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Three Essays in Labor Productivity

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by

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Abstract

This dissertation is a collection of three independent essays in studying the causes and consequences of labor productivity. In the first two chapters, I examine the health and labor productivity effects of pollution. In the third chapter, I study whether government policies can help to improve labor productivity, with special focus on workers' work effort provision.

The first two chapters investigate the casual effects of air pollution on cognitive ability. In the first chapter, I estimate the causal effects of particulate matter (PM_{10}) on cognitive ability. Cognitive ability is measured by the Mini-Mental Status Examination (MMSE), which is one of the most commonly used instrument for systematically screening cognitive function. To exploit the exogenous pollution variation, I use the drastic air pollution regulations around the 2008 Beijing Olympic Games as a quasi-natural experiment. By comparing Beijing with other selected unregulated provinces before and after the regulation period, I find that PM_{10} has significant negative impacts on cognitive ability. In the second chapter, I estimate the causal effects of sulfur dioxide (SO_2) on cognitive ability, using the same quasi-natural experiment as in the first chapter. Since the data on SO_2 are only available for one year, I apply the cross-sectional instrumental variable approach in this study. The results show that SO_2 can significantly reduce cognitive ability. While research on the impacts of air pollution on labor productivity has generally focused on the extensive margin (i.e., labor supply), recent studies find that the impacts also occur on the intensive margin whereby productivity is affected, even when labor supply does not change. Since brain function is highly related to human capital and labor productivity, the findings in the first two chapters highlight the potential mechanism of the impacts of air pollution on the intensive margin.

The third chapter studies the macroeconomic implications of minimum wage incor-

porating workers' work effort responses. I analyze the issue in an environment where work effort positively affects output and determines workers' probability of being laid off. When making search decisions, firms and workers take into account the trade-off between the value of an offer and the associated matching rate. Minimum wage policy affects firms' contracting decision corresponding to workers' effort responses, which further affects workers' and firms' search decisions. These assumptions enable me to analyze the effects of minimum wage on the behavior of both the labor supply and demand sides. The steady state comparison of the calibrated model shows that minimum wage increases work effort and unemployment rate. Moreover, the average hiring, layoff, and quit rates decrease. Due to the higher unemployment, the aggregate output decreases even with the higher average work effort. Lastly, shutting down the effort channel entirely leads to greater labor market impacts. These results suggest that workers' work effort have strong offsetting effects on the cost of higher minimum wage.

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Chapter 1

The Effects of Air Pollution on Cognitive Ability: Evidence from the 2008 Beijing Olympic Games

1.1 Introduction

A sizeable literature documents the negative effects of exposure to particulate matter on human health, such as respiratory infections, cardiovascular diseases, and mortality (Pope et al., 1991; Shah et al., 2013; Currie and Neidell, 2005; He et al., 2016). In addition to the traditional health outcomes, researchers also find evidence that particulate matter can not only penetrate into lungs, but also penetrate into brain. Therefore, exposure to particulate matter could potentially affect human cognitive ability (Pope III and Dockery, 2006). Since poor cognitive ability can have profound health, social, and economic implications, it is essential to understand the causal impacts of particulate matter on cognitive ability.

To estimate the causal effects is challenging, because exposure to pollution levels is typically endogenous.[1] For example, individuals with greater wealth may have greater preferences for cleaner air. Since pollution is capitalized into housing prices (Chay and Greenstone, 2005), these individuals are more likely to sort into areas with better air quality. If individuals also make unobservable investments in their health, then this introduces an important source of confounding.

In order to isolate the causes and minimize the effects of confounding factors, I use the drastic air pollution regulations around the 2008 Beijing Olympic Games (BOG08) as a quasi-natural experiment.[2] To significantly improve air quality during the BOG08,

[1] Zivin and Neidell (2013) provide a detailed discussion about the endogeneity of pollution in their excellent review.

[2] He et al. (2016) use the same quasi-natural experiment to identify the effects of air pollution on mortality.

the Chinese government implemented a series of drastic pollution regulations starting in late 2007. The air pollution regulations enforced during the BOG08 were arguably by far the largest efforts made in human history to control air quality within a short period of time (Chen et al., 2013; He et al., 2016). Besides, the enforcement of the regulations was due to the Chinese government's commitment to ensure good air quality in Beijing during the BOG08.[3] Thus, the BOG08 regulations were strict and likely to be exogenous. By comparing Beijing with other selected unregulated provinces before and after the regulation periods, I find that air pollution has significant impacts on cognitive ability, with a 1 $\mu g/m^3$ reduction in yearly PM_{10} concentrations resulting in a 0.14 increase in the Mini-Mental Status Examination (MMSE) scores.[4]

This study contributes to a variety of different literatures. First, it is related to the literature on the effects of pollution on cognitive ability. Sanders (2012) finds that a one standard deviation increase in total suspended particulates causes a decrease in test scores of 0.07 standard deviation. Lavy et al. (2014) examine the impacts of short-term exposure to ambient air on the standardized test scores among Israeli high school high-stakes tests. They find that one unit increase in daily $PM_{2.5}$ is associated with a 0.046 decline in the Bagrut scores. Roth (2016) analyzes the relationship between short-term exposure to indoor coarse particles and cognitive ability, using a confidential student file which contains the full academic record of all undergraduate students that took exams during the 2012/2013 academic year at a university in London. His findings show that one unit increase in PM_{10} and being above the WHO guideline reduces student's test scores by 0.060 and 2.868, respectively. In another interesting study, Archsmith et al. (2016) observe the decision-making of a panel of Major League Baseball (MLB) umpires. They find that ambient air pollution would reduce the number of correct call from the umpires, suggesting that short-term exposure

[3] The level of air pollution in Beijing was the biggest concern of the International Olympic Committee in the bidding process for the 2008 Summer Olympic Games and the commitment was key to winning the bid (He et al., 2016).

[4] PM_{10} refers to particulate matter 10 micrometers or less in diameter. The Mini-Mental Status Examination (MMSE) is one of the most commonly used instrument for systematically screening cognitive ability.

to ambient air would cause cognitive decline. While previous studies often rely on using proxy to measure cognitive ability, in this study I use the MMSE which is one of the most commonly used instrument for systematically screening cognitive ability. This is because cognition is a broad concept which includes reasoning, remembering, understanding, and problem solving. Therefore, a more direct measure of cognitive ability is preferred.

Second, previous studies predominantly focus on the United States and other developed countries, while developing countries attract relatively little attention. This might be because developed countries have reliable measurement of air quality and impose various environmental regulations, which provide better opportunities to study the effects of air pollution. However, economists have long recognized that individuals' optimizing behaviour may compensate for increases in pollution by cutting off their chances of getting exposed to the pollution so as to protect their health (Shimshack et al., 2007; Malgosia Madajewicz et al., 2007). Thus, empirical evidence on the magnitude derived from developed countries might not be applicable in developing countries.[5] Meanwhile, air pollution regulations are still rare in developing countries, and whether, and to what extent, environmental regulations on air pollution lead to health benefits remains an important question yet to be answered.

Moreover, this study is related to the literature on the impacts of air pollution on labor productivity. Attention to the impacts of air pollution on labor productivity has generally focused to the extensive margin (e.g., Ostro, 1983; Hausman et al., 1984; Hanna and Oliva, 2015). On the other hand, recent studies find that the impacts also can occur on the intensive margin whereby productivity is affected, even when labor supply does not change. Zivin and Neidell (2012) obtain daily measures of worker productivity using a unique panel data set on agricultural workers who are paid by piece rate. They find that air pollution has

[5] For example, given the average year of educational attainment in developing countries is lower than in advanced countries (Barro and Lee, 2001), people in developing countries might have less ability to assess and understand the knowledge of how to avoid or alleviate the damage from pollution. This systematic differences can lead to a gap between the effects of pollution on health in developing and developed countries.

negative impacts on agricultural worker's productivity. Similarly, Chang et al. (2016) investigate the effects of air pollution on worker productivity in the service sector by focusing on two call centers in China. They find that higher levels of air pollution decrease worker productivity by reducing the number of calls that workers complete each day. Since brain function is highly related to human capital and labor productivity, my findings highlight the potential mechanism of the impacts of air pollution on the intensive margin, that is, air pollution may lead to direct neurological insults that affect cognitive ability, therefore, affect brain development and reduce human intelligence.

This paper proceeds as follows. Section 1.2 summarizes the air pollution regulations during the BOG08. Section 1.3 describes the data. Section 1.4 outlines the identification strategy and main results. This is followed by a series of checks of the validity of the identification assumptions in section 1.5. Section 1.6 checks the robustness of the results and section 1.7 explores the heterogenous effects of gender, age, and childhood experience. Section 1.8 concludes.

1.2 Air Pollution Regulations During the BOG08

The air quality in Beijing has been of great concern to the Chinese government, especially after the city won the bid to host the BOG08. To significantly improve air quality during the Games, the Chinese government implemented a series of drastic pollution regulations starting in late 2007.

The regulations can be categorized into two phases. The first phase known as the *Comprehensive Regulations* started in November of 2007 and ended in December of 2008. The second phase known as the *Temporary Olympics Regulations* started in July of 2008 and ended in September of 2008.

During the *Comprehensive Regulations* periods, multiple regulations were enforced to reduce industrial pollution. Power plants were required to reduce their emissions by 30%

from their levels. This reduction was required even for plants that had already met the Chinese emission standards. All coal-fired power plants in Beijing were required to install desulfurization, dust removal, and denitrification facilities. Certain heavily polluting factories were completely shut down or relocated.[6] To control vehicle emissions, the public sector replaced all their heavy-emission vehicles. New emission standards adopted on March 1, 2008 were applied to new vehicles. The government also raised gas prices twice, in November of 2007 and again in June of 2008, to discourage auto mobile usage.

The *Temporary Olympics Regulations* mainly focused on controlling vehicle emissions as vehicle exhaust emissions are the primary air pollutant in large cities. From July 20 to September 20, 2008, privately owed vehicles were allowed on the roads only on alternate days. Vehicles with odd (even) numbered last digit on the license plate were permitted on the road on odd (even) numbered days. From July 1 to September 20, 2008, all on-road vehicles (including trucks and passenger cars) that failed to meet the Euro I Emissions Standards were banned from Beijing's roads. As a result, more than 300,000 heavy-emission vehicles were not allowed on the roads.

A large number of studies has shown that the air pollution control measures used for the BOG08 are effective at lowering air pollution. Cai and Xie (2011) study the effects of Even-Odd License Plate Law on air pollution during the BOG08. They suggest that the traffic control policy can improve the air quality effectively in short term. Schleicher et al. (2012) find that the temporary measures, such as shutting down industries and reducing traffic, during the BOG08 had huge impacts on the reduction of aerosol pollution. Chen et al. (2013) show that these measures significantly improved the air pollution index (API) of Beijing during and after the Games, but 60% of the effects faded away by the end of October 2009.

[6]For example, the Second Beijing Chemical Plant, the Beijing Eastern Petrochemical Company, and the 27 Cement Production factories were shut down and the Capital Steel Company was relocated.

1.3 Data

1.3.1 Health Data

The micro-level health data come from the Chinese Longitudinal Healthy Longevity Survey (CLHLS). The CLHLS conducted face-to-face interviews in 22 of China's 31 provinces and municipalities every 2 to 3 years since 1998. The population in the survey areas constitutes more than 85 percent of total population in China.[7] It provides information on health, socioeconomic characteristics, family, lifestyle, and demographic profile of the elderly aged 60 and older. To match with the air pollution data, I use panel data observations in 2002, 2005, and 2008 in my analysis. The sample consists of 12,674 observations aged from 61 to 119.

Cognitive ability is measured by the Mini-Mental Status Examination (MMSE) in the CLHLS.[8] The MMSE is an instrument used extensively to assess cognitive status in clinical and community settings (Wood et al., 2006). It is a short and easy-to-administer 30-point questionnaire test which consists of five major domains of cognitive ability: Orientation, registration, calculation, recall, and language. Table 1.1 summarizes the average MMSE scores across different age groups.

1.3.2 Air Quality Data

I obtain the daily Air Pollution Index (API) and the primary pollutants from 2002 to 2008 from the Chinese Ministry of Environmental Protection (MEP). MEP has been providing

[7] Han Chinese people are the overwhelming majority in the surveyed provinces and municipalities while ethnic minorities share a very high proportion of the population in the excluded 8 provinces located in the North-Western part of China. This is important because the Han Chinese can usually provide a reliable date of birth for themselves or for their close family members while the age reporting among some ethnic minorities was seriously biased with age exaggeration (Coale and Li, 1991).

[8] The CLHLS uses the Chinese version MMSE. The Chinese version MMSE tries to meet the cultural and socioeconomic conditions in China and make the questions easily understandable and practically answerable among normally functioning oldest-old Chinese (Yi and Vaupel, 2002). Several similar versions of the Chinese MMSE which are all adapted from Folstein et al. (1975), have been proven to be reliable and valid among Chinese old populations (Shyu and Yip, 2001).

Table 1.1: Average Mini-Mental Status Examination Scores across Age Groups

Age group	Number of observations	MMSE	Std. Dev.
<75	3,936	25.13	3.36
75-84	4,269	23.71	4.59
85-94	3,033	21.45	6.65
⩾95	1,436	16.80	9.17
All	12,674	22.83	6.11

Notes and sources: MMSE stands for Mini-Mental Status Examination, which is an instrument currently used extensively to assess cognitive status in clinical and community settings. It is a short and easy-to-administer 30-point questionnaire test which consists of five major domains of cognitive ability: Orientation, registration, calculation, recall, and language. Due to data limitation, the time periods of the MMSE scores data are 2002, 2005, and 2008. The sample consists of 12,674 observations aged from 61 to 119. The average age in the sample is 81.

the daily API for 86 major cities in China since 2000. The API is a single number indicating the air quality on a given day. It goes from 0 to 500.[9] The Chinese official API is determined from three pollutants: Sulfur dioxide (SO_2), Nitrogen dioxide (NO_2), and PM_{10}.

The method used by MEP to construct the API allows me to recover the concentrations of the primary pollutant. During the periods from 2002 to 2008, of the 80.5% days when MEP reported the specific type of pollutant which the API was calculated, 89.57% of pollutants were from PM_{10}, 10.12% from SO_2, and 0.3% from NO_2.[10] Hence, the PM_{10} concentrations can be recovered from the API with high accuracy. To match with the CLHLS, I aggregate the population-weighted yearly average PM_{10} up to the provincial level.[11] The details of the PM_{10} concentrations calculations using the API are presented in Appendix A.1.

The reliability of the official Chinese air quality data has been questioned recently. Chen et al. (2012) and Ghanem and Zhang (2014) find evidence of underreporting of the API at the margin of 100.[12] Nonetheless, Chen et al. (2012) find significant correlation

[9] The greater the number, the worse is the air quality.

[10] MEP doesn't report the primary pollutant when the API is less than 50.

[11] Due to confidentiality reasons, I can only identify respondents' location at the provincial level.

[12] The manipulation is motivated by the blue-sky award. A blue sky day is defined as a day with the API below 100. A city with at least 80% blue sky days in a calendar year is qualified for the "national

between the API and two alternative air quality statistics (NASA's Aerosol Optical Depth data and the China Meteorological Administration's visibility data). These correlations do not significantly change when the API is close to 100. They conclude that the reported API contain useful information on cross-city and over-time variations in air pollution. I also compare the official Chinese reported API with the remotely sensed API data in Appendix A.2 Figure. A.2.1. The similarity of the two measures reduces the concern about the manipulation of the reported API. Summary statistics of the key variables are provided in Table 1.2.

Table 1.2: Summary Statistics of the Main Variables.

	Mean	Std. Dev.	Min	Max
MMSE	22.8	6.1	0	30
PM_{10} ($\mu g/m^3$)	95.3	27.78	53.91	174.1
Humidity	66.9	8.35	49	76
Temperature (°C)	16.6	4.78	5.6	23.2

Notes and sources: The definition of the MMSE is described in the text. The unit of observation is individual-year. Due to data limitation, the time periods of the MMSE data are 2002, 2005, and 2008. Author's calculations with PM_{10} data are described in Appendix A.1. Humidity and temperature data are collected from the China Statistical Yearbooks on Environment. The units of observation of PM_{10}, humidity, temperature are province-year. The time periods of PM_{10}, humidity, and temperature data are from 2002 to 2008.

1.4 Identification Strategy and Empirical Results

This section discusses the empirical strategy to identify the causal effects of air pollution on cognitive ability. The major empirical challenge in identifying the causal effects is that air pollution can be altered in a variety of ways, making it an endogenous variable. To explore the exogenous variation in air pollution, I use the BOG08 as a quasi-natural experiment. I first adopt a difference-in-differences (DID) approach to estimate the effects of the BOG08 on air pollution. I then apply the same approach to estimate the effects of the BOG08 on

environmental protection model city" award.

cognitive ability. The effects of air pollution on cognitive ability can be calculated from these two estimates.

1.4.1 Effects of the BOG08 on Air Pollution

I adopt a DID approach to estimate the causal effects of the BOG08 on air pollution. The first difference is over time and the second difference is across groups. Since the regulations were implemented in Beijing, I define Beijing as the treatment group. The definition of the comparison group is crucial, as it should capture the counterfactual air pollution trends in the absence of air pollution regulations. Since climate conditions, such as humidity and temperature, can affect the PM_{10} concentrations, I define the costal provinces as the comparison group.[13] Due to the concern of spillover effect, I also exclude those provinces which are geographically close to Beijing. Figure 1.1 shows the geographical locations of these provinces.

The DID comparison is implemented by estimating the following regression:

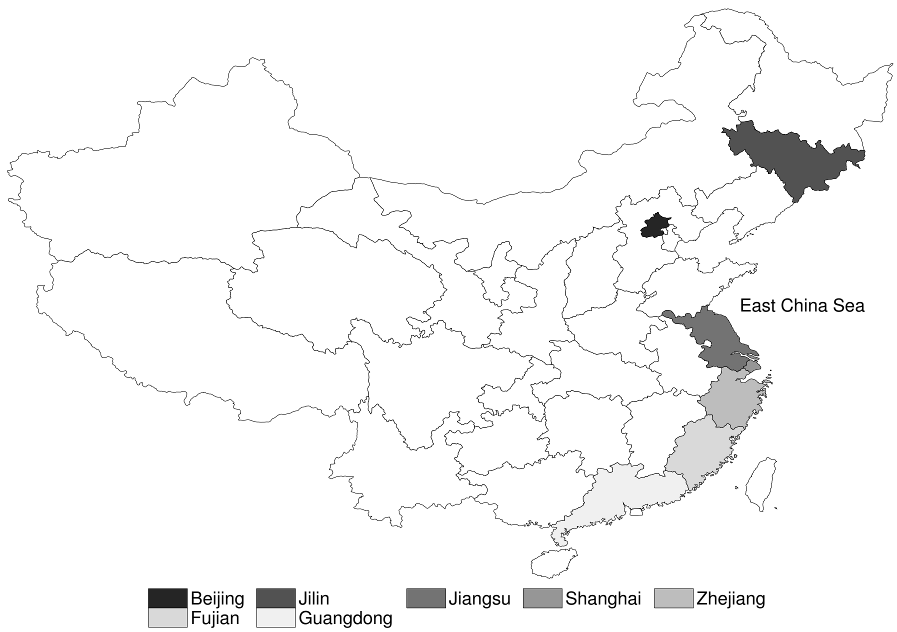
$$y_{jt}^{PM_{10}} = \alpha + \beta(time_t \times Beijing_j) + \gamma_j + \lambda_t + X_{jt}'\delta + \varepsilon_{jt}, \tag{1.1}$$

where j denotes province, t time, and $y_{jt}^{PM_{10}}$ is the PM_{10} concentrations. The variable *Beijing* is a dummy for Beijing. $time_t$ is an indicator variable that takes on the value one for 2008.[14] The province fixed effects, γ_j, control for the permanent heterogeneity across provinces. The year fixed effects, λ_t, control for year-specific shocks that are common to both treatment and comparison groups. The vector X_{jt} is a set of control variables (humidity, temperature). The coefficient of interest is β which measures the effect of the BOG08 on Beijing's air pollution relative to the comparison group, using variation over time. All

[13] Kim et al. (2000) show that the annual average PM_{10} concentrations are low at coastal sites and high at inland sites. Viana et al. (2005) find that atmospheric coastal dynamics can significantly affect the levels and chemical composition of PM_{10}. Tsai et al. (2011) show that sea-land breeze had a regular influence on the physicochemical properties of PM_{10}.

