ABSTRACT

Title of dissertation: ENVIRONMENTAL FEDERALISM: CHINESE GOVERNMENTAL BEHAVIORS IN POLLUTION REGULATIONS

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China's economic growth has come with the cost of environmental deterioration. The economy has faced with many problems in land resource depletion and industrial pollution. I examine two policies that tackle three major environmental aspects on land, water, and air in China. All three chapters share the theme that devolution without enough oversights in environmental policies has lead to unintended consequences in practice, as local officials have their trade-offs to promote local economy and protect environment.

The first chapter explores the local government's behavior in a land conservation program, which intends to reduce soil erosion by subsidizing afforestation of low productive farmland on steep slopes. Theoretically, the incentives created by the program combined with insufficient oversight have led to afforestation of highly productive farmland on level ground. With a unique land transition dataset, I show that this unintended land use effect has been substantial. This unexpected

displacement of highly productive farmland represents a form of leakage that has not been fully explored in the literature. And it is problematic to a country with limited arable land relative to population size as it can negatively impact national food production targets and self-sufficiency goals.

The second chapter investigates water pollution activities under China's Pollution Reduction Mandates. In response to the substantial environmental deterioration, the central government taxes firm emissions and subsidizes abatement technology installation. In theory, devolution to local governments to lower pollution and promote economic growth can create local incentives to allocate subsidies to effectively export pollution. I provide the first evidence of the magnitude of these distortions with unique firm-level pollution panel data and find evidence of water pollution exported to downstream and further away from local residences. A simulation indicates that the distortions created by local jurisdictional control harm the environment substantially: centralized allocation of subsidies could reduce total emissions by 20-30%.

The third chapter keeps investigating the inter-jurisdictional pollution externalities on air pollution under the same mandates. It provides a complimentary evidence to show that local governments have incentives to promote spatial spillovers and free-ride on the downwind neighbors.

ENVIRONMENTAL FEDERALISM: CHINESE GOVERNMENTAL BEHAVIORS IN POLLUTION REGULATIONS

by

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Dedication

To my beloved mom, Ping Yan,

for teaching me to be wise, fearless, and kind,

and to my grandparents,

for giving me endless love, support, and courage.

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Chapter 1: General Introduction

1.1 Overview

China's economic growth has come with the cost of the rapid deterioration of environmental quality and the depletion of natural resources. The economy has faced with many problems in land use, ecological conservation, and industrial pollution to water and air (Deng et al., 2012; Kan et al., 2012; Zhang and Wen, 2008). Although air pollution due to rapid industrialization in China has attracted the world's attention (Chen et al., 2012; Matus et al., 2012; Vennemo et al., 2009), the corresponding industrial activities and waste disposals are the major sources of water pollution and soil contamination as well. Beneficial nutrients and toxic heavy metals in rivers have caused significant impacts to residents' health and local agricultural production (Chen et al., 2005; Singh et al., 2004). China is experiencing land degradation, which is a long-term loss in ecosystem. With 22% of the world's population but 7.2% of the world's arable land, China suffers the most from the impact of land degradation. The estimated loss from land degradation was $38.7 billion in 1999 alone (Bai and Dent, 2009; Zhang et al., 2007). China's major freshwater lakes are also extremely polluted, with the water in half of China's twenty-seven major lakes unsuitable for any use (Vennemo et al., 2009). As noted in Economy (2007), land, water, and air are three major environmental issues in China: "China's environmental problems are mounting. Water pollution and water scarcity are burdening the economy, rising levels of air pollution are endangering the health of millions of Chinese, and much of the country's land is rapidly turning into desert".

My dissertation is comprised of three essays on two environmental policies that tackle these three aspects in China. The first essay focuses on a land conservation program, the latter two essays examine the water and air aspects of a pollution reduction policy, respectively. Because of the political management system in china, all three essays share the same core: devolution without enough oversights in environmental policies in China has lead to unintended consequences in practice. Although the existence of environmental externalities in both agricultural and industrial sectors provide a rationale for governmental intervention, the attempts to correct these market failures may not be efficient or cause additional problems during the implementation process.

I explore the performance of these environmental policies in China with an emphasis on the incentives of local governments, which have their own incentives to promote local economy for their careers, and are pressurized from the central government to protect environment. As noticed by Schofer and Granados (2006), decentralization has empowered local officials to link their self-interest to local economic performance, which is often not completely in lines with the central government's interests. From local authorities' perspectives, industrialization and economic development provide more direct fiscal return, and can further strengthen their legitimacy of political positions.

The three papers are organized as follows. The first paper explores the local government's behavior in a land conservation program, Grain for Green Program, which intends to reduce soil erosion by subsidizing reforestation of farmland located on steep slopes with low crop productivity. I show theoretically that the incentives created by the program combined with insufficient oversight have led to afforestation of non-sloped highly productive farmland. With a unique land transition dataset, I show that this unintended land use effect has been substantial, amounting to nearly one-fifth of the total amount of cropland converted to forest. This unexpected displacement of highly productive farmland represents a form of slippage/leakage that has not been fully explored in the literature on payment for ecosystem services programs. This form of land displacement is significant in the context of China as well as other countries with limited arable land relative to population size as it can negatively impact national food production targets and self-sufficiency goals. This paper points out some weaknesses in China's governance system, which delegates a great deal of authority to local officials with potentially insufficient checks on the part of the central government. The full version of the paper is in Chapter 2.

The second paper provides an investigation of water pollution activities under China's Pollution Reduction Mandates, in which water pollutants are strategically exported across jurisdictional boundaries. In response to the substantial environmental deterioration, the central government taxes firm emissions and recycles the revenue to subsidize installation of abatement technology. In theory, the central government mandates local governments to lower pollution while promoting economic growth, which creates local incentives to allocate pollution control subsidies in ways to effectively export pollution. I provide the first evidence of the magnitude of these distortions in this paper. An econometric investigation using unique firm-level pollution panel data finds evidence of water pollution exported to downstream and further away from local residences. A simulation using the estimated parameters indicates that the distortions created by local jurisdictional control harm the environment substantially: centralized allocation of those subsidies could reduce total emissions by 20-30%. This paper underscores the importance of a certain degree of centralization in environmental policies due to the conflicting incentives between environmental protection and economic growth at the local level. The full version of this paper is in Chapter 3.

The third paper keeps investigating the inter-jurisdictional pollution externalities on air polluting activities under the same Pollution Reduction Mandates. I use the same conceptual framework in Chapter III to explain the observed geographical distortion, i.e., local governments can strategically allocate pollution control subsidies in ways to effectively export discharged air pollution away from their jurisdictions that optimally balance the tradeoff between pollution reduction and promoting local economic growth. The paper provides a complimentary evidence in air pollution to further show that local governments have strong incentives to promote spatial spillovers and free-ride on the downwind neighbors. Specifically, it empirically shows that a firm has a higher pollution incentive if it locates closer to a provincial leeward border or in an area with a higher wind speed on average. The full version of this paper is in Chapter 4.

The following section provides a detailed review of China's political background, which sheds some light on the implementation challenges of environmental policies in China. In summary, the central government has recognized the negative environmental impacts on its economy, and responded with several ambitious environmental goals in the recent two decades. However, China's hierarchic political system with authority devolution can lead to inefficiency in the implementation. Using a cadre responsibility and evaluation system to examine local performance may force local officials to focus on myopic achievements and ignore unrewarding responsibilities. Other countries fell into similar circumstances may draw a lesson from China's inefficient environmental policy implementation process.

1.2 Background on China's Environmental Policies

1.2.1 Evolution of China's Environmental Concerns

While China still gives GDP growth the highest priority, attentions to environmental quality concerns are growing. The boosting economy is accompanied with endangered resource depletion and serious pollution. The conflict between environment and development is prominent. China's leaders have started to worry about the environment's impact on the economy. Several studies estimate that environmental degradation and pollution have costed the Chinese economy between 8 to 12 percent of GDP annually (Economy, 2007). The Chinese central government has correspondingly changed its focus from pure GDP growth to objectives that include environmental protection (Bo, 1996; Chen et al., 2005; Wang, 2013). After the devastating floods in the summer of 1998, the central government has recognized the importance of soil erosion prevention and the urgency of ecological conservation. China started to ban natural forest logging and subsidize steep arable land conversion to forests and grassland with its "Grain for Green" (GfG) Program, which is "a historic shift of focus" in China's environmental protection (Zhang and Wen, 2008). The central government has issued several important ecological conservation decisions since then, including the Law on Prevention and Control of Desertification (2001), the National Zoning of Ecological Function (2004), the Law on Natural Reserves, and the 11th Five-Year Plan for ecological conservation (2005). The number and area of nature reserves increased from approximately 5% to 15% of the country's territory from 1995 to 2005 as a direct result of the change in ecological conservation focus (Zhang and Wen, 2008).

Despite some early successes in soil-erosion reduction and ecological rehabilitation, China is still facing many natural resource problems and significant environmental degradation caused by industrialization. China initiated a program for acid rain control in the SO_2 Control Region in 1998. The Law on the Prevention and Control of Air Pollution was revised in 2000. More laws related to air pollution control has been issued since then. In addition to serious air pollution in major cities, China faces deteriorating water quality as well. It amended the Law on Marine Environment in 1999, and has been implementing the Green Engineering Program since 2001 to promote the treatment of pollution in key catchment (OECD, 2006). Starting in 2005 (the beginning of the 10th Five-Year Plan), the central government began to increase investment in environmental protection, set ambitious targets for the reduction of pollution and energy intensity (the amount of energy used to produce a unit of GDP), and introduce new environmentally friendly technologies (Economy, 2007).

In general, China has gradually shifted its focus from pure economic growth to plans emphasizing environmental protection and other public goals like health care and education. Over the last decade, reduction of environmental pollution loads and better management of natural resources have become priorities of state policies (Yuan et al., 2006). Its 12th five-year plan (2011-2015) sets several environmental achievements under China's Pollution Reduction Mandates as important targets. The country has become more sustainable from the policy's point of view. This shift also relies largely on the change in cadre promotion incentives and assigned responsibilities (Wu et al., 2013).

1.2.2 China's Cadre Responsibility and Evaluation System

The Chinese Communist Party (CCP) manages the country with a credit-based promotion for its Party and government officials (also known as cadres). The CCP politburo and central committee is at the apex of this political hierarchy, which has five layers of administration (center, provinces, prefecture, counties, and townships).[1] Each level of administration (including a village) has a communist party branch ruled by a party secretary and an administrative office ruled by a jurisdictional leader (governor, mayor, or even a village head). Although this dual presence of the communist party and government executive officials at each level

[1] A village is the lowest level in this government system, although it has no formal governmental level.

seems like a balanced coordination of authority, a party secretary usually has greater control over the nominal jurisdictional leader at the same level of governance (Eaton and Kostka, 2014; Li and Zhou, 2005; Zhang et al., 2004).

Due to the great heterogeneity in China, local governments have plenty of discretion powers to direct local economic development and provide pollution reduction services (Wang and Di, 2002). The central government relies heavily on local officials to execute its plans, while the establishment and management of the practices are quantity-, rather than quality-based. Inherited from the previous planned economy, China's environmental governance is largely based on the command-and-control regulation (Liu et al., 2012). Although China has a nominally top-down authoritarian control, its fiscal authority has been greatly decentralized since the start of the economic reform in 1978. Because of the fiscal decentralization, the central government rewards or punish local officials on the basis of their political performance. The central government, or CCP, strengthens the political control among their local governmental cadres based on two means: performance evaluation and rotating positions.

As noticed in a group of studies, a cadre's past performance, evidenced by economic development outcomes, is mainly affecting this person's odds of promotion, conditional on the political conformity. (Blanchard and Shleifer, 2001; Chen et al., 2005; Edin, 2003; Li and Zhou, 2005; Maskin et al., 2000; Whiting, 2017; Wu et al., 2013). The standard yardstick competition among local officials under the reward and punishment mechanism in China forces cadres to concentrate on economic ranking or GDP growth rates (Li and Zhou, 2005; Maskin et al., 2000; Qian and Xu, 1993). Local officials are enthusiastic to collect taxes and levies, implement local plans, and fulfill assigned quotas, while reluctant to provide local public goods and services (Zhang et al., 2004). Similarly, Wu et al. (2013) has shown that CCP cadres intend to fulfill responsibilities that can boost local economy and increase the odds of their promotion, while ignoring the unrewarding responsibilities like certain environmental investment, even when the central government started to emphasize the importance of environmental quality. The next subsection provides more details in the change of this evaluation.

Each level of cadres will be evaluated by the upper level governments, and they will be promoted, demoted, or moved laterally every three to four years. Central government use this periodic turnover as a tool to enhance the control and monitoring of local officials. It is also important to maintain a certainly level of cadre circulation as it helps to bridge departments and jurisdictions vertically and horizontally (Edin, 2003; Huang, 1999; Wright, 2008). However, this short-term rotation could jeopardize the implementation of environmental policies. Local officials are likely to choose a quick and low-quality approach to fulfill the mission, as relatively costly and long-term initiatives are likely to yield outcomes outside their tenure (Eaton and Kostka, 2014).

1.2.3 Authority Devolution in Environmental Governance

Evaluation of local governments' performance is a way to decentralize authorities from the central government. Instead of planning and coordinating from the ministries at the center, higher-level officials can simply assess lower-level officials based on a series of criteria for promotion. Because of the economic reforms in 1978, each local jurisdictional leaders are empowered with the ultimate authority to allocate economic resources within their jurisdictions (Huang, 1999; Qian and Xu, 1993). Since then, local officials have started to be obsessed with the relative economic ranking (along with other competence-related indicators gradually added over the years) among peers.

Other policies are also following the same hierarchical governing process. For instance, when the decentralized pollution reduction mechanism is introduced in China, the environmental protection pressure has passed to local officials due to the new environmental demand. The central government's evaluation adds the criteria on environmental quality, while the evaluation of local economic-growth still remains. Each local government is responsible for the environmental quality under their jurisdiction and shall take measures to improve the environment quality without threatening the local GDP growth.

Although the central government has established this decentralized system to control and prevent pollution in 1980s. Evaluation of environmental performance has not been emphasized and actively enforced until the most recent years. Therefore, local cadres chose to ignore the environmental targets before 2007, as the odds of promotion hinged on economic performance only (Chen et al., 2018; Jia, 2017; Jiang et al., 2014). During the 11th Five-Year Plan (2006-2010), the central government revised the evaluation criteria and assigned pollution reduction targets to each local officials, and has included pollution reduction performance into local governments' promotion evaluation since 2007.

The Ministry of Environmental Protection (MEP) in China (the counterpart of the Environmental Protection Agency in the US), is responsible to set general but vague guidance of environmental policies and regulations (Yang, 2017). Local environmental protection bureaus (EPBs), which are controlled by the corresponding level of local governments, are responsible to set and enforce detailed rules in their own jurisdictions (Rooij and Lo, 2010; Zheng and Kahn, 2013). Conflicts of interests between different layers of governments can emerge due to the substantial discretion at local (Golding, 2011; Lo et al., 2006; Wang et al., 2003).[2] As explained above, the central government adopts the new promotion criteria in hope of emphasizing the environmental concerns at local.

The change in the criteria of the cadre performance evaluation can be viewed as a shift in the goals of the central government. Unfortunately, the central government has relatively "loosely-worded environmental directives", which rely mainly on the improvisation of local leaders (Eaton and Kostka, 2014; Heilmann, 2008). The local governments are required to undertake the major responsibilities of environmental protection, and integrate the tasks into the target responsibility system, a key institutional arrangement for environmental performance evaluation that provides local officials with political incentives to promote pollution control policies (Lo, 2014). However, the flexibility to interpret the policies provide the opportunities for cadres to select the favorable directives strategically. When local economic growth, social

[2]However, conflicts of interests at the same layer of governments will be coordinated by the central government, which believes that lower-level regional negotiation could weaken the power of the center (Tyler, 2005).

planning, and environmental targets are incorporated into one cadre responsibility and evaluation system, local officials have to allocate limited local resources to the projects that are likely to boost the career prospects in the short-run (O'Brien and Li, 2017).

Local governments have strong incentive to boost the local economy for their promotion during the GDP-based competition period, and have to take the responsibilities of both promoting local development and protecting environment under the revised cadre evaluation system. They need to carry out the assigned tasks by the central government, but have their own interests in local economic growth. When the two incentives do not match, the trade-off decisions made by the local governments may increase the conflicts between natural resources and the local communities.

Comparing to local governments' strong favor of economic development, local environmental institutions (EPBs) have very little experience or institutional capacity to conduct local environmental regulations (Jahiel, 1998; Shi and Zhang, 2006). China did not have a strong environmental state with effective monitoring and enforcement capacity to oversee the regime of pollution control (Wang et al., 2004). On the other hand, it has been noticed that local regulators are self-interested utility maximizers, and may favor environmental benefits only because they have some rents to seek. Under the guidelines of concentrating on economic development, industrialization is universally considered by local government officials as the only path leading to modernization. The local officials have a notion called "first pollution and then remediation", which suggests an obsession with the economic development while overlooking other important social aspects and the unintended consequences (Li, 2013). Local economic situations are the key role in determining career advancement of local officials, and the local institutions and government bureaucrats are more inclined to boost economic growth than concerned about environmental pollution control (Guo, 2007; Li and Zhou, 2005).

In general, the hierarchic political system in China has the following three key features that may influence environmental policy implementation: authority devolution with performance evaluation, relatively vague environmental directives, and short-term rotation. Because of this political background, local governments execute environmental policies in a relatively irresponsible way. They tend to prioritize local economic growth over environmental quality, modify the environmental rules locally, and may adopt cheap and quick approaches to fulfill the mission.

If the central government wish to improve environmental quality by relying on local officials' activities, it should (1) go in tandem with checks and balances with an independent monitoring group; (2) use detailed and measurable responsibilities on low-level cadres; and (3) evaluate cadres' performance based on the activities (such as the investment in abatement technologies) rather than the outcomes (such as the level of average BOD in the jurisdiction) during their tenure periods.

Chapter 2: Unintended Land Use Effects of Afforestation in China's Grain for Green Program

2.1 Introduction

Payment for Ecosystem Services (PES) programs are increasingly seen as an attractive means for combatting environmental degradation. They have been shown to provide regional public goods such as hydrological services and erosion control (Alix-Garcia and Wolff, 2014). At the same time, they can alleviate poverty by making provision of environmental services economically desirable for low income land users (Van Hecken and Bastiaensen, 2010; Wunder, 2005). Unfortunately, PES programs are prone to implementation problems, especially in developing countries where governmental oversight tends to be deficient (Alix-Garcia and Wolff, 2014; Pattanayak et al., 2010). This lack of oversight in PES programs can lead to unintended effects. This article investigates a PES program in China to illustrate an unexplored form of land displacement. Specifically, it shows that China's PES program, which aims to reforest sloped farmland with high risk of erosion, inadvertently

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converts flat productive farmland into forest.

Deforestation has been an important contributor to numerous environmental problems in China, most notably soil erosion, which results in land degradation, sedimentation of rivers, downstream flooding, and other problems (Cao et al., 2011; Deng et al., 2012; Feng et al., 2010; Long et al., 2006). A significant share of that deforestation was driven by the national government's goal of increasing domestic food production during the Great Leap Forward (1958-1962). More recently, the Chinese government engaged in a massive effort to reconvert much of that deforested land to forest. In 2000, the Chinese government launched the "Sloped Land Conversion Program" or "Grain for Green" (GfG), which paid farmers to convert cropland on hillsides with high risk of erosion into forest. GfG aimed to reforest nearly 15 million hectares of high-risk cropland by 2010 (Uchida et al., 2005). As one of the largest PES programs in the world, GfG has been successful in reforesting large amounts of land, with forested land area increasing by almost 18%, 1.2% annually (FAO, 2015).

However, the program had the unintended effect of creating incentives to convert highly productive cropland with low risk of erosion to forest, which significantly reduced the cost effectiveness of GfG. This excess land conversion is particularly problematic for China's food production goals. As a result, the costs in terms of foregone output could outweigh any environmental benefits achieved.

This article makes three contributions to the PES literature. First, it studies a new type of leakage in the form of a perverse land use outcome caused by a PES program; namely, enrollment of un-targeted flat farmland with high crop yield potential, while targeted farmland with lower crop yield potential remains in cultivation. Second, it shows that the cost-effectiveness of the program is significantly reduced by this unintended conversion. The subsidies to convert low-erosion-risk farmland, which yields little environmental benefit, account for nearly five-sixths of the total loss under the program. Third, the article explores this unintended effect theoretically and empirically with a unique dataset that specifies transitions of land use in China. This detailed nationwide dataset allows me to conduct a pre/post policy analysis and provide regional comparisons.

I develop a conceptual framework explaining the conditions under which it is optimal for village leaders to use GfG to subsidize afforestation of highly productive flat farmland, contrary to the intended purpose of the program. I use a model of local heads' (village-level administrators) land use decisions to derive the conditions under which GfG subsidies make it optimal for them to convert highly productive farmland into forest. This land allocation is not cost-effective from the central government's perspective, because of the high value it puts on un-targeted land (productive farmland with low erosion risk) and the low social benefit from paying for this type of conversion. The analysis indicates that such unintended land conversion is more likely to occur in (a) areas where the productivity of high quality cropland is low relative to GfG subsidy levels, (b) areas where the value of forested land is relatively high, and (c) in areas where there is an abundance of high quality cropland.

I investigate the extent to which this unintended land conversion occurs using a unique panel dataset containing confidential annual county records of land transitions combined with socioeconomic data from county statistical yearbooks.

The dataset spans the years 1996-2004, covering a period prior to the program, extending through the gradual rollout of the program, and continuing into the years after implementation. I use a difference-in-difference (DID) strategy, with county and year fixed effects to control for unobserved heterogeneity. Two falsification tests (estimating differences in time trends in treated versus un-treated provinces in the pre-treatment period and a placebo test re-estimating the DID model over the pre-treatment period) indicate the common trend assumption is valid. Two major robustness checks using a Seemingly Unrelated Regression (SUR) model and DID-Matching are conducted.

The results indicate that unintended conversion of highly productive/low-erosion-risk cropland was substantial, amounting to nearly one-fifth of the total amount of cropland converted to forest. A share-change model suggests that unintended conversion of high productivity and low-erosion-risk cropland amounted to about 8% of the pre-program stock. As predicted by the theoretical model, conversion of low-erosion-risk cropland was greater in areas where crop productivity was low relative to reforestation subsidies. The estimated highest level of cropland productivity for reforestation is higher for high productive flat cropland than for highly-erosion-risk cropland, indicating that some highly productive, flat cropland was converted to forest while less productive sloped cropland remained in cultivation.

This article is the first to document a form of unintended land use effects that has not been fully explored in the literature on PES programs to date. Displacement of deforestation and unintended cultivation due to enrollment in PES program (leakage/slippage) has been documented in the US (Fraser and Waschik, 2005; Lichtenberg and Smith-Ramírez, 2011; Lubowski et al., 2006; Roberts and Bucholtz, 2005; Wu, 2000; Wu et al., 2001) and in the context of land threatened by deforestation in developing countries (Alix-Garcia et al., 2012; Arriagada et al., 2012). These studies have been concerned with the possibility that PES programs displace deforestation to unenrolled lands, essentially offsetting the environmental benefits achieved by the program. In this article, I show the opposite — that PES programs can enroll land whose benefits in alternative uses outweigh the environmental benefits achieved from conversion. This finding underscores the importance of independent monitoring for verifying compliance with PES restrictions and goals.

2.2 Motivation and Policy Background

PES projects can have both negative and positive unintended consequences. The failures of PES programs include encouraging unintended conservation, as well as deforestation of lands not enrolled in the program (Sills et al., 2008). Both types of these unintended consequences are caused by the displacement of forest exploitation known as leakage or slippage (Wu, 2000). Although slippage leads to production displacement (substitution slippage; see, for instance, Alix-Garcia et al., 2012; Arriagada et al., 2012; Lichtenberg and Smith-Ramírez, 2011) or changing production incentives on un-enrolled land (price slippage; see, for instance, Murray et al., 2004; Robalino, 2007), it may generate some positive land use effects.

Positive land use effects can help discourage additional deforestation or encourage afforestation (Pfaff and Robalino, 2012), yet to date, there is little empirical evidence on such positive effects. Some exceptions include studies of slippage related to the US Conservation Reserve Program (CRP) suggesting that it may increase production on neighboring lands (Fleming, 2010), increase farmland values (Wu and Lin, 2010), and delay non-conservation uses to later periods (Jacobson, 2014). Positive effects are usually considered as a mitigation of slippage and are assumed to be caused by greater enforcement of PES regulations (Pattanayak et al., 2010).

Whether the positive land use effects caused by slippage provide additional conservation benefits or induce problems that mitigate PES program benefits may vary by context. Some have argued that the additional forested areas, such as those on flat farmland, may not yield additional environmental services such as prevention of soil erosion and flood mitigation, as soil erosion mainly occurs on sloped farmland (Ziadat and Taimeh, 2013). Additional land use change will only deliver services when the changes are of appropriate quality and location (Pattanayak and Butry, 2005; Sills et al., 2006). More importantly, the unintended conversion of productive farmland to conservation uses could result in food scarcity in countries with smaller amounts of arable land relative to their population sizes.

This article helps to broaden the literature by showing that land use changes viewed as "positive land use effects from land displacement" in developed countries like the United States may have negative consequences in other contexts. Countries with scarce arable land often have legitimate concerns about food security. In those contexts, additional conservation that jeopardizes quality farmland is no longer a "positive" effect. More importantly, excess spending on subsidies to convert low-erosion-risk farmland to forest significantly reduces a PES program's cost-effectiveness.

Because government and market institutions in developing countries are often relatively weak, the cost-effectiveness of governmental PES programs is often difficult to achieve (Landell-Mills et al., 2002; Lipper et al., 2009; Pattanayak et al., 2010; Wunder et al., 2008). The extent of misallocation documented in this article emphasizes the importance of monitoring and enforcement in incentive-based policies for correcting environmental externalities (Coggan et al., 2010; Stavins, 2007). This article demonstrates that PES programs are likely to be less cost-effective with problematic unintended effects unless there is sufficient monitoring to ensure compliance with PES policies and goals.

2.2.1 Background of the Grain for Green Program

Forest policies in China from 1949 to 1998 demonstrate aggressive deforestation targets. Timber was viewed as a cheap raw material to be used for industrial production and forests were seen as potential farmlands (Delang and Yuan, 2015). To feed the burgeoning population and industrialize the nation, China's central government undertook a massive deforestation campaign beginning in the Great Leap Forward period (1958-1962). By 1979, 38 million hectares of forestland and wetland had been transformed into farmland (Feng et al., 2005). With only 0.08 hectares of arable land per person (in comparison to the world average of 0.20 hectares; see

World Bank, 2012), a central goal of the national government has always been to have domestic crop production meet the needs of the population.[1]

There were no laws governing forests in China until 1978, when the realization began to take hold that China had a "supply and demand crisis due to insufficient reforestation" (Richardson, 1990).[2] Although some traditional forest land was not very fertile and prone to erosion when used for crop production, farmers and local officials had insufficient incentives to reforest since they could not capture for themselves most of the benefits of reduced erosion (e.g. protection of watersheds, reduction of desertification, and restoration of ecosystems). Rapid exploitation, little concern for regeneration, and ineffective afforestation after 1962 resulted in devastating floods of the Yangtze River in the summer of 1998 (Robbins and Harrell, 2014). Environmental and ecological problems of the late 1990s forced the government to change course and institute an extensive reforestation program, the GfG program.

This program is one of the world's largest PES programs, enrolling 40 million hectares at a cost of $100 billion funded entirely by the central government (Cao et al., 2011). The GfG program compensates farmers for enrolling farmland by offering them a combination of cash, grain, and free saplings. Payments vary regionally. In the middle and upper reaches of the Yellow River and its northern region, the compensation package has a monetized value of 3,150 Yuan/ha (equivalent to $380.51/ha

[1]Preserving farmland is one of the seven basic national policies in China, which is regulated in the Land Administration Law.

[2]The Forest Law was officially promulgated in 1984 to formalize the ownership of trees and promote forest investments for the first time. It helped to set the groundwork and the legal framework to implement and operate the Grain for Green program.

in 1999) for the first year, and 2,400 Yuan/ha (equivalent to $289.91/ha in 1999) from the second year on. The corresponding values in the middle and upper reaches of the Yangtze River and its southern region are 4,200 Yuan/ha ($507.35/ha) and 3,450 Yuan/ha ($416.75/ha)(Uchida et al., 2005).[3] Subsidies are paid over 8, 5, or 2 years for cropland conversion to timber-producing forest, orchards, or pasture, respectively. The subsidy can be either viewed as a compensation for the farmland's opportunity cost, or the governmental price to purchase the positive externality from soil erosion reduction. Timber-producing forests serve mainly an ecological function initially, as farmers cannot harvest forest products from them during the period in which subsidies are paid. In contrast, farmers are allowed to harvest non-timber products from orchards. Timber-producing forest and orchards increased substantially when the GfG program started.

The GfG program was primarily designed to reduce the amount of erosion-prone hillside land for ecological benefits (Xu et al., 2006). Afforestation on these lands helps to reduce soil erosion and protect watersheds, as well as restoring ecosystems and preventing desertification. The program was initiated to return farmland with slopes of 25 degrees or more to forests in the upper Yangtze River and Yellow River Basins as a pilot in Sichuan, Shaanxi, and Gansu provinces. It expanded nationwide beginning in 2000 to cover almost all of China. After a rapid roll-out, 1,897 counties from 25 provinces, autonomous regions, and municipalities had enrolled into the program by 2002 (Deng et al., 2012). In 2004, the central government

[3] Unused land (like abandoned grassland and swamps that may be suitable to afforest) conversion has less compensation than farmland conversion, it includes free seed and seedling compensation and the cash subsidy of 50 Yuan/ha/year (the Regulations, Article 36).

decided to modify the GfG program's afforestation policy from mainly converting farmland to converting unused mountainous land, due to the decrease in grain production starting in 2000 (China News, 2013; Xu et al., 2006). Although there is no assessment on the direct effect of the GfG program on county and national-level grain production (Gutiérrez Rodríguez et al., 2016), there is evidence that the GfG program has reduced food production in some locales (Bullock and King, 2011; Zhen et al., 2014). The country suspended the original program in 2007 due to the concern that it was jeopardizing national farmland production goals set to ensure self-sufficiency in food production. The program was then transformed into a rural land maintenance and rural economic development program. At the same time, the State Council decided to extend the subsidies for enrolled farmland in the first phase for another 2 to 8 years (Bennett et al., 2014; Gutiérrez Rodríguez et al., 2016; State Forestry and Grassland Administration, 2007). Although the land maintenance involved in the transformed GfG program still has land use impacts, the scale of these impacts is much smaller. Starting in 2013, when the original subsidies period was ending, several provinces in western China submitted their GfG program reports to the State Council to request a program "reboot" (China News, 2013; Li et al., 2014). Currently, only Sichuan Province has land enrolled in the GfG program due to the severe land damage and soil erosion caused by the 2008 Sichuan Earthquake (China News, 2013).

2.2.2 Program Administration in China

Although the central government set a target for converting farmland (14.67 million ha to forest by 2010), it has been up to the local governments and village heads to determine how much farmland to convert (State Forestry and Grassland Administration, 2003; Xu et al., 2010). Village heads administer rural land in China (Lichtenberg and Ding, 2009), and county-level Forestry Bureaus have been responsible for the overall management of the GfG program, including identifying farmland eligibility, delivering subsidies and saplings, and maintaining newly afforested area. Program participants were subsidized conditionally on their ability to convert eligible farmland and maintain a tree survival rate of at least 70-85%. However, the local land verification and maintenance conducted by the county governments has resulted in high quality farmland enrollment and low survival rates of planted trees (Gutiérrez Rodríguez et al., 2016; Xu et al., 2010). Furthermore, the central government provided subsidies to these county-level authorities based on their reporting of converted land. These subsidy payments were then supposed to be delivered to each village, but issues like insufficient subsidy delivery to farmers and involuntary enrollment were common (Xu and Cao, 2001; Xu et al., 2010). These local officials delayed or withheld subsidy deliveries because they view the program "as an opportunity to bring in much-needed government funding" to local government agencies (Xu et al., 2010).

The objectives of some local officials did not align with those of the central government (Xu et al., 2004), and county-level authorities adjusted the GfG program to fit their local needs and conditions (Delang and Yuan, 2015). In particular, reforestation subsidies made it attractive to village heads (under the instruction of local officials) to convert productive flat farmland to forests regardless of formal restrictions on farmland conversion (Long et al., 2006; Uchida et al., 2005; Xu et al., 2010).

The regulations governing the GfG program, the Regulations on Conversion of Farmland to Forests (hereinafter the Regulations), prohibited unauthorized tree harvesting or damage to ecological functions even after expiration of subsidies (the Regulations, Article 50).[4] The Regulations also emphasized the preservation of farmland that has relatively good productive conditions or no potential risk of soil erosion, especially "basic farmland" (the Regulations, Article 4 and 16).[5] Conversion of basic farmland is illegal and subject to penalties if detected (the Land Administration Law, Article 34 and 36). The program targeted hillside farmland and unused land prone to erosion. The slope of the land is thus the top criterion for farmland enrollment (conversion priority is given to higher slope, which is known as the "slope rule") because hillside land was highly vulnerable to erosion, caused nonpoint source pollution, and could contribute to flooding (Feng et al. 2005; Long et al. 2006; Xu et al. 2004; the Regulations, Article 15).

[4]Rehabilitation and damaging surface vegetation are considered as criminal activities prohibited by the Forest Law, the Grassland Law, and the Law of Water and Soil Conservation (the Regulations, Article 62).

[5]Basic farmland is a type of land under the protection of the Land Administration Law in China. It is relatively flat and has irrigation and drainage facilities. It includes farmland with good irrigation and water conservation facilities even the current yield is low. It is forbidden for tree planting or fish nurturing, but only limited to agricultural uses (the Land Administration Law, Article 34 and 36). This type of land should not be converted under the GfG program.

2.3 Conceptual Model

2.3.1 Model Construction

This section contains a theoretical model deriving the conditions under which it is optimal for village leaders to use the GfG program to subsidize afforestation of potentially highly productive farmland on level ground, contrary to the intended purpose of the program. Converting highly erodible farmland to forests has positive externalities with ecological benefits that affect the whole country, such as preventing soil erosion and reducing sedimentation, flooding, and nonpoint source pollution. There is little or no excess of social benefit over private benefit from afforestation on level farmland. Although the stated policy goal is to subsidize afforestation of only highly erodible hillside land, early survey results in some counties suggest that the program unintentionally paid for converting level farmland as well (Uchida et al., 2005; Xu et al., 2010). As mentioned, a potential cause is weak monitoring by the central government, which delegates both monitoring and vegetation management to officials at the county level (the Regulations, Article 31). Under some conditions, local heads may have incentives to expand afforestation beyond hillside and unused land, and may thus ignore the "slope rule".

The following conceptual model of farmland conversion is developed to explore conditions where unintended conversion is likely to happen. It assumes that the central government has difficulty enforcing the farmland preservation requirement because it relies on county-level governments to both implement the program and monitor compliance. In China, rural land is administered by village collectives (Deininger and Jin, 2003; Jacoby et al., 2002; Lichtenberg and Ding, 2009). However, county-level governments implement and exercise oversight of the GfG program. The corresponding level of Forestry Bureaus are responsible for the overall management of the program, including identifying farmland eligibility. Because local officials may not identify the land carefully before enrollment, which results in some highly productive farmland being converted, the following theoretical model does not have the farmland eligibility constraint. Subsidy payments have value to the local heads either because they appropriate the money themselves or deliver them to farmers (as intended) for rural activities and local economic growth.

To simplify the exposition, possible land uses are restricted to farmland and forest land (F). Farmland is separated into two types: high productivity farmland on level ground (A_l) and highly erodible farmland on hillsides (A_e), only the latter of which is targeted by the program. $F > 0$, $A_l > 0$, and $A_e > 0$ denote the initial stocks. Let a_l and a_e denote the levels of level and erodible farmland converted to forest, respectively, in a village. Positive (negative) a_l or a_e means an increase in forest (farmland) cover.[6] To account for the differential quality of land, define the relative forest productivity with converted land from erodible farmland to the one from level farmland as $0 < \varepsilon \leq 1$.[7] Let $B(F + a_l + \varepsilon a_e)$ and $\pi_j(A_j - a_j)$ represent the annualized revenues the village gets from forestry and agricultural sectors, with

[6] I assume $a_l < A_l$ and $a_e < A_e$ in order to concentrate on the interesting case where an unintended conversion might occur. The assumption reduces only two corner solutions that are less likely to happen and are not the focus of the article.

