005) shows that unreliable power supply lowers the level of firm productivity. Evidence presented in this section in fact can provide an explanation for that. Because electricity constraints signal negative firm performance to employees and create concern over future income, outages encourage workers to leave employers with whom they are badly matched. Although I do not have detailed information about the productivity of workers participating in the flows, it is predicted that long-term workers with high productivity and income expectations are more likely to separate. The separations of trained and skilled workers will eventually reduce firm productivity.

2.5.4 Exploring the mechanisms

Effects of outages on capacity utilization and labour demand

One important reason of the effect on firms' decisions to layoff or hire workers is that the outages directly affect business operations through idling production capital as well as labour. In addition, firms may also choose to reduce the scale of their business to avoid further losses from disputes over past due business contracts. Therefore, it is reasonable to expect that the labour demand will decrease with electricity outages.

In order to test this hypothesis, a firm's capacity utilization rate, which in part reflects a firm's labour demand, is used as the dependent variable in an IV estimation. Results in Table 2.6 show that outages have a significant negative effect on capacity utilization. Because the recent electricity shortages in China emerge initially in mid-2003 (only a year before the ICS survey), it would be difficult for firms to promptly adjust their production technology through a practice such as adopting more labour intensive technology. Therefore, without the adjustment of production technology, a decreasing capacity utilization rate will result in lower demand for labour.

	Capacity utilization rate in 2004	Manpower situation in 2004
	IV (1)	IV (2)
outage	-0.187*	0.182***
	(0.105)	(0.067)
CLR test p-value	0.004	0.006
S.D of the temperature categories?	Yes	Yes
Firm controls?	Yes	Yes
City controls?	Yes	Yes
Hansen J statistics p value	0.04	0.74
N	12175	12175

[1] Note: Robust standard errors clustered at city level are in parentheses. The manpower situation is measured by the reported percentage of surplus of workers (positive numbers), and percentage of shortage of workers (negative numbers), and with a value of zero for those firms which just sufficient number of workers.
[2] * Significant at the 10% level.
[3] ** Significant at the 5% level.
[2] *** Significant at the 1% level.

Table 2.6: Effects of power outages on capacity utilization and manpower situation

To provide complementary evidence, I construct another proxy of firm relative labour demand as the dependent variable. In the survey, managers were asked to evaluate their firm's labour situation in 2004. First, the managers reported whether their firm had adequate manpower or a surplus or shortage. Managers then applied a percentage to cases of labour surplus or shortage. The firm's labour situation in the firm was ultimately measured by this number. A value of zero is used for the firms which were of just sufficient number of workers in 2004. A positive number of this variable implies that a firm's labour supply exceeded its desirable labour demand, while a negative value indicates the opposite. IV regression results presented in column 2 of Table 2.6 suggest that electricity outages lower relative labour demand, which supports the evidence on the capacity utilization rate.

Effects of outages on wages

Many previous studies on worker and job flows suggest that the average wage, relative wage, and wage dispersion within firms are important determinants of firm and worker behaviour (Haltiwanger and Vodopivec, 2003; Parsons, 1972; Galizzi and lang, 1998). Because frequent electricity failures are found to reduce firms' capacity utilization rates and shift labour demand, it is possible that outages also affect workers' wages and wage structures.

Without employee-employer linked data, it is difficult to investigate the impacts of electricity outages on the wages of individual workers, given their personal characteristics. Instead, in this section, I will explore how electrical constraints influence the average monthly wages of long-term and temporary workers. Because of the significant income dispersion among different cities in China, I control the average long-term workers' wage of a city in the regression. The coefficient of *outage* suggests that holding the other factors constant, an additional electricity outage will reduce the average monthly income of long-term workers by approximately 7 RMB (about 1 U.S. dollar). In column 2, the significant negative effect of electrical failures on long-term workers' relative wage within the city also point to the same direction, that is, more frequent

	Long-term workers' wage		Temporary workers' wage		Within firm wage ratio
	pw	$pw/\overline{pw}_{city}$	tw	$tw/\overline{tw}_{city}$	pw/tw
	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
outage	-6.968**	-0.006***	1.855	0.002	-0.008**
	(2.711)	(0.002)	(1.658)	(0.002)	(0.003)
CLR test p-value	0.020	0.007	0.058	0.343	0.001
S.D of the temperature categories?	Yes	Yes	Yes	Yes	Yes
Firm controls?	Yes	Yes	Yes	Yes	Yes
City controls?	Yes	Yes	Yes	Yes	Yes
Hansen J statistics p value	0.37	0.31	0.06	0.06	0.41
N	11760	11760	7616	7616	7616

[1] Note: Robust standard errors clustered at city level are in parentheses. pw indicates the average monthly wage of long-term workers in a firm, while $pw/\overline{pw}_{city}$ represents the relative wage within the city. The definitions of tw and $tw/\overline{tw}_{city}$ are similar for temporary workers.
[2] * Significant at the 10% level.
[3] ** Significant at the 5% level.
[2] *** Significant at the 1% level.

Table 2.7: Effects of power outages on the wage and relative wage

electricity failures lead to a lower ranking of average wage of that firm in the city.

In contrast, estimated coefficients of *outage* in the IV regressions of temporary workers' wages and relative wages are both positive. A CLR test on the coefficient of *outage* in column 3 suggests that the positive effect of outages on the average wages of temporary workers is significant at 10% level. In the last column of Table 2.7, I use the within-firm ratio of long-term workers' wages to temporary workers' wages as the dependent variable. It is interesting to find that the number of outages decrease with the ratio. That is, increased numbers of power outages lower the wage differential between long-term and temporary workers in the same firm.

As the frequent blackouts hit the firms and reduce their capacity utilization rate as well as labour demand, the working hours and working schedule tend to be shifted. Because long-term workers are usually not as flexible as temporary workers but receive a higher wage, firms may choose to substitute temporary workers for long-term workers. Temporary workers' payment usually depends on piece-rate wages or hourly wage, allowing firms to better cope with the uncertainty of future electricity supply. Therefore, shifts in working schedules eventually reduce the wages of long-term workers and increase the wages of temporary workers slightly. As an important determinant of worker flows, the reduction of wage ultimately encourages long-term workers to separate. In fact, the flexibility of temporary workers absorbs the shocks from unreliable power supplies.

2.6 Robustness Checks

The validity of instrumental variable is a major concern of the identification strategy in this study. Because electricity shortages in China initially emerges in mid-2003 and persisted for several years, a firm that faced electrical constraints in 2004 tended to face similar constraints in 2003. This relationship, together with the design of the survey question, indicates that the number of firm-reported outages is likely to contains information on outages in 2003 as well. This measurement error is addressed by the IV approach in the main analysis. In this section, I take a further step to verify the validity of the instrumental variables used in this study.

If the variable *outage* indeed contains considerable information about outages in 2003, the data generating process of this variable, therefore, should be partially driven by temperature shocks in 2003. In order to test this, I use the temperature shocks in 2003 as instrumental variables for the number of outages. Moreover, using the temperature shocks in 2003 as IV can also estimate the potential dynamic effects of outages. Because blackouts in previous years may have lagged effects on worker reallocation, identifying these dynamic impacts is important for the interpretation of causal effects of electricity outages.

Column 1 in Table 2.8 reports the results of the first stage regression. The estimated coefficients of fluctuations within each temperature category are much smaller than those reported in the main analysis, implying that temperature shocks in 2003 have only a limited ability to predict firm-reported power outages. Across column 2 to 7, estimated coefficients of *outage* are statistically insignificant under the standard

	First stage	Long-term worker			Temporary worker		
	outage OLS (1)	Quit rate IV (2)	Layoff rate IV (3)	Hire rate IV (4)	Quit rate IV (5)	layoff rate IV (6)	Hire rate IV (7)
outage		0.049	0.050	-0.051	0.083	0.004	0.050
		(0.058)	(0.036)	(0.096)	(0.081)	(0.051)	(0.084)
CLR test p-value		0.393	0.450	0.100	0.161	0.808	0.002
$fluc_{2003}(\leq 10\,°\mathrm{F})$	1.100***						
	(0.245)						
$fluc_{2003}(10\,°\mathrm{F}, 20\,°\mathrm{F}]$	0.058						
	(0.083)						
$fluc_{2003}(20\,°\mathrm{F}, 30\,°\mathrm{F}]$	0.180***						
	(0.043)						
$fluc_{2003}(30\,°\mathrm{F}, 40\,°\mathrm{F}]$	0.007						
	(0.037)						
$fluc_{2003}(40\,°\mathrm{F}, 50\,°\mathrm{F}]$	-0.156***						
	(0.023)						
$fluc_{2003}(70\,°\mathrm{F}, 80\,°\mathrm{F}]$	0.214***						
	(0.024)						
$fluc_{2003}(80\,°\mathrm{F}, 90\,°\mathrm{F}]$	0.252***						
	(0.021)						
$fluc_{2003}(90\,°\mathrm{F}, 100\,°\mathrm{F}]$	0.213***						
	(0.025)						
$fluc_{2003}(> 100\,°\mathrm{F})$	-0.029						
	(0.034)						
S.D of the temperature categories?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City controls?	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic on IVs in first stage	-	33.64	33.64	33.64	25.62	25.62	25.62
Hansen J statistics p value	-	0.74	0.06	0.10	0.09	0.87	0.26
N	12175	11760	11760	11760	7616	7616	7616

[1] Note: Robust standard errors clustered at city level are in parentheses. $fluc_{2003}(.)$ indicates the shocks in each temperature category in 2003.
[2] * Significant at the 10% level.
[3] ** Significant at the 5% level.
[2] *** Significant at the 1% level.

Table 2.8: Robustness: Dynamic effects of outages on worker flows

inference from 2SLS regression. However, the CLR test of the effect of electricity outages on the hiring rates of temporary workers is significant at the 1% level. These results indicate that there is no lagged effect of electricity outages on workers' separations. The only exception is that the electricity shortage in 2003 may have led to an increased hiring rate of temporary workers in 2004. Similarly, the estimated lagged effects of power outages on job reallocation, worker reallocation, and excess worker reallocation in Table 2.9 are all statistically insignificant for both the long-term and temporary workers.

	Job reallocation		Worker reallocation		Excess worker reallocation	
	Long-term workers	Temporary workers	Long-term workers	Temporary workers	Long-term workers	Temporary workers
	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
outage	0.000	0.020	0.048	0.137	0.048	0.117
	(0.097)	(0.078)	(0.137)	(0.172)	(0.082)	(0.136)
CLR test p-value	0.194	0.879	0.912	0.230	0.845	0.236
S.D of the temperature categories?	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls?	Yes	Yes	Yes	Yes	Yes	Yes
City controls?	Yes	Yes	Yes	Yes	Yes	Yes
Hansen J statistics p value	0.22	0.49	0.19	0.32	0.24	0.55
N	11760	7616	11760	7616	11760	7616

Note: Robust standard errors clustered at city level are in parentheses.
* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 2.9: Robustness: Dynamic effects of outages on worker reallocation

2.7 Conclusion

Estimating the impacts of infrastructure quality on worker reallocation at a micro-level provides a new and crucial angle for understanding how infrastructure influences firms' performance. This understanding is particularly important for the policy-makers in the developing world. Using recent power outages in China as an example, this chapter provides empirical evidence for how the quality of energy infrastructure affects worker reallocation among Chinese manufacturing firms. I also explore the mechanisms through which the impacts of power outages operate.

To address the well-acknowledged problem of endogeneity in electrical outages at the firm-level, I use temperature shocks as instrumental variables of outages, which allow me to exploit the exogenous variation in the occurrences of blackouts. Estimation results from IV regressions show that frequent power outages lead to higher separation rates for long-term workers through both voluntary quits and layoffs. Outages also increase employment volatility and excess worker reallocation for long-term workers. In contrast, impacts of outages on the reallocation of temporary workers are economically and statistically insignificant. An investigation into the mechanisms underlying these effects suggests that frequent electricity failures considerably reduce a firm's labour demand and the wages of its long-term workers. However, outages cause the average wage of temporary workers in a firm to increase slightly. In other words, shocks from unreliable power supplies are absorbed by the flexibility of temporary workers; long-term workers respond to shocks with increased reallocation. The final analysis in this chapter examines potential dynamic effects of electricity outages on the outcome variables. With the exception of a positive lagged effect in which electricity outages impact hiring decisions in subsequent years, no other significant dynamic effects were observed.

The policy implications of this chapter are clear. First, it is evident that global climate change will lead to more frequent extreme weather events in the future, which will threaten already weakened energy systems in many developing countries. Without significant investment in energy infrastructure, power provision will become even more challenging in the future. Second, although rolling blackouts can partially alleviate electricity shortages, consistent unavailability of energy inputs will reduce job security, human capital investment, and firm performance through worker reallocation. As the labour market in China becomes more flexible, the effects of outages on worker flows and related business operations should also be considered by policy makers.

Chapter 3

Unreliable Power Supply, Generator Use and Investment in Indian Firms

3.1 Introduction

India has risen to be one of the fastest growing economies in recent years. However, the speed of building the necessary infrastructure (e.g. transportation, power and water facilities) is not fast enough to sustain its growth. Although the government has engaged in investing more on infrastructure construction and launching some ambitious projects, such as planning to increase the investment in infrastructure from the present 4.7 percent of GDP to around 7.5 to 8 percent of GDP in the 11th Five Year Plan from 2007 to 2011 (Prabir De, 2007), the quantity and quality of public infrastructure services are still unable to meet the rapid economic growth. The 2011-2012 Global Competitiveness Report ranks India 56th of 142 survey countries, behind China (26th), South Africa (50th) and Brazil (53rd) in the BRICS . The investment environment in India is seriously penalized for its inadequate and inefficient supply of basic infrastructure. The Indian business community continues to cite infrastructure as the biggest obstacle in doing business in the country (World Economic Forum, 2011).

In particular, the electric power supply remains a major challenge for India despite some improvement in recent years. Still, more than 6 percent of the population in the urban areas and 43 percent of the population in the rural areas lived without a connection to the public grid in 2005 (Khandker et al., 2010). The development of firms has also been hindered by the poor quality of electricity provisions. In a 2005 enterprise survey of manufacturing firms in India conducted by the World Bank, around 70 percent of the firms quoted the electricity provisions as an obstacle for business. After dividing the degree of obstacles into five grades from 0 to 4, which represent no obstacle, minor obstacle, moderate obstacle, major obstacle and very severe obstacle respectively, I find that the mean value of the electricity problem as the highest among 21 different issues, followed by high taxes, tax administration, corruption and labour regulations. Figure 3.1 depicts the evaluation of the top five obstacles from this survey.

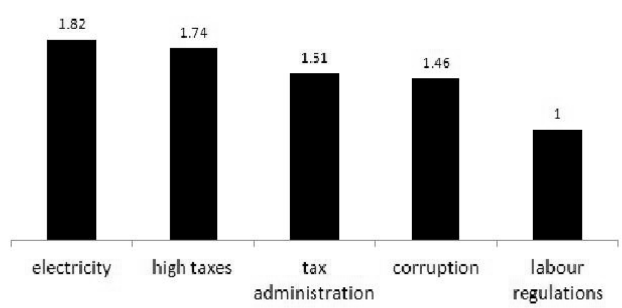


Figure 3.1: Top five obstacles for business in India in 2004

As an indicator of the unreliable power supply, the reported number of electricity outages or surges in the public grid varies greatly across firms. Figure 3.2 illustrates the distribution of the number of blackouts. On average, firms in India experienced about 95 electricity outages in 2004. Conseuqently, to contend with the poor electricity provisions, over 51 percent of the firms have invested in a private generator. However, the adoption of a self-owned generator is costly. First, on average, the fixed cost accounts for more than 5 percent of the gross book value of the machinery and equipment. Second, the electricity produced by a generator is much more expensive. It is estimated that the diesel generator typically cost two to three times as much to produce power as does electricity from the public grid. Overall, whether firms can benefit from this costly adoption still remains questionable.

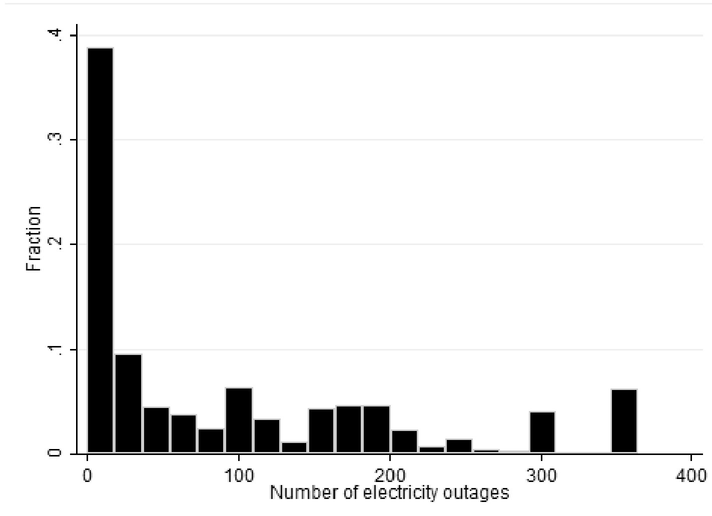


Figure 3.2: Distribution of electricity outages in India in 2004

The importance of public infrastructure on growth and investment has been widely discussed in empirical research (Berndt and Hansson, 1992; Nadiri and Mamuneas, 1994; Demetriades and Mamuneas, 2000; Aiello et al., 2010). However, few studies have been undertaken on the impact of electricity outages and in-house generation, mainly due to the lack of appropriate micro survey data. Dollar et al. (2005) and Aterido et al. (2011) use the frequency of power outages to proxy infrastructure quality, which is deemed to be an important factor in the investment climate. Initiated by Reinikka and Svensson (2002), some research has focused on the impact of public power outages as well as self-generation. Fisher-Vanden et al. (2012) finds that the enterprises in China facing electricity scarcity have learnt to adopt to more material-intensive and energy-efficient production techniques to substitute for electricity input, and they do not find evidence of an increase of in-house electricity generation. Foster and Steinbuks (2009) estimates a probit model of generator ownership by controlling a set of firm characteristic variables, such as the age, size, sector and export status, and concludes that these characteristics have a major influence on the decision to own a generator. The unreliable electricity supply, however, was not the unique or even the largest factor deriving generator ownership, moreover, Steinbuks (2011) shows that the firms with better access to credit were more likely to invest in generators. Rud (2011) takes a further step to look at the effect of adopting a power generator. He claims that the presence of a generator would increase the level of productivity needed to survive and would reallocate the sales and profits to the more productive firms, eventually, this would affect the market's equilibrium.

This chapter attempts to estimate the extent that electricity outage influences the decision of installing a generator and to investigate whether the adoption can increase investment in production capital. I first develop a two-period model to show the reaction of heterogeneous firms to unreliable electricity provisions. After setting up the profit maximization problem, I then derive the investment in production capital conditional on the adoption of a generator. Unlike previous studies, the model considers the cost of operating a generator, which adversely affects the marginal benefit of production capital. To avoid causality estimation bias due to observable controls, this chapter applies the propensity score matching method on s India's enterprise survey data for 2004. Moreover, the interval matching approach also allows me to investigate the heterogeneous treatment effect of generator adoption on the investment rate.

In summary, this chapter provides a number of unique contributions to this field of research. First, as India is a rapidly developing country but suffers severly from a poorly provisioned public service, this chapter can provide a meaningful evaluation of the consequences of electricity outages in a developing country. Second, the theoretical model in this study highlights the cost of operating a generator, which has been ignored in previous research. Third, the estimation results from the propensity score matching method have a more credible causality interpretation compared to the conventional ordinary least squares (OLS) method, which is used in other studies. Moreover, the interval matching approach allows me to investigate a the heterogeneous treatment effect of generator adoption.

The rest of the chapter is organized as follows. Section 3.2 sets out a model highlighting the decision of private investment on electricity generator and how does it influence a firm's sequential investment. Section 3.3 specifies the empirical estimation model. In Section 3.4, I make a simple data description. Section 3.5 reports the estimation results. and conclusions are provided in Section 3.6.

3.2 Theoretical Model

Reinikka and Svensson (2002) has developed a three-period model to show the influence of public capital provision quality on a firm's investment in complementary capital (e.g. a electricity generator) and productive capital. Their model illustrates that only firms which are expecting a low probability of available public capital will invest in private substitutes. Furthermore, for the firms that own substitute equipment, their investment rate will be independent of the failure of publicly provided infrastructure services, suggesting that there is a perfect substitute of private complementary capital for public infrastructure. However, for the firms that do not have private substitutes, their investment rate is reduced because of the poor public capital supply.