[14] As discussed in the previous sections, radical air pollution regulations started in November 2007. Thus, I treat 2008 as the post-treated periods.

Figure 1.1: Geographical Locations of the Treatment and Comparison Groups



Notes: This graph shows the geographical locations of the treatment (Beijing) and control provinces (Jilin, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong). Since climate conditions, such as humidity and temperature, can affect the PM_{10} concentrations, I define the costal provinces as the comparison group. Due to the concern of spillover effect, I exclude those provinces which are geographically close to Beijing. It is worth mentioning here that Beijing and Shanghai are municipality. They have the same rank as provinces, and form part of the first tier of administrative divisions of China.

standard errors are clustered at the provincial level allowing for an arbitrary correlation within provinces over time (Bertrand et al., 2004). It is worth mentioning here that I also calculate the standard errors using wild cluster bootstrap resampling method here and after to deal with issue with small number of clusters.

Table 1.3 presents the OLS estimates of Equation (1.1). Column (1) provides the results with both province and year fixed effects. Columns (2) and (3) control for humidity and temperature, respectively. Column (4) controls for both fixed effects, humidity, and temperature. The estimates are robust to the inclusion of these covariates and remain significant at the 1 percent level.

The results suggest that the BOG08 effectively reduced the PM_{10} concentrations in Beijing by 25.92 $\mu g/m^3$. He et al. (2016) use city-monthly level data to examine the air pollution effects of the BOG08. They find that the monthly PM_{10} concentrations decreased by approximately 26 $\mu g/m^3$ in 2008, which is consistent with my results.[15]

Table 1.3: The Effects of the BOG08 on Air Pollution

Dependent Variable: PM_{10}	(1)	(2)	(3)	(4)
$\hat{\beta}$	-25.11***	-26.06***	-24.83***	-25.92***
	(3.16)	(4.62)	(3.44)	(4.72)
R^2	0.965	0.965	0.965	0.965
Observations	49	49	49	49
Province Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y
Humidity	N	Y	N	Y
Temperature	N	N	Y	Y

Notes and sources: Author's calculations with PM_{10} data are described in Appendix A.1. Humidity and temperature data are collected from the China Statistical Yearbooks on Environment. The unit of observation is province-year. The time periods are from 2002 to 2008. The dependent variable is PM_{10}. The main entries in the first row of columns (1) to (4) report the estimates of β from Equation (1.1) in the text. Column (1) provides the results with both province and year fixed effects. Columns (2) and (3) control for humidity and temperature, respectively. Column (4) controls for both fixed effects, humidity, and temperature. The number of observations is 49 because it contains 7 provinces across 7 years. Robust standard errors in parentheses are clustered at the level of province. The significance remain under the wild cluster bootstrap resampling method. * indicates significance at the 10 percent level, ** significance at the 5 percent level, and *** significance at the 1 percent level.

1.4.2 Effects of the BOG08 on Cognitive Ability

I again adopt a DID approach to estimate the causal effects of the BOG08 on cognitive ability. The definitions of the treatment and the comparison groups are the same as the previous section. The DID comparison is implemented by estimating the following regression:

$$y_{it}^{MMSE} = \alpha + \beta(time_t \times Beijing_i) + \gamma_i + \lambda_t + X_{it}'\delta + \varepsilon_{it}, \tag{1.2}$$

where i denotes the individual, t time, and y_{it}^{MMSE} is the MMSE scores. The variable *Beijing* is 1 if the individual i is in Beijing, otherwise it is 0. $time_t$ is an indicator variable that takes on the value one for 2008. γ_i is the individual fixed effects, and λ_t is the year fixed

[15] He et al. (2016) focus on the effect of air pollution on mortality, rather than on cognitive ability.

effects. The vector X_{it} is a set of time varying individual specific characteristics and weather conditions to control for any observable differences that might confound the analysis. They include age, the number of times the respondents have taken the survey, income, have enough medical services or not, marital status, smoke or not, drink or not, exercise or not, humidity, and temperature.[16] All standard errors are clustered at the province level, allowing for an arbitrary correlation within provinces over time.

Table 1.4 presents the OLS estimates of Equation (1.2). Column (1) provides the results with both individual and year fixed effects. Columns (2) and (3) control for individual characteristics and weather conditions, respectively. Column (4) controls for both fixed effects, individual characteristics, and weather conditions.

The results suggest that the BOG08 effectively increased the MMSE scores by 3.62. The estimates are robust to the inclusion of these covariates and remain significant at the 1 percent level.

1.4.3 Effects of the Air Pollution on Cognitive Ability

In the first stage, I estimate Equation (1.1) to assess the effects of the BOG08 on the PM_{10} concentrations. In the second stage, I estimate Equation (1.2) to find the effects of the BOG08 on the MMSE scores. The results show that the BOG08 significantly reduced the PM_{10} concentrations and increased the MMSE scores. If the BOG08 only affected health through the channel of air pollution abatement, the effects of air pollution on the MMSE scores is $3.62/-25.92 \approx -0.14$, which is saying that a 1 $\mu g/m^3$ decline in yearly PM_{10} concentrations can increase the MMSE scores by 0.14 on average.

[16] Having enough medical services or not is a polar question in the CLHLS.

Table 1.4: The Effects of the BOG08 on the MMSE Scores

Dependent Variable: MMSE	(1)	(2)	(3)	(4)
$\hat{\beta}$	3.647***	3.829***	3.414***	3.622***
	(0.674)	(0.749)	(0.479)	(0.473)
R^2	0.889	0.893	0.890	0.893
Observations	4821	4651	4821	4651
Individual Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y
Individual Characteristics	N	Y	N	Y
Weather Conditions	N	N	Y	Y

Notes and sources: The definition of the MMSE is described in the text. The unit of observation is individual-year. Due to data limitation, the time periods are 2002, 2005, and 2008. The dependent variable is the MMSE. Individual characteristics include age, the number of times the respondents have taken the survey, income, have enough medical services or not, marital status, smoke or not, drink or not, and exercise or not. Having enough medical services or not is a polar question in the CLHLS. Weather conditions include humidity and temperature. Humidity and temperature data are collected from the China Statistical Yearbooks on Environment. The main entries in the first row of columns (1) to (4) report the estimates of β from Equation (1.2) in the text. Column (1) provides the results with both individual and year fixed effects. Columns (2) and (3) control for individual characteristics and weather conditions, respectively. Column (4) controls for both fixed effects, individual characteristics, and weather conditions. The slight decrease in the number of observations in column (2) and (4) is due to the missing data in the individual characteristics. Robust standard errors in parentheses are clustered at the level of province. The significance remain when standard errors are clustered at the level of individual. The significance also remain under the wild cluster bootstrap resampling method. * indicates significance at the 10 percent level, ** significance at the 5 percent level, and *** significance at the 1 percent level.

1.5 Validity of the Identification Assumptions

To ensure the credibility of the identification strategy, I test whether the following assumptions are satisfied: (1) there are parallel trends in the pre-treatment outcome variables of interest between Beijing and the comparison group; (2) there are parallel trends in the outcome variables of interest across the provinces in the comparison group; (3) the BOG08 only affected health through air pollution abatement.

1.5.1 Assessing the Common Trend Assumption

Trends in Air Pollution

The key identification assumption for causal inference in Equation (1.1) is that there is no systematic difference in pre-treatment trends in air pollution between Beijing and the comparison group. I test the assumption using the following regression:

$$y_{jt}^{PM_{10}} = \alpha + \sum_{l \neq 2007} \beta_l (time_l \times Beijing_j) + \gamma_j + \lambda_t + X_{jt}' \delta + \varepsilon_{jt}, \tag{1.3}$$

where $time_l$ is a dummy that is 1 in year l and 0 otherwise. The definitions of the other variables remain the same as in Equation (1.1). The pre-2008 interaction terms provide pre-treatment specification test. Figure 1.2 plots the estimated coefficients of the interaction terms over the periods from 2002 to 2008. Each dot is the coefficient of the interaction and a 95-percent confidence interval is shown by dashed lines. As shown in Figure 1.2, the estimated coefficients before 2008 are not significantly different from zero. This evidence suggests that Equation (1.1) is not simply picking up long-run differences in trends between Beijing and the comparison group.

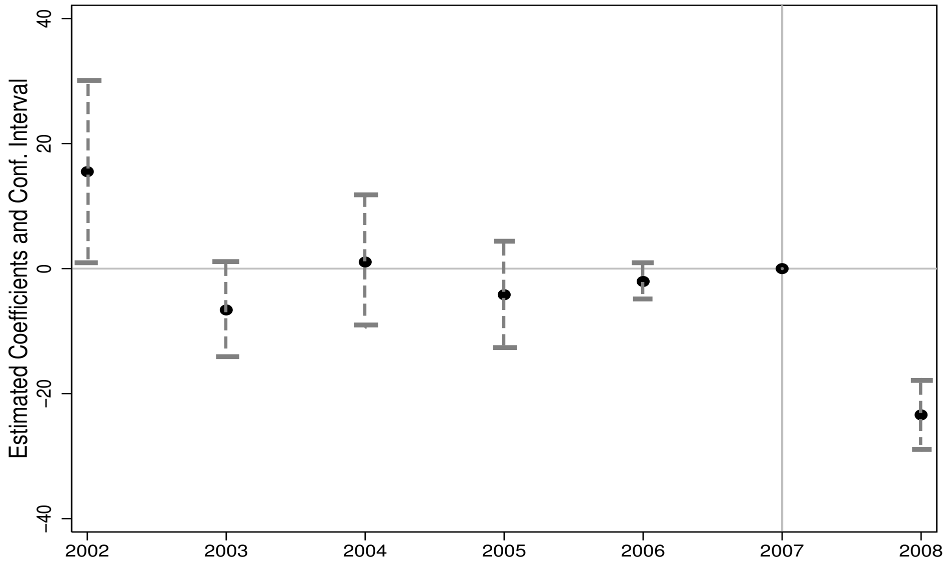
Trends in the MMSE

I also test the common trend assumption for the MMSE between Beijing and the comparison group in the pre-intervention periods. This assumption is key in identifying the effect of the BOG08 on the MMSE. As before, I test the assumption using the following regression:

$$y_{jt}^{MMSE} = \alpha + \sum_{l \neq 2005} \beta_l (time_l \times Beijing_i) + \gamma_i + \lambda_t + X_{it}' \delta + \varepsilon_{it}, \tag{1.4}$$

where $time_l$ is a dummy that is 1 in year l and 0 otherwise. The definitions of the other variables remain the same as in Equation (1.2). The pre-2008 interaction terms provide pre-treatment specification test. Figure 1.3 plots the estimated coefficients of the interaction terms over the periods 2002, 2005, and 2008. Each dot is the coefficient of the interaction

Figure 1.2: Pretreatment Specification Test: Common Trends in PM_{10}



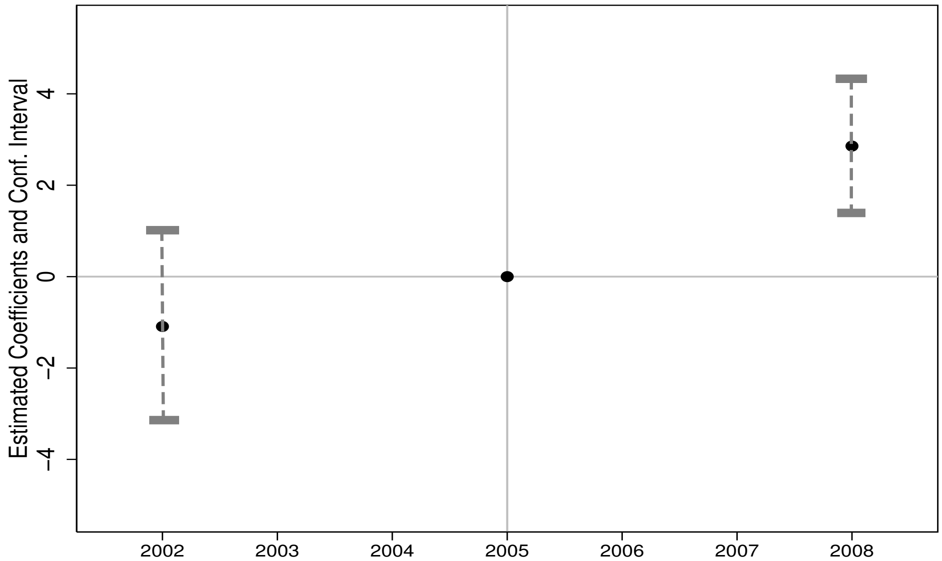
Notes: This figure shows the estimated effects of the BOG08 regulations on PM_{10} before and after the regulations. Author's calculations with PM_{10} data are described in Appendix A.1. The unit of observation is province-year. The time periods are from 2002 to 2008. Each dot is the estimated coefficients of the interaction terms over the periods from 2002 to 2008 in Equation (1.3). 2007 is selected as the reference year. A 95-percent confidence interval is shown by dashed lines. The estimation controls for provincial fixed effects, year fixed effects, humidity and temperature. The estimated coefficients before 2008 are not significantly different from zero. This evidence suggests that Equation (1.1) is not simply picking up long-run differences in trends between Beijing and the comparison group.

and a 95-percent confidence interval is shown by dashed lines. Figure 1.3 shows that the estimated pre-treatment coefficients are not significantly different from 0. It suggests that Equation (1.2) is not simply picking up long-run trend differences between Beijing and the comparison group.

Trends among the Comparison Provinces

The similar trends between the treatment group and its comparison group in the pre-intervention periods suggest that they would have been the same in the post-intervention periods if the BOG08 regulations had not been implemented. However, this inference would be less credible if there is systematic difference in trends among the provinces in the comparison group. To test the common trend assumption among the provinces in the comparison group, I redefine each province in the comparison group as a pseudo-treatment province, and compare the trends in PM_{10} and the MMSE between the pseudo-treatment

Figure 1.3: Pretreatment Specification Test: Common Trends in the MMSE



Notes: This figure shows the estimated effects of the BOG08 regulations on the MMSE scores before and after the regulations. The definition of the MMSE is described in the text. The unit of observation is individual-year. Due to data limitation, the time periods are 2002, 2005, and 2008. Each dot is the estimated coefficients of the interaction terms over the periods 2002, 2005, and 2008 in Equation (1.4). 2005 is selected as the reference year. A 95-percent confidence interval is shown by dashed lines. The estimation controls for individual fixed effects, year fixed effects, individual characteristics, and weather conditions. Individual characteristics include age, the number of times the respondents have taken the survey, income, have enough medical services or not, marital status, smoke or not, drink or not, and exercise or not. Weather conditions include humidity and temperature. The estimated coefficients before 2008 are not significantly different from zero. This evidence suggests that Equation (1.2) is not simply picking up long-run differences in trends between Beijing and the comparison group.

province and the remained comparison provinces. The comparison is conducted by the following regression:[17]

$$y_{jt} = \alpha + \sum_{l \neq 2007} \beta_l (time_l \times Pseudo_j) + \gamma_j + \lambda_t + X'_{jt}\delta + \varepsilon_{jt}, \tag{1.5}$$

where j denotes province, t time, and y_{jt} is the PM_{10} concentrations. The variable *Pseudo* equals to 1 if the province is the pseudo-treatment province, otherwise it is 0. γ_j is the province fixed effects, and λ_t is the year fixed effects. The vector X_{jt} is a set of time varying control variables. The subscript j in Equation (1.5) can be substituted by i, where i denotes the individual, y_{it} is the MMSE scores, and γ_i is the individual fixed effects.

Figure B.1.1 and B.1.2 in Appendix B.1 plot the estimated coefficients of the interaction terms from Equation (1.5). Each dot is the coefficient of the interaction and a 95-percent confidence interval is shown by dashed lines. Figure B.1.1 suggests that most of the

[17] Beijing is excluded in this regression.

provinces in the comparison group have similar trends in air pollution with the exception of Jiangsu and Zhejiang which present different trends when compared to other provinces in the comparison group. Figure B.1.2 suggests that the provinces in the comparison group have similar trends in the MMSE. To quantify the effect of these provinces on my results, I repeat the estimation of Equations (1.1) excluding Jiangsu and Zhejiang. Tables B.2.1 in Appendix B.2 shows that the main results are robust to these changes in the comparison group.

1.5.2 Assessing the Exclusion Restriction Assumption

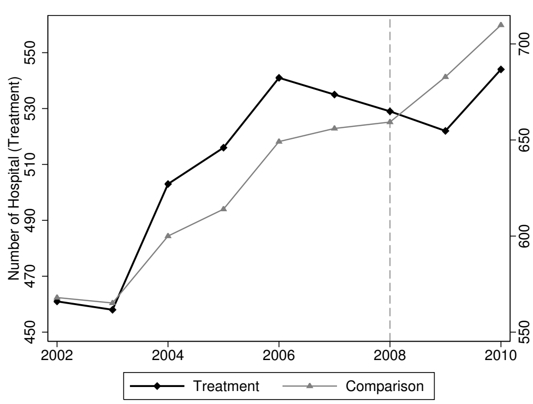
Another concern is that the BOG08 might have led to not only air quality improvement, but also other factors affecting health. For example, it could be that medical services became more available in Beijing during the BOG08. For the identification to be valid, the BOG08 must affect health outcomes only through the channel of air pollution reduction. I address the validity of this identification assumption in two ways.

First, I check whether the results are robust to the inclusion of weather conditions. Weather conditions are typical confounders in the identification of the health effect of air pollution because it changes air pollution levels and also affect health (He et al., 2016). Table 1.3 shows that the estimated effects of the BOG08 regulations on air pollution are statistically significant and robust after controlling weather conditions. Moreover, the estimated coefficients in Table 1.4 only slightly change when the weather controls are included. In other words, these weather conditions are not correlated with the variations in air pollution induced by the regulations.

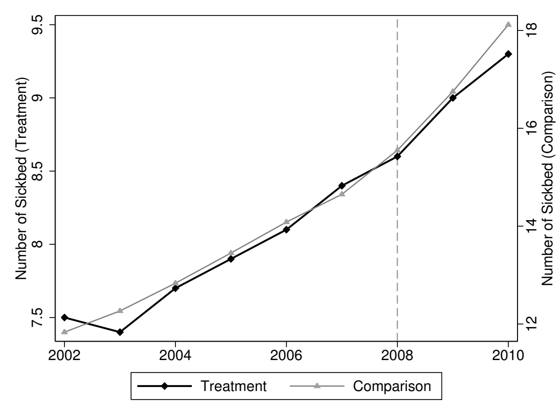
Second, I check whether the BOG08 also changed other health-influencing factors. Figure 1.4 plots the trends in the number of hospital, sickbed, physician, and nurse between the treatment and the comparison groups. As shown in Figure 1.4, there is no sharp change in the treatment and the comparison groups in 2008 which suggests that the BOG08 did not change the availability of medical services.[18]

Moreover, He et al. (2016) find that the BOG08 regulations have negative impacts on all-cause and cardio-cerebrovascular and respiratory (CVR) mortality but no impact on non-CVR, cancer, and injury mortality. They claim that the reduced mortality during the BOG08 is likely only caused by the improved air quality rather than other factors. These evidences support the assumption that the BOG08 regulations only affect health through air pollution abatement.