[7] For simplicity, assume the relative forest productivity of converted land from level farmland to forest land as 1. Adding another quality adjust factor will yield similar results but complicate the model.

$j = \{l, e\}$ representing the land types of level and erodible farmland, respectively. They are functions of land alone under the assumption that labor and capital used in production are not constrained, i.e., they adjust instantaneously with the land.[8]

The costs of conversion include both labor costs and seedling purchases. Because the seeds are produced locally and redistributed to adjacent areas in this program (the Regulations, Article 26), transportation costs and profit seeking from seedling purchases can be ignored. Let $C_l(a_l)$ and $C_e(a_e)$ represent the total cost of converting level and erodible farmland, respectively. Assume diminishing marginal returns of the benefit and revenue functions, $B'(\cdot)$, $\pi_j'(\cdot) > 0$ and $B''(\cdot)$, $\pi_j''(\cdot) \leq 0$, and convex cost functions $C_j'(a_j) > 0$, $C_j''(a_j) \geq 0$ when $a_j > 0$ and $C_j'(a_j) < 0$, $C_j''(a_j) \geq 0$ when $a_j < 0$. The costs of converting farmland to forest and forest to farmland are expected to be different.[9] I assume tree logging and land rehabilitation requires higher effort than reforestation on farmland: $-C_j'(\hat{a}_j) > C_j'(\tilde{a}_j)$ when $\hat{a}_j < 0 < \tilde{a}_j$ and $\hat{a}_j, \tilde{a}_j \in a_j$. The cost functions are thus kinked at the origin and $C_j'(0)$ is undefined. The subsidy for converting a unit of farmland of either type is fixed. Let S be the total monetized subsidy payment per unit of farmland conversion, and $S \cdot [\max(a_l, 0) + \max(a_e, 0)]$ be the total compensation the local area received because of the unintended payment to convert level farmland. Assume S is converted to the present value in the first year's implementation.[10]

[8] A social planner from the central government's perspective may have a higher weight on the benefits of level farmland.

[9] The assumption of convex conversion cost is because in a village, increasing area of conversion involves more households and more local negotiation, as well as additional costs of sapling delivery paid at the local, which may increase the marginal cost of conversion.

[10] Conversion constraints under the program are not included because local officials have the bargaining power to undershoot or overshoot land conversion quotas.

The village head chooses the area of level and erodible farmland to enroll in the GfG program to maximize net benefits of land to the village:

$$
\begin{aligned}
&\max W(a_l, a_e) = V(a_l, a_e) + S \cdot [\max(a_l, 0) + \max(a_e, 0)] \\
&\text{s.t. } a_l < A_l \text{ and } a_e < A_s \\
&\text{where } V(a_l, a_e) = B(F + a_l + \varepsilon a_e) + \sum_{j=l,e} \pi_j(A_j - a_j) - \sum_{j=l,e} C_j(a_j)
\end{aligned}
\tag{2.1}
$$

The individual rationality condition should also be satisfied: prior to the subsidy (when $S = 0$), no additional conversion is needed because land must have been distributed across the three types of land in an optimal way for the local area, i.e., $(0, 0)$ solves $\max V(a_l, a_e)$. Because $C_j(x)$ is kinked at the origin, so is $V(a_l, a_e)$, and the conditions $V_j^+(0, 0) \le 0$ and $V_j^-(0, 0) > 0$ are assumed to be satisfied to guarantee this optimum.[11] The superscripts $+$ and $-$ denote right and left partial derivatives. The subscript j under V or W represents partial derivatives with respect to a_j.

An implicit requirement to the local condition is also needed($V_l^+(0, 0) < V_e^+(0, 0)(\le 0)$), in order to guarantee that a certain subsidy level is able to induce afforestation of only the erodible farmland in that region. The condition means that even if forest output on the level farmland would be weakly more valuable, afforesting on one unit of level farmland results in a higher loss than afforesting on one unit of erodible farmland.

[11] The conditions can be interpreted as converting one additional unit of farmland(forest) to forest(farmland) costs more effort than the received land values.

2.3.2 Conditions of Unintended Level Farmland Conversion

The primary interest is to find out when converting level farmland is more likely to occur, which is equivalent to deriving the conditions under which village heads convert only erodible farmland. All cases violating these conditions may lead to unintended phenomenon. Because the first order condition of (2.1) suggests that $a_j > 0$ if $W_j^+(0,0) = S + V_j^+(0,0) > 0$. To follow the Regulations without converting level farmland, $S + V_l^+(0,0) \leq 0 < S + V_e^+(0,0)$ is required, which is equivalent to the following conditions that the subsidy level must satisfy:

$$S + B'(F) - \pi_l'(A_l) - C_l'(0^+) \leq 0 \tag{2.2}$$

$$S + \varepsilon B'(F) - \pi_e'(A_e) - C_e'(0^+) > 0 \tag{2.3}$$

Violating these conditions may lead to not only cases of positive conversion in both types of farmland (when both (2.2) and (2.3) are positive) or no participation in the program (when both (2.2) and (2.3) are nonpositive), but also the possibility of afforestation only on level farmland (when (2.2) is positive and (2.3) is nonpositive).[12] The condition is more likely to be violated when one or more situations described in the following two paragraphs happen.

Condition (2.2) is more likely to be violated in areas that have (a) higher marginal value of forest, (b) lower marginal value of level farmland, (c) relatively lower marginal cost of converting level farmland, (d) lower stock of forest, or (e)

[12] Because S is set exogenously by the central government before the program started, it may or may not reflect the true external benefits that a PES program intends to capture.

higher stock of level farmland. The first three conditions are most likely to be found in western China, where crop profitability is low relative to forest profitability, and where level farmland conversion is relatively easier due to low rural population density. Western China also has a relatively low stock of forested land due in part to deforestation during the Great Leap Forward period. Some conditions are also satisfied in eastern China, where there is high stock of level farmland, and where forest profitability is relatively high.

Condition (2.3) is more likely to be violated in areas that have (a) lower marginal value of forest, (b) higher marginal value of erodible farmland, (c) relatively higher marginal cost to convert erodible farmland, (d) higher stock of forest, (e) lower stock of erodible farmland, or (f) subsidy levels are relatively low to local conditions. These conditions are most likely to be found in southern China, which has a low stock of erodible farmland, low forestry productivity, and an average output of farmland 1.5 times as much as that in northern China. These conditions give local authorities in southern China less incentive to participate.

2.3.3 Factors Affecting the Amount of Level Farmland Conversion

This subsection explores the conditions under which excess conversion of level farmland is likely to be more extensive. In the case of converting both types of farmland, there are a pair of interior solutions for the maximization problem, $a_l^* > 0$ and $a_e^* > 0$, with detailed comparative statics included in the supplementary appendix online.

It is straightforward to show:

1. A higher unit subsidy leads to a higher converted amount of both types of farmland.

2. A smaller amount of forested land or a higher value of forest production leads to a higher converted amount of both types of farmland.

3. A larger amount of level (erodible) farmland, or a lower value of its farmland value, leads to a higher converted amount of level (erodible) farmland, and a lower converted amount of erodible (level) farmland.

4. Larger conversion costs of erodible farmland relative to those of level farmland lead to a larger (smaller) amount of level (erodible) farmland conversion.

These results suggest different land use impacts driven by local conditions. Local heads in western China may be more likely to convert both types of farmland due to their low forest stock, and to convert more level farmland because converting erodible land on hillsides is relatively costly. The latter may cause serious unintended conversion of highly productive farmland because labor could be scarce and costly for sloped land conversion. Local heads in eastern China have a high stock of level farmland and a low stock of forest, both of which could induce them to convert more level farmland to forest. Participation and conversion of farmland to forest are likely to be low in southern China, where agricultural profitability is high, both absolutely and relatively, compared to returns to forestry.

2.4 Data

To test the hypotheses derived in the preceding section, I create a unique panel by combining detailed transition data from the Ministry of Land and Resources (MLR) of China with socioeconomic data from statistical yearbooks. The annually land transition and land stock data come from confidential records maintained by MLR from 1996 to 2004 at the county level. This dataset thus spans the period during which the program was being implemented. Land use reports from MLR personnel are compared to China's Land Survey of 1996 and satellite imagery, as well as being subject to periodic inspection by central government MLR officials (Feng et al., 2005; Lin and Ho, 2003).[13]

The MLR dataset (1996 to 2004) documents the yearly land transition with 47 classes of land cover (8 major categories) in every county and includes stocks and transitions for all types of land that measured to the nearest 0.1 *mu* (1 *mu* is equivalent to 1/15 hectare) and converted to hectares. There are several major advantages of the dataset: (1) the dataset documents the uses land came from and went to as a land transition matrix; (2) the dataset allows me to examine afforestation of unused land, which has largely been ignored in the previous literature; and (3) with the nationwide data, I am able to evaluate the land use and land cover impacts of the GfG program on a yearly basis for the whole country and to examine regional heterogeneity.

[13] I have checked the reliability of the MLR land use dataset with data from satellite imagery available from the Chinese Academy of Sciences. Differences between land uses at the county level were small in magnitude and not statistically significant. The interested reader can find the details in a supplementary appendix online.

Level and erodible farmland are differentiated according to two criteria, the land gradient and the presence of irrigation facilities. As well, these criteria are used to define "basic farmland" (the Land Administration Law, Article 34). Irrigated paddy and irrigated cropland are characterized as level farmland, and rain-fed paddy and dry land as erodible farmland. Both irrigated paddy and irrigated cropland have flat topography and relatively high-level productivity. These types of arable land fit the classification of basic farmland, and have sufficient water and irrigation/drainage facilities.[14] In general, they are not the target of the GfG program. Rain-fed paddy and dry land, on the other hand, are located near or at the middle and upper parts of mountains and hills. Hilly land is more prone to soil erosion and has less organic matter content and is thus less fertile (see Feng et al., 2005). Grain yield from these types of land depends mainly on natural precipitation. These two types of land fit the target of the GfG program described in the Regulations.

County-level socioeconomic data from 1996 to 2004 are collected from the statistical yearbooks published from 1997 to 2005. The dataset includes GDP by sector (primary, secondary, and tertiary), the value of grain and forestry output, rural labor population, and local government's revenue and expenditure, all measured at the county level.[15] All the monetary variables in Chinese Yuan are normalized to

[14] From the definition of basic farmland, even low-yield fields can be classified as basic farmland as long as they are equipped with good irrigation practices and water conservation facilities (the Land Administration Law, Article 34). The presence of these fixed infrastructure investments are a defining feature indicates that their category does not include hillside land in close proximity to level farmland.

[15] Two types of statistical yearbooks are used: annual Provincial Statistical Yearbooks and Chinese Counties (Cities) Socioeconomic Statistical Yearbooks. The first one contains data at the provincial and prefectural level, with partial county-level data provided, and the second one provides more observations for certain variables.

real 2005 terms, and converted to US dollars using the 2005 average annual exchange rate. GDP deflators for each sector are used to deflate the local GDP from respective sectors. Both GDP deflators and exchange rates are provided by the Federal Reserve Bank of St. Louis.

The GfG program was phased in gradually, with the process determined by the central government. The program was implemented in: Gansu, Sichuan, and Shaanxi provinces in 1999; Yunnan, Guizhou, Chongqing, Hubei, Qinghai, Ningxia, Inner Mongolia, Shanxi, Henan, and Xinjiang in 2000; Hebei, Heilongjiang, Jilin, Liaoning, Hunan, Guangxi, and Jiangxi in 2001; and Beijing, Tianjin, Anhui, Henan, and Tibet in 2002 (Administration, 2002; Deng et al., 2012; the GfG Office of National Forestry Administration, 2000). By 2002, the phase-in process was complete and the GfG program covered 25 out of 31 provinces, autonomous regions, and provincial level municipalities. The indicator for whether the policy was in effect thus varies by year as well as province. Table 2.1 includes the descriptive statistics of the data I use. Table 3.2 includes the selected descriptive statistics of the data for different cohorts of counties before and after the implementation of the GfG program.

2.5 Empirical Model

I use the panel of county land transition data to test the hypotheses derived in the theoretical section. I examine the subset of conversions between forested land, level farmland, and erodible farmland. The equations below represent the aggregated decision-making process from each village at the county level. County-level officials exhibit oversight in the program and may have some influence to local land use decisions as well. The hypotheses remain relatively the same. Measurement errors at the village-level should not be correlated to the GfG indicator. The theoretical analysis indicates that the amount of land converted from use j to use k in county i at time t, a_{jkit}, is a function of the GfG subsidy (specifically, whether the GfG program was in effect), the amount of land of each type at the beginning of the period $\boldsymbol{A_{it-1}}$, and other factors influencing land conversion, $\boldsymbol{X_{it-1}}$:

$$a_{jkit} = \beta_0^{jk} GfG_{it} + \boldsymbol{\beta_A^{jk}} \boldsymbol{A_{it-1}} + \boldsymbol{\beta_X^{jk}} \boldsymbol{X_{it-1}} + e_i + e_t + e_{it} \tag{2.4}$$

Other factors, $\boldsymbol{X_{it-1}}$, include crop profitability and forestry profitability (proxied by the value of farmland and forested land in county i at the previous period $t-1$), the relative conversion cost (proxied by the rural labor density in county i at the previous period $t-1$), and local government's financial status (annual revenue and expenditure). The last are included to absorb certain land conversion incentives made by county governments. The value of land is measured by GDP or output divided by the corresponding land area. Specifically, the average values of farmland, timber-producing forest, orchards, and urban land are calculated or proxied as grain output per unit of farmland, output of forestry per timber-producing forest, output of fruits per unit of orchard, and secondary and tertiary industrial GDP per unit of urban land, respectively. The value of urban land, as well as other urban related variables (urban average GDP, average wage in urban and rural areas, and the number of workers in urban and rural areas) are added. Rapid urbanization has been shown to lead to the conversion of farmland into urban uses (Lichtenberg and Ding, 2009). Road expansion may have impacts on forests (Uchida et al., 2009), so incentives for urban expansion may indirectly influence farmland transitions to other uses.

To accommodate the potential regional heterogeneity suggested in the theoretical model, I interact the GfG indicator with regional indicators as follows:

$$a_{jkit} = \sum_{r}(\beta_{0r}^{jk}(GfG_{it} \cdot region_i)) + \boldsymbol{\beta_A^{jk} A_{it-1}} + \boldsymbol{\beta_X^{jk} X_{it-1}} + e_i + e_t + e_{it} \tag{2.5}$$

where r is the region type, $region_i = south$ or $north$ to distinguish the effect of subsidies and production conditions. I also estimate a model to identify the program's regional impacts by further breaking down the equation by allowing $region_i = southwest$, $southcentral$, $northwest$, $northcentral$, and $northeast$.

The theoretical model suggests there may be a critical value of farmland at which unintended conversion effect occurs: lower (higher) value of level (erodible) farmland is more likely to be converted (maintained). Because only the average farmland value in each county is observable, I create two variables, $farmland\_value_{li,t-1}$ and $farmland\_value_{ei,t-1}$, using the farmland shares in each county and the average farmland yield ratio to represent the average level farmland value and the average erodible farmland value, respectively. In order to test this hypothesis and estimate the critical value for each type of farmland in different regions, two other variables, $GfG_{it} \cdot farmland\_value_{ji,t-1}$ (or $GfG_{it} \cdot region_i \cdot farmland\_value_{jit}$ in a regional model like equation (2.5), where $j = l$ or e), are added to evaluate the impacts of cropland productivity:

$$a_{jkit} = (\beta_0^{jk} + \beta_1^{jk} farmland\_value_{ji,t-1}) \cdot GfG_{it} + \boldsymbol{\beta_A^{jk} A_{it-1}} + \boldsymbol{\beta_X^{jk} X_{it-1}} + e_i + e_t + e_{it} \tag{2.6}$$

Equations (2.4) to (2.6) use county and time fixed effects models to control for unobserved heterogeneity. I use cluster-robust standard errors clustered at the provincial level to cope with possible serial correlation and heteroskedasticity. The effects of the program are estimated by β_0^{jk}s (and β_1^{jk}s in equation (2.6)) from the land use outcomes of the two groups: the observations affected by the GfG program, and the non-participated observations, after controlling for observed influences and unobserved factors in each county in a given year. The expected signs for β_0^{jk}s are positively significant for all land transitions. The expected signs for β_1^{jk}s are negatively significant when j is level or erodible farmland.

To adjust for the level of land stock and explore the relative sizes of unintended conversion effect in different regions, I estimate another model with shares $a_{jkit}/A_{ji,t-1}$ as the dependent variable in equation (2.4) and (2.6). The coefficients β_0^{jk} and β_1^{jk} in the share model show the effects of the GfG program on a certain type of land relative to its total stock. The expected signs are the same as in equation (2.4) and (2.6). On the other hand, given the stock effect observed in the theoretical model, interactions of land stock with the policy indicator can also be included in the model:

$$a_{jkit} = \beta_0^{jk} GfG_{it} + \boldsymbol{\beta_{GA}^{jk}}(GfG_{it} \cdot \boldsymbol{A_{it-1}}) + \boldsymbol{\beta_{A}^{jk}} \boldsymbol{A_{it-1}} + \boldsymbol{\beta_{X}^{jk}} \boldsymbol{X_{it-1}} + e_i + e_t + e_{it} \quad (2.7)$$

The main focus of the empirical analysis is to investigate whether GfG causes unintended conversion of level farmland to forest and, additionally, the extent to which this unintended conversion depends on the value of farmland. To put the unintended conversion in context, I examine six types of transitions from three sources (level farmland, erodible farmland, and unused land) to two end uses (timber-producing forest and orchards). Although two types of afforestation are subsidized, only significant conversion to timber-producing forest is expected due to the conversion restriction on orchards. Descriptive statistics of the data used in the regression for regions are given separately in table 2.1.

To examine the validity of the parallel trend assumption, I conduct two tests: (1) estimating differences in time trends in treated versus un-treated provinces in the pre-treatment period and (2) a placebo test re-estimating the DID model over the pre-treatment period. To examine if the land-use effect varies under different model and data specifications, I also conduct a series of robustness checks. I interact provincial/prefectural-level and year indicators to control for the corresponding level of time-variant unobservables. I estimate the group of equations for each land transition simultaneously to account for cross-equation errors. I also use propensity score matching and DID-matching methods to account for observable differences in characteristics between enrolled and un-enrolled counties. The interested reader can find both the test results and robustness checks in a supplementary appendix online.

2.6 Estimation Results and Implications

Tables 2.3 and 2.4 report the estimated coefficients of the GfG indicator for the pooled and regionally disaggregated models. Table 2.3 provides the land transitions from farmland or unused land to timber-producing forest and orchards under the GfG program from 1996 to 2004. Table 2.4 provides the corresponding estimates in the share model. Table 2.6 shows the farmland value effect estimated in equation (2.6).[16] In general, the estimated coefficients have signs consistent with expectations. The first panel of each table reports the coefficient of the GfG program indicator in equation (2.4). The second and the third panels show the coefficients of the GfG indicator interacted with regional dummies. All models include a complete set of covariates along with county and year fixed effects. The robustness checks with different functional forms also provide the estimated coefficients showing the same land transition pattern. The assumption of the parallel trend is valid. Because unused land is not significantly converted (possibly due to the low subsidy rate) and the Regulations require that newly afforested area be composed of at most 20% orchards, the following subsections focus mainly on timber-producing forest based on the estimation in table 2.3 (with a certain percentage reference drawn from table 2.4).

[16]Land stock effects estimated in equation (2.7) are shown at the end of Appendix III.

2.6.1 Effects of the GfG program on Erodible Farmland

The stated goal of the GfG program is to convert highly erodible farmland to timber-producing forest to prevent soil degradation and water erosion. The estimated coefficients of the GfG indicator suggest that the program was quite successful in meeting that goal, with an estimated 7.6% (1.52% per year from table 2.4) of erodible farmland converted to timber-producing forest in the five years from initial program implementation to the end of the study period. At the average timber-producing forest value in each region, the estimates indicate that the cumulative effect of the GfG program over the whole study period (1999-2004) was an increase in timber-producing forest with a value of nearly $21.84 million.[17]

There was significant geographical heterogeneity in the effects of the program. Consistent with the theoretical analysis, erodible farmland conversion was higher in northern China, which has a large stock of erodible farmland, a low stock of forested land, and relatively low farmland productivity. The difference between northern and southern China was statistically significant ($F(1, 6008) = 54.18$ and $p - value = 0.000$) and large in magnitude. Because the program was designed to use a uniform subsidy rate (for a large region), the program indicators in the regional regression model capture the impacts of subsidy. Specifically, each dollar of subsidy was associated with 0.073-0.300 hectare of conversion of erodible farmland in northern China, compared to 0.028-0.054 hectare in southern China.

[17] To calculate this, I multiply the average value of forest in each subregion (northwestern, north-central, northeastern, southwestern, and south-central China) with the number of counties that participated in the program in each subregion and year, then add up all the regions.

The regionally disaggregated coefficients indicate that the program was most successful in northwestern, northeastern, and south-central China. This finding is consistent with the prediction in theory, because these regions have larger stocks of erodible farmland and higher forestry value. Northern China also has a large stock of erodible farmland and relatively low farmland productivity. With the highest stock of erodible farmland and forestry productivity, northeastern China had the highest conversion, which is almost twice as much as the second highest (in northwestern China) with a statistically significant difference ($F(1, 6004) = 10.52$, and $p-value = 0.001$). These two regions converted 10.0% and 6.3% of erodible farmland to forest after four years of implementation, respectively. In contrast, central China is less likely to participate in the program due to higher farmland productivity, lower hillside farmland stock, and a lower return in forestry. In south-central China, conversion is relatively similar to that of north-central China ($F(1, 6004) = 0.01$ and $p - value = 0.9144$), even though it has a relatively low stock of erodible farmland. Thus, its conversion share is sizable, amounting to 12.5% of erodible farmland conversion after four years of implementation.

The impacts of erodible farmland stock on the GfG program's erodible farmland conversion decision is high in northwestern and northeastern China, which follows the expectation from the theoretical analysis. Higher stock of erodible farmland would further stimulate the conversion of the corresponding farmland, while higher stock of level farmland would reduce this incentive. This finding suggests that the GfG program worked as intended, because more erodible farmland conversion would occur in a relatively erosion-prone region.

The GfG program was designed to incentivize conversion of farmland to timber-producing forest rather than orchards. Consistent with that program design, the GfG program had a smaller effect on conversion of farmland to orchards. Two features of the program's design are likely responsible: (1) the low monetary value of subsidy packages for orchard and (2) the requirement that orchards account for no more than 20% of total afforestation, which the central government was able to realize by rationing seedlings of orchard trees. Only in northeastern China, where orchards are relatively profitable, was a substantial amount of erodible farmland converted to orchards.

2.6.2 Unintended Land Use Effects of the GfG program

The GfG program targeted hillside land but specifically exempted productive farmland with little risk of soil erosion. Unintended conversion of flat productive farmland to forest yields little environmental benefit but is costly in terms of excess spending on subsidies and risks to food security. Table 2.3 suggests this type of unintended conversion was substantial, amounting to nearly one-fifth of the total amount of cropland converted to timber-producing forest.

Consistent with the theoretical analysis, the estimated coefficients in table 2.3 indicate that unintended level farmland conversion was greatest in northern China, where this type of unintended conversion was nearly three times greater than in southern China. (The difference is statistically significant with $F(1, 5560) = 18.66$ and $p - value = 0.000$.) This leakage caused a cumulative 2.5% loss in total stock of level farmland during the study period in northern China.

The theoretical model also predicts that the unintended conversion of level farmland could be considerable in both eastern and western China, because the former has relatively high returns in forestry and a high stock of level farmland and the latter has a relatively low stock in forestry, low returns on level farmland, and relatively low-cost conversion of level farmland. Western China has a low stock of productive level farmland, so that a 0.2% - 0.45% annual rate of loss of level farmland per county due to program subsidies represents a sizable relative loss of productive capacity. Unintended conversion of high quality farmland is also substantial in the southern part of central China, where forested area is relatively small but value of forest production is relatively high. In this region, unintended conversion amounted to nearly one-fourth of the total amount of cropland converted to timber-producing forest. Higher subsidy payment would also stimulate additional level farmland conversion. On average, each dollar of subsidy was associated with an increase of 0.009-0.035, and 0-0.016 hectares of level farmland conversion in northern China and southern China, respectively.

Similar to the conversion of erodible farmland, local land stock effects are sizable in the conversion of level farmland. Regions with limited area of highly productive farmland may choose to enroll more erodible farmland into the program, while regions with a high stock of productive farmland have incentives to violate the program's regulations. Unintended land use conversion is more likely to be observed in south-central China, because this region has a relatively abundant stock of level farmland. This is also consistent with the coefficient in the land transition model reported in table 2.3.

2.6.3 Impacts on Farmland Productivity

Land quality is likely an important factor that affected local officials' decisions when applying the rules of the GfG program. Level farmlands may have had low yields due to drought or pest problems. Relatively poor households may have been selected to enroll low productive flat farmland into the program due to local equity concerns (Uchida et al., 2005). My theoretical analysis of the Chinese situation indicates that unintended conversion of level farmland is more likely to occur in areas where the value of that farmland is relatively low. I investigate this possibility by calculating maximum levels of county-average cropland productivity at which conversion to timber-producing forest is desirable as $\overline{farmland\_value} = -\beta_0^{jk}/\beta_1^{jk}$ from equation (2.6).

Under the program, farmland is converted to forest only if its productivity is below the maximum value. I estimate these values using the delta method conditional on local land stocks, land values, local characteristics, and unobserved time-invariant characteristics. These estimated maximum productivity levels are shown in table 2.5. They imply that in some parts of China, high-quality level farmland was enrolled in program while low-quality, high degradation risk farmland remained in production, consistent with the findings of earlier descriptive studies in the pilot regions (Uchida et al., 2005; Xu et al., 2004).

At the national level, the maximum grain yield for level farmland conversion is

1.25 times higher than corresponding values for erodible farmland. The difference in maximum yields implies that some level farmland was converted to forest, while some lower yielding, erodible farmland remained in crop production. In northern China specifically, where unintended land conversion is high, the difference in maximum yields indicates that erodible farmland with nearly 36.4% lower yields remained in production while some level farmland was converted to forest. The maximum yield differential discrepancy was the greatest in north-central China.

One possible explanation for the difference in maximum yields at which conversion is desirable between level farmland and erodible farmland is the relative cost of land conversion. As indicated in theory, higher amounts of this unintended conversion can occur in areas where it is considerably more costly to convert erodible farmland to forest than it is to convert level farmland. In relatively poor areas, such as the western and central parts of northern China, land conversion depends mainly on rural labor. Rural labor density is low in northern China, making labor more scarce and costly. Since converting erodible farmland to forest requires more labor than does converting level farmland, the relative conversion cost differential tends to be high, making it attractive to convert high quality farmland while leaving erodible farmland in production.

2.6.4 Policy Implications

At the national level, the Ministry of Forestry (MOF) is responsible for afforestation and forest management. The MOF has its own hierarchical structure at provincial, prefecture, and county levels. Forestry Bureaus at the county level are charged with both implementing and monitoring GfG and other programs. However, environmental administration at the local level is generally controlled by village leaders (OECD., 2005; Wu, 2005). In the case of the GfG program, village leaders are given incentives to allow high productive level farmland to be converted to forest, while simultaneously, these same officials are meant to ensure compliance with restrictions on farmland conversion.

If lack of independent compliance monitoring is the cause of unintended land displacement, then it could be reduced or even eliminated by the central government establishing its own independent monitoring system as a check on local authorities' behavior. As a rough estimate of the potential avoided loss from establishing an independent compliance monitoring system, I calculate the sum of (1) subsidies paid to cropland subject to the unintended conversion and (2) the value of the lost grain production net of the increased forest production value. Because the land displacement is substantial in certain regions of China, amounting to one-fifth of total forest conversion annually, excess subsidy payments for this unintended land conversion amount to $572.1 million.[18]

Valued at the central government's average grain price (1.4 yuan per kilogram of grain), the potential loss in grain production is roughly $107.9 million in total.[19]

[18] I calculate the average payment to level farmland conversion per county per year by multiplying the regionally differentiated subsidy level to the estimated annual leakage. Multiplying the average payment by the number of counties that receive the subsidy in each region (northwestern, north-central, northeastern, southwestern, and south-central China) and each year yields the regional potential avoided payments. Then I add up all the regions to receive the total potential reduction. Note that the number of participated counties varies from region-to-region and year-to-year. The total number of county-year observations with the GfG program in effect is 4819 from 1996 to 2004.

[19] I first find the estimated annual loss of grain in value by multiplying the grain price to the

The estimated corresponding value of forest products is \$2.92 million. Thus, potential avoidable net losses are around \$677.06 million from 1996 to 2004, or \$140,498 per participating county per year. In the northwestern and northeastern regions of China, which have relatively sizable unintended conversion, the total avoidable losses reached \$ 257,726 per county per year, suggesting the compliance monitoring system could double the budget if it focuses on these two regions alone. Whether an independent central government compliance monitoring system would be economical depends on the cost and effectiveness of that system. Nevertheless, the preceding calculations suggest that independent compliance monitoring could be well worthwhile.

2.7 Conclusion

Starting in 1999, the Chinese government implemented an extremely ambitious afforestation program, Grain-for-Green (GfG), with the aim of preventing soil erosion by converting farmland with high risk of erosion into forests and pasture. The GfG program has gained public interest in recent years because the central government intends to reboot the program in the near future. GfG is widely considered a great success in terms of soil erosion reduction and flood prevention (Gutiérrez Rodríguez et al., 2016). Because of the central government's concern for food production, high quality flat farmland was never meant to be enrolled in the

average yield in each county per year. Multiplying the average value of yield lost by the estimated annual leakage and the number of counties that receiving the subsidy in each region and year yields the regional loss in grain production. Then I add up all the regions to receive the potential savings in grain production.

program. Yet, authority for compliance with program regulations was delegated to local officials whose incentives did not fully align with the central government's. This article provides a systematic nationwide land use analysis focusing on the first phase of the program. It studies the potential unintended land use effect of converting productive farmland into forest for conservation uses, which reduces program efficiency and undermines the country's goal of protecting productive farmland.

This article suggests that PES programs can err by enrolling too much land, a form of leakage that has not been recognized in the literature to date. In the context of China as well as other countries, with limited arable land relative to population size, this type of land displacement can negatively impact national food self-sufficiency goals.

I derive theoretical conditions under which this form of land use effect is likely to occur, then estimate the magnitude of excess conversion of productive farmland in China using a unique land transition/use dataset from 1996 to 2004. I find substantial unintended conversion in western and coastal China, especially in the northern portions of those regions, consistent with predictions derived from the theoretical model. Also as predicted, slippage is more prevalent on lower-value land. The results of the empirical analyses suggest that it might be worthwhile for the central government to establish a compliance monitoring system to avoid losses in both crop production and undesirable subsidy payments.

The extent to which this unintended conversion occurs suggests that local officials exercise a significant amount of discretion in implementing national policies. The central government relies largely on reports from local officials to monitor how its policies are being carried out. In the GfG program, bolstering local government finances with reforestation subsidies appears to have taken precedence over the central government directives to preserve level farmland in order to meet the country's stated food production goals.

This article provides elements of a more nuanced evaluation of China's GfG program. These findings in this article suggest that substantial leakage may occur in some regions due to insufficient oversight by the central government, which may also lead to other local maintenance issues like low survival rates of trees or incomplete payment delivery. Conducting field surveys to gain a clear picture of the effects of GfG in those regions seems important. A closer examination of conversion in southern China also seems of potential interest. To fully understand how land value would influence farmland conversion in this region may rely on analysis of other local land use programs. Finally, the misallocation observed in the GfG program suggest the desirability of considering how the central government might implement compliance monitoring. Further examination of these issues are beyond the scope of this article and are left for future research.

	Subregions by Geography						Subregions by Subsidy Level			
	Eastern		Central		Western		Northern		Southern	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Transition (ha) from										
level farmland to timber forest	1.47	38.86	4.30	50.28	1.91	122.52	1.30	114.38	3.40	40.77
erodible farmland to timber forest	73.16	531.32	54.02	281.11	242.05	1015.03	181.20	913.58	93.94	505.81
unused land to timber forest	23.24	284.79	5.19	194.38	44.37	585.72	29.82	380.65	24.58	453.37
level farmland to orchards	-3.54	111.06	8.33	313.31	14.62	114.64	12.94	254.74	1.07	78.33
erodible farmland to orchards	0.83	167.70	20.23	439.95	25.83	186.72	14.66	333.72	17.11	193.75
unused land to orchards	2.37	58.13	0.49	62.45	9.61	99.13	3.47	37.64	6.08	103.00
Stock (1k ha) at year t of										
level farmland	26.26	21.72	24.84	23.47	16.86	22.13	23.28	25.03	20.98	20.32
erodible farmland	38.82	60.34	27.76	27.15	37.35	42.89	46.77	58.79	24.56	27.21
orchards	5.30	7.10	3.31	4.22	2.24	3.15	2.88	5.24	4.18	5.15
timber forest	7.64	14.83	4.99	6.97	6.54	12.99	4.23	9.62	8.68	14.39
Output level at year t of										
grain per farmland (ton/ha)	5.05	5.54	5.22	2.44	2.66	2.56	3.34	4.68	4.87	3.06
fruits per orchard land (ton/ha)	3.29	29.89	3.42	9.62	2.83	13.52	3.92	25.96	2.39	11.81
forestry per forestland ($1k/ha)	0.13	0.76	0.05	0.30	0.06	0.92	0.11	0.66	0.05	0.83
Socio-econ. data at year t:										
urban land value ($1k/ha)	29.38	29.11	18.06	16.84	12.08	15.57	14.63	17.44	24.09	25.87
rural labor density (person/ha)	2.54	2.16	2.43	1.94	1.26	4.24	2.00	1.91	1.98	4.04
county gov. revenue($1m)	18.15	19.88	14.54	12.39	8.00	14.99	10.94	15.95	14.42	17.35
county gov. expenditure($1m)	27.99	23.28	24.12	17.87	18.75	17.22	19.82	19.68	25.59	19.83
Number of observations	3352		2545		4114		5018		5193	

Table 2.1: Descriptive Statistics of Data Used in Analysis in Eastern, Central, and Western China (1996-2004)

	1999		2000		2001		2002	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Transition (ha) from								
level farmland to timber forest	-1.24	25.90	-5.52	111.22	-3.83	170.81	19.76	250.63
	4.34	53.55	18.51	273.74	45.62	180.09	351.16	491.15
erodible farmland to timber forest	56.44	446.71	93.38	887.68	10.13	527.97	24.998	166.62
	591.50	1499.31	535.25	1403.38	462.88	1087.63	1391.62	1114.67
level farmland to orchards	10.42	126.47	15.38	250.50	4.06	71.72	9.72	132.86
	10.55	92.08	31.60	265.81	14.79	74.89	114.17	383.35
erodible farmland to orchards	34.83	284.26	32.63	352.69	20.90	139.60	2.68	87.474
	173.53	1649.01	43.17	221.11	36.98	197.47	75.90	166.47
Stock (1k ha) at year t of								
level farmland	12.38	16.14	20.58	26.42	20.96	16.62	19.01	26.19
	12.31	16.04	20.62	26.60	21.02	16.72	18.80	26.28
erodible farmland	36.89	34.78	35.82	40.17	43.99	63.04	18.16	33.59
	35.23	33.88	34.55	38.47	43.78	62.99	18.00	33.64
orchards	3.41	4.13	2.17	3.22	3.81	5.81	2.65	5.48
	3.76	5.04	2.31	3.39	3.93	5.88	2.73	5.61
timber forest	2.72	4.29	4.59	10.32	7.85	11.14	1.69	3.14
	3.82	5.29	5.30	11.42	8.07	11.25	1.93	3.30
Output level at year t of								
grain per farmland (ton/ha)	3.59	3.13	2.77	2.88	5.46	9.32	3.71	3.83
	3.54	3.02	2.71	2.80	4.89	7.41	3.52	1.41
fruits per orchard land (ton/ha)	0.00	0.00	3.26	16.41	3.07	33.13	0.00	0.00
	1.72	9.00	3.63	12.19	3.05	30.96	0.00	0.00
forestry per forestland ($1k/ha)	0.06	0.41	0.04	0.19	0.14	0.78	0.13	1.62
	0.08	0.60	0.06	0.38	0.04	0.24	0.67	5.83
Socio-econ. data at year t:								
county gov. revenue($1m)	9.95	35.91	12.63	35.68	21.82	63.72	15.13	7.26
	12.03	44.10	17.65	57.39	23.93	52.21	15.31	6.65
county gov. expenditure($1m)	16.42	39.00	20.23	41.16	32.59	80.49	23.99	9.86
	27.08	51.27	36.93	78.59	46.01	69.35	36.25	11.47
Number of Observations	2744		6589		4704		1435	

The two rows of data for each variable represent the descriptive statistics summarized before and after the GfG program's implementation, respectively.