A salient feature of their model is that they presume a constant cost of owning and operating a generator. However, as observed from the survey data, it is costly to generate electricity privately and a larger firm usually has a higher demand for electricity. Therefore, the total running cost should be a decreasing function of the probability of available public electricity p but an increasing function of the capital stock K. Below I will relax the constant production cost assumption in a two-period model and revisit the question of how privately invested substitutes influence the investment decisions.

To simplify the analysis of the model, I assume that capital K is the only production input and that there are two decision stages for each firm. The timing of the investment is as follows. Initially, the firm perceives the probability of available public infrastructure as p, which is assumed to be realized in the next period. Then, at the end of the current period, it will decide whether or not to invest in a generator to contend with the unreliable public power supply. The fixed cost of a generator is a linear function of the capital stock and is represented as $g \cdot K_i$. In period 2, the firm will decide how much to invest to maximize its production profits. The investment rate is denoted as I and the marginal cost of capital is constant at r. For the firms with a private generator, they can ensure a full capacity production. Their production function $\phi_i \cdot (K_i + I \cdot K_i)^{\alpha}$ is a concave function of the capital input $(\alpha < 1)$, where ϕ_i represents the varying firm's productivity. However, for the firms that do not own a generator, the production output depends partly on the public power supply in a Cobb-Douglas functional form of $\phi_i \cdot p_i^{\beta} \cdot (K_i + I \cdot K_i)^{\alpha}$.

An important setting of the model is the variable electricity cost. Here, I assume that the electricity consumption per unit of production capital is a constant m. In addition, the prices of electricity from the public grid and the in-house generator are P_0 and P_1 respectively, with $P_0 < P_1$. Therefore the corresponding variable costs for a firm that owns a generator and a firm that does not are equal to $(p \cdot P_0 + (1-p) \cdot P_1) \cdot m \cdot (K + I_1 \cdot K)$ and $p \cdot P_0 \cdot m \cdot (K + I_0 \cdot K)$, respectively. The discount factor in this two-period model is assumed to be 1. Consequently, the profit maximization problem of a firm with a generator can be formally stated as:

$$\max_{i_{1i}} \pi_{1i} = \phi_i \cdot (K_i + I_{1i} \cdot K_i)^{\alpha} - (p \cdot P_{0i} + (1-p) \cdot P_{1i}) \cdot m \cdot (K_i + I_{1i} \cdot K_i) - r \cdot (K_i + I_{1i} \cdot K_i) - g \cdot K_i \tag{3.1}$$

In contrast, for a firm without a generator, it is:

$$\max_{i_{0i}} \pi_{0i} = \phi_i \cdot p_i^{\beta} \cdot (K_i + I_{0i} \cdot K_i)^{\alpha} - p_i \cdot P_{0i} \cdot m \cdot (K_i + I_{0i} \cdot K_i) - r \cdot (K_i + I_{0i} \cdot K_i) \tag{3.2}$$

The optimal investment rates following the first order condition of these two problem are denoted as $I_{1i}^{*}(p_i, K_i)$ and $I_{0i}^{*}(p_i, K_i)$. the main results of the theoretical model analysis are summarized in the two propositions below.

Proposition 3.1. Given the capital stock K, the probability of investing in a generator is decreasing with the availability of public capital.

Proof. See Appendix B.1 .

Proposition 3.2. Under certain conditions, it can be predicted that the effect of adopting a generator on the investment rate decreases with a firm's size but increases with the availability of a public power supply.

Proof. See Appendix B.2 .

Firstly, in proposition 3.2, it indicates that due to a concave production function, the marginal output of capital and the marginal benefit of investment decreases. Thus, a firm's size affects the optimal investment rate adversely. Given a low availability of public power, a larger firm without a generator needs to invest more to compensate for the loss of production. Hence, the treatment effect of geenrator adoption on ivnestment rate will decrease with the firm size. Secondly, given a firm's capital stock, the impact on available public capital differs between a firm with a generator and a firm without one. For the firms that have installed a generator, although they can ensure a full capacity production, their average production cost increases with the frequency of electricity outages, which will reduce the marginal benefit of the production capital and, consequently, reduce the investment rate. On the other hand, for the firms without a back-up generator, as their output is determined by both the available public electricity supply and private capital stock, one possible way to cope with the unreliable electricity supply is to invest more on the production capital to compensate for the loss during the blackouts. Therefore, the investment rate will increase with the failure of the public electricity sector under some conditions. In order to illustrate the aforementioned results explicitly, Figure 3.3 and Figure 3.4 provide a numerical example of the model.[1]

[1] The numerical example is based on the following assumptions: $p_i = 13.3$, $p_0 = 5.97$, $m = 0.07$, $\alpha = 0.75$, $\phi = 16.28$, and $\beta = 0.02$. These parameters come from the simple regression using the dataset that mentioned below. Admittedly there may be some estimation bias by the naive regression, and the theoretical model is too simple to calculate the true investment rate. However, it should be stressed that the objective of this graph illustration is not to predict the investment rate but to reveal

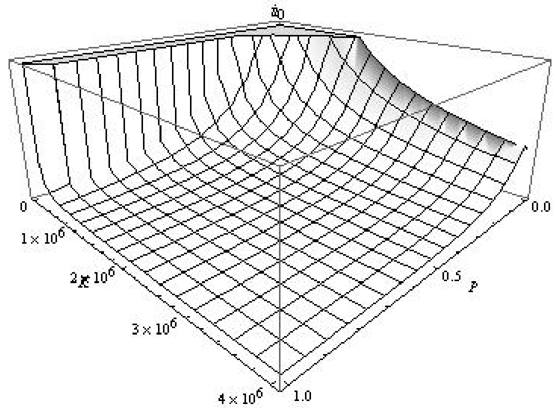


Figure 3.3: Investment rate for a firm without a generator

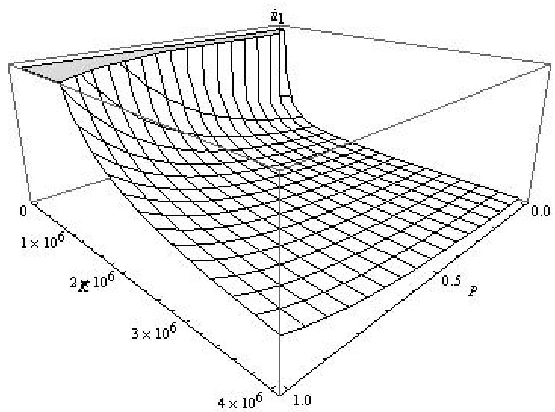


Figure 3.4: Investment rate for a firm with a generator

3.3 Empirical Model Specification

To test the theoretical model predictions laid out above, I use India's firm-level data compiled from the 2004 World Bank Enterprise Surveys. As the firms differ only in terms of the initial capital stock and the quality of the public power supply in the theoretical model, the other characteristics should be controlled to avoid the potential for omitted variable bias. Below, I will make a detailed empirical model specification.

Proposition 3.1 predicts that a firm is likely to invest in a generator if it perceives

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the change of it with respect to the capital and the quality of the public electricity supply.

a lower quality of public power supply. In order to test this hypothesis, I follow the binary choice model used in Reinikka and Svensson (2002). Let the binary variable indicate the firm's choice of installing the private substitutes, where 1 means installed a generator and 0 otherwise. In proposition 3.1, I show that one of the most important determining factors in the decision to purchase a generator is the quality of the public electricity supply, which can be proxied by the frequency of electricity outages in a typical year. Although there is no clear justification of what other firm characteristics should be included, failure to control the important variables might lead to an omitted variable bias problem. For this reason, I follow Reinikka and Svensson (2002) and Steinbuks and Foster (2010) to include the size (proxied by the total employment), the age, a dummy variable indicating whether the firm is an exporter or not, and the credit constraint into the estimation model. Therefore, the empirical model can be expressed as:

$$Generator_i = \alpha_0 + \beta_1 Outage_i + \beta_2 Worker_i + \beta_3 Age_i + \beta_4 Exporter_i + \beta_5 Credit\_con_i + \varepsilon_i \tag{3.3}$$

The reason for including a firm's size as a control variable comes from the existing empirical evidence that a larger firm is more likely to afford the investment of a generator. It is also plausible to control the credit constraints as one of the determinants since a firm facing less financial constraints would have a greater possibility to purchase a back-up generator when there is a deficient electricity supply (Steinbuks, 2011; Alby et al., 2011). In addition, exporters may need to be able to generate their own power in order to meet the International Organization for Standardization (ISO) standards (Steinbuks and Foster, 2010). However, the effect of age is more ambiguous. On one hand, an older firm might have installed a generator many years ago, but on the other hand, a mature firm might have also learnt how to deal with electricity outages through other methods, such as adopting more energy efficiency techniques (Reinikka and Svensson, 2002), which influence the probability of owning a generator adversely.

Proposition 3.2 summarizes the different effects of a private generator on the investment rate under certain conditions. The investment rates are influenced by the initial capital stock together with the frequency of electricity outages. Unfortunately, there is no information on the firms' start-up capital in the data. In addition, it is inappropriate to control the current capital stock owing to the 'bad control' problem (Angrist and Pischke, 2009). Specifically, because the adoption of a generator is expected to affect the investment rate, which will in turn affect the current capital stock, including the current capital stock and the generator indicator simultaneously in the equation will lead to a bias casual interpretation of the effects of a generator. To avoid this 'bad control' problem, I should only control variables caused by the adoption of a generator or variables that are predetermined. The number of workers serves as a good candidate to proxy a firm's size as it is relatively stable and controlled by other factors, such as the strict labour regulations in India. Meanwhile, the same set of independent variables as in Equation (3.3) are also included. Finally, the estimation model is specified as follows:

$$Inv_i = \alpha_0 + \beta_0 Generator_i + \beta_1 Outage_i + \beta_2 Worker_i + \beta_3 Age_i + \beta_4 Exporter_i + \beta_5 Credit\_con_i + \varepsilon_i \tag{3.4}$$

Following Reinikka and Svensson (2002), the dependent variable is the investment rate in the 2004 fiscal year, measured by the share of investment in machinery and equipment (excluding generators) in 2004 over the capital stock in 2003.

3.4 Data

This study uses a comprehensive firm-level dataset from Enterprises Survey (ES) to examine the theoretical propositions above. The survey was initially conducted by the World Bank in 2002 and covers more than 120,000 firms from 125 countries. It contains extensive information about the firms' performance as well as a broad range of aspects of the investment climate faced by the firms, such as infrastructure, finance, crime, corruption and competition. The data from India used in this study was collected in 2005 and covers 2286 establishments across 64 cities and 22 industries. It provides detailed information on the ownership of generators and electricity outages. Thus, it allows me to investigate the impact of public electricity provision failures on private generator adoption decisions as well as the subsequent effect on investment. In order to examine the heterogeneous treatment effects of generator adoption by applying the interval propensity matching approach, I use multi-industries data, containing firms from six major industries in India. Even though I control the industry dummies in computing the propensity score and test the balance property of each covariate, only industries with more than 80 observations are selected in the multi-industries sample to minimize the potential mismatch problem. Only 887 firms from the following 6 industries are included: garments, textiles, machinery, auto components, food processing, and structural metals. The advantage of using a multi-industries sample is the larger sample size and hence a better within-stratum balancing performance for more strata. Besides, there will be a more general interpretation of the treatment effect of generator adoption on investments for the Indian industries. In the sensitivity analysis section, I restrict the sample to 334 garment and textile firms to check for robustness, which makes the estimation results are affected by little industrial heterogeneity.

I have shown in the theoretical model that the decisions of adopting a generator and production capital investment depend on the probability of the available public electricity supply p. However, since this probability cannot be observed directly, I thus alternatively utilize the number of electricity outages in 2004 as a proxy for $1-p$ in the empirical estimation. The reported number of electricity outages in the dataset ranges from 0 to 7355. Approximate 4 percent of the sample reported a number over 365, which is extremely high compared to the mean value of 125. To avoid the estimation bias due to these potential outliers, I censor the number at 365 by assuming that the average maximum number of electricity blackout is one per day. After doing this, the average number for the whole sample is 118. Table 3.1 presents the definition and summary statistics of each variable for the sample of six selected industries.

Variable	Description	Mean	S.D
Inv	Investment rate	0.034	0.114
Outage	Number of reported electricity outages	118.277	113.595
Generator	Owning a private generator or not: 1 yes, 0 no	0.571	0.495
Worker	Number of workers	82.696	256.738
Age	Age of the establishment	16.618	11.362
Exporter	Export or not: 1 yes, 0 no	0.231	0.421
Credit_con	Percentage of inputs bought on credit	74.003	19.316
Observations	887		

Table 3.1: Summary statistics for the variables

The dependent variable is the investment rate, measured by the investment in machinery and equipment in 2004 over the total assets in 2003. For the entire sample, the magnitude of the investment rate ranges from 0 to 1 with a mean value of 0.034. The mean value of the reported number of electricity outages is 118. Over 50 percent of the firms reported ownership of a private generator. However, the ownership of a generator in the garment and textile industries is around 68 percent, much higher than most of the other industries, partly reflecting the fact that the garment and textile industries rely heavily on the electricity supply. The average number of workers also varies greatly across industries. The average size of the firms in the six major industries is about 82 workers, fewer than the average size of the firms in garments and textiles, which are typically labour intensive industries. I use the percent of inputs bought on credit to measure the financial constraint that a firm faces, by assuming that if a larger percentage of inputs is bought on credit, then there is less financial constraints on the firm.

Table 3.2 depicts the same summary statistics split into two groups, one for firms that own a generator and one for firms that do not. There are 507 firms in the sample that reported owning an electricity generator. As shown in the table, a firm that adopts a generator, on average, shows a much higher investment rate compared to a firm that does not. Moreover, the firms that own a generator experience more electricity outages, are typically larger and have a higher likelihood to export. The age and financial constraints, however, merely show small differences between these two groups.

Variable	Own a generator	Do not own a generator
Inv	0.046	0.019
Outage	136.236	94.315
Worker	111.931	43.692
Age	17.763	15.092
Exporter	0.341	0.084
Credit_con	76.488	70.686
Observations	507	380

Table 3.2: Summary statistics (mean value) by ownership of generator

3.5 Estimation and Results

3.5.1 Empirical Strategy

The objective of Equation (3.4) is to estimate the causal effect of installing a generator on a firm's capital investment. Let treatment indicator D_i equals one if firm i owns a generator and zero otherwise. Then, let I_{1i} and I_{0i} denote their respective investment rates correspondingly. Thus, the treatment effect of adopting a generator for a single firm i can be written as:

$$\tau_i = I_{1i} - I_{0i} \tag{3.5}$$

For a group of firms with a generator, the average treatment effect on the treated (ATT) is measured by $E[I_{1i} - I_{0i} \mid D_i = 1]$. However, there is a fundamental problem in identifying the causal effect by using the equations above: either I_{1i} or I_{0i} is observed for every firm i, and the unobserved outcome for each individual is usually called the counterfactual outcome. Generally the naive comparisons of those firms which do and do not install a generator are likely to be a biased estimator of the average treatment effect of a generator. To cope with the potential selection bias problem, two additional assumptions are imposed as follows: (Rosenbaum and Rubin, 1983; Angrist and Pischke, 2009).

Assumption 1: Conditional Independence Assumption (CIA), $\{I_{1i}, I_{0i}\} \perp\!\!\!\perp D_i \mid X_i$

This assumption implies that, given a set of observable covariates X which are unaffected by the treatment, potential outcomes are independent with treatment assignment, equivalently, unobservable factors play no role in determining the treatment assignment given a set of observable covariates. Although strong, the consistent estimation of ATT by OLS or matching relies crucially on this assumption. Besides the CIA, there is a further requirement which ensures that for each treated unit there are control units with the same observables.

Assumption 2: Overlap, $0 < P(D_i = 1 \mid X_i) < 1 \quad \forall i.$

Under assumption (1) and (2), several estimation strategies can be used to identify the ATT. In principle, using regression to control many pre-determined variables and estimate the parameter of treatment dummy is a good strategy to serve that purpose. However, as Angrist and Pischke (2009) illustrate that the regression imposes an implausible weight in estimating the ATT, a matching approach is usually preferred because it utilizes a more reasonable weight distribution.

Matching by cell is the finest estimator of ATT, but it is not practical to apply this when X is a high dimensional vector or when there are many continuous covariates. Instead, a possible solution is to reduce the problem to a single dimension by using a propensity score. Rosenbaum and Rubin (1983) show that the propensity score, which indicates the probability of having been assigned to treatment, is a coarsest balancing score. If the potential outcomes are independent of treatment conditional on covariates X_i, they are also independent of treatment conditional on the propensity score $P(X_i)$, that is, the CIA can be expressed in an alternative way as $\{I_{1i}, I_{0i}\} \perp\!\!\!\perp D_i \mid P(X_i)$.

Given that the CIA and overlap conditions hold, the average treatment effect at a certain score can be estimated by the outcome difference between the treatment group and control group. The propensity score matching estimator is simply the mean difference in outcomes weighted by the propensity score distribution of participants, expressed as

$$\tau_{ATT}^{PSM} = E_{P(X_i)|D_i=1}\{E[I_{1i} \mid D_i = 1, P(X_i)] - E[I_{0i} \mid D_i = 0, P(X_i)]\} \tag{3.6}$$

There are several algorithms to apply the propensity score matching method, including the nearest neighbour matching, radius matching, interval matching, and kernel matching. I will primary apply the interval (stratification) matching approach in this study as it is very straightforward to observe the heterogeneous treatment effect across different strata. However, other algorithms will also be used to test the robustness. The interval matching algorithm can be described in the following way. First, estimate the propensity score $P(X)$ by using a logit or probit model. Second, partition the common support of propensity score into a set of strata. While there is no standard number of intervals to be divided, Cochran (1968) shows that the use of five subclasses can remove 95 percent of bias associated with one single covariate. Additionally, Imbens (2004) suggests that all bias under unconfoundedness are associated with the propensity score. Hence it means that the five strata will be enough to remove most of the bias from the observable covariates. One formal way to justify the appropriate number of strata is to test the balancing property of the propensity score within each stratum. In other words, I need to check whether there are statistically significant differences between the means of the propensity score in both the treatment and control groups in the same stratum. If so, then the stratum should be split. Third, check the balancing property of the covariates within each stratum. This balancing property is crucial for the matching method. Lastly, estimate the average treatment effect on the treated within each stratum by taking the mean difference in outcomes between the treatment and control group (Morgan and Harding, 2006; Caliendo and Kopeinig, 2008). For each interval, the matching estimator is estimated separately using the following equation:

$$\tau_q^S = \frac{\sum_{i \in I(q)} Y_i^T}{N_q^T} - \frac{\sum_{i \in I(q)} Y_i^C}{N_q^C} \tag{3.7}$$

where N_q^T is the number of treatment cases in block q, i is the index over treatment cases, and j is the index over control cases, N_q^C is the number of comparison units in the same interval. The estimator of the ATT based on the stratification method is then computed by

$$\tau^S = \sum_{q=1}^{Q} \tau_q^S \cdot \frac{\sum_{i \in I(q)} D_i}{\sum_{\forall i} D_i} \tag{3.8}$$

Assuming independence of outcomes across units, the analytical variance of τ^S is given by

$$Var(\tau^S) = \frac{1}{N^T} \cdot [Var(Y_i^T) + \sum_{q=1}^{Q} \frac{N_q^T}{N^T} \cdot \frac{N_q^T}{N_q^C} \cdot Var(Y_j^C)] \tag{3.9}$$

3.5.2 Results

Notwithstanding I have shown that the propensity score matching provides more reliable estimates of average treatment effect, regression is still a good start point for the analysis. Table 3.3 illustrates the regression results for equation (3.3) by using a sample of 887 observations. The number of electricity outage is positively correlated to the ownership of a generator in probit regression and remains highly significant after I augment the regression model by adding more control variables, suggesting that the more electricity blackouts the firm experiences, the more likely that it will install a generator.