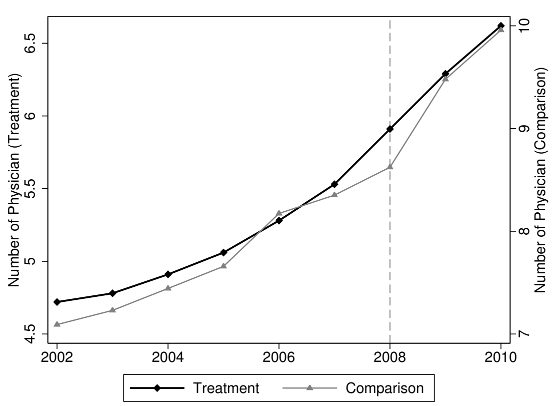
Figure 1.4: Trends in Number of Hospital, Sickbed, Physician, and Nurse



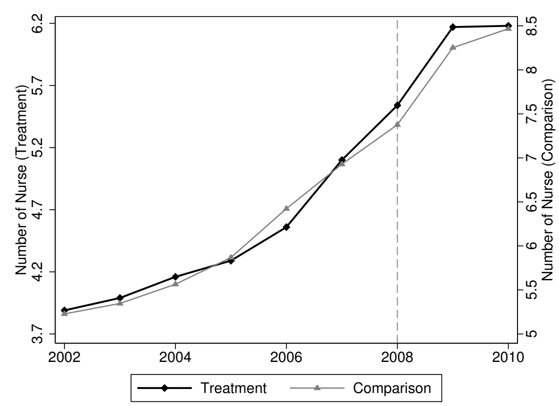
(a) Number of Hospital



(b) Number of Sickbed



(c) Number of Physician



(d) Number of Nurse

Notes and sources: Data are collected from the China Statistical Yearbook. I calculate the average number across the comparison provinces. There is no sharp change in Beijing and the comparison group in 2008 which suggests that the BOG08 did not change the availability of medical services.

[18] Appendix C.1 Table C.1.1 provides the estimation results of the impacts of the BOG08 on the availability of medical services.

1.6 Robustness Checks

In this section, I provide robustness checks for my main results. First, I provide robustness check using different measures of air pollution. Then, I deal with the sample attrition using inverse probability weighting. I also repeat the estimation using the balanced panel observations and compare the results with those using the unbalanced panel observations.

1.6.1 Different Measures of Air Pollution

I reestimate the effects of the BOG08 on air pollution using different measures. The results are presented in Table 1.5. For convenience of comparison, column (1) provides the previous results. Column (2) presents estimates using the non-weighted PM_{10}. The estimated results are very close to those of column (1). Column (3) and (4) use the population-weighted API and non-weighted API, respectively. The negative effects on air pollution remain when use the API. Furthermore, the estimated magnitudes are smaller.[19]

1.6.2 Sample Attrition

Panel studies typically suffer from attrition, which reduces sample size and can result in biased inference. Table 1.6 shows that the attrition rates of the sample are over 50% in both 2005 and 2008. Around half of the attrition is due to the death of the respondents which can potentially bias the estimation. Other possible reasons could be respondents refused to participate in the survey, unfavourable weather and transportation difficulties for interviewers, migration, and hospitalization, where the last two reasons might also bias the results.

To deal with attrition, I first weight observations by their corresponding inverse probability weights (Fitzgerald et al., 1998; Wooldridge, 1999, 2002). This involves estimating separate probit equations for whether an individual responds or not at each of the waves of

[19] These estimates using different measures are consistent with He et al. (2016)

Table 1.5: Robustness Check: Different Measures of Air Pollution

	(1)	(2)	(3)	(4)
$\hat{\beta}$	-25.92***	-26.78***	-13.73***	-13.13***
	(4.73)	(4.86)	(2.77)	(2.45)
R^2	0.966	0.969	0.965	0.965
Observations	49	49	49	49
Province Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y
Humidity	Y	Y	Y	Y
Temperature	Y	Y	Y	Y

Notes and sources: Author's calculations with PM_{10} and API (Air Pollution Index) data are described in Appendix A.1. Humidity and temperature data are collected from the China Statistical Yearbooks on Environment. The unit of observation is province-year. The time periods are from 2002 to 2008. The main entries in the first row of columns (1) to (4) report estimates of β from Equation (1.1) in the text using different measures of air pollution. The dependent variable in column (1) is population-weighted PM_{10}. In column (2) is non-weighted PM_{10}. In column (3) is population-weighted API and in column (4) is non-weighted API. All columns control for province and year fixed effects, humidity, and temperature. The number of observations is 49 because it contains 7 provinces across 7 years. Robust standard errors in parentheses are clustered at the level of province. The significance remain under the wild cluster bootstrap resampling method. * indicates significance at the 10 percent level, ** significance at the 5 percent level, and *** significance at the 1 percent level.

the panel.[20] Then I reestimate Equation (1.2) using the inverse probability weights. Table 1.7 presents the results. For convenience of comparison, column (1) provides the previous results. In column (2), I only deal with the attrition caused by death, and in column (3) I correct for the attrition caused by all factors. The estimated coefficients controlling for attrition across all model specifications appears very similar to those without. I also construct a balanced panel using respondents who respond at all of the waves of the panel. As shown in column (4) of Table 1.7, the estimated coefficients only change slightly. These results suggest that the sample attrition bias is not severe.

[20]The rationale for this approach is that a type of individual who has a low probability of responding represents a higher fraction of individuals in the underlying population and therefore should be given a higher weight (Jones, 2009)

Table 1.6: Attrition Rate and Causes of Attrition

	2002	2005	2008
Attrition Rate	–	51.9%	50.5%
Death	–	58.9%	40.9%
Lost	–	41.1%	59.1%
Observations	2806	1348	667

Notes: The row "Attrition Rate" shows the overall attrition rate from 2002 to 2005 and from 2005 to 2008. The row "Death" shows how much percentage of those attrition is due to the death. The row "Lost" shows the percentage of the attrition which are due to the other reasons. These reasons could be respondents refused to participate in the survey, unfavourable weather and transportation difficulties for interviewers, migration, and hospitalization.

1.7 Heterogeneous Effects

To account for gender differences in health outcomes, I investigate the effects of the BOG08 on males and females separately. Column (1) and (2) of Table 1.8 show that the impacts of air pollution on the MMSE for male are larger than for female. This is consistent with Wu et al. (2015) who find that the association between PM_{10} exposure and dementia risk is higher in men than in women. He et al. (2016) also find that the impacts of PM_{10} on male mortality is slightly higher than on female mortality.[21]

I also separately investigate the effects of air pollution on people who had and didn't have adequate medical treatment in their childhood. Column (3) and (4) of Table 1.8 suggest that the effects on the MMSE scores for those who had adequate medical treatment is smaller than those who did not. This difference is reasonable because developmental and biological disruptions during the earliest years of life may result in weakened immune system (Shonkoff et al., 2010; Mistry et al., 2012). It is worth mentioning here that this finding does not have any causal interpretation.[22] Nevertheless, it highlights the potential role of childhood health on health disparities.

[21] A 10 $\mu g/m^3$ reduction in monthly PM_{10} concentrations on average leads to a 8.47 and a 8.28 percent decrease in male and female mortality, respectively.

[22] A person who did not have adequate medical treatment in childhood is likely to come from a poor family, therefore had less nutrient intakes or education.

Table 1.7: Robustness Check: Sample Attrition

	(1)	(2)	(3)	(4)
$\hat{\beta}$	3.622***	3.781***	3.767***	3.199***
	(0.473)	(0.413)	(0.375)	(0.528)
R^2	0.893	0.768	0.825	0.594
Observations	4651	4567	4567	1017
Individual Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y
Individual Characteristics	Y	Y	Y	Y
Weather Conditions	Y	Y	Y	Y

Notes and sources: The definition of the MMSE is described in the text. The unit of observation is individual-year. Due to data limitation, the time periods are 2002, 2005, and 2008. Individual characteristics include age, the number of times the respondents have taken the survey, income, have enough medical services or not, marital status, smoke or not, drink or not, and exercise or not. Having enough medical services or not is a polar question in the CLHLS. Weather conditions include humidity and temperature. Humidity and temperature data are collected from the China Statistical Yearbooks on Environment. All column control for individual and year fixed effects, individual characteristics, and weather conditions. The slight changes in the number of observations are due to the missing data. For convenience of comparison, column (1) provides the previous results in Table 1.4. In column (2) and (3), I deal with the attrition caused by death and by all factors, respectively. I first separately estimate probit equations for whether an individual responds or not at each of the waves of the panel and calculate each individual's corresponding inverse probability weights. Then I reestimate Equation (1.2) using the inverse probability weights. I also construct a balanced panel using respondents who respond at all of the waves of the panel. Column (4) shows the results using the balanced panel. The estimated coefficients controlling for attrition across all model specifications appears very similar to those without. The estimated coefficients from using the balanced panel are also similar to the results obtained from the unbalanced panel. These evidences suggest that the sample attrition bias is not severe. Robust standard errors in parentheses are clustered at the level of province. The significance remain when standard errors are clustered at the level of individual. The significance also remain under the wild cluster bootstrap resampling method. * indicates significance at the 10 percent level, ** significance at the 5 percent level, and *** significance at the 1 percent level.

Lastly, I examine the heterogeneous effects across ages by estimating the air pollution effects separately for different age groups. The results are reported in Table 1.9. Column (1) shows that the impacts of air pollution on the MMSE increase with age on general. This finding is reasonable because the immune system becomes less effective as people age. Besides, possibly due to the limited sample size, I do not find statistically significant effects for people who are 85 or older.

Table 1.8: Heterogeneous Effects: Gender and Adequate Medical Treatment in Childhood

	(1)	(2)	(3)	(4)
	Gender		Adequate Medical Treatment	
	Male	Female	Yes	No
$\hat{\beta}$	4.09***	2.93***	2.51**	4.21***
	(0.456)	(0.678)	(0.766)	(0.894
Observations	2688	1903	4567	2054
Individual Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y
Individual Characteristics	Y	Y	Y	Y
Weather Conditions	Y	Y	Y	Y

Notes and sources: Column (1) and (2) present the estimated effects of the BOG08 on the MMSE across genders. Column (3) and (4) present the estimated effects of the BOG08 on the MMSE of people who had and did not have adequate medical treatment in their childhood. The definition of the MMSE is described in the text. Having adequate medical treatment in childhood or not is a polar question in the CLHLS. The unit of observation is individual-year. Due to data limitation, the time periods are 2002, 2005, and 2008. Individual characteristics include age, the number of times the respondents have taken the survey, income, have enough medical services or not, marital status, smoke or not, drink or not, and exercise or not. Weather conditions include humidity and temperature. Humidity and temperature data are collected from the China Statistical Yearbooks on Environment. All column control for individual and year fixed effects, individual characteristics, and weather conditions. Robust standard errors in parentheses are clustered at the level of province. The significance remain when standard errors are clustered at the level of individual. The significance also remain under the wild cluster bootstrap resampling method. * indicates significance at the 10 percent level, ** significance at the 5 percent level, and *** significance at the 1 percent level.

1.8 Conclusion

This study investigates the causal link between air pollution and cognitive ability, using the BOG08 as a quasi-natural experiment. The findings show that air pollution has a significant impacts on cognitive ability, with a 1 $\mu g/m^3$ reduction in yearly PM_{10} concentrations resulting in a 0.14 increase in the MMSE scores.

Recent studies have shown that air pollution has labor productivity impacts on the intensive margin (Zivin and Neidell, 2012; Chang et al., 2014). Since brain function is highly related to human capital and productivity, my findings highlight the potential mechanism of the impacts on the intensive margin, that is, air pollution may lead to direct neurological insults that affect cognitive ability, therefore, affect brain development and reduce human

Table 1.9: Heterogeneous Effects: Age Groups

	MMSE	Observations
	(1)	(2)
Age 65-69	3.12***	945
	(0.838)	
Age 70-74	2.82***	875
	(0.654)	
Age 75-79	3.79**	679
	(1.314)	
Age 80-84	5.91***	675
	(0.968)	
Age 85-89	9.21	489
	(7.152)	
Age 90-95	10.36	463
	(8.130)	

Notes and sources: The above table presents the estimated effects of the BOG08 on the MMSE across age groups. Age groups represent respondents' age in 2002. The dependent variable in column (1) is the MMSE scores. Column (3) is the number of observations. The definition of the MMSE is described in the text. The unit of observation is individual-year. Due to data limitation, the time periods are 2002, 2005, and 2008. All regressions control for individual and year fixed effects, individual characteristics, and weather conditions. Individual characteristics include age, the number of times the respondents have taken the s, income, have enough medical services or not, marital status, smoke or not, drink or not, and exercise or not. Weather conditions include humidity and temperature. Humidity and temperature data are collected from the China Statistical Yearbooks on Environment. Robust standard errors in parentheses are clustered at the level of province. The significance remain when standard errors are clustered at the level of individual. The significance also remain under the wild cluster bootstrap resampling method. * indicates significance at the 10 percent level, ** significance at the 5 percent level, and *** significance at the 1 percent level.

intelligence.

I am aware of three limitations in this study that call for cautious interpretation of the results. First, due to data limitation, this study focuses only on the people aged 60 and older. Since the dose-response function might be non-linear and perhaps negligible below a certain threshold, the findings in this study should not be simply generalize to the younger population (He et al., 2016). Nevertheless, the findings here are still policy-relevant. This is because the older people are the most vulnerable members of society and the policy makers are highly motivated to protect them. Moreover, due to the rising of the retirement age, focusing on older population is still relevant to labor productivity study.

Second, people's emotional changes during the study periods are not examined due to lack of data. If the BOG08 can affect people's cognitive ability through the channel of people's affective states, the estimated impacts on cognitive ability in this study may be biased. von Stumm (2016) finds that there is no link between people's affective states and cognitive ability. However, her study span is short (i.e. fives days). Moreover, the measures of cognitive ability are different in hers and in this study. Thus, the consequences of such emotional changes on cognitive ability are worthy of further investigation.

Lastly, due to data limitation, I am not able to identify whether the cognitive decline caused by the BOG08 is temporary or permanent. The further investigation of this question requests the data on post-Olympic periods.

Chapter 2

The Impacts of Air Pollution on Cognitive Ability of Older Adult: The Case of China

2.1 Introduction

Air pollution is one of the many environmental challenges facing the world today. The primary goal of pollution abatement is to protect human health, but there is still much debate about the specific health effects (Currie et al., 2009). A sizeable literature has examined the impacts of air pollution on physical health, such as respiratory infections, cardiovascular diseases, and lung cancer. On the other hand, recent physiological studies hypothesize that air pollution can affect the central nervous system and therefore reduce cognitive ability.[1] Cognitive abilities are brain-based skills. They include reasoning, remembering, understanding, and problem solving. Since poor cognitive ability can have profound health, social, and economic implications, it is essential to understand the causal impacts of air pollution on cognitive ability.

In this paper, I study the impacts of sulfur dioxide (SO_2) on cognitive ability of elderly people in China. The major empirical challenge in identifying the causal effects is that pollution exposure can be altered in a variety of ways, making it an endogenous variable with all of the usual concerns that come with it.[2] The causal relationship can be identified if one can find an appropriate instrumental variable that is correlated with air pollution level but have no impact on cognitive ability. In 2008, Beijing together with six other provinces

[1] Block and Calderón-Garcidueñas (2009) summarize several hypothesized physiological pathways by which ambient pollution exposure can affect the function of the central nervous system.

[2] Economists have long recognized that individuals' optimizing behaviour may compensate for increases in pollution by cutting off their chances of getting exposed to the pollution so as to protect their health (Malgosia Madajewicz et al., 2007; Shimshack et al., 2007).

hosted the 29^{th} Olympic Games. In order to carry out the “Green Olympics” promise, these “Olympic host provinces” implemented a series of measures to reduce air pollution. Thus, the change in air pollution caused by the Olympic Games can be thought of as an exogenous “shock”. It provides a rare quasi-experimental setting to address the impacts of air pollution on cognitive ability.

My findings show that SO_2 can significantly reduce cognitive ability of elderly people. Using the Olympics Games to instrument the changes in air pollution, my results show that one unit increasing in yearly SO_2 concentrations leads to a decrease in the Mini-Mental Status Examination (MMSE) scores by 8.5.[3] An alternative way to interpret the results is a one standard deviation change in the yearly SO_2 concentrations is expected to result in a -0.25 standard deviation change in the MMSE scores.

This study contributes to a variety of different literatures. First, it is related to the literature on the effects of pollution on cognitive ability. Sanders (2012) finds that a one standard deviation increase in total suspended particulates causes a decrease in test scores of 0.07 standard deviation. Lavy et al. (2014) examine the impacts of short-term exposure to ambient air on the standardized test scores among Israeli high school high-stakes tests. They find that one unit increase in daily $PM_{2.5}$ is associated with a 0.046 decline in the Bagrut score. Roth (2016) analyzes the relationship between short-term exposure to indoor coarse particles and cognitive ability, using a confidential student file which contains the full academic record of all undergraduate students that took exams during the 2012/2013 academic year at a university in London. His findings show that one unit increase in PM_{10} and being above the WHO guideline reduces student’s test scores by 0.060 and 2.868, respectively. In another interesting study, Archsmith et al. (2016) observe the decision-making of a panel of Major League Baseball (MLB) umpires. They find that ambient air pollution would reduce the number of correct call from the umpires, suggesting that short-term exposure

[3]The unit of SO_2 concentrations in this study is the Dobson unit. The Dobson unit is a unit of column density used in ozone research, and in measurements of SO_2. The Mini-Mental Status Examination (MMSE) is one of the most commonly used instrument for systematically screening cognitive ability.

to ambient air would cause cognitive decline. While previous studies often rely on using proxy to measure cognitive ability, in this study I use the MMSE which is one of the most commonly used instrument for systematically screening cognitive ability. This is because cognition is a broad concept which includes reasoning, remembering, understanding, and problem solving. Therefore, a more direct measure of cognitive ability is preferred.

Second, previous studies predominantly focus on the United States and other developed countries, while developing countries attract relatively little attention. This might be because developed countries have reliable measurement of air quality and impose various environmental regulations, which provide better opportunities to study the effects of air pollution. However, economists have long recognized that individuals' optimizing behaviour may compensate for increases in pollution by cutting off their chances of getting exposed to the pollution so as to protect their health (Shimshack et al., 2007; Malgosia Madajewicz et al., 2007). Thus, empirical evidence on the magnitude derived from developed countries might not be applicable in developing countries.[4] Meanwhile, air pollution regulations are still rare in developing countries, and whether, and to what extent, environmental regulations on air pollution lead to health benefits remains an important question yet to be answered.