Table 2.2: Selected Pre/Post Descriptive Statistics of Data Used in Analysis by Program's Implementation

		Land Transition					
		level farmland	erodible farmland	unused land	level farmland	erodible farmland	unused land
Model	Variable	to timber-producing forest			to orchards		
Pooled	GfG	74.13***	272.8***	28.82	-15.78*	16.43*	8.866*
		(14.79)	(31.64)	(20.75)	(7.476)	(7.197)	(3.793)
Regional	GfG·N	42.29***	464.9***	40.98	-15.79	25.78**	9.312*
		(5.664)	(40.93)	(26.04)	(9.105)	(9.319)	(4.738)
	GfG·S	13.50*	119.3**	18.54	-15.77	8.769	8.470
		(5.811)	(37.79)	(24.65)	(9.489)	(8.677)	(4.555)
Subregional	GfG·NW	84.08***	447.9***	30.88	-20.19	18.61	10.00
		(9.115)	(53.63)	(34.48)	(11.79)	(12.22)	(6.396)
	GfG·NC	20.99	176.6*	49.90	2.092	8.934	10.98
		(13.35)	(79.30)	(47.59)	(17.25)	(17.95)	(8.664)
	GfG·NE	35.13**	723.9***	48.36	-23.18	54.81***	7.002
		(12.15)	(71.75)	(41.99)	(15.73)	(16.42)	(7.593)
	GfG·SW	-2.101	94.57*	-3.501	0.630	23.70*	4.390
		(8.818)	(44.25)	(29.96)	(11.38)	(10.26)	(5.608)
	GfG·SC	53.14***	186.1***	17.30	-43.54**	-10.35	10.61
		(10.74)	(50.42)	(32.92)	(13.93)	(11.63)	(6.097)
Number of Observations		8566	9003	10012	8564	8949	9838

Clustered standard errors (at province level) in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
County and time fixed effects are included. The table reports the coefficients of β_{0r}^{jk} in the following equation. Pooled, regional, and subregional models are separate regressions.
Fixed effects model: $a_{jkit} = \sum_r \beta_{0r}^{jk}(GfG_{it} \cdot region_i) + \boldsymbol{\beta_A^{jk} A_{it-1}} + \boldsymbol{\beta_X^{jk} X_{it-1}} + e_i + e_t + e_{it}$

Table 2.3: Land Transition to Forests in China from 1996 to 2004 (in Hectare)

Model	Variable	Land Transition: level farmland to timber-producing forest	erodible farmland to timber-producing forest	unused land to timber-producing forest	level farmland to orchards	erodible farmland to orchards	unused land to orchards
Pooled	GfG	0.00233***	0.0152***	0.0195	-0.000241	0.00328*	0.000837
		(0.000652)	(0.00133)	(0.0109)	(0.000284)	(0.00152)	(0.00463)
Regional	GfG·N	0.00483*	0.0203***	0.0170	-0.000472	0.00462*	0.0000415
		(0.00216)	(0.00271)	(0.0139)	(0.000348)	(0.00203)	(0.00585)
	GfG·S	-0.000875	0.0138***	0.0215	0.00000758	0.00235	0.00150
		(0.00150)	(0.00156)	(0.0128)	(0.000358)	(0.00179)	(0.00549)
Subregional	GfG·NW	0.00199***	0.0162***	0.0154	-0.000525	0.00781**	0.00146
		(0.000544)	(0.00246)	(0.0189)	(0.000460)	(0.00286)	(0.00812)
	GfG·NC	0.000452	0.00630*	0.00129	-0.000368	0.000180	-0.00101
		(0.000769)	(0.00321)	(0.0252)	(0.000649)	(0.00370)	(0.0106)
	GfG·NE	0.00450***	0.0261***	0.0302	-0.000507	0.00373	-0.00113
		(0.000701)	(0.00293)	(0.0219)	(0.000593)	(0.00341)	(0.00915)
	GfG·SW	0.0000402	0.00152	0.0131	0.000620	0.00269	-0.000469
		(0.000508)	(0.00179)	(0.0156)	(0.000428)	(0.00212)	(0.00675)
	GfG·SC	0.00273***	0.0327***	0.0308	-0.000993	0.00177	0.00358
		(0.000619)	(0.00204)	(0.0171)	(0.000524)	(0.00240)	(0.00734)
Number of Observations		8363	8685	9566	8361	8631	9392

Clustered standard errors (at province level) in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
County and time fixed effects are included. The table reports the coefficients of β_{0r}^{jk} in the following equation. Pooled, regional, and subregional models are separate regressions.
Fixed effects model: $a_{jkit}/A_{ji,t-1} = \sum_r \beta_{0r}^{jk}(GfG_{it} \cdot region_i) + \boldsymbol{\beta_A^{jk} A_{it-1}} + \boldsymbol{\beta_X^{jk} X_{it-1}} + e_i + e_t + e_{it}$

Table 2.4: Land Transition to Forests in China from 1996 to 2004 (in Share)

Model		Land Type	
		Level Farmland	Erodible Farmland
Pooled		10.262***	6.178***
		[5.58,14.94]	[4.82,7.54]
Regional	Northern	9.012***	5.246***
		[5.84,12.19]	[4.47,6.02]
	Southern	-7.437	5.865***
		[-39.85,24.97]	[3.46,8.27]
Subregional	Northwestern	5.676***	5.538*
		[3.89,7.46]	[1.16,9.91]
	Northcentral	10.593***	6.548***
		[6.16,15.03]	[4.90,8.19]
	Northeastern	11.516*	4.964***
		[0.72,22.32]	[4.59,5.34]
	Southwestern	1.569	3.547***
		[-14.45,17.59]	[1.61,5.48]
	Southcentral	3.381	6.374***
		[-2.70,9.46]	[5.21,7.54]

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
The Delta Method is used to calculate the *95%* Confidence Intervals.
Pooled, regional, and subregional models are separate regressions.

Table 2.5: Estimated Maximum Farmland Values (ton/ha) for Unintended Conversion to Timber-producing Forest

Model		Land Type	
		Level Farmland	Erodible Farmland
Pooled	GfG	113.2***	514.6***
		(18.69)	(78.56)
	GfG·farmland_value	-11.03***	-83.30***
		(3.241)	(19.40)
Regional	GfG·N	67.46***	949.6***
		(8.546)	(174.3)
	GfG·N·farmland_value	-7.485***	-181.0***
		(1.900)	(43.16)
	GfG·S	8.152	234.5***
		(8.843)	(60.75)
	GfG·S·farmland_value	1.096	-39.99**
		(1.412)	(14.03)
Subregional	GfG·NW	130.7***	622.9***
		(13.77)	(79.42)
	GfG·NW·farmland_value	-23.02***	-112.5
		(5.148)	(72.16)
	GfG·NC	128.0***	512.1**
		(37.40)	(184.5)
	GfG·NC·farmland_value	-12.09*	-78.21*
		(5.759)	(35.41)
	GfG·NE	64.17*	3059.0***
		(26.33)	(702.8)
	GfG·NE·farmland_value	-5.572	-616.2***
		(4.479)	(152.2)
	GfG·SW	1.813	219.0**
		(11.30)	(76.03)
	GfG·SW·farmland_value	-1.155	-61.74*
		(2.338)	(29.98)
	GfG·SC	-26.03	700.1***
		(45.94)	(156.6)
	GfG·SC·farmland_value	7.698	-109.8***
		(7.140)	(30.61)
Number of Observations		8363	8685

Clustered standard errors (at province level) in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

County and time fixed effects are included. The table reports the coefficients of β_0^{jk} and β_1^{jk} below.
Pooled, regional, and subregional models are separate fixed effects regression models:
$a_{jkit} = \beta_0^{jk} GfG_{it} + \beta_1^{jk}(GfG_{it} \cdot farmland\_value_{ji,t-1}) + \boldsymbol{\beta_A^{jk} A_{it-1}} + \boldsymbol{\beta_X^{jk} X_{it-1}} + e_i + e_t + e_{it}$.

Table 2.6: Land Transition to Forests in China (1996-2004) with Interaction

Chapter 3: Political Pressure under Pollution Reduction Mandates: Downstream Spillovers in China

3.1 Introduction

China's rapid industrialization has been the heart of its equally rapid economic growth but has also created serious problems of air and water pollution (Buckley and Piao, 2016; Deng, 2017; Webber, 2017). The central government has responded by levying fines on emissions and using the revenue from those fines to subsidize installation of abatement technology. Enforcement of China's environmental policies is decentralized, as it is in many countries (see Millimet (2013) for a review). The central government sets the basic policy structure, delegates enforcement to local governments, and monitors implementation (in terms of fines levied and distribution of revenue for pollution control subsidies), with an emphasis on the heaviest polluting firms.

China's combination of a highly centralized political system with the decentralized fiscal system put in place in the 1990s has created a number of distortions of economic activity, including excessive land development, overemphasis on industrial

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activity relative to domestic consumption, exacerbation of regional inequality, etc. (Jin et al., 2005; Knight and Shi, 1999; Lin and Liu, 2000; Park et al., 1996; West and Wong, 1995; Zhang, 1999; Zhang and Zou, 1998). How that combination of centralized political authority and decentralized fiscal responsibilities affects environmental policies has received relatively little attention. This paper examines how pollution control regulations are implemented in China, with a focus on the export of water pollutants to downstream jurisdictions (the "downstream effect").

China provides a good context to study the downstream effect because of the incentives created by its top-down political structure. Governance in China is highly centralized, with the Communist Party controlling government at all levels, from the central government down through hundreds of prefectural bodies and thousands of county bodies. The process through which the central government promotes officials at these lower levels of government to higher level positions creates a tournament-style competition among those lower level officials (Knight, 2014; Li-an, 2007; Lü and Landry, 2014; Yang and Muyang, 2013). That competition affects implementation of policy at each level of government (Oates, 1999). While performance in terms of economic growth and fiscal management were the predominant metrics in the past, environmental quality has now been added to the mix (Guo, 2007; Li and Zhou, 2005; Lo, 2014).

This paper investigates theoretically and empirically how local governments' efforts to meet the central government's pollution reduction mandates while maintaining high levels of economic growth and demonstrating responsible fiscal management affect environmental quality outcomes. It makes three contributions to the literature in doing so. First, it advances the theoretical literature on environmental federalism by combining the strategic pollution incentives of local governments and firms into a single analytical framework. Second, it uses a unique dataset of firm-level data to study the spatial allocation of emissions and installation of abatement equipment within counties, providing direct quantitative evidence about the magnitude of the downstream effect in water quality. Third, it uses a simulation model to quantify the magnitude of the distortions created by local governments' implementation of water pollution control policy by comparing observed emissions with optimal emissions under centralized national control. The paper is organized as follows.

First, I develop a theoretical model to study local governments' strategies for allocating subsidies to local firms for abatement technology investments in order to influence pollution-related adverse effects. It combines both perspectives from a local government and from a firm to fully examine the incentives of excessive pollution in less environmentally sensitive areas. I show that local governments act as self-interested utility maximizers to balance both performance in terms of promoting their jurisdictions' economic growth and protecting their jurisdictions' environmental quality across all the heterogeneous firms within their jurisdictions. Firms located in less environmentally sensitive areas (that is, areas with fewer jurisdictional residents, and areas close to downstream jurisdictional borders) will produce less health damage per unit of pollution to residents living within the jurisdiction. These "border firms" are less likely to be funded for abatement technologies and will pollute more. If the pollutants generated by local industries are carried outside the province by rivers, so that serious environmental or health impacts are likely to happen elsewhere, local officials might reduce the enforcement of pollution abatement while still enjoying the economic benefits brought by these industries.

The theory of the paper is based on the anecdotal evidence and previous literature of transboundary pollution. Some studies argue from a firm's perspective to show that facilities near jurisdictional borders often fail to consider inter-jurisdictional externalities (for instance, see Cai et al., 2015; Helland and Whitford, 2003a). Others argue from a jurisdiction's view to show that local governments enforce less near borders (Dijkstra and Fredriksson, 2010; Hall, 2008; Sigman, 2002). Combining both perspectives into a sequential game model supports the role of political pressure in environmental policy (Hird, 1990; Magat et al., 1986; Oates, 2001). It also helps to explain the incentive to increase pollution or decrease abatement for border firms, and provide channels (levies and subsidies) for local governments to govern local pollution reduction. The theoretical model assuming that each firm has its unique pollution level and locational information in each jurisdiction is also close to reality.

Second, I quantify the pollution and abatement incentives based on firms' geographic information using a unique panel dataset. Specifically, the paper tests if polluting firms located closer to the downstream border of a jurisdiction or further away from a residential area within the jurisdiction will have a higher pollution output and a lower scale of installed abatement technology. The empirical analysis builds on the literature of the geographical impacts of pollution spillover effects. With decentralized policy structure, free-riding behavior in pollution may occur all over the world (Banzhaf and Chupp, 2012; Kahn, 1999; Kahn et al., 2013; Konisky and Woods, 2010; Lipscomb and Mobarak, 2017; Murdoch et al., 1997; Sigman, 2005, 2007). However, adopting county-level data, or assigning a border-or-not indicator to a firm's location, is a method commonly used to investigate the rough pollution spillover effects of jurisdictional governments' pollution response (Cai et al., 2015; Helland and Whitford, 2003a; Novel, 1992; Rauscher, 1995; Santore et al., 2001; Sigman, 2002, 2005). The sole study examining pollution spillovers along 24 major rivers in China, that of Cai et al. (2015), uses indicators of economic activity (industrial value added and the number of firms) as indirect measures of pollutant emissions to investigate this downstream effect in China with county-level data (1998-2008). My study closely relates to these studies, yet expands the empirical work to a more nuanced evaluation.

The paper uses quarterly pollution tax data from firms subject to intensive monitoring by the central government from 2011 to 2015, which is a direct measure of pollution since the tax rate is uniform for all water-polluting firms. It also uses an abatement technology adoption dataset for those firms to further examine the abatement incentives. Firms' coordinates are extracted from Google API to calculate distances in ArcGIS from each firm to the provincial downstream border along the river network and to the closest residential area within the jurisdiction. These distances are more accurate proxies of a firm's pollution impact to a local jurisdiction than a dummy variable. They also create variations across firms that allow quantifying the pollution and abatement distortion within a jurisdiction.

I adopt a within-between random effects model (Chamberlain, 1982; Mundlak, 1978; Wooldridge, 2009) to estimate the firm's time-invariant locational impacts. A fixed effects model interacting the distance variables with the quarter dummies shows that the geographical impacts on pollution are similar over time. I also examine the heterogeneous locational impacts based on region and jurisdictional river lengths. Possible endogeneity of a firm's location (Carlton, 1983; De Beule and Duanmu, 2012; Kahn, 2003; Piga and Poyago-Theotoky, 2005; Wagner and Timmins, 2009) is tested based on the assumption that functional land use planning is determined beforehand. I do not find any evidence of endogeneity. The corresponding test, along with other robustness checks, are reported in the Supplementary Figures. The econometric analysis indicates that a water-polluting firm emits more pollutants if it is closer to the jurisdictional downstream border or if it is further away from a jurisdictional residential area. These firms are less likely to adopt abatement equipment with high capacities. Sector-wise analysis suggests that heavy polluters - including the fuel processing, metal, and cement industries - exhibit a stronger downstream effect.

Third, with detailed locational information, the paper also provides a simulation built upon the empirical analysis to show the advantage of centralized mandates. With certain inter-jurisdictional negotiation, both total pollution level and involved costs in the mandates are significantly reduced by 20-30%. The simulation result extends the debate over environmental federalism[1] to the Chinese semi-centralized system of governance. Under a decentralized policy structure, although efficiency

[1]The literature of environmental federalism debates the appropriate role of the various levels of government in environmental regulations. Whether decentralized environmental policy performs better than centralized policy in an inter-jurisdictional competition framework varies by countries (Levinson, 1999; Oates, 2008; Oates and Portney, 2003)

can be achieved with a Pigovian remedy (Oates and Schwab, 1988; Wellisch, 1995), local governments may "race to the bottom", i.e., over-compete for industry and under-provide localized public goods (Kunce and Shogren, 2005; Oates, 1999, 2008; Shobe and Burtraw, 2012). In China, even the central government monitors firms and local officials' behaviors, yet large pollution and abatement distortions still exist due to jurisdictional competitions. Also, in contrast to the literature on the advantage of China's fiscal decentralization, this paper argues that unleashing fiscal controls over the environmental protection sector may cause a striking pollution distortion. The conflicting incentives between environmental protection and economic growth at the local level underscore the importance of regional cooperation and a certain degree of centralization in general environmental policies worldwide.

3.2 Institutional Background

Environmental deterioration, as the byproduct of China's industrial growth during the period of economic reform, has resulted in the death of nearly a million people every year (World Bank, 2007). With industrial expansion, China's SO_2 emissions are almost as high as those of Europe and the United States combined (Vennemo et al., 2009). The welfare deduction from particulate matter concentrations has increased from an estimated \$22 billion in 1975 to an estimated \$112 billion in 2005 (Chen et al., 2012; Matus et al., 2012). Pollutants like nitrogen, phosphorus and toxic heavy metals in rivers have caused significant impacts to residents' health and local agricultural production (Chen et al., 2005; Singh et al., 2004). China's major freshwater lakes are extremely polluted, with the water in half of China's twenty-seven major lakes unsuitable for human use (Vennemo et al., 2009).

While China still gives GDP growth the highest priority, attention to environmental quality is growing. China's leaders have started to worry about the environmental impacts on the economy. Several studies estimate that environmental degradation and pollution cost the Chinese economy between 8 to 12 percent of its GDP annually (Economy, 2007). China has responded to the problem with pollution reduction mandates including a new pollution levy system throughout the whole country. The system is different from those in the U.S. and Canada, because plants are allowed to pollute above pollution standards as long as they pay the corresponding levies (Hering and Poncet, 2014; Lin, 2013; Ma and Zhao, 2015; Wang et al., 2003; Wang and Wheeler, 2005). Starting in 2005, the central government began to increase investment in environmental protection, setting ambitious targets for the reduction of pollution and energy intensity (the amount of energy used to produce a unit of GDP), and introducing new environmentally friendly technologies (Economy, 2007).

The major focus of the pollution reduction mandates for monitoring and levy collection is on chemical oxygen demand (COD) and SO_2. Pollution tax charges are levied for 61 water pollutants and 44 air pollutants. All the other pollutants are converted to COD-equivalent or SO_2-equivalent units when calculating the pollution tax. Since July 1, 2004, the pollution tax is calculated as 0.7 Chinese Yuan (CNY) times the sum of the top three COD-equivalent pollutants for water-pollution. The charge rate and conversion rate for each pollutant were set by the central government in the Regulations on the Administration of the Charging and Use of Pollutant Discharge Fees (hereinafter, the Regulations) issued on February 28, 2003. China's pollution reduction mandates also include the installation of pollution abatement technology, as well as shutting down small-scale coal-fired plants, which are generally inefficient in the use of natural resources and highly polluting (Cao et al., 2009; Jin and Lin, 2014; Ma and Zhao, 2015). Plant shutdowns or the installation of abatement technology are mainly enacted by local governments, while the levy system is based on universal self-reporting by firms (Wang and Wheeler, 2005).

While municipal and county authorities have been known to manipulate reporting of environmental activities (Cai et al., 2015; Lin, 2013), the most heavily polluting firms are monitored directly by the central Ministry of Environmental Protection (MEP), which reduces the chance of data manipulation and misreporting from local officials. In an effort to establish and improve the information disclosure systems in China, the MEP, since 2010, has released a list of firms subject to intensive monitoring and control, as well as their corresponding quarterly charged pollution taxes (the Regulations, Article 1). The central government updates the selection of the firms every year and most of the heavily polluting firms remain on the list year after year.[2] Local officials are required to provide pollution reduction plans for the polluting firms that demonstrate the proposed use of levies. These plans include details about the investment required for firms' abatement technology

[2]The selection criteria is the following: For water polluters: sort the firms based on the emission (production) level of COD or NH_3, select the top of those that account for 65% (50%) of the total emission (production), then merge the four groups of firms to the final selected water-polluter monitoring list. The MEP also monitors large-scale sewage treatment plants with capacity $\geq$ 5,000 ton/day.

adoptions, or constructions of new sewage treatment plants.

Contrary to studies in the United States and Canada (Laplante and Rilstone, 1996; Magat and Viscusi, 1990), Lin (2013) argues that China's pollution regulation does not help reduce pollution but only improves plants' self-reporting accuracy. With strong incentives to pursue economic growth and tax revenue, local governments in China often turn a blind eye to extensive pollution in their jurisdiction (Cai et al., 2015; Zhang et al., 2013). Jia (2012) and Zheng et al. (2014a) also show that Chinese politicians are strongly motivated by promotion incentives regardless of their social costs. Wang (2013) argues that the central government's motivation for emphasizing pollution reduction is to seek legitimacy with Chinese people and to signal that the Communist Party leadership cares about its own people. Targets related to energy efficiency and pollution reduction are now linked to local officials' performance and evaluation. Local officials are incentivized to invest in pollution abatement technology and environmental infrastructure because credit (recognition) for pollution reduction may be granted (Qi, 2013). Seemingly, local officials become more concerned about local environmental quality and local residents' lives because actions to reduce pollution may also help their political careers. With sustainability and social stability included in political promotion criteria, local GDP growth remains the main criterion for promotion. Because local government officials have their own incentives to promote the local economy for their careers while receiving pressure from the central government to protect the environment, it is important to understand local government trade-off behaviors in environmental regulations.

3.3 Conceptual Model

To motivate the empirical work, a theoretical model is developed highlighting the downstream effect of a firm's pollution. The Chinese tournament-style competition to promote local officials has a significant influence on local pollution reduction and environmental protection (Wu et al., 2013). In order to retain their political power, local government officials must boost their local economy by attracting dirty industries, and reduce pollution to improve local residents' quality of life (Wang, 2013; Zheng et al., 2014a). Given the externalities inherent in downstream pollution, local governments benefit most from pollution reduction higher upstream in their jurisdiction, and thereby exert the least enforcement effort near the downstream boundary of their administrative regions (Cai et al., 2015). This paper elaborates on this downstream effect. It assumes that per unit of pollutants emitted from firms located at less environmentally sensitive areas have less health impacts to local residents. Specifically, for water-polluting firms, identical emissions from firms located closer to the jurisdictional downstream border or further away from a residential area have less of an overall impact on jurisdictional residents' well-being. Those firms can easily export pollutants outside the jurisdiction and are therefore assigned with a lower health-risk index inside the jurisdiction based on their locations. This paper hypothesizes that local governments care less about pollution from firms with relatively low health-risk indices.

The central government has stipulated that pollution levies can only be spent on funding abatement controls. Because there are no specific requirements beyond that, it is assumed that the local government decides the portion of abatement technology investment s_i to subsidize for each firm i as the policy instrument. The share of the investment reflects the level of pollution reduction enforcement from the local government, and could potentially be based on the firms' health-risk index θ_i, i.e., the relative pollution damage from each unit of pollutants based on the firm's location in a jurisdiction. Because locations of firms do not change over the study period, I assume that θ_is are determined prior to environmental quality being a concern. The firms understand their geographical influence on jurisdictional residents' well-being, and plan their intended output level y_i, unintended output (emission) level e_i, and abated amount a_i to maximize its profit:

$$\pi(y_i, e_i, a_i; s_i) = \max_{y_i, e_i, a_i} \{py_i - C(y_i, e_i; w) - (1 - s_i)A(e_i, a_i; q) - \tau(e_i - a_i)\} \quad (3.1)$$

where p, τ, w, q, are the exogenous prices of the intended output, the unintended output (levy rate of emission), the production inputs, and the abatement inputs, respectively. $C(y_i, e_i; w)$ and $A(e_i, a_i; q)$ are the production costs and abatement costs, respectively. The model implicitly includes two types of technologies, y_i and e_i are the outputs with a non-negative "trade-off" under the production technology, then e_i becomes the input under the abatement technology, with a_i as the output. It is assumed that $C_y > 0$, $C_e > 0$, $A_e < 0$, $A_a > 0$, $C_{ye} \leq 0$, and $A_{ea} \geq 0$, where the subscripts under A or C represent partial derivatives with respect to the corresponding variables. Again, s_i represents the share of $A(e_i, a_i; q)$ that is subsidized by the local government.

To solve (3.1), notice that:

$$
\begin{aligned}
\frac{\partial \pi(y_i, e_i, a_i; s_i)}{\partial(-y_i)} &= C_y - p \\
\frac{\partial \pi(y_i, e_i, a_i; s_i)}{\partial(-e_i)} &= C_e + (1 - s_i)A_e + \tau \\
\frac{\partial \pi(y_i, e_i, a_i; s_i)}{\partial a_i} &= -(1 - s_i)A_a + \tau \\
\frac{\partial \pi(y_i, e_i, a_i; s_i)}{\partial s_i} &= A(e_i, a_i; q)
\end{aligned}
\tag{3.2}
$$

Because all the 6 pairs of cross partial derivatives are nonnegative,[3] $\pi(y_i, e_i, a_i; s_i)$ exhibits increasing differences for all pairs of its arguments and is supermodular in $(-y_i, -e_i, a_i, s_i)$. This provides the following results: $\partial y_i/\partial s_i \leq 0$, $\partial e_i/\partial s_i \leq 0$, and $\partial a_i/\partial s_i \geq 0$, i.e., both intended and unintended outputs are decreasing if the local government provides a higher share of investment on the abatement technology for the corresponding firm, and the abatement level is increasing.

The local government knows the impact of their investment on the local economy, and decides s_i in a strategic way. It has its own tradeoffs between promoting the local economy and preventing environmental damage, which are two key factors evaluated by the central government. Because the local government's choices will indirectly influence the firm's actions, firm i's optimized production and abatement in equation (3.1) are functions of s_i ($y_i(s_i)$, $e_i(s_i)$, $a_i(s_i)$) from the local government's perspective. The local government chooses $s_1, ...s_n$ for each firm i to maximize its

[3]From (3.2), the cross partial derivatives are $\frac{\partial \pi}{\partial(-y_i)\partial(-e_i)} = -C_{ye} \geq 0$, $\frac{\partial \pi}{\partial(-y_i)\partial a_i} = 0$, $\frac{\partial \pi}{\partial(-y_i)\partial s_i} = 0$, $\frac{\partial \pi}{\partial(-e_i)\partial a_i} = (1 - s_i)A_{ea} \geq 0$, $\frac{\partial \pi}{\partial(-e_i)\partial s_i} = -A_e > 0$, $\frac{\partial \pi}{\partial a_i \partial s_i} = A_a > 0$.

utility from aggregate impacts in its jurisdiction:

$$\begin{aligned} U(s_1, ...s_n, \theta_1, ...\theta_n) = \max_{s_1,...s_n} \Big\{ & t \sum_{i=1}^{n} y_i(s_i) + \tau \sum_{i=1}^{n} (e_i(s_i) - a_i(s_i)) \\ & - \sum_{i=1}^{n} s_i A(e_i(s_i), a_i(s_i); q) - \sum_{i=1}^{n} D(e_i(s_i) - a_i(s_i), \theta_i) \Big\} \end{aligned} \tag{3.3}$$

where t is the exogenous tax rate of output, which is assumed as another source of governmental revenue aside from pollution levies. $D(z_i(s_i), \theta_i) = D(e_i(s_i) - a_i(s_i), \theta_i)$ is the pollution damage caused by firm i inside the jurisdiction. I assume that $D_{z\theta} \geq 0$, i.e., marginal pollution damage is nondecreasing as a firm locates in more environmentally sensitive areas.

To solve (3.3), notice that:

$$\begin{aligned} \frac{\partial U(s_1, ...s_n, \theta_1, ...\theta_n)}{\partial s_i} &= t y_s + \tau(e_s - a_s) - A - s_i(A_e e_s - A_a a_s) - D_z(e_s - a_s) \\ \frac{\partial U(s_1, ...s_n, \theta_1, ...\theta_n)}{\partial \theta_i} &= -D_\theta \end{aligned} \tag{3.4}$$

Because $\partial U(s_1, ...s_n, \theta_1, ...\theta_n)/(\partial s_i \partial \theta_i) = -D_{z\theta}(e_s - a_s) \geq 0$ and the other cross partial derivatives are zero, $U(s_1, ...s_n, \theta_1, ...\theta_n)$ has increasing differences for all pairs of their arguments and is supermodular in $(s_1, ...s_n, \theta_1, ...\theta_n)$. Thus, $\partial s_i/\partial \theta_i \geq 0$, i.e., the local government subsidizes a higher share of a firm's abatement investment if the firm locates in a more environmentally sensitive area, such as places closer to an upstream border or a residential area within the local government's jurisdiction.

An interesting testable result can be derived from the equations above. Each firm's emission level is increasing as it locates in a less environmentally sensitive area (lower health-risk index):

$$\frac{\partial z_i}{\partial \theta_i} = \frac{\partial (e_i - a_i)}{\partial \theta_i} = \Big(\frac{\partial e_i}{\partial s_i} - \frac{\partial a_i}{\partial s_i}\Big)\frac{\partial s_i}{\partial \theta_i} \leq 0 \tag{3.5}$$

The model provides a detailed explanation of a possible cause for the downstream effect. Water-polluting firms closer to the downstream border of a jurisdiction or further away from a jurisdictional residential area yield less damage to jurisdictional residents, which leads to less environmental-related complaints that may jeopardize a local government official's promotion. At the same time, local officials can still enjoy the economic growth brought from such a firm's production. Local officials may be more likely to ignore pollution from these firms because increased production is more likely to offset the corresponding pollution damage at less environmentally sensitive areas. For firms that may cause health damage to local residents, the local government has the ability either to shutdown the firm, or to require the installation of pollution abatement technology to part or all of its units (Chang and Wang, 2010).

Moreover, because the subsidized portion of abatement investment is higher for firms located in more environmentally sensitive areas ($\partial s_i/\partial \theta_i \geq 0$), those firms also have a higher total investment in their abatement technology:

$$\frac{\partial A(e_i, a_i; q)}{\partial \theta} = A_e \cdot \frac{\partial e}{\partial s}\frac{\partial s}{\partial \theta} + A_a \cdot \frac{\partial a}{\partial s}\frac{\partial s}{\partial \theta} \geq 0 \tag{3.6}$$

This shows why local officials may respond to the pollution reduction mandates by shifting enforcement efforts away from the least geographically significant firms, essentially allowing those firms to continue polluting because their emissions flow outside the jurisdiction where it is less harmful to jurisdictional residents' health.

In summary, this section provides two testable hypotheses about relationships between firm emission levels, investment in abatement technology, and firms' geographical information. The following sections provide detailed empirical tests of these hypotheses. Specifically, they test that for water-polluting firms, those that are closer to the downstream border of a jurisdiction, or those that are further away from a jurisdictional residential area, will have higher emission levels and lower abatement technology investment.

3.4 Data

To test the hypotheses of the inter-jurisdictional spillovers explored in the preceding section, I create a unique panel of firm and socioeconomic data. The firm data is collected from a number of governmental documents recently released by the MEP. In particular, these are the lists of enterprises subject to Intensive Monitoring and Control of the State (2011-2015), and the latest lists of Running Desulfurization and Denitrification Facilities. The first list contains the quarterly pollution levies charged to each firm subject to intensive monitoring and control by the state, with the corresponding firm's names at plant-level. According to the central MEP, these high production firms account for nearly 65% of total emissions. The last two lists provide the end-of-the-pipe desulfurization and denitrification technology installation information before 2015 for all installed firms, including firm's name, firm's sector, installation date, capacity, and types of technology. To ensure the reliability of the monitoring information, local Environmental Protection Bureaus (EPBs) must conduct monitoring activities and unannounced field inspections before reporting to superior level EPBs and the MEP (Wu et al., 2016).

Firms' locations were obtained from Google Maps API, which provides each firm's longitude and latitude information. This coordinate layer was projected and merged to other layers of administrative, hydrological, transportation, and residential maps that are collected from the National Fundamental Geographic Information System (NFGIS) to generate distance variables. The ArcGIS Proximity toolset (Near) was used to calculate the distances from a firm to its closest residential area, industrial park, and transportation infrastructure, and the ArcGIS Network Analyst extension was used to find the distance to downstream estuaries along river networks. All distances were then converted from *Decimal Degrees* to *Meters* using the *Gauss Kruger-Beijing 1954* projection, the most commonly used projected coordinate system in China. The detailed firm-level locational information was merged with county, prefectural, and provincial-level socioeconomic data.

There are six major water-polluting sectors from the intensive monitoring lists: power; cement; steel; paper; food and beverage; and the clothing/dyeing sectors. Table 3.1 shows descriptive statistics by sector to compare water-polluting firm's relative locations. The power sector has the highest average COD−equivalent pollution level, the cement and steel sectors are heavy polluters as well. While heavy polluting sectors in the US tend to be located together (Monogan III et al., 2013), that is not the case in China. The ranges of all the distance variables are wide in each sector, and there are no significant differences across sectors. This is important for my analysis, because firms clustered together with similar geographical patterns (i.e., all located near the border) would not provide enough "between variation" in each sector, and cross-sector comparison as in Monogan III et al. (2013) is not the major interest of this paper. No significant geographical variations by sector may suggest that heavy polluters are not strategically placed before or at the moment they enter the market, pollution level variations, if any, are more likely to be generated after the placement.

The socioeconomic data for the corresponding study time period comes from the published statistical yearbooks from 2011 to 2015 and the monthly data released on the website of the National Bureau of Statistics of China, including: local aggregate production in each industry and sector; administrative information; population; income; GDP or value added by sector; education; welfare; local government budgets; as well as aggregate industrial solid waste information. All the monetary variables in Chinese Yuan (CNY) are normalized to their 2015 values. GDP deflators for each sector are used to deflate the local GDP from respective sectors. Both deflators and normalized rates are provided by the Federal Reserve Bank of St. Louis, their sources being the Organization for Economic Co-operation & Development (OECD).

Other sources include county, prefectural, and provincial-level statistical yearbooks compiled by the National Bureau of Statistics of China, and monthly provincial sectorial data published on its website. Weather data is included for better control under the consideration that certain production activities may be influenced by local precipitation and temperature. It is collected from the hourly weather station reports of the U.S. National Oceanic and Atmospheric Administration (NOAA). The standard inverse distance weighting (IDW) tool in ArcGIS Spatial Analyst is used to find the estimated weather information for each firm and aggregate the weather data to quarterly level. Information about local terrain types and whether the firm is located in a designated historical industrial city is also extracted from maps in ArcGIS.

Because these socioeconomic variables are included only for control purposes I report descriptive statistics in Table 3.2 for some selected variables to show that control variables are relatively similar for firms from sector to sector. In general, there are no significant differences across sectors. Firms from the power and cement sectors are located in counties with higher governmental revenues on average, as well as higher governmental expenditures. Areas with more paved roads also suggests these counties have better public goods provisions. Relatively similar population densities and shares of firms in designated historical industrial cities suggests that firms in different sectors have similar socioeconomic backgrounds as well. Similar average precipitation and local terrain types also suggest that these firms have no significant geographical variations, confirming the information from Table 3.1.