I then estimate Equation (3.4) by gradually adding covariates to the regression model. The results are depicted in the Appendix B.3. the variable of interest is *Generator*. The coefficient represents the impact of generator adoption on the investment rate. In the first regression, I exclude all other controls except the number of electricity outages. The coefficient of *Generator* is 0.03 and statistically significant at

Dependent Var. Method	Regression 1 GENERATOR Probit	Regression 2 GENERATOR Probit	Regression 3 GENERATOR Probit	Regression 4 GENERATOR Probit	Regression 5 GENERATOR Probit
Constant	0.241**(0.112)	0.152(0.116)	0.003(0.127)	-0.263(0.136)	-0.723***(0.235)
Outage	0.002***(0.000)	0.002***(0.000)	0.002***(0.000)	0.001***(0.000)	0.001***(0.000)
Worker		0.0009***(0.000)	0.0009***(0.000)	0.0005**(0.000)	0.0005*(0.000)
Age			0.011***(0.004)	0.011***(0.004)	0.011***(0.004)
Exporter				0.766***(0.130)	0.773***(0.130)
Credit_con					0.005**(0.002)
Industry Dummies	Yes	Yes	Yes	Yes	Yes
Observations	887	887	887	887	887

Note: *, **, and *** indicate statistical significance at 10%, 5%, and 1% level respectively

Table 3.3: Probit regression results for Equation (3.3)

1 percent level, indicating that installing a generator will increase the investment rate by 0.03. Next I add the interaction term of *Generator* and *Outage*. The coefficient of *Outage* turns out to be insignificant due to the potential multi-collinearity problem between those variables, but the coefficient of *Generator* remains significantly positive. Another interesting finding is that the coefficient of interaction term is negative, which implies a diminishing influence of installing a generator with an increasing blackout frequency.

Next I apply the propensity score matching approach to investigate the causal effect of generator adoption on capital investment. The propensity score is computed by the probit model above. Figure 3.5 depicts a histogram of the results. The black bins demonstrate the distribution of the propensity score in the treatment group while the dash-outline bins illustrate those in the control group. The common support for both groups is (0.13, 0.99), only 4 out of 887 observations in the sample are out of the common support. Although Heckman et al. (1998) found that a large part of selection bias comes from the observations outside common support, it is negligible in the study due to a very small proportion of them.

The essence of interval matching suggests that the sample should be divided into

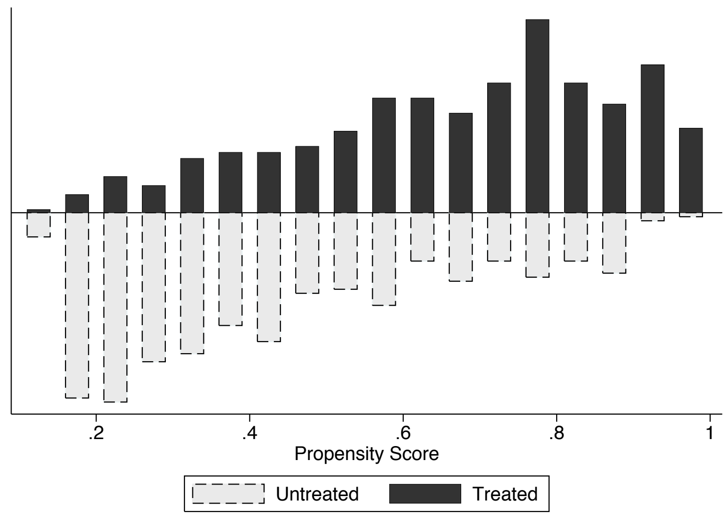

Figure 3.5: Histogram of estimated propensity score

groups where their background variables are approximately equivalent. That is, I am comparing the comparable firms in every subsample. To do this, I firstly partition the propensity score into eight strata and ensure that the mean propensity score is not statistically different for treated and controls in each stratum. Next, I check the balancing property of each covariate within every stratum. Finally I calculate the treatment effect of generator adoption within each segment by taking the difference in mean investment rate for the firms with and without generators.

Table 3.4 shows the mean investment rates of the firms with and without generators within each stratum, together with the results of the treatment effect estimated by taking the difference between them. There are eight propensity score strata for the entire sample, although the number of observation within each stratum is not evenly distributed. The balancing property of the propensity score and covariates have been tested strictly at a significant level of 0.01, indicating that the characteristics between the treatment group and the control group in each stratum do not deviate much. Hence, it is reasonable to estimate the treatment effect for every cohort by simply taking the mean difference of outcomes between them.

The number of treated observations in each stratum increases gradually while that of untreated firms decreases. 7 treated and 52 untreated firms are found in the first stratum. In contrast, the stratum eight, which has the highest propensity of installing generators, includes only 3 untreated comparison firms. The treatment effect of a generator by stratum is presented in column 4. It can be observed that there is positive treatment effect in seven out of eight strata. Furthermore, another interesting finding is the decreasing trend of the mean outcome of the treatment group. Moreover, the control group generally decreases with strata (the propensity score), which reflects that the effect of generator adoption on the investment rate is larger for those firms with a lower likelihood of installing a generator. To illustrate this trend more explicitly, the left panel of Figure 3.6 plots the within-stratum treatment effect along with a linear trend. It can be seen clearly from the graph that the treatment effect fluctuates with a significant downward trend, which indicates that for the firm with the highest probability of installing a generator, the investment rate increment by adopting a remedial infrastructure is even smaller than those with less propensity of adoption. The right panel of Figure 3.6 breaks down the within-stratum treatment effect into an average investment rate for the treatment group and the control group respectively. It illustrates a significant decreasing trend of average investment rate for the treatment group and a rather flat trend for the control group. Finally the average treatment effect (ATT) is identified by averaging the treatment effects in all strata on the distribution of the treated sample. The estimated ATT is 0.027 with a standard error of 0.008 and hence it is statistically significant. Comparing the findings to the result from the OLS regression, I find that using the conventional OLS method will slightly over-estimate the treatment effect. In order to test the robustness of the estimation results of the interval matching approach, I also apply other matching approaches to compute ATT, including nearest neighbour matching, calliper matching and kernel matching algorithms. The standard errors of ATT are obtained analytically as well as by bootstrapping 1000 times of replications, and all of those algorithms present similar results.

One important result from the above interval propensity score matching approach, is

Stratum	Number	Investment rates	Difference in investment rate		
1 Treatment	7	0.119			
Control	52	0.038	0.082		
2 Treatment	21	0.037			
Control	84	0.011	0.026		
3 Treatment	38	0.062			
Control	63	0.011	0.051		
4 Treatment	42	0.044			
Control	52	0.015	0.029		
5 Treatment	65	0.051			
Control	42	0.020	0.031		
6 Treatment	178	0.055			
Control	57	0.016	0.039		
7 Treatment	79	0.024			
Control	27	0.041	-0.016		
8 Treatment	77	0.034			
Control	3	0.009	0.025		
Total:					
Treatment	507	0.046	ATT	Std. Err	P-value
Control	377	0.019	0.027	0.008	0.000
Other matching algorithms			ATT	Std. Err	P-value
Nearest Neighbour Matching			0.032	0.012	0.002
Radius Matching (Caliper:0.1)			0.027	0.008	0.000
Kernel Matching (Gaussian, bs=1000)			0.022	0.012	0.031

Table 3.4: Estimated ATT of generator adoption

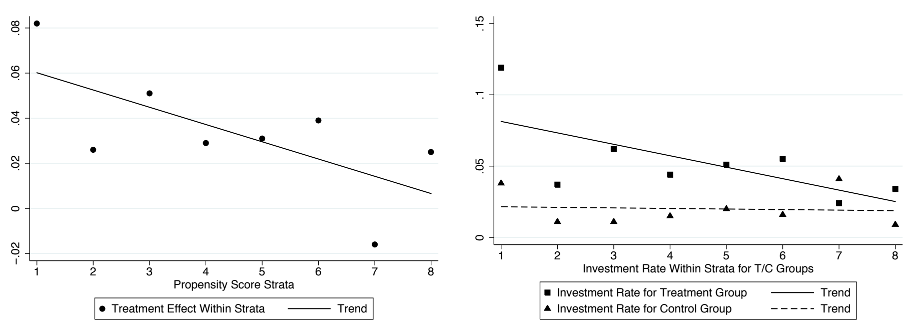

Figure 3.6: Interval propensity score matching results

that the treatment effect of generator adoption decreases with the likelihood of getting the treatment. That is, firms which are most likely to install a generator benefit least from it and thus invest least on capital stock. This type of counter-intuition result is commonly called negative selection hypothesis (Brand and Xie, 2010). One may be curious as to what is the typical firm in each stratum to have different probabilities of generator adoption. In order to illustrate this clearly, I summarize the mean of the observable controls by stratum in Table 3.5. As shown in the table, a firm with a smaller propensity score value is typically smaller, is younger, has less probability to export, and has fewer reported electricity outages. Therefore I can conclude that the treatment effect is higher for the smaller firms experiencing less electricity outages, and vice versa. In Figure 3.6, it is shown that the decreasing treatment effect is a result of a decreasing average investment rate in the treatment groups and almost unchanged investment rate in the control groups, which fits the diagonal slope seen in Figure 3.3 and Figure 3.4. The explanation for this, as I have shown in the theoretical model, is the higher cost of in-house electricity production together with the diminishing marginal capital production reduces the marginal profit of the capital for the firms with a generator, and as a result, lowers the treatment effect of generator adoption on the investment rate.

Stratum	Number	Pscore	Outage	Worker	Age	Exporter	Credit_con
1 Treatment	7	0.174	66.714	15.714	7.571	0	57.142
Control	52	0.175	38.846	13.365	7.576	0	58.173
2 Treatment	21	0.242	105.714	33.523	20.476	0	63.952
Control	84	0.246	106.381	37.19	14.416	0.011	65.833
3 Treatment	38	0.356	61.078	32.552	16.868	0.026	68.157
Control	63	0.347	64.111	20.38	14.38	0.015	73.603
4 Treatment	42	0.452	53.347	31.69	16.428	0	73.095
Control	52	0.44	53.173	18.519	14.75	0	67.692
5 Treatment	65	0.556	116.107	41.2	14.723	0.092	76.138
Control	42	0.553	84.761	35.476	17.904	0.023	80
6 Treatment	178	0.711	146.123	89.808	17.432	0.252	75.358
Control	57	0.704	166.456	62.473	18.964	0.157	79.035
7 Treatment	79	0.847	186.531	131.873	17.708	0.721	79.189
Control	27	0.848	170.037	163.777	21.666	0.629	76.074
8 Treatment	77	0.944	175.61	315.389	22.506	0.831	87.766
Control	3	0.941	147	354.666	13	1	76.666

Table 3.5: Mean value of covariates in strata

3.5.3 Sensitivity Analysis

Selection on Unobserved Variables

The estimation model in Section 3.3 depends heavily on the Conditional Independence Assumption (CIA), which assumes that firms with and without a generator only differ in terms of observed variables. Although I have controlled many pre-treatment variables in computing the propensity score before applying the matching method, the treatment effects in this study may be contaminated with selection bias due to unobservable variables, such as motivation and preferences. The purpose of sensitivity analysis in this section is to assess potential bias and alter inference results of the ATT outcomes when the CIA is assumed to fail. I follow the simulation-based approach developed by Ichino et al. (2008) to measure the potential bias of the causal effect. Next, I present a brief introduction of this method and the corresponding sensitivity test outcomes.

One central assumption of the analysis is that the treatment assignment is not unconfounded given the set of covariates X. The unobservables are presumed to be binary, independently and identically distributed in the cells, and associated with both the treatment and the response. Therefore, it is assumed that the CIA holds given X and an unobserved binary variable U

$$Y_0 \perp\!\!\!\perp T \mid (X, U) \tag{3.10}$$

U is essential for the consistent estimation of the ATT. A good way to measure the impact of U on the final result is to characterize the distribution of it and simulate this potential confounder. For simplicity, I categorize the continuous dependent variable y into a binary variable, that is, give the new dummy $y\prime$ a value of 1 when y is greater than the mean value, and 0 otherwise. Then, the distribution of the binary confounding factor U is fully characterized by the choice of four parameters:

$$p_{ij} = \Pr(U = 1 \mid T = i, y\prime = j) = \Pr(U = 1 \mid T = i, y\prime = j, X) \tag{3.11}$$

with $i, j \in [0, 1]$, which gives the probability of $U = 1$ in four different groups by assuming the value of the treatment and the outcome. Then for any configuration of the parameters p_{ij}, a value of U is attributed to each cell, which is then treated as other observed covariates and used to recompute the propensity score and the ATT. This procedure is repeated 1000 times and finally a simulated estimate of the ATT is retrieved by averaging the set of simulating ATTs.

The assumption above indicates that the distribution of U given T and $y\prime$ does not vary with the control variables X. However, in principle, the unobserved variables may be associated with other covariates explicitly. For example, the motivation for installing a generator may be correlated with a firm's size. Then the chosen U cannot be used to simulate a confounder like this since they are determined disregarding the value of X. Instead, Ichino et al. (2008) shows another merit of the simulated confounder U as follows:

$$p_{01} > p_{00} \Rightarrow \Pr(y_0 = 1 \mid T = 0, U = 1, X) > \Pr(y_0 = 1 \mid T = 0, U = 1, X) \tag{3.12}$$

which means

$$\Gamma = \frac{\frac{\Pr(y_0=1|T=0,U=1,X)}{\Pr(y_0=0|T=0,U=1,X)}}{\frac{\Pr(y_0=1|T=0,U=0,X)}{\Pr(y_0=0|T=0,U=0,X)}} > 1 \tag{3.13}$$

Hence, by simply assuming that $p_{01} > p_{00}$, I can simulate a confounding factor that has a positive effect on the potential outcome in the case of no treatment. The measurement of this outcome is computed by taking the average of relative probability to have a positive outcome in the case of no treatment, which is denoted as Γ, for all iterations. $\Gamma > 1$ indicates the simulated confounder has a positive effect on the outcome variable. Similarly, by estimating the logit model of $\Pr(T = 1 \mid U, X)$, the average odds ratio of U would measure the effect of U on the relative probability to be assigned to the treatment $T = 1$, which is the selection effect of U.

$$\frac{\frac{\Pr(T=1|U=1,X)}{\Pr(T=0|U=1,X)}}{\frac{\Pr(T=1|U=0,X)}{\Pr(T=0|U=0,X)}} = \Lambda \tag{3.14}$$

	P_{11}	P_{10}	P_{01}	P_{00}	Γ	Λ	ATT	S.E
No confounder	0	0	0	0	-	-	0.027	0.008
Neutral confounder	0.50	0.50	0.50	0.50	1.063	1.010	0.027	0.008
Confounder-like								
$I(Worker > 10)$	0.90	0.86	0.75	0.55	2.907	5.374	0.024	0.008
$I(Worker > 20)$	0.74	0.55	0.47	0.24	3.409	4.232	0.024	0.008
$I(Worker > 50)$	0.50	0.32	0.22	0.07	4.754	4.131	0.024	0.008
$I(Worker > 100)$	0.26	0.19	0.60	0.02	11.525	6.640	0.025	0.008
$I(Worker > 500)$	0.06	0.03	0.08	0.01	37.433	2.970	0.027	0.008
$I(Outage > 0)$	0.85	0.92	0.67	0.80	0.526	2.860	0.028	0.008
$I(Outage > 10)$	0.76	0.87	0.45	0.67	0.393	3.201	0.028	0.008
$I(Outage > 50)$	0.54	0.72	0.31	0.50	0.448	2.458	0.028	0.008
$I(Outage > 100)$	0.41	0.56	0.20	0.35	0.432	2.310	0.027	0.008
$I(Outage > 200)$	0.23	0.24	0.08	0.17	0.428	1.761	0.027	0.008
$I(Outage > 300)$	0.12	0.08	0.04	0.09	0.523	1.146	0.027	0.008
$I(Age > 5)$	0.79	0.89	0.75	0.82	0.694	1.622	0.027	0.008
$I(Age > 15)$	0.40	0.51	0.29	0.42	0.589	1.439	0.027	0.008
$I(Age > 25)$	0.26	0.33	0.16	0.27	0.510	1.379	0.027	0.008
$I(Age > 30)$	0.12	0.16	0.02	0.10	0.280	1.859	0.027	0.008
Exporter	0.39	0.33	0.10	0.08	1.367	5.975	0.026	0.008
$I(Credit\_con > 50)$	0.89	0.89	0.88	0.82	2.476	1.582	0.027	0.008
$I(Credit\_con > 80)$	0.43	0.35	0.29	0.18	2.098	2.463	0.026	0.008

Table 3.6: Sensitivity analysis with simulated confounders

Table 3.6 reports the sensitivity results for different configurations of p_{ij}. The first row shows that the baseline ATT estimate obtained with no confounder in the matching set yields no outcome effect and no selection effect. The ATT is computed by the radius matching approach with a calliper of 0.1. Since I have found that the results from various matching algorithms are consistent in terms of the ATT and the standard error, radius matching can provide reliable estimation results in the sensitivity analysis. The second row reports the ATT estimated with a neutral confounder. The outcome effect and the selection effect of the neutral confounder should both be expected to be 1 from the definition of Γ and Λ above. As observed from Table 3.6, the real estimated outcome effect and selection effect are 1.06 and 1.01, respectively, and the small deviations are due to the relative small numbers of replication in the simulation. The other rows in Table 3.6 show how the baseline estimate changes when the binary confounding factor U is calibrated to mimic different observable covariates and is then included in the set of matching variables. Since many variables in the matching model are continuous, such as the number of workers, number of outages, age, and measurement of credit constraints, I categorize those variables by different magnitudes. For example, $I(Worker > 10)$ implies that the distribution of confounder U is similar to that of the dummy which indicates whether the number of worker is greater than 10 or not. it shows that the distribution of p_{ij} varies significantly for different mimic control variables. In the sixth and seventh column, the estimated outcome effect differs from 0.28 to 37.433, while the selection effect varies between 1.146 and 6.64. However, the estimated ATTs and their corresponding standard errors change very little for different configurations. In column eighth, the estimated ATTs range from 0.024 to 0.028, which deviates only 11.1 percent from the baseline ATT of 0.027. Moreover, this deviation is relatively small compared to the standard error. In summary, although the tested outcome effect and selection effect may be very strong, they do not threaten the estimation and inference of the ATT. These simulations simply convey an impression of robustness of the baseline matching estimate of the ATT in the previous section.

Sample Without Industrial Heterogeneity: Example of Garments and Textiles

In Section 3.4, I used a sample of firms from six different industries to estimate the ATT. Although we have included industry dummies in the calculations of the propensity scores and have tested the balancing property at a high confidence level of 99 percent, there is still a probability that a firm in a particular industry matches a firm in another. In order to reduce the probability of mismatch and estimate a more precise ATT without the impact of industrial heterogeneity, I narrow the sample to the firms only within the garment and textile industries and check the robustness. The garment and textile industries share some similar industrial characteristics and are two of the most important industries for India. There are 230 out of 334 observations owning a generator in the samples taken, and the average ownership of a generator is much higher than most of the other industries, partly reflecting the fact that the garment and textile industries rely heavily on the electricity supply. The mean value of the investment rate is close to what I found for the larger sample. Moreover, the mean value of the reported number of electricity outages is 131, which is slightly higher than expected. Besides, garments and textiles are typically labour intensive industries. The average size of a firm measured by the number of workers is around 139 and is much larger than what have been observed in other multi-industries samples. I then use the same procedure to estimate the ATT by utilizing the interval propensity matching method and other algorithms as I have done in Section 3.5.2. The estimated ATTs by various approaches differ slightly from 0.008 to 0.012, which are much smaller than the results from the sample of six industries. The analytical and bootstrap standard errors are both around 0.018, suggesting that the positive treatment effect is statistically insignificant. Figure 3.7 illustrates the results from the interval matching approach. There is an obvious downward trend of the treatment effect across different propensity score strata. Moreover, the average investment rate of the treatment group increases but it decreases in the control group. These empirical results still fit the theoretical model prediction very well.