Moreover, this study is related to the literature on the impacts of air pollution on labor productivity. Attention to the impacts of air pollution on labor productivity has generally focused to the extensive margin (e.g., Ostro, 1983; Hausman et al., 1984; Hanna and Oliva, 2015). On the other hand, recent studies find that the impacts also can occur on the intensive margin whereby productivity is affected, even when labor supply does not change. Zivin and Neidell (2012) obtain daily measures of worker productivity using a unique panel data set on agricultural workers who are paid by piece rate. They find that air pollution has

[4] For example, given the average year of educational attainment in developing countries is lower than in advanced countries (Barro and Lee, 2001), people in developing countries might have less ability to assess and understand the knowledge of how to avoid or alleviate the damage from pollution. This systematic differences can lead to a gap between the effects of pollution on health in developing and developed countries.

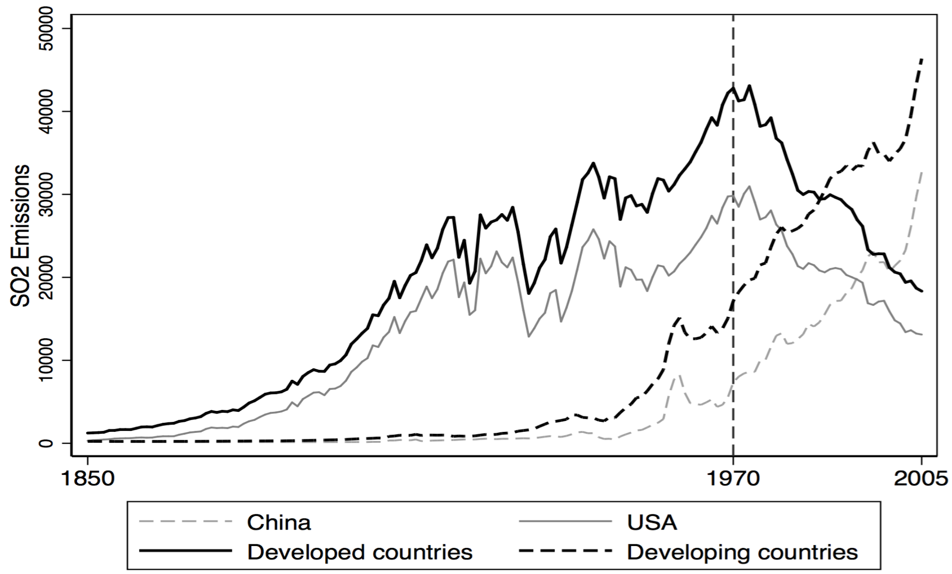
negative impacts on agricultural worker's productivity. Similarly, Chang et al. (2016) investigate the effects of air pollution on worker productivity in the service sector by focusing on two call centers in China. They find that higher levels of air pollution decrease worker productivity by reducing the number of calls that workers complete each day. Since brain function is highly related to human capital and labor productivity, my findings highlight the potential mechanism of the impacts of air pollution on the intensive margin, that is, air pollution may lead to direct neurological insults that affect cognitive ability, therefore, affect brain development and reduce human intelligence.

The remainder of the paper proceeds as follows. The following section summarizes the background of SO_2 and China's Olympic Cleanup Act. Section 2.3 describes the data. In section 2.4, the empirical strategies are presented. The empirical results are provided in section 2.5. The last section concludes.

2.2 Background of SO_2 and China's Olympic Cleanup Act

In many developing countries, SO_2 pollution are relatively high. As shown in Figure 2.1, although developed countries have made significant SO_2 emission reductions since 1970, SO_2 emissions in developing countries are still increasing. SO_2 is a toxic gas with a pungent, irritating, and rotten smell which in the atmosphere is emitted from both anthropogenic and natural sources. SO_2 irritates the skin and mucous membranes of the eyes, nose, throat, and lungs. High concentrations of SO_2 can cause inflammation and irritation of the respiratory system. The resulting symptoms may include pain when taking a deep breath, coughing, throat irritation, and breathing difficulties. High concentrations of SO_2 can also affect lung function, worsen asthma attacks, and aggravate existing heart disease in sensitive groups. Besides, children, older adults, and people with lung diseases are particularly sensitive to SO_2.

Figure 2.1: National SO2 Emissions: 1850-2005



Notes: This figure shows the SO_2 emissions in developed and developing countries from 1850 to 2005. Developed countries include USA, UK, Canada, and Australia. Developing countries include China, India, Brazil, Russia. The source of the data is from the NASA Socioeconomic Data and Application Center (SEDAC).

According to the United States Environmental Protection Agency, the largest sources of SO_2 emissions are from fossil fuel combustion at power plants (73%) and other industrial facilities (20%).[5] As the second largest energy consumer in the world, approximately 69% of China's total energy source comes from coal. According to the National Bureau of Statistics, China's annual coal consumption was more than 1300 million tons during 1995-1997. Due to the massive increase in fossil-fuel consumption, and the lag in the introduction of desulfurization devices, China is infamous for its SO_2 emissions. Since 1990s, China contributed to about one-forth of the global SO_2 emissions and more than 90% of East Asian SO_2 emissions (Ohara et al., 2007; Streets et al., 2009).

In 2008, Beijing and another six provinces hosted the 29^{th} Olympic Games.[6] When Beijing was awarded the Games in 2001, the International Olympic Committee (IOC) noted: "Beijing currently faces a number of environmental pressures and issues, particularly air

[5] http://www.epa.gov/airquality/sulfurdioxide/

[6] The provinces are Beijing, Tianjin, Hebei province (Qinhuangdao), Shandong province (Qingdao), Liaoning province (Shenyang), and Shanghai

pollution. However, it has an ambitious set of plans designed, which are comprehensive enough to greatly improve Beijing's overall environmental condition." In order to carry out the "Green Olympics" promise, the Chinese government implemented a series of measures to reduce the air pollution in these provinces.[7] For example, specific industrial pollution control policy was enforced in 2008. Power plants were required to reduce their emissions by 30% from their levels in June. This reduction was required even for plants that had already met the Chinese emission standards (Huijuan et al., 2013). Moreover, certain heavily polluting factories were ordered to reduce their operating capacities, whereas others were completely shut down (Liu et al., 2012).[8] Beijing-Tianjin-Hebei area recycled the gas at 557 gas stations to reduce the emissions of volatile organic substances. To strictly control air pollutant emissions, the Beijing municipal government announced an "Air Quality Guarantee Plan for the 29th Olympic Games in Beijing". Similar control measures were extended to Tianjin, Hebei, and Shandong (Wang et al., 2010). By the end of 2007, these regions had put into operation 17000 megawatt of desulfurization facilities. Furthermore, Liaoning province and Shanghai municipality primarily relied on vehicle emission regulation such as more severe emission standard, road restrictions, and Even-Odd License Plate Law to improve the air quality.[9]

A large number of studies has shown that the temporary and permanent air pollution control measures used for Beijing Olympic Game are effective. Wang et al. (2010) find that the daily emissions of SO_2 in Beijing were significantly reduced during the Olympic Games. Cai and Xie (2011) study the effects of Even-Odd License Plate Law on air pollution during the Olympic Games and suggest that the traffic control policy can improve

[7]The "Green Olympics" concept was launched by the Beijing's Olympic Games Organizing Committee (BOCOG) and the Beijing's Municipal Government to promote the environmental sustainability of the Games.

[8]For example: the Beijing No.2 Chemical Factory and No.6 and 7 coal-fired units of Jingfeng Thermal Power Plant were completely shut down.

[9]Odd-even license plate rule, a traffic ban based on license plate number, requires that private owned vehicle with last digit number on license plate odd can travel on public road only on odd days of each month, and vehicle with last digit on license plate even can travel on public rad only on even days of each month.

the air quality effectively in short term. Schleicher et al. (2012) find that the temporary measures, such as shutting down industries and reducing traffic, during the 2008 Beijing Olympic Games had huge impacts on the reduction of aerosol pollution. He (2013) compares the regulated and non-regulated areas and observes that the regulated areas are associated with a sharp decrease in air pollution index (API) in 2008. Huijuan et al. (2013) show that the improvements of air quality in Beijing during the Olympic Games were largely due to the implementation of several temporary measures, including factory closures and traffic control.

2.3 Data

2.3.1 Cognitive Ability

The micro-level data come from the Chinese Longitudinal Healthy Longevity Survey (CLHLS). The CLHLS conducted face-to-face interviews in 22 of China's 31 provinces and municipalities. The population in the survey areas constitutes more than 85 percent of total population in China. Han Chinese people are the overwhelming majority in the surveyed provinces and municipalities, while ethnic minorities share a very high proportion of the population in the excluded eight provinces.[10] The questionnaire design was based on international standards and was adapted to the Chinese cultural and social context. It was carefully tested by pilot studies and interviews (Yi, 2008). The interview refusal rate was about only 2 percent.

Cognitive ability is measured by the Mini-Mental Status Examination (MMSE) in the CLHLS.[11] The MMSE is the most commonly used instrument for systematically screening

[10] This is important because the Han Chinese can usually provide a reliable date of birth for themselves or for their close family members while the age reporting among some ethnic minorities was seriously biased with age exaggeration (Coale and Li, 1991)

[11] The CLHLS uses the Chinese version MMSE. The Chinese version MMSE tries to meet the cultural and socioeconomic conditions in China and make the questions easily understandable and practically answerable among normally functioning oldest-old Chinese (Yi and Vaupel, 2002). Several similar versions of the Chinese MMSE which are all adapted from Folstein et al. (1975), have been proven to be reliable and valid

cognitive ability (Wood et al., 2006). It is a brief 30-point questionnaire test which consists of five major domains of cognitive ability: Orientation, registration, calculation, recall, and language.[12] According to Folstein et al. (1975), cognitive ability can be classified into four categories: unimpaired (with a score of 24-30), slightly impaired (with a score of 18-23), moderately impaired (with a score of 10-17) and severely impaired (0-9). Table 2.1 summarizes the MMSE scores across the categories.

Table 2.1: Statistical Summary of MMSE Scores in the 2008 CLHLS

MMSE	Number of observations	Percentage	Mean	Std. Dev
Unimpaired (24-30)	4312	61.2%	25.17	0.805
Slightly impaired (18-23)	1855	26.3%	21.33	1.612
Moderately impaired (10-17)	468	6.6%	14.64	2.125
Severely impaired (0-9)	412	5.8%	0.803	2.296
Total	7047	100%	22.04	6.154

2.3.2 Air Pollution: SO_2

The air pollution data is satellite data. The monthly tropospheric SO_2 vertical column concentrations data are requested from the International Institute for Earth System Science, Nanjing University (ESSI).[13] I extract the monthly provincial level tropospheric SO_2 vertical column concentrations in 2008 and calculate the yearly provincial SO_2 concentrations. Table 2.2 summarizes the yearly SO_2 concentrations in 2008 across provinces in China.

among the Chinese old populations (Salmon et al., 1989; Shyu and Yip, 2001).

[12] Appendix D.1 provides more details about the questionnaire.

[13] ESSI retrieved tropospheric SO_2 information from the Scanning Imaging Absorption Spectrometer for Atmospheric Chartography (SCIAMACHY) measurements which is originally from the Royal Netherlands Meteorological Institute (KNMI). SCIAMACHY aboard the Environmental Satellite (ENVISAT) satellite, was launched by ESA (European Space Agency). It is a passive remote sensing spectrometer observing backscattered, reflected, transmitted or emitted radiation from the atmosphere and Earth's surface, in the wavelength range between 240 and 2380 nm. The spatial resolution is 30 km x 60 km.

Satellite pollution data is preferable in this study for two reasons. First, according to the Towards a China Environmental Performance Index (2010), the official Chinese pollution statistics for most indicators lacked detailed information on data collection methods and monitoring systems. Thus, it is hard to assess the validity and reliability of the official Chinese pollution data. Second, the official Chinese pollution data can only be converted to the PM_{10} concentrations.[14] It prevents me from studying the effects of other pollutants.

2.3.3 Provincial and Individual Level Characteristics

The provincial level characteristics used in this study are grouped into climatic and environmental characteristics, economic characteristics, energy consumption, and population. Data are collected primarily from the China Statistical Yearbooks and the China Statistical Yearbooks on Environment.[15] Climatic data are collected from the China Meteorological Statistical Yearbooks and the China Water Statistical Yearbooks. The individual characteristics are collected from the CLHLS. Table 2.3 summarizes the provincial and the individual level characteristics.[16]

2.4 Econometric Strategies

In this section, I outline my econometric strategies to estimate the effects of SO_2 on cognitive ability. I first discuss the baseline OLS model and its shortcomings. I then discuss my IV approach which can circumvent the identification problem. This is followed by a

[14]The Chinese Ministry of Environmental Protection (MEP) has been providing the daily API for 86 major cities in China since 2000. The API is a single number indicating the air quality on a given day. It goes from 0 to 500. The Chinese official API is determined from three pollutants: Sulfur dioxide (SO_2), Nitrogen dioxide (NO_2), and PM_{10}. The method used by MEP to construct the API allows me to recover the concentrations of the primary pollutant. Since around 90% of primary pollutants were PM_{10}, I can only recover the PM_{10} concentrations from the Chinese official pollution data.

[15]The China Statistical Yearbooks are published by the National Bureau of Statistics of China (NBSC). I extract the data from http://data.stats.gov.cn

[16]The selection of these control variables is discussed in detailed in the next section.

Table 2.2: China Provincial Level Average Tropospheric SO_2 column vertical concentrations in 2008

Province	Mean	Std. Dev	Min	Max
Beijing	0.46	0.26	0.04	0.87
Tianjin	0.21	0.12	0.06	0.51
Hebei	0.51	0.20	0.10	0.80
Shanxi	0.68	0.31	0.37	1.32
Liaoning	0.18	0.06	0.12	0.33
Jilin	0.20	0.09	0.10	0.43
Heilongjiang	0.54	0.32	0.33	2.20
Shanghai	0.36	0.20	0.13	0.73
Jiangsu	0.50	0.29	0.19	1.13
Zhejiang	0.09	0.02	0.06	0.14
Anhui	0.41	0.25	0.13	0.82
Fujian	0.09	0.04	0.03	0.19
Jiangxi	0.25	0.19	0.05	0.69
Shandong	0.11	0.05	0.05	0.20
Henan	0.67	0.35	0.18	1.22
Hubei	0.21	0.16	0.01	0.48
Hunan	0.29	0.14	0.13	0.57
Guangdong	0.11	0.04	0.04	0.17
Guangxi	0.11	0.05	0.05	0.19
Hainan	0.03	0.02	0.01	0.08
Chongqin	0.29	0.12	0.18	0.62
Sichuan	0.32	0.19	0.17	0.78
Shaanxi	0.53	0.21	0.20	0.89

[1] The unit of the SO_2 concentrations is the Dobson unit. The Dobson unit is a unit of measurement of the columnar density of a trace gas in the Earth's atmosphere.

[2] Min and Max represent the minimum and maximum monthly SO_2 concentrations in 2008, respectively.

Table 2.3: Provincial and Individual Control Variables

Variable	Mean	Std. Dev	Obs	Min	Max
Individual Characteristic					
Ability of selecting location					
age	80.694	11.585	7047	39	111
year of schooling (year)	3.585	4.085	7030	0	24
year of father's schooling (year)	1.145	2.494	6850	0	20
total income of the household last year (yuan)	21429.84	23296.38	6941	0	96000
if the respondent is the first son	0.199	0.399	7047	0	1
number of children	4.124	1.974	7047	0	13
Preference of health					
expense of medical care last year (yuan)	1091.179	2960.762	6810	0	70000
exercise or not at present	0.396	0.489	7046	0	1
smoke or not at present	0.242	0.428	7047	0	1
drink alcohol or not at present	0.228	0.419	7047	0	1
Provincial Characteristic					
Economic Characteristics					
GDP per capita (yuan)	29081.78	15786.07	23	14448	66932
number of automobile per person (10000)	0.0452	0.0339	23	0.0189	0.1771
passenger flow volume (100 million man-km)	790.28	459.35	23	124.92	1705.55
Climatic and Environmental Characteristics					
total area of afforestation (khm)	138.47	146.83	23	1.9	574.6
annual average precipitation (mm)	1080.48	516.48	23	466.4	2140.8
† annual average temperature (celsius degree)	15.81	4.42	23	6.6	23.4
† annual average sunshine hours (hour)	1870.04	477.34	23	703.8	2570.7
† annual average relative humidity	66.39	8.88	23	52	82
† annual average atmospheric pressure (hPa)	998.44	21.94	23	927.6	1016.8
Energy Consumption					
coal consumption (million ton)	12127.04	8752.22	23	471.95	34389.61
crude oil consumption (million ton)	1409.46	1480.95	23	0	5945.19
gasoline consumption (million ton)	306.27	206.84	23	38.85	886.9
kerosene consumption (million ton)	62.11	91.78	23	0.51	321.47
diesel consumption (million ton)	521.29	329.48	23	93.8	1518.92
furnace oil consumption (million ton)	164.81	268.26	23	5.93	1077.76
electric power consumption (100 million kWh)	1291.077	908.01	23	121.72	3504.82
Population					
population density (10000/km^2)	538.35	675.69	23	84.99	3395.18

[1] For the binary variables: exercise, smoke, drink, and first child in the family or not, 0 represents no and 1 represents yes.
[2] Variables with † are not available in provincial level and used the provincial capital data instead.
[3] The respondents without the MMSE scores are excluded in the summary.
[4] All of the data are in 2008.

discussion of the validity and advantages of this empirical design. Before getting into the details of the identification strategy, it is worth mentioning here that the analyses below are cross-sectional. This is because the satellite data is only available for one year.[17] Hence, I cannot implement the difference-in-differences approach as in Chapter 1.

2.4.1 OLS model

The baseline model I use to estimate the impacts of SO_2 on cognitive ability is a cross-sectional OLS model:

$$H_{ij} = \beta P_j + X_i'\eta + X_j'\gamma + \varepsilon_{ij} \tag{2.1}$$

where H_{ij} is the measure of cognitive ability (e.g., the MMSE scores) for individual i at province j, P_j is the SO_2 concentrations at province j, X_i is a vector of individual characteristics, and X_j is a vector of local provincial characteristics.

Many provincial characteristics can affect SO_2 concentrations and cognitive ability. For example, energy consumption can directly affect the SO_2 concentrations and indirectly affect cognitive ability.[18] Rainfall is negatively correlated with the SO_2 concentrations as rain cleans the air (Wilson et al., 1996). It can also affect people's cognitive ability by changing the amount of time spent outdoor. Table 2.3 lists the four aspects of provincial level characteristics controlled in this study.

Individual characteristics can also be important confounding factors if these characteristics not only affect cognitive ability but also affect individual's ability of sorting into cleaner locations. For example, educational attainment, income, and age can affect both cognitive ability (Rushton and Ankney, 1996; Luszcz et al., 1997; Deary and Der, 2005; Falch and Sandgren Massih, 2011; Paxson and Schady, 2007) and the determinants of migration (Hunt, 2006; Fuchs-Schündeln and Schündeln, 2009; Gould, 1982; Zivin et al.,

[17] Although the Chinese official air pollution index data is longitudinal, it can only be converted to the PM_{10} concentrations.

[18] Provinces with more energy consumption tend to be wealthier. Wealthier provinces tend to have better infrastructure and hospitals which can affect individuals' cognitive ability.

