ESSAYS ON SOCIAL CONNECTIONS AND ENVIRONMENTAL ECONOMICS

A Dissertation

by

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ABSTRACT

To discuss the issues that may reduce social happiness, in this dissertation, I investigate the movement of social connections as wage increases, the impact of exogenous pollution on green innovation, and apply the synthetic control method to estimate the treatment effect of a short-period policy.

In the first chapter, I develop a model of social connections, in which players are required to share resources to establish social connections. In the basic model, I show that the equilibrium is not Pareto efficient by introducing a compensation mechanism, and showing that a Pareto improving trade could be made. I then show that if a wage increase for one player leads to a reduction in social connections, under some circumstances a mutually beneficial agreement could be reached in which the player foregoes the wage increase in exchange for a cash transfer.

Does environmental quality affect firms' activities that might improve that quality? In the second chapter, I use China's public heating policy as a quasi-experiment to investigate the impact of exogenous pollution differences on green innovation behavior. I use a regression discontinuity model, and carry out a suite of robustness tests. I consistently find that firms located in cities with an exogenous source of heavy pollution tend to adopt green innovation at a lower rate while we find no difference in the rate at which they adopt non-green innovation. I find a strong causal effect: being north of the boundary, where pollution levels are higher, leads firms to adopt less green innovation. Firms located in the heating areas report roughly 1 less green innovation per billion RMB

of assets, a substantial difference given the average number of green innovations per billion RMB of assets of northern firms is 0.641.

In the third chapter, I use the synthetic control method to estimate the treatment effect of the environmental policy during the 2016 G20 Hangzhou summit. I estimate the treatment effects based on the different tiers of the policy implementation. Although the overall finding is not significant, I show that the synthetic control method is an appropriate method to estimate the cost from a short-period policy.

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NOMENCLATURE

CSMAR	China Stock Market & Accounting Research
GDP	Gross Domestic Product
GPS	Global Positioning System
IPC	International Patent Classification
KM	Kilometer
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary Least Squares
RD	Regression Discontinuity
RMB	Ren Min Bi (China's currency)

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CHAPTER I INTRODUCTION

"Life is short and truth works far and lives long: let us speak the truth."

— Arthur Schopenhauer

While the individuals' seek to find personal happiness, the development of a country sometimes deviates from that goal, which leads to a situation where the people are richer than before, but not as happy as economists expected (Easterlin, 1974b). Therefore, my research focus on the issues that may reduce social happiness, specifically, social connections and environmental economics. Through social connections research, I would like to find a way to improve social well-being through a warm and kind society. Through environmental economics research, I would like to find a way to improve social well-being through a clean and beautiful sky. In the following essays, I build a model to investigate the relationship between wage increases and social connections (Chapter 2), estimate the impact of pollution on green innovations (Chapter 3), and show that the synthetic control method is a useful tool to estimate the treatment effect of a short-term policy (Chapter 4).

1.1 Wage Increase and Social Connections

In the first chapter, I study the relationship between wage increases and social connections, and the welfare consequence as wage increases impacts social connections. Based on Easterlin (1974) and Easterlin et al. (2010), there is no significant relationship between income and happiness in the long-run, while many studies have found that social connections play an important role in human happiness (Cornwell & Laumann, 2015; Eisenberger & Cole, 2012; Stiglitz et al., 2009a). Social connections are important to social welfare, and including social connections into welfare analysis is important. The objective of this chapter is to understand the changes in social connections that occur as wages increase, and how that would impact social welfare. I build a model based on the weighted network formation framework (Bloch & Dutta, 2009; Brueckner, 2006), and my model is very close to the model proposed in Baumann (2019) since we use similar assumptions. I will first set up a utility function to include the feature of social connections, then derive players' equilibrium behavior. Based on the property of players' equilibrium behavior, I introduce the concept of compensation offer. Under the compensation offer, I discuss the impact of the wage increase on the level of social connections and show my findings on how wage increase reduces total welfare through social connections.

1.2 Exogenous Pollutions and Green Innovations

In my second chapter, I consider the impact of exogenous pollution on green innovation. Since existing literature shows that when pollution levels are high, consumers and environmental regulations tend to push firms to have more green innovations (Cai and Li 2018; Horbach 2008), which in turn leads to less pollution. However, in most situations, firms generate pollution and the government regulates firms, leading to green innovation. In such circumstances, it is difficult to separate the effect of regulations on firm behavior from the effect that pollution itself might have on firms' innovation choices.

In this chapter, I take advantage of a unique policy threshold that allows me to study the causal relationship between pollution levels and green innovation. This policy installed a public heating system in a city that significantly increased pollution to the north of the threshold (Almond et al. 2009; Chen et al. 2013; Xiao et al. 2015). Since there is a clear cut-off in the policy implementation, I use a sharp regression discontinuity design to estimate the treatment effect. I will begin the discussion by discussing how this policy established a quasi-experiment. Then, I describe the data used for the analysis, introduce the regression discontinuity design model used, and discuss the main findings. Next, I conduct seven robustness checks to test the main findings.

1.3 The Synthetic Control Method and a Short-Period Policy

In my third chapter, I use the synthetic control method to estimate a treatment effect of a short-period policy. When pollution levels are high, consumers demand more environmental regulations to make firms reduce pollution (Cai & Li, 2018). Nonetheless, the fact that high pollution levels persist suggests that the perceived cost of pollution reduction in these countries may be higher than their perceived benefit. The existing literature on the cost estimation of environmental policies mostly studies the long-lasted policies, since such policies provide enough data to traditional econometrics.

In this chapter, I study the air pollution regulation policy during the 2016 G20 Hangzhou summit which only lasted for 2 weeks. Therefore, I cannot use traditional econometrics to estimate the policy effect, as the data are very unbalanced. Instead, I use the synthetic control method, which generates a control group from a pool of untreated units, and the method could take advantage of the rich dataset. I will start with a discussion of policy interventions. Then, I describe the data used for the analysis, introduce the synthetic control method used, and discuss the results.

CHAPTER II A SIMPLE MODEL ON SOCIAL CONNECTIONS, WAGES, AND WELFARE

2.1 Motivation

When comparing two countries in terms of welfare, people usually use GDP or income since more GDP or income means a higher living standard. Hence, many economic policies target improving GDP, especially in developing countries. Such policies may increase GDP, but may also bring social problems at the same time; in the end, the welfare increase from more GDP may be offset by the increase in social problems. Evidence from economic growth shows that more output does not mean more happiness. Based on Easterlin (1974a), on average, people who live in a developed country do not necessarily feel more happiness than people who live in a developing country, sometimes, people who live in a developing country are happier, and there is no strong relationship between income and happiness.

Therefore, social happiness does not rely on output only, it also relies on other social factors. Many studies, including the Study of Adult Development at Harvard Medical School, have shown that good relationships keep people happier and healthier, and social connections are important to human physical and psychological health. So social connection can improve happiness.

In this paper, we will build a theoretical model to include social connections and show its relation to economic welfare.

2.2 The welfare consequences of social connections

There are many studies on the relationship between economic growth and wellbeing in happiness economics. Easterlin (1974a) and Easterlin et al. (2010) show significant evidence of the weak relationship between income and happiness. They compare people's happiness in different income groups, countries, and times, and find that income and happiness are positively related within a country, but such relation is weak when we compare across different countries or different times. This result is called Easterlin Paradox and is supported by many studies. Easterlin (2009) finds that in Eastern Europe, although the GDP per capita in 2005 was about 25 percent higher than its early 1990s level, life satisfaction went back to the earlier level. This phenomenon is because the increased satisfaction from more material goods happens with the decreased satisfaction with work, health, and family life. Schalembier et al. (2020) investigates the relationship between income and life satisfaction and find that life satisfaction is strongly correlated with relative income, instead of absolute income. Deaton (2008) uses the Gallup World Poll data, which contains 123 countries, and finds that the growth of GDP per capita has a negative impact on average life satisfaction, and the objective measures do not provide a reliable indicator for population wellbeing. Di Tella et al. (2010) provide an explanation for the Easterlin paradox: there is a strong adaptation to changes in income, people adapt fully to income in four years. Together, these studies show that there is no strong correlation between economic growth and wellbeing in the long-run. Therefore, there is no significant relationship between the policies improving output and the happiness for a country in the long-run, and, to improve happiness, we must find a different way of development.

Many studies have found that social connections play an important role in human happiness. In Eisenberger and Cole (2012), social connection is defined as “the experience of feeling close and connected to others. It involves feeling loved, cared for, and valued, and forms the basis of interpersonal relationships.” The positive aspect of social connection is usually referred to as social capital. In both psychology and economics, social connections are considered an important factor in human wellbeing. In psychology, ever since Durkheim (1897/1951), many studies have found that social connections have powerful effects on human physical and mental health. Na and Hample (2016) show that social integration has a significant positive effect on health; the number of close friends that a person has and the frequency of face-to-face contact with friends both have impacts on health. Cornwell and Laumann (2015) use longitudinal data from the National Social Life, Health, and Aging Project (NSHAP) and find that network shrinking is associated with worse subsequent health, and it could be counterbalanced by adding fresh ties to one's network. In economic research, a report of the commission on the measurement of economic performance and social progress (CMEPSP), Stiglitz et al. (2009b) identify the limitations of GDP as an index of economic performance and social progress and consider social connections as a key dimension of measuring human wellbeing. Riyanto and Jonathan (2018) find that people who have closer social connections are also more trustworthy in a controlled laboratory experiment. On the other hand, a study done by Bailey et al. (2018), defining social connectedness by friendship links on Facebook, finds that people who have more friends at a close distance, tend to have a lower income, lower life expectancy, and lower social capital. Notwithstanding the work on Facebook connections, in general, the body of research strongly supports the conclusion that social connections have an important positive effect on individual wellbeing. Therefore, social connections are important to social welfare, and including social connection into welfare analysis is important.

A number of economic studies have emphasized the value of social connections to workers and the economy overall. Montgomery (1991) assumes that social connection transmits job information, thus firms tend to hire the "well-connected" workers, and firms might get more profit from hiring these workers. Montgomery (1991) also shows that if the density of social networks[1] increases, wage dispersion will also increase. Similarly, assuming social connection transmits job information, Calvó-Armengol and Jackson (2007) use social networks to explain different drop-out rates in different races and the sustained inequality in wage and employment rate. Some studies investigate other functions of social connections. David et al. (2010) study the role of social connections in geographical mobility; they introduce the local social capital and assume that if a player moves to another region, only part of her social capital in the original region can be enjoyed. Their model shows that, in the case of local social capital, players who have larger social capital tend to stay in the original region. Anchorena and Anjos (2015) build a general equilibrium model to study the effect of social connections on economic development, using a model in which social connections are produced using the time of the two connecting players, and assuming social connections affect transaction costs and trading, thus affect economic growth. Not surprisingly, the model shows more social capital leads to more income. Glaeser et al. (2002) study individual investment in social capital, in which they consider social capital as a feature of a community, and players gain utility from the aggregate per-capita social capital. Glaeser et al. (2002) show that social capital investment is negatively correlated with social mobility and the opportunity cost of time, positively correlated with social skills. In this paper, we take a different angle of viewing social connections. Instead of providing information and public service, we treat social

[1] Social network means "a network of individuals (such as friends, acquaintances, and coworkers) connected by interpersonal relationships," from Merriam-Webster dictionary.

connections as a necessary good, following previous psychology research, and we investigate the relationship between social welfare and wage through social connections.

2.3 Game-theoretic literature review

There is also formal game-theoretic literature on social connections, and this paper will build mostly on this literature focusing on the formation of social networks. While Jackson and Wolinsky (1996) and Ballester et al. (2006) established a solid theory for social connections research, our focus is closer to the weighted network formation, where players use the limited resource to build social connections. Brueckner (2006) studies friendship formation assuming that the formation of friendship is based on both the effort input and the threshold of a friendship, and discusses player's behavior in equilibria. In Bloch and Dutta (2009) and Deroïan (2009), players choose the input level on a relationship based on on the link strength, which is defined as the quality of a social link, and they analyze the efficiency of a network architecture when players could choose the quality of links. Salonen (2016) applies a cost to reflect the opportunity cost of players' input on link formation, and establishes centrality measures to investigate the equilibria of link formation games. Similar to our model, Baumann (2021) assumes that players possess a limited amount of resource to invest in relations or private activity. She shows that there are two types of equilibria in such an economy, one is reciprocal equilibrium, where the two players of a connection input the same amount of resource, the other one is nonreciprocal, where the two players of a connection input different amount of resource.

While these models show how players distribute limited resource on social connections, they largely neglect the resource used to build social connections, which in our model could also be used for consumption. For example, when people spend time to work to earn income for consumption, they sacrifice time with family. We focus on this inherent tradeoff, focusing on the opportunity cost of resources used in social connection and showing that when the opportunity cost of that resource increases for one party, both parties decrease their investment in social connections. To our limited knowledge, this is the first time for a weighted network formation model to focus on the other usage of the resource used on build connections.

In this paper, we build a simple model to show the change of social welfare, when different levels of wage increase happen. In the context of this model, we prove that not all wage increases will increase social welfare.

2.4 Basic model[2]

2.4.1 Utility function

In this model, there are 2 players, player *i* and player *j*. Following Jackson and Wolinsky (1996) and Ballester et al. (2006), each player gains utility from consumption, and the connections with other players within the economy, so the payoff function for player *i* is:

$$u_i = u\left(x_i, g\big(\theta_i, c(r_i, r_j)\big)\right).$$

where variable $x_i \in \mathbb{R}_+$ is the consumption of player *i*, function $g\big(\theta_i, c(r_i, r_j)\big)$ is the production function of social connections, parameter $\theta_i \in \mathbb{R}_+$ is player *i*'s social connections preference, function $c(r_i, r_j)$ is the production function of the common pool resource used to generate social connections, variable $r_i \in \mathbb{R}_+$ is the resource invested into the common resource pool to make a connection with player *j* by player *i*.

To establish a social connection between two players, both of them need to input some resources into creating that connection. Based on real-life, in most cases, people need to spend

[2] A table of the most-used notations is provided in the appendix.

time with each other to build social connections; they need to spend time together. In our model, we assume that players can only establish social connections with each other by spending time together. For simplicity, we will assume that the effective social connections input is the minimum of two player's inputs so that *CR*, which implies if a single player alone cannot build a social connection with another. The common pool resource of social connections, is given by

$$CR = c(r_i, r_j) = \min(r_i, r_j).$$

Function $g(\theta_i, c(r_i, r_j))$ is the social connection generation function, parameter θ_i is an exogenous parameter that determines player *i*'s preference for social connection with player *j* reflecting cultural, personal, and other factors. A larger θ_i means player *i* gains more utility from the social connection with player *j*, so play *i* is more willing to input more resources with player *j*, thus r_i is larger.

Assumption 1 Utility function u_i is continuous and increasing with x_i, θ_i, and CR, also u_i is concave in x_i, θ_i and CR.

Assumption 2 Players need both consumption and social connections, which implies

$$\lim_{x_i \to 0} \frac{\partial u_i}{\partial x_i} = \infty, \lim_{CR \to 0} \frac{\partial u_i}{\partial CR} = \infty.$$

Assumption 3 If there is no social connections input, there is no social connections generated, which implies

$$g(\theta_i, 0) = 0.$$

2.4.2 Initial endowment and player action

Each player has T units of time in their endowment, which is infinitely divisible. They allocate time between work, $l_i \epsilon [0, T]$, and the common resource pool, $r_i \epsilon [0, T]$, with $r_i + \ l_i \leq T$.

Players also have exogenous income, m_i is the external income of player i. Players earn a wage for working, then spend this wage and exogenous income to buy consumption goods, x_i. Since there is only one good, the price is normalized to 1, thus individual income and consumption are the same.

2.4.3 Utility maximization and the ideal choice

Player i's utility maximization problem is

$$\max_{\boldsymbol{l_i},\boldsymbol{r_i}} u_i = u\left(x_i, g\big(\theta_i, \min(r_i, r_j)\big)\right)$$

$$s.t.\, l_i + r_i \leq T,$$

$$x_i \leq w_i l_i + m_i.$$

By solving the problem, it yields,

$$r_i^* = r(T, w_i, m_i, \theta_i, r_j)$$

and

$$l_i^* = T - r_i^* = l(T, w_i, m_i, \theta_i, r_j)\,.$$

To focus on instances in which there is a trade-off between higher wages and social connections, we make an additional assumption:

Assumption 4 The labor supply function $l(T, w_i, m_i, \theta_i, r_j)$ is increasing with w_i and concave in w_i.

Given the assumed utility function, the labor supply curve will have both upward sloping and backward-bending portions. By assumption 4, we restrict our analysis only to the upward sloping portion, where labor supply is increasing with the wage.

Let $r_i^T = \arg\max u_i\big(x_i, g\big(\theta_i, \min(r_i, r_j)\big), m_i \big| r_j = T\big)$ denote the ideal choice of social connections input, which is the optimal input of resource into making social connections by player *i* assuming that player *j* is inputting all their resource into the pool. This is equivalent to the amount that *i* would choose if she could dictate r_j. For example, if $r_i^T = 5$, then if $r_j = 3$, *i* would choose $r_i = 3$, because $CR = 3$ is the most social connections player *i* could reach, while if r_j=7, then *i* would choose $r_i = 5$ because CR=5 is the optimal amount of social connections player *i* wants. Note that r_i^T is exogenous, determined by θ_i, m_i and w_i. Since r_i^T is the ideal level for player *i* whenever $r_j \geq r_i$, so r_i^T could also be defined by

$$r_i^T = \arg\max u\big(x_i(w_i, l_i, m_i), g\big(\theta_i, \min\big(r_i, r_j\big)\big)\big| r_j \geq r_i\big).$$

Similarly, define $l_i^T = T - r_i^T$, which is the corresponding working time of the optimal pre-decision choice of social connection input.

If player *i* distributes time into r_i^T and l_i^T, *i*'s choices are optimal so the marginal utility of social connections input is equal to the marginal utility of working. Since when player *j* is donating *T*, player *i* can distribute her time in any way. Let MU_r^i denotes player i's marginal utility of r, and MU_l^i denotes player i's marginal utility of l. **Lemma 1** *When player i has her ideal allocation,* $MU_r^i = MU_l^i$.

Proof:

If r_i^T<r_j, player *i*'s utility function now becomes

$$u_i = u\big(x_i, g(\theta_i, \min(r_i, T))\big) = u\big(x_i, g(\theta_i, r_i)\big).$$

Player *i*'s utility maximization problem when $r_j = T$ is

$$\max_{\boldsymbol{l_i}, \boldsymbol{r_i}} u_i = u\big(x_i, g(\theta_i, r_i)\big)$$

$$s.t.\, l_i + r_i \leq T,$$

$$x_i \leq w_i l_i + m_i.$$

The first-order condition gives

$$\frac{\partial u}{\partial x} w_i = \frac{\partial u}{\partial g} \frac{\partial g}{\partial r},$$

therefore,

$$MU_r^i = MU_l^i. \blacksquare$$

Lemma 2 When player i inputs $r_i = \hat{r}_i < r_i^T$, $MU_r^i > MU_l^i$.

Proof:

Since $r_i < r_i^T$, by monotonicity and concavity assumptions,

$$MU_r^i\left(r_i = \hat{r}_i\right) > MU_r^i\left(r_i = r_i^T\right) = MU_l^i\left(l_i = T - r_i^T\right) > MU_l^i\left(l_i = T - \hat{r}_i\right). \blacksquare$$

2.4.4 Decision process and the initial equilibrium

We assume that each player has perfect information, so that they know each other's wage, social connection preference, external income, and the optimal pre-decision choice. Based on such information, they make their time allocation choice.

Players make decisions on their time allocations simultaneously. If two players input different times into establishing social connections, the player who inputs more will waste the additional time and gain no utility from that. For the rest of the paper, assume that $r_i^T < r_j^T$, which means player *i* is the one who wants to input the least into making the social connections.

Proposition 1 *The initial equilibrium choice*

When there is perfect information, and the utility function is monotonic, concave, and continuous, each player will choose $r = min\left(r_i^T, r_j^T\right)$ in the initial equilibrium.

The logic of the proof is that, if player *i* does not choose r_i^T, then r_i^T is not true. If player *j* does not choose r_i^T, she will have lower utility.

Proof:

Since each player has perfect information, they know θ_i, θ_j, m_i, m_j, w_i and w_j, so that they also know r_i^T and r_j^T. Without loss of generality, assume that $r_i^T < r_j^T$.

For any $CR = \min(r_i, r_j) > r_i^T$, it is not optimal, because player *i* will never choose a level of r_i that is greater than r_i^T, by the definition of r_i^T. And player *j* knows player *i* will never choose a level of r_i that is greater than r_i^T, so player *j* will not choose a level of r_j that is greater than r_i^T neither. Therefore, $r_i > r_i^T$ and $r_j > r_i^T$ is not the equilibrium allocation. Thus, the possible equilibrium allocation falls in $r_i \le r_i^T$ and $r_j \le r_i^T$.