3.6 Conclusion

The firms' response to poor public capital provision and its effect on their performance have received little attention in current economic literature. In this chapter, I develop a two-period theoretical model to illustrate the impact of a public electricity provision failure on private generator adoption as well as the subsequent influence on production

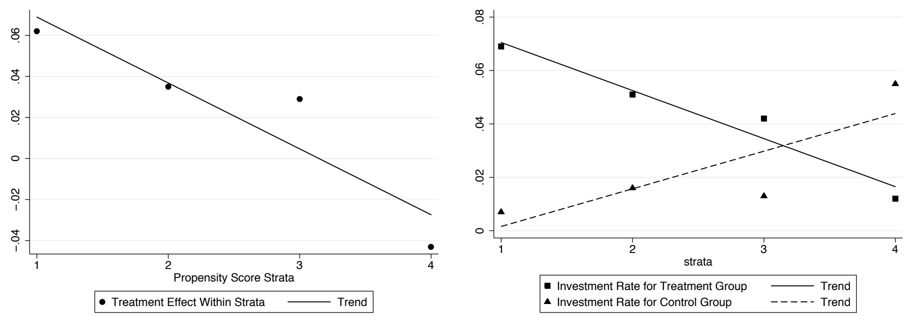

Figure 3.7: Interval propensity score matching results (Garment and textile firms)

capital investment decisions. In order to address the bias from observable controls and estimate the heterogeneous treatment effect of generators, I apply the interval propensity score matching approach on an Indian firm-level dataset. the empirical analysis suggests that an electricity supply failure increases the likelihood of installing a private generator significantly. Moreover, there is a significantly positive treatment effect of generator adoption on investment in a multi-industries situation, but this positive effect becomes insignificant when I narrow it to a sample without much industrial heterogeneity. This, in turn, suggests that the treatment effect may vary between different industries. Empirical results also illustrate a negative selection of the treatment effect. That is, the treatment effect of a back-up generator on the investment rate is greater for the firms with less likelihood to obtain one. These are the firms which are typically smaller and experience less electricity blackouts. This empirical finding is consistent with the theoretical model prediction. Finally, I test the robustness of the empirical results by applying a simulation-based sensitivity analysis approach and utilizing a different measure of the investment rate. Sensitivity analysis findings show that the empirical results are robust with respect to the potential endogenous unobservable confounder and sample selections.

Chapter 4

Air Pollution and Land Prices in China

4.1 Introduction

Concurrent with rapid economic growth since the 1970s, China has experienced severe environmental degradation. Approximately 1% of China's urban population breathes air that is considered to be safe by the European Union (The New York Times, 2007).[1] Air pollution is now recognized as an increasing concern affecting China's public health, industrial development and economic growth (Brandt and Rawski, 2008). Substantial efforts have been made to address the serious pollution problem. For example, the Environmental Protection Law was promulgated in 1989 to regulate pollution behaviour. Additionally, the 12^{th} Five-Year Plan (2011-2015) presents a comprehensive air pollution and prevention control plan, which sets ambitious air quality targets, city attainment requirements and detailed projects for pollution reduction (Clean Air Alliance of China, 2012).[2]

It is important to assess the economic costs and benefits of pollution control policies.

[1] See http://www.nytimes.com/2007/08/26/world/asia/26china.html?pagewanted=all

[2] http://www.epa.gov/ogc/china/air%20pollution.pdf

A large body of literature has linked pollution with human health. Empirical studies, using different data, largely show strong causal effects of pollution on poor health outcomes, suggesting a substantial welfare loss because of the environmental degradation.[3] However, the total costs of air pollution are not limited to health damage. It is also essential to incorporate the potential effects on other aspects, such as labour market outcomes or property values, into a welfare analysis of air quality change.[4] Further, information on these effects is particularly crucial for developing countries. The developing world is typically suffering higher levels of pollution but lacks effective technology and institutional conditions for environmental protection. Improved knowledge of the effects of pollution can help communities, market agents, and policy makers put pressure on polluters and efficiently internalize the externalities of polluting behaviour.

The primary objective of this chapter is to investigate the causal effects of air pollution on urban land prices in China. China is of particular interest because of its unique institutional setting. The urban land in China is state-owned and land leasehold sales account for a substantial proportion of the local government's revenue. Capitalizing the air quality into land prices demonstrates the direct benefit of air quality improvement on government income, consequently providing an incentive for local environmental regulation.

However, it is challenging to estimate the causal relationship because the pollution levels are endogenous. The endogeneity issue of air pollution in this study typically comes from two channels. First, there may be some unobserved or unmeasurable

[3] Many recent studies use U.S data and exploit exogenous variation in pollution levels in different ways to reveal the causal effects of air pollution on health. For example, Chay and Greenstone (2003) and Currie and Walker (2011) show the significant impacts of air pollution on the infant mortality rate, prematurity, and low birth weight in U.S, respectively. Schlenker and Walker (2011) investigate the effects of local pollution levels on contemporaneous health for different population groups. In contrast, fewer empirical studies link pollution to health outcomes in China. Chen et al. (2013) find that the higher total suspended particulate (TSP) concentration in north China due to the winter heating policy lowers life expectancy by about 5.5 years. Ebenstein (2010) shows a significant association between China's water pollution and digestive cancer death rate.

[4] Graff Zivin and Neidell (2012) investigate the effects of ozone exposure on agricultural workers' productivity in California. Evidence from Currie et al. (2009) shows a negative effect of pollution on human capital accumulation through the channel of increasing school absences.

variables, such as local policies targeting urban air pollution reduction or economic shocks, omitted in the analysis. If these variables influence the urban land prices, then the ordinary least square (OLS) estimates will be biased. Second, promotion incentives may cause the reported air pollution index (API) to be manipulated by the local governments (Chen et al., 2012; Ghanern and Zhang, 2013). The measurement errors in air pollution readings are likely to be correlated with the real levels of air pollution, which may also contribute to biasing the OLS estimation. Furthermore, the estimation of the average impact can also be biased by heterogeneous tastes for clean air and the subsequent self-selection behaviour across areas (Chay and Greenstone, 2005; Graff Zivin and Neidell, 2012).

To address the endogeneity of air pollution, this chapter exploits the natural forces of atmospheric circulations to provide exogenous variations in a city's pollution concentrations. Conditional on the total emissions of pollutants into the atmosphere, a city's monitored pollution level is partially determined by a set of meteorological variables including wind speed, relative humidity, and vertical temperature-gradients of the atmosphere, and their interactions with the local topography. After controlling for an elaborate set of covariates, these selected instrumental variables (IV) are able to generate exogenous variations on local air quality for the identification of causal effects of air pollution on land prices.

This study uses the most detailed and comprehensive micro-level datasets available on air pollution and land prices in China. The daily air pollution data for 119 major cities, during the years from 2001 to 2012, are collected. This high-frequency API dataset allows me to calculate the average pollution levels for every city over different time periods. In addition, a unique dataset of land transactions in China provides detailed land characteristics and prices for approximately one million land conveyances between 2001 and 2012. Finally, these different datasets are correlated according to the dimensions of time and locations.

Results from the two-stage least squares (2SLS) regressions indicate that the elasticity of land prices with respect to average annual air pollution is -1.369, this is larger than the estimates from previous studies that usually show absolute values less than 1.[5] Although the negative signs of both the OLS and IV estimates point to the same result that air quality degradation will reduce the land values, without accounting for the endogeneity of air pollution, the OLS regression tends to underestimate the elasticity. The main conclusions are shown to be robust to regression methods, presence of extreme values in observations, and different measures of average pollution levels.

Regressions on different land types shows various effects of air pollution on land prices. The estimated elasticity for residential land is -1.79, which is the largest among different land uses and statistically significant. The elasticities for industrial and commercial land are 0.17 and 0.5, respectively, with large estimated standard errors. These large differences in the estimated elasticities of different land uses may result from the strong disutility of pollution of residential land buyers and the local governments' land control policies for pollution reduction. Finally, a random coefficient regression model is implemented to allow for the heterogeneous tastes for clean air and self-selection behaviour. The control function estimations show that the estimated average effects are close to the IV estimates. Similar to the previous research by Chay and Greenstone (2005), the selection bias in this study is less significant than the endogeneity problems resulting from omitted variables or measurement errors. There is also modest evidence indicating that pollution abatement will have a larger effect on land prices in the more polluted areas in China.

This chapter contributes to the existing literature in several ways. First, whereas many previous studies have estimated the economic damages associated with pollution in developed countries, little is known about the effects in the developing world (Das-

[5] The previous research mainly focuses on the elasticities of housing values rather than land values, therefore the results are not directly comparable. Using IV estimations, Chay and Greenstone (2005) find that the elasticity of housing values with respect to TSP concentrations range from -0.2 to -0.35, Zheng and Kahn (2008) show similar results using micro-level real estate transaction data for Beijing. However, in the recent research of Zheng et al. (2013), using the imported pollution from neighbour cities as IV to account for the endogeneity of pollution of Chinese cities, the estimated elasticity increases to about -0.7.

gupta et al., 2001). This chapter adds to this relatively small, but growing, body of literature by presenting evidence on the effects of air pollution on China's land market.[6] The estimation results of this study will be important for the welfare analysis of environmental protection policies. Second, this study uses the most detailed and comprehensive micro-level data on air pollution and land transactions within China. Considerable existing research employs aggregate data at the city- or county-level for estimating the implicit prices of air quality. However, using the aggregate data for regression will make it difficult to control the land characteristics that can explain the majority of land prices. Because the hedonic model framework, usually fitted to estimate the implicit price of air quality, is originally derived at the individual-level, using aggregate data for regression analysis may induce biased estimations (Chay and Greenstone, 2005). Third, this chapter uses novel instrumental variables to estimate the causal effect of air pollution on land prices. The careful application of IV methods in this study can address the well-acknowledged endogeneity problem of air pollution.

4.2 Background

4.2.1 Air pollution in China

The air pollution problem in China can be attributed to production technology, economic development and the institutional setting. First, coal combustion is primarily responsible for the high level of total suspended particulates (TSP) and sulfate concentrations. In China, coal-firing accounts for over 70% of electric power generation and 80% of the industrial fuel. The heavy reliance on coal power, with a low energy efficiency, produces a tremendous amount of TSP and sulphate emissions (Fang et al.,

[6] In some recent empirical works using Beijing's housing transaction data or city-level aggregate data in China (Zheng and Kahn,2008; Zheng et al., 2010; Zheng et al., 2013), air amenity quality is capitalized into housing values. However, this chapter differs from the previous research by looking into the effects of air pollution on land values. The housing market and land market are different in terms of market mechanisms, major buyers, and sellers, which will be discussed in next section.

2009). Moreover, vehicle emissions are a new source of pollution. Along with the rapid development of transportation infrastructure systems, the vehicular fleet in China has increased by approximately 20% every year since 1990, which has led to more pollution in urban areas (He et al., 2002).

Some recent research sheds light on the roles of incomplete enforcement of environmental regulations and the fundamental institutions of China. For example, as an important instrument of internalizing the externality of air pollution into industrial production, pollution levy enforcement in China has been found to be endogenous and determined by firm characteristics and regulator-manager negotiations (Wang and Wheeler, 2005). Xu (2011) investigated the institutional background of China, particularly the effect of the local government officers being appointed by the central government based on their past performance. As the performance is measured by tangible indicators such as GDP, the promotional systems incentivizes the subnational governments to boost economic growth rather than invest in environmental protection. This argument is supported by recent empirical research on the relationship between pollution and the promotion of governors (Jia, 2013; Wu et al., 2013).

With increasing awareness of the continuing environmental damage and the severe consequences, the Chinese government has implemented various environmental protection policies. One recent policy which is closely related to this study is the disclosure of city-level daily air pollution index (API) data from 2001. Additionally, the reported APIs are linked to the performance evaluation of local governments to provide incentives for air pollution abatement.[7] Benefiting from the transparency policy, this chapter collects and uses the published daily API data from the website of the Ministry of Environmental Protection for the empirical analysis.

[7] Specifically, days with an API lower than 100 are defined as "blue sky" days. Since 2003, more than 80% "blue sky" days in a year qualifies a city for the "national environmental protection model city" award. This standard increased to 85% from 2007. (Chen et al., 2012)

4.2.2 Land market in China

According to the 1982 Constitution of China, land is publicly owned and private ownership is legitimately prohibited.[8] Initially, administration orders, rather than market mechanisms, were adopted in land redistribution. However, the administrative reallocations were shown to be very inefficient and have resulted in numerous severe consequences (Deininger and Jin, 2005). To address these problems, the 1988 Amendments of Constitution and the subsequent Amendments of Land Administration Law (LAL) formally separated the land use rights from its ownership,[9] Allowing urban land in China to be transferred through pay-for-use leasehold for the first time. Subsequently, a land leasehold market emerged and expanded with some unique features.

Figure 4.1 illustrates the main structure of the Chinese land market. First, land is classified into two distinct categories: urban and rural; the urban land is owned by the state and rural land is owned by the collectives. The prefectural city governments act as an important bridge connecting the two separate market sectors and are the only legitimate agents for transforming local rural land into urban use. In the rural sector, the collectives have the power to assign land for different uses, such as for farmland, farmers' residential use, and township and village enterprises (TVE) constructions. However, without a formal acquisition by the city government to convert rural land into state-owned urban land, the rural land cannot be exchanged in the urban land market (Ho and Lin, 2003; Su, 2008).

This chapter focuses on the urban land market for two major reasons. First, as guaranteed by the Constitution and Land Administration Law on transferable land use rights, the urban land leasehold market, after 25 years of development, is more developed than that of the rural sector. It is now playing an important role in the allocation of urban land resources. Second, the public transparency policy of early 2004 allows me to collect the detailed urban land conveyances data through the Internet,

[8] The 1982 Constitution of China specifies the detailed ownership of urban and rural land in Article 10 of Chapter 1. See http://www.gov.cn/gongbao/content/2004/content_62714.htm

[9] See http://www.law-lib.com/law/law_view.asp?id=95544

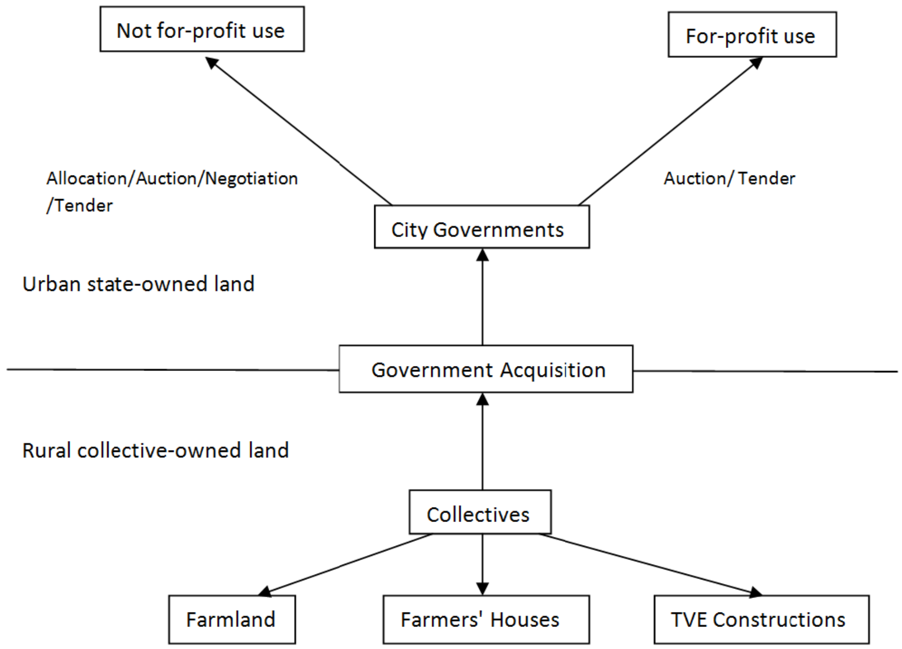

Figure 4.1: China's Land Market Structure and Management

Note: Following Su (2008), this figure describes the main structure of China's land market. However, to simplify the presentation, it does not contain any secondary market or black market. See Xie et al. (2001) and Ho and Lin (2003) for a complete discussion.

making the econometric analysis of this study possible.

There have been numerous progressive reforms in the urban land market to improve efficiency, increase government revenue, and reduce corruption. Since the 2002 reforms that officially banned the negotiation sales of for-profit use land after August 31, 2004,[10] the urban land market system in China is refined by setting uniform relevant procedures and standards. At the beginning of each year, an overall land use plan is developed by the city government. A detailed use plan for each individual land parcel is subsequently developed by an independent committee, defining the land class, development purpose, use constraints and the reserve price (Cai et al., 2009).[11] Finally, the land ready for development will be turned over to the local land bureau where the method of

[10]This is referring to the Rules on the Assignment of State-owned Land Use Right by Bidding, Auction and Quotation, issued on April 3, 2002.
Source: http://www.mlr.gov.cn/zwgk/flfg/dfflfg/200504/t20050406_636761.htm

[11]The reserve price varies across cities. see http://www.creva.org.cn/show.aspx?id=3509&cid=27

distribution will be chosen. In particular, part of the land will be allocated to users free of charge, or with an allocation fee which is much lower than the market price, for projects of public interest, such as transportation infrastructure, hospitals, schools, government agency buildings, etc. Other land is authorized to be transferred through a leasehold of a fixed term with usage restrictions (Ho and Lin, 2003).[12]

There are four methods of land conveyance: negotiation, public tender, English auction, and a "two stage auction" (*Zhao Pai Gua ChuRang*), usually adopted in the leasehold market.[13] The major differences among these methods are the number of bidders and transparency levels. In the negotiation sales there is only one bidder involved; the bidder will bargain with the local land bureau on the land prices, with neither a public procedure nor any competition. In the 1990s, a substantial proportion of land conveyances were conducted by negotiated sales. However, because they were criticized as being inherently corrupt and decreased government revenues, the Ministry of Land and Resources of China has banned the negotiation sales of for-profit use land since August 31, 2004.[14] The urban land allocated for for-profit development is thereafter transferred through more transparent methods.

4.3 Conceptual Framework

Similar to previous literature, the research question presented in this chapter fits into the hedonic price framework that explains how air quality affects land prices. Based on China's unique land market structure, I discuss an extension of the classic hedonic model to consider the existence of market power. This model can thus help add new insights into the interpretations of the empirical results.

[12]For example, the lease for residential use land is 70 years, and it is 40 or 50 years for industrial or commercial use land.

[13]The name of "two stage auction" is from Cai et al (2009). It is equivalent to "listing" in other literature.

[14]The definition of "for-profit use" is ambiguous here. Literally it means using land as an input for production, however, neither the law nor administrative documents provides a detailed list of for-profit use; they are usually determined by the local land bureaus.

4.3.1 The Standard Hedonic Price Model

The hedonic model introduced by Rosen (1974) is widely used to estimate the implicit prices of different characteristics in the property market. The fundamental idea is that although the goods are collections of characteristics that are not directly tradable, the implicit price of each characteristic can still be revealed through the trades when the consumers choose the heterogeneous combinations of characteristics in a competitive and thick market. In the case of the land market, a land parcel i can be described by a vector of attributes, including its own characteristics, neighbourhood surroundings and environmental amenities. To simplify, I denote the measure of air quality as A_i and all other land attributes as X_i. The price of a land parcel i, $P(A_i, X_i)$, is then a function of A_i and X_i. Assuming that the land market is perfectly competitive and is sufficiently thick to allow a wide variety on any single attribute of the heterogeneous land parcels, then the buyers and sellers are price takers and bargaining does not affect the equilibrium prices. Additionally, information on land parcels, buyers, and sellers is assumed to be completely observed by the market players.

Rosen (1974) demonstrates that under the assumptions above, in equilibrium, land is traded between the seller with the lowest offer and the buyer with the highest bid. The implicit price of each attribute can be revealed and they equal the partial derivative of the price with respect to each attribute. The marginal implicit price of air quality can then be represented by $\partial P_i(A_i|X_i)/\partial A_i$.