3.5 Empirical Model

This section illustrates the empirical methods to test the hypotheses derived above. I first examine the existence and the magnitude of the downstream effect among the monitored water-polluting firms. The theoretical model suggests that a firm's pollution level and the scale of installed abatement technology are both functions of its location in a jurisdiction. The scale of installed abatement technology may also influence firm's pollution level. Let $pollution_{it}$ represent the quarterly pollution of firm i at the quarter t, which is converted from the charged quarterly pollution tax to COD-equivalent pollution in kilograms. Let $Tech_{it}$ represent the aggregated desulfurization or denitrification capacity of the installed abatement technology in firm i at the beginning of quarter t. The main empirical model is given by:

$$\begin{aligned} pollution_{it} &= \alpha + \beta_1 downstream_i + \beta_2 residential_i + \delta Tech_{it} + \boldsymbol{\gamma X_{it}} + e_i + e_t + e_{it} \\ Tech_{it} &= a + b_1 downstream_i + b_2 residential_i + \boldsymbol{g X_{it}} + \epsilon_i + \epsilon_t + \epsilon_{it} \end{aligned} \tag{3.7}$$

where $downstream_i$ and $residential_i$ represent the distances from the firm i to its downstream estuary along the river network and to its nearest residential area within the jurisdiction in kilometers, respectively, and $\boldsymbol{X_{it}}$ includes weather data and all the county, prefectural, and provincial-level controls mentioned in the preceding section, such as local demographic information, administrative size, education facilities, hospital facilities, social service facilities, and aggregate gross/per capita industrial values. Including $\boldsymbol{X_{it}}$ also helps to reduce possible biases caused by other local impacts that are time-varying, because previous studies suggest variation in local enforcement may depend on local incomes, accessibility to information, and average education level. (Cai et al., 2015; Helland and Whitford, 2003a; Wang and Wheeler, 2005).

Because the key variables $downstream_i$ and $residential_i$ are time-invariant, I adopt two different estimation methods. As noted before, the pollution reduction mandates started before the study period. There is no policy change that creates significant impacts on regulatory stringency. I use a within-between random effects (WBRE) model to estimate the impacts of a firm's location on pollution levels and installation levels of abatement technology in different sectors. To do so, I adopt the Mundlak-Chamberlain Approach (Allison, 2009; Chamberlain, 1982; Mundlak, 1978; Schunck and others, 2013; Wooldridge, 2009) by including the time averages of the time-variant variables:

$$\begin{aligned} pollution_{it} &= \alpha + \beta_1 downstream_i + \beta_2 residential_i + \delta_1 Tech_{it} + \delta_2 \overline{Tech_i} \\ &\quad + \boldsymbol{\gamma_1} \boldsymbol{X_{it}} + \boldsymbol{\gamma_2} \overline{\boldsymbol{X_i}} + \boldsymbol{u_{it}} + e_i + e_{it} \\ Tech_{it} &= a + b_1 downstream_i + b_2 residential_i + \boldsymbol{g_1} \boldsymbol{X_{it}} + \boldsymbol{g_2} \overline{\boldsymbol{X_i}} + \epsilon_i + \epsilon_t + \epsilon_{it} \end{aligned} \tag{3.8}$$

I estimate both the reduced form equations (in which the abatement technology variable is not included in the pollution estimation), and the 2SLS equations (in which the abatement technology variable is included in the pollution estimation and is instrumented by local governmental revenue and expenditure). I choose county-level governmental revenue and governmental expenditure as instruments, because as explained earlier, abatement technology installation is mainly enacted by local governments. Firms' financial situations are very likely to be linked to the scale of their abatement technology, but unlikely to have direct impacts on their pollution levels.

The WBRE model estimates the time-invariant locational impacts on a firm's pollution level directly. The model decomposes between and within variation and estimates the respective effects in a single equation. However, for the estimates of β_1, β_2, b_1, and b_2 to be unbiased, $E(e_i|X_{it}, u_i) = 0$ and $e_i|X_{it}, u_i$ $N(0, \sigma_e^2)$ have to hold. I include additional time-invariant variables that potentially influence a firm's pollution levels, u_i, to further reduce the possible bias, where u_i includes local terrain types, provincial-wide total water volume on average, and whether firm i is located in the historical industrial base.[4] The estimated coefficients are reported in Table 3.3, which includes both the reduced form estimation and the 2SLS-WBRE estimation.

To examine if the Mundlak-Chamberlain Approach provides non-biased coefficients, I conduct a series of robustness checks in the Conceptual Framework. I include detailed plant-level control variables for a representative subgroup of data to reduce possible bias from the plant's time variant variables. I use a two-stage least

[4] There are 120 cities in 27 provinces designated as the historical industrial base, where heavy industries were concentrated during China's early industrial development period (1953-1970).

square fixed-effects (2SLS-FE) model to examine possible regime or policy change during the study period by interacting time-invariant locational variables with quarter indicators. I examine the heterogenous locational impacts by separating the dataset based on region and jurisdictional river lengths. I also treat locational variables, $residential_i$ and $downstream_i$, as endogenous in equation (3.7) with a control function approach. The estimated coefficients have the same magnitudes and follow the expectations.

3.6 Estimation Results and Implications

This section reports the estimated coefficients for water-polluting firms. Sections 3.6.1.1 to 3.6.1.3 under the subsection 3.6.1 provide extensive interpretation of the downstream effect in water pollution. And subsection 3.6.2 provides policy implications and one policy simulation that allows jurisdictional negotiation in the water pollution case. It can be considered as a general economic method to potentially reduce transboundary pollution.

Table 3.3 and Table B.1 (& B.2) report key estimated coefficients for water-polluting firms using the within-between random effects model and the two stage least square fixed effects model, respectively. In general, the estimated coefficients have signs consistent with expectations. The second panels of Table 3.3 and Table B.2 also report the 2SLS estimated impacts of the scales of installed abatement technology on water-polluting firm emission levels, and the coefficients have the same magnitudes across different sectors. Two instrumental variables for the abatement technology installation, local governmental expenditure and revenue, are significantly different from zero in both models, and have signs following the expectation. Over-identification tests and the weak instrument tests indicate that these instruments are strong and valid.

The coefficients reported in Table 3.3 from the reduced form model (panel 1) and the model that includes the abatement technology variable (panel 2) have signs and magnitudes that are consistent with each other. In general, the reduced form estimation of distance variables have higher magnitudes, because the locational impacts on pollution and abatement technology capacities have opposite signs, and higher abatement technology capacities reduce total pollution levels. Moreover, the standard errors in panel 2 are generally larger compared to those in the first panel, because using instruments brings more variation to the model.

3.6.1 Strategic Polluting Behavior in Water Pollution

This paper broadens the concept of the "downstream effect" in water pollution by separating this strategic pollution behavior into the spillovers inherent in river network and related those to residential locations. Although firms closer to a downstream border or further away from a residential area have incentives to reduce local pollution based on the same theoretical grounds, the political implications may be different. I will illustrate these separately in the following subsections.

3.6.1.1 Spillovers Inherent in River Pollution

China's Pollution Reduction Mandates charge each unit of pollutant at the same price and return the levy as abatement subsidies to each firm in order to reduce pollution in the whole country. However, the theoretical section suggests that a firm locating closer to the downstream border along the river network within each jurisdiction will have higher pollution levels. The estimated coefficients in Table 3.3 follow the expectation of this hypothesis for all the six industrial sectors.

On average, firms will pay an extra pollution tax of 25.68 to 50.43 Yuan ($3.98 to $7.81 in 2011 exchange rate), and emit 0.009% to 0.118% of additional COD-equivalent pollutants if it locates one kilometer closer to a provincial downstream estuary. Firms further downstream along the river network, where emitted pollutants to rivers are less likely to generate health impacts to the whole jurisdiction, have less incentive to reduce emission. Sector-wise analysis suggests that firms in heavy polluting sectors, such as the power sector, steel sector, and cement sector are more sensitive to locational changes along the river network. These firms' incentives to emit additional pollution emissions into rivers increases as they locate further downstream. However, these sectors have a lower percentage change of pollution based on locational variation. Firms in the clothing/dyeing sector and food/beverage sector increase their percentage of pollution almost 12 times faster as they locate further downstream, although increases in their pollution emission levels over distance amount to only half of those firms in the power sector. With the average distances to the downstream border, the average pollution in COD-equivalent would increase by 5.48-13.92 tons in different sectors if the firms were locating near the border, which are 1.3% to 20.6% of the current average, suggesting the downstream spillovers would be significant.

The regionally disaggregated coefficients are similar to the main regression results. Figure B.1 plots the coefficients using the WBRE model and the 2SLS-FE model for eastern China and western China. The dashed lines represent the WBRE model's coefficients and the dots (with the corresponding standard errors) represent the 2SLS-FE model's coefficients over 20 quarters. In general, the coefficients remain almost identical over time, and the magnitudes are higher for the power and the steel-manufacturing sectors, and lower for the clothing/dyeing and the food/beverage sectors, corresponding with the results in Tables 3.3 and B.1.

Eastern China in general exhibits a stronger downstream effect compared to western China. Firms in the eastern region, which are relatively further downstream of the whole country, are more likely to have increased incentives to pollute. These firms can export pollution outside the entire country along the river network. This is consistent with the literature showing that international rivers and seas are more polluted than rivers within a country. Shallow waters along China's vast coast have failed to meet national quality standards for clean oceanic water, with 29,000 square kilometers of seriously polluted seawater (Liu and Diamond, 2005; Pan and Wang, 2012). The level of major pollutants, such as inorganic nitrogen and phosphate, remain high in contaminated seawater. My estimation suggests that local officials have more motivation to free-ride on water pollution in the eastern coastal area of China. They have less of an incentive to promote pollution reduction among heavy industrial facilities compared to those in western regions in general, because emitted pollutants are more likely to be exported outside the country.

3.6.1.2 Trade-off Effect for Local Support

The theoretical analysis suggests that firms located further away from residential areas may increase pollution emissions, because local officials have less of an incentive to subsidize abatement for those firms. This is similar to the downstream effect observed above, which is that each jurisdiction shifts pollution downstream, and focuses on reducing pollution impacts to its own residents. The corresponding coefficients in Table 3.3 suggest that these types of pollution incentives, which potentially allow local authorities to acquire more local support, are substantial and have a similar magnitude to the spillover effect along a river network. This may indicate that shifting pollution to the downstream or further away from residential areas are similar decision-making processes for balancing the local economy and local environment, which is consistent with the theoretical model.

To retain its local public support and avoid pollution complaints, the local government has more of an incentive to strengthen the abatement enforcement near jurisdictional residential areas and meet the demand for environmental quality under its jurisdiction with the least effort. On average, a firm will emit 0.009% to 0.093% of additional COD-equivalent pollutants if it locates one kilometer away from a residential area. Given the average distances to the closest residential area, a firm would have incentives to decrease 0.12 to 0.86 tons of COD-equivalent pollutants if it locates next to it.

Similar to the spillover effects inherent in river pollution, local officials have the highest incentives to reduce pollution for firms in the power sector and the steel-manufacturing sector as the firm is located closer to a jurisdictional residential area. While the percentage reductions of pollution from these sectors are lower than for firms in industries such as the clothing/dyeing sector and the food/beverage sector.

Region-wide comparisons are shown in Figure B.2, which plots the coefficients using both a WBRE model and a 2SLS-FE model (with the corresponding standard errors) of the distances to the closest jurisdictional residential area over the study period. These figures suggest similar incentive patterns as with distances to downstream estuaries, with higher magnitudes in eastern China. This is possibly due to the difference in population density. Western China has lower population density, and the pollution level of a firm in western China is less sensitive to a firm's distance to a residential area.

3.6.1.3 Downstream effect and the Installation of Abatement Technology

Based on my theoretical model, firms with less per unit local environmental damage will receive a smaller subsidy share of abatement technology investments from the local government, and their total level of abatement technology installation will be lower, compared to firms located in more environmentally sensitive areas. Table 3.3 shows the estimated coefficients for the impact of firms' location on installed abatement technology level from both the direct estimation (panel 1) and the first stage estimation (panel 2). In general, the estimated coefficients follow the expectation of the theoretical hypothesis and have the same magnitudes between different estimation methods, although the magnitudes of the coefficients are generally higher in the first stage estimation. I illustrate the following implications based on the coefficients reported in the first panel in Table 3.3.

On average, the scale of installed abatement technology will increase from 0.004% to 0.080% if a firm locates one kilometer upstream from the downstream estuary, or from 0.008% to 0.133% if it locates one kilometer closer to a residential residential area, depending on the sector that it is in. Local officials' incentives to abate pollution may vary by sectors: variation of abatement technology installation is more sensitive to a firm's relative location on a river network for firms in the paper and power sectors, and more sensitive to a firm's relative location with regard to residential areas for firms in the steel manufacturing sector. Given the descriptive statistics in Table 3.2, these sectors are generally located in counties with relatively high expenditures compared to the governmental revenues, and where the impacts of local governments' financial situations are relatively high. It is possible that a certain share of governmental expenditure is allocated to investing in abatement technology installation for firms in these sectors inside the jurisdiction. Higher revenue (lower expenditure) from the previous year stimulates significantly more installation of abatement technology for these heavily polluting firms, suggesting local governmental financial status plays an important role when it strategically allocates pollution and abatement resources inside each jurisdiction.

With the average locational information from the descriptive statistics in Table 3.1, the average abatement capacities would decrease from 0.78% to 11.44% or from 0.04% to 0.93% if firms from different sectors are gathering at the downstream border or next to the closest jurisdictional residential area, respectively. Firms in the power and the paper sectors have higher decreases for the former situation, and firms in the clothing/dyeing and the steel-manufacturing sectors have higher decreases for the latter situation. These estimated results suggest that geographical variation impacts local officials' incentives to promote additional abatement technology installation. The total savings from the pollution levies for all the firms in this dataset would be $57.84 million (in 2011 exchange rate) if all of them increased the scale of abatement technology by one additional ton (approximately a 10% to 132% increase based on the current installation scales, depending on the sector), and the total emission reduction would be 0.62 million tons of COD-equivalent pollutants.

3.6.2 Policy Implication and Pollution Reduction

In this subsection, I estimate the magnitude of distortions caused by inter-jurisdictional spillovers by comparing an optimum from a hypothesized central policy to the current decentralized optimum from the water-pollution regression, and provide policy implications related to it. Currently, in water pollution, each jurisdiction acts like a self-interested utility maximizer and exports pollution outside the jurisdiction through the river network or away from jurisdictional residential areas. However, the country could internalize all the pollution spillovers across jurisdictions while still exporting pollution outside the country by acting like one jurisdiction. This new policy scenario can be easily designed for water pollution, and I will illustrate this centralized scenario using the water pollution case as an example.

To simulate the new policy scenario, I use the estimated coefficients in the first panel of Table 3.3, which estimates firms' pollution levels using the following equation:

$$pollution_{it} = \alpha + \beta_1 downstream_i + \beta_2 residential_i + \boldsymbol{\gamma_1 X_{it}} + \boldsymbol{\gamma_2 \overline{X_i}} + \boldsymbol{u_{it}} + e_i + e_{it} \tag{3.9}$$

The new policy scenario will change the firm's relative location along the river network or relative to a residential area. I assume everything else remains the same. I define the new distance to the closest residential area, $new\_residential_i$, to be the distance from the firm i to the closest residential area within or outside the jurisdiction (while the previous distance only considers the residential area within the jurisdiction). I define the distance to the downstream estuary, $new\_downstream_i$, to be the distance from the firm i along the river network to the most downstream estuary in the country. I substitute $new\_residential_i$ and $new\_downstream_i$ for $residential_i$ and $downstream_i$ in the above equation to estimate the new pollution levels for each firm. For those negative pollution levels, I replace them to zero. Comparing the total pollution level in this new policy scenario to the current situation, the estimated pollution reduction is reported in Table 3.4.

Table 3.4 suggests that a centralized policy will bring additional pollution reduction to the whole country. Specifically, the power sector and the steel-manufacturing sector have the highest pollution reduction in absolute terms, and the cement sector has the highest pollution reduction percentage. Given the corresponding county population of where the firm is located, the reduced COD-equivalent pollution per person-exposure per year is the highest from the power sector. Other sectors also have positive reduction levels. The centralized policy can be achieved by allowing inter-jurisdictional negotiation and financial transfers across provinces. Downstream provinces may use charged pollution levies for abatement in upstream provinces, which is beneficial both in financial and pollution-reduction terms. Total charged levies from heavily polluting firms will be reduced on average, because upstream jurisdictions' polluting incentives are lessened further. Reduced average COD- or BOD-equivalent pollution per person per year may also improve regional health outcomes and thus human capital outcomes.[5]

In general, as mentioned before, the central MEP is responsible for managing and monitoring firm's polluting activities at the national level. Local officials at the provincial level have the power to collect levies and provide pollution reduction plans within their jurisdictions. Although the central MEP selects high production high pollution firms into its own monitoring system, local governments still have a certain level of freedom and can strategically pollute by allocating fewer abatement funds in places where environmental impacts are less likely to be internalized. However,

[5]Note that polluting incentives may shift to the most downstream firms to pollute into international seas. International impacts have not been considered in this estimation.

the pollution spillovers could be reduced with inter-jurisdictional financial transfers. Although the centralized optimum estimated above still generates spillovers across jurisdictions, it will increase the nationwide welfare in health compared to the current decentralized optimum.

Additionally, to reduce pollution spillovers based on the current situation, the central government may strengthen pollution regulation in places where local officials tend to be more lenient toward local emissions. For instance, the central government may have to enforce pollution abatement at facilities closer to the downstream border in a jurisdiction where pollutants could fall into other jurisdictions. They could require heavily polluting firms located in those regions to install pollution abatement technology. Moreover, the MEP could provide more transparent pollution data to the public. Thus, local residents and media members, who care about water quality would be better equipped to put pressure on local governments to reduce pollution across jurisdictional borders.

3.7 Conclusion

China's rapid industrialization and the corresponding environmental deterioration have led to the central government enacting stricter regulations for water quality. Water pollutants are levied under the pollution reduction mandates. Since 2001, the central government has set pollution reduction targets for each province. Local officials are now evaluated on their ability to reduce pollution and sustain economic growth. More recently, the central government has stipulated that pollution levies be spent only on funding abatement controls. Although the central government has been monitoring the most heavily polluting firms, provincial governments may strategically allocate fewer funds or less enforcement effort in places where environmental improvements are less likely to be internalized by their own jurisdictional residents.

This paper explores the downstream effect theoretically and empirically. This study uses a sequential game model to portray the interaction between the local government and firms under China's pollution reduction mandates. It hypothesizes that local officials exhibit more lenient pollution control when the pollution is less likely to cause environmental damage inside the jurisdiction. This results in increased pollution levels from firms located at downstream borders or away from jurisdictional residential areas. The paper tests these hypotheses using quarterly pollution data from heavily polluting firms from 2011 to 2015. The dataset is merged with firm abatement control technology information, as well as local weather and socio-economic data in China. I adopt both a fixed effects model and a correlated random effects model to estimate the firm's time-invariant locational impacts on pollution activities and installation of abatement technologies. The estimated coefficients are consistent with the expectations: A water-polluting firm emits more pollutants if it is closer to a downstream border and further away from a residential area within the jurisdiction. These types of firms will invest less in abatement technology. These results suggest the existence of strategic polluting behavior, which is potentially caused by local officials' incentives from the stipulations of the pollution reduction mandates.

The results presented in this paper suggest that the pollution level has a significant geographic pattern under each jurisdiction in China, consistent with the environmental federalism literature of pollution spillovers. In particular, local officials may allow more pollution activities for water polluting firms located closer to its downstream estuaries, where the pollutants would be more easily be exported away from its jurisdiction. The paper argues that these effects are possibly caused by the promotion pressure from the central government, which leads local governments to allocate most of their pollution reduction enforcement efforts to zones that help boost the economy and residential support within their jurisdictions.

Reducing transboundary pollution will be a challenging policy problem for the central government. In the water pollution case, specifically, decentralized decision-making structure is not appropriate as it results in excessive level of overall pollution. A centralized pollution control policy would be preferred to improve cost-effectiveness. It seems that a centralized decision, even preserves the downstream effect, can reduce significant pollution distortions under the decentralized settings. The centralized decision forces officials in one jurisdiction to include the pollution costs imposed on their downstream neighbors into their considerations. It is easier for a central authority to recognize that $1 abatement effort is worth more upstream than downstream. The centralized policy may moderate differences among jurisdictions and lower the overall pollution costs.

If the central government intends to improve environmental quality in the whole country, it may allocate a percentage of the charged pollution levies to help install pollution reduction technologies on border facilities and heavy-industry facilities. It could also use extra funds to encourage local officials to exert enforcement efforts near downstream borders. It may also increase the tax rates for facilities located in environmentally sensitive areas. Moreover, if pollution data is made available to the public, it may help arouse citizens' concerns and feedback. In turn, citizen and media pressure could incentivize local officials to set pollution reduction targets for downstream border regions and areas further away from residential centers. Regional cooperation and negotiation may also be required. Because water polluting flows are unidirectional, the centralized policy may involve compensation from downstream to upstream for reduced polluting activities. Provinces further downstream may provide funding to upstream provinces for additional abatement technology investment. The proposed method will decrease upstream pollution but may stimulate additional pollution further downstream. However, based on the estimation, the total pollution in the whole country would decrease and the average welfare would increase.

In general, this paper provides a new and important pollution spillovers evaluation in China that has not been adequately addressed in the existing literature. It examines spillover effects with detailed distance measures rather than rough firm locations and links the explanation of the downstream effect to politicians' promotion evaluations. It seems that certain modifications in the current pollution levy design are desirable if the central government wants to properly address the strategic polluting incentives that currently influence local governments. Although this paper illustrates some economic and political means to reduce pollution spillovers, the question of how costly these political means (better enforcement from the central government and providing more pollution data to the public) are compared to the economic means (financial transfer across jurisdictions) is beyond the scope of this paper. As well, it would be interesting to design other mechanisms to reduce pollution from centralized or decentralized structure. I will leave these issues for future research.

Statistics	*Mean*	*SD*	*Min*	*Max*	*Mean*	*SD*	*Min*	*Max*
Sector	Power				Cement			
Distance to downstream boundary	140645.7	114620.6	155.64	977120.1	177129.1	140496.2	70.89	1000457
Distance to the closest residential area	10480.54	12702.46	15.49	106038.8	6619.01	9014.87	3.72	96105.41
Distance to the closest road	9542.96	26844.72	0.14	256686.5	9579.95	18421.44	0.29	253938
Distance to the closest railroad	12249.63	19580.35	0.69	212948.8	23720.35	30669.06	0.59	277080.3
Distance to the closest industrial park	25943.69	35723.27	0.11	448470.8	41724.54	44337.35	0.15	303329.8
Distance to the closest commercial center	25769.56	31266.41	14.96	297393	30163.7	32827.09	24.36	295534.1
Pollution (COD-equivalent) in ton	914.49	2163.46	0	75000	225.4	1277.27	0	61510.45
Abatement technology	4.79	45.56	0	1320	9.81	110.89	0	3280
N	75628				39860			
Sector	Steel				Paper			
Distance to downstream boundary	165665.6	113685.9	39.37	955219.3	143910.3	97809.88	155.64	651708.4
Distance to the closest residential area	7023.95	9403.82	12.46	94255	5405.13	8029.39	11.97	109398
Distance to the closest road	10878.24	23427.77	1.17	232562.1	13279.14	29916.46	0.3	253938
Distance to the closest railroad	19677.05	23711.21	6.02	179207.1	17820.05	20667.77	1.51	246856.1
Distance to the closest industrial park	30385.61	31641.41	0.15	244392.8	22864.21	25883.18	0.22	190376.5
Distance to the closest commercial center	28147.26	27245.44	23.29	323912.9	22670.44	21749.12	19.48	141642.7
Pollution (COD-equivalent) in ton	159.63	413.26	0	7826.43	59.32	304.96	0	8225.36
Abatement technology	1.42	34.02	0	1200	2.49	19.4	0	340
N	70572				21552			
Sector	Clothing/Dyeing				Food/Bev			
Distance to downstream boundary	174319.4	122552.8	358.22	1000457	128142.3	86038.18	2256.5	844230.9
Distance to the closest residential area	7761.38	10779.74	3.6	95185.8	4193.16	4887.04	17.55	48329.48
Distance to the closest road	9717.54	22418.2	0.46	256686.5	19140.51	42003.27	0.91	256579.6
Distance to the closest railroad	25709.17	40503.65	4.56	287967.3	13877.38	15076.63	11.04	90462.91
Distance to the closest industrial park	38642.61	47802.99	0.08	449460.2	19092.11	19082.37	0.11	153914.8
Distance to the closest commercial center	31764.18	32822.49	17	294949.2	18587.02	18424.84	3.65	146094.3
Pollution (COD-equivalent) in ton	38.54	249.35	0	11644.04	37.18	230.07	0	10891.12
Abatement technology (ton)	1.56	29.38	0	800	0.76	9.08	0	240
N	29444				32636			

All the distance variables are measured in meters.
Abatement technology is production capacity (tons) installed with denitrification technology for Cement, Paper, and Food Sectors, and with desulfurization technology for Power, Cement, and Clothing/Dyeing Sectors.

Table 3.1: Descriptive Statistics of Data Used in Water Pollution Analysis in Various Sectors (2011-2015)

Statistics	*Mean*	*SD*	*Mean*	*SD*	*Mean*	*SD*
Sector	Power		Cement		Steel	
County-level governmental revenue (100 million CNY)	22.25	30.13	28.4	33.87	12.06	16.27
County-level governmental expenditure (100 million CNY)	32.29	27.53	36.14	30.57	24.8	17.04
County-level value added (100 million CNY)	191.8	228.91	253.6	262.2	109.86	125.14
County-level population (10k person)	66.99	34.38	74.48	38.54	69.36	36.54
County-level number of industrial enterprises	342.05	451.91	554.38	593.25	189.25	259.59
Prefectural-level number of employees (10k person)	89.77	117.7	94.68	92.94	82.65	139.86
Prefectural-level population density (person per sq. km)	580.46	531.05	663.31	378.21	509.9	501.27
Prefectural-level average wage (CNY)	40847.24	13504.99	39146.4	11238.39	37288.22	16469.51
Provincial-level area of paved road (10k sq. m)	2877.04	2794.81	2615.67	2456.81	2238.68	2812.95
Precipitation (mm)	72.54	66.71	101.9	80.09	91.2	73.82
Terrain (average land slope)	5.16	6.57	4.22	5.84	8.34	9.04
In a designated historical industrial city (0/1)	0.24	0.43	0.29	0.45	0.28	0.45
N	75628		39860		70572	
Sector	Paper		Clothing/Dyeing		Food/Bev	
County-level governmental revenue (100 million CNY)	15.14	19.51	10.61	14.61	15.29	26
County-level governmental expenditure (100 million CNY)	25.93	18.62	23.34	16.67	25.73	23.8
County-level value added (100 million CNY)	144.28	160.01	98.25	112.74	144.9	222.83
County-level population (10k person)	71.15	33.81	66.53	34.92	60.94	33.69
County-level number of industrial enterprises	287.13	354.62	175.15	243.66	201.8	343.65
Prefectural-level number of employees (10k person)	83.95	102.59	72.37	109.52	61.71	91.21
Prefectural-level population density (person per sq. km)	540.98	388.14	458.13	455.09	444.89	410.39
Prefectural-level average wage (CNY)	38375.94	14945.44	37150.31	14762.7	37144.9	13166.45
Provincial-level area of paved road (10k sq. m)	2372.28	2384.82	2179.18	2411.45	1888.18	2231.15
Precipitation (mm)	100.14	80.03	84.68	73.17	85.29	72.57
Terrain (average land slope)	6.65	7.56	7.32	8.43	11.1	12.4
In a designated historical industrial city (0/1)	0.27	0.44	0.23	0.42	0.18	0.38
N	21552		29444		32636	

Table 3.2: Descriptive Statistics of Selected Control Variables in Various Water-Polluting Sectors (2011-2015)

Comparison between Mundlak-RE and Mundlak-RE with IV results

dep. var.		Power	Steel	Cement	Paper	Clothing/Dyeing	Food/Bev
Pollution (COD)	Distance in km to	-84.05***	-78.60***	-77.91***	-53.34***	-45.60***	-42.82***
(Mundlak)	Downstream estuary	(1.090)	(1.001)	(0.783)	(0.748)	(0.493)	(0.391)
	Distance in km to	82.45***	63.62***	66.31***	42.83***	35.85***	29.67***
	Residential area	(0.793)	(0.840)	(0.917)	(0.734)	(0.284)	(0.502)
Abatement Tech.	Distance in km to	0.00244***	0.00043***	0.00065***	0.00198***	0.00016***	0.00028***
(Mundlak)	Downstream estuary	(0.00018)	(0.00005)	(0.00006)	(0.0002)	(0.00003)	(0.00003)
	Distance in km to	-0.00038***	-0.00135***	-0.00189***	-0.0002***	-0.00032***	-0.00018***
	Residential area	(0.00005)	(0.00027)	(0.00023)	(0.00002)	(0.00004)	(0.00005)
Pollution (COD)	Distance in km to	-70.43***	-63.25***	-63.04***	-40.20***	-26.19***	-25.98***
(Mundlak-IV)	Downstream estuary	(2.628)	(2.660)	(4.186)	(1.264)	(3.022)	(4.333)
	Distance in km to	72.50***	62.47***	61.00**	41.10***	27.22***	25.75***
	Residential area	(4.044)	(1.781)	(19.47)	(0.834)	(0.452)	(5.461)
	Abatement tech.	-3352.6***	-2210.6**	-1803.2**	-803.8**	-2887.4***	-2606.7***
	(in tons)	(806.5)	(858.0)	(647.3)	(291.2)	(685.4)	(300.8)
Abatement Tech.	Distance in km to	0.00789***	0.00294***	0.00125***	0.005***	0.00064***	0.00057***
(Mundlak-IV)	Downstream estuary	(0.00026)	(0.00025)	(0.00024)	(0.00023)	(0.00004)	(0.00006)
	Distance in km to	-0.00655***	-0.00172***	-0.00485***	-0.00082***	-0.00971***	-0.00073***
	Residential area	(0.00021)	(0.00031)	(0.00025)	(0.00006)	(0.00025)	(0.00005)
	Governmental	-6.3834***	-0.1768***	-5.0455***	-3.5132***	-5.1563***	-0.1818***
	Expenditure	(1.628)	(0.0513)	(1.2278)	(1.0155)	(0.9829)	(0.0528)
	Governmental	0.4604**	0.1812***	4.2733***	4.2332***	3.2729***	0.1847***
	Revenue	(0.1502)	(0.042)	(1.0514)	(0.854)	(0.9062)	(0.0433)
† *Kleibergen-Paap rk Wald F*		25.185	69.912	24.442	84.63	69.442	54.298
Sargan-Hansen Stat		1.357	0.257	0.217	0.261	2.168	0.169
p-val		0.2441	0.612	0.641	0.6096	0.1409	0.6807
N		70572	75628	21552	39860	29444	32636

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Abatement technology is production capacity (tons) installed with denitrification technology for Cement, Paper, and Food Sectors, and with desulfurization technology for Power, Cement, and Clothing/Dyeing Sectors.

† Stock-Yogo weak ID test critical values (maximal IV size): *10%* 19.93, *15%* 11.59, *20%* 8.75, *25%* 7.25. Source: Stock-Yogo (2005)

Table 3.3: Firm's Locational Impact on Water Pollution and Installed Abatement Technology: 2011-2015

Sector	Power	Cement	Steel	Paper	Clothing/Dyeing	Food/Bev	*Sum*
Reduction Percentage	23.12%	32.68%	29.73%	21.27%	13.66%	24.64%	
in Million CHYuan	9923.93	717.92	3267.3	258.17	94.24	105.86	14367.42
average BOD-equivalent per person·year	1494.07	117.44	409.84	44.02	14.34	15.63	2095.34

Table 3.4: Water Pollution Reduction with Inter-jurisdictional Negotiation

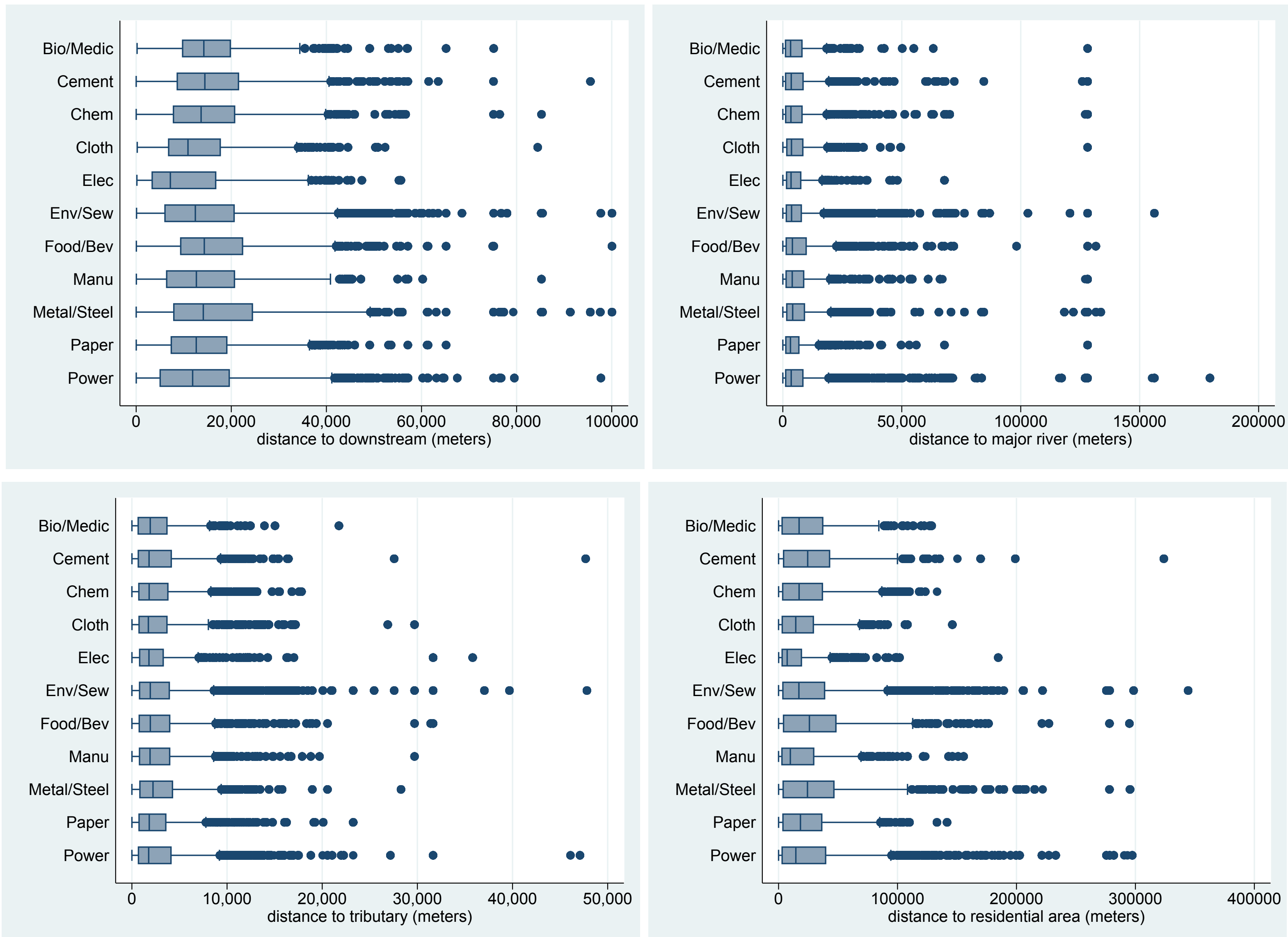

Figure 3.1: Summary of Distances by Industrial Sectors

Chapter 4: Geographic Spillovers in China: Strategic Air Polluters

4.1 Introduction

Air quality in China is among the worst in the world, due to the country's heavy reliance on fossil fuel consumption during its rapid economic growth and industrialization in the last three decades (Ghanem and Zhang, 2014). Coal accounts for more than 70% of the total energy consumption, which contributes the most to air pollution due to its combustion (Chan and Yao, 2008; Fang et al., 2009). Severe SO_2, NO_2, and particulate matter pollution have caused tremendous health and economic problems (Zhang and Wang, 2011). The problems were exacerbated in China by the large population, the lack of capital, and the poor education (Fang et al., 2009). Although China has made considerable efforts to limit air pollution, such as installing desulfurization and denitrification systems and strengthening vehicle-emissions standards, these measures have not kept up with the growth of its economy and fossil-fuel use (Zhang et al., 2012). The monetized health costs of premature mortality and morbidity associated with air pollution was 157.3 billion Yuan in 2003 alone (Sun and Gu, 2008). Non-health-related air pollution impacts, such as crop and fishery damage from acid rain, are substantial in economic value terms as well (He et al., 2016; World Bank, 2007).