First, we show that player *i* will choose $r_i = r_i^T$.

Since $r_i^T < r_j^T$, by the definition of r_i^T,

$$u\left(x_i^T, g\left(\theta_i, \min\left(r_i^T, r_j^T\right)\right)\right) \ge u\left(x_i, g\left(\theta_i, \min\left(r_i, r_j^T\right)\right)\right), \forall r_i \epsilon (0, T],$$

therefore $r_i = r_i^T$.

Secondly, we show that $r_j = r_i^T$.

Since $r_i^T < r_j^T$, player *j* cannot reach her ideal choice where $MU_r^j = MU_l^j$. By Lemma 2, since $r_j \le r_i^T < r_j^T$, $MU_r^j < MU_l^j$. Hence, the largest $r_j \in [0, r_i^T]$ will give player *j* the highest utility, i.e. $r_j = r_i^T$.■

Thus, each player's social connections choice in equilibrium is bounded by the lowest ideal choice of social connections. In the initial equilibrium, player *i* reaches her ideal level of time allocation, but player *j* does not. For player *j*, the marginal utility of working is lower than the marginal utility of social connections.

Is it possible that a trivial Nash equilibrium exists at the initial equilibirum? In which, both players choose 0 together, and no one can input more since the social connection is based on the minimum input. Given our assumptions, no. Because r_i^T and r_i^T are common knowledge to players both players, since the determinates of r_i^T and r_i^T are common knowledge. When player *i* selects r_i, she knows her best choice is r_i^T, and player *j*'s best choice is r_j^T. When $r_i^T < r_j^T$, player *i* will not pick any $r_i < r_i^T$, since she needs more to be optimal, and she knows player *j* would be happy to accept any $CR \leq r_j^T$. For player *j*, she knows the same thing as player *i*, including player *i* are willing to accept any $CR \leq r_i^T$ to be optimal, and player *j* needs r_j^T level be optimal. Since they know exactly what the other player wants, they will make decision based on this information, and will not make any decision that lowers their own utility. Therefore, such Nash equilibrium does not exist. This is a situation that the transaction cost is 0 and each player knows exactly each other's wants, so the equilibrium would be reached immediately.

2.5 Compensation offer

In this section, we introduce the possibility of a compensation offer in which player *j* pays player *i* to increase the level of social connections. In so doing, we show that when social connections affect the individual utility, the initial equilibrium is not Pareto efficient.

Continue assuming that $r_i^T < r_j^T$. From Proposition 1, the initial equilibrium choice will be $r_i = r_j = r_i^T$. In this case, player *j* chooses $r_j < r_j^T$, thus player *j*'s marginal utility of working and social connections are not equal, and social connections have higher marginal utility than working to player *j*. Therefore, with the knowledge of the initial equilibrium, player *j* would be willing to pay player *i* to obtain an increase in the level of social connections.

A compensation offer is defined by $(o_m, o_r) \in \mathbb{R}_+^2$, where o_m is the payment part of the offer and o_r is the social connection part of the offer. A compensation offer (o_m, o_r) means player *j* wants player *i* to increase social connections by o_r, and player *j* compensates player *i* with o_m

amount of income as player i's income. The payment part, o_m, is a cost to player j, but a benefit to player i; the social connection part, o_r, is a benefit to player j, but a cost to player i.

Under the offer (o_m, o_r), player j will reduce her working time from l_i^T to $l_i^T - o_r$, and increase her time on social connections from r_i^T to $r_i^T + o_r$. After making the offer, therefore, player j's consumption would be

$$x_j^1 = w_j(l_i^T - o_r) + m_j - o_m,$$

where x_j^1 is the consumption of player j under the compensation offer. Therefore, the utility of player j under the compensation offer (o_m, o_r) is

$$u\left(w_j(l_i^T - o_r) + m_j - o_m, g\big(\theta_j, \min(r_i^T + o_r, r_i^T + o_r)\big)\right).$$

To simplify the analysis, we rewrite the utility function in the following way,

$$u\left(w_j(l_i^T - o_r) + m_j - o_m, g\big(\theta_j, \min(r_i^T + o_r, r_i^T + o_r)\big)\right)$$

$$= u_j\big(w_j(l_i^T - o_r) + m_j - o_m, r_i^T + o_r\big) = u_j\big(x_j^1(o_m, o_r), r_j^1(o_r)\big),$$

where r_j^1 is player j's input of the social connection under the compensation offer, which is equal to $r_i^T + o_r$. Albeit all three expressions mean player j's utility, the later ones are simpler than the original expression.

If the offer is accepted, player i's utility changes to

$$u_i(w_i(l_i^T - o_r) + m_i + o_m, r_i^T + o_r) = u_i\big(x_i^1(o_m, o_r), r_j^1(o_r)\big),$$

where $x_i^1(o_r, o_m)$ is the consumption of player i under the compensation offer, which is equal to $w_i(l_i^T - o_r) + m_i + o_m$. Since this is how player i considers player j's offer, $r_i = r_j^1(o_r) = r_i^T + o_r$. Note that under the offer, both players would increase r, but player j would decrease her consumption of x while player i would increase her consumption.

Player i will accept the offer if whenever the extra income brings at least as much the individual rationality constraint is satisfied:

$$u_i\big(x_i^1(o_m, o_r), r_j^1(o_r)\big) \geq u_i\left(x_i^1(0{,}0), r_j^1(0)\right),$$

where $u_i\big(x_i^1(0{,}0), r_j^1(0)\big)$ is player i's utility at the equilibrium point.

For player j, the utility maximization problem of the compensation offer (o_m, o_r) is

$$\max_{o_m, o_r} u_j\big(x_j^1(o_m, o_r), r_j^1(o_r)\big)$$

$$s.t.\, u_i\big(x_i^1(o_m, o_r), r_j^1(o_r)\big) \geq u_i(x_i(w_i, l_i^T, m_i), r_i^T),$$

$$0 < o_m, 0 < o_r.$$

2.6 The possible compensation offer

In this section, we will show that there is a Pareto improving agreement exists in which player j pays player i o_m in exchange for an agreement to increase the social connection by o_r. Under the assumptions above, the slope of the indifference curves for players i and j guarantees there is a Pareto improving trade.

We start by focusing on the indifference curves for player j, who seeks a greater level of social connection. This is presented graphically in Figure 1. Assume that each player's utility function is continuous, monotonic, twice differentiable at any point, and concave in both x and CR. At the equilibrium point, player j does not have her ideal level of social connections, which means $MU_r^j > MU_l^j$, therefore, player j is willing to trade consumption for social connections. Thus, we have Proposition 2.

Proposition 2 Player j's indifference curve under compensation offer

When there is perfect information, and the utility function is monotonic, concave, and continuous, the slope of player j's indifference curve under compensation offer at the origin is positive.

Proof:

Given player *j*'s utility function in the compensation offer problem, the total derivative of the utility function is

$$du_j = \left[\frac{\partial u_j}{\partial x_j}(-1)\right]do_m + \left[\frac{\partial u_j}{\partial x_j}\frac{\partial x_j}{\partial l_j}(-1) + \frac{\partial u_j}{\partial r_j}\right]do_r,$$

so that, setting this equal to zero, yields the slope of the indifference curve:

$$\frac{do_m}{do_r} = -\frac{-\frac{\partial u_j}{\partial x_j}\frac{\partial x_j}{\partial l_j} + \frac{\partial u_j}{\partial r_j}}{\frac{\partial u_j}{\partial x_j}} = \frac{\partial u_j}{\partial r_j}\frac{\partial x_j}{\partial u_j} - w_j.$$

By Lemma 2, at $r_i^T < r_j^T$, $MU_j^r > MU_j^l$. Since when $o_m = o_r = 0$, $r_j = r_i^T$ it follows that $MU_j^r - MU_j^l > 0$, which implies that $\frac{\partial u_j}{\partial r_j}\frac{\partial x_j}{\partial u_j} - w_j > 0$. ■

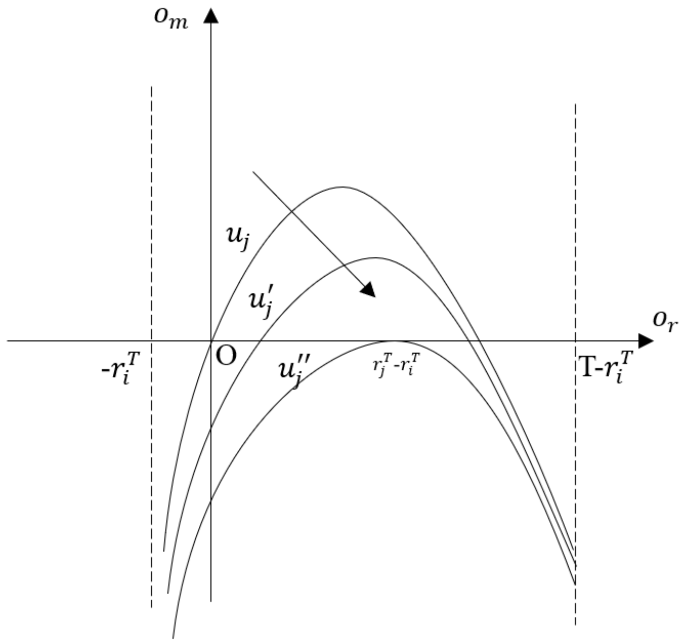

Figure 1 Player *j*'s indifference curves under compensation offer, where $u_j < u_j' < u_j''$.

Figure 2 shows player *j*'s indifference curve. Since o_r brings more social connections to player *j*, as o_r increases, o_m increases along an indifference curve, until the marginal utility of o_m and o_r are equal. As o_r increases beyond the peak, o_m would decrease along the indifference curve since *j* would be willing to pay less to achieve higher and higher levels of social connection. Eventually, the indifference curve crosses the horizontal axis, indicating that player *j* would need to be compensated to provide such high levels of social connection. At $o_r = T - r_i^T$, the offer would mean that player *j* allocates his entire time allocation, *T* to social connections; player *j* would ask for a large enough compensation, $-o_m$, to make the marginal utility of working and social connections equal, so that player *j* will not deviate from the time allocations $(l_j, r_j) = (0, T)$. If m_j is 0, then player *j*'s indifference curve would never cross $o_r = T - r_i^T$, but asymptotically close to the line $o_r = T - r_i^T$. By assumption, social connections are necessary for player *j*. Hence, o_r

asymptotically approaches to $-r_i^T$, at which point player j would allocate no time to social connections, the compensation that player *j* would ask for, $-o_m$, would become infinite.

The point $(o_m, o_r) = (0, r_j^T - r_i^T)$ means this offer gives player j $r_j^T - r_i^T$ more social connections for free, which will make player *j* reaches her ideal choice. Hence, this point is the tangent to *j*'s indifference curve – higher levels of utility can be achieved only if the player received a payment $(o_m < 0)$.

Now consider the analogous indifference curves for player i, which we present in Figure 2. At the equilibrium point, player i has her ideal level of social connections, which means $MU_r^i = MU_l^i$, so for i to increase their allocation of time to social connection, $o_r > 0$, i would have to be compensated by player *j*, $o_m > 0$. And here we have Proposition 3.

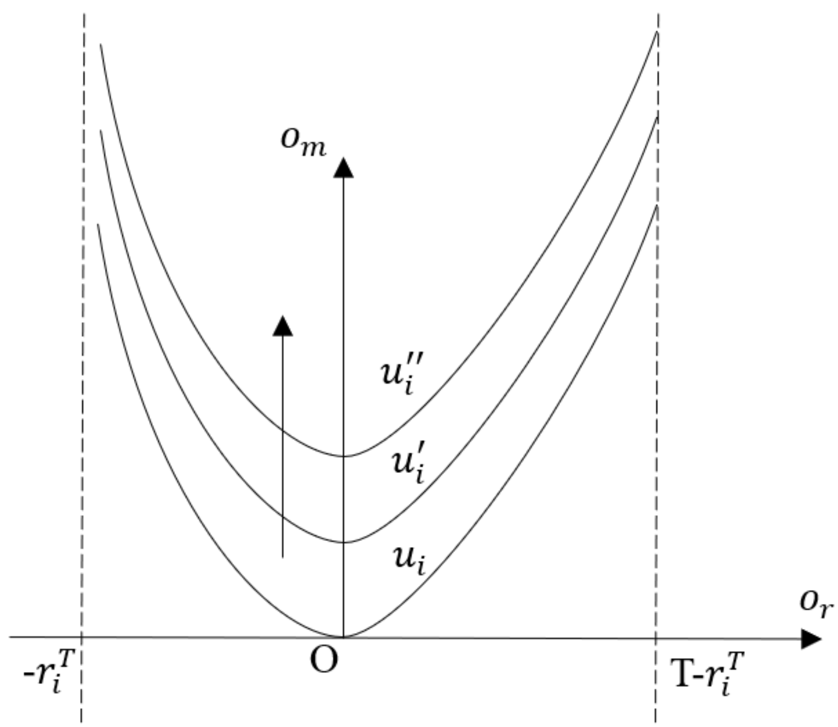

Figure 2 Player *i*'s indifference curves under compensation offer, where $u_i < u_i' < u_i''$.

Proposition 3 Player i's indifference curve under compensation offer

When there is perfect information, and the utility function is monotonic, concave, and continuous, the slope of player i's indifference curve under compensation offer at the origin is 0.

Proof:

Given player *i*'s utility function in the compensation offer problem, the total derivative of the utility function is

$$du_i = \frac{\partial u_i}{\partial x_i} do_m + \left[\frac{\partial u_i}{\partial x_i} w_i(-1) + \frac{\partial u_i}{\partial r_i} \right] do_r,$$

set this equal to zero, the slope of player *i*'s indifference curve of the compensation offer is

$$\frac{do_m}{do_r} = \frac{\frac{\partial u_i}{\partial x_i}\frac{\partial x_i}{\partial l_i} - \frac{\partial u_i}{\partial r_i}}{\frac{\partial u_i}{\partial x_i}} = w_i - \frac{\partial u_i}{\partial r_i}\frac{\partial x_i}{\partial u_i}.$$

The first-order condition from player *i*'s utility maximization problem under the ideal choice condition gives

$$\frac{\partial u_i}{\partial r_i}\frac{\partial x_i}{\partial u_i}\left(r_i = r_i^T\right) = w_i$$

Therefore,

$$\frac{do_m}{do_r}\left(r_i = r_i^T\right) = \frac{\partial u_i}{\partial r_i}\frac{\partial x_i}{\partial u_i}\left(r_i = r_i^T\right) - w_i = 0$$

which means, at the origin, the slope of player *i*'s indifference curve is 0.■

Figure 3 shows player *i*'s indifference curve in compensation offer space. Similar to player *j*'s indifference curve, if the offer requires $o_r = T - r_i^T$, player *i* requires an o_m that is large enough to make the marginal utility of working and social connections equal; as o_r approaches to $-r_i^T$, the required compensation moves toward infinity. Since o_m is the only way player *i* could gain more utility, player *i*'s indifference curve moves upward as the utility is higher.

Overlaying the indifference curves of players i and j in Figure 3, we see that a Pareto improving offer exists, which is formalized Proposition 4.

Proposition 4 The existence of the Pareto improving compensation offer.

From the initial equilibrium, player j could always make a compensation offer $(o_m > 0, o_r > 0)$ that is a Pareto improvement.

Proof:

From Propositions 2 and 3, at the equilibrium point where $o_r = o_m = 0$

$$\frac{-MU^j_{o_m}}{MU^j_{o_r}} > \frac{-MU^i_{o_m}}{MU^i_{o_r}} = 0 .$$

If $m = \frac{-MU^j_{o_m}}{MU^j_{o_r}}$, then a compensation offer that gives m unit of o_r and requires 1 unit of o_m would, on the margin, not change player j's utility, and a compensation offer that gives m+1 unit of o_r and requires 1 unit of o_m would increase player j's utility. Therefore, we construct a compensation offer in the following way, let $\varepsilon_1 > 0$ and $\varepsilon_2 > 0$, we have $(o_m, o_r) = (\varepsilon_1, \varepsilon_1(m+\varepsilon_2))$. Since $\frac{-MU^i_{o_m}}{MU^i_{o_r}} = 0$ the offer $(\varepsilon_1, \varepsilon_1(m+\varepsilon_2))$ does not change player i's utility.

For player j,

$$du_j = MU_{o_m}\varepsilon_1 + MU_{o_r}\varepsilon_1(m+\varepsilon_2) = -mMU_{o_r}\varepsilon_1 + MU_{o_r}\varepsilon_1(m+\varepsilon_2) = MU_{o_r}\varepsilon_1\varepsilon_2 > 0 ,$$

which means, under offer $(\varepsilon_1, \varepsilon_1(m+\varepsilon_2))$, player i's utility is unchanged, and player j's utility is increased, therefore the compensation offer $(\varepsilon_1, \varepsilon_1(m+\varepsilon_2))$ is a Pareto improvement. ■

The reason Proposition 4 holds is because, at the equilibrium point, player *i* is indifferent between using time for working and social connections, asking player *i* inputs a small amount of time on social connections will not change player *i*'s utility much, therefore the required compensation from player *j* is also very small.

The utility maximization problem for player *j* is represented in figure 3. In figure 3, u_i^E represents player i's utility at the equilibrium, which is $u_i(x_i(w_i, l_i^T, m_i), r_i^T)$, and u_j^E represents player j's utility at the equilibrium, which is $u_j\big(x_j\big(w_j, l_i^T, m_j\big), r_i^T\big)$. Since at the equilibrium point, both o_m and o_r are 0, both u_i^E and u_j^E cross the origin. The shaded area is the feasible set of offers available to player *j*. For player *j*, (o_m^*, o_r^*) is the tangent point of u_i^E and the indifference curve of u_j that moves furthest to the downright within the feasible set, and (o_m^*, o_r^*) is the optimal compensation offer. Further, we get Corollary 1 from rephasing Proposition 4.

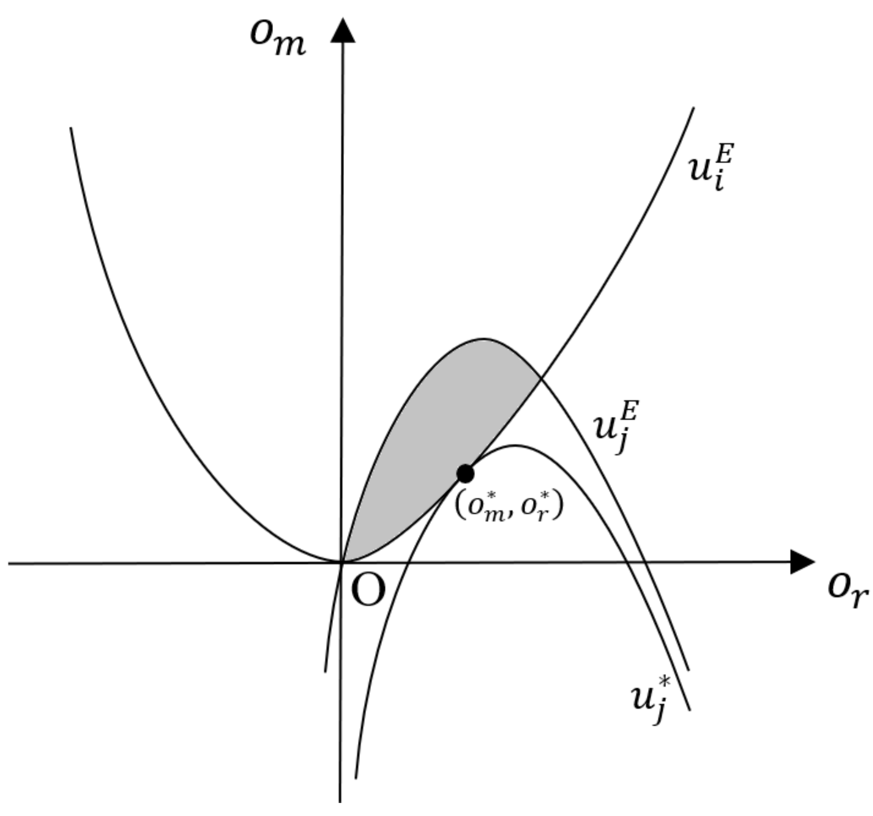

Figure 3 The representation of the utility maximization problem of the compensation offer

Corollary 1 When there is perfect information, and the utility function is monotonic, concave, and continuous in x and CR, the equilibrium is not Pareto efficient.

Proof: From Proposition 4, a Pareto Improving trade from the equilibrium exists, therefore the pre-trade equilibrium is not Pareto efficient.■

And based on the assumptions, we also get Corollary 2.

Corollary 2 When there is perfect information, and utility function is monotonic, concave, and continuous in x and CR, there exists a unique compensation offer, (o_m^*, o_r^*), such that (o_m^*, o_r^*) is a Pareto improvement and optimal for player j.