2011). I also control for whether an individual is the first son in the family. Due to the strong son preference in China, the first son in the family can possibly gain more care, sources, and education opportunity from their parents which might affect their cognitive ability. Meanwhile, whether an individual is the first son in the family can be an important determinant of his migration decision since he has responsibility to take care of his parents or carrying out the family's responsibilities when the father can no longer make important decisions. Moreover, if an individual has strong health preference, he would have healthier behaviours which can affect his cognitive ability. Meanwhile, strong health preference can also affect an individual's migration decision.[19] In order to control for respondents' health preferences, I include information on their medical care expense, whether the individual exercise, drink alcohol, and smoke.

The main concern of the OLS model is the omitted-variable bias. For example, the estimators would be downwardly biased if the polluted provinces happen to be where the wealthier people reside and the wealthier people are more likely to make unobservable investment on their health (Tanaka, 2015).

2.4.2 IV model

The bias from the omitted variables can be alleviated if one can find an appropriate instrumental variable that can only affect individuals' cognitive ability through the channel of variations in air pollution. Economists exploit a variety of natural experiments such as temporary closure of polluting plants (Pope III et al., 1992), economic recessions (Chay and Greenstone, 2003), wind directions (Luechinger, 2009), and wildfires (Jayachandran, 2009) to isolate the changes in the concentrations of pollutants from other unobservable variables. In this study, I exploit plausibly exogenous variations in air pollution generated by the 2008 China's Olympic Pollution Cleanup Act. The IV frameworks are:

$$P_j = \pi Z_j + X_i' \rho + X_j' \theta + \eta_j \tag{2.2}$$

[19] If an individual has strong preference of health, he would have incentive to move to a cleaner location.

$$H_{ij} = \beta \hat{P}_j + X_i' \eta + X_j' \gamma + \varepsilon_{ij} \quad (2.3)$$

where Z_j is a dummy variable that takes a value 1 if province j was a host of Olympic Games. $\hat{P}_j$ is the predicted pollution level derived from Equation (2.3).

2.4.3 Validity of the Instrumental Variable

The identification assumptions for a valid instrument are: 1. Instrument relevance (i.e., $Cov(Z_j, P_j) \neq 0$); 2. Exclusion restriction (i.e., $Cov(Z_j, \varepsilon_{ij}) = 0$). As discussed in section 2.2 , the first assumption is likely to be valid.

The second assumption is that the instrument can only has impacts on outcomes through the first-stage channel. In this study, the instrument is an environmental regulatory policy. There is little evidence that environmental policy can affect cognitive ability directly. However, the instrument may be invalid if hosting the Olympic Games can improve the availability of medical services, which might in turn change cognitive ability of the residents.[20] As discussed in Chapter 1, the Olympic Game did not affect the availability of medical services. Moreover, the instrument may be invalid if the exposure of the elderly would be adjusted by the regulations.[21] To investigate this, I use the CLHLS data in 2002, 2005, and 2008 to compare the trends of the proportion of the elderly who participate in outdoor and social activities in the Olympics host provinces with the trends in other provinces.[22] Figure 2.2 and 2.3 show that the Olympics host provinces and the other provinces have approximately the same trends for the two activities. This supports the assumption that the Olympics pollution regulations do not affect the exposure of the elderly.[23]

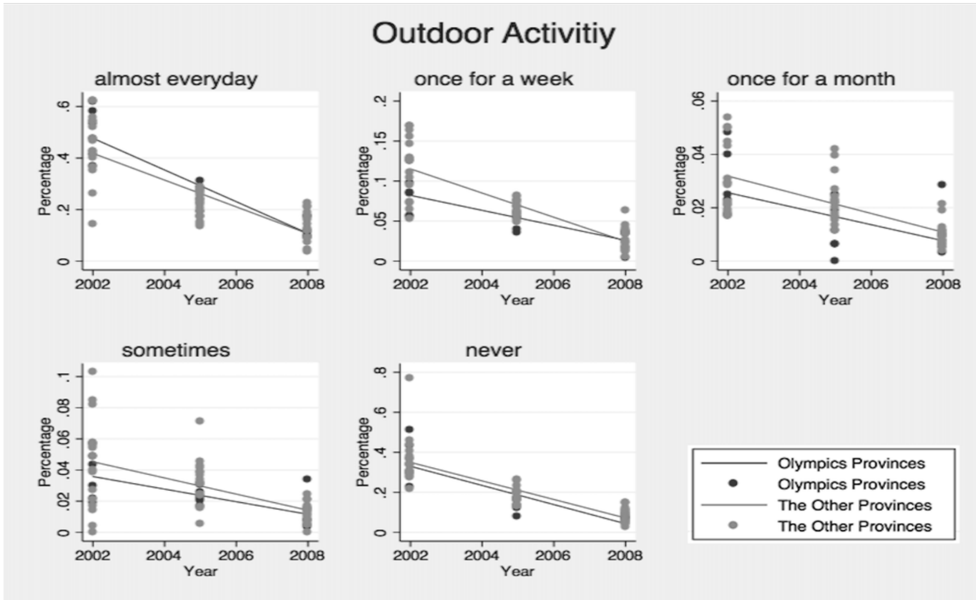
[20] For instance, new hospitals may be built due to the Olympic Games.

[21] For example, the Even-Odd License Plate Law might decrease the elderly's outdoor activities which can affect their exposure time.

[22] In the CLHLS, the frequency of outdoor and social activity participation are grouped into five categories: almost everyday, once a week, once a month, sometimes, and never.

[23] It is worth mentioning that I only plot individuals who were originally in the 1998 or 2002 survey waves. Therefore, the sharp declines of the participation rate can be caused by the increase in age and the decrease in health status.

Figure 2.2: The Frequency of Outdoor Activity



Notes: This graph shows the similar trends of people's outdoor activity between the Olympic provinces and the control provinces. In the CLHLS, the frequency of outdoor activity participation are grouped into five categories: almost everyday, once a week, once a month, sometimes, and never.

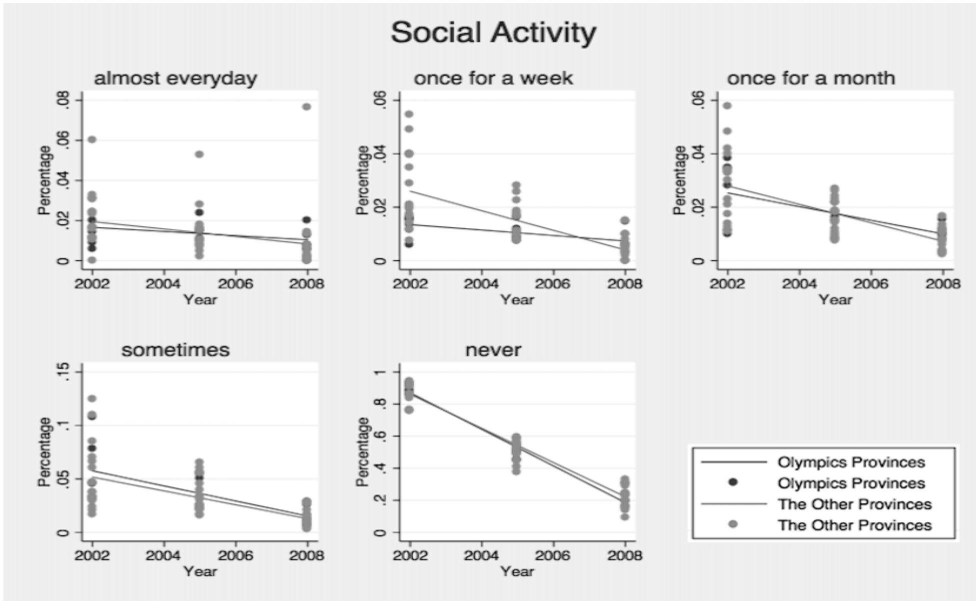
2.5 Empirical Results

In this section, I provide the estimated results. I first present the OLS estimates. Then, in order to overcome the endogeneity problem, I use the instrumental variable I discussed above to reestimate the impacts of SO_2 on cognitive ability.

2.5.1 OLS Estimation Results

The OLS estimates are reported in Table 2.4. Column (1) presents the estimates without any control variables. In order to alleviate bias, I control for economic and population characteristics, energy consumption, climatic and environmental characteristics, and individual characteristics in a stepwise manner. The results are reported in columns (2) to (6). The robust standard errors are reported in parentheses, and the number of observations and R-squared are reported in the bottom of the table. Overall, all of the estimated coefficients are negative. Moreover, with the controls, the estimates are statistically significant. These suggest that SO_2 can negatively affects cognitive ability. The magnitude of the point esti-

Figure 2.3: The Frequency of Social Activity



Notes: This graph shows the similar trends of people's outdoor activity between the Olympic provinces and the control provinces. In the CLHLS, the frequency of social activity participation are grouped into five categories: almost everyday, once a week, once a month, sometimes, and never.

mates are sensitive to the inclusions of the control variables. This supports the notion that omitted variables can cause severe bias in OLS estimation.

2.5.2 IV Estimation Results

The findings above highlight the important role of omitted variables in OLS estimation. Since it is difficult to include all plausible and appropriate control variables, I address the identification problem by exploiting the exogenous variation in pollution induced by the 2008 Olympic Games. Table 2.5 documents the IV results. The estimate with no control is reported in column (1). Then, I control for energy consumption, economic and population characteristics, climatic and environmental characteristics, and individual characteristics. The results are reported in column (2) to (6). I report the first stage regression outcomes. They are highly significant suggesting that I do not have a weak IV problem. Moreover, I report the weak identification tests for the instrumental variable. As shown in the bottom of Table 2.5, the Cragg-Donald Wald-F statistics are larger than the 10% tolerable

Table 2.4: The Impacts of SO_2 on Cognitive Ability: OLS

	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{\beta}$	-1.54	-1.94	-4.87**	-8.23***	-6.30***	-7.10***
	(1.092)	(1.205)	(1.747)	(0.791)	(0.332)	(0.528)
Control Variables						
Economics and Population		✓	✓	✓	✓	✓
Energy Consumption			✓	✓	✓	✓
Climate and Environment				✓	✓	✓
Ability of Selecting Location					✓	✓
Preference of Health						✓
R^2	0.002	0.004	0.011	0.025	0.251	0.268
Observations	7047	7047	7047	7047	6713	6568

[1] Dependent variable is the Mini-mental state examination (MMSE)
[2] * indicates 10% level significance. ** indicates 5% level significance. *** indicates 1% level significance.
[3] Standard errors are adjusted for 23 clusters in province.
[4] Due to the missing observation in the MMSE, I am left with 7047 observations in the final sample.

bias level Stock-Yogo threshold in each of the specification. This further suggests that the instrumental variable is not weak.

The results show that a one unit increase in yearly SO_2 concentrations can reduce the MMSE scores by 8.45. In other words, if the yearly SO_2 concentrations in Beijing raise from 0.46 DU to 1.46 DU, the average MMSE scores in Beijing would be reduced from 23.74 to 15.29. It means that the average cognitive status of Beijing's elderly would change from unimpaired to moderately impaired.

Another interpretation is in terms of standard deviation. I report the standardized beta coefficients in Table 2.5. It suggests that a one standard deviation change in the yearly SO_2 concentrations is expected to result in a -0.25 standard deviation change in the MMSE scores.

Table 2.5: The Impacts of SO_2 on Cognitive Ability: IV

	(1)	(2)	(3)	(4)	(5)	(6)	beta
IV estimates							
$\hat{\beta}$	-6.06	-7.56*	-6.28	-6.78***	-7.82***	-8.45***	-0.254
	(7.334)	(4.497)	(3.957)	(1.184)	(0.799)	(1.117)	
Control Variables							
Energy Consumption		✓	✓	✓	✓	✓	
Economics and Population			✓	✓	✓	✓	
Climate and Environment				✓	✓	✓	
Ability of Selecting Location					✓	✓	
Preference of Health						✓	
Centered R^2	-0.0156	-0.0028	0.0108	0.0252	0.2510	0.2681	
Observations	7047	7047	7047	7047	6713	6568	
1st stage IV estimates							
Olympics dummy	-0.086	-0. 263*	-0.312**	-0.414***	-0.415***	-0.415***	
	(0.084)	(0.139)	(0.137)	(0.081)	(0.082)	(0.082)	
Centered R^2	0.0415	0.696	0.782	0.963	0.963	0.963	
Postestimation tests							
Underidentification test							
LM statistics	0.688	4.051	4.375	8.327	8.213	8.183	
P-val	0.4067	0.0442	0.0365	0.0039	0.0042	0.0042	
Overidentification test							
Sargan statistics	0.000	0.000	0.000	0.000	0.000	0.000	
Weak identification test							
Cragg-Donald Wald F statistics	304.648	1601.271	2224.408	1.2e+04	1.2e+04	1.1e+04	
Stock-Yogo threshold (10% tolerable bias level)	16.38	16.38	16.38	16.38	16.38	16.38	

[1] Column beta is the standardized beta coefficients for the IV estimates in column (6).
[2] Standard errors are adjusted for 23 clusters in province.
[3] * indicates 10% level significance. ** indicates 5% level significance. *** indicates 1% level significance.

2.6 Conclusion

This paper exploits the exogenous variation in air pollution induced by the 2008 Olympic Games. This quasi-experimental design provides me a rare opportunity to address the impacts of air pollution on cognitive ability. The findings show that SO_2 has negative impacts on cognitive ability. This study also shed light on the benefits of environmental regulations in terms of the air pollution abatement and mental health.

However, the complete analysis of the benefits induced by the air pollution abatement is far beyond the scope of this study. It is likely that the benefits of the abatement are understated because it does not take into account the decrease in social and individual medical costs due to the illnesses reduction caused by better air quality (Tanaka, 2015). More importantly, environmental pollution can affect human capital, such as education and productivity via human physical and mental health (Currie et al., 2009; Clay et al., 2010; Carson et al., 2011). Given the human capital is a factor in economic growth (Romer, 1989; Stokey, 1991; Mankiw et al., 1992; Barro, 2001), understanding the benefit of pollution abatement is important.

I am aware of three limitations in this study that call for cautious interpretation of the results. First, due to data limitation, this study focuses only on the people aged 60 and older. Since the dose-response function might be non-linear and perhaps negligible below a certain threshold, the findings in this study should not be simply generalize to the younger population (He et al., 2016). Nevertheless, the findings here are still policy-relevant. This is because the older people are the most vulnerable members of society and the policy makers are highly motivated to protect them. Moreover, due to the rising of the retirement age, focusing on older population is still relevant to labor productivity study.

Second, people's emotional changes during the study periods are not examined due to lack of data. If the BOG08 can affect people's cognitive ability through the channel of people's affective states, the estimated impacts on cognitive ability in this study may be biased. von Stumm (2016) finds that there is no link between people's affective states and cognitive ability. However, her study span is short (i.e. fives days). Moreover, the measures of cognitive ability are different in hers and in this study. Thus, the consequences of such emotional changes on cognitive ability are worthy of further investigation.

Lastly, due to data limitation, I am not able to identify whether the cognitive decline caused by the BOG08 is temporary or permanent. The further investigation of this question requests the data on post-Olympic periods.

Chapter 3

Minimum Wage Effects on Labor Market Outcomes Incorporating Workers' On-the-Job Effort

3.1 Introduction

In recent years, minimum wage has once again been gaining attention and systems have been established or strengthened in many countries. For example, many cities in the U.S. have passed minimum wage laws, with some going as high as \$15 per hour over the next few years. The UK has introduced a National Living Wage of £7.20 (\$10.25) for workers aged over 25 in 2016, with more increases thereafter. And in Canada, the average minimum wage will be about \$11.43 per hour by late 2017. The opponents of minimum wage increases often argue that such hikes could result in job loss because it imposes additional costs on firms. On the other hand, it is also said that raising minimum wage might motivate workers to work harder, thus aiding firms in offsetting the higher labor costs. However, when trying to understand the macroeconomic implications of minimum wage, little attention has been paid to how it affects workers' work effort provision. It is important for policymakers to understand the underlying mechanism of this incentive effect and its macroeconomic consequences in order to design an effective minimum wage regime.

This paper studies the macroeconomic implications of minimum wage incorporating workers' work effort responses. In the model, workers' probability of being laid off depends on the effort they provide on the job. At the same time, workers search for better offers if they can stay on the current job. Firms design contracts to induce workers' unobservable effort, which positively affects the output. In addition, search is assumed to be directed. That is, all firms post contracts on the labor market. Each worker observes all offers and chooses the most attractive one to apply for. When making search decisions, firms and workers take into account the trade-off between the value of an offer and the matching rate at the offer. If a new minimum wage is introduced, firms need to adjust the contracting decisions corresponding to workers' effort responses, which will further affect workers' and firms' search decisions. This directed search framework with workers' work effort responses allows me to analyze the effects of minimum wage on the behavior of both the labor supply and demand sides.

The starting point of the directed search model can at least go back to Moen (1997). Shi (2009) and Menzio and Shi (2010) incorporate wage-tenure contracts in the directed search framework. Tsuyuhara (2016) builds on the Menzio and Shi (2010) model by embedding the moral hazard problem of workers' work effort. In this study, I apply the Tsuyuhara (2016) model and introduce a minimum wage by imposing a constraint on firm's contracting problem.

The main contribution of this paper is quantitatively showing that minimum wage has crucial impact on workers' optimal choice of effort and consequently on aggregate output, average wage, labor market transition rates (hires, layoffs and quits), and unemployment. I calibrate the model to the U.S. labor market using the Current Population Survey (CPS) for January 2000 to December 2011. The calibrated model shows that a 5% increase in minimum wage raises the unemployment rate by 1.78%. This is because the higher minimum wage increases the labor cost. As a result, some firms are driven out of the market. Moreover, the exit of firms makes jobs harder to find. Thus, the higher minimum wage lowers the average hiring and quit rates by 2.5% and 5.6%, respectively. On the other hand, the higher minimum wage rises average workers' work effort by 0.29%. This is because the lower hiring rate increases the cost of being laid off. Therefore, employed workers are working harder to try to avoid being laid off, which consequently lowers the average layoff rate by 0.7%. Due to the higher unemployment, the aggregate output decreases by

0.14% even with the higher work effort. In addition, the higher minimum wage rises the highest equilibrium wage and the average equilibrium wage by 0.04% and 2.1%, respectively. This is because firms respond to the policy by demanding more effort, and therefore wages increase. Besides, the higher minimum wage shifts the distribution of employed workers toward jobs with a higher wage offer. In other words, the minimum wage has a general equilibrium effect on the wages of workers who previously earned above the new minimum wage.

To highlight the role of workers' on-the-job effort, I shut down the effort channel and compare the results with those from the model with workers' on-the-job effort decision. Since firms do not respond to the higher minimum wage by inducing workers' work effort, the higher labor cost cannot be compensated by the rise in induced effort. As a result, more firms are driven out of the market and unemployment rate goes up by 3.57%. Since more firms exit the market, the average hiring and quit rates decrease by 5.8% and 11.8%, respectively. The higher minimum wage also lowers the aggregate output by 0.28%, which is caused by the higher unemployment rate. These larger negative impacts imply that workers' on-the-job effort has strong offsetting effect on the costs of higher minimum wage. In addition, without workers' work effort decision, a higher minimum wage simply eliminates low wage jobs without causing a significant change in the employed worker distribution. Thus, the general equilibrium effect on the higher income groups disappears. As a result, the increase in the average wage is smaller and the highest equilibrium wage does not change.