All these pollution caused incidents have threatened the legitimacy of the central government, which has created bottom-up pressures for its local governments to reduce air pollution within the jurisdiction (Zheng et al., 2014a). To incentivize air pollution abatement in China, the central government evaluate local officials' performance, by including local air pollution index, the pollution reduction levels, and installation of abatement technologies as part of the promotion criteria. Major cities are required to disclose their classified air quality data, yet the manipulation of the disclosed pollution data has been noticed (Ghanem and Zhang, 2014). Fortunately, the central government has started to intensively monitoring the most heavily-polluted firms directly, and released the pollution levels in terms of charged pollution levies to establish and improve the information disclosure systems. This step also helps to reduce the chance of interference and misreporting from local officials. However, as noted before, jurisdictions have strong incentives to actively promote spatial pollution externalities to capture the benefits of economic development within their own borders.

This paper keeps investigating the inter-jurisdictional pollution externalities under the Pollution Reduction Mandates in China, with a focus on air-polluting firms. Under the decentralized environmental pollution control situation, it provides a complimentary evidence to show that local governments have incentives to promote spatial pollution spillovers among air-polluting firms as well. Following the theoretical model in Chapter 3, each firm has an assigned health-risk index representing its heterogeneous locational information. This value is used to proxy the relative health impact from its emitted air pollutants on residents' well-being within a local jurisdiction. Firms with relatively low health-risk index receive lower concerns from local governments, and are likely to emit higher pollution.

To adopt the theory in the air pollution circumstance, this paper hypothesizes that a firm has a lower health-risk index if it is closer to the downwind border of a jurisdiction or locating in an area with a higher average wind speed. Its pollution level is higher and its abatement investment is lower, comparing to an equivalent firm with a higher health-risk index in the same jurisdiction. To test the hypothesis empirically, I quantify the pollution and abatement incentives based on firm's geographic information using a unique firm-level panel dataset. I have constructed this dataset including each firm's relative distance to the leeward provincial border in each season, average wind speed at the firm's coordination, its quarterly SO_2-equivalent pollution level and the scale of installed abatement technology, as well as other socio-economic variables.

Similar to the econometric analysis adopted in the previous chapter, this chapter validates the hypothesis and shows that an air-polluting firm emits more pollutants if it is closer to the downwind border or in a location with higher wind speed (so that more emissions are carried downwind); these type of firms are also less likely to adopt abatement equipment with high capacities. Sector-wise analysis suggests that heavy polluters including the chemical and manufacturing industries exhibit a stronger "downwind effect". In general, this chapter shares part of the contribution to the literature in the previous chapter. It explores the geographical impacts of air pollution and abatement incentives with the direct measure of the pollutant levels and the firms locational information in China. This paper further examines the free-riding behavior that is possibly exhibited among local governments in environmental pollution issues, and serves as a complementary chapter for Chapter 3.

The remainder of the paper is organized as follows. Section 4.2 provides additional detailed literature review of China's pollution reduction mandates and the role of promotion criteria in environmental regulation. This section focuses mainly on the air pollution side. Sections 4.3 and 4.4 are the empirical portion with a within-between random effects model and a fixed effects model to test the hypothesized "downwind effect" for air pollution. The conceptual framework behind the empirical work follows the theoretical model in the previous chapter, and is further explained in the empirical section. Section 4.5 shows the main empirical results with a discussion of the caveat in theory. Section 4.6 concludes the paper.

4.2 Institutional Background and Literature Review

Environmental deterioration, as the byproduct of China's industrial growth during the period of economic reform, has resulted in the death of nearly a million people every year (World Bank, 2007). With its strong industrial expansion and relatively lax environmental regulation, China's air quality is among the worst in the world. Its SO_2 emissions are almost as high as for Europe and the United States combined (Vennemo et al., 2009). Less than 1% of the major cities in China meet the World Health Organization recommended air quality standards (Zhang and Crooks, 2012). Fossil fuel consumption, as a major result of rapid economic growth in China, has led to severe pollution of SO2, NO2, and particulate matter (Zhang and Wang, 2011).

Air pollution has substantial economic and health impacts to the society. Based on a World Bank report, the monetized health costs of air pollution in china are reached to 1.2% and 3.8% of GDP (World Bank, 2007). The welfare deduction from particulate matter concentrations, which are five times higher than the safety level, has increased from an estimated $22 billion in 1975 to an estimated $112 billion in 2005 (Chen et al., 2012; Ghanem and Zhang, 2014; Matus et al., 2012). Air pollution is also associated with elevated rates of mortality in developing countries (Chen et al., 2013; Ebenstein et al., 2015; Greenstone and Hanna, 2014; Zhang and Mu, 2018). The Global Burden of Disease Study shows that air pollution has become the leading health-risk factor for Chinese residents, which causes between 350,000 and 500,000 premature deaths each year in China (Chen et al., 2013; Yang et al., 2013).

China's leaders have started to worry about the corresponding environmental impacts on the economy and the society. Based on their concerns, air pollution is not only decreasing the speed of GDP growth in China, but also jeopardizing the legitimacy of the Chinese Communist Party. As noticed by Ghanem and Zhang (2014), because of the corresponding health impacts, air pollution "has stirred widespread discontent among the emerging middle class in urban areas" to threaten the stability of the society, which pressurizes both the central and the local governments to systematically reduce pollution for their residents.

While China still gives GDP growth the highest priority, the central government responded to the pollution problem with pollution reduction mandates including a new pollution levy system throughout the whole country. Starting in 2005 (the beginning of the 10th Five-Year Plan), the central government began to increase investment in environmental protection, set ambitious targets for the reduction of pollution and energy intensity, and introduce new environmentally friendly technologies (Economy, 2007).

The major focus of the pollution reduction mandates for monitoring and levy collection is on SO_2 for air-polluting firms. Pollution tax charges are levied on 44 air pollutants. All the other pollutants are converted to SO_2-equivalent units when calculating the pollution tax. Since July 1, 2004, the pollution tax is calculated as 0.6 Yuan (approximately $0.10) times the sum of the top three SO_2-equivalent pollutants for air-pollution. The charge rates and conversion rates for each pollutant are set by the central government in the Regulations on the Administration of the Charging and Use of Pollutant Discharge Fees (hereinafter, the Regulations) issued on February 28, 2003.

Under the decentralized pollution regulation, local governments are also empowered the ultimate authorities to manage local polluting firms. Inefficient small-scale coal-fired units with high polluting levels are forced to shut down (Cao et al., 2009; Jin and Lin, 2014; Ma and Zhao, 2015), other firms are subsidized to install pollution abatement technology under technology mandates. As explained above, environmental performance at the local level has incorporated in the cadre promotion and evaluation system to better motivate officials' pollution abatement incentives. The promotion tournament created among local officials forces them to focus both local economic growth rate and pollution reduction performance since 2007

(Chen et al., 2005; Li and Zhou, 2005; Shih et al., 2012). However, economic growth is always the top priority in China, even environmental compliance has been explicitly written into the cadre evaluation system (Zhang and Crooks, 2012; Zheng et al., 2014b). Local governments might trade local environmental services for faster economic growth, as the latter ones linkage to financial rewards and political promotion is well-known in Chinese political system (Ghanem and Zhang, 2014).

Because of the apparent tradeoffs between economic growth and pollution reduction, the literature to date suggests that local jurisdictions are likely to account for local conditions but ignore inter-jurisdictional spillovers when the decision of providing a public good is made locally. For instance, Rauscher (1995) and Santore et al. (2001) show that differences in state-level policies may lead to strategic pollution and asymmetric pollution spillovers. Novel (1992) finds that emissions of volatile organic compounds or nitrogen oxides in downwind states have more lax regulation. Helland and Whitford (2003b) notice that industrial toxic chemical releases to the air are systematically higher in counties on the eastern edge of states, because prevailing wind patterns could carry pollution across the border. Another related study conducted by Ghanem and Zhang (2014) also shows that wind speed is important for local pollution management.[1] The studies evaluating environmental free riding are largely based on county-level evidences. Detailed firm location data, on the other hand, could provide additional evidence of polluting facilities' geographic distribution. One of the most recent studies, Monogan III et al. (2013),

[1]They show that pollution data manipulation is likely to happen when the wind speed is low, as the pollutants are not "gone with the wind" under that circumstance.

uses stationary firms' locations in latitude and longitude to show that air polluting facilities are more likely to be located near a state's downwind border than other industrial facilities.[2]

This paper links closely to the above series of literature. Similar to other countries, after the economic reforms and the devolution of authorities, Chinese local governors can influence the location and scale of dirty industries' production with their administrative power. Because of the flexibility at the local level in the pollution reduction mandates, local leaders can strategically shift pollution activities without jeopardizing the production benefits within their jurisdictions. To provide a more nuanced empirical evidence in air pollution, I use a rich dataset to examine the relationship between the emission/abatement level and the location of a firm in the Chinese context.

4.3 Conceptual Framework and Data

Conceptually, a theoretical model of a firm's pollution highlighting the "downstream effect" has been developed in the previous chapter. As explained above, the Chinese "tournament competition" system to promote local officials has a significant influence on local pollution reduction and environmental protection (Wu et al., 2013). Local governments have incentives to both boost their local economy by attracting dirty industries and reduce air pollution to improve local residents' quality of life in order to retain their political power (Wang, 2013; Zheng et al., 2014a).

[2] Although this pattern of location may be the result of government's strategy, my study further argues that within each industry, higher pollution facilities are more likely to be located near the downwind border as well.

Similar to the externalities inherent in river, natural prevailing wind direction and average wind speed can lead to free-riding behaviors in air pollution at local level. Presumably, local governments benefit most from pollution reduction higher upwind in their jurisdiction, and thereby exert the least enforcement effort near the downwind boundary of their administrative regions. Higher wind speed could also take pollution away without additional abatement effort. Similar to the settings in the previous chapter, this paper assumes that per unit of pollutants from firms locating at less environmentally sensitive area have less health impacts to local residents, or firms locating closer to the downwind border or in an area with a higher average wind speed for the air-pollution case. Those firms can export pollutants outside easily and are assigned with lower health-risk index inside a jurisdiction based on their locational information.

The paper hypothesizes that local governments care less about pollution from firms with relatively low health-risk indices. Those firms yield less damage to local residents, which leads to less environmental-related complaints that may jeopardize local government's promotion. In theory, one dollar spent upwind brings more local health welfare than a dollar spent downwind. To enjoy the economic growth brought from firm production, local officials may be more likely to ignore pollution from downwind firms because increased production is likely to offset the corresponding pollution damage at less environmentally sensitive areas.

Similar to the theoretical conclusions in the previous chapter, I derive two testable hypotheses about the relationships between an air-polluting firm's geographical information with its emission levels and abatement technology scales:

firms closer to the downwind border or with higher wind speed will have higher emission levels and lower abatement technology investment. This pollution distortion or spillovers is examined using a unique panel of firm and socioeconomic data.

To construct the dataset, I use the data from the quarterly pollution tax data of firms subject to intensive monitoring from 2010-2015, and extract coordinates of firms in air polluting sectors using Google API. Same as the previous chapter, the pollution and abatement data is collected from a number of governmental documents recently released by the Ministry of Environmental Protection (the lists of Enterprises subject to Intensive Monitoring and Control of the State (2011-2015), and the lists of Running Desulfurization and Denitrification Facilities).[3] With the coordinate information for each firm, I use the layers of map from the National Fundamental Geographic Information System (NFGIS) to generate similar distance variables in the previous chapter. The ArcGIS Proximity toolset (Near) was used to calculate the distances from a firm to its closest residential area, industrial park, and transportation infrastructure.

To measure the distance to the provincial leeward border, I find the prevailing wind direction in each province using NOAA's hourly weather station data in China (346 stations with valid observations in total). I then interpolate the prevailing wind direction at all firms with a circular kriging model. This interpolating model

[3]The first list contains the quarterly pollution levies charged to each firm subject to intensive monitoring and control by the state, with the corresponding firm's names at plant-level. According to the central MEP, these high production firms account for nearly 65% of the total emissions. The last two lists provide the end-of-the-pipe desulfurization and denitrification technology installation information before 2015 for all installed firms, including firm's name, firm's sector, installation date, capacity, and types of technology. To ensure the reliability of the monitoring information, local EPBs must conduct monitoring activities and unannounced field inspections before reporting to superior level EPBs and the MEP (Wu et al., 2016).

accounts for the unique features of angular data, where 1° and 359° are almost the same in terms of wind direction. Each firm's average wind speed and wind direction data are extracted from the generated kriging rasters in each season. Figure 4.1 and 4.2 display the examples of average prevailing wind direction in winter and summer across China, respectively.[4] The figures follow the common sense that the prevailing winds blow across southern China from the southeast: Cold air pours down from Siberia in the winter; Warm air comes up from Southeast Asia and the South China Sea in the summer.

Given the wind direction information at each firm, I draw a line based on the interpolated wind angle to find the border intersect, and calculate the distance from the firm to this intersect in ArcGIS. All distances were then converted from *Decimal Degrees* to *Meters* using the *Gauss Kruger-Beijing 1954* projection, the most commonly used projected coordinate system in China. The detailed firm-level locational information was merged with county, prefectural, and provincial-level socioeconomic data for additional controls. The corresponding data is collected from the published statistical yearbooks and the website of the National Bureau of Statistics.

There are five major air-polluting sectors: the power, the electronics, the manufacturing, the chemistry, and the medical sectors. The power sector has a high share of firms in the monitoring list, and potentially pollute both water and air. Table 4.1 shows descriptive statistics by sector to compare air-polluting firm's

[4]Figure 4.3 shows an example of the interpolated wind direction for all firms in Anhui province in winter.

relative locations. The power and electronic sectors have relatively high average SO_2-equivalent pollution levels. Again, no significant geographical variations by sector may suggest that heavy polluters are not strategically placed before or at the moment they enter the market, pollution level variations (if any) are more likely to be generated after the placement.

4.4 Empirical Model

4.4.1 Main Regression Model

For the air-polluting firms, I adopt the same empirical methods to further explore the strategic polluting behavior, which has the same theoretical grounds as the "downstream effect" in the water-polluting case. To quantify the impact of a firm's locational information to its pollution level and abatement technology installation scale, I use the within-between random effects (WBRE) model to estimate the time-invariant variables, $downwind_i$ and $windspeed_i$, by including the time averages of the time-variant variables in the regression (Allison, 2009; Chamberlain, 1982; Mundlak, 1978).

Let $pollution_{it}$ represent the quarterly pollution of firm i at the quarter t, let $Tech_{it}$ represent the aggregated desulfurization or denitrification capacity of the installed abatement technology in firm i at the beginning of quarter t. The main empirical model is given by:

$$\begin{aligned} pollution_{it} &= \alpha + \beta_1 downwind_i + \beta_2 windspeed_i + \delta_1 Tech_{it} + \delta_2 \overline{Tech_i} \\ &\quad + \boldsymbol{\gamma_1 X_{it}} + \boldsymbol{\gamma_2 \overline{X_i}} + \boldsymbol{u_{it}} + e_i + e_{it} \\ Tech_{it} &= a + b_1 downwind_i + b_2 windspeed_i + \boldsymbol{g_1 X_{it}} + \boldsymbol{g_2 \overline{X_i}} + \epsilon_i + \epsilon_t + \epsilon_{it} \end{aligned} \tag{4.1}$$

where $downwind_i$ is the distance from firm i to the downwind border along the prevailing wind direction, and $windspeed_i$ is the average wind speed at firm i. $\boldsymbol{X_{it}}$ includes weather data and all the county, prefectural, and provincial-level controls mentioned in the previous section.[5]

As in the "downstream effect" situation, I estimated both the reduced form model and the model that includes the endogenous technology capacity variable. The instruments for the scale of installed abatement technology are local governmental revenue and expenditure as before. The estimated coefficients are reported in Table 4.3. Similar to the previous section, to examine if the Mundlak-Chamberlain Approach provides non-biased coefficients, I conduct the following robustness checks below.

[5]It includes local demographic information, aggregate production in each industry and sector, administrative information, population, income, education facilities, hospital facilities, social service facilities, local government budgets, and aggregate gross/per capita industrial values. It also contains precipitation, temperature, sun radiation information obtained from NOAA.

4.4.2 Robustness Checks

This subsection provides models that this paper has been adopted as robustness checks. I use a two-stage least square fixed-effects (2SLS-FE) model by interacting each key time invariant variables with quarter dummies to examine the possible variation of the local regimes' regulatory stringency. I also treat locational variables, $downwind_i$ and $windspeed_i$, as endogenous with a control function approach.

4.4.2.1 Regime/Policy Change

I use a 2SLS-FE model to examine possible regime or policy changes during the study period, the corresponding empirical model is the following:

$$\begin{aligned} pollution_{it} &= \alpha + \boldsymbol{\beta_1} downwind_i \cdot q_t + \boldsymbol{\beta_2} windspeed_i \cdot q_t \\ &\quad + \delta Tech_{it} + \boldsymbol{\gamma X_{it}} + e_i + e_t + e_{it} \\ Tech_{it} &= a + \boldsymbol{b_1} downwind_i \cdot q_t + \boldsymbol{b_2} windspeed_i \cdot q_t + \boldsymbol{g X_{it}} \\ &\quad + z_1 Revenue_{it} + z_2 Expenditure_{it} + \epsilon_i + \epsilon_t + \epsilon_{it} \end{aligned} \tag{4.2}$$

The estimated locational impacts on a firm's pollution level are reported in Table 4.4. First stage coefficients of locational impacts on the scale of installed abatement technology are reported in Table 4.5.

4.4.2.2 Endogenous Location

WBRE estimation provides an opportunity to examine a firm's locational impacts when $downwind_i$ and $windspeed$ are endogenous without introducing too many instruments. The difference between the results from the model below and those in Table 4.3 is by treating the two key variables, $downwind_i$ and $windspeed_i$, as endogenous variables. Although the descriptive statistics have suggested that heavily polluting firms may not be able to cluster at the least environmental sensitive areas like downwind borders, it is possible that air-polluting firms' relative location based on prevailing wind speed and wind direction are potentially endogenous to their emission levels. Again, I assume that functional land use planning, such as the construction of transportation infrastructure and designation of economic development zones, are generically determined before the environmental policy is in effect. Firm's locational choice is more likely to be decided according to local land use plans, which relates to firm's supply and procurement management, and is independent to firm's emission level. And the corresponding system of equations for air-polluting firms is:

$$\begin{aligned} pollution_{it} &= \alpha + \beta_1 downwind_i + \beta_2 windspeed_i + \delta_1 Tech_{it} + \delta_2 \overline{Tech_i} \\ &+ \boldsymbol{\gamma_1 X_{it}} + \boldsymbol{\gamma_2 \overline{X_i}} + \boldsymbol{u_{it}} + e_i + e_{it} + \hat{\epsilon_{it}} + \hat{w_{it}} + \hat{v_{it}} \end{aligned} \tag{4.3}$$

$$\begin{aligned} Tech_{it} &= a + b_1 downwind_i + b_2 windspeed_i + \boldsymbol{g_1 X_{it}} + \boldsymbol{g_2 \overline{X_i}} \\ &+ z_1 Revenue_{it} + z_2 Expenditure_{it} + \epsilon_i + \epsilon_t + \epsilon_{it} \end{aligned} \tag{4.4}$$

$$
\begin{aligned}
downwind_i &= \boldsymbol{\phi_1 Z_i} + \boldsymbol{\zeta_1 X_{it}} + w_{it} \\
windspeed_i &= \boldsymbol{\phi_2 Z_i} + \boldsymbol{\zeta_2 X_{it}} + v_{it}
\end{aligned}
\tag{4.5}
$$

where $\boldsymbol{Z_i}$ includes the distances from firm i to the closest road, railroad, industrial park, and commercial center.

I first estimate the reduced form equations by estimating equation 4.3 (excluding the abatement technology variable and the residual estimation: $\hat{\epsilon_{it}} + \hat{w_{it}} + \hat{v_{it}}$) and 4.4 separately using 2SLS-WBRE model. The estimated coefficients are reported in Table 4.6. First stage coefficients and the corresponding statistics are in Table 4.7-4.8. Including the abatement technology variable in equation 4.3 introduces an additional endogenous variable and complicates the model, so the corresponding model is estimated with a control function approach. Table 4.9 provides the corresponding estimated coefficients for air-polluting firms.

4.5 Results

4.5.1 Main Regression Results

This section reports the estimated coefficients for the pollution activity of air-polluting firms under China's Pollution Reduction Mandates from 2011-2015. Table 4.3 and Table 4.4 (& 4.5) report key estimated coefficients for air-polluting firms using the within-between random effects model and the two stage least square fixed effects model, respectively. The results derived in the theoretical section indicate that firms located at less environmentally sensitive areas will have higher emission levels and lower levels of abatement technology installation. In terms of the air-polluting firms, these areas may include places near the downwind border or with relatively high wind speed, where pollutants can be easily exported outside the jurisdiction and have relatively low health impacts to local residents. The estimated coefficients in Table 4.3 follow the expectation of these hypotheses for all the five industrial sectors.

The second panels of Table 4.3 and Table 4.5 also report the 2SLS estimated impacts of the scales of installed abatement technology on air-polluting firm emission levels, and the coefficients have the same magnitudes across different sectors. Two instrumental variables for the abatement technology installation, local governmental expenditure and revenue, are significantly different from zero in both models, and have signs following my expectation. Overidentification tests and the weak instrument tests indicate that these instruments are strong and valid. The coefficients reported in Table 4.3 from the reduced form model (panel 1) and the model that includes the abatement technology variable (panel 2) have signs and magnitudes that are consistent with each other.

On average, a firm will emit 0.0005% to 0.0212% of additional SO_2-equivalent pollutants if it is located one kilometer closer to a provincial downwind border. With the average distances to the downwind border from Table 4.1, the average pollution in SO_2-equivalent would increase from 7.83% to 418.56% for different sectors if all the firms were located near the downwind border. Local officials have more incentives to change pollution based on location for firms in the power and the manufacturing sectors. But the manufacturing and the medical sectors have relatively high percentage change in pollution levels.

Theoretically, higher wind speed helps to export air pollutants, and each jurisdiction may take advantage of it to shift its local pollution away. The corresponding coefficients in Table 4.3 suggest that these types of pollution incentives exist, but have lower magnitudes compared to the spillover effect based on locational variation along the wind direction. On average, a firm will emit 0.0001% to 0.0005% of additional SO_2-equivalent pollutants if the wind speed increases 1mph, with the medical and the manufacturing sectors more sensitive to wind speed in terms of the percentage pollution changes. Given the average wind speed, a firm would have incentives to decrease 0.0002% to 0.0054% of SO_2-equivalent pollutants if the average wind speed at the firm drops to zero.

Based on the theory, an air-polluting firm with less per unit of local damage (closer to the downwind border or with higher wind speed) will have lower scales of installed abatement technology. Tables 4.3 shows the estimated coefficients of the firms' locational impacts on installed abatement technology from both the direct estimation (panel 1) and the first stage estimation (panel 2). The estimated coefficients follow the hypotheses derived from the theoretical model and have the same magnitudes, and I illustrate the implications based the coefficients in the first panel in Table 4.3.

On average, the scale of installed abatement technology will increase from 0.020% to 0.208% if a firm is one kilometer away from the downwind border, or from 0.00003% to 0.0026% if the average wind speed at where the firm is located increases 1mph, depending on the sector that it is in. Local officials' incentives to abate pollution may vary by sectors, and firms in the medical sector are more sensitive to wind speed variation and relative location along the prevailing wind direction. Same as the results among water-polluting firms, firms from this sector are generally located in counties with relatively high expenditures comparing to the governmental revenues, given the descriptive statistics in Table 4.2. The impacts of local governments' financial situation are relatively high compared to that in other sectors as well. Geographical variation gives local officials' certain incentives to reduce pollution by promoting abatement technology among firms. For air-polluting firms, one additional ton of installed technology capacity (approximately 10% to 114% increase based on the current installation scales, depending on the sector that the firm is in) will save a firm \$391.69 to \$772.38 of pollution levies, with a total saving from pollution levies around \$135.95 million for all the firms studies in the dataset. And the total reduced emission would be 1.25 million tons of SO_2-equivalent pollutants.

In terms of the estimation results in the robustness-check section, there is no regime or policy change during the study period. Coefficients of firms' locational impacts on firms' pollution levels and abatement technology installation in the 2SLS-FE model are almost identical over the 20 quarter periods in Tables 4.4 and 4.5. And they have similar magnitudes compared to the WBRE model using the Mundlak-Chamberlain approach in Table 4.3. Coefficients also have the similar magnitudes when treating the variables, $downwind_i$ and $windspeed_i$, endogenous. The observed pollution distortion based on a firm's geographic information is robust in the air pollution case as well.

4.5.2 Caveat and Discussion

China's Pollution Reduction Mandates charge pollution with a uniform rate in the whole country. However, my estimation suggests that local governments have incentives to free-ride on air pollution by taking the advantage of prevailing wind. They tend to have less of an incentive to promote pollution reduction among air polluters locating in a windy area or closer to the leeward border of the jurisdiction, because emitted pollutants are likely to be gone with the wind and exported outside the jurisdiction. Although different jurisdictions may have their own emission targets to share the abatement burden from the central government, the policy within each jurisdiction is also not uniform.

This paper proposes one of the possible theories by following the previous chapter, and argues that variations in the stringency of the regulations is achieved by adjusting levy-recycled subsidies among heterogeneous firms within the jurisdiction. This theory relies on three observed facts in China's political hierarchy system and the environmental policies: (1) The central government evaluates both the economic performance and the pollution reduction performance to promote a local cadre; (2) Other than collecting pollution levies, recycling tax as abatement subsidies for firms, and planning/allocating subsidies within the jurisdiction, the pollution reduction performance also includes reducing possible environmental complaints to maintain social stability; and (3) a local cadre has more of an incentive to strengthen the abatement enforcement to best retain its local public support and avoid pollution complaints.

Because of the data limitation, the allocated abatement investment from the local government or the firm itself is unobserved. The estimated results in this paper is at best indicating that all else equal, the level of air pollution emission is higher (and the abatement technology scale is lower) if the location of firm has a natural advantage to export pollution away from the jurisdiction by wind. Whether local government has any strategic move behind this pollution distortion is still in theory. However, the evidence provided in this paper, along with the results in the previous chapter, has suggested that less-environmentally sensitive areas to a province are likely to have a more lenient emission stringency.

One way to reduce the corresponding free-riding behavior would be assigning responsibilities to lower level cadres directly from the central government. This way may force the relatively downwind or windy towns/counties to share certain pollution abatement burdens within a province as well. It would be very complex to assess the efficiency between this relatively centralized case to the current decentralized policy.[6] A more transparent data from MEP to show the abatement subsidy allocation would also be helpful to reveal the role of local officials in the whole pollution reduction process in China.

4.6 Conclusion

Rapid industrialization in China has caused alarming surges in air pollution. China has responded to its severe environmental deterioration with a series of pol-

[6] The current environmental policy relies on the second layer of governance (the provincial level) in China's hierarchy political system, which is the most decentralized way to implement a policy.

lution reduction mandates since 2001. The mandates are enacted with a series of plans for each provincial government. This decentralized policy relies completely on local officials, who are pressurized to enforce pollution reduction by the revised cadre evaluation system. Although this evaluation system emphasizes on local environmental performances, local economic growth is still prioritized on a cadre's promotion path.

This paper adopts a conceptual framework, in which local officials are balancing their limited local resource to both reduce pollution and sustain economic growth. This is consistent with the previous literature that local governments could strategically allocate firms' pollution levels and export the environmental costs. Although the central government has been monitoring the most heavily polluted firms, provincial governments may strategically allocate fewer funds or less enforcement effort in places where environmental improvements are less likely to be internalized by their own residents, such as downwind or windy counties. However, possibly due to data limitation, this type of "pollution spillover effect" has not been well studied in China until now. The disclosure of pollution information since 2010 provides a good chance to examine the geographical patterns of the pollution levels in heavily-polluted firms among different sectors.

This paper further extends the "downstream effect" explored in the previous chapter empirically using a unique air-pollution dataset in China. It uses the quarterly pollution data from air-polluting firms during 2011 to 2015. The data is further merged with firm abatement control technology information, as well as local weather and socio-economic data in China. I adopt both a within-between random effects model and a fixed effects model to estimate the firm's time-invariant locational impacts on pollution activities and installation of abatement technologies. The estimated coefficients are consistent with the expectations: An air-polluting firm emits more pollutants if it is closer to the downwind border or locating in an area with relatively higher average wind speed. These types of firms also have a lower scale of the installed abatement technology.

These results point out the existence of strategic pollution behavior based on firm geographical information, which is potentially caused by local officials' incentives from China's revised cadre responsibility and evaluation system. In general, the results presented in this paper provide an additional evidence of geographic-based pollution pattern in China. To examine whether a more centralized pollution management is suitable in China, the central government could start a pilot pollution-reduction program by bundling several provinces together with one centralized instruction. The centralized design requires a more nuanced abatement goal in each lower level jurisdiction. The methodology adopted in this paper is transferable to a design for this purpose, and I will leave this issue for future research.

Statistics	*Mean*	*SD*	*Min*	*Max*	*Mean*	*SD*	*Min*	*Max*
Sector	Power				Electronic			
Distance to downwind border	18996.38	20622.44	1.15	182184.8	16898.71	18007.82	1.15	170246.9
Average wind speed (1000mph)	815.7	1049.78	0	7137.64	775.64	1023.28	0	7137.64
Distance to the closest road	9542.96	26844.72	0.14	256686.5	12929.23	38920.79	0.14	260709.9
Distance to the closest railroad	12249.63	19580.35	0.69	212948.8	11395.56	18093.36	0.69	189996.9
Distance to the closest industrial park	25943.69	35723.27	0.11	448470.8	22591.12	32098.44	0.11	448470.8
Distance to the closest commercial center	33765.02	33989.08	124.68	312393	31200.51	30649.82	125.09	296831.5
Pollution (SO_2-equivalent) in ton	783.85	1854.4	0	64285.71	638.96	1838.24	0	56083.37
Abatement technology	4.79	45.56	0	1320	9.05	362.13	0	4309.2
N	78184				70520			
Sector	Chemical				Manufacure			
Distance to downwind border	21954.6	19275.1	1.16	182225.4	19781.06	16667.75	5.26	182225.4
Average Wind Speed (1000mph)	360.88	528.51	1	6127.586	281.16	287.26	1	5431.173
Distance to the closest road	8625.97	20487.84	0.03	248552.4	10623.11	30723.28	0.06	253938
Distance to the closest railroad	15338.05	21142.81	1.84	285919.9	15476.64	23703.25	6.06	285919.9
Distance to the closest industrial park	25831.06	31045.4	0.11	334438.2	24557.76	31136.13	0.11	334438.2
Distance to the closest commercial center	34966.73	28626.67	203.46	181636.5	31265.9	27172.89	203.46	199678
Pollution (SO_2-equivalent) in ton	134.08	710.51	0	39482.34	40.18	270.85	0	17033.38
Abatement technology	9.81	45.56	0	1432.2	0.94	18.24	0	1320
N	46052				47288			
Sector	Medical							
Distance to downwind border	21639.25	15822.49	8.47	165672.9				
Average wind speed (1000mph)	280.08	284.78	1.03	4105.963				
Distance to the closest road	9809.87	22040.91	0.29	217166.3				
Distance to the closest railroad	19127.84	30395.37	4.64	279150.8				
Distance to the closest industrial park	25898.73	30251.35	0.15	233252.3				
Distance to the closest commercial center	36711.24	30087.6	203.46	143756.5				
Pollution (SO_2-equivalent) in ton	50.23	166.06	0	3164.177				
Abatement technology	0.88	7.51	0	142				
N	12220							

All the distance variables are measured in meters.
Abatement technology is production capacity (tons) installed with denitrification technology for Chemical, Manufacturing, and Medical Sectors, and with desulfurization technology for Power and Electronic Sectors.

Table 4.1: Descriptive Statistics of Data Used in Air Pollution Analysis in Various Sectors (2011-2015)

Statistics	*Mean*	*SD*	*Mean*	*SD*
Sector	Electronic		Chemical	
County-level governmental revenue (100 million CNY)	26.97	34.66	16.9	23.65
County-level governmental expenditure (100 million CNY)	37.14	33.57	28.24	22.91
County-level value added (100 million CNY)	232.35	279.31	152.2	185.55
County-level population (10k person)	71.53	33.27	67.93	34.03
County-level number of industrial enterprises	441.91	538.59	273.78	383.44
Prefectural-level number of employees (10k person)	101.16	124.27	78.24	110.53
Prefectural-level population density (person per sq. km)	644.8	552.6	564.08	518.07
Prefectural-level average wage	41361.3	13454.99	38753.87	14993.86
Provincial-level area of paved road (10k sq. m)	3120.95	2931.25	2415.57	2685.82
Precipitation (mm)	88.21	77.97	83.47	71.41
Terrain (average land slope)	5.22	6.79	6.21	8.06
In a designated historical industrial city (0/1)	0.2	0.4	0.29	0.45
N	78140		46052	
Sector	Manufacture		Medical	
County-level governmental revenue (100 million CNY)	20.5	27.67	13.91	18.7
County-level governmental expenditure (100 million CNY)	31.77	27.16	26.15	19.38
County-level value added (100 million CNY)	184.19	231.5	130.97	147.82
County-level population (10k person)	69.04	31.31	69.74	33.23
County-level number of industrial enterprises	340.97	439.4	238	306.43
Prefectural-level number of employees (10k person)	98.19	126.01	80.73	111.71
Prefectural-level population density (person per sq. km)	619.95	557.86	532.7	486.42
Prefectural-level average wage	39848.83	12909.09	37158.64	11573.01
Provincial-level area of paved road (10k sq. m)	2978.6	3080.02	2542.95	2529.58
Precipitation (mm)	97.49	82.61	79.47	69.25
Terrain (average land slope)	5.88	7.28	5.34	7.13
In a designated historical industrial city (0/1)	0.22	0.42	0.26	0.44
N	47288		11592	

Table 4.2: Descriptive Statistics of Selected Control Variables in Various Air-Polluting Sectors (2011-2015)

		Power	Electronic	Chemical	Manufacture	Medical
Pollution (SO_2)	Distance in km to	-5.532***	-2.959***	-1.399***	-8.502***	-1.943***
(Mundlak)	Downwind border	(0.192)	(0.106)	(0.0740)	(0.224)	(0.115)
	Wind spd	457.0***	356.6***	222.0***	128.4**	247.9***
	(1000mph)	(5.058)	(4.302)	(2.113)	(1.142)	(2.306)
Abatement Tech.	Distance in km to	0.0123***	0.00331***	0.00194***	0.0161***	0.00183***
(Mundlak)	Downwind border	(0.00121)	(0.000283)	(0.000298)	(0.00137)	(0.000170)
	Wind spd	-0.0014***	-0.00263***	-0.00256***	-0.00131***	-0.0039***
	(1000mph)	(0.00016)	(0.000241)	(0.000256)	(0.000116)	(0.00032)
Pollution (SO_2)	Distance in km to	-5.159***	-2.923***	-1.362***	-7.217***	-1.879***
(Mundlak-IV)	Downwind border	(0.238)	(0.117)	(0.118)	(0.491)	(0.167)
	Wind spd	427.8***	354.8***	203.9***	116.3***	227.4***
	(1000mph)	(11.86)	(16.18)	(15.62)	(41.31)	(27.01)
	Abatement tech.	-3614.7**	-6155.3***	-4241.6***	-5828.0***	-7128.0**
	(in tons)	(1222.6)	(1379.7)	(1272.2)	(1385.4)	(2428.4)
Abatement Tech.	Distance in km to	0.0081***	0.0037***	0.002***	0.0019***	0.0315***
(Mundlak-IV)	Downwind border	(0.00119)	(0.00029)	(0.0003)	(0.00018)	(0.00141)
	Wind spd	-0.0178***	-0.0052***	-0.0082***	-0.0064***	-0.0225***
	(1000mph)	(0.000837)	(0.00029)	(0.00036)	(0.00018)	(0.000945)
	Governmental	-1.0081***	-1.1082***	-1.491***	-1.3588***	-1.1545***
	Expenditure	(0.23759)	(0.284)	(0.27735)	(0.27075)	(0.28162)
	Governmental	0.205***	0.0729***	0.0961***	0.0687***	0.2066***
	Revenue	(0.04389)	(0.01794)	(0.01817)	(0.01774)	(0.04371)
† *Kleibergen-Paap rk Wald F*		27.007	36.754	23.268	32.655	22.85
Sargan-Hansen Stat		0.096	0.346	0.098	0.29	1.3
p-val		0.7573	0.5566	0.754	0.5901	0.2543
N		69236	74708	45328	46476	11412

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Abatement technology is production capacity (tons) installed with denitrification technology for Chemical, Manufacturing, and Medical Sectors, and with desulfurization technology for Power and Electronic Sectors.