Proof:

Define set A as the set that contains all the offers that make player *i* at least as well off as the at the equilibrium point, which is no offer,

$\{(o_m, o_r) | u_i((l_i^T - o_r)w_i + m_i + o_m, r_i^T + o_r) \geq u_i(l_i^T w_i + m_i, r_i^T)\}$.

Define set B as the set that contains all the offers that make player *j* at least as well off as with no offer,

$\{(o_m, o_r) | u_j\left((l_i^T - o_r)w_j + m_j - o_m, r_i^T + o_r\right) \geq u_j\left(l_i^T w_j + m_j, r_i^T\right)\}$.

Let $U_i(o_m, o_r)$ denote $u_j\left(x_j^1(o_r, o_m), r_j^1(o_r)\right)$, and $U_j(o_m, o_r)$ denotes $u_j\left(x_j^1(o_r, o_m), r_j^1(o_r)\right)$.

From proposition 4, the set $A \cap B$ is non-empty. Since $U_j(o_m, o_r)$ is continuous, for each $(\tilde{o}_m, \tilde{o}_r) \in A \cap B$ such that $U_i(\tilde{o}_m, \tilde{o}_r) = U_i(0,0)$, there exists $U_j(\tilde{o}_m, \tilde{o}_r)$. Thus, there exists $(o_m^*, o_r^*) \in A \cap B$ such that $U_j(o_m^*, o_r^*) \geq U_j(\tilde{o}_m, \tilde{o}_r)$, for all $(\tilde{o}_m, \tilde{o}_r) \in A \cap B$.

From proposition 4, there exists a compensation offer, $(\hat{o}_m, \hat{o}_r) \in A \cap B$, and $(\hat{o}_m, \hat{o}_r)$ is a Pareto improvement. Since $(o_m^*, o_r^*) \in A \cap B$, $U_j(o_m^*, o_r^*) \geq U_j(\hat{o}_m, \hat{o}_r)$. Since $U_j(\hat{o}_m, \hat{o}_r) > U_j(0,0)$, $U_j(o_m^*, o_r^*) > U_j(0,0)$.

Thus, there exists $(o_m^*, o_r^*) \in A \cap B$ such that $U_i(o_m^*, o_r^*) \geq U_i(0,0)$, and $U_j(o_m^*, o_r^*) > U_j(0,0)$, and $U_j(o_m^*, o_r^*) \geq U_j(o_m, o_r)$, for all $(o_m, o_r) \in A \cap B$. ■

2.7 Wage increase under compensation offer

In this section, we consider the case when one of the players receives a wage increase and show that in some circumstances, a Pareto improving alternative offer can be made that would induce the player to forego the wage increase. When the optimal compensation offer (o_m^*, o_r^*) is reached, the social welfare reaches its maximum. Suppose after the society reaches (o_m^*, o_r^*), player *i* gets the wage increase[3]. If she is on the upward-sloping portion of her labor supply curve, she will increase her labor and, therefore, reduce her social connections input. Since $r_i^T < r_j^T$, this will reduce the equilibrium level of social connections, causing player *j*'s utility to fall. The initial equilibrium is broken, and player *j* seeks to make a new compensation offer. As we will show, when the wage increase is not too large, player *j* would be willing to make a compensation offer sufficient to convince player *i* to forego the wage increase; i.e. an offer exists that is Pareto superior to the wage increase.

[3] It does not matter who gets the wage increase here, if player *j* gets the wage increase, she will also reduce her social connections input. Before player *j* inputs less on social connections than player *i*, the wage increase is a Pareto improvement. When the wage increase is large enough, player *j* will be the one who inputs less to establishing social connections.

Lemma 3 There exists a wage increase, $\Delta w_i > 0$, that is sufficiently small that there exists a compensation offer $\left(\tilde{o}_m, \tilde{o}_r\right)$ such that player i would be willing to forego the wage increase and player j would be at least as well off as before i's wage increase, i.e.,

$$u_i\left(\left(w_i + \Delta w_i\right)\left(l_i^T + \Delta l_i\right) + m_i, r_i^T - \Delta l_i\right) \le u_i\left(w_i l_i^T + m_i + \tilde{o}_m, r_i^T + \tilde{o}_r\right)$$

and

$$u_j\left(w_j\left(l_i^T + \Delta l_i\right) + m_j, r_i^T - \Delta l_i\right) \le u_j\left(w_j l_j^T + m_j - \tilde{o}_m, r_i^T + \tilde{o}_r\right).$$

Proof:

Based on the proof of Proposition 4, after the initial equilibrium formed, there exists a compensation offer $\left(\varepsilon_1, \varepsilon_1\left(m + \varepsilon_2\right)\right)$ (as defined there) that is a Pareto improvement over the initial equilibrium, i.e.

$$u_i\left(w_i l_i^T + m_i, r_i^T\right) < u_i\left(w_i l_i^T + m_i + \varepsilon_1, r_i^T + \varepsilon_1\left(m + \varepsilon_2\right)\right).$$

By continuity, it follows that there exists $\Delta\tilde{w}_i > 0$ such that

$$u_i\left(\left(w_i + \Delta\tilde{w}_i\right)\left(l_i^T + \Delta\tilde{l}_i\right) + m_i, r_i^T - \Delta\tilde{l}_i\right) = u_i\left(w_i l_i^T + m_i + \varepsilon_1, r_i^T + \varepsilon_1\left(m + \varepsilon_2\right)\right).$$

For all $\Delta w_i > 0$ such that $\Delta w_i < \Delta\tilde{w}_i$, therefore,

$$u_i\left(\left(w_i + \Delta w_i\right)\left(l_i^T + \Delta l_i\right) + m_i, r_i^T - \Delta l_i\right) < u_i\left(w_i l_i^T + m_i + \varepsilon_1, r_i^T + \varepsilon_1\left(m + \varepsilon_2\right)\right).$$

For player *j*, when there is a small enough $\Delta w_i > 0$, since $r_j = r_i^T - \Delta l_i < r_i^T$,

$$u_j\left(w_j\left(l_i^T + \Delta l_i\right) + m_j, r_i^T - \Delta l_i\right) < u_j\left(w_j l_i^T + m_j + \varepsilon_1, r_i^T + \varepsilon_1\left(m + \varepsilon_2\right)\right).$$

Therefore, there exists a compensation offer $\left(\tilde{o}_m, \tilde{o}_r\right)$, which could be $\left(\varepsilon_1, \varepsilon_1\left(m+\varepsilon_2\right)\right)$ defined in Proposition 4, which is Pareto superior to the alternative in which *i* receives a small enough wage increase.■

As the wage increase for player *i* becomes larger, the room for player *j* to make an acceptable compensation offer to player *i* becomes smaller because player *j* has to increase her payment to compensate for the loss of player *i*. Until the wage increase reaches the first critical wage, where player *j* cannot make any acceptable compensation offer.

Proposition 5 *The existence of the critical wage*

After the system reaches its maximum welfare, when there is perfect information, and the utility function is monotonic, concave, and continuous, there exists $\bar{w}_i^1 > w_i$ such that, for each $w_i' \in \left(w_i, \bar{w}_i^1\right)$, there exists a mutually agreeable compensation offer $\left(o_m^1, o_r^1\right) \in \mathbb{R}_+^2$ such that player i accepts the offer $\left(o_m^1, o_r^1\right)$ and forgoes the wage increase, and for any wage $w_i'' > \bar{w}_i^1$ there is no mutually acceptable compensation offer that would entice player i to forego the wage increase.

We provide the intuition first, then show the formal proof. Figure 4 illustrates the proof of Proposition 5. In Figure 4, the indifference curve I_0 presents player *i*'s utility level under the initial wage, w_0, without any compensation offer. The indifference curve J_0 presents player *j*'s utility level under the initial equilibrium, where there is no compensation offer. The indifference curve I_1 is from moving I_0 upward until there is only one tangent point with J_0, the tangent point is called compensation offer (o_m^{**}, o_r^{**}), which is the point defines $\bar{w}_i^1$. The utility level associated with I_1 is the highest utility level that player *i* could reach under the initial wage, by accepting the compensation offer (o_m^{**}, o_r^{**}). This compensation offer (o_m^{**}, o_r^{**}). will give player *j* the utility level J_0. Based on the continuity assumption, the utility level of I_1 could also be achieved by increasing player *i*'s wage to $\overline{w}_i$ and allowing player *i* to adjust her working time accordingly as if player *i* has already accepted the compensation offer (o_m^{**}, o_r^{**}). The shaded area in Figure 4 represents the set of possible Pareto improvement offers at the initial equilibrium. If *i*'s wage increases to a level higher than $\overline{w}_i$, the equivalent indifference curve of player i will move above I_1 in Figure 4, and the set of the possible Pareto improvement offers is empty. Therefore, no Pareto improvement offer exists.

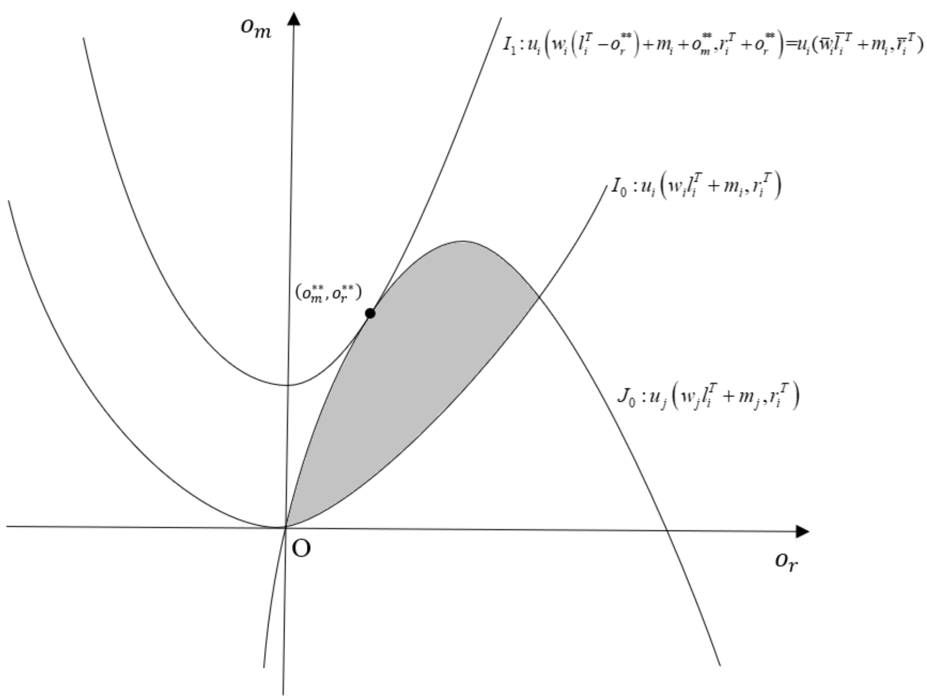

Figure 4 The proof of Proposition 5[4]

Proof:

Based on the proof of Corollary 2, at the initial wage, there exists a set of Pareto improving

[4] In this graph, we assume no income effect that changes player *i*'s working time.

offers, $\left(o_m^{**}, o_r^{**}\right) \in A \cap B$ such that $U_i(o_m^{**}, o_r^{**}) > U_i(0,0)$, and $U_j(o_m^{**}, o_r^{**}) = U_j(0,0)$, which means the compensation offer $\left(o_m^{**}, o_r^{**}\right)$ gives player i

the highest utility under the initial wage. Therefore, $U_i(o_m^{**}, o_r^{**}) \geq U_i(o_m, o_r)$, for all $(o_m, o_r) \in A \cap B$. At this offer, player j is indifferent between $\left(o_m^{**}, o_r^{**}\right)$ and no offer.

Since $U_i(o_m, o_r)$ is continuous, there exists a wage, $\overline{w}_i > w_i$ such that i would be indifferent between $\overline{w}_i$ and the offer $\left(o_m^{**}, o_r^{**}\right)$ under the initial wage, i.e.,

$$u_i\left(w_i\left(l_i^T - o_r^{**}\right) + m_i + o_m^{**}, r_i^T + o_r^{**}\right) = u_i(\overline{w}_i \overline{l}_i^T + m_i, \overline{r}_i^T),$$

where $\overline{r}_i^T$ and $\overline{l}_i^T$ are the ideal choice of player i under wage $\overline{w}_i$. The indifference curve I_1 in Figure 4 represents player i's utility level under $\overline{w}_i$.

Since $\frac{\partial u_i}{\partial o_m} > 0$ and u_i is continuous, there exists a real number $\overline{a} > 0$, such that player i is indifferent between $\overline{a}$ the amount of additional external income under wage w_i and the utility under $\overline{w}_i$,

$$u_i\left(\overline{w}_i \overline{l}_i^T + m_i, \overline{r}_i^T\right) = u_i\left(w_i l_i^T + m_i + \overline{a}, r_i^T\right).$$

For any $w_i^{'} > \overline{w}_i$, there exists a real number $a' > 0$, such that

$$u_i\left(w_i l_i^{T'} + m_i, r_i^{T'}\right) = u_i\left(w_i l_i^T + m_i + a', r_i^T\right),$$

and by monotonicity,

$$a' > \overline{a}.$$

Therefore,

$$u_i\left(w_i l_i^T + m_i + a', r_i^T\right) > u_i\left(w_i l_i^T + m_i + \bar{a}, r_i^T\right) = u_i\left(w_i\left(l_i^T - o_r^{**}\right) + m_i + o_m^{**}, r_i^T + o_r^{**}\right),$$

player i will reject the offer $\left(o_m^{**}, o_r^{**}\right)$. Thus, there is no Pareto improvement offer that exists.

Thus, there exists a critical wage $\vec{w}_i^1 = \bar{w}_i$. ■

Notice that, in Proposition 4, we show that there always exists a possible compensation offer, while Prosition 5 says under the wage increase that is large enough, there is no compentsation offer could be made. The starting conditions for Proposition 4 and Proposition 5 are different. The timing of Proposition 4 is right after the initial equilibrium, while the timing of Proposition 5 is after the optimal compensation offer been reached. In Proposition 5 we show that, there is a critical wage such that forgoing any wage that is smaller than the first critical wage, but larger than the original wage, is a Pareto improvement. A wage increase that is larger than the critical wage will lower player *j*'s utility due to the lower level of social connections, and there is no room for player *j* to make acceptable compensation offer.

2.8 Discussion

The model we presented here implies that a wage increase impacts social connections. A wage increase could benefit the one who receives the wage increase, but hurt another person who has a social connection with the person who gets the wage increase. Based on Proposition 4, a compensation offer could be a Pareto improvement over any initial equilibrium. Based on Proposition 5, a wage that is larger than the first critical wage is not Pareto efficient.

Although our model is simple, it helps in explaining the Easterlin Paradox. When wage increases happen, people who receive higher wages have higher utility, but others who do not receive the wage increase have lower utility due to a reduction in the utility they get through social connections. Hence, total social welfare may not increase as expected. One example is from Japan, where between 1958 and 1991 the income per capita increased by sixfold, but the average happiness has stayed relatively constant (Frey & Stutzer, 2002).

In line with Stiglitz et al. (2009b), we think social connections are important to human well-being. Based on Durkheim (1897/1951), Na and Hample (2016), Cornwell and Laumann (2015), people living with a lower level of social connections tend to have worse physical and mental health. If our economic policies focus on only wage and production, that will lead our societies into a lower level of social connections. Our model also implies that if a country focuses exclusively on having higher wages, this may result in lower levels of social connections.

In this paper, we present a simple model to investigate the relationship between wage and social connections; many extensions can be envisioned. First, we need to discuss the situation of multiple players and weaken the assumption on the generation of social connections. Second, the spatial movement of immigrants from low-wage regions to high-wage regions, could also affect the social connections of these immigrants, and the spatial aggregation of two regions. Third, in our model, the social connection generation only requires time input, in reality, it often requires goods, like the cost of a shared meal or drink, or even durable goods that facilitate social interactions. In Banerjee and Duflo (2019), they tell a story of a man in Morocco who does not have enough food for his family but has a large television. In the book, they call this "herb behavior". If we put the "herb behavior" under the social connections framework, we can see that people need not only food, but also the goods necessary for tight social connections with each other.

Governments might also have a role in establishing social connections. Since a government focusing on having higher GDP will have an impact on productivity and wage, social connections will also be affected by such policy. Governments can help create higher levels of social connections by, for example, funding public gatherings such as festivals. In our model, the offer maker is one of the players, but this simply shows that a potential Pareto improvement exists, thus justifying government intervention on the grounds of economic efficiency.

Nowadays, the development of a society heavily focuses on economic growth, especially in developing countries, which leads to environmental issues and social problems at the same time. Here we show one potential problem with the GDP-focused policies.

CHAPTER III THE IMPACT OF EXOGENOUS POLLUTION ON GREEN INNOVATION[5]

3.1 Introduction and Motivation

Pollution problems are severe in developing countries. For example, both China and India have heavy air pollution problems in many of their large cities (Badami 2005; Rohde and Muller 2015). One way to reduce pollution is through green innovation. Green innovation is defined as "the implementation of new, or significantly improved, products (goods and services), processes, marketing methods, organizational structures and institutional arrangements which, with or without intent, lead to environmental improvements compared to relevant alternatives" (OECD, 2010, 2012). It is one of the most important choices that firms make to deal with environmental issues and build sustainable development (Eltayeb and Zailani 2014; Sezen and Cankaya 2013).

The existing literature shows that when pollution levels are high, consumers and environmental regulations tend to push firms to have more green innovations (Cai and Li 2018; Horbach 2008), which in turn leads to less pollution. However, in most situations, firms generate pollution and the government regulates firms, leading to green innovation. In such circumstances, it is difficult to separate the effect of regulations on firm behavior from the effect that pollution itself might have on firms' innovation choices.

It is possible, however, that the causality could be reversed, because firms are in less polluted areas, they might tend to adopt higher levels of green innovation. One way for this to occur is if pollution affects firm green innovation due to its impact on the labor force movement.

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[5] This chapter has been published: Wang, Ying., Woodward, Richard.T. & Liu, Jing-Yue. 2022. "The Impact of Exogenous Pollution on Green Innovation." *Environmental and Resource Economics*. 81(1):1–24 (2022). https://doi.org/10.1007/s10640-021-00614-5. SJR: 1.27. Reproduced with permission from Springer Nature.

When workers select a job location, a city's pollution level is an important concern (Lu et al. 2018). Since workers tend to move to a city with less pollution, this affects firms' green innovation capacity (Horbach 2008). Another possible way that pollution might affect green-innovation choices is if a firm is set in an area in which there is heavy pollution, firms may perceive the marginal benefit of green innovation on air pollution as negligible, disincentivizing adoption of such technology. Thirdly, since firms in the city with public heating are already polluted by the exogenous source, they may hide their pollution from government regulation. Thus, firms may have less incentive to invest in green innovation since the firms are not regulated as they are in a city without the exogenous pollution.

In this paper, we take advantage of a unique policy threshold that allows us to study the causal relationship between pollution levels and green innovation. The policy in question, known as the Huai River policy, installs a public heating infrastructure on the northern side of a geographic line. Numerous studies have shown that this policy has significantly increased pollution to the north of the threshold (Almond et al. 2009; Chen et al. 2013; Xiao et al. 2015). Using this policy boundary, we find that firms adopt less green innovation on the north side of this line, where pollution is greater than in comparable areas without the exogenous pollution source. Because the policy was established decades ago and not in response to either pollution or firm innovations, our results provide strong evidence of a causal effect of pollution on green innovation.

3.2 Policy Background

In the 1950s, the Chinese government implemented its public heating policy across the country. This policy installs a public heating system in a city if it has a daily average temperature less than or equal to 5 degrees Celsius or 41 degrees Fahrenheit for at least 90 days per year. Based on this criterion, cities in northern China have public heating, while the southern cities do not and this roughly coincides with the Huai River. The public heating system burns coal to generate heat and transmits the heat through water pipes into each household during wintertime. Figure 5 shows the heating boundary.

Studies have found that the policy has a significant effect on air quality. The public heating system worsens air pollution during the winter in cities that use it (Almond et al. 2009; Chen et al. 2013; Xiao et al. 2015). It has also been shown that the public heating system on average reduces 5 years life expectancy of the individuals who live in the cities that have it, compared to individuals who live without public heating (Chen et al. 2013). It would not be surprising if such effects on health and quality of life might affect firm choices, and it is the goal of this paper to look for evidence of such an effect.