Following Harding et al. (2003) and Cotteleer et al. (2008), the hedonic price model discussed above is illustrated in Figure 4.2. In a competitive market, in which the buyers and sellers are assumed to be price takers, given the other characteristics X_i are constant, at any level of A_i, the implicit price of air quality is revealed when the buyers' marginal willingness to pay (MWTP) equals the sellers' marginal willingness to accept (MWTA) (Cotteleer et al., 2008). Because the assumption of a competitive market implies free entry and exit, no excess surplus exists. Consequently, the market price of land with varying air amenities is found on the locus of the tangency of highest

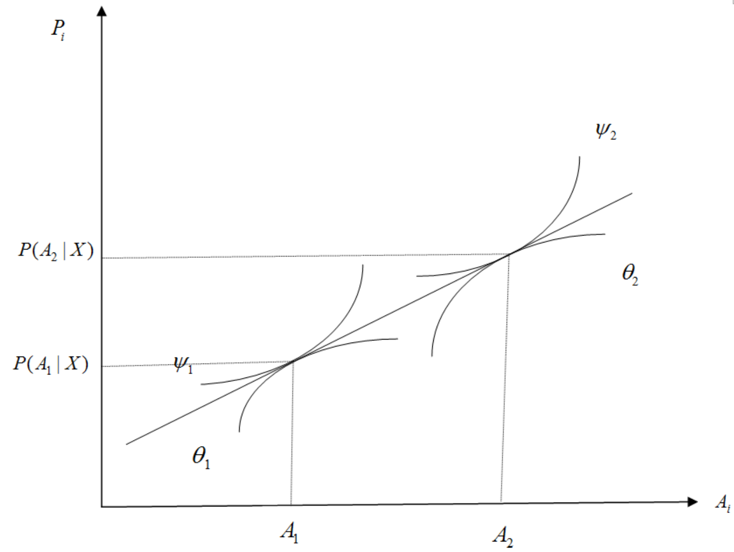

Figure 4.2: Hedonic Price Model with Perfect Competition

bid curve (θ) and lowest offering curve (ψ) in Figure 4.2. From the econometrics side, the value of $\partial P_i(A_i|X_i)/\partial A_i$ is easy to recover by a regression of prices on a vector of characteristics. As very few restrictions are typically placed on the functional form of hedonic regressions, I use a log-log functional form, usually used in the literature, to allow for a non-linear relationship between the land prices and the levels of air pollution. The specification is as follows:

$$ln(P_i) = \alpha + p(A) \cdot ln(A_i) + p(X) \cdot X_i + \varepsilon_i \tag{4.1}$$

where $p(A)$ is the elasticity of land prices with respect to air quality, and ε_i represents the error term.

4.3.2 Discussion of the Assumptions

The assumptions of competitive market, complete information, and a sufficiently thick market are crucial in the standard hedonic framework as they drive the excess surplus to be zero. However, in China's land market these assumptions are difficult to maintain. First, as the unique legitimate seller of urban land leaseholds, the city governments have monopoly power in the local land market. In addition, the household registration system (Hukou) creates institutional obstacles for buyers' mobility across cities. Second, because the land leasehold market system is still not completely transparent, buyers may have asymmetric information between different land markets. Information on some land parcels might only be shared by the local government and a limited number of potential buyers. Third, the housing market or land market is usually thin; there are few substitutes for each heterogeneous land parcel (Harding et al., 2003; Ihlanfeldt and Mayock, 2009). These market structures require the relaxation of the basic assumptions in the hedonic price model. As a result, excess surplus, rather than zero surplus, emerges, and bargaining power plays an important role in explaining how the surplus is divided between buyers and sellers.

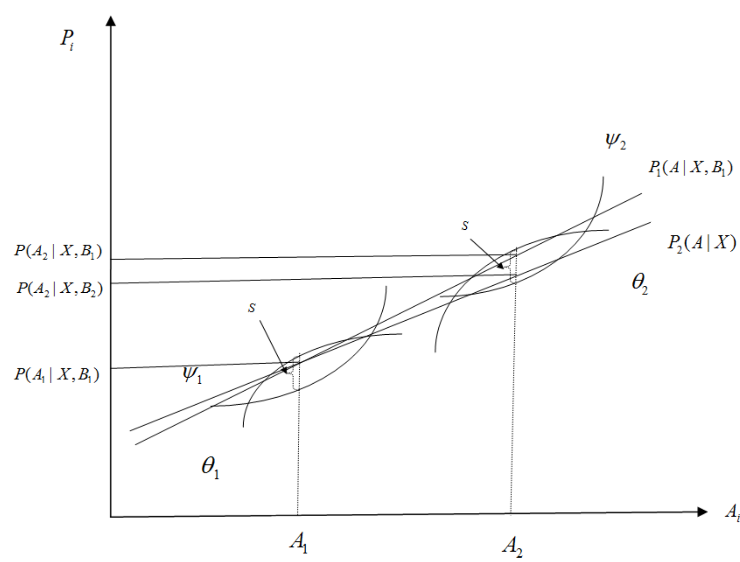

Figure 4.3: Hedonic Price Model with Excess Surplus

Different from the competitive model depicted in Figure 4.2, Figure 4.3 portrays the hedonic model under the relaxed assumptions. In this model, the bid and offer curves overlap rather than being tangent as in Figure 4.2. The excess surplus of trade S exists and is shared between the buyers and sellers, depending on their relative bargaining power B_i. Harding et al. (2003) develop an econometric model for controlling the characteristics of the buyers and sellers as a proxy for bargaining power. They show that, after controlling for these proxies, the interpretations from the standard hedonic model are still valid. In this case, the regression equation is as follows:

$$ln(P_i) = \alpha + p(A) \cdot ln(A_i) + p(X) \cdot X_i + p(B) \cdot B_i + \mu_i \tag{4.2}$$

where $p(A)$ represents the elasticity of land price with respect to air quality and μ_i represents the error term. Without controlling for the B_i, the estimation of implicit prices of land characteristics can be biased because of the potential correlation between A_i and B_i. Figure 4.3 illustrates the surplus of S divided according to the bargaining powers of sellers and buyers. When the buyers share the same proportion of markup in two trades (with prices of $P(A_1|X, B_1)$ and $P(A_2|X, B_1)$), the slope of $P_1(A|X, B_1)$ equals the slope of the price line in Figure 4.2. The term B_i causes parallel shifts in the hedonic price function of Equation (4.2). However, if the buyers' market power correlates with their taste for air quality, that is, $corr(B_i, A_i) \neq 0$, then omitting B_i may cause bias estimates of $p(A)$. Correspondingly, it can be observed from the graph that if the buyers' bargaining power increases with air quality, ignoring this will lead to an estimation of the slope $P_2(A|X)$ unequal to $P_1(A|X, B_1)$.

Following Harding et al. (2003), this chapter uses buyer and seller characteristics to control the bargaining power. In particular, because local governments are the exclusive sellers in the primary market, I include a vector of city-level variables including GDP, population, GDP per capita, and proportions of GDP from agricultural and industrial sectors, to describe them. However, because the land data only provides the buyers' identities, it is impossible to obtain similar demographic variables as those used in the previous studies to control for their characteristics. Instead, I employ the methods of land conveyance as proxies of buyers' relative bargaining power. Different conveyance method options can sort the buyers and affect the number of bidders, which eventually influence the relative market power of buyers and sellers. For example, in the negotiation sales, because there is strictly one buyer,[15] it is expected that the buyer will enjoy more bargaining power than buyers in auctions with competition. Heterogeneity of competition also exists between different auctions. Cai et al. (2009) find that the two stage auction is typically less competitive than the regular English auction.[16] Therefore, it is plausible to use auction types as proxies for relative bargaining power, B_i in Equation (4.2).

4.4 Data

This chapter merges datasets from multiple sources. It uses a comprehensive land transaction database that contains detailed information on over one million urban land conveyances since 2001, and a database that provides official daily air pollution measurements for the major cities in China. In this section, I will describe the data sources, manipulation methods and their descriptive statistics.

4.4.1 Air Pollution Data

The daily Air Pollution Index (API) data for 119 cities are obtained from the website of the Ministry of Environmental Protection of China.[17] In 2001 there were 47 major cities initially selected as pioneers to publish daily APIs online, and the other cities were added gradually in the following years. So the daily API dataset is intrinsically an unbalanced panel. Figure 4.4 shows the coverage of these cities. The sample contains cities from coastal and inland areas and there is at least one city selected from each province, therefore these data are basically representative of urban China. The average APIs of selected cities in Figure 4.4 reflect that north China is more polluted than the

[15] According to the law, if multiple buyers express interest in any land parcel, negotiation sale of the land parcel will be terminated and auction will be the leasing option.

[16] A significant difference between the two stage auction and the regular English auction is that the former method adds a first stage that the bidder can send a costless signal to decide whether to enter the auction.

[17] Source http://datacenter.mep.gov.cn/

south, which can be attributed to the concentration of heavy industry and coal fired power plants, and the winter heating provision policy in the north (Chen et al., 2013).

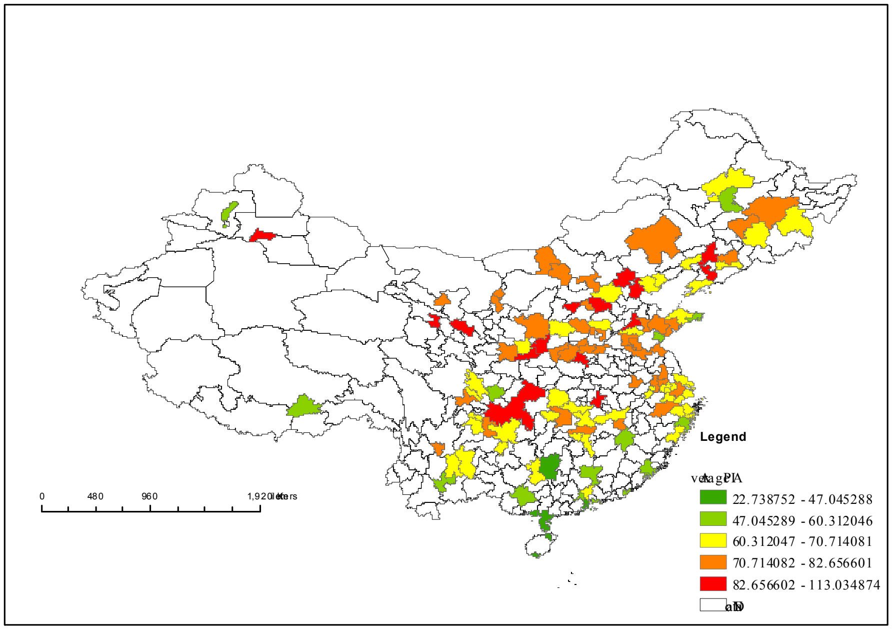

Figure 4.4: Average APIs across Cities: 2001-2012

Note: The original API data are from the Ministry of Environmental Protection of China. Shaded polygons represents the 119 cities with valid APIs, values illustrated by different colours are calculated by averaging all daily APIs of each city over years.

The API index is computed scientifically considering the concentration levels of five major pollutants: SO_2, NO_2, PM_{10}, CO, and O_3.[18] There are a total of 348,048 API readings in the dataset. Figure 4.5 shows the air pollution trend across the 47 selected cities that have been published since 2001.[19] With large seasonal fluctuations, the average air pollution has decreased steadily over time. In 2001, the average API was approximately 84, it then decreased approximately 2% annually and finally reached 65 in 2012. When the API is higher than 100 (the threshold for defining a "blue sky day"), it is considered to be polluted and there maybe damage to people's health.

[18]Detailed calculation method for the API is as described here: http://www.gdepb.gov.cn/oldsite///xcyjy/hjzs/daqi/200510/t20051020_18510.html.

[19]Selecting the 47 cities that published API data consistently from 2001 to 2012 is to cancel out the impacts of other cities that were added into the data pool in latter years.

In 2001, approximately 10% of the days were not ”blue sky” days, but this number decreased to below 5% in 2012. The most common pollutants are the total suspended particulates (TSPs), which account for more than 71% of days with an API greater than 50. Sulfur dioxide ranked as the second major pollutant, but it accounts for only 7%. There are also seasonal fluctuations among different pollutants. Sulphur dioxide appears as the major pollutant at a higher frequency during winter, attributable to the increased heating demand that results in more coal combustion.

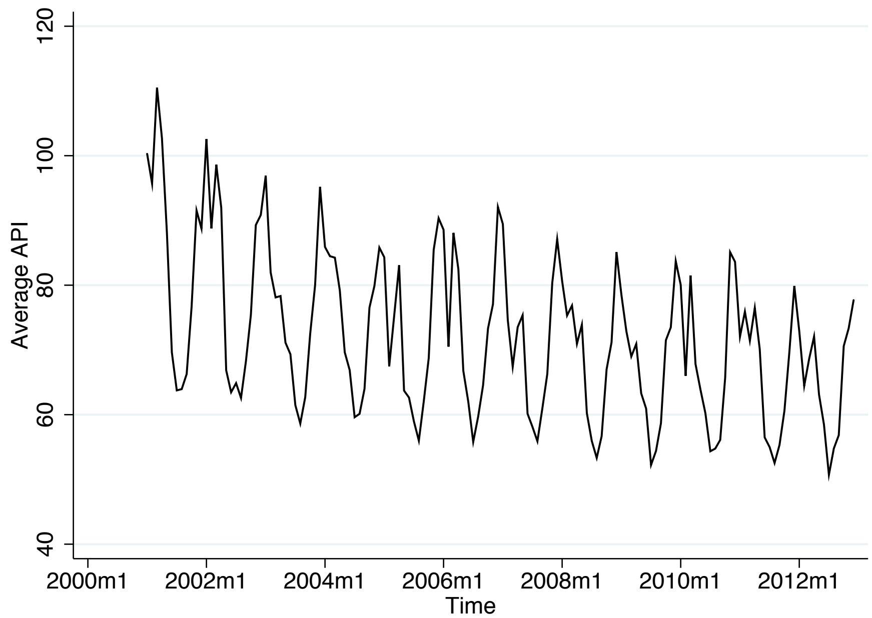

Figure 4.5: Monthly Average APIs of 47 Major Cities from 2001 to 2012

Note: ’m’ indicates month. For example, 2001m1 on the horizontal axis means January, 2001.

Some caveats regarding this variable are worth noting. First, the city-level APIs are calculated by averaging data from different monitoring stations, thus they negate the within-city spatial heterogeneity on air quality. However, more precise air pollution measurements of smaller areas require monitor-level readings, which are still subject to the unavailability of open source data at this stage. The second issue involves the potential measurement errors in APIs. Driven by promotion incentives, the governments tend to manipulate the API data around the "Blue-sky day" cutoff of 100 (Chen et al., 2012; Ghanem and Zhang, 2013). Consequently, even though the published APIs provide general information about air pollution, measurement errors may induce biased estimations. To address this issue, the instrumental variable approach is discussed and applied in this chapter.

4.4.2 Land Transaction Data

The availability of land data has benefited from the urban land market transparency policy adopted in August 2004, which requires local land bureaus to disclose the conveyance information to the public after each transaction is completed. Data are collected from The China Land Market website, one of the largest land market information providers that collects and reposts land transaction outcomes from the Ministry of Land and Resources of China.[20] There were 1,175,651 recorded transactions from 2000 to 2012. However, this database only covers the primary market, in which the sellers are local governments. In addition, some records may have been omitted from the database, particularly for the conveyances before 2004, when the transparency policy was not mandated.

The transaction database includes many important land characteristics, such as land price, area, address, transaction date, transaction method, buyer's identity, and proposed land uses. To measure the price of land, I calculate the average price of land per hectare, and then I adjust it by the CPI to obtain a real price. Figure 4.6(a) illustrates the monthly average land price changes in China from 2000 to 2012. The land market has realized tremendous growth: average land prices in 2012 are almost three times the prices in 2003. Figure 4.6(b) shows the average prices trends for residential land, industrial land, and commercial land. The commercial land leaseholds were sold at the highest prices and the industrial land at the lowest. This is partially because the

[20]See the land conveyance outcomes on www.chinaland.com, same information can also be found here: http://landchina.mlr.gov.cn/

commercial land is usually located in the central business district (CBD) and realizes the highest marginal returns. In contrast, the industrial land is often planned at the urban fringes or far from the population-dense region to minimize the effects of the associated pollution on the urban area, and where land is more abundant.

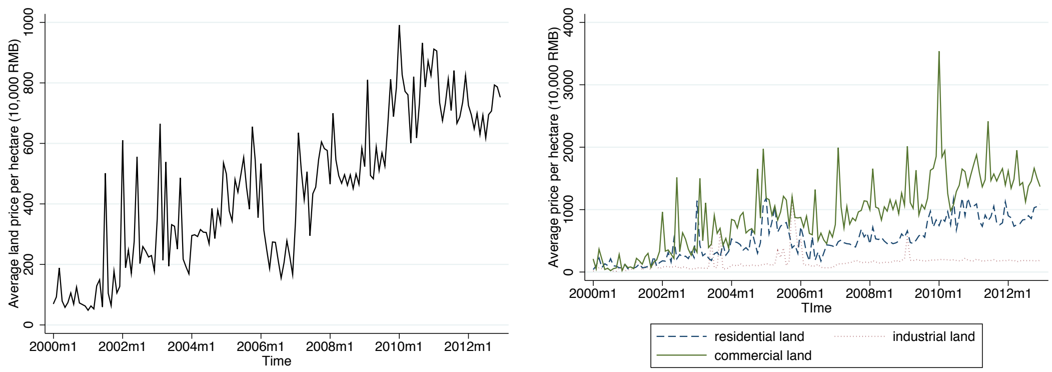

Figure 4.6: Monthly Average Land Prices

A challenge of using the land transaction data is to geocode the land parcels without specific geographic coordinates. Geocoding every land parcel is important because the distance from a land parcel to the CBD determines the commuting cost, which be compensated by the land price. The large within-city disparity on infrastructure may also influence the land price. Therefore, controlling land location plays an important role in explaining land prices. Because no software available for geocoding such a large number of land parcels at a highly accurate level,[21] I employ another geocoding method that trades precision for efficiency. I extract the name of town or district from every address and match them with the geographic information system (GIS) map of China from China Data Online. I can then sort the land parcels into different towns/districts and finally control the town- or district- level fixed effects. Because a town is the lower level of a county and a district is the lower level of a city, they are both small enough to mitigate the significant differences in infrastructure conditions and spatial distances

[21]For example, the Google Earth Pro restricts geocoding to no more than 2500 observations per day, and the success rate has been tested to be lower than 30% to get the correct geographic coordinates, thus it is an inapplicable way in this study because of the large size of the data set.

to central business district.

4.4.3 Data Convergence and Descriptive Statistics

The land data provide dates for every leasehold transaction, making it possible to match air pollution data with land transaction data by the dimensions of city and time. However, because it is not reasonable to use the transaction day's API to describe the air pollution level of a city that may affect land prices, before the matching, I calculate a moving average of APIs over the prior 365 days as follows:

$$\overline{API_t} = \sum_{k=t-1}^{t-365} API_k \tag{4.3}$$

This moving average reflects the average air pollution level during a past fixed period. Although there is no previous evidence on how wide the moving average window should be, it is set at one year (365 days) in the main analysis to mitigate the influences of seasonal air pollution trends and land prices fluctuations. In the robustness checks, I calculate the average air pollution for different time spans, such as 9 months, a half-year, and 3 months, to investigate the short term effects of air pollution on land prices. Finally, there are 282,075 land transactions with matched average APIs.

Table 4.1 describes the summary statistics of selected land characteristics. To compare the characteristics across residential, industrial, and commercial land, columns 1 to 3 show the descriptive statistics for these three land types. I transform the land prices by natural logarithm and the land parcels allocated by administration order with zero cost are dropped from the sample.[22] Consistent with the findings from Figure 4.6(b), the prices for the commercial land are the highest among the three types, whereas the industrial land is much less expensive.

Over 40% of the conveyances are for residential use. China's rapid urbanization has driven this increased demand to accommodate a growing urban population. The

[22] There are 68,008 transactions either report prices as 0 or have missing information.

		Geocoded Data				Original Data
Variable	Description	Residential Land (1)	Industrial Land (2)	Commercial Land (3)	All (4)	All (5)
$ln(P)$	natural logarithm of land prices adjusted by CPI	5.505	5.006	6.405	5.363	5.328
		(1.780)	(0.950)	(1.586)	(1.791)	(1.903)
$area$	land area (hectare)	1.744	3.596	1.784	2.693	2.909
		(6.349)	(62.38)	(17.51)	(42.69)	(37.48)
res_use	residential lands	1	0	0	0.420	0.416
		(0)	(0)	(0)	(0.494)	(0.493)
ind_use	industrial lands	0	1	0	0.343	0.353
		(0)	(0)	(0)	(0.475)	(0.478)
com_use	commercial lands	0	0	1	0.155	0.151
		(0)	(0)	(0)	(0.362)	(0.358)
rtu	land transferred from rural to urban	0.203	0.670	0.271	0.400	0.415
		(0.402)	(0.470)	(0.445)	(0.490)	(0.493)
$tsauction$	sold by "two stage auction"	0.280	0.605	0.428	0.419	0.416
		(0.449)	(0.489)	(0.495)	(0.493)	(0.493)
$allocate$	allocated by government order	0.0298	0.00144	0.00210	0.0562	0.0529
		(0.170)	(0.0379)	(0.0458)	(0.230)	(0.224)
$eauction$	sold by English auction	0.105	0.0427	0.0784	0.0728	0.0670
		(0.307)	(0.202)	(0.269)	(0.260)	(0.250)
$negotiation$	sold by negotiation	0.567	0.338	0.479	0.454	0.447
		(0.496)	(0.473)	(0.500)	(0.498)	(0.497)
$class_1$	first class land	0.238	0.186	0.240	0.211	0.211
		(0.426)	(0.389)	(0.427)	(0.408)	(0.408)
N	number of observations	109,444	80,472	34,613	282,075	430,169

Note: Standard deviation are in parentheses.