† Stock-Yogo weak ID test critical values (maximal IV size): *10%* 19.93, *15%* 11.59, *20%* 8.75, *25%* 7.25.

Source: Stock-Yogo (2005)

Table 4.3: Firm's Locational Impact on Air Pollution and Installed Abatement Technology (Mundlak Approach): 2011-2015

		Power	Electronic	Chemical	Manufacture	Medical
Distance in km to Downwind border	quarter 1	-2.044***	-2.183***	-5.218***	-7.968***	-1.860***
		(0.452)	(0.399)	(0.867)	(0.973)	(0.430)
	quarter 2	-2.178***	-3.116***	-6.628***	-7.022***	-2.458**
		(0.534)	(0.569)	(1.423)	(1.549)	(0.765)
	quarter 3	-2.273***	-1.275	-4.391***	-5.551***	-1.008
		(0.581)	(0.711)	(1.246)	(1.361)	(0.780)
	quarter 4	-2.974***	-1.462***	-2.904***	-5.781***	-1.336**
		(0.384)	(0.436)	(0.761)	(0.959)	(0.425)
	quarter 5	-2.553***	-3.393***	-7.850***	-8.555***	-3.546***
		(0.484)	(0.567)	(0.971)	(1.094)	(0.612)
	quarter 6	-2.051***	-1.883***	-5.394***	-7.499***	-1.809***
		(0.340)	(0.465)	(0.687)	(0.891)	(0.415)
	quarter 7	-1.629***	-1.336***	-4.148***	-6.082***	-1.275***
		(0.287)	(0.388)	(0.526)	(0.722)	(0.335)
	quarter 8	-3.772***	-2.522***	-4.422***	-5.505***	-2.384***
		(0.374)	(0.495)	(0.753)	(0.975)	(0.436)
	quarter 9	-4.627***	-2.509***	-14.99***	-15.45***	-2.642***
		(0.451)	(0.518)	(0.985)	(1.116)	(0.550)
	quarter 10	-3.609***	-1.729***	-8.724***	-9.866***	-1.815***
		(0.366)	(0.423)	(0.916)	(1.055)	(0.453)
	quarter 11	-1.822***	-1.098*	-3.983***	-4.984***	-1.046**
		(0.287)	(0.430)	(0.584)	(0.796)	(0.373)
	quarter 12	-3.516***	-2.062***	-7.316***	-9.009***	-2.356***
		(0.332)	(0.377)	(0.768)	(0.973)	(0.441)
	quarter 13	-2.627***	-3.986***	-14.80***	-16.57***	-4.336***
		(0.383)	(0.587)	(1.327)	(1.422)	(0.681)
	quarter 14	-2.191***	-1.245***	-4.812***	-6.693***	-1.590***
		(0.337)	(0.368)	(0.766)	(1.001)	(0.448)
	quarter 15	-3.348***	-2.043***	-14.23***	-17.90***	-2.033**
		(0.512)	(0.597)	(1.633)	(1.712)	(0.628)
	quarter 16	-3.594***	-2.349***	-12.43***	-16.36***	-2.229**
		(0.620)	(0.652)	(1.822)	(1.941)	(0.693)
	quarter 17	-3.142***	-1.102**	-4.798***	-7.044***	-1.098**
		(0.392)	(0.403)	(0.925)	(1.148)	(0.414)
	quarter 18	-4.234***	-2.774***	-4.914**	-7.416***	-2.839***
		(0.540)	(0.543)	(1.498)	(1.704)	(0.569)
	quarter 19	-3.630***	-1.830**	0.439	-1.763	-1.699**
		(0.703)	(0.600)	(1.346)	(1.528)	(0.631)
	quarter 20	-3.451***	-1.360**	-1.935*	-4.684***	-1.201*
		(0.403)	(0.461)	(0.854)	(1.074)	(0.490)

Table 4.4: Firm's Locational Impact on Air Pollution (Fixed Effects Model): 2011-2015

		Power	Electronic	Chemical	Manufacture	Medical
Wind spd	quarter 1	491.3***	375.7***	182.9***	166.5***	128.9***
(1000mph)		(18.77)	(17.65)	(11.19)	(25.12)	(11.04)
	quarter 2	454.6***	318.9***	199.1***	186.4***	88.21***
		(16.78)	(16.67)	(9.659)	(18.76)	(12.91)
	quarter 3	520.8***	356.3***	198.8***	192.2***	69.65***
		(24.38)	(18.28)	(11.70)	(15.83)	(12.83)
	quarter 4	418.4***	310.9***	209.8***	205.6***	150.2***
		(26.67)	(18.10)	(10.90)	(12.29)	(10.51)
	quarter 5	461.8***	419.7***	178.1***	174.9***	159.0***
		(13.12)	(15.90)	(10.76)	(11.99)	(11.65)
	quarter 6	391.0***	326.8***	168.7***	165.9***	175.3***
		(10.64)	(13.93)	(8.289)	(9.390)	(7.689)
	quarter 7	519.7***	375.6***	179.1***	172.6***	69.93***
		(15.13)	(17.40)	(10.60)	(13.47)	(12.97)
	quarter 8	533.4***	408.9***	248.5***	245.5***	162.8***
		(15.56)	(18.04)	(11.29)	(12.14)	(10.29)
	quarter 9	537.0***	354.3***	212.5***	169.8***	177.8***
		(12.00)	(16.79)	(25.64)	(29.79)	(10.95)
	quarter 10	523.3***	320.7***	214.7***	170.3***	180.9***
		(10.87)	(15.62)	(26.61)	(30.60)	(8.192)
	quarter 11	522.8***	318.3***	231.8***	192.9***	120.4***
		(12.88)	(18.28)	(23.13)	(27.61)	(10.85)
	quarter 12	574.6***	343.6***	254.9***	217.1***	119.4***
		(13.35)	(18.89)	(22.18)	(27.56)	(8.784)
	quarter 13	465.9***	414.2***	201.2***	161.9***	200.7***
		(11.99)	(15.38)	(22.32)	(29.35)	(9.006)
	quarter 14	423.5***	285.0***	190.6***	165.8***	108.2***
		(10.58)	(17.74)	(12.86)	(20.65)	(6.964)
	quarter 15	469.1***	326.7***	184.9***	182.6***	122.9***
		(21.09)	(22.45)	(19.88)	(23.50)	(8.368)
	quarter 16	479.1***	357.1***	225.0***	248.0***	128.8***
		(31.86)	(19.52)	(48.77)	(23.19)	(9.098)
	quarter 17	488.5***	331.2***	181.0***	209.2***	146.6***
		(30.88)	(34.92)	(54.49)	(22.78)	(8.982)
	quarter 18	469.2***	332.0***	172.6***	195.7***	180.6***
		(29.71)	(33.65)	(45.56)	(19.65)	(7.817)
	quarter 19	546.7***	342.0***	232.1***	229.1***	176.0***
		(35.53)	(42.53)	(9.234)	(11.81)	(9.327)
	quarter 20	466.4***	299.5***	167.0***	187.7***	139.2***
		(33.46)	(42.68)	(44.81)	(21.91)	(8.197)
Technology		-3743.4**	-6596.2***	-4149.0**	-5467.0**	-4957.9***
Capacity (in ton)		(1355.8)	(1344.6)	(1278.9)	(1666.3)	(756.1)
	N	69236	74708	45328	46476	11412

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Abatement technology is production capacity (tons) installed with denitrification technology for Chemical, Manufacturing, and Medical Sectors, and with desulfurization technology for Power and Electronic Sectors.

Table 4.4: Firm's Locational Impact on Air Pollution (Fixed Effects Model): 2011-2015 Continued

		Power	Electronic	Chemical	Manufacture	Medical
Governmental Expenditure		-0.08841***	-0.19253***	-1.92677***	-0.20056***	-1.81531***
		(0.022159)	(0.052353)	(0.19027)	(0.051839)	(0.187142)
Governmental Revenue		0.07463**	0.18739***	0.47649***	0.21308***	0.3666**
		(0.025086)	(0.042904)	(0.139469)	(0.042523)	(0.137154)
Distance in km to Downwind border	quarter 1	0.00141***	0.00168***	0.00521***	0.00512***	0.00089***
		(0.000138)	(0.000174)	(0.000834)	(0.000314)	(0.000167)
	quarter 2	0.00272***	0.00347***	0.00727***	0.00267***	0.00066***
		(0.000199)	(0.000235)	(0.000973)	(0.000311)	(0.000165)
	quarter 3	0.00192***	0.0022***	0.00764***	0.0001	0.00108***
		(0.000219)	(0.000241)	(0.001134)	(0.000381)	(0.000202)
	quarter 4	0.00097***	0.00112***	0.00594***	0.00007	0.00011
		(0.000142)	(0.000177)	(0.001011)	(0.000351)	(0.000187)
	quarter 5	0.00185***	0.00202***	0.00576***	0.00168***	0.00087***
		(0.000183)	(0.000202)	(0.000885)	(0.000309)	(0.000164)
	quarter 6	0.00109***	0.00144***	0.00595***	0.00209***	0.00072***
		(0.000134)	(0.000166)	(0.000891)	(0.000326)	(0.000173)
	quarter 7	0.0006***	0.00084***	0.00549***	0.00095**	0.00093***
		(0.000105)	(0.000136)	(0.001124)	(0.000361)	(0.000192)
	quarter 8	0.00101***	0.0013***	0.00593***	0.00097*	0.00023
		(0.000151)	(0.000183)	(0.001049)	(0.00045)	(0.000239)
	quarter 9	0.00162***	0.00159***	0.00578***	0.0005	0.00084***
		(0.000197)	(0.000209)	(0.000908)	(0.000333)	(0.000177)
	quarter 10	0.00111***	0.00112***	0.00604***	0.00009	0.00101***
		(0.000181)	(0.000196)	(0.000928)	(0.000321)	(0.00017)
	quarter 11	0.00036***	0.00053***	0.00579***	0.00178***	0.0013***
		(0.000113)	(0.000147)	(0.001006)	(0.000361)	(0.000191)
	quarter 12	0.00013	0.00017	0.00506***	0.0019***	0.00158***
		(0.000146)	(0.000179)	(0.000942)	(0.000396)	(0.00021)
	quarter 13	0.00049*	0.00054*	0.00017	0.00453***	0.00131***
		(0.000213)	(0.000232)	(0.000938)	(0.000369)	(0.000196)
	quarter 14	0.00066***	0.00085***	0.00486***	0.00376***	0.00097***
		(0.000138)	(0.000179)	(0.000842)	(0.000313)	(0.000166)
	quarter 15	0.00279***	0.00313***	0.00155	0.00389***	0.00097***
		(0.000224)	(0.000259)	(0.000947)	(0.000335)	(0.000178)
	quarter 16	0.00476***	0.00553***	0.01948***	0.00534***	0.0023***
		(0.000253)	(0.000291)	(0.001074)	(0.00039)	(0.000207)
	quarter 17	0.00176***	0.00233***	0.02029***	0.00465***	0.00197***
		(0.000139)	(0.000179)	(0.000906)	(0.00034)	(0.000181)
	quarter 18	0.00355***	0.00471***	0.01872***	0.00478***	0.00106***
		(0.000184)	(0.000223)	(0.000947)	(0.000332)	(0.000176)
	quarter 19	0.00279***	0.00351***	0.02015***	0.00534***	0.0014***
		(0.000186)	(0.000217)	(0.001091)	(0.000382)	(0.000203)
	quarter 20	0.00149***	0.00196***	0.01879***	0.00469***	0.00214***
		(0.000135)	(0.000171)	(0.001024)	(0.000375)	(0.000199)

Table 4.5: Air-Polluting Firm's Locational Impact on Installed Abatement Technology (Fixed Effects Model): 2011-2015

		Power	Electronic	Chemical	Manufacture	Medical
Wind spd	quarter 1	-0.05933***	-0.07381***	-0.02211***	-0.00054***	-0.00108***
(1000mph)		(0.003008)	(0.003283)	(0.002329)	(0.000074)	(0.000117)
	quarter 2	-0.05892***	-0.0725***	-0.02237***	-0.00038***	-0.00127***
		(0.002993)	(0.003274)	(0.002322)	(0.000078)	(0.000124)
	quarter 3	-0.07514***	-0.09175***	-0.02416***	-0.00067***	-0.00176***
		(0.003671)	(0.003998)	(0.002836)	(0.00009)	(0.000142)
	quarter 4	-0.06086***	-0.07405***	-0.01483***	-0.00001	-0.00088***
		(0.003596)	(0.003913)	(0.002775)	(0.000104)	(0.000164)
	quarter 5	-0.05851***	-0.06896***	-0.00196	-0.00053***	-0.00237***
		(0.002861)	(0.003138)	(0.002226)	(0.000078)	(0.000124)
	quarter 6	-0.04753***	-0.05491***	-0.00212	-0.0005***	-0.00112***
		(0.002601)	(0.002836)	(0.002012)	(0.000069)	(0.00011)
	quarter 7	-0.06457***	-0.07401***	-0.00298	-0.00045***	-0.00167***
		(0.003371)	(0.003668)	(0.002602)	(0.000084)	(0.000134)
	quarter 8	-0.06049***	-0.06856***	-0.00834**	-0.00047***	-0.00023
		(0.003461)	(0.003747)	(0.002658)	(0.000088)	(0.000139)
	quarter 9	-0.03941***	-0.04441***	-0.01071***	-0.00035***	-0.00038***
		(0.002837)	(0.003074)	(0.002181)	(0.000074)	(0.000116)
	quarter 10	-0.03556***	-0.03961***	-0.01198***	-0.00037***	-0.00076***
		(0.002758)	(0.003)	(0.002128)	(0.000075)	(0.000119)
	quarter 11	-0.03653***	-0.04141***	-0.01648***	-0.00044***	-0.00092***
		(0.003169)	(0.00342)	(0.002426)	(0.000081)	(0.000129)
	quarter 12	-0.00777*	-0.00767*	-0.02275***	-0.00046***	-0.00116***
		(0.003117)	(0.003367)	(0.002388)	(0.000086)	(0.000136)
	quarter 13	-0.0059*	-0.00948***	-0.02472***	-0.00046***	-0.00042**
		(0.002631)	(0.002876)	(0.00204)	(0.000088)	(0.000139)
	quarter 14	-0.02375***	-0.03077***	-0.02771***	-0.00038***	-0.00036**
		(0.002426)	(0.002651)	(0.00188)	(0.000075)	(0.000118)
	quarter 15	-0.05313***	-0.06553***	-0.03579***	-0.00005	-0.0005***
		(0.002745)	(0.003006)	(0.002132)	(0.000063)	(0.000099)
	quarter 16	-0.08204***	-0.10118***	-0.04147***	-0.00161***	-0.00081***
		(0.002986)	(0.003278)	(0.002325)	(0.000083)	(0.000131)
	quarter 17	-0.07166***	-0.08432***	-0.03841***	-0.00195***	-0.00056***
		(0.002625)	(0.002868)	(0.002034)	(0.00008)	(0.000127)
	quarter 18	-0.07329***	-0.0883***	-0.04051***	-0.00202***	-0.00051***
		(0.002635)	(0.002906)	(0.002061)	(0.000083)	(0.000131)
	quarter 19	-0.09595***	-0.11592***	-0.05023***	-0.00201***	-0.00038**
		(0.003201)	(0.003544)	(0.002514)	(0.000088)	(0.000139)
	quarter 20	-0.0816***	-0.09554***	-0.04191***	-0.00178***	-0.00079***
		(0.002871)	(0.003139)	(0.002227)	(0.000084)	(0.000133)
† *Kleibergen-Paap rk Wald F*		38.236	68.612	21.688	24.886	39.533
Sargan-Hansen Stat		0.437	0.274	0.666	1.600	1.419
p-val		0.5088	0.6005	0.4143	0.2058	0.2335
N		69236	74708	45328	46476	11412

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Abatement technology is production capacity (tons) installed with denitrification technology for Chemical, Manufacturing, and Medical Sectors, and with desulfurization technology for Power and Electronic Sectors.

† Stock-Yogo weak ID test critical values (maximal IV size): *10%* 19.93, *15%* 11.59, *20%* 8.75, *25%* 7.25.

Source: Stock-Yogo (2005)

Table 4.5: Air-Polluting Firm's Locational Impact on Installed Abatement Technology (Fixed Effects Model): 2011-2015 Continued

dep. var.		Power	Electronic	Chemical	Manufacture	Medical
Pollution (SO_2)	Distance in km to	-27.16***	-21.80***	-63.34***	-30.07***	-22.83***
	Downwind border	(2.240)	(2.285)	(4.627)	(7.720)	(2.032)
	Wind spd	263.2***	486.1***	473.7***	219.5***	272.8***
	(1000mph)	(5.056)	(36.48)	(9.154)	(3.931)	(9.311)
Abatement Tech.	Distance in km to	0.0157***	0.00466***	0.00252***	0.00112***	0.0191***
	Downwind border	(0.00163)	(0.000427)	(0.000729)	(0.000167)	(0.00185)
	Wind spd	-0.00260***	-0.00202***	-0.00166***	-0.000281***	-0.00310***
	(1000mph)	(0.000193)	(0.000215)	(0.000193)	(0.0000283)	(0.000139)
	N	69236	74708	45328	46476	11412

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Abatement technology is production capacity (tons) installed with denitrification technology for Cement, Paper, and Food Sectors, and with desulfurization technology for Power, Cement, and Clothing/Dyeing Sectors.

Table 4.6: Firm's Locational Impact on Air Pollution and Installed Abatement Technology: 2011-2015 Mundlak-RE Approach with IV for Location

Dis. in km to	Power	Electronic	Chemical	Manufacture	Medical
First Stage of the Instrumented Variable: Distance in km to the Downwind Border					
Closest Railroad	0.0247*** (0.0074)	0.137*** (0.0096)	0.0526*** (0.0109)	0.0671*** (0.019)	0.1664*** (0.0236)
Closest Main road	0.0317*** (0.003)	-0.0243*** (0.0064)	0.0131* (0.0059)	-0.085*** (0.014)	-0.0741*** (0.0086)
Closest Industr. park	0.0871*** (0.0113)	0.0101 (0.0174)	0.1406*** (0.0209)	0.5161*** (0.0311)	0.752*** (0.0187)
Commercial Center	-0.0281*** (0.006)	0.0079 (0.008)	0.0215* (0.0104)	0.0704*** (0.015)	0.1852*** (0.0196)
First Stage of the Instrumented Variable: Average Wind Speed					
Closest Railroad	-0.0484*** (0.0018)	-0.0306*** (0.0025)	-0.0544*** (0.002)	-0.0902*** (0.0034)	-0.0991*** (0.0051)
Closest Main road	-0.0466*** (0.0009)	-0.0174*** (0.0025)	-0.046*** (0.0013)	-0.0288*** (0.0034)	-0.0428*** (0.002)
Closest Industr. park	0.0525*** (0.0021)	0.0269*** (0.0046)	0.0191*** (0.004)	-0.1655*** (0.0057)	-0.3709*** (0.0036)
Commercial Center	0.0004 (0.0011)	-0.0591*** (0.002)	-0.0015 (0.0017)	-0.02*** (0.0025)	-0.1182*** (0.0037)
Underidentification & Overidentification Test					
Kleibergen-Paap rk LM stat	68.64***	64.52***	70.01***	129.74***	275.92***
Sargan-Hansen Stat	4.169	2.039	0.219	1.339	2.025
p-val	0.1244	0.3608	0.8964	0.5118	0.3632
Weak Identification Test					
† *Kleibergen-Paap rk Wald F*	18.08	17.7	20.96	28.12	81.43
‡ *AP F-val* downwind	23.99	24.68	24.29	41.68	52.29
AP F-val avg. speed	123.3	34.01	72.19	44.48	134.23
N	69236	74708	45328	46476	11412

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

† Stock-Yogo weak ID test critical values (maximal IV relative bias): *5%* 11.04, *10%* 7.56, *20%* 5.57, *30%* 4.73. critical values (maximal IV size): *10%* 16.87, *15%* 9.93, *20%* 7.54, *25%* 6.28. Source: Stock-Yogo (2005)

‡ Critical values for single endog. regressor (maximal IV relative bias): *5%* 16.85, *10%* 9.08, *20%* 6.46, *30%* 5.39. critical values (maximal IV size): *10%* 22.30, *15%* 12.83, *20%* 9.54, *25%* 7.80. Source: Stock-Yogo (2005).

Table 4.7: First Stage Regression (Firm's Locational Impact on Air Pollution)

Dis. in km to	Power	Electronic	Chemical	Manufacture	Medical
First Stage of the Instrumented Variable: Distance in km to the Downwind Border					
Closest	0.2976***	0.1798***	0.0761***	0.2953***	0.0262***
Railroad	(0.0203)	(0.0207)	(0.0155)	(0.0188)	(0.0034)
Closest	0.1556***	0.1708***	0.0583***	0.1457***	0.0223***
Main road	(0.0206)	(0.0308)	(0.0165)	(0.0171)	(0.0036)
Closest	-0.9807***	-1.1068***	-0.4059***	-1.0053***	0.0387***
Industr. park	(0.0185)	(0.0319)	(0.0299)	(0.0178)	(0.009)
Commercial	-0.0821***	-0.0768***	-0.0309	-0.0884***	0.0152***
Center	(0.0143)	(0.0164)	(0.0124)	(0.0138)	(0.0029)
First Stage of the Instrumented Variable: Average Wind Speed					
Closest	-0.0286***	-0.0144***	-0.0052***	-0.0296***	-0.0003***
Railroad	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0001)
Closest	-0.0118***	-0.015***	-0.0045***	-0.0105***	0.0001
Main road	(0.0006)	(0.0006)	(0.0004)	(0.0005)	(0.0001)
Closest	0.123***	0.1294***	0.0514***	0.1225***	0.0058***
Industr. park	(0.0005)	(0.0006)	(0.0008)	(0.0005)	(0.0002)
Commercial	0.0067***	0.0056***	0.0037***	0.0077***	-0.0002***
Center	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0001)
Underidentification & Overidentification Test					
Kleibergen-Paap rk LM stat	450.333***	240.777***	125.264***	95.36***	106.367***
Sargan-Hansen Stat	0.981	1.072	1.876	4.394	2.534
p-val	0.6122	0.585	0.3914	0.1111	0.2816
Weak Identification Test					
† *Kleibergen-Paap rk Wald F*	113.341	60.262	31.296	23.857	26.645
‡ *AP F-val* downwind	301.34	80.25	134.89	171.28	36.08
AP F-val avg. speed	150.77	351.01	44.1	33.57	370.72
N	69236	74708	45328	46476	11412

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

† Stock-Yogo weak ID test critical values (maximal IV relative bias): *5%* 11.04, *10%* 7.56, *20%* 5.57, *30%* 4.73. critical values (maximal IV size): *10%* 16.87, *15%* 9.93, *20%* 7.54, *25%* 6.28. Source: Stock-Yogo (2005)

‡ Critical values for single endog. regressor (maximal IV relative bias): *5%* 16.85, *10%* 9.08, *20%* 6.46, *30%* 5.39. critical values (maximal IV size): *10%* 22.30, *15%* 12.83, *20%* 9.54, *25%* 7.80. Source: Stock-Yogo (2005).

Table 4.8: First Stage Regression (Firm's Locational Impact on Air Pollution)

dep var Pollution (SO_2)	Power	Electronic	Chemical	Manufacture	Medical
Distance in km to	-14.19***	-9.037***	-13.32***	-8.236***	-5.337***
Downwind border	(1.300)	(1.623)	(1.162)	(1.043)	(0.826)
Avg. wind spd	524.8***	481.6***	685.3***	529.0***	630.9***
(1000mph)	(49.74)	(71.02)	(38.81)	(27.34)	(48.18)
Abatement tech.	-4082.7***	-1101.0***	-7167.9***	-3411.8***	-4409.4***
Capacity (tons)	(278.8)	(276.0)	(438.3)	(241.5)	(212.6)
Residual from	-0.448***	0.0383	-0.0121	-0.134***	-53.82***
Downwind equation	(0.0961)	(0.0442)	(0.00821)	(0.0317)	(3.945)
Residual from	5.585*	-10.32***	-3.576***	-2.994***	-25.73***
Speed equation	(2.170)	(1.179)	(0.239)	(0.554)	(3.959)
Residual from	32740.8***	22273.5***	24294.9***	61661.9***	46958.3***
Technology equation	(3433.0)	(1022.2)	(2149.5)	(6685.3)	(7722.6)
N	69236	74708	45328	46476	11412

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Abatement technology is production capacity (tons) installed with denitrification technology for Chemical, Manufacturing, and Medical Sectors, and with desulfurization technology for Power and Electronic Sectors.

Table 4.9: Air-Polluting Firm's Locational Impact on Pollution: Control Function Approach 2011-2015

Figure 4.1: Average Winter Wind Direction at Weather Stations in China

Figure 4.2: Average Summer Wind Direction at Weather Stations in China

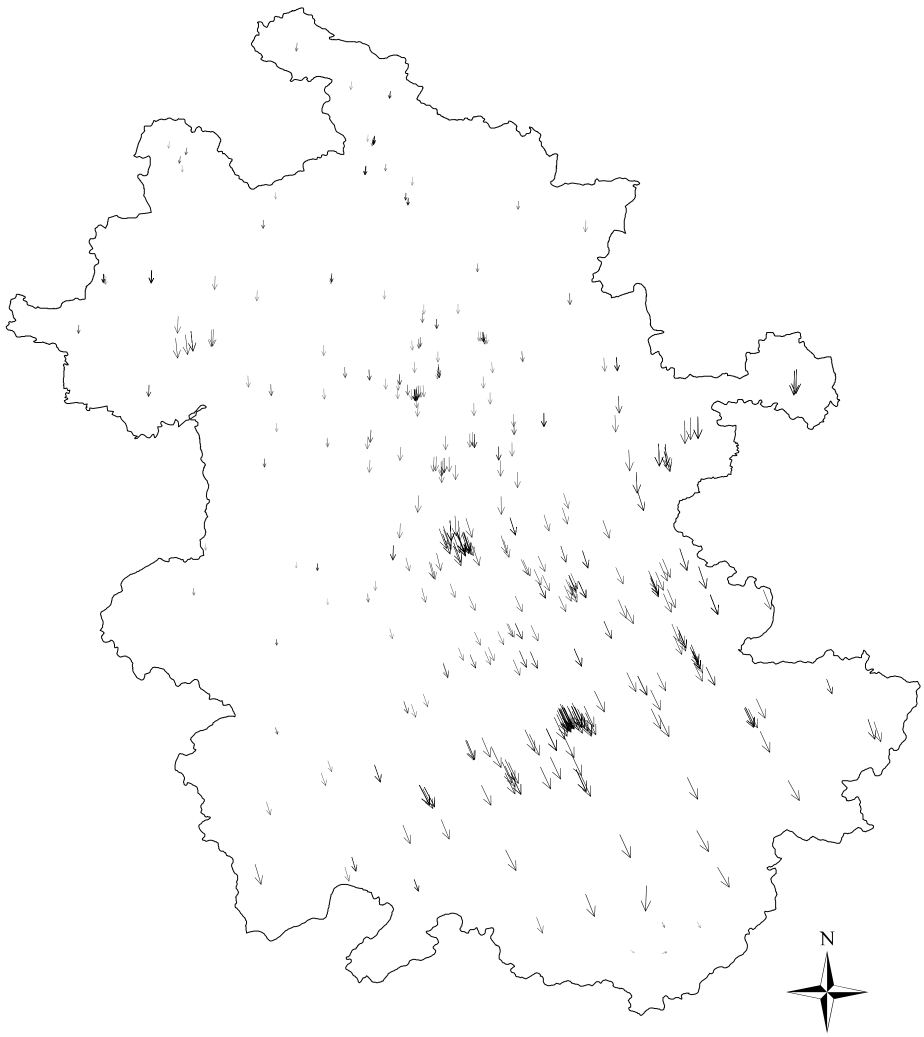

Figure 4.3: Interpolated Winter Wind Direction at All Heavily Monitored Firms in Anhui Province

Appendix A: AJAE Appendix for Chapter 2

Note: The material contained herein is supplementary to the article named in the title and published in the American Journal of Agricultural Economics (AJAE).

A.1 Conceptual Framework

To better understand how different driving forces across local areas influence land-use decisions, a shifter is added to each function, which accounts for demographically-caused shocks that change the value of production or costs. With initial values of shifters to be 1 as in the maximization problem in the theory section, let $\alpha \geq 1$, $\beta \geq 1$, $\gamma \geq 1$, and $\omega \geq 1$ represent shifters for the value of forestry production, level farmland production, erodible farmland production, and the relative cost of erodible farmland conversion to level farmland conversion. The shifter in front of the function $C_l(a_l)$ is normalized to 1.

The benefit maximization problem under the afforestation process with interior solutions when $0 < a_l^* < A_l$ and $0 < a_e^* < A_e$ becomes:

$$\max W(a_l, a_e) = \alpha B(F+a_l+\varepsilon a_e)+\beta\pi_l(A_l-a_l)+\gamma\pi_e(A_e-a_e)-C_l(a_l)-\omega C_e(a_e)+S\cdot(a_l+a_e)$$

Applying Cramer's Rule yields the following comparative statics of a_l^* and a_e^* with respect to the model parameters. Let $g = \begin{pmatrix} \alpha B' - \beta\pi_l' - C_l' + S \\ \\ \alpha\varepsilon B' - \gamma\pi_e' - \omega C_e' + S \end{pmatrix} = \begin{pmatrix} 0 \\ \\ 0 \end{pmatrix}$, and variables $x = (a_l, a_e)$ with parameters $\theta = (F, A_l, A_e, \alpha, \beta, \gamma, \omega, S)$. The determinant of $Dg_x(\theta) = \alpha B''(\gamma\pi_e'' - \omega C_e'') + \varepsilon^2\alpha B''(\beta\pi_l'' - C_l'') + (\gamma\pi_e'' - \omega C_e'')(\beta\pi_l' - C_l'') > 0$, which is guaranteed by the second-order sufficient conditions for a maximum, i.e., $g_{11} = \alpha B'' + \beta\pi_l'' - C_l'' < 0$, and $g_{22} = \varepsilon^2\alpha B'' + \gamma\pi_e'' - \omega C_e'' < 0$.

The following results are the comparative statics with respect to:

$$
\begin{array}{lll}
F\colon & \dfrac{\partial a_l}{\partial F} = \alpha B''(\omega C_e'' - \gamma\pi_e'')/det < 0, & \dfrac{\partial a_e}{\partial F} = \varepsilon\alpha B''(C_l'' - \beta\pi_l'')/det < 0 \\
A_l\colon & \dfrac{\partial a_l}{\partial A_l} = \beta\pi_l''(\varepsilon^2\alpha B'' + \gamma\pi_e'' - \omega C_e'')/det > 0, & \dfrac{\partial a_e}{\partial A_l} = -\beta\pi_l''(\varepsilon\alpha B'')/det < 0 \\
A_e\colon & \dfrac{\partial a_l}{\partial A_e} = -\gamma\pi_e''(\varepsilon\alpha B'')/det < 0, & \dfrac{\partial a_e}{\partial A_e} = \gamma\pi_e''(\alpha B'' + \beta\pi_l'' - C_l'')/det > 0 \\
\alpha\colon & \dfrac{\partial a_l}{\partial \alpha} = B'(\omega C_e'' - \gamma\pi_e'')/det > 0, & \dfrac{\partial a_e}{\partial \alpha} = \varepsilon B'(C_l'' - \beta\pi_l'')/det > 0 \\
\beta\colon & \dfrac{\partial a_l}{\partial \beta} = \pi_l'(\varepsilon^2\alpha B'' + \gamma\pi_e'' - \omega C_e'')/det < 0, & \dfrac{\partial a_e}{\partial \beta} = -\pi_l'(\varepsilon\alpha B'')/det > 0 \\
\gamma\colon & \dfrac{\partial a_l}{\partial \gamma} = -\pi_e'(\varepsilon\alpha B'')/det > 0, & \dfrac{\partial a_e}{\partial \gamma} = \pi_e'(\alpha B'' + \beta\pi_l'' - C_l'')/det < 0 \\
\omega\colon & \dfrac{\partial a_l}{\partial \omega} = -C_e'(\varepsilon\alpha B'')/det > 0, & \dfrac{\partial a_e}{\partial \omega} = C_e'(\alpha B'' + \beta\pi_l'' - C_l'')/det < 0 \\
S\colon & \dfrac{\partial a_l}{\partial S} = [\varepsilon(1-\varepsilon)\alpha B'' + (\omega C_e'' - \gamma\pi_e'')]/det, & \dfrac{\partial a_e}{\partial S} = [-\alpha B''(1-\varepsilon) + C_l'' - \beta\pi_l'']/det > 0
\end{array}
$$

All the signs are following the expectation, except the direction of the subsidy's impact on the conversion of level farmland could be ambiguous and depend on the size of the relative forestry productivity of converted farmland, ε. When ε is close to 1, i.e. when forest land converted from both types of farmland have similar forestry productivity, a higher unit subsidy increases the converted amount of level farmland. When ε converges to 0, it is less likely to happen. It would hint that highly erodible farmland converting to forestland with almost no forestry productivity, as if it was completely abandoned, would backfire the design of the GfG program. The tradeoff could arise in middle cases: namely, when ε is close to 1/2. Whether a high subsidy will induce more conversion of level farmland is ambiguous. It is thus possible that an increased unit subsidy could discourage the conversion of level farmland. The intuition is that a higher unit subsidy will increase erodible farmland conversion. At the same time, the low survival rate of the newly afforested land, along with the assumption that a marginal forestry benefit is decreasing when the forest is expanding, reduces the general incentive of afforestation on farmland. If the erodible farmland is relatively easy to convert or the marginal benefit to keep the erodible farmland in use is very low, the incentive to convert level farmland is further reduced.

A.2 Robustness Check with GIS Data

In China, there are three types of land use data sources: the official statistical data by the State Statistical Bureau; the national land resources inventory data sponsored by the Ministry of Land and Resources (the MLR dataset); and the satellite remote-sensing data maintained by the Chinese Academy of Sciences (the GIS dataset) (Liu et al., 2005). The first source potentially underestimates the actual cultivated land area, while the latter two are mapping based on aerial photos and Landsat images and are validated against field surveys (Deng et al., 2006; Liu et al., 2005, 2002). The MLR dataset (1996 to 2004) includes the yearly land transition data with 47 classes of land cover (8 major categories) in every county, and the GIS dataset documents the 1:100,000-scale national land use database with 31 classes of land cover (6 major categories) that was applied to the Landsat TM/ETM in the late 1980s, 1995, 2000, 2005, and 2010 (Liu et al., 2014). Because the MLR dataset remains confidential, it is crucial to show its data quality and data reliability against the broadly accepted remote-sensing data. To compare the land use data from the two data sources, I convert the $1km \times 1km$ raster data from 1995 to 2010 into geospatial vector data, spatially join these layers of land use databases with the administrative map at the county-level, and calculate the aggregated area of each class of land in each county (figure A.1 provides an example of the mapping process).