3.3 Data

The International Patent Classification (IPC) system includes the "IPC Green Inventory" category, which includes 7 types of innovations: alternative energy production, transportation, energy conservation, waste management, agriculture/forestry, administrative regulatory or design aspects, nuclear power generation. However, there is no formal definition of green innovation in China, therefore we cannot apply the IPC system in our analysis. Instead, we gather our data by searching a database of patents using keywords based on He and Shen (2019), Li, Huang, et al. (2018), Li et al. (2017), Bansal and Clelland (2004) and Brunnermeier and Cohen (2003). We use the Baiten database, which includes a comprehensive database of patents in China, yielding a count of the number of firm-level patents registered with

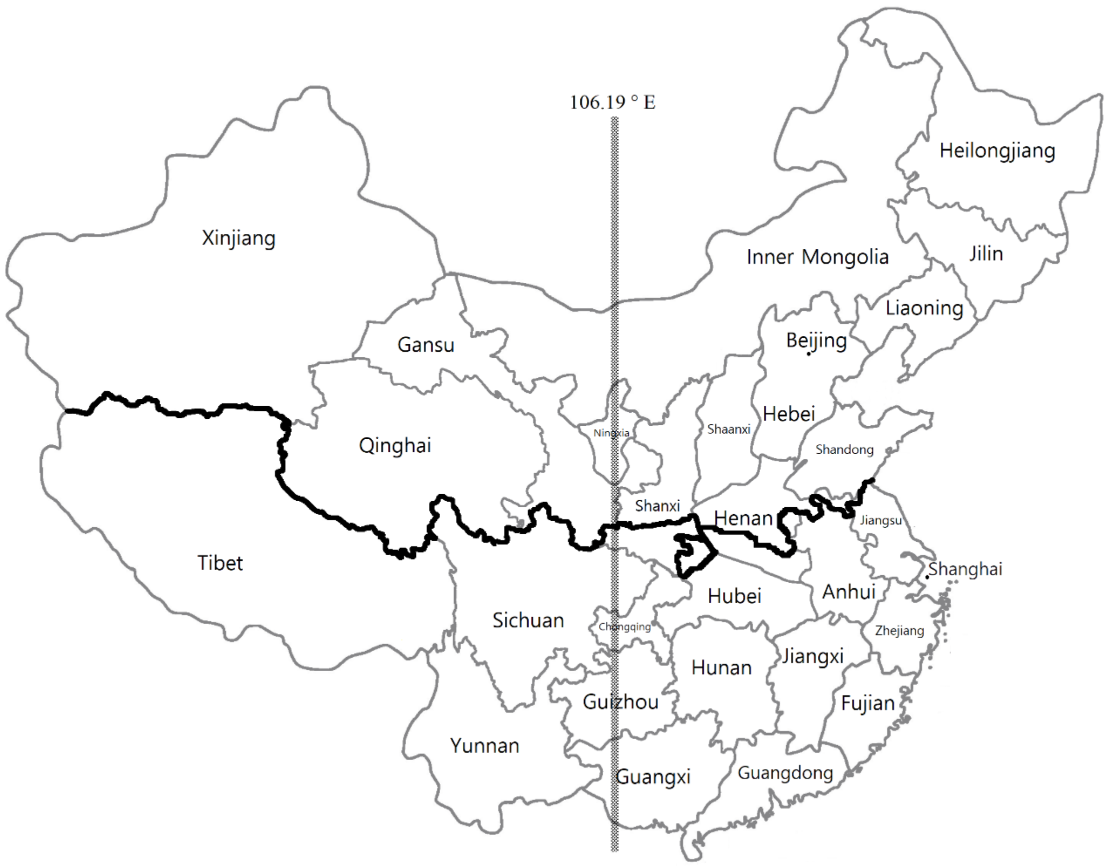

Figure 5 The heating boundary in mainland China. The black line shows the heating boundary, the cities north of the boundary have public heating, while the cities south of the boundary do not. The dashed line indicates longitude 106.19 ° E, the heating boundary east of the yellow line mostly does not coincide with provincial political boundary, while the heating boundary at the west of the yellow line mostly coincides with provincial political boundary.

China National Intellectual Property Administration from 2013-2017.[6] The Baiten database has also been used in other innovation research (Chen et al., 2018; Li, Huang, et al., 2018; Li, Zhao, et al., 2018; Li et al., 2017).Other data about the firms are obtained from the China Stock

[6] Website link: https://www.baiten.cn.

Market & Accounting Research Database (CSMAR).[7] To measure firms at different scales, our measure of a firm's green innovation behavior variable is the number of green innovations per billion RMB of a firm's total assets. The location of each firm is identified using the firm's address in the CSMAR database.[8] It is possible that firms have production plants in locations other than their registered address, and thus affected by conditions elsewhere. However, based on the 2017 annual reports of the 46 firms within 100 km of the heating boundary, only 3 have production plants in provinces other than the registered province. Hence, we believe that it is reasonable to assume that firms' innovations decisions are primarily affected by conditions at their registered location.

Our geographic data were obtained as follows. First, the heating boundary was marked in Google Earth based on the historical policy implementation. This boundary was exported as GPS coordinates. Then, using the R geosphere package (Hijmans et al.), we calculate the distance between the city of each firm in our dataset and the closest point on the heating boundary.

3.4 Identification Strategy

Since the public heating policy has a clear geographic policy boundary, we use a regression discontinuity (RD) design to estimate the policy effect. The RD design has been widely used in literature to investigate the effect of geographically implemented policies (Keele and Titiunik 2015; Lee and Lemieux 2010). When a policy treatment has a clear cut-off point, samples around the cut-off point make a good comparison to estimate the treatment effect (Lee and Lemieux 2010).

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[7] Website link: http://us.gtadata.com.

[8] In Appendix B, we describe what data are being used, and how we downloaded the data.

The Huai River policy is well suited to this type of analysis because it was implemented based on a meteorological feature, and that feature is exogenous to firms. It has been shown that this policy leads to greater pollution in the northern cities, providing an opportunity to study firm behavior under an exogenous pollution source. The assumption implicit in RD models is that within a small range of the boundary, cities will tend to have a similar unobserved feature, for example, infrastructure. Our RD approach controls for unobserved variation over space by including the distance from the border, helping to isolate the effect of public heating on innovation. We make use of the exogenous variation in pollution caused by the public heating policy to identify the effect of pollution on firm green innovation.

As the probability of getting public heating treatment is 1 or 0, we apply a sharp RD design (Imbens and Lemieux 2008). Our base regression model is as follows:

$$GI_{it} = \beta_0 + \beta_1 heating_i + \beta_2 distance_i + \beta_3 heating_i \cdot distance_i + X_{it}\delta + \varepsilon_{it} \qquad (1)$$

where, GI_{it} is the number of green innovations per billion RMB in total assets for firm *i* at time *t*; $heating_i$ is a dummy variable, equal to 1 if the firm *i* is located in a city with public heating; and $distance_i$ is the measure in KM from the city in which firm *i* is located in and the closest point on the heating boundary, which is positive if the city has public heating and negative otherwise. Finally, X_{it} is a vector of firm-specific control variables: return on net assets (RoNA), which is calculated as the net income divided by net assets; earnings per share (EpS); growth rate of main business income (GRoMBI); and number of directors (NoD). Most of the variables in X_{it} are clear indicators of firm performance; NoD may be relevant as a larger board is correlated with positive corporate income while smaller boards have higher group cohesiveness and easier to reach consensus (Dalton et al. 1999). As required in RD estimation, in the set of control variables we seek to control for as much firm variation as possible with variables that do not show a significant discontinuity around the cut-off point. Our coefficient of interest is β_1, which captures the marginal effect on GI_{it} of being in the region with public heating.

As mentioned above, the impact of pollution on the labor force is one possible mechanism through which pollution might affect green innovation. If this holds, then firms in the higher pollution area would tend to have lower innovation capacity, which should affect both green innovation and non-green innovation. On the other hand, if the higher pollution disincentives only green innovation, then non-green innovation would be unaffected. To provide some evidence about the causal mechanism, therefore, we also test the treatment effect on firms' non-green innovation. We calculate the number of non-green innovations by the difference between a firm's total innovations and its number of green innovations.

Figure 6 shows the kernel densities for the green innovation measurement for firms within 100 km of the boundary. Within 100 km of the boundary, the portion of firms that have a small amount of green innovation per assets is higher in the north side of the boundary than the south side. Table 1 shows summary statistics for variables used for firms within different distances both north and south of the policy boundary, and we also show the p-value for the t-test comparing the means of control group and treatment group.[9] As seen in the table, within 100 km of the boundary, the total number of green innovations is not different between the two sides at the 5% level. When we normalize by firm assets, however, we see in both Figure 6 and Table 1 that southern firms have significantly more innovations per million RMB in assets than the northern firms. This

[9] In the appendix, we show a detailed summary statistics.

provides some preliminary evidence that the public heating treatment may affect the general innovation behavior of the northern firms, so they have fewer innovations overall.

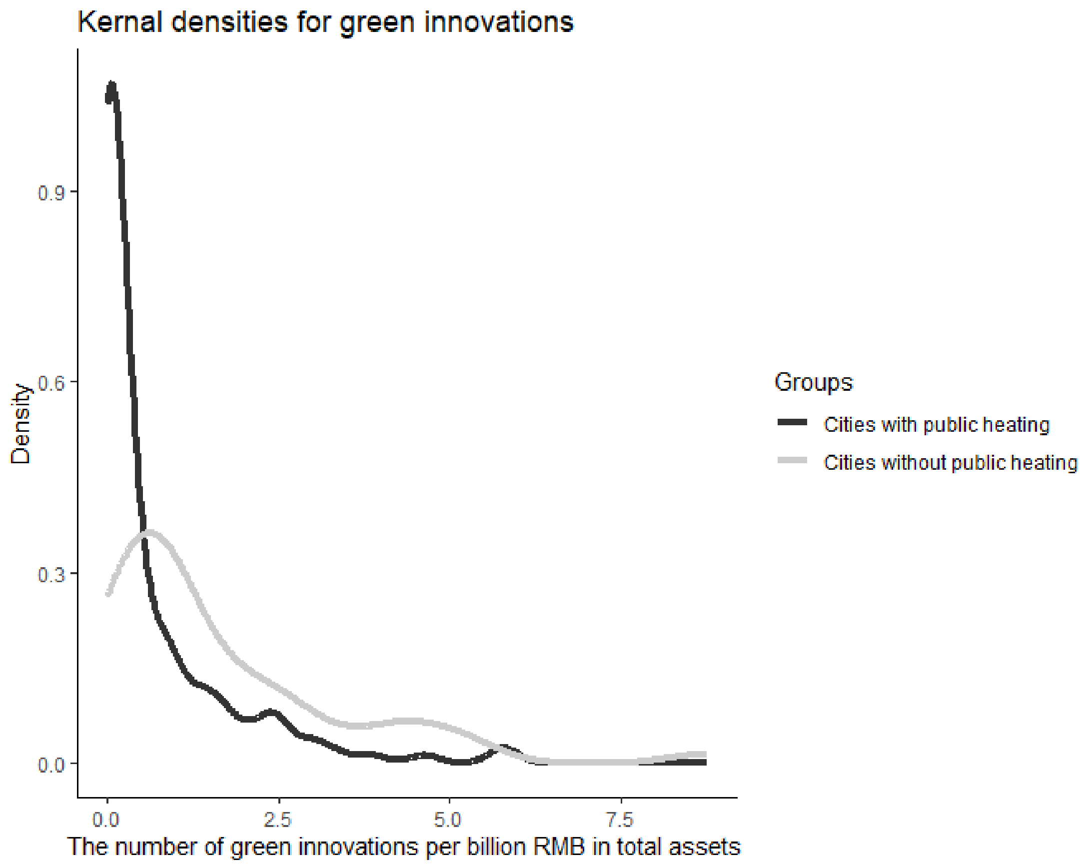


Figure 6 The kernel densities for green innovations for firms within 100 km of the boundary.

Table 1 Summary Statistics.

	All Firms within					
	<100 km of the Heating Boundary			<200 km of the Heating Boundary		
	South No Public Heating (N=52)	North Have Public Heating (N=150)	p value[a]	South No Public Heating (N=171)	North Have Public Heating (N=270)	p value
The Number of Total Innovations per Firm						
Mean (SD)	27.592 (38.226)	12.930 (19.716)	< 0.001	19.066 (34.052)	12.833 (19.490)	0.019
The Number of Green Innovations per Firm						
Mean (SD)	6.184 (6.033)	4.359 (7.610)	0.13	6.232 (11.779)	4.081 (6.226)	0.016
The number of Non-Green Innovation						
Mean (SD)	21.408 (33.210)	8.570 (14.861)	< 0.001	12.834 (25.413)	8.752 (16.351)	0.049
Total Assets (unit: billions of RMB)						
Mean (SD)	5.157 (4.455)	15.738 (31.388)	0.02	9.731 (13.718)	13.459 (25.283)	0.095
The Number of Green Innovation per Billion RMB of Assets						
Mean (SD)	1.638 (1.800)	0.641 (1.089)	< 0.001	1.472 (2.808)	0.788 (1.341)	< 0.001
The Number of Non-Green Innovation per Billion RMB of Assets						
Mean (SD)	3.418 (4.237)	1.577 (3.325)	0.002	2.848 (5.395)	2.300 (8.368)	0.471
Return on Net Assets						
Mean (SD)	0.080 (0.076)	0.035 (0.133)	0.024	0.057 (0.196)	0.025 (0.229)	0.154
Earnings per Share						
Mean (SD)	0.400 (0.427)	0.254 (0.610)	0.123	0.360 (0.797)	0.232 (0.537)	0.052
Distance to the Heating Boundary (unit: kilometers)						
Mean (SD)	37.542 (16.800)	53.187 (23.999)	< 0.001	129.112 (67.519)	93.957 (51.748)	< 0.001
Growth Rate of Main Business Income (unit: 100%)						
Mean (SD)	0.007 (0.046)	0.005 (0.032)	0.714	3.941 (48.348)	0.003 (0.024)	0.191
Number of Directors						
Mean (SD)	9.020 (1.199)	9.014 (2.186)	0.985	8.735 (1.018)	8.884 (1.880)	0.37

[a] The p-value is for the t-test for the difference of means between the treated (public heating) and control groups

Table 2 Chi-Square Test on Industrial Structure

	Firms within			
	<100 km of the Heating Boundary	<200 km of the Heating Boundary	<300 km of the Heating Boundary	<400 km of the Heating Boundary
p-value[a]	0.362	0.141	0.344	0.211

[a] The p-value is for the chi-square test for testing the difference in the industrial structure around the heating boundary

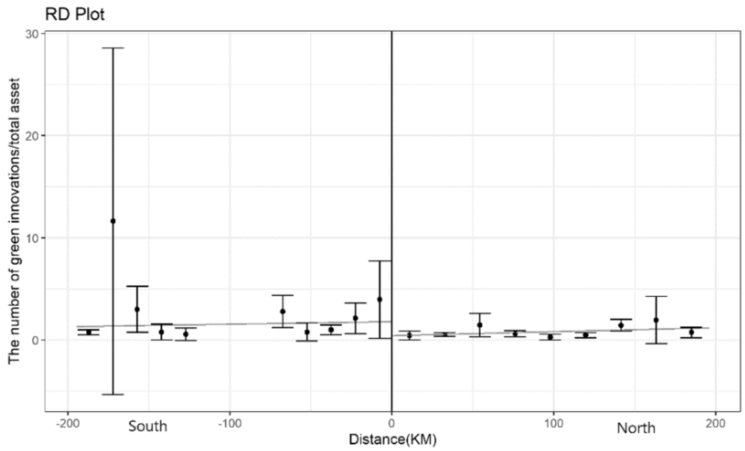
One possible reason for the significant difference in innovation could be different industrial distributions on either side of the boundary. For example, one side might have a large concentration of an industry that tends to innovate a lot more. Our data include 10 industries,[10] we calculate the number of firms in each industry on both sides. In Table 2, we report the chi-squared test for different industrial structures across the boundary. The results show that there is no significant difference in the industrial structure around the boundary, supporting the conclusion that the differences in innovation behavior are not because of significant differences in the industries on the two sides of the boundary.

3.5 Results

3.5.1 Graphical Analysis

In Figure 7 we plot the number of green innovations per billion RMB in total assets against distance from the boundary for firms within 200km of the heating boundary. Our plot uses evenly-spaced bins introduced by Calonico et al. (2015), which

[10] The 10 industries include: mining, power generation, textile, steel, chemical, petrochemical, cement, metallurgical, pharmaceutical, paper.



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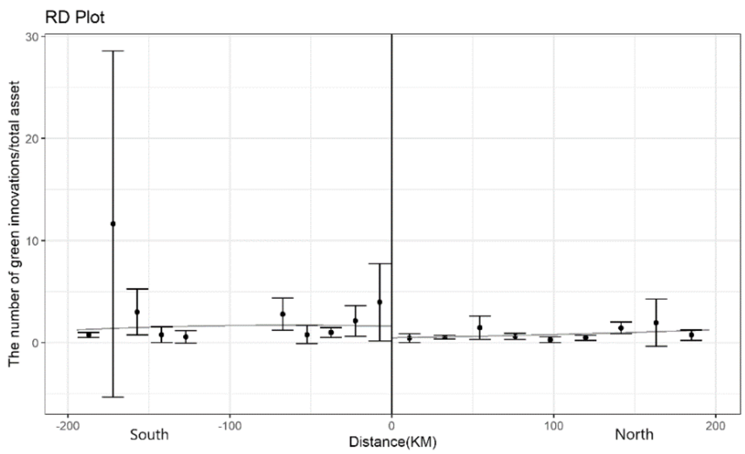

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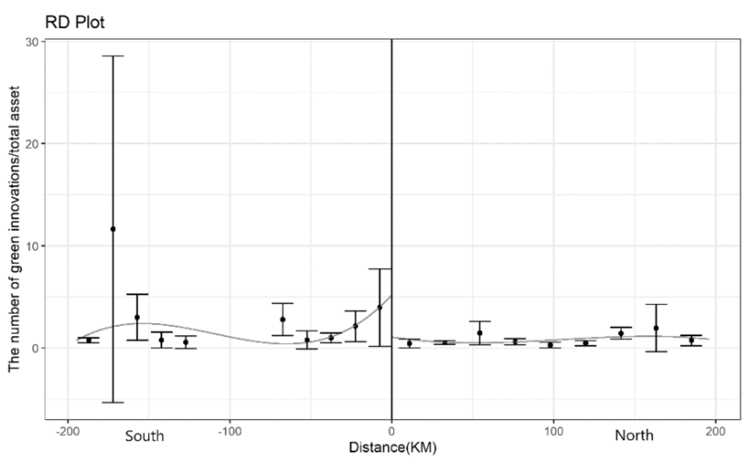

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Figure 7 Plots of the green innovation rate over distances from the boundary. The data used to create these plots only include the firms located within 200km around the heating boundary. The orders of the polynomial used for regression lines are 1, 2, and 3 respectively.

separate distance evenly and presents the green innovation measures for all firms within a given bin and includes first, second and third degree polynomial regression lines.

In Figure 7a, the conditional mean function is linear, the left fitting line at the cut-off point is in the 95% confidence interval of the first right data point, which implies there is no strong statistical evidence of discontinuity from left the right, but there is discontinuity from right to left. As we use high-order polynomial to estimate the conditional mean function, the discontinuity from left to right appears in Figure 7c. Overall, we see a very slight break at the policy boundary.

3.5.2 Regression results

In Table 3 we report simple OLS regressions using samples in different ranges. When a narrow band is used, there is probably less spatial variation except for the exogenous treatment, but the number of observations is relatively small. As the range increases, there is more room for unexplained variation in the firms, but we also obtain more data points for our estimation. We start using firms located within 100 km on either side of the treatment boundary, then expand the range in 100 km increments to 400 km.

Based on OLS results, the effect on firm green innovation of the public heating threshold is significant within 300 km around the boundary. The results indicate that on average, with everything else held constant, firms in areas with public heating have less green innovation, with an average effect of 1.018 innovation per billion RMB total assets for firms located within 100 km of the boundary, falling to 0.379 when looking at firms within 300 km of the boundary. When all firms within 400 km of the boundary are considered, the effect falls to 0.034 and is no longer statistically significant.

The OLS estimators from Table 3 are unbiased only if unobserved variables are not correlated with heating after controlling for our covariates. One concern is that the city-level infrastructure data that cover all the cities in our sample are not available, and infrastructure is important to firm productivity (Wan and Zhang 2018). To the extent that infrastructure varies from north to south for reasons unrelated to the provision of public heating, missing infrastructure data could result in a biased OLS estimator of the causal effect of public heating on green innovation.