Related literature. Recent studies have shown that a higher minimum wage can contribute to higher labor productivity (Forth and O'Mahony, 2003; Croucher et al., 2012; Riley and Bondibene, 2017). However, the observed positive relationship between minimum wage and labor productivity cannot distinguish between (1) selection: firms can choose to dismiss (or not hire) low productive workers; and (2) an incentive effect: workers can increase their work effort and hence productivity to preempt being laid off. While many studies have been focusing on the selection problem, the incentive effect is largely overlooked in the literature, mainly due to the difficulty in measuring effort. To overcome this challenge, Brandts and Charness (2004) and Owens and Kagel (2010) introduce minimum wage in gift-exchange experiments in laboratory. Although the former finds that minimum wage was counterproductive in terms of effort provision, the latter shows a positive relationship between minimum wages and workers' work effort.[1] One major concern of the laboratory gift-exchange results is the degree to which these mean anything in the field environment (Charness and Kuhn, 2011). To address the limitations, this study uses a calibrated model with survey data to provide direct implications that minimum wage increases work effort and hence productivity.

This paper is also related to the literature addressing the issue of spillover effect of minimum wages.[2] Grossman (1983) is the first study that attempts to directly estimate the spillover effects of minimum wages. She finds that an increase in minimum wage increases the wages of occupations above the new minimum wage. DiNardo et al. (1996) and Lee (1999) examine the changes in the U.S. wage distribution and find evidence of spillover effect of minimum wage. Neumark et al. (2004) estimate the impact of changes in minimum wage on the wages of workers who previously earned above the new minimum wage. Their results suggest that minimum wage has substantial spillover effect on higher wage group. Two broad alternative classes of explanations have been proposed for the spillover effect. The first explanation builds on the monopsonistic competition among firms for workers. The other emphasizes that workers' job satisfaction and productivity are affected by their level of wages relative to their colleagues (Fehr and Schmidt, 1999). This paper contributes

[1] Owens and Kagel (2010) claim that the differences between the two studies may come from subject population or cultural differences as their experiments were conducted in the U.S., and the experiments in Brandts and Charness (2004) were conducted in Spain.

[2] The spillover effect of minimum wage refers to the impact of minimum wage on the pay for workers who previously earned above the new minimum wage. Comprehensive reviews of the empirical literature on spillover effects of minimum wages are provided by Card and Krueger (2015) and Neumark and Wascher (2008).

to the literature by showing that the general equilibrium effect of minimum wage on workers' optimal choice of effort and firms' contracting decisions can be another explanation of the spillover effect.

There are a handful of papers that have directly estimated the effects of minimum wages on labor market transition rates. Portugal and Cardoso (2006) study the separations and hires of teenagers before and after a youth-specific minimum wage increase in Portugal.[3] They find that both the teen share of separations and hires declined due to the increase in minimum wage. Brochu and Green (2013) use Canadian data and find that higher minimum wages result in lower hiring, quit, and layoff rates of unskilled workers of all ages. Dube et al. (2016) use pairs of counties across state borders in the U.S. to control for spatial heterogeneity. And they find significant negative effects of the minimum wage on hiring and separation rates, particularly for teenagers and in the restaurant workforce.[4] This paper is complementary to those studies in the sense that it indicates workers' optimal choice of effort play an important role in mediating the effects of minimum wage on labor market transition rates.

Lastly, there is a small body of literature that takes into account incentives when analyzing the minimum wage policies. Rebitzer and Taylor (1995) develop an efficiency wage model where a higher minimum wage makes it easier for firms to prevent a given number of employees from shirking. Kadan and Swinkels (2013) analyze the effect of the minimum wage in a standard moral hazard setting.[5] They show that minimum wage generally has negative impact on induced effort level. This is because higher minimum wage increases the marginal costs of inducing effort. In contrast, the current model incorporates equilibrium interactions between incentive decisions and labor market conditions, such as

[3] There are two types of job separation: voluntary separation (quits) and involuntary separation (layoff). Unfortunately, Portugal and Cardoso (2006) do not distinguish one from the other.

[4] Like Portugal and Cardoso (2006), Dube et al. (2016) also do not distinguish quits and layoffs from separation.

[5] Kadan and Swinkels (2013) and the current model both assume that workers are risk averse, effort cannot be observed, and an explicit contract is feasible.

job finding probabilities. By taking the labor market conditions into account, I find that minimum wage has positive impact on induced effort level.

3.2 Model Environment

3.2.1 The labor Market

Consider a labor market that lasts forever in discrete time, and time is indexed by t. There is a unit continuum of infinitely lived, *ex-ante* homogeneous, and risk-averse workers whose periodical utility function of consumption is $u(\cdot)$, which is strictly increasing, strictly concave, and twice continuously differentiable. Workers cannot save or borrow against their future income, so their consumption is wage w if employed or unemployment benefit b if unemployed. Employed workers exert unobservable effort e on the job each period, and the disutility of effort is given by $c(\cdot)$, which is strictly increasing, strictly convex, and twice continuously differentiable. Both employed and unemployed workers search for jobs with probability λ_e and λ_u, respectively. Each worker maximizes the expected lifetime sum of utilities discounted at rate $\beta \in (0,1)$.

There is a continuum of *ex-ante* homogenous firms whose measure is determined by competitive entry. Entering firms create a vacancy and post a job offer at a flow cost $k > 0$. Depending on the employed worker's effort, a job in each period results in one of two possible outcomes: y, called *success*, with probability $r(e)$ and 0, called $failure$, with probability $1 - r(e)$. The probability of success function $r(\cdot)$ is strictly increasing, strictly concave, and twice continuously differentiable. If the project succeeds, the job continues in the next period; if it fails, the job is destroyed and the worker becomes unemployed. Each firm maximizes the expected sum of profits discounted at the rate β.

Firms announce wage-tenure contracts to recruit. A contract specifies the wage at each tenure length t, conditional on the worker staying with the firm. There is a minimum wage legislation so that the wage offers cannot be lower than the minimum wage w_{min}.

A worker may leave a job at any time if a job fails or if she finds a new job via on-the-job search. Firms are assumed to commit to the contracts. That is, once a contract is initiated, a firm cannot adjust it or respond to the worker's outside offers. Moreover, because the worker's effort is unobservable, firms need to design a contract to optimally induce and compensate for the workers' efforts. One can consider a contract as it specifies a wage profile $\{w_t\}_{t\geqslant 0}$ and a *recommended* effort profile $\{e_t\}_{t\geqslant 0}$. For a given wage and effort profile, workers can calculate a discounted lifetime expected utility that the contract would deliver, taking into account the possibility of job destruction and the worker's job-to-job transition. The utility delivered by a contract is referred to as the *value* of a contract and is denoted by x.

The labor market consists of a continuum of submarkets indexed by $x \in X = [\underline{x}, \bar{x}]$. A submarket x consists of all the firms that promise to deliver value x. The worker's job search is directed with respect to the value of job offers. That is, workers observe all the contracts and choose which submarket to visit. The tightness of a submarket $\theta(x)$ is defined as the ratio of vacant jobs to searching workers. The job-finding probability and job-filling probability in submarket x is given by $p(\theta(x))$ and $q(\theta(x))$. $p(\cdot)$ is strictly increasing, strictly concave, twice continuously differentiable, and satisfies $p(0) = 0$, $p'(0) < \infty$. $q(\cdot)$ is strictly decreasing, strictly convex, twice continuously differentiable, and satisfies $p(\theta) = \theta q(\theta)$, $q(0) = 1$. In addition, the matching technology is assumed to satisfy the condition that $p(q^{-1}(\cdot))$ is concave.

Let the value of contract x and the value of unemployment U represent the worker's employment state in some periods. Let G_t denote the distribution of workers over X in period t. The fraction of unemployed workers in period t is $u_t = G_t(U)$. The evolution of the state is generically denoted by an operator Ψ so that $G_{t+1} = \Psi(G_t)$, where Ψ is endogenously determined according to workers' job search and firms' contracting decisions.

3.2.2 Job Search Problem

A worker who gets the opportunity to search chooses which submarket to enter, taking into account the value of the job offer and the probability of finding a job in each submarket. The optimal job search decision depends on the reservation value. For an employed worker, her reservation value is the value of her current contract for the rest of her life. For an unemployed worker, her reservation value is the value of unemployment. Consider a searching worker whose reservation value is W. If she visits submarket x, she gains net value of search $x - W$ with probability $p(\theta(x))$. Thus, her optimal job search decision maximizes $p(\theta(x))x + (1 - p(\theta(x)))W$ with respect to x. The optimal net expected value of search given W is:

$$D(W) = \max_{x \in X} p(\theta(x))(x - W) \tag{3.1}$$

The worker's optimal search policy given W is denoted by $m(W)$. Given $m(W)$, the probability of a worker successfully finding a job is given by the composite function $\hat{p}(W) = p(\theta(m(W)))$.

To define the value of unemployment, let U denote the value of unemployment. In the current period, unemployed workers receive and consume unemployment benefit b. In the next period, if an unemployed worker gets the opportunity to search for a job with probability λ_u, the expected life time utility is $U + D(U)$. Otherwise, the worker stays unemployed, which gives U. Since the unemployment benefit b is constant over time, the value of unemployment U satisfies the following recursive equation:

$$U = u(b) + \beta(U + \lambda_u D(U)) \tag{3.2}$$

3.2.3 Optimal Contracting Problem

Given the value V currently promised to the worker, the choices of a firm in the recursive contracting problem are the current wage w, the recommended effort e, and the reservation value W that the firm promises to deliver in the following period.[6] Let $J(x)$ denote a firm value function for a job that offers a contract of value x. The maximized value of a job $J(V)$ is expressed recursively by:

$$J(V) = \max_{\xi=\{w,e,W\}} r(e)y - w + \beta r(e)(1-\lambda_e \hat{p}(W))J(W) \tag{3.3}$$

subject to

$$V = u(w) - c(e) + \beta[r(e)(W + \lambda_e D(W)) + (1-r(e))U], \tag{3.4}$$

$$e \in \arg\max_{e \in \mathbb{R}} (-c(e) + \beta(r(e)(W + \lambda_e D(W)) + (1-r(e))U)), \tag{3.5}$$

$$W \in \{X : J(W) \geqslant 0\}, \tag{3.6}$$

$$w \geqslant w_{min} \tag{3.7}$$

The firm's choice is subject to the promise-keeping constraint (3.4), which requires ξ to provide the worker with the lifetime utility V , the incentive compatibility (IC) constraint (3.5), which requires the contract to induce the worker to voluntarily exert the desired level of effort, the individual rationality (IR) constraint (3.6), which requires that the firm does not choose a continuation value that leads to a negative value, and minimum wage constraint (3.7), which requires that the minimum wage legislation is binding.

3.2.4 Competitive Firm Entry and Market Tightness

During the search stage, a firm chooses what contract to offer to attract a searching worker. The firm's expected value of opening a vacancy in submarket x is given by $q(\theta(x))J(x)$. For a given $\theta(x)$, if the cost k of creating a vacancy is strictly greater that the expected value, then no firm offers a contract with value x. If k is strictly smaller than the expected value,

[6]To prove the existence of a recursive equilibrium, Tsuyuhara (2016) introduces a lottery and allows the firm to randomize over these choices. The purpose of introducing the lottery is to guarantee that the firm's optimal value function J is concave. However, computed examples shows that the firm's value function is concave without lottery for all the parameter configurations, which implies that lottery is not used at the optimal. Since the purpose of this study is to solve the model numerically and describe some quantitative features, the lottery is excluded in the model description.

then there are an infinite number of firms offering contracts with value x. Therefore, in any submarket that is visited by a finite and positive number of workers, the market tightness $\theta(x)$ is consistent with the firm's optimal job creation strategy if and only if

$$q(\theta(x))J(x) - k \leqslant 0, \tag{3.8}$$

and $\theta(x) \geqslant 0$, with complementary slackness.

3.2.5 Block Recursive Equilibrium

Definition: A Block Recursive Equilibrium (BRE) *consists of the set of individual objects* $\{D^*, m^*, U^*, J^*, \xi^*, \theta^*\}$ *and the operator* Ψ^* *such that*

1. *the value of job search* D^* *and the optimal search policy* m^* *satisfy Equation (3.1).*
2. *the value of unemployment* U^* *satisfies Equation (3.2),*
3. *the value of firm* J^* *and an optimal contract policy* ξ^* *satisfy Equation (3.3),*
4. *the market tightness* θ^* *satisfies condition (3.8),*
5. Ψ^* *is derived from the optimal policy functions,* ξ^* *and* m^**, and*
6. *the individual objects* $\{D^*, m^*, U^*, J^*, \xi^*, \theta^*\}$ *are independent of the distribution of workers* G_t^* *for all* t*.*

The existence of the BRE and the qualitative characterizations are discussed in Tsuyuhara (2016).

3.3 Policy Experiments

In this section, I first solve the model numerically. Then, using the calibrated model, I study how a higher minimum wage affects workers' optimal choice of effort and labor market outcomes such as aggregate output, average wage, labor market transition rates, and unemployment. To highlight the role of workers' on-the-job effort, I mute workers' effort decision and compare the results with those from the model with workers' effort decision.

3.3.1 Model Calibration

To solve the model numerically, I first impose functional forms to compute the model's steady-state. The worker's utility function is assumed to be a standard CRRA utility function $u(w) = \frac{w^{1-\sigma}}{1-\sigma}$, where σ is the CRRA coefficient. The disutility of effort is $c(e) = \frac{1}{2}e^2$. The matching technology is summarized by the employment probability function $p(\theta) = \theta(1+\theta^{\gamma})^{(-1/\gamma)}$, where θ captures market tightness. The probability of success is given by a function $r(e) = \exp(-\frac{\rho}{e})$. The functional forms are collected in Table 3.1.

Table 3.1: Functional Form Assumptions

Utility function	$u(w) = \frac{w^{1-\sigma}}{1-\sigma}$
Effort cost function	$c(e) = \frac{1}{2}e^2$
Matching function	$p(\theta) = \theta(1+\theta^{\gamma})^{-1/\gamma}$
Probability of success function	$r(e) = \exp(-\frac{\rho}{e})$

Given the choices of functional form, I have 10 parameters which are needed to compute the model's equilibrium. The parameter values are documented in Table 3.2. Following the process described in Shimer (2012), I use the Current Population Survey (CPS) for January 2000 to December 2011 to compute the US labor market transition rates using all workers aged 16 and above.[7] Worker's productivity ρ, employed worker's search probability λ_e, and the minimum wage w_{min} are jointly set so that the computed average unemployment-to-employment (UE/hires), employment-to-unemployment (EU/layoffs), and

[7] Empirical studies on minimum wage effects often focus on the teens and/or the restaurant workforce because a high proportion of them work for minimum wage. However, simply calibrate the model using different groups of workers cannot provide any reasonable comparison of the minimum wage effects across different workers. This is because the productivity y is assumed to be the same across workers in the current model. However, the productivity of the teens and the restaurant workers are likely to be different. Thus, in order to conduct reasonable comparison, the heterogeneity in worker productivity needs to be introduced in the current model, which is beyond the scope of this study.

employer-to-new employer (EE/quits) transition rates match the empirical moments in the US data.

Table 3.2: Parameter Values

β-Discount factor	0.996
σ-CRRA	2
γ-Matching technology	0.5
λ_u-Probability of search (unemployed)	1
y-Output level	1
k-Vacancy creation cost	0.474
b-Unemployment benefit	0.38
ρ-Worker productivity	0.005
λ_e-Probability of search (employed)	0.925
w_{min}-Minimum wage	0.6

The model period is set to be a month. I set the discount factor β equal to 0.996, so that the annual interest rate in the model is around 4.8%. The CRRA coefficient σ equals to 2, which is a common value in the literature. Following Menzio and Shi (2010), the matching technology parameter γ is set to be 0.5 so that the elasticity of substitution between vacancies and applicants is 2/3. Two more parameters are normalized to 1: the production level of successful project y, and unemployed worker's search probability λ_u so that unemployed workers always search. The vacancy cost k is set to be 0.474 so that the vacancy creation cost is around 47% of worker's average productivity. The unemployment benefit b is 0.38 so that b is 40% of the average wage (Shimer, 2005). Table 3.3 summarizes the calibration results. The calculated labor market transition rates and replacement rate match their empirical counterparts. In addition to the target moments, the model also generates reasonable unemployment rate and the share of minimum wage worker.

Table 3.3: Calibration Targets

	Data moments (CPS2000-2011)	Model moments
Average hiring rate (UE)	24%	24%
Average layoff rate (EU)	1.4%	1.43%
Average quit rate (EE)	2%	1.8%
Replacement	40%	39.9%
Unemployment rate	5.9%	5.6%
Share of minimum wage worker	1.0%	1.3%

Note: The share of minimum wage worker excludes those who paid below prevailing federal minimum wage.

3.3.2 Effects of Minimum Wage

Consider an increase in the minimum wage by 5% from the above benchmark calibration.[8] Table 3.4 summarizes the effects after the policy change. First, the average workers' effort level increases, suggesting that the higher minimum wage contributes to higher labor productivity. As a result, the output in low-paying market increases by 0.76%. Moreover, the unemployment rate increases by 1.8%. Due to the higher unemployment, the aggregate output decreases by 0.15%, even with the higher work effort. The average hiring, layoff, and quit rates decrease by 2.5%, 0.7%, and 5.6%, respectively. In addition, both the highest equilibrium wage and the average wage increase after the policy change.

The hiring rate is lower after the policy change for the following reasons. First, the policy decreases the value of the firms who are in the minimum wage market. This is because the policy increases the production cost of firms who offer minimum wage. On the other hand, a higher minimum wage also increases minimum wage workers' cost of

[8] For the minimum wage to be nontrivial, I assume that the minimum wage is higher than the lowest equilibrium wage in the absence of the minimum wage, which is also true in the model calibration. I use a 5% increase because this is calibration exercise using few empirical moments to pin down model parameters, and small deviations from the benchmark level of minimum wage would provide more reliable results.