As mentioned in the data section, the MLR dataset has three advantages. The GIS dataset shares the same advantages, except that there is a time gap in the corresponding panel of five years. I use the GIS data as a major descriptive statistical reference in this paper, but conduct the empirical analysis using the MLR dataset.

A comparison of county-level averages for the amounts of major types of land is shown in table A.1. Because of the inconsistency between the two datasets, I compare the 1996, 2000, and 2004 land stock data in the MLR dataset with the 1995, 2000, and 2005 land stock data in the GIS dataset. Because there was no land use program during 1995-1996 and the GfG program was slowed down after 2004, I expect a relatively low level of land conversion across the compared types. None of the differences in county-average land stocks are statistically different from zero. Two possible sources of measurement errors are (1) the GIS dataset is measured to the nearest 100 hectares (1 km^2) while the MLR dataset is to the nearest 0.0067 hectares; and (2) the GIS dataset is developed by digitalization and visual interpretation, which may involve certain measurement errors.

The comparison of land transition between the 5-year based GIS data and the MLR data would be less suggestive and are not reported here. This is because the MLR dataset documents the detailed yearly land conversion from land type A to type B and from land type B to type A, which gives the net conversion of any two types of land. The difference of two GIS maps, on the other hand, are the five-year summation of the corresponding net conversion plus the net conversion from other types to type B (such as pasture conversion, road construction, etc.). The latter involves other economic incentives that beyond the scope of this paper.

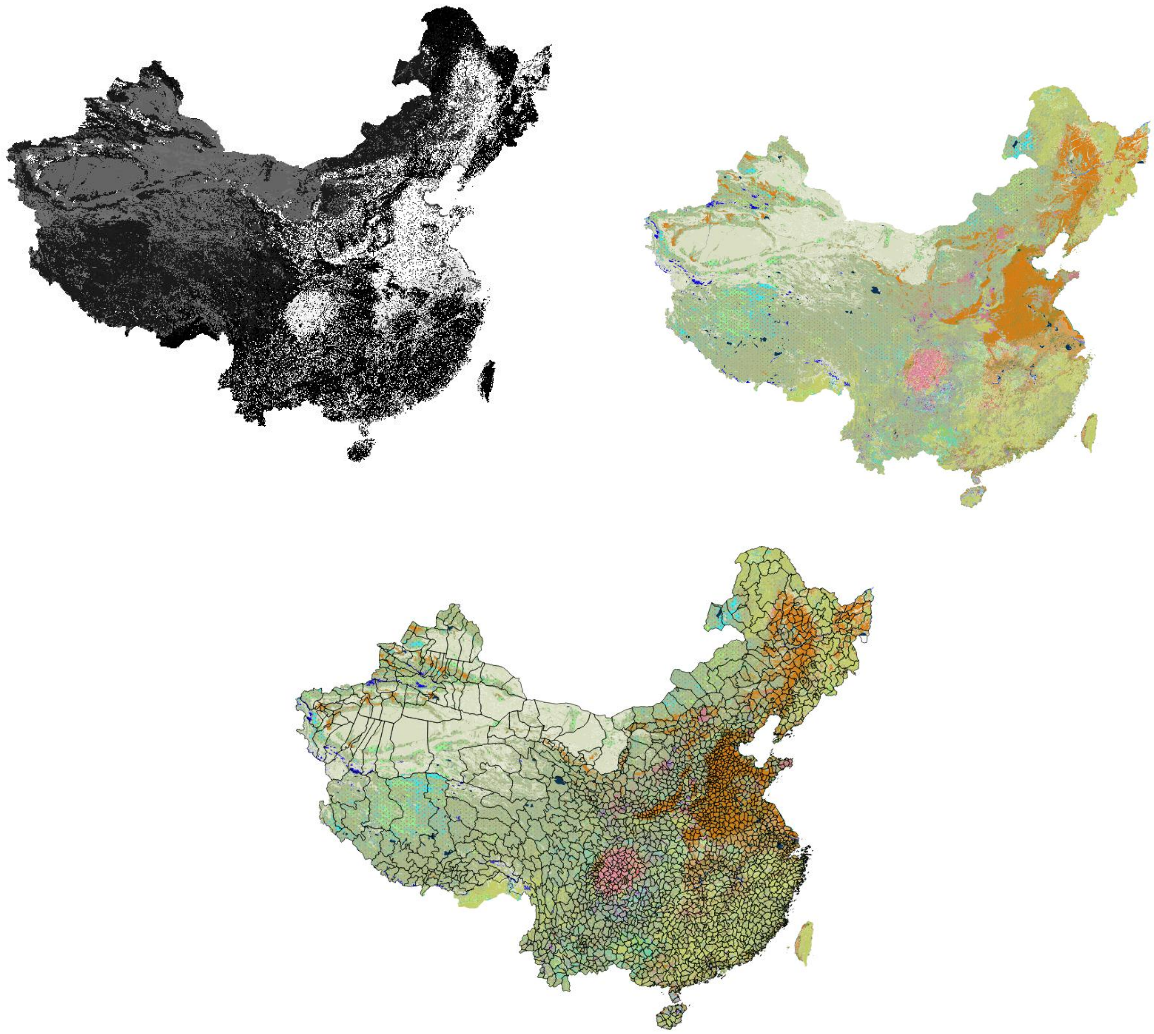

Figure A.1: China Land Use (2000): 1km by 1km Raster Data Conversion to Vector Data at the County Level

Data Source		MLR		GIS		difference		H0:mean(diff)=0	
Comparison	Land Type	mean	SD	mean	SD	mean	SD	t-val	p-val
MLR-1996	level farmland	21096.27	22277.12	20975.25	34178.08	121.0207	37202.88	0.1478	0.8825
vs. GIS-1995	erodible farmland	34455.31	46029.27	32457.14	53586.64	1998.165	57763.04	1.572	0.1161
	all types of forests	84844.62	191137.2	83806.61	92699.76	1038.009	188735.6	0.2494	0.8031
	pasture	24300.54	192723.4	24418.81	43567.53	-118.2705	196892.6	-0.0273	0.9782
	unused land	22721.76	191569.8	21254.13	64513.62	1467.631	195645.9	0.3409	0.7332
MLR-2000	level farmland	21174.22	22488.76	22313.55	37214.58	-1139.33	39312.34	-1.3179	0.1877
vs. GIS-2000	erodible farmland	33730.65	45382.79	33743.05	54145.93	-12.39979	58092.84	-0.0097	0.9923
	all types of forests	84350.67	190327.3	81966.61	90187.13	2384.06	187988.3	0.5755	0.5650
	pasture	24845.89	192660.7	22904.35	42340.65	1941.536	196663.8	0.4489	0.6535
	unused land	23129.04	191840.2	20978.83	65460.56	2150.21	196776.4	0.4969	0.6193
MLR-2004	level farmland	20772.72	22175.34	21885.53	36448.83	-1112.807	38343.02	-1.3198	0.1870
vs. GIS-2005	erodible farmland	31832.47	43644.39	33416.65	53817.1	-1584.178	58125.58	-1.2394	0.2153
	all types of forests	80375.54	189830.7	81594.19	89902.52	-1218.653	186057.3	-0.2972	0.7663
	pasture	24933.87	192635.5	22833.75	42181	2100.124	196569.8	0.4859	0.6271
	unused land	22874.61	191783.7	20870.05	64490.64	2004.564	196479.7	0.464	0.6427
GIS-2010	level farmland			21861.75	36332.57		(Compare to	-0.1252	0.9004
	erodible farmland			32927.4	52816.76		GIS-2005)	-1.6039	0.1089
	all types of forests			82140.72	90284.59			1.5031	0.1330
	pasture			22604.45	41845.07			-5.1592	0.0000
	unused land			20935.65	64839.38			0.4573	0.6475

County Level Land Use Data Source: The Ministry of Land and Resources of China (1996-2004)

GIS Data Source: Chinese Academy of Sciences. (Based on Landsat TM scenes with a spatial resolution of 1km $\times$ 1km.

The main analysis in the paper focuses on the newly afforested timber-producing forest. The GIS data does not parse out this category. I compare the total area of all types of forests in this table instead.

Table A.1: Land Use Data in China: Data Comparison (Area in Hectare)

A.3 Robustness Check Regressions

This section includes a series of robustness checks and the main estimated coefficients of the robustness-check regressions. After that, tables providing additional information about the land stock effect in the GfG program are included.

A. Time-Variant Unobservables at Provincial and Prefectural Level

The above empirical specification controls for county-level fixed effects and yearly fixed effects, but time-variant unobservables at provincial and prefectural level can also be controlled by including interactions between the regional and year indicators. The tables reporting the coefficients of the program effect (along with the interaction with farmland values) are reported in tables A.2 and A.3. The derived maximum county-average productivity levels under this model specification are reported in table A.4. Because the county-level land values, land stock, and average worker characteristics that have been controlled in the model have absorbed and can reflect many regional shocks, the coefficients have the same magnitudes as those reported in the main text.

B. Seemingly Unrelated Regression Model

Because the error terms in each land transition estimation equation are potentially correlated across the equations, I estimate the group of equations simultaneously to increase the estimation efficiency. The coefficients of the GfG program's land use impacts are expected to remain the same magnitudes. The seemingly unrelated regression (SUR) model consists of six equations of land transition. And I estimate the pooled, regional, and sub-regional land transition separately. The coefficients are reported in tables A.5 and A.6. The derived maximum yields at which conversion is desirable are reported in table A.7.

A major difference between the SUR model estimation and the FE model is that the former improve the estimation efficiency. In the FE model, the main table suggests that the GfG program has almost no impact on unused land conversion or orchard afforestation, while in table A.5, a significant amount of erodible farmland and unused land has been converted to orchards. In northern China, unused land conversion to orchards amounts to one-sixth of its total afforestation level, which is very close to the regulation that orchards can account for at most 20% of afforestation.

C. Propensity Score Matching and Difference-in-Difference Matching

As a conservation program to reduce soil erosion and prevent floods, the GfG program was phased in based on major river flow directions. Although the region-based enrollment selection made by the central government has been well controlled by the fixed-effects model, the enrolled counties may be systematically different from non-enrolled counties. To mitigate this concern, I use a propensity score matching (PSM) method to account for observable differences in characteristics between enrolled and un-enrolled counties.

I group the counties based on the years that they have been treated. Denote the treatment status of each county as $GfG_i(m)$ where $GfG_i = 0$ if a county is never treated and $GfG_i = m$ if a county receives the GfG subsidy starting in year

m. The probability of being enrolled in year m can be estimated as:

$$p_m(X_i) = Pr(GfG_i = m|X_i) = f(X_i) + e_i \tag{A.1}$$

where the potential set of observables X_i includes all the characteristics that have been used in the fixed effects model above *before treatment*. It also includes some time invariant characteristics that might influence local land-use policy decisions, including: regional indicators; local terrain types (average percentage of mountainous area, desert, and water area); local weather (precipitation, average temperatures in winter and summer, and humidity); and average worker wage at the prefectural and provincial level (to control for farmers' outside options).[1]

With an estimate of $\hat{p}_m(X_i)$, I estimate the average treatment effects (ATE) δ_{mt} for each year's land transition between one treated cohort and the untreated group:

$$\delta_{mjt} = \frac{1}{\sum_{i=1}^{N} \frac{I(GfG_i=m)}{\hat{p}_m(X_i)}} \times \sum_{i=1}^{N} \frac{I(GfG_i = m) y_{ijt}}{\hat{p}_m(X_i)} - \frac{1}{\sum_{i=1}^{N} \frac{I(GfG_i=0)}{\hat{p}_0(X_i)}} \times \sum_{i=1}^{N} \frac{I(GfG_i = 0) y_{ijt}}{\hat{p}_0(X_i)} \tag{A.2}$$

for land transition type j at year t. The expected treatment effects are not significant to zero if $t < m$. The average of the treatment effects with $t \geq m$ is the overall ATE of the GfG program for each land transition type j. The corresponding coefficients are reported in tables A.8 and A.9.

[1]The last three groups of variables are averaging from 1990 to 1995. The data sources are from the National Geomatics Center of China, the National Oceanic and Atmospheric Administration (NOAA), and China's provincial yearbooks, respectively.

The PSM model can be used both as a robustness check and as a placebo test. This model is able to examine the yearly conversion effects across different treated cohorts. It compares the same land transition type in a certain year between one treated group and the control group that have similar pre-treatment characteristics.[2] Presumably, land transition should be similar for years before the treatment. At the same time, the treatment effects over the treated years for a certain treatment cohort have the same pattern as the placebo test in the FE model (see figures A.4 and A.5 and tables A.13 and A.14), and the average of the treatment effects have the same magnitude with the effects estimated in the main text.

To further reduce the bias from unobserved systematic county characteristics, I combine matching with the difference-in-difference (DID) estimator to control for time-invariant characteristics. More specifically, I re-estimate the fixed effects model on the *trimmed* or *matched* sample that has been derived from the PSM method. I compare the treatment effects separately across different treated cohorts, because even the pool of the control group is the same, and the matched control group to different treated cohorts could be different. The ATEs for each treated cohort have been reported in the last columns of tables A.8 and A.9. The ATEs are almost identical to the coefficients in the FE model.

D. Variable and Data Variation

Changing the identification of $farmland\_value$ from output grain/ha to GDP of agricultural industry/ha, value added of agricultural industry/ha, output value of farm/ha, and output of grain/ha from another source of data also provides virtually

[2] This is done by converting the long panel to wide panel.

identical results. Dropping the top or bottom 5% and 10% of the transitional observations also yields estimated coefficients of the same magnitude, suggesting the estimated coefficients are not influenced by outliers.

Tables A.10 and A.11 show the estimated coefficients in the absolute value model and share model, respectively. Panel 1 to 4 report the results of changing the identification of $farmland\_value$ from output grain/ha to GDP of agricultural industry/ha, value added of primary industry/ha, output value of farm/ha, and output of grain/ha from another source of data, respectively. Panel 5 to 8 report the results of dropping the top 5% and 10%, and bottom 5% and 10% of the transitional observations, respectively.

Tables A.15 and A.16 provide additional information about land stock effect in the GfG program: a type of land is likely to be enrolled in the program when its stock is high, or the other type of land's stock is low. This finding suggests that the GfG program worked as intended from this aspect, because more erodible farmland conversion would occur in a relatively erosion-prone region. On the other hand, similar to the conversion of erodible farmland, local land stock effects are sizable in the conversion of level farmland. Regions with a limited area of highly productive flat farmland may choose to enroll more erodible farmland to the program, while regions with a high stock of productive flat farmland have incentives to violate the program's regulations. Although the land stock effects on level farmlands are similar in both northern and southern China, unintended land use conversion is more likely to be observed in south-central China, because this region has a relatively abundant stock of level farmland.

E. Validity of the parallel trend assumption

To examine the validity of the parallel trend assumption, I conduct two tests. I first check the differences in the pre-treatment trends of the treatment and comparison groups separately for each cohort of provinces that implemented the GfG program in a given year. As figures A.2 and A.3 show, there are no discernible differences in pre-treatment trends in average conversion to timber-producing forests from level farmland and erodible farmland, respectively. I also perform a set of placebo tests for each implementation-year cohort. I estimate the farmland transition model under the assumption that the program was implemented in 1997, 1998, and so on up to a year before the end of the sample period. The estimated coefficients of the GfG indicator for the level farmland and erodible farmland conversion showed in figures A.4 and A.5 are not significantly different from zero. Tables A.12 to A.14 following these figures report the corresponding coefficients in the figures. Comparisons and placebo tests of other types of conversion are very similar and not reported.

		Land Transition					
		level farmland	erodible farmland	unused land	level farmland	erodible farmland	unused land
Model	Variable	to timber-producing forest			to orchards		
Pooled	GfG	52.14***	238.9***	-1.468	6.400	34.17**	-0.977
		(7.839)	(45.02)	(32.21)	(15.02)	(12.84)	(5.703)
Regional	GfG·N	86.12***	293.0***	59.68**	-16.27	-0.386	-3.258
		(11.24)	(70.57)	(18.46)	(48.46)	(23.35)	(8.519)
	GfG·S	20.18*	201.8***	10.25	-10.25	11.19	0.875
		(8.91)	(58.46)	(43.11)	(17.87)	(19.62)	(7.677)
Subregional	GfG·NW	173.0***	440.3***	69.89	115.8***	14.27	-10.82
		(17.98)	(104.8)	(68.22)	(26.21)	(34.69)	(11.99)
	GfG·NC	24.85*	67.98*	117.3	-13.98	-12.42	2.522
		(12.56)	(33.9)	(80.42)	(30.66)	(37.37)	(14.16)
	GfG·NE	44.61*	428.9*	-67.00	19.12	70.03	9.704
		(22.32)	(178.5)	(132.9)	(48.88)	(59.09)	(23.31)
	GfG·SW	9.285	196.9**	12.52	-12.79	4.045*	0.0159
		(13.99)	(70.97)	(52.86)	(20.78)	(2.05)	(9.424)
	GfG·SC	56.26*	191.3*	-21.41	-3.112	-0.756	23.56*
		(23.32)	(75.9)	(75.22)	(34.96)	(34.83)	(11.97)
	N	8566	9003	10012	8564	8949	9838

Clustered standard errors in parentheses at the provincial level, with county, year fixed effects included.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Pooled, regional, and subregional models are separate regressions.
The model also includes the program indicator and provincial, prefectural indicators interactions.

Table A.2: Land Transition to Forests in China (1996-2004) with Prefecture-Year Indicators

Model		Land Type	
		Level Farmland	Erodible Farmland
Pooled	GfG	132.7***	736.7***
		(34.44)	(128.1)
	GfG·farmland_value	-12.45*	-111.5***
		(5.309)	(25.95)
Regional	GfG·N	67.46***	606.9***
		(8.546)	(63.88)
	GfG·N·farmland_value	-7.485***	-119.1***
		(1.900)	(12.95)
	GfG·S	-0.806	443.5***
		(9.047)	(35.76)
	GfG·S·farmland_value	-0.105	-59.18***
		(1.522)	(8.229)
Subregional	GfG·NW	509.1***	97.26***
		(54.29)	(11.45)
	GfG·NW·farmland_value	-90.85***	-18.68***
		(10.32)	(4.430)
	GfG·NC	260.6***	386.4
		(45.25)	(281.4)
	GfG·NC·farmland_value	-24.76*	-70.8
		(9.689)	(54.21)
	GfG·NE	156.0***	2865.9***
		(17.26)	(226.6)
	GfG·NE·farmland_value	-13.46***	-633.3***
		(2.807)	(35.41)
	GfG·SW	2.286	1240.1***
		(19.03)	(103.4)
	GfG·SW·farmland_value	3.672	-331.7***
		(3.578)	(23.11)
	GfG·SC	1018.9***	696.4***
		(86.92)	(51.04)
	GfG·SC·farmland_value	-284.5***	-135.0***
		(20.42)	(16.34)
	N	8363	8685

Clustered standard errors in parentheses at the provincial level,
with county, year fixed effects included. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Pooled, regional, and subregional models are separate regressions. The model also includes the program indicator and provincial, prefectural indicators interactions. This is the table that used to derive the estimated breakeven farmland values.

Table A.3: Land Transition to Forests in China (1996-2004) with Interaction Terms (with Prefecture-Year Indicators)

Model		Land Type	
		Level Farmland	Erodible Farmland
Pooled		10.656***	6.609***
		[6.64,14.68]	[5.38,7.84]
Regional	Northern	9.012***	5.095***
		[5.84,12.19]	[4.18,6.01]
	Southern	-7.68	7.494***
		[-365.51,350.16]	[5.96,9.03]
Subregional	Northwestern	5.604***	5.207***
		[4.47,6.73]	[3.55,6.86]
	Northcentral	10.524***	5.457*
		[4.44,16.61]	[0.90,10.01]
	Northeastern	11.591***	4.525***
		[7.85,15.33]	[3.96,5.09]
	Southwestern	-0.622	3.739***
		[-11.82,10.58]	[3.24,4.24]
	Southcentral	3.581***	5.160***
		[3.08,4.08]	[4.33,5.99]

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
The Delta Method is used to calculate the *95%* Confidence Intervals.
Pooled, regional, and subregional models are separate regressions.

Table A.4: Estimated Maximum Farmland Values (ton/ha) for Unintended Conversion to Timber-producing Forest (with Prefecture-Year Indicators)

		Land Transition					
		level farmland	erodible farmland	unused land	level farmland	erodible farmland	unused land
Model	Variable	to timber-producing forest			to orchards		
Pooled	GfG	74.93***	276.4***	6.033	-1.353	19.52**	8.943**
		(12.10)	(33.24)	(17.67)	(13.18)	(7.314)	(2.950)
Regional	GfG·N	42.38***	376.8***	54.65***	-17.89***	10.66*	10.04***
		(2.309)	(13.78)	(8.595)	(3.696)	(4.416)	(1.553)
	GfG·S	13.41***	181.9***	-6.024	0.124	47.71***	7.428***
		(2.369)	(13.08)	(8.550)	(3.788)	(4.219)	(1.543)
Subregional	GfG·NW	84.47***	375.6***	34.74**	-22.47***	17.90**	10.06***
		(3.729)	(17.38)	(11.47)	(4.645)	(5.572)	(2.077)
	GfG·NC	20.89***	135.1***	138.2***	-10.94	-26.97***	12.52***
		(5.503)	(23.60)	(13.34)	(6.211)	(7.537)	(2.432)
	GfG·NE	35.19***	727.0***	-1.888	-19.04**	45.66***	7.660**
		(4.959)	(27.73)	(13.83)	(7.279)	(8.931)	(2.628)
	GfG·SW	-2.165	190.9***	-24.88*	14.78***	74.94***	4.087*
		(3.606)	(14.43)	(9.771)	(4.214)	(4.671)	(1.776)
	GfG·SC	53.29***	218.5***	-3.769	-41.97***	-11.15	10.83***
		(4.385)	(19.45)	(12.59)	(6.457)	(6.318)	(2.283)
	N	49828					

Clustered standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Pooled, regional, and subregional models are separate regressions.

Table A.5: Land Transition to Forests in China (1996-2004): Seemingly Unrelated Regression

Model		Land Type	
		Level Farmland	Erodible Farmland
Pooled	GfG	79.57***	443.5***
		(12.73)	(35.76)
	GfG·farmland_value	-7.589**	-59.18***
		(2.365)	(8.229)
Regional	GfG·N	103.7***	952.8***
		(11.09)	(64.23)
	GfG·N·farmland_value	-12.33***	-182.0***
		(2.258)	(18.76)
	GfG·S	11.15	233.7***
		(11.00)	(51.97)
	GfG·S·farmland_value	1.949	-40.05***
		(1.913)	(11.75)
Subregional	GfG·NW	131.0***	623.3***
		(13.81)	(79.64)
	GfG·NW·farmland_value	-22.99***	-111.9*
		(5.157)	(44.66)
	GfG·NC	128.3***	515.5*
		(37.46)	(254.5)
	GfG·NC·farmland_value	-12.10*	-78.95
		(5.767)	(57.38)
	GfG·NE	64.46*	3058.6***
		(26.38)	(156.3)
	GfG·NE·farmland_value	-5.615	-616.2***
		(4.487)	(36.90)
	GfG·SW	1.718	218.4***
		(11.35)	(53.58)
	GfG·SW·farmland_value	-1.141	-61.60***
		(2.345)	(16.56)
	GfG·SC	-27.89	698.4***
		(46.65)	(135.1)
	GfG·SC·farmland_value	8.008	-109.8***
		(7.280)	(27.32)
	N	48745	

Clustered standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Pooled, regional, and subregional models are separate regressions.

This is the table that used to derive the estimated breakeven farmland values.

Table A.6: Land Transition to Forests in China (1996-2004) with Interaction Terms: Seemingly Unrelated Regression

Model		Land Type	
		Level Farmland	Erodible Farmland
Pooled		10.484***	6.167***
		[5.63,15.34]	[5.10,7.24]
Regional	Northern	8.411***	5.236***
		[6.40,10.42]	[4.55,5.92]
	Southern	-5.723	5.834***
		[-26.32,14.87]	[3.40,8.27]
Subregional	Northwestern	5.697***	5.572**
		[3.90,7.50]	[2.14,9.01]
	Northcentral	10.603***	6.530***
		[6.16,15.05]	[2.71,10.35]
	Northeastern	11.479*	4.964***
		[0.80,22.16]	[4.70,5.23]
	Southwestern	1.506	3.546***
		[-14.88,17.89]	[1.92,5.17]
	Southcentral	3.483	6.360***
		[-2.28,9.25]	[5.13,7.59]

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
The Delta Method is used to calculate the *95%* Confidence Intervals.
Pooled, regional, and subregional models are separate regressions.

Table A.7: Estimated Maximum Farmland Values (ton/ha) for Unintended Conversion to Timber-producing Forest: Seemingly Unrelated Regression

Counties enrolled	Sample	1997	1998	1999	2000	2001	2002	2003	Avg. ATT	DID-Match
1999	Unmatched	-7.329	0.886	-32.475	-2.572	-4.891	8.931	-6.397		
Cohort		*4.268*	*0.981*	*29.956*	*1.939*	*4.924*	*58.779*	*4.4*		
	ATT	-2.501	0.553	**-1.445**	**-0.026**	**0.66**	**14.489*****	**0.243**	2.784	3.989
		60.03	*13.259*	*2.047*	*28.36*	*72.247*	*4.343*	*64.567*		(2.662)
2000	Unmatched	-5.226	0.131	-3.366*	7.916	1.828	20.874***	193.518***		
Cohort		*2.731*	*1.561*	*1.4*	*7.555*	*3.395*	*4.725*	*25.02*		
	ATT	-12.082	13.092*	-1.095	**10.967**	**11.631**	**23.463****	**210.356*****	64.104	47.00***
		12.778	*5.725*	*6.361*	*11.758*	*15.002*	*7.88*	*38.63*		(7.276)
2001	Unmatched	-2.33	0.643	3.034	8.443	15.575	49.643***	114.23***		
Cohort		*6.777*	*2.298*	*2.862*	*5.753*	*10.278*	*15.025*	*13.28*		
	ATT	20.394	12.563	2.505	4.769	**19.424**	**53.783****	**132.047*****	68.418	63.49***
		18.877	*7.289*	*8.714*	*12.701*	*20.489*	*19.687*	*21.545*		(10.06)
2002	Unmatched	-1.079	-2.721	-34.696*	12.949	-2.694	51.09***	116.812***		
Cohort		*9.053*	*4.251*	*16.978*	*7.246*	*26.638*	*8.03*	*18.9*		
	ATT	23.29	27.951	-1.92	-28.017	7.942	**72.62*****	**149.88*****	111.25	106.8***
		35.701	*14.897*	*4.427*	*24.078*	*103.791*	*21.577*	*36.987*		(16.77)
								Total Average:	61.639	55.320

Note: The average ATT is the average of each year's land use effect on the treated group since its enrollment year (in bold).
The balance test has been satisfied.

Table A.8: Land Use Effects for Level Farmland Conversion between the Enrolled Counties and the Never-enrolled Counties (Kernel-based Propensity Score Matching Method)

Counties enrolled	Sample	1997	1998	1999	2000	2001	2002	2003	Avg. ATT	DID-Match
1999	Unmatched	10.176	5.086	-83.104	685.756***	315.111***	490.939***	198.371***		
Cohort		*10.64*	*21.165*	*74.138*	*41.365*	*33.739*	*34.66*	*31.461*		
	ATT	12.147	2.049	**107.3***	**464.139***	**235.466***	**435.254***	**223.607**	293.153	319.9***
		133.546	*59.223*	*19.827*	*116.461*	*113.854*	*170.856*	*146.408*		(20.51)
2000	Unmatched	7.154	12.167	7.949	145.876**	175.758***	414.207***	261.753***		
Cohort		*6.898*	*8.622*	*6.544*	*51.917*	*38.324*	*40.088*	*26.471*		
	ATT	23.707	18.648	-8.889	**166.385***	**165.11***	**424.313***	**302.428***	264.559	256.5***
		25.731	*25.489*	*27.358*	*67.522*	*51.76*	*59.297*	*57.108*		(12.19)
2001	Unmatched	7.949	1.204	15.023	17.813*	11.973	291.966***	210.186***		
Cohort		*6.544*	*5.285*	*13.417*	*8.631*	*9.107*	*32.912*	*25.113*		
	ATT	-8.889	3.774	8.255	26.122	**11.699**	**314.842***	**245.578***	190.706	232.8***
		27.358	*8.893*	*18.436*	*15.844*	*16.587*	*45.007*	*42.21*		(12.31)
2002	Unmatched	-7.712	-8.249	-10.394	-13.295*	-76.584**	105.571***	228.71***		
Cohort		*5.56*	*4.738*	*5.454*	*6.67*	*28.819*	*16.403*	*25.232*		
	ATT	-9.105	-6.433	-2.105	-4.003	-9.055	**120.054***	**254.57***	187.312	134.9***
		21.099	*14.588*	*18.522*	*25.201*	*9.105*	*48.708*	*72.996*		(11.62)
								Total Average:	233.933	236.025

Note: The average ATT is the average of each year's land use effect on the treated group since its enrollment year (in bold).
The balance test has been satisfied.

Table A.9: Land Use Effects for Sloped Farmland Conversion between the Enrolled Counties and the Never-enrolled Counties (Kernel-based Propensity Score Matching Method)

Model	Variable	Land Transition: level farmland	erodible farmland	unused land	level farmland	erodible farmland	unused land
		Panel 1			Panel 5		
Pooled	GfG	74.50***	264.5***	29.49	80.74***	209.0***	23.86
		(14.71)	(31.23)	(20.49)	(16.21)	(32.26)	(21.58)
Regional	GfG·N	40.96***	437.9***	41.94	43.78***	406.1***	46.20
		(5.571)	(39.96)	(25.46)	(6.009)	(41.86)	(26.96)
	GfG·S	13.50*	118.7**	18.41	15.92*	51.29	3.413
		(5.765)	(37.59)	(24.51)	(6.286)	(38.63)	(26.17)
	N	8653	7703	8474	8130	7110	7930
		Panel 2			Panel 6		
Pooled	GfG	74.99***	263.5***	29.36	70.55***	234.9***	9.917
		(14.67)	(31.24)	(20.51)	(16.08)	(33.39)	(21.65)
Regional	GfG·N	41.36***	438.4***	41.91	41.20***	429.3***	12.81
		(5.571)	(39.96)	(25.47)	(6.025)	(42.11)	(26.47)
	GfG·S	13.28*	116.2**	18.14	12.41*	66.88	7.237
		(5.763)	(37.61)	(24.55)	(6.133)	(40.06)	(25.83)
	N	8648	7701	8472	8046	7157	7834
		Panel 3			Panel 7		
Pooled	GfG	78.12***	272.3***	25.92	93.59***	189.6***	28.15
		(14.81)	(31.33)	(20.61)	(16.82)	(35.52)	(23.20)
Regional	GfG·N	41.40***	446.5***	38.51	46.51***	398.2***	50.49
		(5.604)	(40.10)	(25.60)	(6.181)	(44.91)	(28.82)
	GfG·S	13.55*	125.7***	14.76	17.93**	-5.206	6.093
		(5.800)	(37.72)	(24.62)	(6.506)	(43.80)	(28.69)
	N	8644	7695	8466	7753	6550	7445
		Panel 4			Panel 8		
Pooled	GfG	74.87***	270.6***	30.67	74.44***	220.8***	4.851
		(14.82)	(31.64)	(20.84)	(14.87)	(36.18)	(22.01)
Regional	GfG·N	42.13***	460.1***	43.28	41.43***	427.6***	10.25
		(5.653)	(40.94)	(26.08)	(5.665)	(45.09)	(26.93)
	GfG·S	13.53*	119.4**	19.98	12.78*	34.35	-0.0548
		(5.805)	(37.78)	(24.71)	(5.732)	(43.53)	(26.14)
	N	8573	7628	8396	7753	6571	7428

Clustered standard errors (provincial level) in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Pooled and regional models are separate regressions. County and fixed effects are included.

Table A.10: Land Transition to Forests in Hectare in China (1996-2004)

Model	Variable	level farmland	erodible farmland	unused land	level farmland	erodible farmland	unused land
		Land Transition					
		Panel 1			Panel 5		
Pooled	GfG	0.00228***	0.0156***	0.0193	0.00251***	0.0107***	0.0185
		(0.000649)	(0.00137)	(0.0108)	(0.000717)	(0.000957)	(0.0117)
Regional	GfG·N	0.00278	0.0176***	0.0167	0.00287	0.0121***	0.0168
		(0.00147)	(0.00183)	(0.0137)	(0.00157)	(0.00130)	(0.0148)
	GfG·S	-0.000907	0.0143***	0.0214	-0.000888	0.00974***	0.0200
		(0.00150)	(0.00161)	(0.0128)	(0.00164)	(0.00112)	(0.0140)
	N	8379	7353	8091	7927	6819	7575
		Panel 2			Panel 6		
Pooled	GfG	0.00229***	0.0156***	0.0192	0.00219**	0.0144***	0.00492***
		(0.000649)	(0.00137)	(0.0108)	(0.000703)	(0.00141)	(0.00139)
Regional	GfG·N	0.00278	0.0175***	0.0167	0.00261	0.0169***	0.00295
		(0.00147)	(0.00183)	(0.0137)	(0.00157)	(0.00185)	(0.00172)
	GfG·S	-0.000858	0.0142***	0.0213	-0.00108	0.0126***	0.00661***
		(0.00150)	(0.00161)	(0.0128)	(0.00159)	(0.00166)	(0.00164)
	N	8374	7351	8089	7843	6866	7482
		Panel 3			Panel 7		
Pooled	GfG	0.00231***	0.0156***	0.0195	0.00282***	0.00744***	0.0194
		(0.000653)	(0.00137)	(0.0109)	(0.000666)	(0.000873)	(0.0127)
Regional	GfG·N	0.00271	0.0176***	0.0168	0.00281	0.0114***	0.0182
		(0.00147)	(0.00183)	(0.0137)	(0.00168)	(0.00115)	(0.0160)
	GfG·S	-0.000958	0.0143***	0.0216	-0.000832	0.00440***	0.0206
		(0.00151)	(0.00161)	(0.0128)	(0.00176)	(0.00104)	(0.0155)
	N	8377	7351	8087	7550	6259	7090
		Panel 4			Panel 8		
Pooled	GfG	0.00229***	0.0153***	0.0195	0.00227***	0.0136***	0.00447**
		(0.000653)	(0.00133)	(0.0110)	(0.000655)	(0.00153)	(0.00141)
Regional	GfG·N	0.00279	0.0174***	0.0169	0.00264	0.0163***	0.00273
		(0.00147)	(0.00179)	(0.0139)	(0.00147)	(0.00198)	(0.00175)
	GfG·S	-0.000870	0.0138***	0.0215	-0.000959	0.0115***	0.00594***
		(0.00150)	(0.00156)	(0.0129)	(0.00148)	(0.00181)	(0.00166)
	N	8363	7333	8037	7563	6280	7077

Clustered standard errors (provincial level) in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Pooled and regional models are separate regressions. County and fixed effects are included.