Table 3 The Effect of Public Heating Using OLS

	Dependent variable: Green Innovations per Billion RMB of Assets			
	<100km[a]	<200km	<300km	<400km
(Intercept)	2.120 ***	1.588 **	1.510 ***	1.182 ***
	(0.500)	(0.575)	(0.384)	(0.345)
Heating	-1.018 ***	-0.660 **	-0.379 **	-0.034
	(0.220)	(0.208)	(0.143)	(0.133)
RoNA	0.011	0.509	0.475	0.120
	(1.162)	(0.520)	(0.434)	(0.183)
EpS	-0.110	0.116	0.184	0.351 **
	(0.261)	(0.175)	(0.135)	(0.121)
GRoMBI	-2.834	-0.003	-0.002	-0.002
	(2.962)	(0.003)	(0.003)	(0.004)
NoD	-0.046	-0.020	-0.039	-0.033
	(0.049)	(0.062)	(0.042)	(0.039)
Observations	191	409	843	1101

[a] 100km regression uses only the data of firms located in the cities within 100km around the boundary, so on and so forth. Standard errors are reported in parenthesis. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

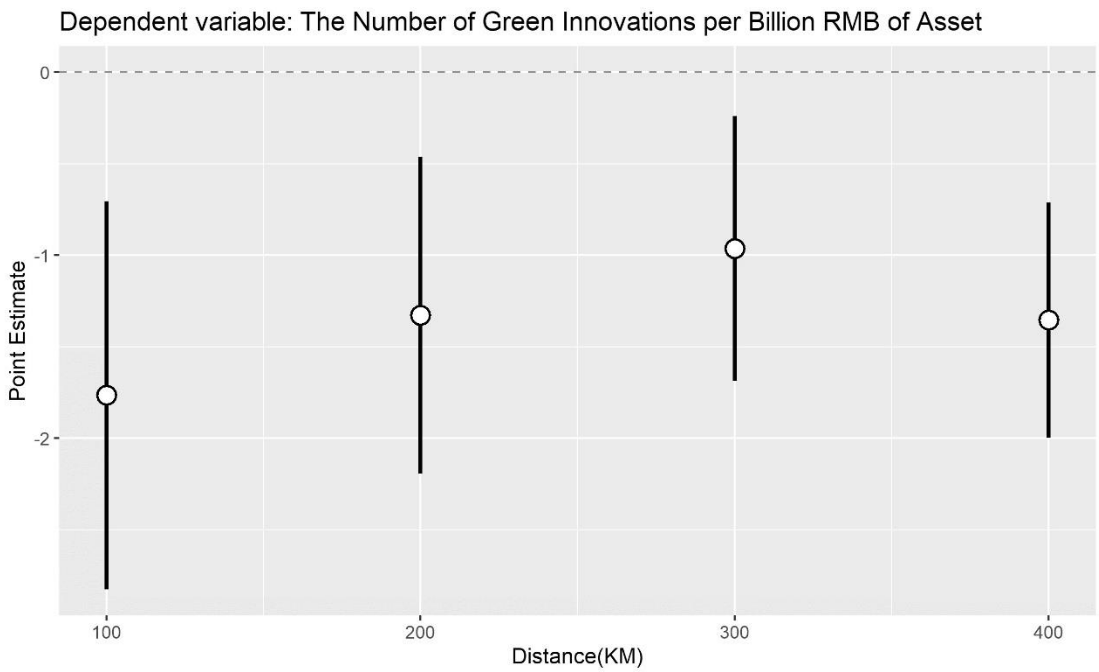
Using a local linear regression, we can control the spatial heterogeneity, yielding a preferred identification of the treatment effect. Table 4 presents our base results. Using this approach, we see that within 100 km, firms with public heating are estimated to have 1.765 fewer green innovations per billion RMB of a firm's total assets. This effect is significant at the 1% level. As the distance from the border expands, the magnitude of the effect falls, to 1.328 less for all cities within 200km and 0.964 at 300 km, but remains statistically significant at the 1% level. This finding strengthens the evidence for a causal effect since the group nearest to the cut-off point would tend to have the fewest systematic differences.

Table 4 also shows the treatment effect on non-green innovation. Here we find no statistically significant effects; the heating boundary appears to affect only green innovation, not all innovation. That is, our results suggest that being north of the public heating boundary leads to lower rates of green innovation without affecting non-green innovation.

Table 4 The Effect of Public Heating from Regression Discontinuity

	Dependent variable:							
	Green Innovations per Billion RMB of Assets				Non-Green Innovations per Billion RMB of Assets			
	100kma	200km	300km	400km	100km	200km	300km	400km
Intercept	2.811 ***	1.896 **	2.005 ***	2.142 ***	3.880 *	7.142 **	4.550 **	6.169 ***
	(0.665)	(0.682)	(0.499)	(0.437)	(1.814)	(2.512)	(1.433)	(1.083)
Heating	-1.765 **	-1.328 **	-0.964 **	-1.354 ***	-1.662	-2.974	-0.549	-1.172
	(0.537)	(0.440)	(0.368)	(0.327)	(1.467)	(1.619)	(1.056)	(0.811)
distance	0.018	0.002	0.002	0.004 ***	-0.024	0.008	0.001	0.006 *
	(0.011)	(0.002)	(0.001)	(0.001)	(0.031)	(0.009)	(0.004)	(0.002)
heating*distance	-0.016	0.002	-0.001	-0.001	0.039	0.008	-0.003	-0.010 **
	(0.012)	(0.003)	(0.002)	(0.001)	(0.033)	(0.013)	(0.005)	(0.004)
RoNA	0.015	0.490	0.456	0.090	4.000	1.705	1.052	0.273
	(1.161)	(0.519)	(0.434)	(0.182)	(3.169)	(1.911)	(1.246)	(0.452)
EpS	-0.107	0.119	0.186	0.338 **	-0.627	-0.092	0.399	0.537
	(0.261)	(0.175)	(0.135)	(0.120)	(0.712)	(0.643)	(0.388)	(0.297)
GRoMBI	-2.885	-0.002	-0.002	-0.002	-6.026	-0.005	-0.006	-0.006
	(2.959)	(0.003)	(0.003)	(0.004)	(8.077)	(0.013)	(0.010)	(0.009)
NoD	-0.050	-0.021	-0.046	-0.041	-0.155	-0.378	-0.213	-0.304 **
	(0.049)	(0.062)	(0.043)	(0.039)	(0.135)	(0.230)	(0.122)	(0.096)
Observations	191	409	843	1101	191	409	843	1101

[a] 100km regression uses only the data of firms located in the cities within 100km around the boundary, so on and so forth. Standard errors are reported in parenthesis. *** p < 0.001; ** p < 0.01; * p < 0.05



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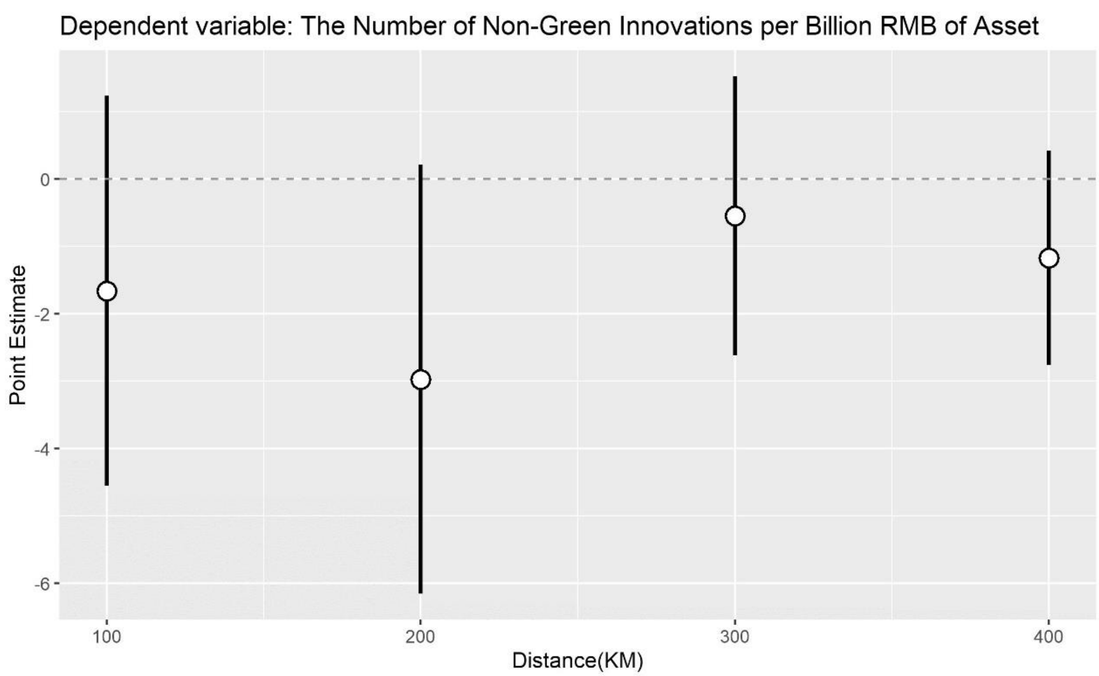

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Figure 8 The point estimate of $\boldsymbol{\beta_1}$ in regression (1) using samples within different ranges. Figure 8a shows the result using the number of green innovations per billion RMB of assets as dependent variables. Figure 8b shows the result using the number of non-green innovations per billion RMB of assets as dependent variables. The whiskers represent the 95% percent confident interval. The results here are the same as reported in Table 4.

3.6 Robustness Test

3.6.1 The discontinuity in control variables

The validity of the RD approach requires the covariates are smooth around the cut-off point (Imbens & Lemieux, 2008). As seen in the summary statistics, there are several variables that show significantly different means between the two sides of the boundary. Therefore, we estimate the following regression for each of our control variables to test the discontinuity in our covariates,

$$X_{it} = \beta_0 + \beta_1 heating_i + \beta_2 distance_i + \beta_3 heating_i * distance_i + \varepsilon_{it} \quad (2)$$

where X_{it} is a vector of firm performance control variables.

In Table 5, we show the point estimate of β_1 in regression (2) for each control variable used in regression (1). Table 5 shows that most of the point estimates of treatment coefficients, β_1 in regression (2), are not significantly different from 0 at the 5% level using data within different ranges for all variables. One exception is earnings per share at 400 km. However, the effect of public heating on green innovation is not significant at 400 km either, so the discontinuity in earnings per share does not change our main results and we believe the covariates are sufficiently smooth across the boundary to support the use of the RD approach to identify a causal treatment effect.

Table 5 Results of Tests on the Discontinuity in Control Variables

Range	Covariates							
	Return on Net Assets (RoNA)		Earnings per share (EpS)		Growth Rate of Main Business Income (GRoMBI)		Number of directors (NoD)	
	Point estimate	p-value	Point estimate	p-value	Point estimate	p-value	Point estimate	p-value
100km	-0.056	0.255	-0.231	0.318	-0.007	0.661	-0.496	0.542
200km	-0.051	0.287	-0.138	0.331	2.972	0.643	-0.170	0.630
300km	-0.046	0.181	-0.134	0.222	-2.055	0.575	-0.433	0.147
400km	-0.08	0.136	-0.183	0.033	-2.789	0.302	-0.055	0.829

The table reports the point estimate and p-value of β_1 in regression (2) using the samples within different ranges around the boundary

3.6.2 Reducing between-province compound effect

Another potential confounding effect in spatial RD design occurs when two or more geographically defined borders occur in the same place (Keele and Titiunik 2015). As shown in Figure 4, the western part of the heating boundary coincides with some political boundaries. If different provinces have different policies that affect green innovations, then the boundary not only affects the heating policy and air pollution, but it may also coincide with policy differences that affect firm choices. This would lead to a biased estimate of the effect of public heating because the firms on different sides of the boundary are also being treated differently with regard to government policies.

As seen in Figure 5, the heating boundary that is at the west of longitude 106.19° E coincides with the political boundary with Sichuan, Yunnan, and Tibet areas, the heating boundary to the east of this longitude is mainly inside Shanxi, Hubei, Henan, Anhui, Jiangsu provinces. Hence, using only the sample to the east of this longitude will reduce the potential compound effect. It turns out that our dataset changes little at 100 km and 200 km ranges, but we lose 18.47% and 20% of the observations at 300 km and 400 km accordingly. Table 6 shows the regression results using the subsample data for equation (1). Considering only the portion of the boundary that does not divide provinces, the effect of public heating is largely unchanged for all distance ranges. This suggests that the effect of the heating boundary on green innovation is not an artifact of policy differences between provinces.

Table 6 The Effect of Public Heating Reducing Between-Province Compound Effect.

	Dependent variable: Green Innovations per Billion RMB of Assets			
	100km[a]	200km	300km	400km
(Intercept)	2.811 ***	1.972 **	2.128 ***	1.959 ***
	(0.665)	(0.690)	(0.531)	(0.517)
Heating	-1.765 **	-1.371 **	-1.155 **	-1.372 ***
	(0.537)	(0.445)	(0.368)	(0.354)
distance	0.018	0.002	0.002	0.003 **
	(0.011)	(0.002)	(0.001)	(0.001)
heating*distance	-0.016	0.002	0.000	0.000
	(0.012)	(0.003)	(0.002)	(0.002)
RoNA	0.015	0.476	0.510	0.406
	(1.161)	(0.523)	(0.447)	(0.481)
EpS	-0.107	0.110	0.093	0.231
	(0.261)	(0.176)	(0.141)	(0.150)
GRoMBI	-2.885	-0.002	-0.002	-0.002
	(2.959)	(0.003)	(0.003)	(0.004)
NoD	-0.050	-0.025	-0.048	-0.021
	(0.049)	(0.063)	(0.047)	(0.046)
Observations	191	400	691	886

[a] 100km regression uses only the data of firms located in the cities within 100km around the boundary, so on and so forth. Standard errors are reported in parenthesis. *** p < 0.001; ** p < 0.01; * p < 0.05

3.6.3 Functional form test

In RD design, using an incorrect functional form may generate a biased treatment effect (Lee and Lemieux 2010). Since the true functional form is unknown, our finding could be a biased result from the misspecification of our regression model. To test this concern, we run the two additional regression models with quadratic and cubic terms:

$$X_{it} = \beta_0 + \beta_1 heating_i + \beta_2 distance_i + \beta_3 distance_i^2 + \beta_4 heating_i * distance_i + \varepsilon_{it}, \quad (3)$$

and

$$X_{it} = \beta_0 + \beta_1 heating_i + \beta_2 distance_i + \beta_3 distance_i^2 + \beta_4 distance_i^3 + \beta_5 heating_i * distance_i + \varepsilon_{it}. \quad (4)$$

Table 7 shows the results of these regressions. While the estimated treatment effect is still significantly negative, its magnitude varies dramatically across different functional form specifications. Our base specification in Table 4 is linear. As we use higher-order polynomial as our regression model, the magnitude of the treatment effect at the 100 km range increases from 1.765 to 3.858 in the quadratic specification and 5.415 in the cubic case. The results indicate that our linear model may underestimate the treatment effect, the true effect may be even larger. With only two exceptions, the estimated treatment effects remain statistically significant at least the 5% level, confirming the evidence that the heating policy has an effect on green innovation. However, the variation in magnitudes across functional forms does mean that quantitative inferences from our results should be made with a great deal of caution.

Table 7 The Regression Results of RD Using 2ed-order and 3rd-order Polynomial

	Dependent variable: Green Innovations per Billion RMB of Assets							
	Quadratic Specification				Cubic Specification			
	100kma	200km	300km	400km	100km	200km	300km	400km
(Intercept)	3.378 ***	1.765 *	2.343 ***	1.967 ***	4.322 ***	2.638 **	2.166 ***	2.100 ***
	(0.681)	(0.737)	(0.528)	(0.507)	(0.958)	(0.859)	(0.596)	(0.540)
Heating	-3.858 ***	-1.045	-1.732 **	-1.090 *	-5.415 ***	-2.891 *	-1.334	-1.444 *
	(0.896)	(0.740)	(0.544)	(0.505)	(1.428)	(1.198)	(0.823)	(0.704)
distance	0.061 **	-0.002	0.010 *	0.002	0.127 *	0.041	0.003	0.007
	(0.019)	(0.009)	(0.004)	(0.003)	(0.051)	(0.024)	(0.011)	(0.008)
distance2	-0.001 **	0.000	-0.000	0.000	-0.002	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
distance3	0.002	0.002	-0.002	-0.001	0.000	0.000	-0.000	0.000
	(0.013)	(0.004)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
heating*distance	0.000	0.000	-0.000	-0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RoNA	-0.383	0.490	0.447	0.087	-0.248	0.530	0.441	0.083
	(1.147)	(0.520)	(0.433)	(0.182)	(1.148)	(0.518)	(0.434)	(0.182)
EpS	-0.005	0.125	0.178	0.338 **	-0.090	0.119	0.181	0.336 **
	(0.258)	(0.175)	(0.135)	(0.120)	(0.265)	(0.175)	(0.135)	(0.120)
GRoMBI	-3.339	-0.002	-0.002	-0.002	-2.677	-0.002	-0.002	-0.002
	(2.906)	(0.003)	(0.003)	(0.004)	(2.937)	(0.003)	(0.003)	(0.004)
NoD	-0.035	-0.022	-0.038	-0.040	-0.051	-0.029	-0.038	-0.038
	(0.049)	(0.063)	(0.043)	(0.039)	(0.050)	(0.062)	(0.043)	(0.039)
Observations	191	409	843	1101	191	409	843	1101

[a] 100km regression uses only the data of firms located in the cities within 100km around the boundary, so on and so forth. Standard errors are reported in parenthesis. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

3.6.4 Placebo test

Many unobserved variables could change firm behavior. It is possible, therefore, that our finding is because of some unobserved features that are different across the boundary, and firm behavior is very sensitive to these features. To test this concern, we conduct a placebo test in which we re-estimate our model (equation 1) after artificially moving the heating boundary to the south and north. To be specific, we moved the boundary to the north by 100km, 200km, 300km, then moved the boundary to the south by 100km, 200km, 300km. After we moved the boundary, we compare the firms within 100km, 200km, 300km, 400km around the boundary. Table 8 shows the point estimate of β_1 in regression (1) under different placebo treatments.

As shown in Table 8, for the most part when the heating boundary treatment is artificially moved north or south, the statistical significance of the public heating effect disappears. This lack of significance in the vast majority of the specifications supports our conclusion that the heating boundary does affect green innovations and it is not a spurious result.

Table 8 Results of Placebo Test

		Dependent variable: Green Innovations per Billion RMB of Assets			
		100km	200km	300km	400km
North 100km	Point estimate	-0.998	0.659	0.179	0.222
	p-value	0.535	0.196	0.579	0.367
North 200km	Point estimate	0.119	0.444	0.705	0.587
	p-value	0.780	0.112	0.003	0.006
North 300km	Point estimate	0.862	0.338	0.299	0.521
	p-value	0.008	0.209	0.143	0.002
South 100km	Point estimate	-0.080	0.187	-0.293	0.049
	p-value	0.763	0.417	0.305	0.808
South 200km	Point estimate	0.182	0.110	0.174	0.018
	p-value	0.450	0.649	0.361	0.915
South 300km	Point estimate	1.830	1.041	0.391	0.247
	p-value	0.011	0.008	0.089	0.251

The point estimate and p-value of β_1 in regression (1) under different placebo treatments using the samples within different ranges around the boundary are reported here

3.6.5 Balanced dataset

As seen in Table 1, the number of firms within 100km of the boundary and on the north side is almost 3 times that number on the south side, and the average firm size as measured in total assets was significantly larger to the north across all ranges. It is possible, therefore, that the treatment effect is due at least in part to systematic firm differences on the two sides of the boundary. To address this concern, we re-estimate our model using a balanced sample, matching each firm on the south with a similar firm to the north based on the firms' assets and industry codes. The balanced dataset is created using a nearest-neighbor matching algorithm without replacement based on the estimated propensity score (Table 9), which captures the probability of being treated as a function of a set of firm characteristics, and Mahalanobis distance matching (Table B.2).[11]

Table 9 and Table B.2 show the results of the model estimated with the balanced datasets. A statistically significant treatment effect of public heating on green innovation is still found for all but the 200 km range in Table B.2. The magnitude of the estimated effect changes by a small amount within 100 km increasing from 1.765 to 1.859 in Table 9 and decreasing to 1.473 when Mahalanobis distance matching is used (Table B.2).

Table 9 The Effect of Public Heating Using a Balanced Dataset

	Dependent variable: Green Innovations per Billion RMB of Assets			
	100km[a]	200km	300km	400km
(Intercept)	3.113 ***	1.794 *	1.776 ***	1.937 ***
	(0.890)	(0.830)	(0.508)	(0.451)
Heating	-1.859 **	-1.389 **	-0.921 *	-1.329 ***
	(0.640)	(0.535)	(0.368)	(0.338)
distance_running	0.018	0.002	0.002	0.003 ***
	(0.011)	(0.003)	(0.001)	(0.001)
heating_distance	-0.022	0.001	-0.002	-0.001
	(0.014)	(0.005)	(0.002)	(0.001)
RoNA	-0.438	0.684	0.315	0.092
	(1.782)	(0.967)	(0.428)	(0.183)
EpS	0.178	0.074	0.213	0.367 **
	(0.449)	(0.224)	(0.134)	(0.131)
GRoMBI	-0.062	-0.000	-0.000	-0.002
	(0.043)	(0.000)	(0.000)	(0.003)
NoD	-0.086	-0.010	-0.021	-0.022
	(0.078)	(0.079)	(0.045)	(0.040)
Observations	98	302	758	1016

[a] 100km regression uses only the data of firms located in the cities within 100km around the boundary, so on and so forth. Standard errors are reported in parenthesis. *** p < 0.001; ** p < 0.01; * p < 0.05

[11] The variables used to calculate the propensity score and the Mahalanobis distance are firm's total asset and the industry they belong to. In Appendix Table A.2 we also show the regression result using dataset created using Mahalanobis distance matching.