Table 4.1: Descriptive statistics of Land Characteristics

variable rtu indicates whether the land parcel is newly acquired from rural to urban use. The newly acquired land parcels are more likely to first be developed for industrial use. The first-class land accounts for a higher proportion in the commercial and residential land than the industrial land.

The geocoding manipulation induces sample attenuation by dropping approximately 34% of the conveyances that do not have detailed address information. However, it is crucial to ensure that this geocoding process has not caused significant sample bias. To check this, columns 4 and 5 show the summary statistics of the samples before and after geocoding. There is no significant difference in the mean value and standard deviation of each variable between the two samples, suggesting that the geocoding process has minimal effects on sample distribution.

4.5 Identification Strategy

4.5.1 OLS Regression and the Endogeneity Issue

The main objective of this chapter is to estimate the impact of air pollution on land prices. To begin, the OLS regression model is specified as follows:

$$ln(P_i) = \beta_0 + \beta_1 ln(\overline{API_i}) + \beta_2 Control_i + \epsilon_i \tag{4.4}$$

where $ln(P_i)$ is the natural logarithm of the unit price of land parcel i, and $ln(\overline{API_i})$ is the log of the average API for the city prior to the transaction. $Control_i$ denotes a vector of covariates including land characteristics X_i, proxies of bargaining power B_i, and the town/district, year, and month fixed-effects. To identify the true causal effect of air pollution on land prices, the assumption of OLS regression on Equation (4.4) is that conditional on a full set of covariates $Control_i$, there is no unobserved shock on land price that correlates with air pollution.

However, the assumption above is strong and it can be violated in some circumstances. For example, suppose a city government adopts regulatory policies targeting air pollution, such as controlling the land supply for industrial uses. Because such policies can influence the land prices, but are usually unmeasurable or unobservable from the data, failure to control them will result in omitted variable bias. Second, the measurement errors on $ln(\overline{API_i})$ can also result in biased estimation of β_1. In particular, assume that the promotion incentives drive the local bureaus to reduce their reported air pollution levels when the real level is higher than a threshold, the deviations of the manipulated data from the real values therefore are not randomly distributed and have a non-zero expectation, which will bias the estimation.

4.5.2 Instrumental Variable Approach

Atmospheric Circulation, Topography and Air Pollution

The identification strategy of this chapter exploits the exogenous effects of atmospheric circulation and topography features on monitored pollution levels, based on findings in environmental science. Given the amount of pollutants emitted into the air, the weather events and the topographic features largely determine the speed of dispersion (Beaver et al., 2010). Figure 4.7 illustrates a simple model of these mechanisms. First, there are two forces of pollutant transportation: wind in the horizontal direction and ascending currents in the vertical direction. As an important form of air movement that dilutes the pollutant density, wind has long been recognized as playing an important role in ground level air quality. The atmospheric temperature gradient affects the pollutant dispersion vertically by transferring between currents from lower to higher atmosphere. The air generally becomes cooler with increasing altitude. As is shown in Figure 4.7, the warm air layer is covered by the cool air in the atmosphere, forming the ascending convection currents of air that transport pollutants. However, under some conditions, the warmer layer can lie above the cooler layer, stopping this important channel of dispersion and trapping the pollutants in the lower atmosphere (Milionis and Davies, 1994). There are numerous causes for the temperature inversion, such as the movement of a warm and less dense air mass over a cold dense air mass, the overnight radiative cooling of surface air (radiation inversion) or the formation of a "marine layer" when the ocean is becoming cold.[23] The relative humidity of the air is also considered because it has been shown to be conducive to the accumulation and formation of small particles (Heal et al., 2012; De Hartog et al., 2005). It is expected that the TSP concentration level is higher in dry air than in moist air.

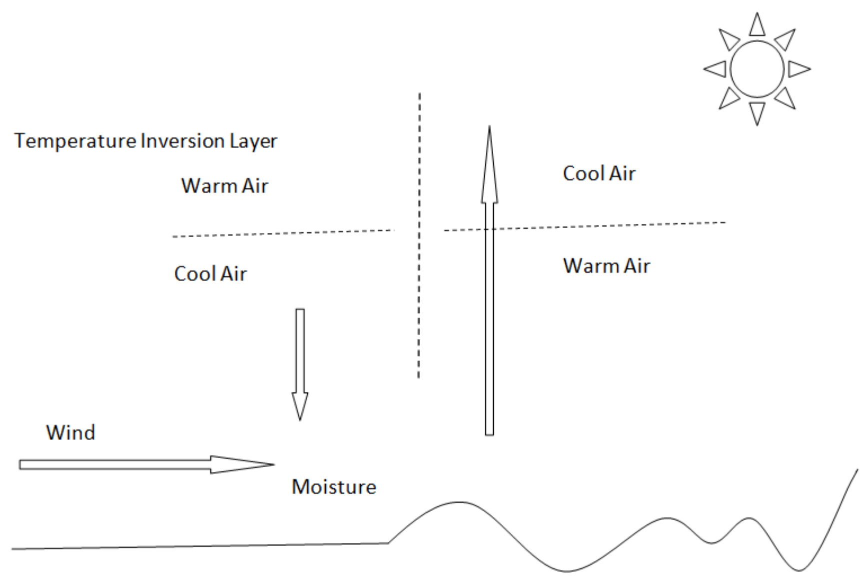

Figure 4.7: Weather and Topography Factors Affecting Air Pollution

To construct the instrumental variables above, detailed station-level historical weather data from the U.S. National Oceanic and Atmospheric Administration (NOAA), which has daily monitored weather data from more than 300 stations in China from 2000 to 2012, are used. Figure 4.8 illustrates the locations of these stations. The stations are then matched with the closest cities based on the geometric centroids. The weather data can then be correlated with the air pollution and land conveyances datasets.

The first meteorological variable is wind speed. It is provided directly by the NOAA

[23]See http://geography.about.com/od/climate/a/inversionlayer.htm

weather data. The daily wind speed ranges from 0 to 36.9 knots, with a significant seasonal cycle. A measure of relative humidity is not provided by the data. However, there is daily information on dew point. The relative humidity is calculated using the August-Roche-Magnus approximation method using the dew point values and mean temperatures.[24] The resulting relative humidity (rh) values range from 1.59 to 100. The last meteorological variable is the indicator of temperature inversion. The NOAA data only provides mean, maximum, and minimum temperatures at ground level rather than temperatures at different altitudes, so it is impossible to observe the temperature inversion occurrences directly. Nevertheless, the within-day temperature changes are strongly correlated with the radiation inversion, which is the most common form of temperature inversion.[25] Therefore, the daily change in temperature is an appropriate proxy for the probability of radiation type temperature inversion. In the data, this within-day temperature change can be measured by $gap_t = max_t - min_t$, where max_t is the daily maximum temperature and min_t is the daily minimum temperature.

The effects of weather events on air quality are also dependent on the topographical features (Banfield, 1973). For example, other factors being constant, the efficiency of wind on pollutant dispersion would be greater on a flat surface. An uneven landscape can trap the flow of pollutants and hence increase the pollution levels. To capture these heterogeneous effects of weather conditions on monitored air pollution, I include the interaction terms between the three weather indicators and the terrain of each city. The land slope is used to measure a city's terrain. To do that, I first use the digital elevation model (DEM) data from the China Historical GIS database to calculate the land slope of China at a grid resolution of 1km^2,[26] then I divide the slopes into four

[24] The equation is $100 \cdot exp(\frac{17.625 \cdot dew\_point}{243.04 + dew\_point})/exp(\frac{17.625 \cdot temperature}{243.04 + tempearture})$, where dew_point and $temperature$ are measures of daily dew point and mean temperature in Celsius degrees. This calculation method refers to: http://andrew.rsmas.miami.edu/bmcnoldy/Humidity.html.

[25] This is because the ground loses heat very quickly once the sun goes down, resulting in the cooling of air in contact with the ground. Because the air itself is a poor conductor of heat, this change of air temperature will lead to temperature inversion. Details can be seen at http://www.wrh.noaa.gov/slc/climate/TemperatureInversions.php

[26] According to the CHGIS database http://www.fas.harvard.edu/ chgis/data/chgis/downloads/v4/, the DEM data of China is derived originally from the GTOPO-30 project.

categories: $slope \leq 1°$, $1° < slope \leq 3°$, $3° < slope \leq 5°$, and $slope > 5°$. I calculate the fraction of area of each land slope category by city. Using the resolution of 1km^2, approximately 55% of the land in the selected cities has a slope no greater than 1°, which is considered a flat surface. The land with a slope between 1° and 3° accounts for approximately 23%, whereas land with a slope between 3° and 5° accounts for 10%. To avoid a perfect multi-collinearity problem in the first stage regression, the category of $slope > 5°$ is dropped. Finally, the terrain data are merged with the dataset by location.

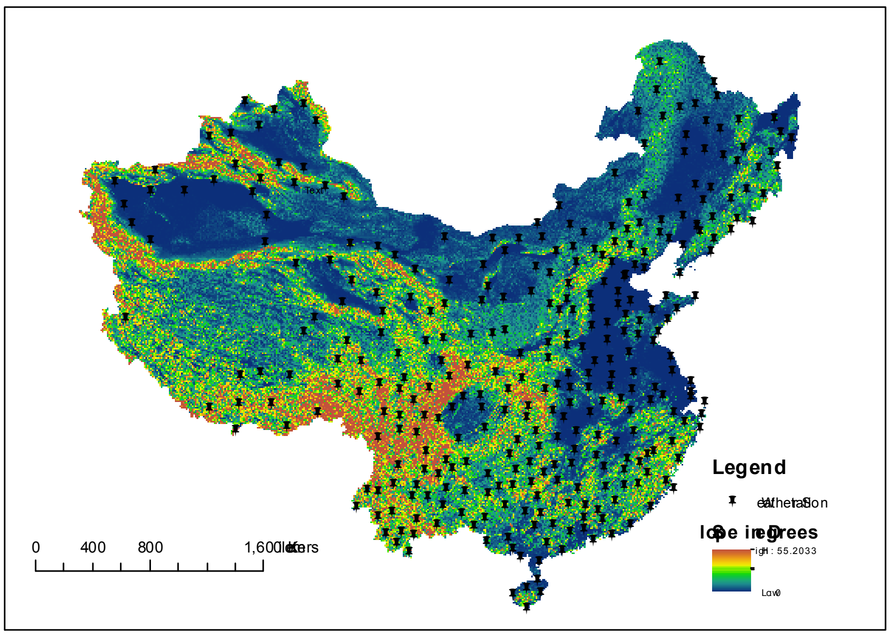

Figure 4.8: Weather Stations and Land Terrain of China

Note: Weather Stations are mapped according to the geographic coordinator provided by NOAA. Land slope is calculated by using the digital elevation model (DEM) of China, the original source of DEM is a raster produced by GTOPO-30 at 1km × 1km resolution.

Effects of Rainfall on Land Prices

One concern on the instrumental variable identification strategy of this study is that the average wind speed, relative humidity, and within-day temperature change might correlate with the average rainfall, thus affecting the land prices through a channel other than affecting the air quality only. Omitting average rainfall from the regression can potentially lead to an inconsistent estimation of β_1. According to the Land Management Law, the acquisition fee for transferring rural land to urban use, which is paid to the collectives by the local government, depends on the agricultural production of the land over the past three years. Because rainfall significantly correlates with agricultural sector performance in developing countries (Miguel et al., 2004), any economic shocks to the acquisition cost of rural land could become a corresponding change to the reserve price of leasehold, especially for the land on urban fringes. Therefore, it is important to include the average rainfall as a control variable in the regression equation (4.4) to rule out this potential channel.

The Two-Stage Least Squares Regression Model

Finally, the 2SLS model that identifies the causal effect of air pollution on land prices is presented as follows:

First stage

$$\begin{aligned} ln(\overline{API_i}) =& \alpha_0 + a_1 \cdot \overline{wdsp_i} + a_2 \cdot \overline{rh_i} + a_3 \cdot \overline{tgap_i} + \sum_{k=1}^{3} b_k \cdot \overline{wdsp_i} \cdot slopecat(k)_i \\ &+ \sum_{k=1}^{3} c_k \cdot \overline{rh_i} \cdot slopecat(k)_i + \sum_{k=1}^{3} d_k \cdot \overline{tgap_i} \cdot slopecat(k)_i + \alpha_2 Control_i + \nu_i \end{aligned} \tag{4.5}$$

Second stage

$$ln(P_i) = \beta_0 + \beta_1 \widehat{ln(\overline{API_i})} + \beta_2 Control_i + \varepsilon_i \tag{4.6}$$

In the first stage, the average wind speed ($\overline{wdsp_i}$), average relative humidity ($\overline{rh_i}$), average within-day temperature change ($\overline{tgap_i}$), and their interactions with the city's terrain features together serve as instruments to predict the average pollution level. To describe the topographical features in detail and generate sufficient variations, the land slopes are categorized into three groups: $slopecat(1) = \%(slope \leq 1°)$, $slopecat(2) = \%(1° < slope \leq 3°)$, and $slopecat(3) = \%(3° < slope \leq 5°)$. $Control_i$, the vector of covariates, includes land characteristics, city-level controls, proxy of relative bargaining power of the buyers, town/district, year, and month fixed effects and the average rainfall over the past year. Conditional on $Control_i$, the exclusion restriction of this model is that the average wind speed, average relative humidity, average within-day temperature change, and their interactions with land slopes do not impact on land prices except through their effects on the city's air pollution.

4.5.3 Correlated Random Coefficient Model

If the buyers' tastes for air quality are identical, then the estimated elasticity in Equation (4.6) is consistent estimate of the average elasticity for the population. However, this conclusion will be threatened by the presence of heterogeneous tastes and self-sorting behaviour. To address this issue, Chay and Greenstone (2005) use a correlated random coefficient (CRC) model that relaxes the strong assumption of homogeneous tastes. Following their methods, I will discuss the assumptions that are sufficient to obtain a consistent estimate of the average elasticity in the IV estimation framework and provide an alternative estimation method.

If the population has heterogeneous tastes on clean air, it may self-select into areas by taste-sorting. For example, the people who have a higher marginal willingness to pay for clean air, or equivalently, a higher elasticity of land prices with respect to air pollution in Equation (4.6), may choose to live in communities with better environmental amenities. Although the Household Registration System (Hukou) in China still restricts migration, its role has been greatly reduced in the 2000s to allow for more efficient reallocation of human resources (Wang, 2004). Therefore, setting the taste-sorting assumption and testing its importance are plausible for this study. Equation (4.4) can be rewritten as:

$$
\begin{aligned}
ln(P_i) =& \beta_0 + \bar{\beta}_1 \cdot ln(\overline{API_i}) + \beta_2 \cdot Control_i + (\beta_{1i} - \bar{\beta}_1) \cdot ln(\overline{API_i}) + \epsilon_i \\
=& \beta_0 + \bar{\beta}_1 \cdot ln(\overline{API_i}) + \beta_2 \cdot Control_i + e_i
\end{aligned} \tag{4.7}
$$

To simplify the notation, I denote the exogenous variables as a vector Z, which includes all instrumental variables z_1, and the other covariates as $Control$. As discussed in Wooldridge (2010), the potential problem of applying the 2SLS method to Equation (4.7) is that the newly constructed error term e is possibly correlated with Z, even under the strong assumptions of $E(\epsilon_i|Z_i) = E(\beta_{1i}|Z_i) = 0$. The dependence of $E((\beta_{1i} - \bar{\beta}_1) \cdot ln(\overline{API_i})|Z_i)$ on Z_i results in an inconsistent 2SLS estimate of $\bar{\beta}_1$. To correct for this problem, following Wooldridge (2003) and Chay and Greenstone (2005), consider the following stronger assumptions.

Assumption 4.1. $E(\epsilon_i|Z_i) = E((\beta_{1i} - \bar{\beta}_1)|Z_i) = 0$.

Assumption 4.2. $E(\epsilon_i|ln(\overline{API_i}), Z_i) = \lambda_A ln(\overline{API_i}) + \lambda_Z Z_i$.

Assumption 4.3. $E((\beta_{1i} - \bar{\beta}_1)|ln(\overline{API_i}), Z_i) = \varphi_A ln(\overline{API_i}) + \varphi_Z Z_i$

The second equality in Assumption 4.1 is a key assumption, it states that the conditional expectation of heterogeneous elasticity is independent of the instrumental variables. In this chapter, because the selected IVs are the natural variations in atmospheric activities, it is reasonable to assume that the tastes for air quality are not a function of them. In fact, the combination of Assumption 4.1 with Assumption 4.2 and with Assumption 4.3 imply that $E(\epsilon_i|ln(\overline{API_i}), Z_i) = \lambda_A \nu_i$ and $E((\beta_{1i} - \bar{\beta}_1)|ln(\overline{API_i}), Z_i) = \varphi_A \nu_i$, see the Appendix C.1 for proofs. Applying these results to Equation (4.7) produces:

$$
ln(P_i) = \beta_0 + \bar{\beta}_1 \cdot ln(\overline{API_i}) + \beta_2 \cdot Control_i + \lambda_A \hat{\nu}_i + \varphi_A \hat{\nu}_i \cdot ln(\overline{API_i}) + \xi_i \tag{4.8}
$$

where $\hat{\nu}_i$ are the predicted residuals from the first stage regression. This is an extension of the standard control function approach to IV estimation by including $\varphi_A \hat{\nu}_i \cdot ln(\overline{API_i})$, an interaction term of the estimated residuals with the endogenous variable. Under the three assumptions above, the $\bar{\beta}_1$ in Equation (4.8) is shown to be a consistent estimate of the average elasticity (Chay and Greenstone, 2005). The estimated parameters of interaction terms in Equation (4.8) are of important implications. Because $\lambda_A = Cov(\epsilon_i, \nu_i)/Var(\nu_i)$ and $\varphi_A = Cov((\beta_{1i} - \bar{\beta}_1), \nu_i)/Var(\nu_i)$, they measure the importance of estimation bias because of the omitted variables and self-selection, respectively. In particular, under the assumption of diminishing marginal utility of clean air and no taste sorting, the value of φ_A should be negative. Otherwise, there is evidence of sorting into different environmental amenities according to their heterogeneous tastes.

4.6 Results

4.6.1 OLS Regression Results

The empirical analysis of this study starts with the conventional OLS estimates of Equation (4.4). OLS is widely used in the conventional hedonic literature and provides a benchmark for the IV estimations in this chapter. Table 4.2 presents the estimation results. In column 1, there is no other control variable except the town/district fixed effects included in the regression. The estimated elasticity of unit land prices with respect to air pollution is -1.856, which is statistically significant at the 1 percent level. From columns 2 to 4, as more control variables are added into the regression model, the magnitude of the elasticity decreases steadily. After controlling for a full set of covariates, the estimated elasticity finally drops to -0.312, which is statistically insignificant at any conventional level. The dramatical changes in magnitudes and significance levels of the estimated elasticities from OLS regressions imply that the estimation results are sensitive to the inclusion of more control variables, probably because of the large correlations between air quality and the other covariates.