Table 3.4: Effect of a 5% Increase in Minimum Wage

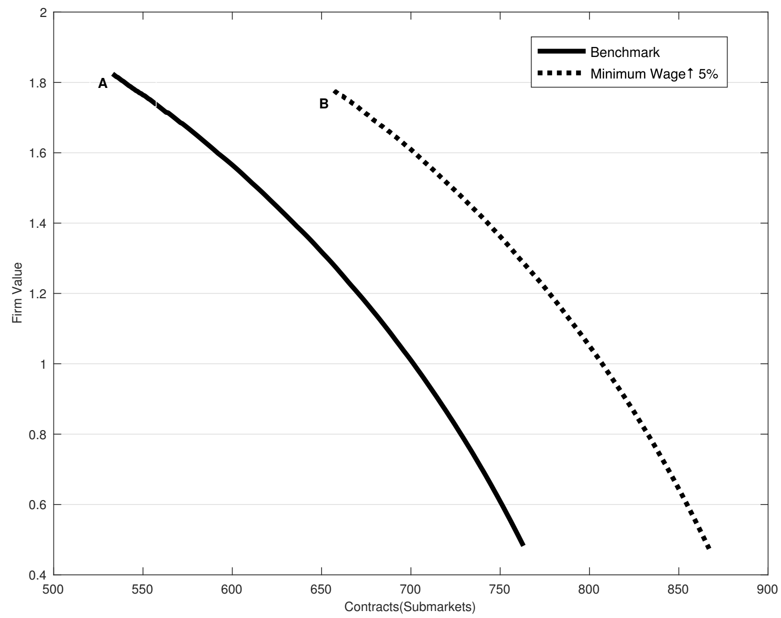
	Baseline	↑ by 5%	No Effort	↑ by 5%
Average effort	0.348	0.349	-	-
Output in minimum wage market	0.0132	0.0133	0.0132	0.0131
Aggregate output	0.9306	0.9292	0.9444	0.9417
Highest equilibrium wage	0.9855	0.9859	0.9926	0.9926
Average wage	0.952	0.954	0.965	0.966
Average hiring rate (UE)	24%	23.4%	24%	22.6%
Average layoff (EU)	1.43%	1.42%	1.4%	1.4%
Average quit rate (EE)	1.8%	1.7%	1.85%	1.63%
Unemployment rate	5.6%	5.7%	5.6%	5.8%

Notes: The second and third column present the results from the current model. The fourth and fifth column present the results from the model without workers' on-the-job effort decision. Layoffs is determined by an exogenous job destruction rate $\delta = 0.014$.

being laid off, and therefore provides firms more incentives to induce effort from them. Since the increases in cost cannot be adequately compensated by the rise in induced effort, those firms' value are lower after the policy change. As shown in Figure 3.1, the value of the firms who offer minimum wage before the policy (Point A) is higher than the value after the policy (Point B). Besides, recall condition (3.8), a lower firm's value implies a "thinner market" (smaller θ) and a lower job finding probability. As shown in Figure 3.2, the minimum wage market tightness before the policy (Point A) is larger than the tightness after the policy (Point B). Since an unemployed worker always searches in the minimum wage market, the average job finding probability on unemployed workers (hiring rate) is lower after the policy change.[9]

[9] An unemployed worker always searches in the minimum wage market for the following reasons: First, as discussed in Tsuyuhara (2016) (Lemma 1 and Proposition 3), wage and effort is monotone in the value of contract. Therefore, the contract with minimum wage provides the lowest value among the equilibrium offers. In addition, the job finding probability is strictly decreasing with contract value. With directed search, low-value workers optimally choose to search for offers with relatively low value because those offers are easier to get (Lemma 4.1 in Menzio and Shi (2010) and Lemma 3.1 in Shi (2009)). Thus, an unemployed worker always targets on the minimum wage market.

Figure 3.1: Firm Value Function



Notes: Point A represents the value for firms who offer minimum wage before the policy change. Point B represents the value for firms who offer minimum wage after the policy change. The figure implies that an increase in minimum wage by 5% from the above benchmark calibration reduces the value for firms who offer minimum wage.

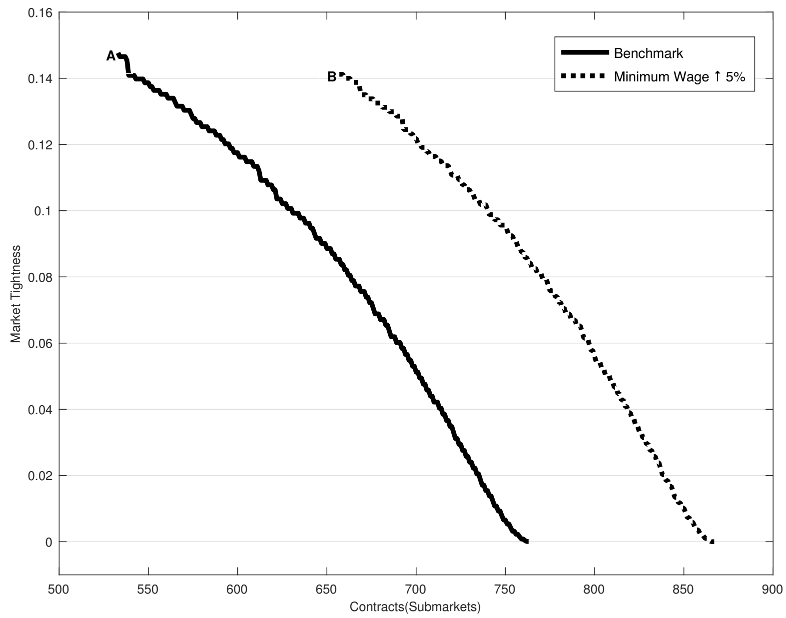
The calibration results suggest that the policy reduces the value for unemployed workers, despite raising the target value of an unemployed worker's search.[10] Recall Equation (3.2), an unemployed worker's value is determined by her expected value of job search, $D(U)$.[11] $D(U)$ is determined by the trade-off between an unemployed worker's target value and the job finding probability. As discussed above, her job finding probability is lower after the policy change. Since the reduction of the job finding probability cannot be adequately compensated by the rise in the target value, the policy reduces $D(U)$ and therefore lowers the unemployment value.[12]

[10]The unemployment benefit decreases from -609.5267 to -609.8535.

[11]An unemployed worker's value is also determined by the unemployment benefit b and her search probability λ_U, which are exogenous in the model.

[12]Figure 3.1 and 2 show that the value of contract with minimum wage increases after the policy change. In Figure 3.1 and 3.2, point A represents the submarket which offers minimum wage before the policy change. Point B represents the submarket which offers minimum wage after the policy change. Since B is on the right side of A, the value of contract at B is larger than the value at A.

Figure 3.2: Market Tightness Function

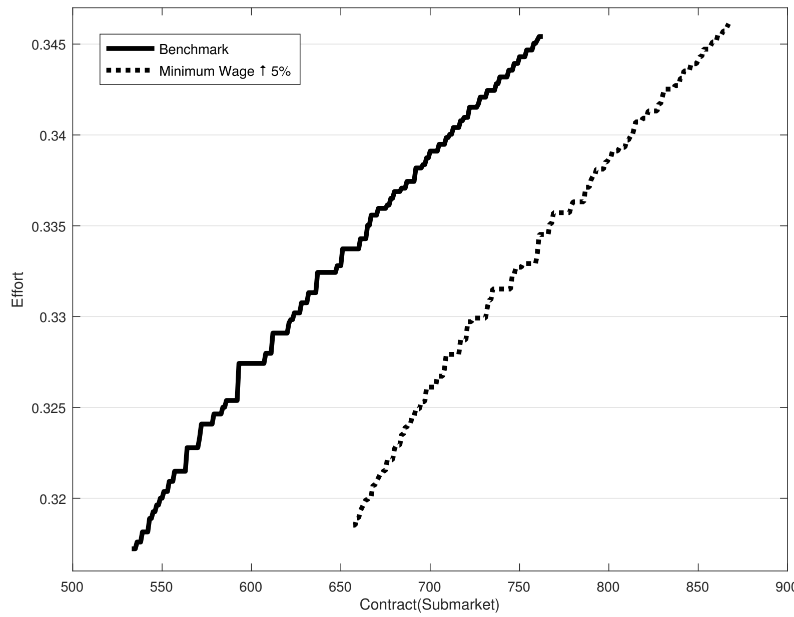


Notes: Point A represents the market tightness for the submarket which offers minimum wage before the policy change. Point B represents the market tightness for the submarket which offers minimum wage after the policy change. The figure implies that an increase in minimum wage by 5% from the above benchmark calibration decreases the market tightness for the submarket which offers minimum wage.

An employed worker chooses how much effort to exert by comparing the benefit of staying employed with the cost of being laid off. A lower unemployment value increases the cost of being laid off and thus encourages employed workers to exert effort. Figure 3.3 shows the effort profile before and after the policy change. In addition to the above contractual effect, a higher minimum wage causes the distributional effect. That is, a higher minimum wage shifts the distribution of employed workers toward jobs with higher recommended effort (induced effort). Figure 3.4 illustrates the distributional effect of a higher minimum wage. As a result of the higher work effort, the output in low-paying market increases and the average layoff rate decreases. However, due to the higher unemployment, the aggregate output decreases even with the higher work effort.

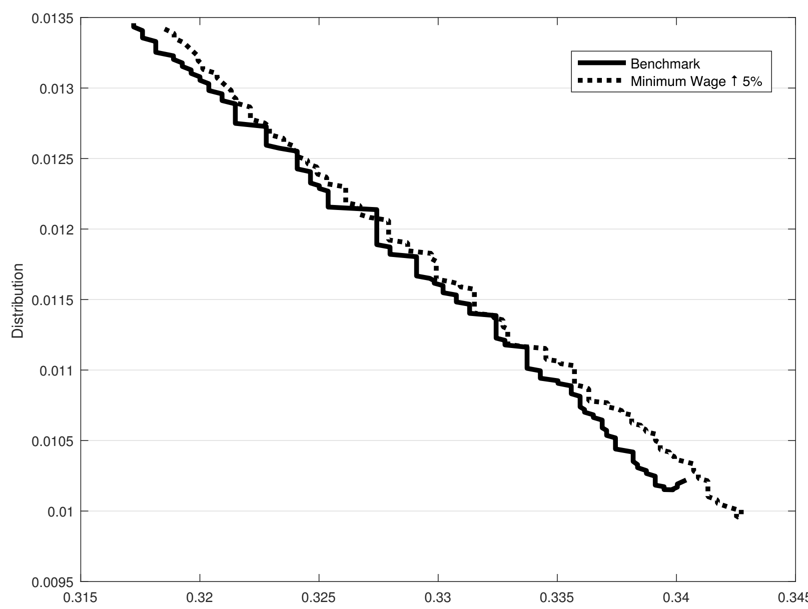
For an employed worker to make a job transition, she first needs to succeed in the cur-

Figure 3.3: Effort Profile



Notes: The figure illustrates that an increase in minimum wage by 5% from the above benchmark calibration encourages employed workers to exert effort, and thus lowers the employed-to-unemployed transition rates. .

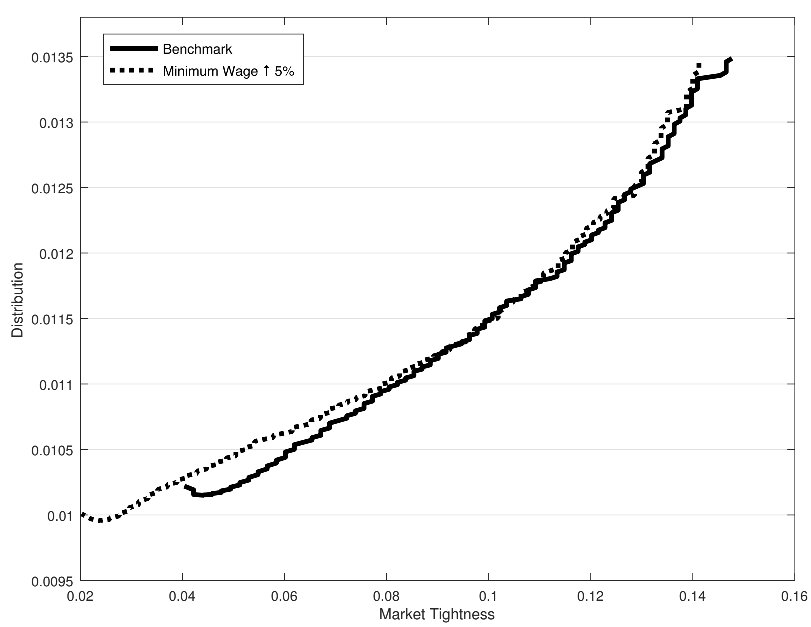
Figure 3.4: Distributional Effect on Average Effort



Notes: The figure illustrates that an increase in minimum wage by 5% from the above benchmark calibration shifts the distribution of employed workers toward jobs with higher recommended effort.

rent job. Therefore, the more the effort she exerts, the higher the chance she can find a new job. As discussed above, the policy change raises the average level of induced efforts. Hence, a higher minimum wage increases the average quit rate. On the other hand, the probability of an employed worker finding a new job is also determined by the market tightness of her target market. As shown in Figure 3.5, the policy change shifts the distribution of employed workers toward jobs with lower market tightness. Thus, the average target market tightness is lower after the policy change, which decreases the average quit rate. The calibration results suggest that the policy reduces the quit rate. In this sense, the distributional effect on target market tightness dominates the combination of the contractual effect and distributional effect on average effort.

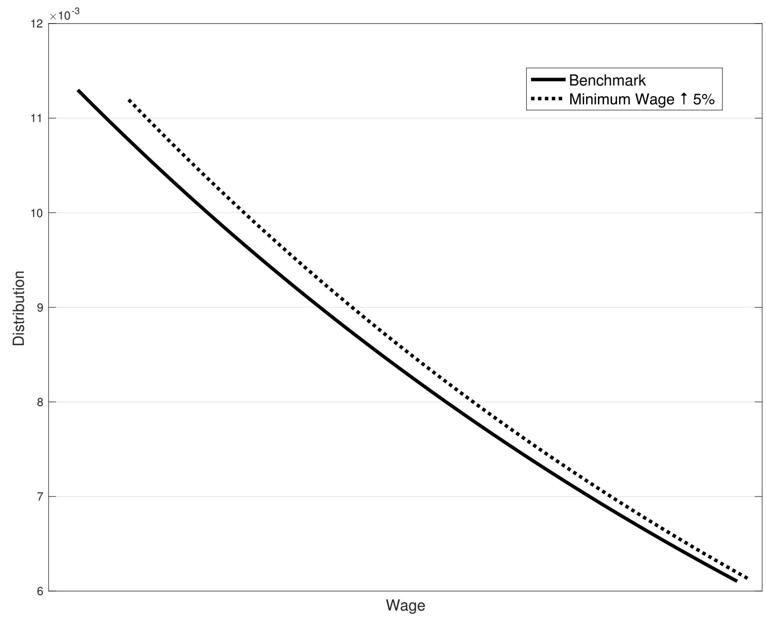
Figure 3.5: Distributional Effect on Target Market Tightness



Notes: The figure illustrates that an increase in minimum wage by 5% from the above benchmark calibration shifts the distribution of employed workers toward jobs with lower market tightness. Thus, the average target market tightness is lower after the policy change, which decreases the employer-to-new employer transition rates.

The minimum wage raises both the highest minimum wage and the average minimum wage. This is because: first, firms respond to the policy by demanding more effort, and therefore wages increase; second, as shown in Figure 3.6, a higher minimum wage shifts the distribution of employed workers toward jobs with higher wages.

Figure 3.6: Distributional Effect on Wage



Notes: The figure illustrates that an increase in minimum wage by 5% from the above benchmark calibration shifts the distribution of employed workers toward jobs with higher wages. Thus, the highest equilibrium wage and average equilibrium wage increase after the policy change.

3.3.3 The Role of Workers' On-the-Job Effort

To highlight the role of workers' on-the-job effort, I shut down the effort channel and compare the results with those from the model with workers' on-the-job effort decision. For employed workers, the exogenous probability of being laid off is given by $\delta = 0.014$. Table 3.4 summarizes the results. Since firms do not respond to the higher minimum wage by inducing workers' effort, the higher labor cost cannot be compensated by the rise in induced effort as before. As a result, more firms are driven out of the market and unemployment rate goes up by 3.57%. Since more firms exit the market, the average hiring and quit rates decrease by 5.8% and 11.8%, respectively. The higher minimum wage also lowers the aggregate output by 0.28%, which is caused by the higher unemployment rate. These larger negative impacts imply that workers' on-the-job effort has strong offsetting effect on the costs of higher minimum wage. In addition, without workers' effort decision, a higher minimum wage simply eliminates low wage jobs without causing a significant change in the employed worker distribution. Thus, the general equilibrium effect on the higher income groups disappears. As a result, the increase in the average wage is smaller and the highest equilibrium wage does not change.

3.4 Robustness

To examine the robustness of the above results, I first increase the minimum wage by 0.5% and 1% point. This is because a 5% increase in the current model is fairly large compare to the change of minimum wage in the real world.[13] Table 3.5 summarizes the results. The previous results remain with the relatively moderate increase in the minimum wage. Moreover, the decrease in the hiring and layoff rates are offsetting each other, resulting in little impact on the unemployment rate. This finding suggests that a minimum wage that is set too high would be expected to cause employment declines.

Second, the level of risk aversion affects how workers evaluate the cost of being laid off and how they respond to the change of the minimum wage. Hence, I raise the coefficient of risk aversion to $\sigma = 3$. Table 3.6 summarizes the results. Since the workers are more afraid of being unemployed, a higher minimum wage allows firms to induce more effort from the workers. As shown in Table 3.6, a 5% increase in the minimum wage reduces the average layoff rate as above. On the other hand, since the rise in the induced effort can overcome the increase in the labor cost, the average hiring and quit rates increase after the

[13] Since the highest equilibrium wage is 0.9857 in the calibrated model, a 5% increase in minimum wage from 0.6 is fairly large even compare to the change from \$7.25 to \$15 (In U.S., the current federal minimum wage is \$7.25 per hour and the highest minimum wage is \$15).

Table 3.5: Robustness: Effect of 0.5% Point and 1% Point Increases in Minimum Wage

	Baseline	$\uparrow$ 0.5% point	$\uparrow$ 1% point
Average effort	0.348	0.34832	0.34834
Output in minimum wage market	0.0132	0.0132	0.0133
Aggregate output	0.9306	0.9304	0.9303
Highest equilibrium wage	0.9855	0.9855	0.9855
Average wage	0.952	0.952	0.952
Average hiring rate (UE)	24%	23.98%	23.93%
Average layoff (EU)	1.43%	1.4257%	1.4256%
Average quit rate (EE)	1.8%	1.79%	1.78%
Unemployment rate	5.6%	5.61%	5.62%

policy change. As a result, the unemployment rate decreases with higher minimum wage. Moreover, the aggregate output increases, which is caused by both higher work effort and employment.

Table 3.6: Robustness: Higer Risk Aversion ($\sigma = 3$)

	Baseline	$\uparrow$ 0.5% point	$\uparrow$ by 5%
Average effort	0.41	0.4108	0.4113
Output in minimum wage market	0.012	0.012	0.012
Aggregate output	0.9424	0.9425	0.9427
Highest equilibrium wage	0.988	0.988	0.988
Average wage	0.9558	0.9560	0.9548
Average hiring rate (UE)	25.13%	25.08%	25.18%
Average layoff (EU)	1.212%	1.209%	1.208%
Average quit rate (EE)	2.22%	2.23%	2.37%
Unemployment rate	4.6%	4.6%	4.57%

3.5 Conclusion

By using a model with dynamic incentive contracts and directed search, this paper quantitatively shows that minimum wage has crucial impact on workers' optimal choice of effort and consequently on labor market outcomes. The calibrated model shows that a higher minimum wage can motivate workers to work harder and therefore contribute to higher labor productivity. It also shows that the spillover effect of minimum wage can arise from the workers and the firms' incentive decisions. Moreover, a higher minimum wage lowers the average hiring, layoff, and quit rates. By comparing the results from the model with workers' effort decision with those from the model without workers' effort decision, this paper suggests that workers' on-the-job effort has strong offsetting effect on the cost of higher minimum wage.

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Appendix A

PM_{10} Concentrations

A.1 Construction of the Air Pollution Index and PM_{10} Concentrations

The API is a single number indicating the air quality on a given day. The API goes from 0 to 500. The higher the number, the worse the air quality is on that day. It is constructed based on the concentrations of three atmospheric pollutants, sulphur dioxide (SO_2), nitrogen dioxide (NO_2), and particulate matter (PM_{10}). The average daily concentrations of each pollutant are converted to a normalized index using the following table:

Table A.1.1: Air Pollutant Concentrations to the API

		SO_2		NO_2		PM_{10}	
L	U	L_s	U_s	L_n	U_n	L_p	U_p
0	50	0	0.05	0	0.08	0	0.05
50	100	0.05	0.15	0.08	0.12	0.05	0.15
100	200	0.15	0.8	0.12	0.28	0.15	0.35
200	300	0.8	1.6	0.28	0.565	0.35	0.42
300	400	1.6	2.1	0.565	0.75	0.42	0.5
400	500	2.1	2.62	0.75	0.94	0.5	0.6

1.Pollutant concentrations are measured by $\mu g/m^3$

The API is constructed in four steps: (1) measure the daily average concentrations of each pollutant; (2) determine L and U for each pollutant from the pollutant's concentrations using Table A.1.1. For example, if NO_2's concentrations is 0.15, it's L_n is 0.12 and U_n is 0.28. And its L is 100 and U is 200 ; (3) calculate the pollution index (PI) of each pollutant using:

$$PI_x = \frac{U-L}{U_x-L_x} \times (C-L_x)+L \qquad \text{(A.1)}$$

where x denotes each pollutant; (4) define the API as: $API = \max\{PI_{SO_2}, PI_{NO_2}, PI_{PM_{10}}\}$.