3.7 Conclusion

In this paper, we use China's public heating policy as a quasi-experiment to investigate the impact of exogenous pollution differences on green innovation behavior. We find that firms located in cities with an exogenous source of heavy pollution tend to have less green innovation. After multiple robustness and specification tests, we believe that the data strongly imply a causal effect: being north of the boundary, where pollution levels are higher, leads firms to adopt less green innovation. Firms located in the heating areas report roughly 1 less green innovation per billion RMB of assets. This is a substantial difference given the average number of green innovations per billion RMB of assets of northern firms is 0.641; the estimated effect represents a more than two-fold increase.

Although the robustness tests provide evidence of a non-trivial impact from exogenous pollution source on green innovation, our results do have some limitations. One limitation of our analysis is that the Huai River policy also creates exogenous changes in the economic environment in addition to the exogenous difference in pollution. Most directly, there is a difference in the availability and cost of heating. The family heating cost per unit (RMB/m^2) in the south is 2.2 times that in the north (Wei et al. 2014). However, on average the total heating cost for each family per year in the north is 3-10 times of the cost in the south due to the longer heating season in the north.[12] Hence, people in the south pay more for each unit of heating, but may pay less in total, so it seems unlikely that this alone would have a significant effect on firm behavior. Moreover, while

[12] A comparison between the cost of heating in the south and north: the heating cost in the north is proximately 10 times of the cost in the south.

Source: https://finance.sina.com.cn/china/20140102/162117824915.shtml?from=wap.

households are provided heating through the policy, firms do not receive subsidized heating in the north through the policy. The differences in heating costs and availability for the public could affect firms' green innovation practices, though we believe that is quite unlikely.

While we are unable to test the causal mechanism behind our results with the data that we have available, we can speculate on what might be causing the effect. One explanation of such effect is that air pollution impacts labor force movement in China, especially for highly educated workers, who tend to select cities with lower pollution levels (Li 2017). However, if this were the case, it seems that it would affect both green and non-green innovation. Since we do not find evidence that the treatment affects non-green innovation, our evidence does not support this hypothesized mechanism. A second possible explanation is that when pollution is exogenous to firms, green technology for a cleaner production process may be less attractive since it has a minimal discernible effect on the environment or there is little social pressure to innovate in ways that reduce environmental harm. A third potential mechanism is that, due to the exogenous pollution source, society may have difficulty to find out the pollution from the firms, so regulations on polluting firms are not as strictly enforced as in the south without the exogenous pollution source (Pargal and Wheeler, 1996). In the second and third case, the exogenous change in pollution would only affect firms' choice with regard to investments in green technology. Our findings, therefore, are more consistent with the second and third mechanisms. Future research should test for the presence of this effect in other situations and explore the mechanisms that are behind the effect.

Our findings are novel because in other situations it has been found that lower environmental quality leads to more stringent environmental regulations, and stringent regulations lead to more green innovations (Lanoie et al. 2011; Popp 2019). What distinguishes our case is that a major part of pollution in the northern cities does not come from the firms, but a single exogenous source. Thus, we have a situation where northern firms, which are in a more polluted environment through no fault of their own, adopt fewer green innovations. While it is highly speculative to generalize our results from the current setting, these findings suggest that there may be virtuous circles in which better environmental conditions lead firms to adopt technology that makes things even better.

CHAPTER IV THE ESTIMATION OF THE COST OF A SHORT-PERIOD ENVIRONMENTAL REGULATION

4.1 Introduction and Motivation

As many studies point out, air pollution may lead to a serious public health problem (Abe & Miraglia, 2016; Kan & Chen, 2004), but the air pollution problem persists in reality, like in China, India. When pollution levels are high, consumers demand more environmental regulations to make firms reduce pollution (Cai & Li, 2018). Nonetheless, the fact that high pollution levels persist suggests that the perceived cost of pollution reduction in these countries may be higher than its perceived benefit.

In this paper, we use a natural experiment to analyze the cost of a sharp and significant reduction in air pollution in China. During the 2016 G20 Hangzhou summit, the local provincial government applied stringent air pollution regulations. Studies have shown that, during the policy, there was a significant improvement in local air quality (M.-W. Wang et al., 2018; Ye Wang & Liao, 2020; Wu et al., 2019). In this study, we make use of this policy to investigate the cost to firms of this pollution-reducing policy.

We use quarterly firm performance data, which provide many variables on firms' operation. However, the policy period is short, from August 24th to September 6th in 2016. So, the treated firms have only one observation that is directly affected by the policy, from the quarter when the policy was implemented. Therefore, we cannot use traditional econometrics to estimate the policy effect, as the data is very unbalanced. Instead, we use the synthetic control method, which generates a control group from a pool of untreated units, and the method could take advantage of the rich dataset. We show that using a machine learning approach could estimate the treatment effect based on a large but unbalanced dataset.

Since the cost is induced by a short-time policy, firms generally do not have the time to adjust their investment and production. Therefore, such cost may not be indicative of the costs of the policy if it were sustained for a longer, allowing firms to reoptimize. We will discuss the meaning of such costs for environmental policy in the discussion section of the paper.

4.2 Literature Review

There are many different approaches to estimate costs of environmental regulations. Marten et al. (2019) use a numerical computable general equilibrium model to study the cost of regulations in different sectors, using different abatement technologies, and under a variety of regulatory designs. Using an econometrically estimated structural model of firm behavior, Berman and Bui (2001) study the impact of environmental regulation on the productivity of oil refiners, and Marks (2018) estimates the abatement cost of methane emissions from the natural gas industry. Using a stochastic linear programming model, Schinas and Stefanakos (2012) study the cost of environmental regulation on ship operation. Finally, Blackman et al. (2018) use contingent valuation to evaluate the cost of an environmental regulation reducing air pollution at the individual level, in which they design a program that could exempt people from the regulation and ask their willingness-to-pay for the program. All the previous studies are based on regulations that last for a long period, so they will have enough observations in the data to estimate the cost. In our case, the policy only lasted for a short period, which leads to a very limited data. One of our contributions is to show that using the synthetic control method we could estimate the cost of environmental policy based on a limited dataset.

Another contribution of this study is that it studies a rather extreme reduction in pollution. Typically, environmental policies do not seek to eliminate nearly all pollution, since it could be very costly. Even if the local government implements such policy, the policy would not last long. Hence, empirical cost estimation studies cannot estimate how much it would cost to eliminate all pollution. In our case, we are able to look at a brief intervention that sought to eliminate a much greater share of the pollution. Hence, it is an opportunity to look at a part of the cost curve that is typically not observed in practice.

4.3 Policy background

The 2016 G20 Hangzhou Summit lasted from September 4th to 5th, but the environmental regulation lasted from August 24th to September 6th. The policy announcement was made on May 11th, 2016. The policy shut down all the firms in the area during the policy period. The policy has 3 regulatory zones: core zone, stringent zone, and control zone. For simplicity, we call them Tiers 1, 2, and 3 respectively, with Tier 1 being the most stringent zone. There are several differences in regulation among different regulatory zones. First, the frequency and strength of water cleaning varied across different regulatory zones. Second, the transportation that generates dust was banned in the Tier-1 zone, but restricted in the Tier-2 and Tier-3 zones. Thirdly, the outside operation in construction sites was banned in the Tier-1 and Tier-2 zones, but restricted in the Tier-3 zone. These differences in regulation provide us the opportunity to investigate the policy effect at different tiers.

Since firms were shut down during the policy period, production is stopped in all three zones. Our first question is to what degree this policy would reduce affected firms' profit? Since firms' operation is interrupted, that should lead to a reduced profit. Our second question is, how did this short-period policy affect firms' operations? Since the policy announcement was made three months before its implementation, firms may prepare for it. Therefore, we could investigate the policy effect using data on profit, revenue, cost, inventory, etc.

4.4 Data

Based on the policy implementation, only the firms in Zhejiang province, where city Hangzhou is, were treated by the policy, firms in other provinces were not. This provides a quasi-experiment in which firms in Zhejiang are the treatment group while firms in the provinces adjunct to Zhejiang are the control group.

The synthetic control method uses a large dataset to construct a data-driven control group (Abadie et al., 2011; Alvarez & Argente, 2020; Dustmann et al., 2017). As it is a machine learning approach, it is also good at using rich past data to predict the future movement of the dependent variable (Mair et al., 2000), which is a better fit for our purpose. In our case, the policy only lasted for 2 weeks, from August 24th to September 6th, and the data are quarterly. Therefore, the policy happened and ended within 2016 Q3, and there is only one observation that got treated for each firm.

To use synthetic control properly, we construct a large dataset using data from listed firms on the Shanghai Stock Exchange. Our variables are from the balance sheet and income statement of the listed firms. The dataset includes 1057 firms in the control group in different cities, and 272 firms in the treatment group, and 202 variables. All of our data were obtained from the China Stock Market & Accounting Research Database (CSMAR), and our data are quarterly between the 4th quarter in 1990 and the 1st quarter in 2021.

The treated group in our dataset includes all the firms affected by the policy in Zhejiang province, and we used listed firms in Shanghai as our control groups, which leads to 131 firms in the control group, since Shanghai is the closest developed city to Hangzhou, and they similar economy. According to China's National Bureau of Statistics, in 2020, the GDP per capita in Shanghai was 155,768 Chinese yuan, and 136,617 China yuan in Hang Zhou. Using the control group based on the firms from a similar area to where the treated firms located at can help us to reduce the computation load and fast our process to explore the research question. We could use the abundant unused data to improve our estimation once after. After data cleaning in which we removed the variables that have too many missing values, and select the time range based on the treated group, we have 216 firms in the treated group consisting of 42, 126, and 48 firms in Tier-1, 2, 3 zones respectively. The data range from 2004 Q1 to 2021 Q1.

4.5 Methods

Our model is an application of the synthetic control method based on Abadie et al. (2010). For each treated firm, the model identifies a weight vector $W = (w_1, w_2, ..., w_N)$, where N is the number of firms in the control group, of the synthetic control estimated through:

$$\left\| X_1 - X_0 W \right\| = \left(\sum_{h=1}^{k} v_h \left(X_{h1} - w_2 X_{h2} - \cdots - w_{N+1} X_{hN+1} \right)^2 \right)^{1/2}$$

where, X_1 is the variables of the treated firm, X_0 is the variables of the firms in the control group, v_h is a non-negative constant, k is the number of variables.

The treatment effect is estimated through:

$$Y_{1t} - \sum_{n=1}^{N} w_n^* Y_{nt}$$

where, Y_{1t} is the profit of the treated firm, Y_{nt} is the profit of the firms in the control group. The initial interest for the dependent variable is profit. However, since we have a rich dataset, we could investigate the treatment effect from many aspects, like revenue, cost, production, etc. The treatment effect is estimated as the difference between the synthetic control and the treatment group during the treatment period.

Since we have multiple treated units, to estimate the aggregate treatment effect, we first calculate the average of all the treated firms based using a weighted average based on the revenue of each firm for a given period. After we build this representative firm, we use that single firm as a treated firm in the synthetic control model and use all the firms in the control group to construct the synthetic control for the representative firm.

After we have the representative firm, we will use the synthetic control method to estimate the counterfactual movement of the representative firm in the treatment period. So, we can estimate the impact of the policy on the treated firms' profit, as a cost of the policy.

4.6 Overall treatment effect

After running the model, Table 10 reports the mean of some selected variables before the treatment, including the dependent variable operating profit, other variables are predictors. Columns 1 and 2 are the mean of the variable between 2005 Q1 and 2016 Q2, since the treatment happened in 2016 Q3; column 3 are the mean of all the 132 firms in the sample, including the representative firm and all the control firms. Based on columns 1 and 2, the difference between the firm's actual data and the synthetic control is small.

Table 10 Means of Selected Pretreatment Characteristics Before the Treatment

Variable	Representative Firm	"Synthetic" Representative Firm	Sample Mean
Unit: Billion China Yuan	(1)	(2)	(3)
Total Operating income	11,721.0	11,712.9	5,447.4
Total Operating cost	11,330.4	11,330.4	5,194.7
Operating tax and additions	92.4	92.4	80.6
Operating profit	590.3	590.3	353.2
Income before tax	622.6	622.8	394.7
Net income	491.9	491.9	315.9
Net income attributable to ordinary equity holders of the parent	415.7	415.8	256.4

Note: Numbers in the table are the mean of the variable between 2005 Q1 and 2016 Q2, the sample mean is the mean of all the 132 firms in the sample, including the representative firm and all the control firms.

Table 11 Top 16 Weights Used to Construct the Synthetic Control for the Representative Treated Firm

Weights	Stock Code	Weights	Stock Code
0.161	600822	0.008	600009
0.060	600741	0.008	601607
0.045	600837	0.007	600500
0.021	600606	0.007	600655
0.019	600170	0.006	000571
0.016	600019	0.006	002048
0.010	600642	0.006	600061
0.009	600827	0.006	600072

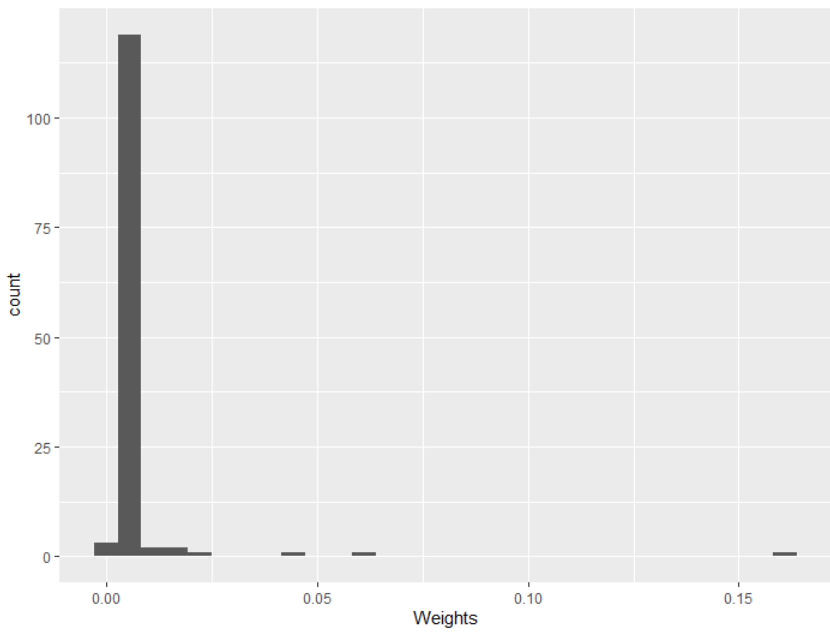

Figure 9 The histogram of the weights on control firms

Table 11 and Figure 9 show the weight distribution used to construct the synthetic control for the representative firm. While the sum of the weight equal to 1, firm 600822 contributes the most, and almost all the firms in the control group received a small weight. Most of the firms have weights less than 1%; only 2 firms received 0 weight. Since most of the firms have positive weights, they all contribute to the construction of the synthetic control.

Figure 10 shows the paths of the operating profit of the representative firm and the synthetic control from 2005 Q1 to 2020 Q1. Figure 11 shows the gap between the firm and the synthetic control. In the pre-treatment period, there is a large difference between the representative firm and the synthetic control in the pretreatment period. This indicates the pretreatment fitness could use some improvement. In the policy period, there is a increase in the profit of the representative firm, but the magnitude of the increase is similar to the maximum gap in the pretreatment period, which suggests that the treatment effect is positive and potentially insignificant. In Table 12, we report the number of the gap between the firm and the synthetic control between 2014 and 2017.

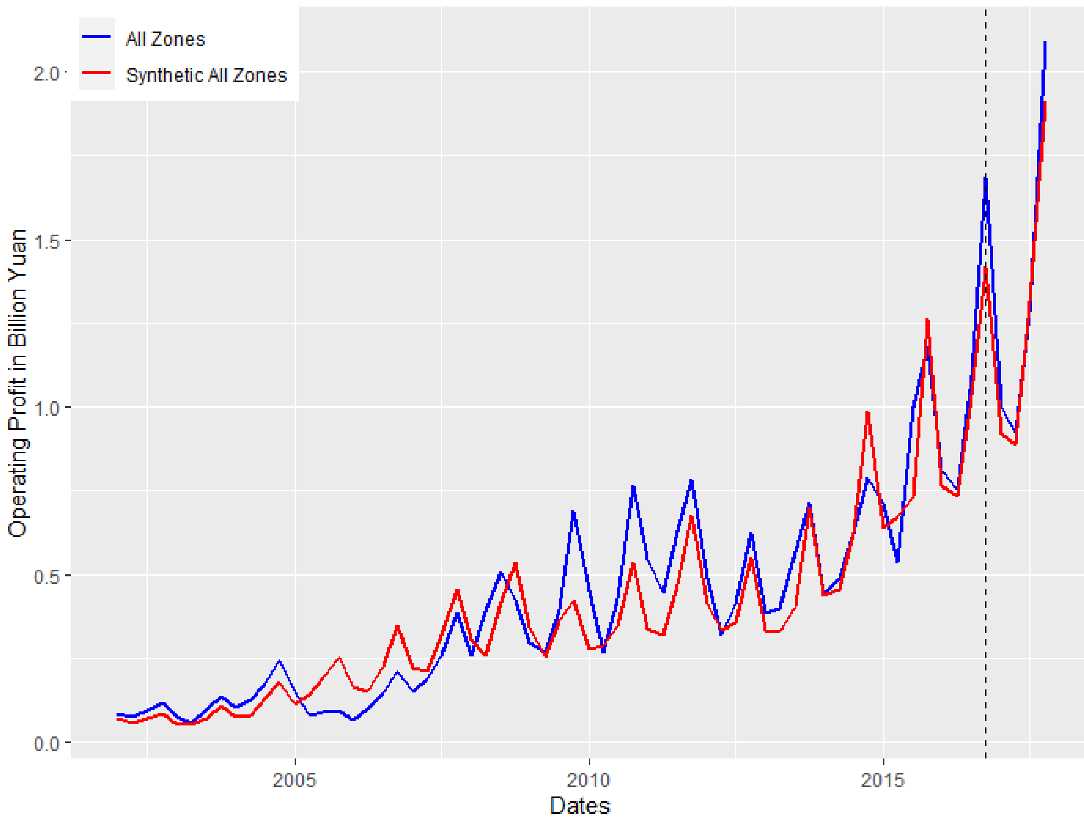

Figure 10 The paths of the representative firm and the synthetic control. The dashed line shows the time when the policy was implemented.

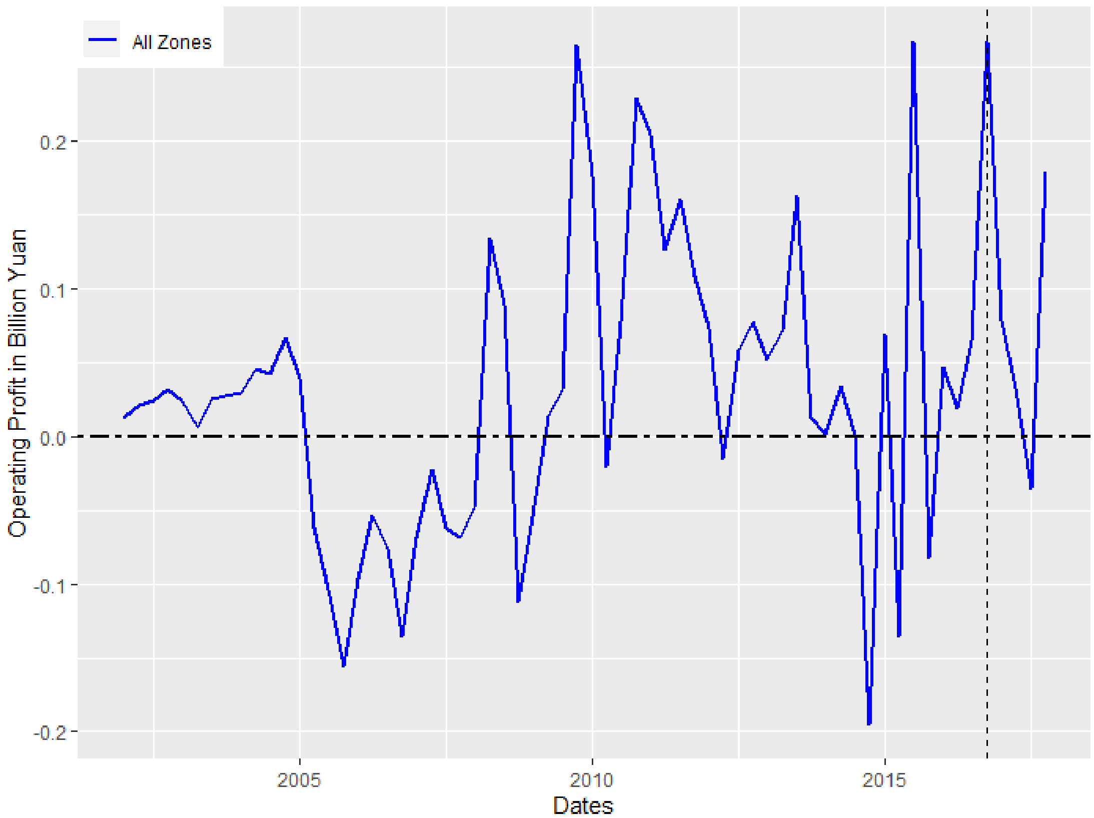

Figure 11 The gap between the representative firm and the synthetic control. The dashed line shows the time when the policy was implemented.