	$ln(P_i)$			
	(1) *OLS*	(2) *OLS*	(3) *OLS*	(4) *OLS*
$ln(\overline{API_i})$	-1.856^{***}	-0.752^{**}	-0.412^{*}	-0.312
	(0.607)	(0.312)	(0.243)	(0.258)
Land characteristics	*No*	*No*	*Yes*	*Yes*
City controls	*No*	*No*	*No*	*Yes*
Time fixed effects	*No*	*Yes*	*Yes*	*Yes*
Town/district fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
N	214,067	214,067	209,363	209,259

Note: Robust standard errors clustered at city level are in parentheses. The land characteristics and city controls are defined in the text. Time fixed effects are controlled for by adding year and month dummies.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

Table 4.2: OLS Estimates of Effects of Air Pollution on Log Land Prices

4.6.2 2SLS Estimation Results

Using the specified instrumental variables to generate exogenous variations in the local average pollution level, IV estimations are expected to provide consistent estimates of the elasticity. To begin, Table 4.3 presents the first stage regression results. The dependent variable is the natural logarithm of the annual average API. Across columns 1 to 4, the magnitudes and significance levels of the coefficients of instrumental variables do not vary considerably with the inclusion of additional control variables, suggesting that the predictive power of the IVs on air pollution is very robust against the inclusion of other covariates. This is because the variations of the IVs, which are driven by the natural forces of atmospheric activities, are largely orthogonal with respect to the land or city characteristics.

The estimated parameters of the IVs in Table 4.3 show that the average wind speed, within-day temperature change, and relative humidity significantly associate with the average local air pollution. I only use the land slopes to roughly describe the topographic features, which will be incapable of capturing the other important information such as the earth surfaces, location of mountains and valleys, etc. The estimations in Table 4.3 still demonstrate varying partial impacts of meteorological

	$ln(\overline{API_i})$				
	(1)	(2)	(3)	(4)	(5)
$\overline{wdsp_i}$	0.485***	0.699***	0.684***	0.615***	0.615***
	(0.185)	(0.202)	(0.200)	(0.202)	(0.006)
$\overline{rh_i}$	-0.042**	-0.019	-0.019	-0.021	-0.021***
	(0.020)	(0.017)	(0.017)	(0.019)	(0.001)
$\overline{tgap_i}$	-0.213**	-0.213**	-0.217**	-0.211**	-0.211***
	(0.087)	(0.098)	(0.097)	(0.093)	(0.002)
$\overline{wdsp_i} \times \%(slope \leq 1°)$	-0.527***	-0.750***	-0.735***	-0.636***	-0.636***
	(0.192)	(0.204)	(0.203)	(0.206)	(0.006)
$\overline{wdsp_i} \times \%(1° < slope \leq 3°)$	-0.252	-0.466**	-0.452**	-0.498***	-0.498***
	(0.223)	(0.194)	(0.198)	(0.189)	(0.006)
$\overline{wdsp_i} \times \%(3° < slope \leq 5°)$	-1.598**	-1.900***	-1.876***	-1.601**	-1.601***
	(0.684)	(0.658)	(0.662)	(0.651)	(0.019)
$\overline{tgap_i} \times \%(slope \leq 1°)$	0.201**	0.197*	0.201**	0.194**	0.194***
	(0.088)	(0.100)	(0.100)	(0.095)	(0.002)
$\overline{tgap_i} \times \%(1° < slope \leq 3°)$	0.279***	0.244***	0.247***	0.229***	0.229***
	(0.074)	(0.075)	(0.078)	(0.072)	(0.003)
$\overline{tgap_i} \times \%(3° < slope \leq 5°)$	0.355	0.297	0.313	0.344	0.344***
	(0.254)	(0.275)	(0.272)	(0.259)	(0.007)
$\overline{rh_i} \times \%(slope \leq 1°)$	0.037*	0.012	0.013	0.014	0.014***
	(0.021)	(0.018)	(0.017)	(0.020)	(0.001)
$\overline{rh_i} \times \%(1° < slope \leq 3°)$	0.065***	0.061***	0.064***	0.061***	0.061***
	(0.021)	(0.019)	(0.020)	(0.020)	(0.001)
$\overline{rh_i} \times \%(3° < slope \leq 5°)$	0.063	-0.042	-0.044	-0.030	-0.030***
	(0.071)	(0.052)	(0.049)	(0.054)	(0.003)
Land characteristics	No	No	Yes	Yes	Yes
City controls	No	No	No	Yes	Yes
Time fixed effects	No	Yes	Yes	Yes	Yes
Town/district fixed effects	Yes	Yes	Yes	Yes	Yes
F-stastic of the Instrumental variables	2.12	3.29	3.17	3.93	2757.24
N	282,075	282,075	268,708	268,553	268,553
Robust standard errors	Yes	Yes	Yes	Yes	No
Standard errors clustered at city level	Yes	Yes	Yes	Yes	No

Note: Robust standard errors clustered at city level are in parentheses across columns 1 to 4. In column 5, the standard errors are calculated under the assumption of independent and identically distributed error terms. The dependent variable $ln(\overline{API_i})$ is the natural logarithm of the city's one-year average APIs before land i was conveyed. $\overline{wdsp_i}$, $\overline{rh_i}$, and $\overline{tgap_i}$ are the city's average wind speed, average relative humidity, and average within-day temperature gaps of the same period, respectively. The percentage of land slope in different categories are calculated at city level, and they are assumed to be the same over time.

* Significant at the 10 percent level.

** Significant at the 5 percent level.

*** Significant at the 1 percent level.

Table 4.3: First Stage Regression

variables on pollution concentration levels. The terrain features interact with the two major forces of atmospheric flows: winds and temperature reversions, rather than the relative humidity of air, in influencing air pollution. An uneven land surface will generally reduce the pollutant dispersion effects of the wind, but it can also reduce the effects of temperature reversions on pollutant concentrations.

The estimation in column 5 of Table 4.3 assumes independent and identically distributed error terms. With an F-statistic of 2,757, the instruments in the first stage regression are highly significant. However, after adjusting for heteroskedasticity and clustering standard errors at the city-level, the F-statistic of joint significance of instruments drops sharply to approximately 4. Although there is no established evidence on how close the relation is between the robust version of the first stage F-statistic and relative bias (Bun and de Haan, 2010), the potential weak instrument problem is still a concern in this study. To cope with this, I will use the Anderson-Rubin (AR) Wald test in the 2SLS IV estimations to verify the inference of the endogenous variable, and I will also use the limited information maximum likelihood (LIML) estimation as a robustness check.

Table 4.4 presents the results of the estimated effects of air pollution on land prices. Unlike the results from the OLS regressions, the similar coefficients on $ln(\overline{API_i})$ across columns 1 to 4 suggest that the estimated elasticity of land price with respect to air pollution is relatively robust against adding other controls. This is because the selected IVs are primarily associated with air pollution, rather than the other covariates that influence the land prices. However, the results from the regression in column 4 that controls all the other covariates is preferred.

The magnitude of the estimated elasticity is approximately -1.4, indicating that every 1% decline in annual air pollution will, on average, result in a 1.4% increase in land prices. The land parcels in the same area may share some similar characteristics that are unobserved from the data, and the error term of the 2SLS estimation may be serial correlated. Because the correlation between error terms within the same group

	$ln(P_i)$			
	(1) $2SLS$	(2) $2SLS$	(3) $2SLS$	(4) $2SLS$
$ln(\overline{API_i})$	-1.819	-2.460^{**}	-1.766^{**}	-1.369^{**}
	(1.601)	(1.106)	(0.741)	(0.681)
Anderson-Rubin test p value	0.000	0.000	0.003	0.013
Land characteristics	No	No	Yes	Yes
City controls	No	No	No	Yes
Time fixed effects	No	Yes	Yes	Yes
Town/district fixed effects	Yes	Yes	Yes	Yes
Hansen J statistics p value	0.142	0.147	0.485	0.485
N	$212,399$	$212,399$	$207,692$	$207,585$

Note: Robust standard errors clustered at city level are in parentheses. The Anderson-Rubin test, which is robust to weak instruments, is provided for the inference of $ln(\overline{API_i})$ in 2SLS estimation.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

Table 4.4: 2SLS Estimates of Effects of Air Pollution on Log Land Prices

will bias the estimated standard error of the regressors, the clustered standard errors are used for the 2SLS estimation inferences. However, before the error structure is known, it is uncertain whether the standard errors should be clustered at the town/district-level or the city-level. In this chapter, I cluster the standard errors at the city-level, which is lower than town/district and will produce more conservative inferences. The conventional 2SLS inference in column 4 of Table 4.4 is significant at the 5% level. Likewise, the AR test that is robust to weak instruments also points in the same direction. Consistent with previous studies, without accounting for the endogeneity of a city's air pollution, the OLS regression tends to underestimate the causal effect of air pollution on land prices.

The estimation of the elasticity of land price with respect to air pollution is important for environmental policy because it can be incorporated into the calculation of the benefits of environmental protection within the city. For example, the total land leasehold revenue in Beijing in 2009 was approximately 69 billion RMB, therefore every 1% reduction of average API is estimated to result in approximately 0.9 billion RMB increase in government revenue. In addition to the other benefits from improving air quality, such as the reduction of medical expenses and an increase in worker productivity, this significant benefit from air quality improvement should be considered in the evaluation of a local government's environmental policy.

Robustness

LIML estimation—In the case of an overidentified model and potential weak IVs, it has been shown that the bias of 2SLS is an increasing function of the number of instruments. In contrast, the limited information maximum likelihood (LIML) estimator has the same asymptotic distribution as 2SLS but is median-unbiased in the overidentified models (Angrist and Pischke, 2008). However, LIML is less precise than the 2SLS. Table 4.4 reports the the results of LIML estimation using the same set of instrumental variables as in the 2SLS regressions. The estimated elasticity is -1.39, close to -1.37 in Table 4.3. As expected, the standard error of LIML estimates is higher than that of 2SLS, but it does not change the main conclusion: air pollution causes significant negative effects on urban land prices, with an elasticity larger than 1.

	$ln(P_i)$
	(1) $LIML$
$ln(\overline{API_i})$	-1.390^{**}
	(0.697)
Anderson-Rubin test p value	0.013
Land characteristics	Yes
City controls	Yes
Time fixed effects	Yes
Town/district fixed effects	Yes
Hansen J statistics p value	0.483
N	$207,585$

Note: Robust standard errors clustered at city level are in parentheses.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

Table 4.5: Robustness Checks: LIML Estimation

Average APIs of Different Period Lengths—In the main analysis of this study, the air amenities of the land are measured using a one year API average for the city prior to the transaction date because there are evident seasonal cycles in air pollution, land prices and meteorological variables. For example, the average APIs are typically higher during winter because of higher heating demand, drier air and frequent temperature reversions. Using annual average APIs and hence the annual meteorological variables as instruments has the advantage of accounting for these cycles.

It is also important to observe the elasticities of land prices over different time periods, with respect to average air pollution. This is driven by the hypothesis that the pollution shocks in different periods may influence buyers' evaluations of land values. The average API of every observation is thus recalculated as follows

$$\overline{API_t} = \sum_{k=t-1}^{t-m} API_k \tag{4.9}$$

where m varies from 30, 90, 180, and 270 days to represent different time periods. The instruments for average air pollution are constructed for the same periods. Regression results are presented in Table 4.6. From columns 1 to 4, the period length increases with an inverted-U shape of the magnitudes of estimated elasticities. The elasticity is as low as -0.606 when the period length m is set as 30, implying that every one percent increase of the average API for one month before the land was conveyed will result in only approximately a 0.6 percent decrease in the land price. The elasticity then reaches its peak value when the average APIs are measured at a half year, suggesting that the average pollution over the past six months may have the strongest effect on land values.

Influences of the Extreme Values—In the land transaction data, there is a considerable proportion of land parcels transacted at either very low prices or extremely high prices. Figure 4.9 illustrates the distribution of the dependent variable $ln(P)$. The tails of the distribution are long and thin. There are 1,779 observations with negative values of $ln(P)$ and 702 observations with $ln(P)$ higher than 10.

Although it is impossible to determine whether the extreme values result from a

	$ln(P_i)$			
	(1) $2SLS$ $30Days$	(2) $2SLS$ $90Days$	(3) $2SLS$ $180Days$	(4) $2SLS$ $270Days$
$ln(\overline{API_i})$	-0.606^{**}	-0.943^{*}	-1.804^{*}	-1.657^{**}
	(0.241)	(0.554)	(1.043)	(0.815)
Anderson-Rubin test p value	0.000	0.000	0.002	0.003
Land characteristics	Yes	Yes	Yes	Yes
City controls	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Town/district fixed effects	Yes	Yes	Yes	Yes
Hansen J statistics p value	0.649	0.509	0.399	0.401
N	$207,585$	$207,585$	$207,585$	$207,585$

Note: Robust standard errors clustered at city level are in parentheses. Across columns 1 to 4, the regressions are based on the average APIs and their corresponding IVs that are calculated in different period lengths. For example, the endogenous variable of the regression of column 1 is defined as the 30 days API average prior to the transaction date.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

Table 4.6: Robustness Checks: Average APIs of Different Period Lengths

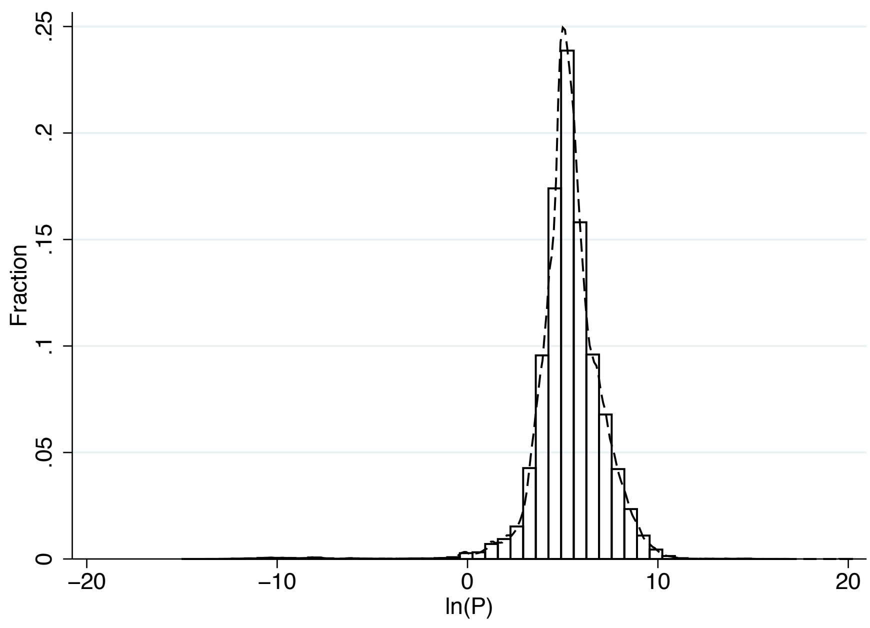

Figure 4.9: Distribution of the Dependent Variable: $ln(P_i)$

misreporting land transaction information or not, it is meaningful to check the sensitivity of estimations to potential outliers. Column 1 of Table 4.7 presents the estimation results on a sample excluding the 2,562 observations with $ln(P)$ lower than 0 or higher than 10, which are equivalent to unit land prices of 10,000 RMB and 22 million RMB per hectare, respectively. The estimated elasticity of -1.367 rounds to the same estimate of -1.4 from the previous section. In next regressions, there are more observations in the right tail and left tail of the price distribution excluded from the regression sample. Specifically, in Column 2 and 3, I only keep the observations with values of $ln(P)$ between the 1st percentile and 99th percentile, and between the 5th percentile and 95 percentile, respectively. The magnitudes and inferences of these two estimated elasticities finally turn out to be robust.

	$ln(P_i)$		
	(1) $2SLS$ $0 < ln(P_i) < 10$	(2) $2SLS$ $p(1) < ln(P_i) < p(99)$	(3) $2SLS$ $p(5) < ln(P_i) < p(95)$
$ln(\overline{API_i})$	-1.367^{**}	-1.305^{*}	-1.216^{**}
	(0.591)	0.688	(0.529)
Anderson-Rubin test p value	0.000	0.019	0.000
Land characteristics	Yes	Yes	Yes
City controls	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Town/district fixed effects	Yes	Yes	Yes
Hansen J statistics p value	0.256	0.524	0.446
N	$205,023$	$205,481$	$188,570$

Note: Robust standard errors clustered at city level are in parentheses. Across columns 1 to 3, regression samples are selected based on the values of dependent variables. The regression of column 2 excludes observations with log land prices either lower than the value of the 1st percentile or higher than the value of the 99th percentile. In column 3, the range contracts to between the 5th percentile and the 95th percentile.

* Significant at the 10 percent level.

** Significant at the 5 percent level.

*** Significant at the 1 percent level.

Table 4.7: Robustness Checks: Excluding Extreme Values of the Dependent Variable

Regression Sample with Lower Geocoding Precision—Because of the large disparity of urban development both within and across cities, controlling the town/district-level fixed effects can help to explain the variations in land prices, and more importantly, reduce the estimated standard errors. Therefore, I geocode the original samples at the town/district-level using addresses. However, as many land conveyance records do not provide sufficiently precise addresses, the regression sample size decreases considerably from 317,485 to 207,585 after geocoding. To check whether the estimates are sensitive to the sample attenuation, I employ the original data without geocoding at the town/district level for the 2SLS estimations. I control the city-level fixed effects by using the city codes from the data. This is equivalent to geocoding the addresses at a lower precision level. The estimated elasticity in Table 4.8 is -1.532, which does not deviate significantly from the previous results. However, the estimated standard error is much larger than that in Table 4.4, making it statistically insignificant at the conventional levels. This is a result of the failure to absorb the large variation in land prices in different areas within cities.

	$ln(P_i)$
	(1) $2SLS$
$ln(\overline{API_i})$	-1.532
	(1.018)
Anderson-Rubin test p value	0.000
Land characteristics	Yes
City controls	Yes
Time fixed effects	Yes
City fixed effects	Yes
Hansen J statistics p value	0.139
N	$317,485$

Note: Robust standard errors clustered at city level are in parentheses. The regression sample has been geocoded at a less precise level, the city fixed-effects, rather than the town/district fixed-effects, are controlled.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

Table 4.8: Robustness Checks: Regressions on a Sample with a Lower Geocoding Precision

4.6.3 Regressions on Different Land Uses

In this section I estimate the various elasticities by land uses. Different planned uses of land can sort the buyers based on different preferences for air quality. For example, it is expected that the buyers of residential land may have a greater willingness to pay for clean air than their industrial or commercial counterparts. The elasticities are likely to also be affected by the land supply. To achieve the environmental protection goals, the local government may adjust their industrial policy by regulating the land supply for specific uses.

	$ln(P_i)$		
	(1) 2SLS *ResidentialLand*	(2) 2SLS *IndustrialLand*	(3) 2SLS *CommercialLand*
$ln(\overline{API_i})$	-1.788^{*}	0.166	0.500
	(1.011)	(0.644)	(1.209)
Anderson-Rubin test p value	0.000	0.000	0.376
Land characteristics	*Yes*	*Yes*	*Yes*
City controls	*Yes*	*Yes*	*Yes*
Time fixed effects	*Yes*	*Yes*	*Yes*
Town/district fixed effects	*Yes*	*Yes*	*Yes*
Hansen J statistics p value	0.323	0.019	0.636
N	87,143	70,749	28,748

Note: Robust standard errors clustered at city level are in parentheses.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

Table 4.9: Estimates of the Impacts of Air Pollution on Land Prices by Land Uses

I categorize the proposed land uses into four major groups: residential land, industrial land, commercial land, and others. Table 4.9 reports the estimation results. As expected, air pollution has a significantly negative effect on residential land prices: every 1 percent increase in average API will lead to 1.7 percent decrease in the unit price of residential land. This result is consistent with the findings in the existing literature that shows negative effects of air pollution on housing prices. In contrast, the elasticity for industrial land is positive but small. The robust AR test shows that this effect is significant at the 1% significance level. A possible explanation for this is that urban air quality degradation tends to induce the local government to regulate the development of the polluting industrial sector using land control, which causes higher industrial land prices. Finally, the 2SLS estimates show no significant effect of air pollution on commercial land prices.