The pollutant with the highest PI is the primary pollutant. The method used to construct the API allows me to recover the concentrations of it. For example, if the primary pollutant is PM_{10}, I can convert the API to the PM_{10} concentrations using the following formulas:

API=0-51: PM_{10} concentrations=API/1000

API=51-200: PM_{10} concentrations=(API -25)/500

API=201-300: PM_{10} concentrations=(API + 300)/1429

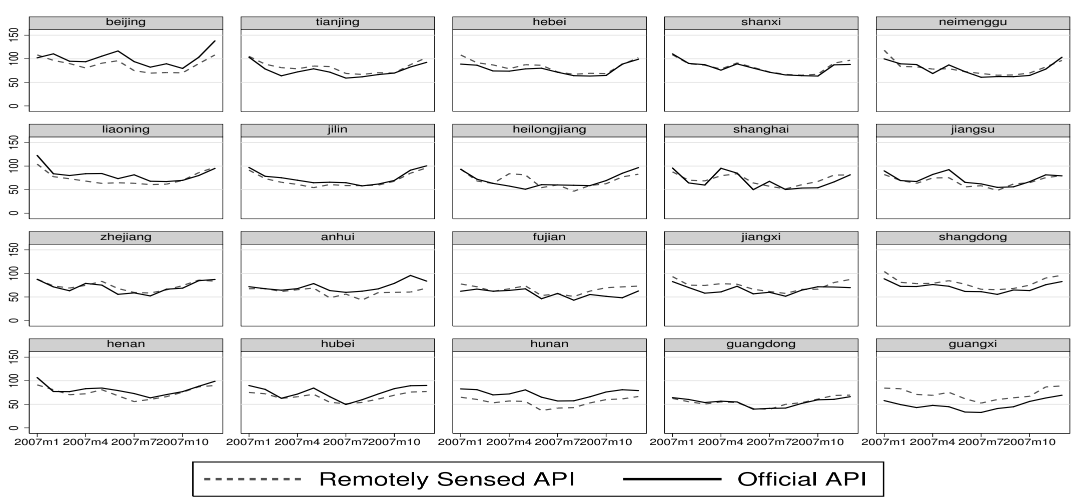
API=301-400: PM_{10} concentrations=(API + 225)/1250

API=401-500: PM_{10} concentrations=(API + 100)/1000

A.2 Comparison of the Remotely Sensed API and Official API

In order to verify the credibility of the official Chinese air quality data, I obtain the remotely sensed API data.[1] Due to the data availability, I only compare the monthly remotely sensed API with the monthly official API in 2007 across provinces. Fig A.2.1 shows that both the magnitudes and trends in the official API and the remotely sensed API are similar, suggesting that the Chinese official API data are reliable in my study.

Figure A.2.1: Comparison of the Remotely Sensed API and Official API



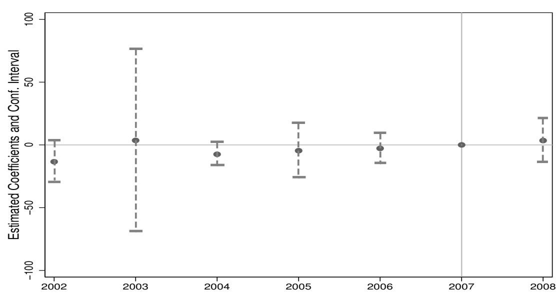
[1]The remotely sensed API data is obtained from National Science & Technology Infrastructure of China, National Earth System Science Data Sharing Infrastructure (`http://www.geodata.cn`). This data is originally from NASA. The spatial resolution is 10km.

Appendix B

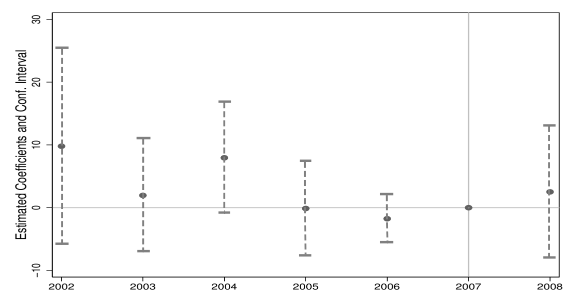
Common Trends among the Comparison Provinces

B.1 Trends among the Comparison Provinces

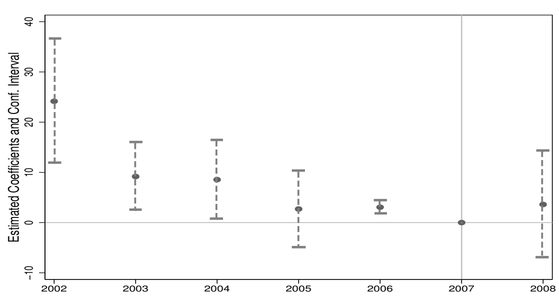
Figure B.1.1: Placebo Test: Trends in Air Pollution among the Comparison Provinces



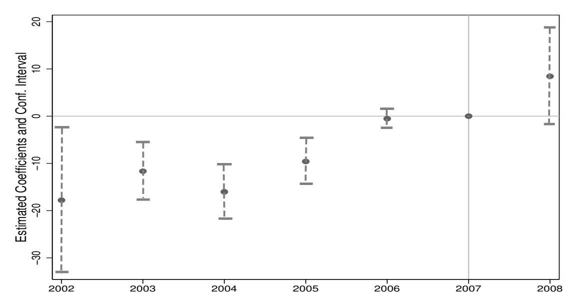
(a) Pseudo-Treatment: Jilin



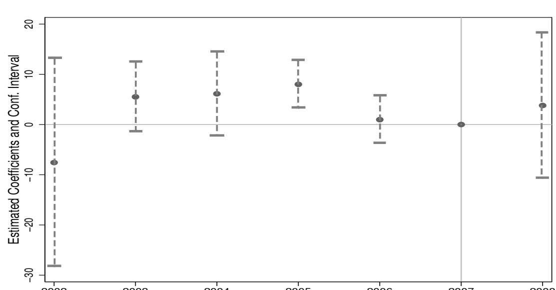
(b) Pseudo-Treatment: Shanghai



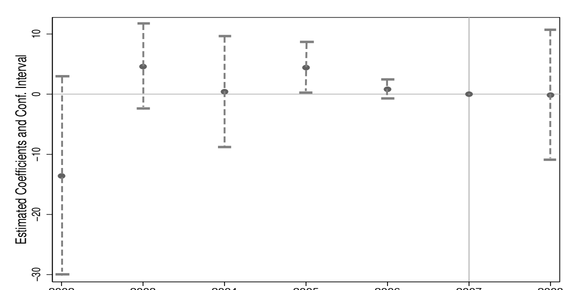
(c) Pseudo-Treatment: Jiangsu



(d) Pseudo-Treatment: Zhejiang

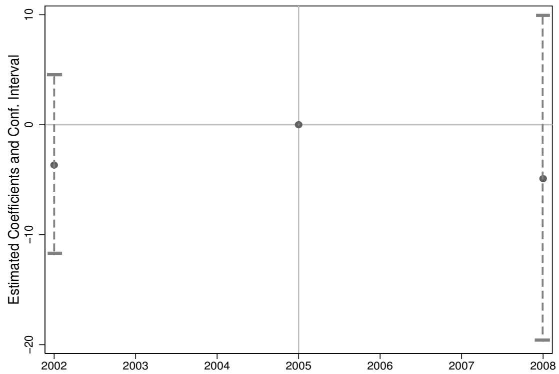


(e) Pseudo-Treatment: Fujian

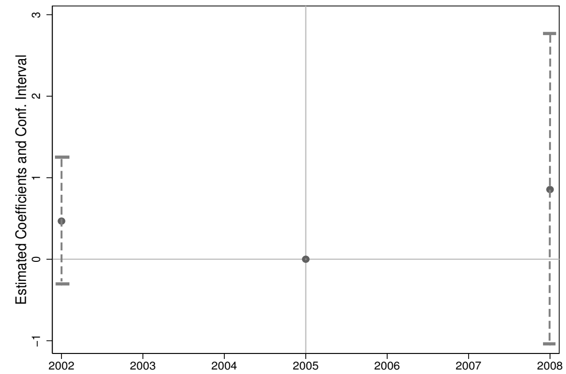


(f) Pseudo-Treatment: Guangdong

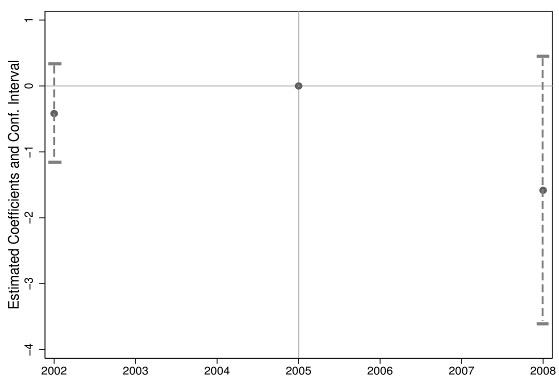
Figure B.1.2: Placebo Test: Trends in the MMSE among the Comparison Provinces



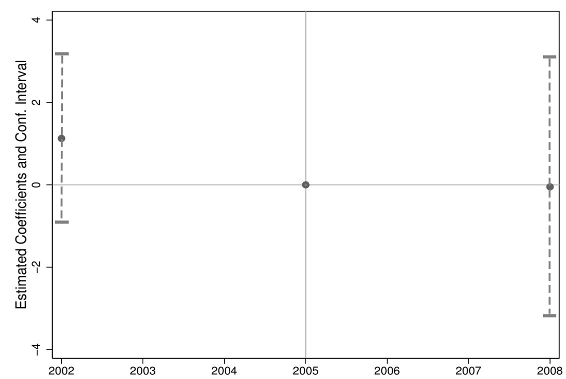
(a) Pseudo-Treatment: Jilin



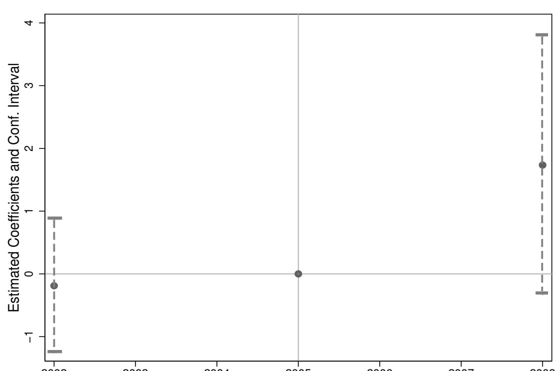
(b) Pseudo-Treatment: Shanghai



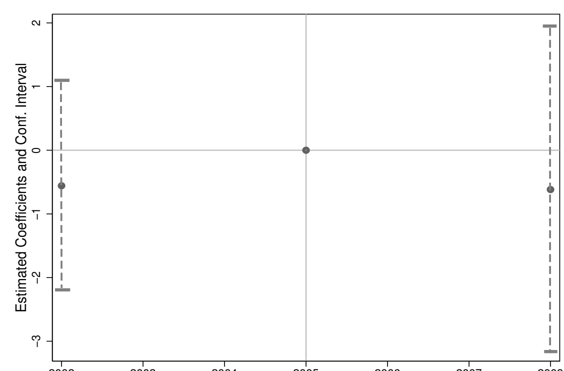
(c) Pseudo-Treatment: Jiangsu



(d) Pseudo-Treatment: Zhejiang



(e) Pseudo-Treatment: Fujian



(f) Pseudo-Treatment: Guangdong

B.2 Robust Results without the Problematic Comparison Provinces

Figure B.1.1 and B.1.2 plot the estimated coefficients of interactions from Equation (1.5). Each dot is the interaction coefficient and a 95-percent confidence interval is shown by dashed lines. Figure B.1.1 suggests that most of the provinces in the comparison group have similar trends in air pollution with the exception of Jiangsu and Zhejiang province which present different trends when compared with other provinces in the comparison group. To quantify the effects of these provinces on my results, I repeat the estimation of Equations (1.1) excluding Jiangsu and Zhejiang. Tables B.2.1 shows that the main results are robust to these changes in the comparison group.

Table B.2.1: The Effects of the BOG08 on Air Pollution: Exclude Jiangsu and Zhejiang

Dependent Variable: PM_{10}	(1)	(2)	(3)	(4)
$\hat{\beta}$	-23.96***	-25.81***	-23.55***	-25.62***
	(1.64)	(3.23)	(1.77)	(3.21)
R^2	0.982	0.983	0.983	0.984
Observations	35	35	35	35
Province Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y
Humidity	N	Y	N	Y
Temperature	N	N	Y	Y

Notes and sources: This table shows the estimates from equation (1.1) using Jilin, Shanghai, Fujian, and Guangdong as the comparison provinces. Author's calculations with PM_{10} data are described in Appendix A.1. Humidity and temperature data are collected from the China Statistical Yearbooks on Environment. The units of observation are province-year. The time period are from 2002 to 2008. The dependent variable is PM_{10}. The main entries in the first row of columns (1) to (4) report estimates of β from Equation (1.1) in the text. Column (1) provides the results with both province and year fixed effects. Columns (2) and (3) control for humidity and temperature, respectively. Column (4) controls for both fixed effects, humidity, and temperature. The number of observations is 35 because it contains 5 provinces across 7 years. Robust standard errors in parentheses are clustered at the level of province. The significance remain under the wild cluster bootstrap resampling method. * indicates significance at the 10 percent level, ** significance at the 5 percent level, and *** significance at the 1 percent level.

Appendix C

Exclusion Restriction: Medical Services

C.1 Effects of the BOG08 on Medical Services

The panel A of Table C.1.1 shows that the BOG08 had little impact on the number of hospital, sickbed, physician, and nurse. This rules out the possibility that the health improvement in Beijing was derived from the changes in the availability of medical services due to the BOG08. Besides, the panel B of Table C.1.1 shows that the common trends assumption is satisfied, which ensures the credibility of the estimation.

Table C.1.1: The Effects of the BOG08 on the Availability of Medical Services.

	(1)	(2)	(3)	(4)
Dependent Variables:	Hospital	Sickbed	Physician	Nurse
Panel A				
$\hat{\beta}$	-0.026	-0.056**	0.061	0.051
	(0.050)	0.024	0.042	0.051
R^2	0.986	0.994	0.986	0.980
Observations	49	49	49	49
Panel B				
$\hat{\beta}_{2002}$	-0.009	0.074	-0.038	-0.036
	(0.090)	(0.044)	(0.081)	(0.087)
$\hat{\beta}_{2003}$	-0.011	0.026	-0.035	-0.030
	(0.076)	(0.043)	(0.058)	(0.079)
$\hat{\beta}_{2004}$	0.024	0.027	-0.036	-0.024
	(0.060)	(0.033)	(0.059)	(0.065)
$\hat{\beta}_{2005}$	0.027	0.010	-0.027	-0.039
	(0.049)	(0.027)	(0.049)	(0.052)
$\hat{\beta}_{2006}$	0.019	-0.007	-0.042	-0.056
	(0.043)	(0.024)	0.042	(0.036)
$\hat{\beta}_{2008}$	-0.018*	-0.034	0.032**	0.020
	(0.010)	(0.017)	(0.013)	(0.018)
Province Fixed Effect	Y	Y	Y	Y
Year Fixed Effect	Y	Y	Y	Y

Notes and sources: Data are collected from the China Statistical Yearbook. The units of observation are province-year. The main entries in the first row of columns (1) to (4) in Panel A report estimates of β from Equation (1.1) in the text. Panel B presents the estimates of β from Equation (1.3) in the text. Robust standard errors in parentheses are clustered at the level of province. The significance remain when standard errors are clustered at the level of individual. The significance also remain under the wild cluster bootstrap resampling method. * indicates significance at the 10 percent level, ** significance at the 5 percent level, and *** significance at the 1 percent level.

Appendix D

The Mini-Mental Status Examination (MMSE)

D.1 The Calculation of the Mini-Mental Status Examination (MMSE) Scores

There are 23 questions each with a score of one if answered correctly and a zero otherwise. The answer can be correct, wrong, or not able to answer. There are eight reasons why a respondent is not able to answer the question: 1.visually impaired, but can hear; 2.hearing impaired, but can see; 3.visually and hearing impaired; 4.paralyzed; 5.did not wish to participate; 6.could not understand because of cognitive impairment; 7.not able to participate at the moment because of some temporary illness such as cold; 8.other. Except the 6th reason, I treat respondent who partly answer the examination as missing. The remaining question ask respondents to name as many types of food as possible in a minute. This question has a maximum possible score of 7. The maximum types of food named in the sample is 25 and the minimum is 0. Table D.1.1 illustrates the scores I assign to this question.

Table D.1.1: Scores of the Question Asking Respondents to Name Types of Food

Number of food type	Score	Number of food types	Score
[0, 3)	0	[12, 15)	4
[3, 6)	1	[15, 18)	5
[6, 9)	2	[18, 21)	6
[9, 12)	3	[21, 25]	7

Appendix E

The Tropospheric Sulfur Dioxide Vertical Column Concentrations Data

E.1 Data Backgroud

The tropospheric sulfur dioxide (SO_2) vertical column concentrations data are from the Scanning Imaging Absorption Spectrometer for Atmospheric Chartography (SCIAMACHY) aboard the European Space Agency's (ESA) Environmental Satellite (ENVISAT). SCIAMACHY is a passive remote sensing spectrometer observing backscattered, reflected, transmitted or emitted radiation from the atmosphere and Earth's surface, in the wavelength range between 240 and 2380 nm.

For SCIAMACHY, I use the monthly product with grid cells of $0.25^o \times 0.25^o$ from the International Institute for Earth System Science, Nanjing University (ESSI).[1] ESSI retrieved tropospheric SO_2 information from SCIAMACHY measurements which is originally from the Royal Netherlands Meteorological Institute (KNMI). In order to close spatial gaps between the measurements and to generate synoptic maps of tropospheric SO_2, a geostatistical interpolation (Kriging) is applied.

E.2 Extraction of the Data

I extract the values from the satellite image using Arcgis. The extraction process are described as follows:

1. Add the satellite image (.tif) and map (.shp) using File $\rightarrow$ add data;

[1]The spatial resolution is 30 km x 60 km.

2. Due to the interpolation, some values are negative. I substitute the negative values by zero as follows:

   (a) toolbox $\rightarrow$ spatial analyst tools $\rightarrow$ map algebra $\rightarrow$ raster calulator

   (b) outraster=Con("file name"<0, 0, "file name")

3. Use the map (.shp) to extract provincial level data:

   (a) Make sure that the coordinates in the satellite image (.tif) and map (.shp) are the same;

   (b) toolbox $\rightarrow$ data management $\rightarrow$ raster $\rightarrow$ raster processing $\rightarrow$ clip.

4. Extraction: spatial analyst $\rightarrow$ zonal $\rightarrow$ zonal statistics as table.