Table 12 Gaps Between the Profits of the Representative Firm and the Synthetic Control Between 2014 and 2017

Date	Gap	Date	Gap
2014Q1	0.001635	2016Q1	0.046873
2014Q2	0.034308	2016Q2	0.018622
2014Q3	-0.00021	2016Q3	0.064297
2014Q4	-0.19547	2016Q4	0.267778
2015Q1	0.068872	2017Q1	0.078801
2015Q2	-0.1356	2017Q2	0.032313
2015Q3	0.26761	2017Q3	-0.03496
2015Q4	-0.08213	2017Q4	0.179106

To test if the treatment effect is insignificant, I applied a placebo test, which is suggested in (Abadie, 2021). To implement the placebo test, I pick 1 firm in the control group as the treated firm, and use the remaining unpicked firms in the control as the new control group, then I run the model to estimate the treatment effect. After I run the process for all the firms in the control group, I remove the top and bottom 5% of the result for each period. Figure 12 shows the results. Based on the placebo test, the overall treatment effect is trivial, suggesting the policy has no impact on treated firms' profit.

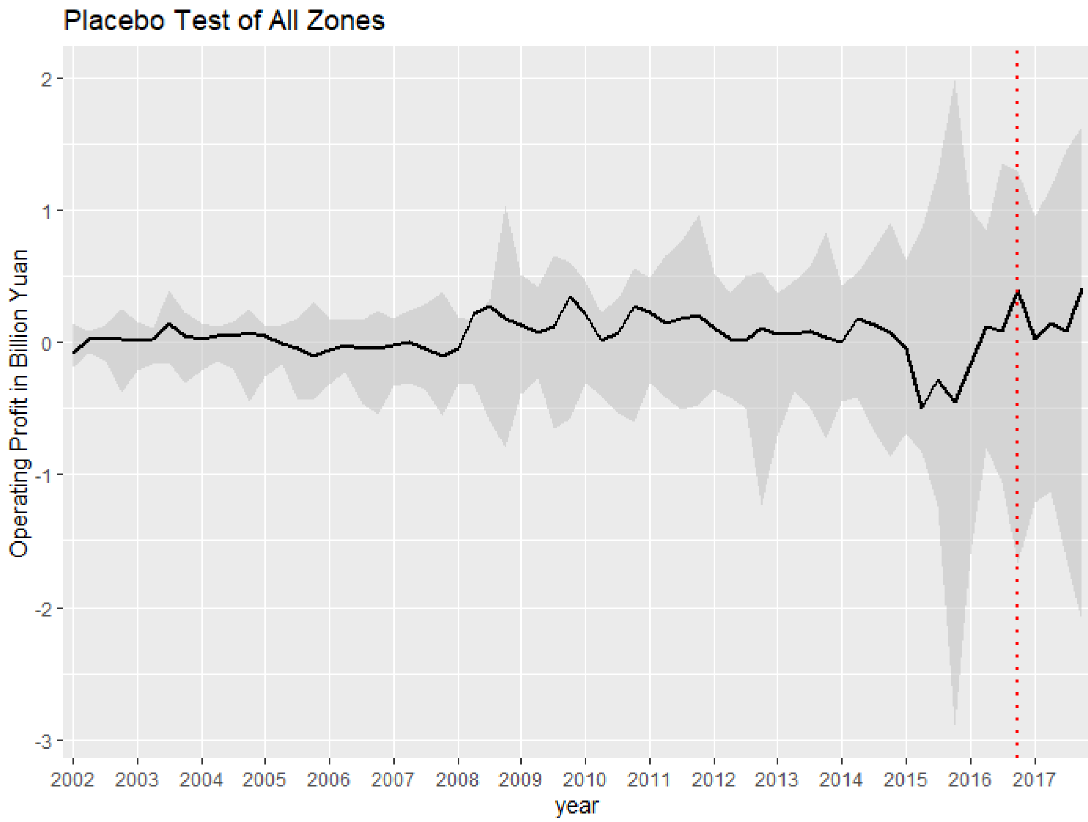

Figure 12 The placebo test of the all zones. The solid black line shows the gap between the representative firm of the Tier-1 zone and the synthetic control. The grey area shows the range between the max and min of the 90% of the placebo test results. The dashed line shows the time when the policy was implemented.

4.7 Treatment effects on different zones and the placebo test

Next, we show the results of different zones. Figure 13 shows the paths of the representative firm from the aggregation of all the treated firms in the Tier-1 zone and its synthetic control. In the policy period, there is hardly any difference between the movement of the two.

We use a placebo test approach to evaluate the statistical significance of the treatment effect as follows. First, we randomly pick firms from the 131 firms in the control group, and the number of firms picked is the same as the number of firms in the treated group. Since the Tier-1 zone has 42 firms, we randomly draw 42 firms from the control group. Then, we aggerate these randomly picked 42 firms group into a single placebo representative firm as was done for the treated firms. Secondly, we run our synthetic control model using the remaining unpicked firms in the control group as the control group for the placebo test and get the result on the gap between the synthetic control and the placebo representative firm. In this case, there are 89 firms in the control group. We then repeat these two steps 100 times, so we have 100 placebo test results. For each time period, we calculate the difference between the placebo representative firm and the synthetic control and remove the top 5% and bottom 5% of the results. We plot the range for the remaining 90% of the differences, together with the estimation of the treatment effect for the treated representative firm for the firms in the Tier-1 zone. Figure 14 shows the result. Based on this placebo test, the treatment effect on firms in the Tier-1 zone is not significantly different from no treatment.

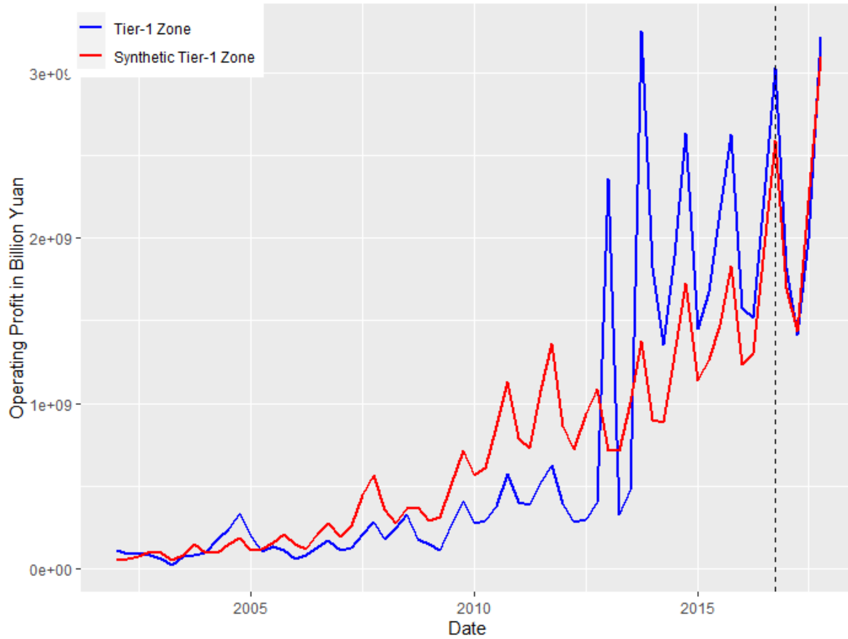

Figure 13 The paths of the representative firm of Tier-1 zone and the synthetic control. The dashed line shows the time when the policy was implemented.

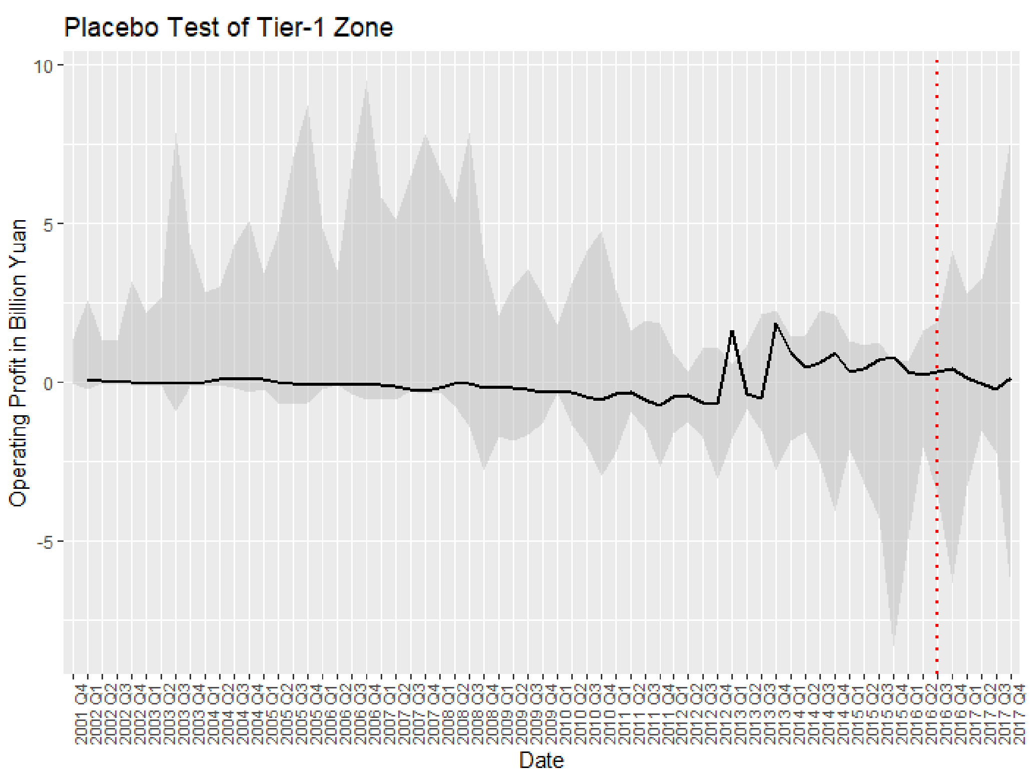

Figure 14 The placebo test of the Tier-1 zone. The solid black line shows the gap between the representative firm of the Tier-1 zone and the synthetic control. The grey area shows the range between the max and min of the 90% of the placebo test results. The dashed line shows the time when the policy was implemented.

Figure 15 shows the paths movement of the Tier-2 zone, and Figure 16 shows the placebo test of the Tier-2 zone. Although the placebo result for the Tier-2 zone looks nonsensical, in the policy period, there is a decrease in the profit of firms in the Tier-2 zone, and such decrease is lower than the minimum value of the 90% placebo test range. This implies that the policy effect on the firms in the Tier-2 zone may not be trivial, and has a negative impact on treated firms' profit. Due to the poor pretreatment fitting and seasonality effects, such impact needs further investigation.

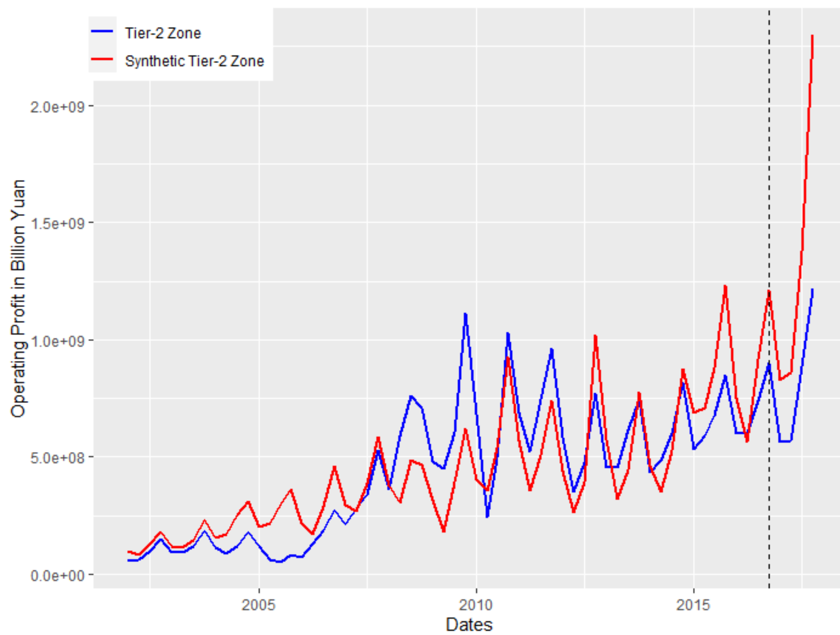

Figure 15 The paths of the representative firm of the Tier-2 zone and the synthetic control. The dashed line shows the time when the policy was implemented.

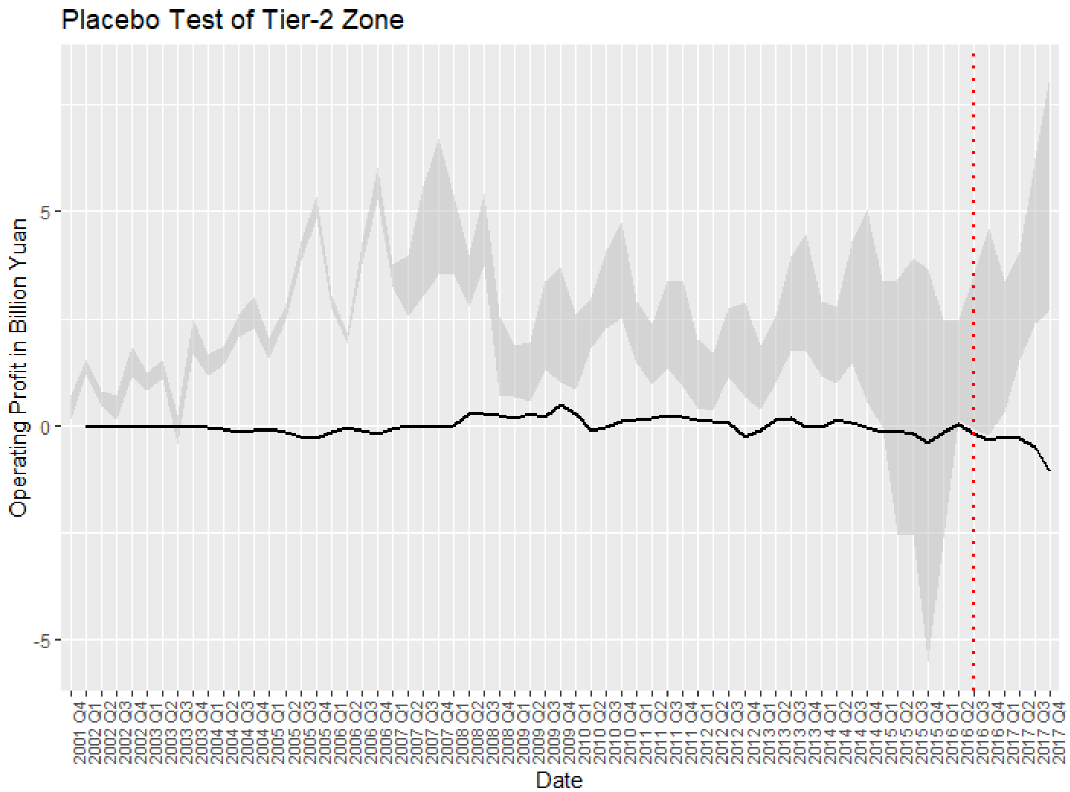

Figure 16 **The placebo test of the Tier-2 zone. The solid black line shows the gap between the representative firm of the Tier-2 zone and the synthetic control. The grey area shows the range between the max and min of the 90% of the placebo test results. The dashed line shows the time when the policy was implemented.**

Figure 17 shows the paths movement of the Tier-3 zone, and Figure 18 shows the placebo test of the Tier-3 zone. Based on these results, there is a small increase in profit in the policy period, but such change is not different from no treatment. So, the policy has a trivial impact on the firms in the Tier-3 zone.

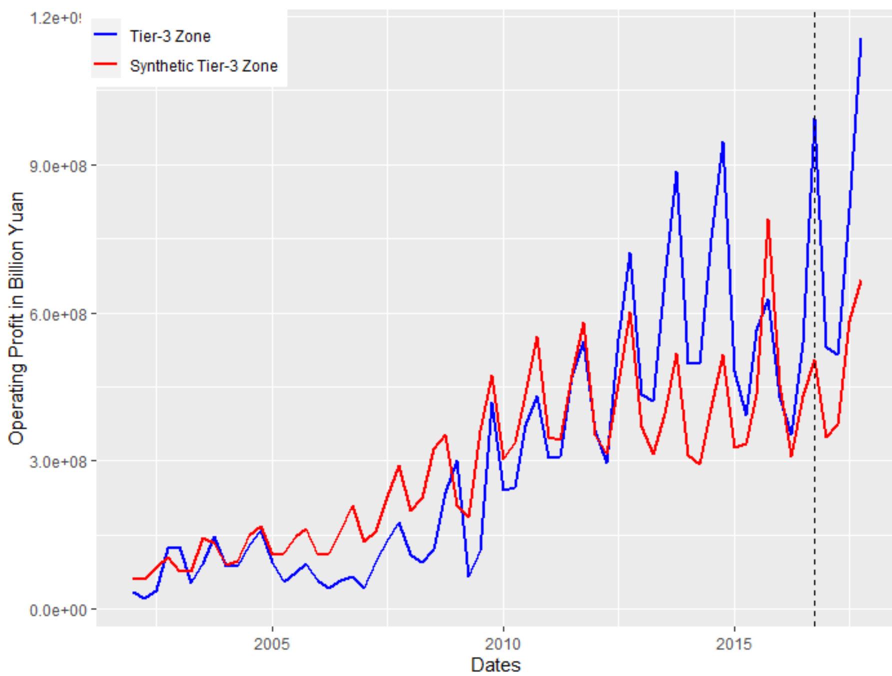

Figure 17 The paths of the representative firm of the Tier-3 zone and the synthetic control. The dashed line shows the time when the policy was implemented.

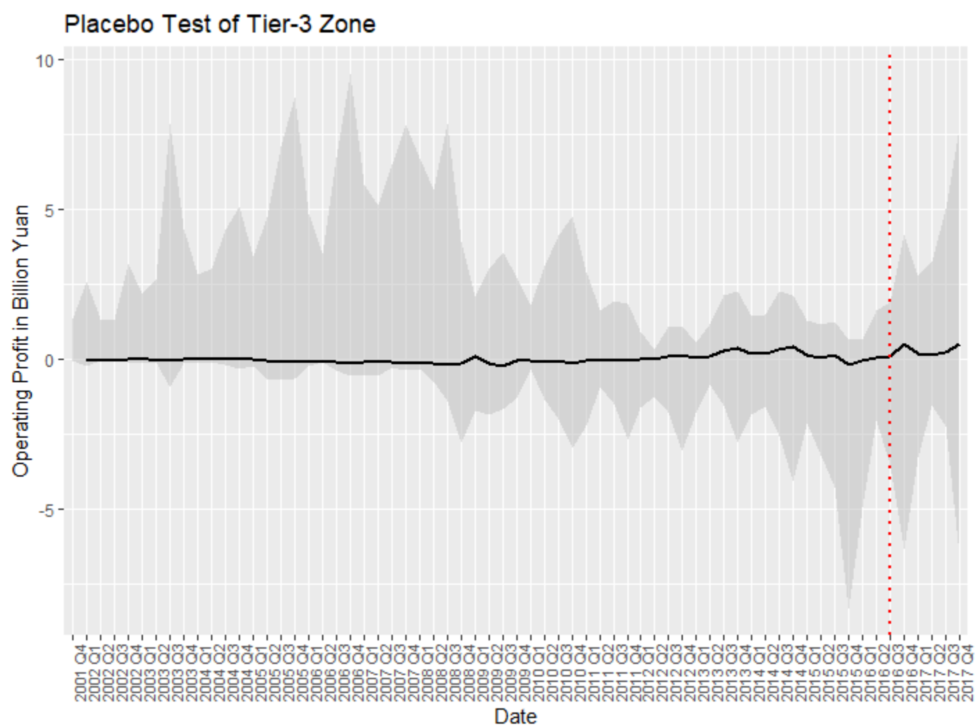

Figure 18 The placebo test of the Tier-3 zone. The solid black line shows the gap between the representative firm of the Tier-3 zone and the synthetic control. The grey area shows the range between the max and min of the 90% of the placebo test results. The dashed line shows the time when the policy was implemented.