4.6.4 Evidence on Taste-Sorting

Table 4.10 depicts the estimation results of the control function approach after relaxing the assumptions of homogeneous tastes and non-sorting behaviour. As discussed in the Section 4.5, with the random coefficient model framework and the assumptions from 1 to 3, the coefficient of $\overline{API_t}$ in Equation (4.8) is a consistent estimate of the average elasticity. In column 3 of Table 4.10, the estimated average elasticity is -1.434, only slightly higher than the results from the 2SLS regressions. This result implies that the 2SLS regressions are able to provide reliable estimates on the average elasticity of land prices with respect to air pollution. As a complement to this finding, the significance levels of the estimated coefficients on $\hat{\nu}_i$ and $ln(\overline{API_i}) \times \hat{\nu}_i$ suggest that the bias is primarily the result of omitted variables or measurement error problems, rather than heterogeneous tastes and self-selection. Unlike the results on Chay and Greenstone (2005), the coefficient on $ln(\overline{API_i}) \times \hat{\nu}_i$ is negative, which provides modest evidence suggesting that the elasticity is higher in more polluted areas.

	$ln(P_i)$		
	(1) OLS	(2) OLS	(3) OLS
$ln(\overline{API_i})$	-2.521^{***}	-1.731^{**}	-1.434^{*}
	(0.863)	(0.850)	(0.779)
$\hat{\nu}_i$	6.732^{*}	5.626	3.589^{**}
	(3.921)	(3.690)	(1.751)
$ln(\overline{API_i}) \times \hat{\nu}_i$	-1.133	-1.024	-0.562
	(0.941)	(0.852)	(0.576)
Land characteristics	No	No	Yes
City controls	No	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Town/district fixed effects	Yes	Yes	Yes
N	$214,067$	$213,963$	$209,259$

Note: Robust clustered standard errors are calculated by 500 times bootstrap replications. ν_i is the predicted residual of the first stage estimation.
* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

Table 4.10: Random Coefficient Estimates

4.7 Conclusions

Environmental degradation has become an significant issue for the development of China, however, little is known regarding the associated economic costs. This chapter focuses on estimating the effects of air pollution on urban land prices in China and to measure the potential economic benefits of environmental protection. Consistent with recent literature, the endogeneity problem of observed air pollution is highlighted. I exploit the natural mechanisms of pollutant dispersions driven by meteorological variables and their interactions with topographical features to provide exogenous variations on local air pollutant concentrations. Using a unique land transaction dataset matched with detailed city-level air pollution historical readings, instrumental variable estimations demonstrate that the elasticity of land prices with respect to annual air pollution is -1.4. The OLS estimates that do not account for the endogeneity problem appear to underestimate the causal association between them. Furthermore, the impact on residential land prices is found to be much greater than that on industrial or commercial land prices, this finding might be explained by the strong disutility of pollution for residential land buyers and the local governments' land control policies that target towards pollution reductions. Finally, the random coefficient estimation shows no evidence of taste-sorting behaviour in China, indicating that the pollution controls can achieve higher economic gains in the areas of worse air quality.

Chapter 5

Conclusion

The importance of energy infrastructure on economic growth and industrial development has been widely discussed by economists. However, the mechanisms of the development effects of energy infrastructure have long been ignored. Chapter 2 uses recent power outages in China as an example to show how the quality of energy infrastructure affects worker reallocation among Chinese manufacturing firms. To address the well-acknowledged endogeneity problem of electrical outages at the firm level, I use temperature shocks as an instrumental variable of outages. Empirical results from IV estimation show that frequent power outages lead to higher separation rates for long-term workers through both voluntary quits and layoff. Moreover, outages also increase employment volatility and excess worker reallocation for long-term workers. In contrast, impacts of outages on the reallocation of temporary workers are economically and statistically insignificant. Furthermore, investigation of the potential mechanisms suggests that shocks from unreliable power supplies are absorbed by the flexibility of temporary workers in terms of wage and working hours adjustments, while long-term workers respond to shocks with increased reallocation.

In response to the frequent electricity outages, many firms in developing countries have installed private generators to partly substitute the unreliable pubic grid services. However, due to the cost of self-generation being much higher than purchasing electricity from the public grid, it is still a puzzle whether the adoption of the private remedial infrastructure can have significant development effects on the firms. Chapter 3 develops a two-period theoretical model to demonstrate a firm's decision in adopting a generator and the subsequent influence on production capital investment. I then examine the theoretical implications by using an Indian firm survey dataset. Empirical results support the prediction of the theoretical framework. That is, unreliable electricity provision significantly encourages private investment in a generator. Moreover, the estimated effect of generator adoption on investment is significantly positive. Furthermore, there is a heterogeneous treatment effect of private generator adoption on the investment rate, specifically, firms that are the least likely to install generator however would benefit the most and have a larger impact on their investment in other production capital.

Severe environmental degradation in China has been considered to be partly caused by the inefficient energy production. The authorities have imposed various policies to achieve pollution reduction. However, still, little is known regarding the associated economic costs of air pollution in China. Chapter 4 attempts to estimate the implicit price of air quality in China's urban land market. I collected very detailed and comprehensive micro-level datasets on urban air pollution and land transactions in China from 2000 to 2012. Consistent with recent literature, I highlight the endogeneity problem of local air pollution. I exploit the natural mechanisms of pollution dispersions driven by meteorological variables and their interactions with topographical features to provide exogenous variations on local air pollution concentrations. Results from instrumental variable estimations suggest that air pollution has economically and statistically significant effects on urban land prices in China. However, the impact on residential land prices is much greater than on industrial or residential land prices, which can be explained by the strong disutility of pollution for residential land buyers as well as the local land regulation policies. Finally, the random coefficient estimation demonstrates no evidence of taste-sorting behaviour in China, indicating that the pollution controls can achieve higher economic gains in the areas of worse air quality.

The research can be extended in several directions. Although I have shown the significant impacts of poor energy infrastructure on the labour market outcomes and firm's investment decision in Chapter 2 and Chapter 3, it is still unclear about the development effect of other types of infrastructure. Therefore, as a first extension to this thesis, I suggest analysing the economic effect of transportation infrastructure systematically. As public transportation infrastructure has been found to significantly affect regional growth in the existing literature, it is interesting and important to examine its potential time- or spatially-varying effects on the land market, firm dynamics, and labour market outcomes, which could be incorporated into the economic analysis of transportation facilities. Further, due to the unique institutional background of China, this research can help understand the incentives of massive transportation infrastructure investment by the governments.

In Chapter 4, I have shown that the people's willingness to pay for clean air in China is relatively high, which can be reflected in the property price differences in urban areas. However, as it is very important to investigate the reason of this high willingness to pay for air quality in China's urban areas, I suggest extending the analysis of Chapter 4 by estimating the health impacts of air pollution. If the health impact of air pollution is high, which will lead to considerable health costs, then it may be able to significantly explain the high estimated willingness to pay for clean air in Chapter 4. To conduct this research, I have matched the daily air pollution data at city level with the individual-level hospitalization data of Fujian Province from 2010 to 2011. The rich data allow me to investigate the heterogeneous health impacts of air pollution by different ages as well as by various social groups. This study will provide important implications for the environmental protection policy in China.

My future research plan will expand and deepen investigations on the implications of land market development in China. Concurrent with the rapid urbanization, China's land markets have been booming over the past two decades. However, little is known about its social and economic impact. My research projects will include an examination of urban land prices on entrepreneurship. The results will contribute to the debates about whether the wealth shocks, e.g. through the fluctuations of land values, influence firm creation and growth.

As part of this plan, I have collected the land transaction data and firm-level census data in China. These different datasets will be matched according to the dimensions of time and locations. The comprehensive data allow me to estimate the impacts of land value shocks on firm dynamics and performance. Further, I will also empirically investigate the mechanisms of these impacts to provide insightful explanations. These findings will carry important policy implications for developing countries, which are expected to experience rapid urbanization and industrialization in the future but are typically constrained by obstacles that inhibit entrepreneurship.

Chapter A

Appendix for Chapter 2

A.1 2004 Investment Climate Survey Sample

A.2 Worker flows

There is some confusion on translation between the English questionnaire and the original Chinese questionnaire around the questions on quit, layoff, and hiring rates. In the English questionnaire, firm managers were asked to provide the percentage of resigned, laid-off, and newly-hired staff that were formerly long-term or temporary workers. In this case, the values of $quit_p + quit_t$, $layoff_p + layoff_t$, and $hire_p + hire_t$ should equal exactly 100. This does not turn out to be true because as observed in Table 2.1, the average values of $quit_p$, $quit_t$, $layoff_p$, $layoff_t$, $hire_p$ and $hire_t$ are all less than 11.

However, in the Chinese questionnaire that was used during the survey, corresponding questions ask about the quit, layoff and hiring rates of long-term and temporary workers in 2004. To avoid misunderstandings related to the survey questions, I drop 154 observations in which the values of $quit_p+quit_t$, $layoff_p+layoff_t$, and $hire_p+hire_t$ consistently equal 100. These observations account for only 1.2% of the sample. The Chinese questionnaire and other supporting materials were obtained from the World

	Percent		Percent
Sector		Ownership	
Food from Agricultural Products	7.81	State-owned	9.05
Foods	1.96	Collective-owned	7.01
Beverage	1.44	Share joint-owned units	2.94
Tobacco	0.37	Limited liability corporation	36.88
Textile	7.68	Shareholding corporations	10.12
Textile Wearing Apparel	1.66	Private-owned	13.51
Leather	1.12	Enterprises invested by HK, Macau, Taiwan	7.98
Processing of Timbers and Wood	1.14	FIE	11.27
Furniture	0.44	Others	1.23
Paper and Paper Products	1.90		
Printing	0.50	Size	
Culture, Education and Sport Activity	0.33	Micro (1-10 employees)	0.29
Petroleum	1.47	Small (11-50 employees)	12.84
Chemical Raw Material and Chemical Products	11.62	Medium (51-200 employees)	30.80
Medicines	3.44	Large (201+ employees)	56.07
Chemical Fiber	0.38		
Rubber	0.17	Age	
Plastic	2.65	1-5	26.81
Non-metallic Mineral Products	10.48	6-10	31.67
Ferrous Metals	3.96	11-20	24.39
Non-ferrous Metals	2.78	21-50	14.21
Metal Products	2.95	51+	2.92
General Purpose Machinery	8.69		
Special Purpose Machinery	3.92		
Transport Equipment	7.98		
Electrical Machinery	6.97		
Electronic Equipment	4.82		
Measuring Instrument	0.48		
Artwork	0.88		
Recycling and Disposal of Waste	0.02		

Table A.1: Sample composition

Bank.

A.3 Temperature data

Temperature data were obtained from the U.S. National Oceanic and Atmospheric Administration (NOAA). The data set provides information from 1995 to 2004 on daily weather conditions at 377 weather stations, together with the latitude and longitude of each station. Using the coordinates of each station, I project the weather stations onto a digital geographic information system (GIS) map of China provided by the GADM spatial database (www.gadm.org). Finally, weather stations are matched with survey cities according to their geographic locations. For cities matching with more than one station, temperature data are averaged across all stations. For cities that do not match with any weather station, data from the nearest station to the city boundary is used. Projection and matching tasks are performed using ArcGIS.

Chapter B

Appendix for Chapter 3

B.1 Proof of Proposition 3.1

Substitute the optimal investment rates $I^*_{1i}(p_i, K_i)$ and $I^*_{0i}(p_i, K_i)$ in the profit function and it is observed that the optimal profit is a function of probability p_i (given K_i). As the condition for adopting a generator is $\Delta\pi_i(p) = \pi^*_{1i}(p) - \pi^*_{0i}(p) > 0$, I now prove that: For every given set of parameters, there exists a specific point p^*, and the firm will install a generator when the perceived probability p is lower than it.

For the real-valued and continuous function $\Delta\pi_i(p)$ defined on a compact interval $p \in [0, 1]$, when the electricity power is perfectly provided by the public grid, firms installing a generator will have a lower profit due to the fixed cost G, therefore, $\Delta\pi_i(p = 1) < 0$. When there is no electricity provided from the public grid, the firms without a generator will earn a zero profit, which implies $\Delta\pi_i(p = 0) > 0$. Let

$$\mathrm{A} = \{p : p \in [0, 1] \text{ and } \Delta\pi_i(p) \leq 0\} \tag{B.1}$$

Then A is nonempty since $i \in$ A, and A is bound lower by 0. Let $p^* = \inf\mathrm{A}$. Then $0 < p^* < 1$, I next prove that $\Delta_i(p^*) = 0$.

If $\Delta\pi_i(p^*) \neq 0$, there is a 1-ball $\mathrm{B}(\mathrm{p}^*; \delta)$ in which $\Delta\pi_i(p)$ has the same sign as

$\Delta\pi_i(p^*)$. If $\Delta\pi_i(p^*) < 0$, there are points $p < p^*$ at which $\Delta\pi_i(p) < 0$, contradicting the definition of p^*. If $\Delta\pi_i(p^*) > 0$, then $p^* + \delta/2$ is a lower bound for A, again contradicting the definition of p^*. Therefore $\Delta\pi_i(p^*) = 0$.

I thus have proved that: for every set of parameters, there indeed exists a point p^* satisfying $\Delta\pi_i(p) > 0$ when $p < p^*$. So when the probability of available public electricity provision is sufficiently low, the firm will be inclined to install a generator.

B.2 Proof of Proposition 3.2

The first order condition for the maximization problem in the two cases above yields:

$$\frac{\partial \pi_{1i}}{\partial i_{1i}} = \phi_i \cdot \alpha \cdot (K_i + I_{1i} \cdot K_i)^{\alpha-1} \cdot K_i - (p_i \cdot P_{0i} + (1-p_i) \cdot P_{1i}) \cdot m \cdot K_i - r \cdot K_i = 0 \quad \text{(B.2)}$$

and

$$\frac{\partial \pi_{0i}}{\partial i_{0i}} = \phi_i \cdot p^{\beta} \cdot \alpha \cdot (K_i + I_{0i} \cdot K_i)^{\alpha-1} \cdot K_i - p_i \cdot P_{0i} \cdot m \cdot K_i - r \cdot K_i = 0 \quad \text{(B.3)}$$

Let $I^*_{1i} = \frac{1}{K_i} \cdot [\frac{(p_i \cdot P_{0i} + (1-p_i) \cdot P_{1i}) \cdot m + r}{\phi_i \cdot \alpha}]^{\frac{1}{\alpha-1}} - 1$ and $I^*_{0i} = \frac{1}{K_i} \cdot [\frac{p_i \cdot P_{0i} \cdot m + r}{\phi_i \cdot \alpha \cdot p_i^{\beta}]}]^{\frac{1}{\alpha-1}} - 1$ be the optimal investments by the firms with and without generators, respectively. Those equations are both functions of the initial capital stock K_i and the probability of available public capital p_i. The first order derivative of ΔI^*_i with respect to capital stock K_i equals to

$$\frac{\partial \Delta I^*_i}{\partial K_i} = \frac{\partial (I^*_{1i} - I^*_{0i})}{\partial K_i} = -\frac{1}{K_i^2} \cdot \left\{ [\frac{(p_i \cdot P_{0i} + (1-p_i) \cdot P_{1i}) \cdot m + r}{\phi_i \cdot \alpha}]^{\frac{1}{\alpha-1}} - [\frac{p_i \cdot P_{0i} \cdot m + r}{\phi_i \cdot \alpha \cdot p_i^{\beta}}]^{\frac{1}{\alpha-1}} \right\} \quad \text{(B.4)}$$

This value will be negative conditional on $p_i^{\beta} \cdot [(p_i \cdot P_{0i} + (1-p_i) \cdot P_{1i}) \cdot m + r] <$

$p_i \cdot P_{0i} \cdot m + r$ I next take the first derivative of ΔI_i^* with respect to the probability

$$\frac{\partial \Delta I_i^*}{\partial K_i} = \frac{\partial I_{1i}^*}{\partial K_i} - \frac{\partial I_{0i}^*}{\partial K_i} \tag{B.5}$$

where

$$\frac{\partial I_{1i}^*}{\partial p_i} = \frac{1}{K_i} \cdot \frac{1}{\alpha - 1} \cdot [\frac{(p_i \cdot P_{0i} + (1 - p_i) \cdot P_{1i}) \cdot m + r}{\phi_i \cdot \alpha}]^{\frac{1}{\alpha-1}-1} \cdot \frac{(P_{0i} - P_{1i}) \cdot m}{\phi_i \cdot \alpha} \tag{B.6}$$

and

$$\frac{\partial I_{0i}^*}{\partial p_i} = \frac{1}{K_i} \cdot \frac{1}{\alpha - 1} \cdot [\frac{p_i \cdot P_{0i} \cdot m + r}{\phi_i \cdot \alpha \cdot p_i^{\beta}}]^{\frac{1}{\alpha-1}-1} \cdot [\frac{P_{0i} \cdot m}{\phi_i \cdot \alpha} \cdot (1-\beta) \cdot p_i^{-\beta} - \frac{r}{\phi_i \cdot \alpha} \cdot \beta \cdot p_i^{-\beta-1}] \tag{B.7}$$

For the firms that have installed a generator, as I assume that the electricity price from the public grids is lower than the in-house generation cost, that is, $P_{0i} < P_{1i}$, and thus $\frac{\partial I_{1i}^*}{\partial p_i} > 0$, indicating that the optimal investment rate increases with the availability of public power supply. However, the sign of $\frac{\partial I_{0i}^*}{\partial p_i}$ is ambiguous, since it depends on the sign of $\frac{P_{0i} \cdot m}{\phi_i \cdot \alpha} \cdot (1 - \beta) \cdot p_i^{-\beta} - \frac{r}{\phi_i \cdot \alpha} \cdot \beta \cdot p_i^{-\beta-1}$. If the probability of available public electricity supply satisfies $p_i > \frac{\beta \cdot r}{(1-\beta) \cdot P_{0i} \cdot m}$, then $\frac{\partial I_{0i}^*}{\partial p_i} < 0$, which implies the investment rate of the firms is a decreasing function of the probability p_i when a generator is not adopted. This will lead to an increasing treatment effect of generator adoption on the investment rate.

B.3 OLS Regression Results

	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
Dependent Var.	INV	INV	INV	INV	INV
Method	OLS	OLS	OLS	OLS	OLS
Constant	0.025***(0.006)	0.008(0.010)	0.007(0.011)	-0.020(0.019)	-0.019(0.019)
Generator	0.030***(0.007)	0.033***(0.008)	0.034**(0.011)	0.033**(0.011)	0.031***(0.008)
Outage	-0.00006*(0.00003)	-0.00005*(0.00003)	-0.00005*(0.00005)	-0.00005*(0.00005)	-0.00006*(0.00003)
Outage*Generator			-9.63e-06(0.00006)	0.00001(0.00006)	
Worker				-2.29e-07(0.00001)	-2.93e-07(0.00001)
Age				-0.001**(0.0003)	-0.001**(0.0003)
Exporter				0.013(0.010)	0.014(0.010)
Credit_con				0.0004**(0.0002)	0.0004**(0.0002)
Industry dummies	NO	YES	YES	YES	YES
Observations	887	887	887	887	887

Table B.1: OLS Regression Results of Equation (3.4)

Chapter C

Appendix for Chapter 4

C.1 Proofs of the Conditions for Equation (4.8)

Proof:

$$
\begin{aligned}
E(\epsilon_i|Z_i) =& E[E(\epsilon_i|ln(\overline{API_i}), Z_i)|Z_i] \\
=& E[\lambda_A ln(\overline{API_i}) + \lambda_Z Z_i|Z_i] \\
=& \lambda_A E[ln(\overline{API_i})|Z_i] + \lambda_Z Z_i \\
=& \lambda_A E[\Pi Z_i + \nu_i|Z_i] + \lambda_Z Z_i \\
=& \lambda_A \Pi Z_i + \lambda_A E[\nu_i|Z_i] + \lambda_Z Z_i \\
=& \lambda_A \Pi Z_i + \lambda_Z Z_i \\
=& 0
\end{aligned}
$$

and because

$$
\begin{aligned}
E[\epsilon_i|ln(\overline{API_i}), Z_i] =& \lambda_A ln(\overline{API_i}) + \lambda_Z Z_i \\
=& \lambda_A(\Pi Z_i + \nu_i) + \lambda_Z Z_i \\
=& \lambda_A \Pi Z_i + \lambda_A \nu_i + \lambda_Z Z_i
\end{aligned}
$$

since it has shown that $\lambda_A \Pi Z_i + \lambda_Z Z_i = 0$, therefore, $E[\epsilon_i|ln(\overline{API_i}), Z_i] = \lambda_A \nu_i$. Applying a similar method, $E((\beta_{1i} - \bar{\beta}_1)|ln(\overline{API_i}), Z_i) = \varphi_A \nu_i$ can also be proved.

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