Based on the results on different zones, we find that the policy effect shows heterogeneity across different zones. This could be because the industrial structures are different, and requires further investigation.

4.8 Discussion and Conclusion

In this paper, we use the synthetic control method to estimate the cost of an environmental policy based on a limited dataset, and show that the synthetic control method is an appropriate method to estimate the cost from a short-period policy. Based on the placebo test, the policy has insignificant impact on affected firms' profit. This insignificance might be because the quarterly data are not enough to capture the shock in two weeks. Based on the results on different zones, we find that the policy effect shows heterogeneity across different zones. This could be because the industrial structures are different, and requires further investigation.

The advantage of our approach is that, the synthetic control method could use an unbalanced dataset and a limited number of treated observations. It is effective to investigate the impact of a short-term policy, not only on environmental policies, but also on other economic policies, like the trade war between the U.S. and China between 2018 and 2019.

One future line of work is that, we could use firms in other cities to add more to the control group. Since we have performance data on firms in different cities, using more data could help the estimation. Another future line of work is that, since the variables include many aspects of the firms, we could investigate other impacts of the policy on firms such as revenue, cost, and inventory. Thus, we could tell a detailed story of the policy impact.

In addition, we could discuss the meaning of the estimated cost, since the cost of a short-term shut-down does not mean the cost of a long-term shut-down. We could also compare our results to the studies on the willingness to pay for better air quality in China (Sun et al., 2016), to discuss the possible reduction in air pollution, since if the cost is larger than the benefit, no improvement could be achieved.

CHAPTER V CONCLUSION

This chapter will conclude the research by summarizing the key findings of each chapter and discussing the contributions of the research. Additionally, it will review limitations within the studies and suggest opportunities for future research.

This dissertation represents three essays focused on the issues that may reduce social happiness. Starting with the analysis on social connections, I presented a model that studies the relationship between social connections and wage increase. Then, I presented empirical research on the impact of exogenous pollution on green innovations. In the end, I presented the synthetic control method as an appropriate method to estimate the cost from a short-period policy.

5.1 Wage Increase and Social Connections

5.1.1 Key Findings and Contributions

My primary finding of the study is that under certain conditions, a wage increase could reduce total welfare through the reduction in social connections. My finding is consistent with the change in total social welfare in some countries. Based on Durkheim (1897/1951), Na and Hample (2016), Cornwell and Laumann (2015), people living with a lower level of social connections tend to have worse physical and mental health. If our economic policies focus on only wage and production, that will lead our societies into a lower level of social connections. My model suggests that a narrow focus on higher wages, this may result in lower levels of social connections.

5.1.2 Limitations and Future Research

The model I presented is a simple model to investigate the relationship between wage and social connections; many extensions can be envisioned. First, I need to discuss the situation of multiple players and weaken the assumption on the generation of social connections. Second, the spatial movement of immigrants from low-wage regions to high-wage regions could also affect the social connections of these immigrants. Third, in my model, social connections are generated only using the input of time; in reality, it often requires goods, like the cost of a shared meal or drink, or even durable goods that facilitate social interactions.

5.2 Exogenous Pollutions and Green Innovations

5.2.1 Key Findings and Contributions

In Chapter 3 I use China's public heating policy as a quasi-experiment to investigate the impact of exogenous pollution differences on green innovation behavior. I find that firms located in cities with an exogenous source of heavy pollution tend to have less green innovation. My findings are novel because in other situations it has been found that lower environmental quality leads to more stringent environmental regulations, and stringent regulations lead to more green innovations (Lanoie et al. 2011; Popp 2019). What distinguishes my case is that a major part of pollution in the northern cities does not come from the firms, but a single exogenous source. While it is highly speculative to generalize the results from the current setting, these findings suggest that there may be virtuous circles in which better environmental conditions lead firms to adopt technology that makes things even better.

5.2.2 Limitations and Future Research

Although the robustness tests provide evidence of a non-trivial impact from exogenous pollution sources on green innovation, my results do have some limitations. One limitation is that the Huai River policy also creates exogenous changes in the economic environment in addition to the exogenous difference in pollution. However, based on the heating cost of two sides and the availability for the public, I believe that is quite unlikely.

In addition, I am unable to identify the causal mechanism behind my results with the data that I have available; I can speculate on what might be causing the effect. Firstly, air pollution impacts labor force movement in China (Li 2017). Secondly, when pollution is exogenous to firms, green technology for a cleaner production process may have a reduced marginal return. Thirdly, due to the exogenous pollution source, regulations on polluting firms are not as strictly enforced as in the south without the exogenous pollution source (Pargal and Wheeler, 1996). Future research should test for the presence of this effect in other situations and explore the mechanisms that are behind the effect.

5.3 The Synthetic Control Method and a Short-Period Policy

5.3.1 Key Findings and Contributions

In Chapter 4 I use the synthetic control method to estimate the cost of an environmental policy based on a limited dataset and show that the synthetic control method is an appropriate method to estimate the cost from a short-period policy. The advantage of my approach is that the synthetic control method could use an unbalanced dataset and a limited number of treated observations. It is effective to investigate the impact of a short-term policy, not only on environmental policies but also on other economic policies.

5.3.2 Limitations and Future Research

Future research could benefit from using firms in other cities to add more to the control group. And I could investigate other impacts of the policy on firms. Additionally, the cost of a short-term policy could also shed light on the long-term cost. I could also compare my results to other studies to discuss the possible reduction in air pollution.

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APPENDIX A

Table 13 The table of selected notations

Notation	Meaning	Page
r_i	The resource invested into the common resource pool to make a connection with player *j* by player *i*.	6
CR	The amount of resources used by player *i* and player *j* to establish a social connection between them.	6
c_i	Player i's social connection with player *j*	6
θ_i	An exogenous parameter that determines the player *i*'s social connection preference about player *j*.	6
x_i	The consumption of player *i*.	6
m_i	The external income of player *i*.	7
r_i^T	The optimal input of resources into making a social connection with player *j* by player *i* assuming that player *j* is inputting all the resources into the pool before any allocation decision been made.	8
l_i^T	The corresponding working time of the optimal pre-decision choice of social connection input.	8
o_r	Player *j* wants player *i* to increase r_i^T by o_r amount by a compensation offer.	12
o_m	the amount of wage that player *j* pays player *i*.	12

APPENDIX B

Table B.1 Detailed Summary Statistics with p-values for t-tests of difference in means between firms on either side of the boundary

	All Firms within											
	<100 km of the Heating Boundary			<200 km of the Heating Boundary			<300 km of the Heating Boundary			<400 km of the Heating Boundary		
	No Public Heating (N=52)	Have Public Heating (N=150)	p-value	No Public Heating (N=171)	Have Public Heating (N=270)	p-value	No Public Heating (N=424)	Have Public Heating (N=487)	p-value	No Public Heating (N=659)	Have Public Heating (N=531)	p-value
The Number of Total Innovations per Firm												
Mean	27.592	12.930	<0.001	19.066	12.833	0.019	17.702	16.166	0.644	13.432	15.585	0.404
(SD)	(38.226)	(19.716)		(34.052)	(19.490)		(41.853)	(52.378)		(34.570)	(50.441)	
Min -	0.000 -	0.000 -		0.000 -	0.000 -		0.000 -	0.000 -		0.000 -	0.000 -	
Max	190.000	112.000		190.000	127.000		330.000	719.000		330.000	719.000	
The Number of Green Innovations per Firm												
Mean	6.184	4.359	0.13	6.232	4.081	0.016	5.211	5.705	0.657	4.039	5.817	0.048
(SD)	(6.033)	(7.610)		(11.779)	(6.226)		(12.564)	(18.403)		(10.728)	(18.607)	
Min -	0.000 -	0.000 -		0.000 -	0.000 -		0.000 -	0.000 -		0.000 -	0.000 -	
Max	25.000	39.000		69.000	39.000		117.000	255.000		117.000	255.000	
The number of Non-Green Innovations												
Mean	21.408	8.570	< 0.001	12.834	8.752	0.049	12.491	10.461	0.396	9.393	9.768	0.839
(SD)	(33.210)	(14.861)		(25.413)	(16.351)		(31.541)	(36.801)		(25.934)	(35.252)	
Min -	0.000 -	0.000 -		0.000 -	0.000 -		0.000 -	0.000 -		0.000 -	0.000 -	
Max	167.000	96.000		167.000	121.000		235.000	464.000		235.000	464.000	
Total Assets (unit: billions of RMB)												
Mean	5.157	15.738	0.02	9.731	13.459	0.095	9.068	11.909	0.032	7.844	11.938	< 0.001
(SD)	(4.455)	(31.388)		(13.718)	(25.283)		(16.649)	(20.913)		(14.509)	(20.469)	
Min -	1.120 -	0.462 -		0.458 -	0.423 -		0.310 -	0.112 -		0.310 -	0.112 -	
Max	18.039	194.887		74.493	194.887		122.143	194.887		122.143	194.887	

Table B.1-Continued

	All Firms within											
	<100 km of the Heating Boundary			<200 km of the Heating Boundary			<300 km of the Heating Boundary			<400 km of the Heating Boundary		
	No Public Heating (N=52)	Have Public Heating (N=150)	p-value	No Public Heating (N=171)	Have Public Heating (N=270)	p-value	No Public Heating (N=424)	Have Public Heating (N=487)	p-value	No Public Heating (N=659)	Have Public Heating (N=531)	p-value
The Number of Green Innovations per Billion RMB of Assets												
Mean (SD)	1.638 (1.800)	0.641 (1.089)	< 0.001	1.472 (2.808)	0.788 (1.341)	< 0.001	1.265 (2.542)	0.846 (1.553)	0.003	1.025 (2.197)	0.954 (2.183)	0.587
Min - Max	0.000 - 8.776	0.000 - 5.828		0.000 - 25.839	0.000 - 7.902		0.000 - 25.839	0.000 - 11.654		0.000 - 25.839	0.000 - 27.675	
The Number of Non-Green Innovations per Billion RMB of Assets												
Mean (SD)	3.418 (4.237)	1.577 (3.325)	0.002	2.848 (5.395)	2.300 (8.368)	0.471	2.811 (5.126)	1.823 (6.456)	0.016	2.330 (4.634)	1.716 (6.187)	0.06
Min - Max	0.000 - 20.718	0.000 - 28.046		0.000 - 33.341	0.000 - 94.763		0.000 - 33.341	0.000 - 94.763		0.000 - 33.341	0.000 - 94.763	
Return on Net Assets												
Mean (SD)	0.080 (0.076)	0.035 (0.133)	0.024	0.057 (0.196)	0.025 (0.229)	0.154	0.061 (0.162)	0.036 (0.211)	0.061	0.042 (0.472)	0.036 (0.208)	0.799
Min - Max	-0.469	-1.228		-2.312	-3.408		-2.312	-4.545		-11.669	-4.545	
Earnings per Share												
Mean (SD)	0.400 (0.427)	0.254 (0.610)	0.123	0.360 (0.797)	0.232 (0.537)	0.052	0.381 (0.675)	0.265 (0.558)	0.006	0.353 (0.586)	0.266 (0.550)	0.012
Min - Max	-2.544	-5.868		-8.573	-5.868		-8.573	-6.061		-8.573	-6.061	

Table B.1-Continued

	All Firms within											
	<100 km of the Heating Boundary			<200 km of the Heating Boundary			<300 km of the Heating Boundary			<400 km of the Heating Boundary		
	No Public Heating (N=52)	Have Public Heating (N=150)	p-value	No Public Heating (N=171)	Have Public Heating (N=270)	p-value	No Public Heating (N=424)	Have Public Heating (N=487)	p-value	No Public Heating (N=659)	Have Public Heating (N=531)	p-value
Distance to the Heating Boundary (unit: kilometers)												
Mean (SD)	37.542 (16.800)	53.187 (23.999)	< 0.001	129.112 (67.519)	93.957 (51.748)	< 0.001	198.816 (73.799)	154.824 (80.559)	< 0.001	251.963 (93.328)	170.332 (92.337)	< 0.001
Min - Max	13.840 - 71.229	11.237 - 99.271		13.840 - 194.598	11.237 - 195.823		13.840 - 290.990	11.237 - 298.302		13.840 - 383.885	11.237 - 398.232	
Growth Rate of Main Business Income (unit: 100%)												
Mean (SD)	0.719 (4.598)	0.499 (3.232)	0.714	3.941 (48.348)	0.003 (0.024)	0.191	1.573 (30.517)	0.028 (0.398)	0.276	1.006 (24.397)	0.026 (0.381)	0.366
Min - Max	-32.847	-38.457		-594.125	-0.385		-594.142	-7.458		-594.142	-7.476	
Number of Directors												
Mean (SD)	9.020 (1.199)	9.014 (2.186)	0.985	8.735 (1.018)	8.884 (1.880)	0.37	8.625 (1.198)	8.897 (1.972)	0.019	8.535 (1.438)	8.813 (1.957)	0.007
Min - Max	5.000 - 11.000	5.000 - 15.000		5.000 - 11.000	5.000 - 15.000		5.000 - 12.000	5.000 - 17.000		5.000 - 15.000	5.000 - 17.000	

Note: The p-value is for the t-test for the difference of means between the treated (public heating) and control groups.

Table B.2 The Effect of Public Heating from a Balanced Dataset from Mahalanobis Distance Matching

	Dependent variable: Green Innovations per Billion RMB of Assets			
	100km	200km	300km	400km
(Intercept)	3.381 **	2.251 *	2.203 ***	2.025 ***
	(1.214)	(0.879)	(0.576)	(0.460)
Heating	-1.905 *	-0.948	-0.673	-1.322 ***
	(0.890)	(0.574)	(0.417)	(0.343)
distance_running	0.017	0.002	0.002	0.003 **
	(0.015)	(0.003)	(0.002)	(0.001)
heating_distance	-0.007	-0.002	-0.003	-0.001
	(0.019)	(0.005)	(0.002)	(0.001)
RoNA	-0.752	0.425	0.463	0.093
	(2.208)	(0.589)	(0.460)	(0.187)
EpS	-0.182	0.158	0.186	0.376 **
	(0.533)	(0.207)	(0.145)	(0.129)
GRoMBI	-3.165	-0.002	-0.002	-0.002
	(4.557)	(0.004)	(0.004)	(0.004)
NoD	-0.104	-0.061	-0.068	-0.033
	(0.111)	(0.085)	(0.052)	(0.041)
Observations	98	302	758	1016

APPENDIX C

Detailed data description on green innovation data

Our green innovation data are from the Baiten company, which is a company that provides patent service, searching, and consulting services.[13] On their website, https://www.baiten.cn/, one can search for the patent data of China and other countries. This paper uses only Chinese patent data. According to the user manual,[14] the patent data are from China National Intellectual Property Administration,[15] thus every patent filed in that bureau will be included as a patent count.

We first obtained the listed firms from China Stock Market & Accounting Research Database (CSMAR); there are 997 firms on the list. We also used the firm performance data from CSMAR. The location data used are the registration addresses from CSMAR. These are firm-level data, not plant-level data. The full list of firms is included in the dataset provided on Github.

[13] Here is the company's registration page:

https://data.cyzone.cn/content/dbase/company?cat_id=637&content_id=1312510

[14] The user manual only has Chinese version, and can be downloaded here:

https://www.baiten.cn/download?name=user_manual.pdf

[15] The English website of China National Intellectual Property Administration:

http://english.cnipa.gov.cn/

For each listed firm, two searches were carried out, first to identify the firm's patents that can be characterized as green innovations between 2013 and 2017, and then for all patents over this period. To gain access to the data, the Baiten company requires one to register using a Chinese phone number. Therefore, those who do not have a Chinese phone number cannot download the data through the website.

For example, for the Datang International Power Generation Co., Ltd., we carried out the following search from the search window at https://www.baiten.cn/:

cpa:(大唐国际发电股份有限公司) AND (ad:[2013 TO 2017]) AND (碳 or 环境 or 环保 or 节能 or 生态 or 废 or 清理 or 清洁 or 绿色 or 回收 or 能耗 or 循环 or 净化 or 脱硫 or 节约资源 or 无污染)

There are different parts of the search code:

- the name of the company searched: "大唐国际发电股份有限公司";
- the time range searched: "2013 TO 2017"; and
- the types of patents to be reported

Our keywords to identify green innovation patents are primarily based on Li et al. (2018) and Li et al. (2017), patents in the following categories are included in the list of green innovations: carbon (碳), environment (环境), environmental protection (环保), energy-saving (节能), ecology (生态), waste (废), clean (清理, 清洁), green (绿色), recycling (回收), energy consumption (能耗), natural cycling (循环), purification (净化), desulfurization (脱硫), resource-saving (节约资源), pollution-free (无污染).

The number of green innovations for each firm are then found by clicking on “专利趋势分析” (Patent trend analysis), revealing an image like the one below:

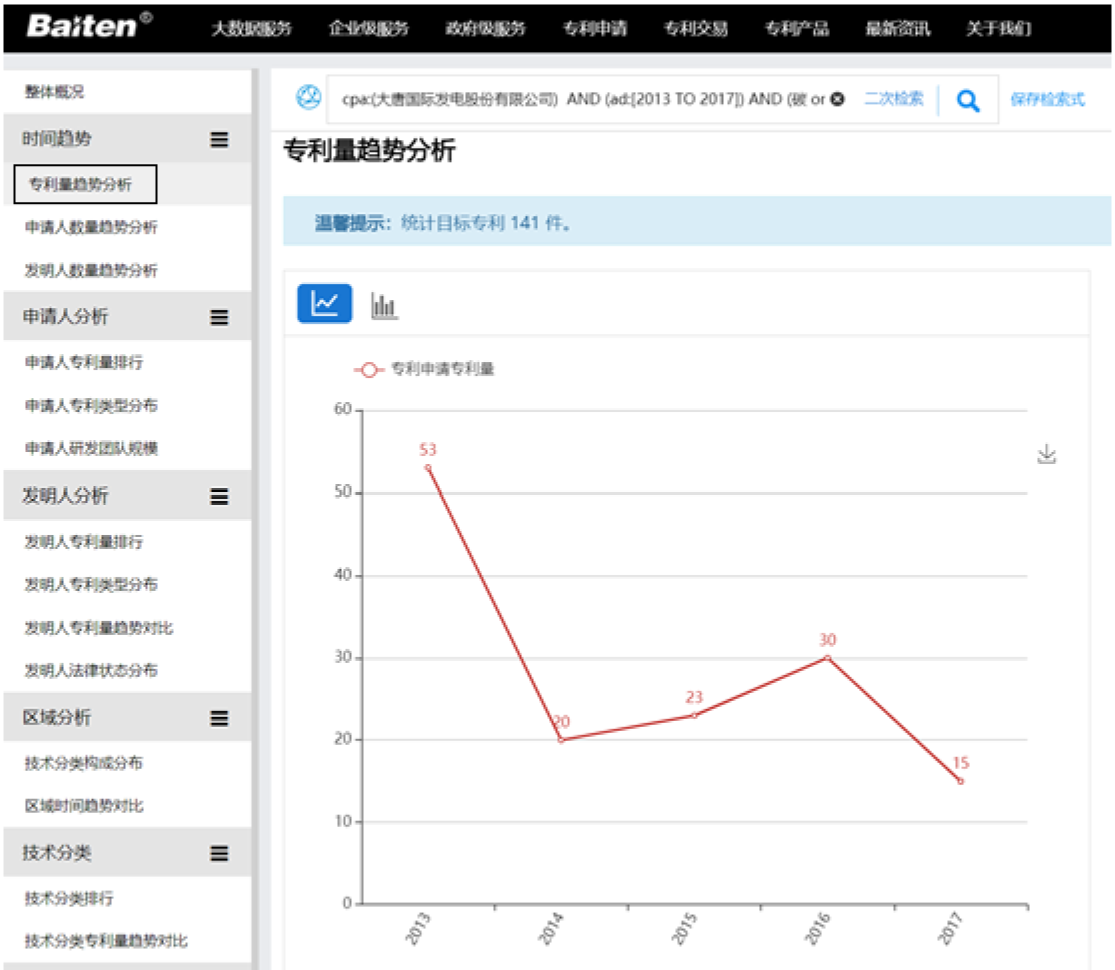

Figure C1: Representative figure showing the number of green innovations by a firm between 2013 and 2017.

The central part of Figure C1 shows the year and the number of green innovations for each year. These numbers were manually typed into our dataset.

To obtain the complete count of innovations, we use the same process, excluding the types of patents to be reported different searching codes. The search code for all innovations by a firm would be:

cpa:(大唐国际发电股份有限公司) AND (ad:[2013 TO 2017])

These steps are repeated for each company, until we have all the innovation data for all the listed companies.

All data and code in R used are available at https://github.com/faust1987/The-Impact-of-Exogenous-Pollution-on-Green-Innovation. Data are presented in both the original Chinese, and with key words translated into English.