Table A.11: Land Transition to Forests in Share in China (1996-2004)

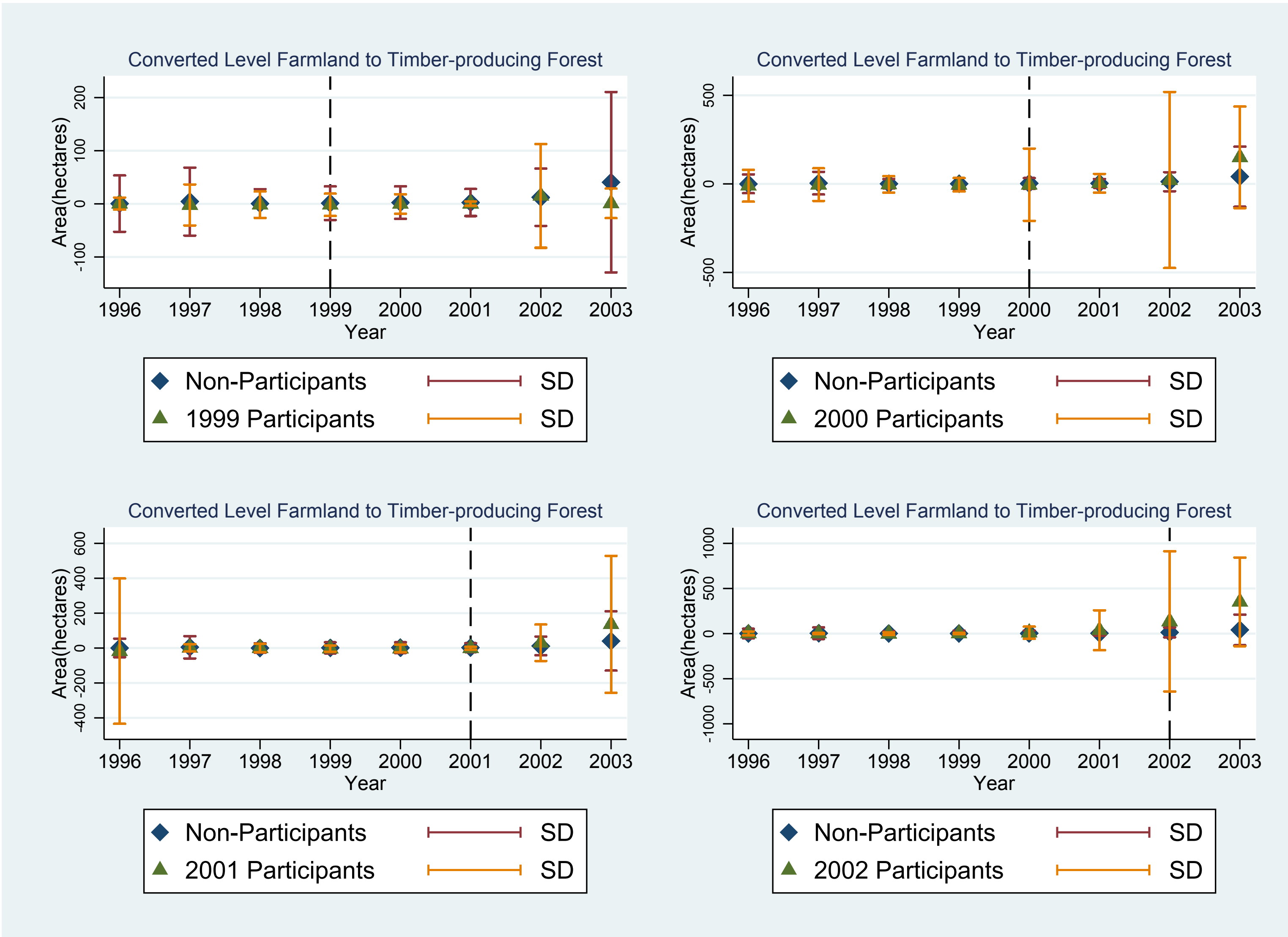

Figure A.2: Comparison of Average Level Farmland Conversion to Timber-producing Forest

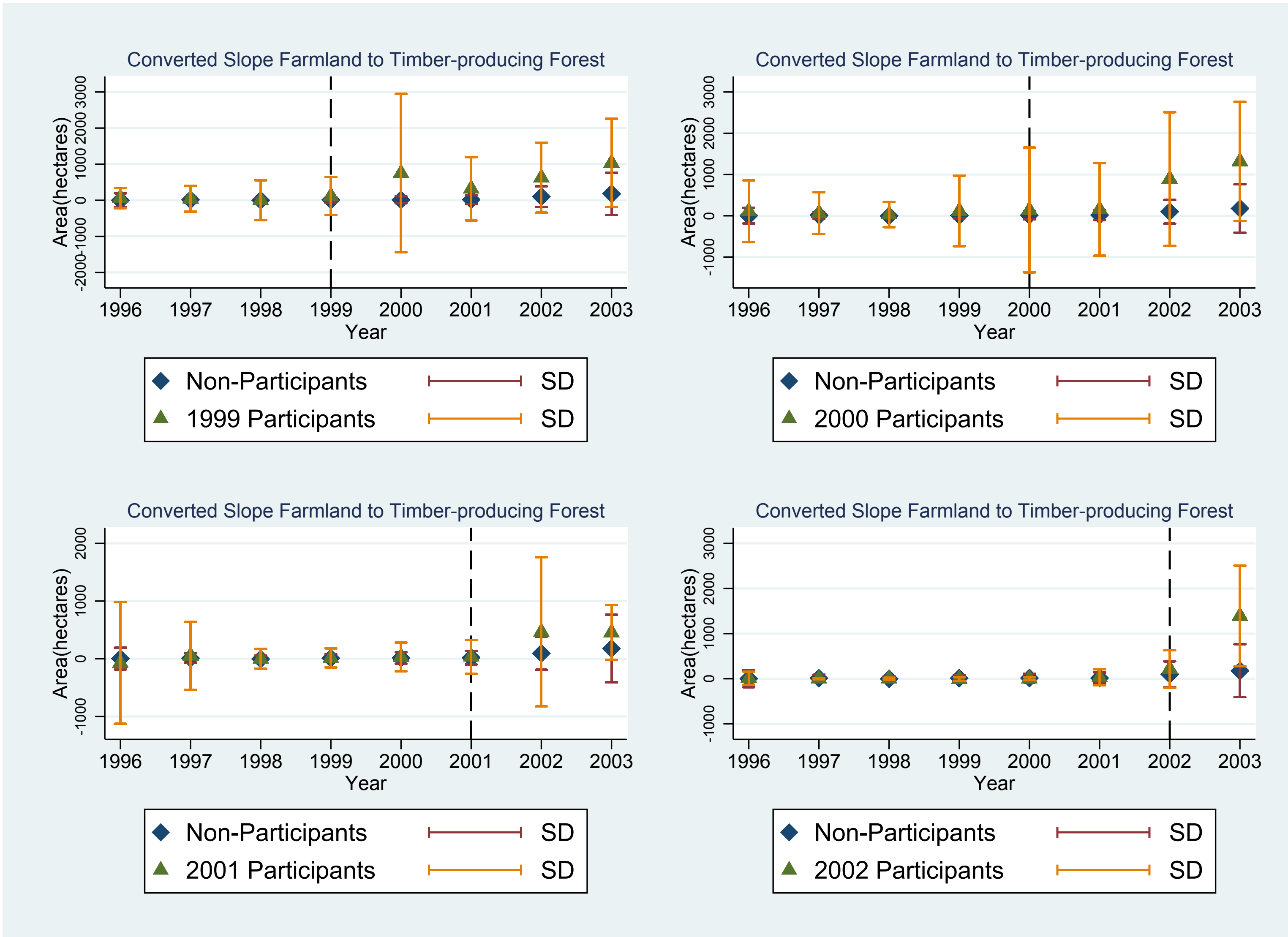

Figure A.3: Comparison of Average Sloped Farmland Conversion to Timber-producing Forest

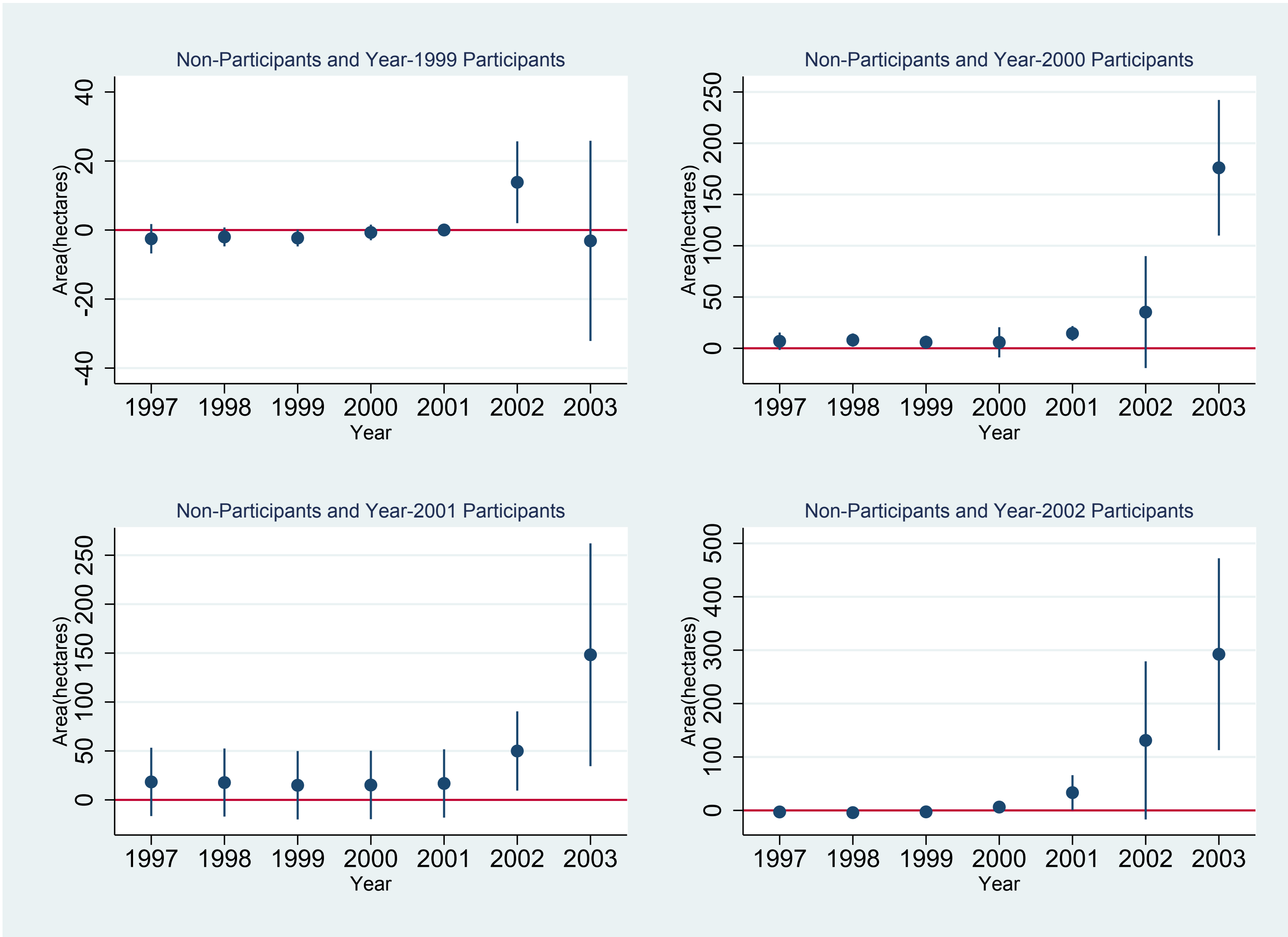

Figure A.4: Placebo Treatment Effects for Level Farmland Conversion from Timber-producing Forest

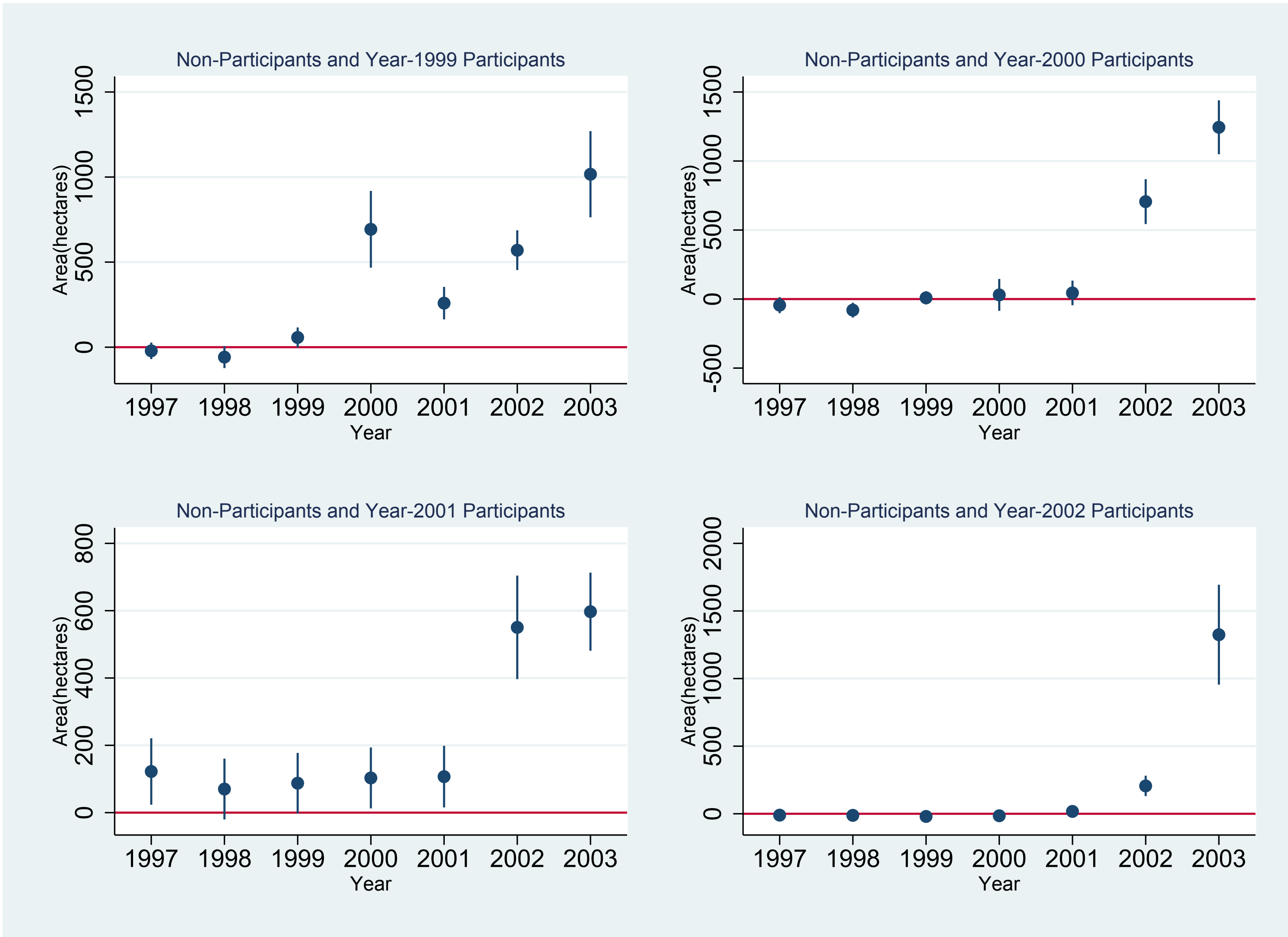

Figure A.5: Placebo Treatment Effects for Sloped Farmland Conversion from Timber-producing Forest

	Sample	1996	1997	1998	1999	2000	2001	2002	2003
Level Farmland	control group	0.53 (-52.539, 53.6)	4.264 (-59.651, 68.178)	0.751 (-26.257, 27.759)	1.252 (-30.416, 32.919)	2.333 (-28.227, 32.894)	2.485 (-22.988, 27.958)	12.398 (-41.458, 66.254)	40.712 (-129.102, 210.527)
	1999 cohort	0.45 (-10.947, 11.847)	-2.046 (-40.64, 36.548)	-1.524 (-26.506, 23.458)	-1.843 (-22.865, 19.178)	-0.232 (-18.558, 18.093)	0.482 (-3.766, 4.73)	15.007 (-82.652, 112.666)	0.959 (-26.806, 28.724)
	2000 cohort	-10.824 (-100.629, 78.98)	-3.984 (-95.99, 88.021)	-2.879 (-49.321, 43.563)	-4.867 (-42.824, 33.09)	-5.012 (-208.991, 198.967)	3.684 (-49.208, 56.576)	21.937 (-474.962, 518.836)	149.865 (-137.087, 436.816)
	2001 cohort	-17.629 (-434.109, 398.85)	0.708 (-20.2, 21.616)	0.041 (-23.288, 23.37)	-2.734 (-20.544, 15.077)	-2.485 (-24.053, 19.082)	-0.908 (-9.55, 7.733)	30.489 (-73.978, 134.956)	136.09 (-256.439, 528.618)
	2002 cohort	3.547 (-17.58, 24.674)	0.705 (-5.579, 6.988)	-0.641 (-14.006, 12.724)	0.852 (-6.695, 8.399)	9.815 (-57.459, 77.09)	36.81 (-183.429, 257.05)	135.131 (-642.002, 912.263)	351.157 (-139.989, 842.302)
Sloped Farmland	control group	2.908 (-186.63, 192.447)	10.323 (-72.632, 93.278)	-2.867 (-62.302, 56.568)	10.614 (-58.694, 79.923)	13.59 (-84.929, 112.108)	18.524 (-100.267, 137.315)	97.171 (-190.562, 384.904)	177.805 (-408.895, 764.504)
	1999 cohort	64.206 (-217.576, 345.989)	41.519 (-314.953, 397.99)	2.26 (-550.164, 554.685)	117.785 (-411.783, 647.354)	752.123 (-1440.188, 2944.435)	317.949 (-557.163, 1193.061)	626.65 (-343.572, 1596.872)	1037.379 (-184.759, 2259.516)
	2000 cohort	110.892 (-635.263, 857.047)	66.431 (-440.272, 573.134)	29.912 (-273.279, 333.104)	118.963 (-736.851, 974.776)	139.99 (-1372.614, 1652.594)	154.279 (-966.17, 1274.728)	890.907 (-729.167, 2510.981)	1318.128 (-124.997, 2761.253)
	2001 cohort	-71.107 (-1127.716, 985.502)	50.952 (-536.986, 638.89)	-1.609 (-171.794, 168.576)	15.881 (-150.195, 181.958)	31.442 (-217.553, 280.438)	35.125 (-258.263, 328.514)	466.364 (-826.263, 1758.991)	456.01 (-19.306, 931.326)
	2002 cohort	12.403 (-132.98, 157.787)	2.324 (-14.447, 19.096)	0.868 (-18.298, 20.035)	-7.236 (-46.878, 32.405)	-1.957 (-33.822, 29.908)	29.931 (-148.066, 207.928)	213.561 (-201.664, 628.786)	1391.62 (276.949, 2506.292)

Values are in hectares. ±1 Standard deviations in parentheses

Table A.12: Comparison of Average Farmland Conversion to Timber-producing Forest

Treatment Cohorts	Placebo Treatment at Year						
	1997	1998	1999	2000	2001	2002	2003
1999 cohort	-2.518	-1.99	-2.31	-0.698	0.0162	13.84*	-3.134
	(2.170)	(1.398)	(1.244)	(1.151)	(0.707)	(6.040)	(14.77)
2000 cohort	6.842	7.989	5.962	5.818	14.51*	35.29***	176.1***
	(7.067)	(7.087)	(7.064)	(7.064)	(7.064)	(9.615)	(17.37)
2001 cohort	18.38	17.73	14.95	15.2	16.78	49.97*	148.3*
	(17.79)	(17.73)	(17.81)	(17.80)	(17.79)	(20.63)	(58.00)
2002 cohort	-2.842	-4.188	-2.702	6.261	33.26	131.1***	292.5***
	(16.63)	(16.63)	(16.66)	(16.66)	(16.97)	(19.77)	(31.24)

Clustered standard errors in parentheses. $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Placebo treatment effects are compared between the non-participants and the participants in different enrollment-year cohorts.
Regression model: $a_{jkit} = \sum_t \beta_0^{jk} treatment_{it} + \boldsymbol{\beta_A^{jk} A_{it-1}} + \boldsymbol{\beta_X^{jk} X_{it-1}} + e_i + e_t + e_{it}$

Table A.13: Placebo Treatment Effects for Level Farmland Conversion from Timber-producing Forest

Treatment Cohorts	Placebo Treatment at Year						
	1997	1998	1999	2000	2001	2002	2003
1999 cohort	-21.64	-58.48	57.04	693.0***	258.8***	569.9***	1016.7***
	(24.68)	(32.82)	(29.93)	(114.8)	(48.61)	(59.53)	(129.0)
2000 cohort	6.842	7.989	5.962	5.818	14.51*	35.29***	176.1***
	(7.067)	(7.087)	(7.064)	(7.064)	(7.064)	(9.615)	(17.37)
2001 cohort	122.3	70.05	87.54	103.1	107	550.4*	597.0**
	(109.6)	(113.5)	(115.6)	(116.9)	(109.2)	(196.4)	(170.8)
2002 cohort	-10.08	-11.54	-19.67	-14.39	17.5	206.2***	1324.7***
	(18.10)	(18.10)	(18.13)	(18.13)	(18.13)	(21.31)	(33.56)

Clustered standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Placebo treatment effects are compared between the non-participants and the participants in different enrollment-year cohorts.
Regression model: $a_{jkit} = \sum_t \beta_0^{jk} treatment_{it} + \boldsymbol{\beta_A^{jk}} \boldsymbol{A_{it-1}} + \boldsymbol{\beta_X^{jk}} \boldsymbol{X_{it-1}} + e_i + e_t + e_{it}$

Table A.14: Placebo Treatment Effects for Sloped Farmland Conversion from Timber-producing Forest

Farmland transition to forest		from level farmland		from erodible farmland	
Sample restriction		*Mean*	*SD*	*Mean*	*SD*
top 25%	level farmland	2.437315	167.4992	43.62078	460.9976
bottom 25%	stock	.6742652	26.29976	241.9261	1031.033
top 25%	erodible farmland	-.6992145	108.8343	138.8657	978.6556
bottom 25%	stock	7.767845	231.3312	14.28482	102.1118

Table A.15: Descriptive Statistics of Farmland Conversion (Different Farmland Stocks)

Model	Variable	level farmland	erodible farmland	(con'd) Model	Variable	level farmland	erodible farmland
Pooled	GfG	41.62**	310.2**	Subregional	GfG·NC	17.85**	430.6***
		(14.21)	(115.1)			(6.578)	(79.65)
	GfG·level stock	0.00237***	-0.00116*		GfG·NC	0.00887***	-0.000242*
		(0.000151)	(0.000543)		·level farmland_stock	(0.00106)	(0.000114)
	GfG·sloped stock	-0.000238**	0.0177**		GfG·NC	-0.000240*	0.000535*
		(0.0000885)	(0.00546)		·sloped farmland_stock	(0.000115)	(0.000251)
Regional	GfG·N	67.19*	429.5***		GfG·NE	15.36*	522.1***
		(29.49)	(79.86)			(6.725)	(73.74)
	GfG·N	0.00230***	-0.00139*		GfG·NE	0.000512*	-0.00709***
	·level stock	(0.000154)	(0.000548)		·level farmland_stock	(0.000255)	(0.00131)
	GfG·N	-0.000282**	0.00723***		GfG·NE	-0.00499***	0.0206***
	·sloped stock	(0.0000904)	(0.000509)		·sloped farmland_stock	(0.000306)	(0.00544)
	GfG·S	37.35*	160.7***		GfG·SW	14.63*	311.8**
		(18.69)	(38.66)			(7.156)	(114.9)
	GfG·S	0.00220***	-0.00171		GfG·SW	0.000122	-0.00403**
	·level stock	(0.000156)	(0.000896)		·level farmland_stock	(0.000261)	(0.00140)
	GfG·S	-0.00267***	0.00977***		GfG·SW	-0.00109	0.00783***
	·sloped stock	(0.000182)	(0.000590)		·sloped farmland_stock	(0.000879)	(0.00153)
Subregional	GfG·NW	160.3***	309.6*		GfG·SC	118.7*	102.5*
		(35.89)	(154.1)			(55.54)	(47.80)
	GfG·NW	0.00881***	-0.00215*		GfG·SC	0.00460***	-0.00171
	·level stock	(0.00106)	(0.000902)		·level farmland_stock	(0.000327)	(0.000896)
	GfG·NW	-0.00262***	0.00909***		GfG·SC	-0.00014	0.00723***
	·sloped stock	(0.000187)	(0.000596)		·sloped farmland_stock	(0.000249)	(0.000509)
	N					7155	7602

Clustered standard errors in parentheses at the provincial level, with county, year fixed effects included.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Pooled, regional, and subregional models are separate regressions.

The model also includes the program indicator and other land stocks interactions, but most of the coefficients are small and insignificant.

Due to the space limit, the table reports only the farmland stock effects. Level (sloped) stock represents level (erodible) farmland stock.

Table A.16: Land Transition to Forests in China (1996-2004) with Land Stock Interaction

A.4 Supplementary Figures

This section includes three supplementary figures. Figure A.6 shows the geographical regions and the GfG subsidizing regions in China. Figure A.7 shows how the GfG program was expanded to a nation-wide program from 1999 to 2002. Figure A.8 indicates that the areas of timber-producing forest and orchards were increasing after the implementation of the program.

Figure A.6: Regions in China

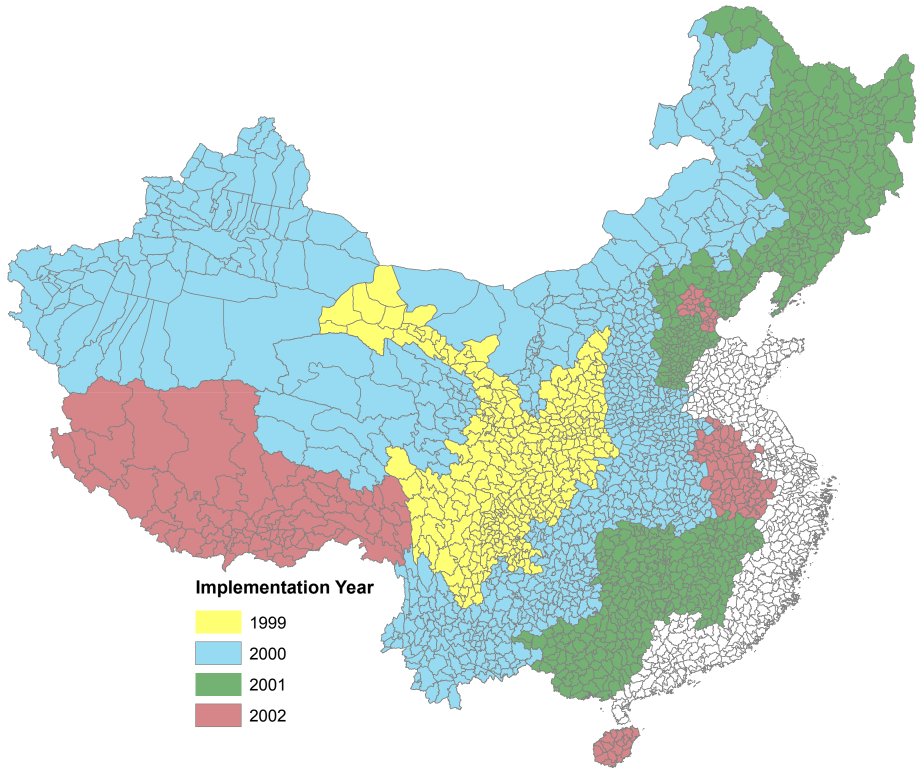

Figure A.7: Implementation of the GfG Program by Year

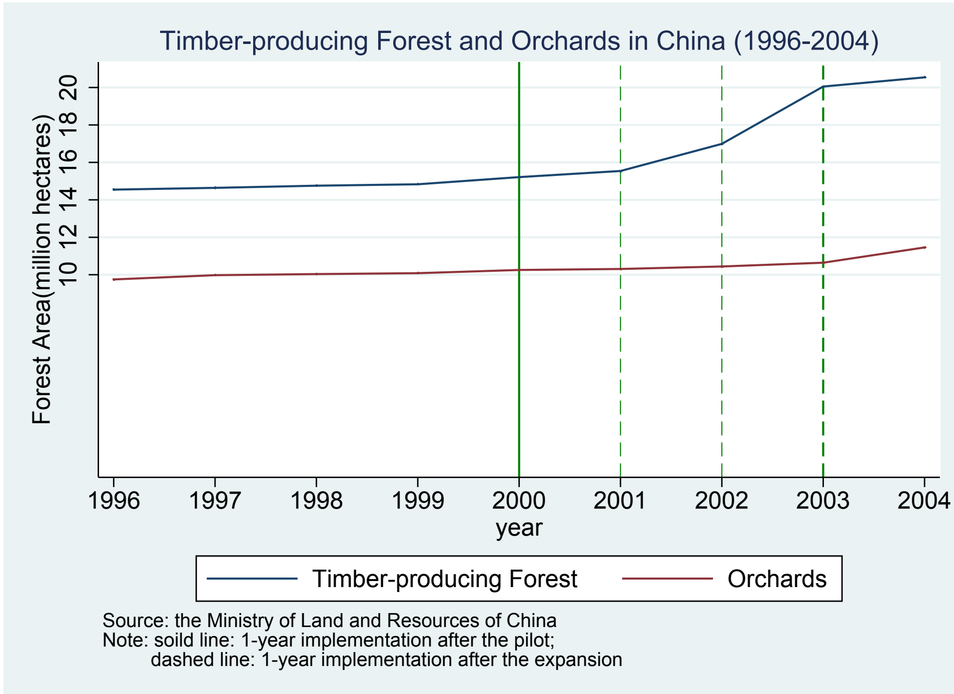

Figure A.8: Timber-producing Forest and Orchards Uses in China (1996-2004)

Appendix B: Additional Robustness Checks for Chapter 3

This section provides the details of the robustness checks of the firm's locational impacts to its pollution and its scale of installed abatement technology. The following robustness checks reduce concerns related to omitted variable bias, endogeneity, and heterogeneity.

Plant-Level Bias

I include detailed plant-level control variables for a subgroup of firms to reduce the corresponding bias. The representative subgroup of firms accounts for 12.7% of total observations. They have the detailed quarterly financial reports, including the number of employees, revenue, cost, production level, etc., that are published by Bloomberg.I use the WBRE model with and without these additional controls for these plants in Table B.3. The coefficients are following my expectation and are almost identical, suggesting that the WBRE model helps control the time-invariant unobservables.

Regime/Policy Change

I use a 2SLS-FE model as a robustness check to examine possible regime or policy changes during the study period. The WBRE model would not provide the "downstream effect" derived from fixed locational information if the policy is changing. To do so, I interact time-invariant locational variables with quarter indicators. This method creates variation in time and allows me to examine the regulatory stringency of local regimes over time. $Tech_{it}$ is instrumented (by local governmental revenue and expenditure as in the WBRE model) to reduce possible bias from unobserved firm or governmental characteristics that affect both abatement technology installation and a firm's pollution. The 2SLS-FE model is the following:

$$\begin{aligned} pollution_{it} &= \alpha + \boldsymbol{\beta_1} downstream_i \cdot q_t + \boldsymbol{\beta_2} residential_i \cdot q_t \\ &\quad + \delta Tech_{it} + \boldsymbol{\gamma X_{it}} + e_i + e_t + e_{it} \\ Tech_{it} &= a + \boldsymbol{b_1} downstream_i \cdot q_t + \boldsymbol{b_2} residential_i \cdot q_t + \boldsymbol{g X_{it}} \\ &\quad + z_1 Revenue_{it} + z_2 Expenditure_{it} + \epsilon_i + \epsilon_t + \epsilon_{it} \end{aligned} \tag{B.1}$$

The expected signs of the coefficients that I am interested in are as follows: $\boldsymbol{\beta_1} \leq 0$, $\boldsymbol{\beta_2} \geq 0$, $\delta \leq 0$, $\boldsymbol{b_1} \geq 0$, $\boldsymbol{b_2} \leq 0$. The estimated locational impacts to firm's pollution level are reported in Table B.1. First stage coefficients including locational impacts to the scale of installed abatement technology are reported in Table B.2.

To account for regional heterogeneity, I also plot the coefficients of distance variables across the whole time period by region in Figures B.1 and B.2, which provide comparisons of coefficients between eastern China and western China. The dashed horizontal lines represent the estimated coefficients using the WBRE model for the corresponding sector.

In general, there is no regime or policy change during the study period. Coefficients of firms' locational impacts on firms' pollution levels and abatement technology installation in the 2SLS-FE model are almost identical over the 20 quarter periods in Tables B.1-B.2. And they have similar magnitudes compared to the random effects model using the Mundlak-Chamberlain approach in Table 3.3. The reason that the coefficients in the 2SLS-FE model are larger in terms of the downstream effects is possibly because that the FE model could not control for time-variant unobservables like production. Although the FE model provides additional locational impacts over time, the coefficients may be slightly overestimated comparing to the WBRE model.

Locational Heterogeneity

The western-eastern comparison in the above FE model confirms that there may be region-wide heterogeneity in generating negative pollution spillover effects. Another local variable that may influence the negative externalities across the boundary is the size or river length in each jurisdiction. I separate my dataset into two groups, one has plants in the jurisdiction with total river length less than the average, and the other has the rest of the plants. Table B.4 reports the coefficients of the corresponding downstream effects for both groups.

Slightly modifying equation 3.7 allows every jurisdiction react differently:

$$\begin{aligned} Pollution_{it} = \alpha + \{\beta_1 \cdot river\_length_i\} \frac{downstream_i}{river\_length_i} \\ + \beta_2 residential_i + \boldsymbol{\gamma_1 X_{it}} + \boldsymbol{\gamma_2 \overline{X_i}} + \boldsymbol{u_i} + e_i + e_{it} \end{aligned} \tag{B.2}$$

To see if the model is robust comparing to equation 3.7, I examine the ratio of the coefficients $\{\beta_1 \cdot river\_length_i\}$ over the average river length. Table B.5 shows the corresponding ratios for each sector.

Both tables B.4 and B.5 have the same magnitudes of coefficients comparing to the WBRE model. They also suggest that pollution increases more aggressively towards the border of a jurisdiction if the river segment in it is shorter. It is possible that, instead of reacting by real distance, local governments determine the health risk impact based on relative location of plants in the jurisdiction. In terms of the downstream effects, strategic allocation of pollution in the jurisdiction can be viewed as a reaction of both real and relative geographic information across all the plants. Allowing each jurisdiction to react differently can be more flexible for future policy designs as shown in Section 3.6.2.

Endogenous Location

WBRE estimation provides an opportunity to examine a firm's locational impacts when $downstream_i$ and $residential_i$ are endogenous without introducing too many instruments. The difference between the results from this model and those in Table 3.3 for water-polluting firms is by treating locational variables $downstream_i$ and $residential_i$ endogenous. Although the descriptive statistics have suggested that heavily polluting firms may not be able to cluster at the least environmentally sensitive areas like downstream borders, it is still legitimate to believe that water-polluting firms' relative locations on a river network are potentially endogenous to their emission levels. Local firms with high expected pollution may strategically locate closer to the downstream border or further away from the jurisdictional residential area. However, each jurisdictional general land use planning is less likely to be related to any environmental regulations that impact the whole country simultaneously.

I assume that functional land use planning, such as the construction of transportation infrastructure and designation of economic development zones (including major industrial parks and commercial centers), are generically determined. A firm's locational choice is more likely to be decided according to local land use plans, which relate to a firm's supply and procurement management, and is independent of a firm's emission level. The estimated system of equations for water-polluting firms is given by:

$$\begin{aligned} pollution_{it} &= \alpha + \beta_1 downstream_i + \beta_2 residential_i + \delta_1 Tech_{it} + \delta_2 \overline{Tech_i} \\ &+ \boldsymbol{\gamma_1 X_{it}} + \boldsymbol{\gamma_2 \overline{X_i}} + \boldsymbol{u_{it}} + e_i + e_{it} + \hat{\epsilon_{it}} + \hat{w_{it}} + \hat{v_{it}} \end{aligned} \tag{B.3}$$

$$\begin{aligned} Tech_{it} &= a + b_1 downstream_i + b_2 residential_i + \boldsymbol{g_1 X_{it}} + \boldsymbol{g_2 \overline{X_i}} \\ &+ z_1 Revenue_{it} + z_2 Expenditure_{it} + \epsilon_i + \epsilon_t + \epsilon_{it} \end{aligned} \tag{B.4}$$

$$\begin{aligned} downstream_i &= \boldsymbol{\phi_1 Z_i} + \boldsymbol{\zeta_1 X_{it}} + w_{it} \\ residential_i &= \boldsymbol{\phi_2 Z_i} + \boldsymbol{\zeta_2 X_{it}} + v_{it} \end{aligned} \tag{B.5}$$

where $\boldsymbol{Z_i}$ includes the distances from firm i to the closest road, railroad, industrial park, and commercial center.

I first estimate the reduced form equations by estimating equation B.3 (excluding the abatement technology variable and the residual estimation: $\hat{\epsilon_{it}} + \hat{w_{it}} + \hat{v_{it}}$) and B.4 separately using 2SLS-WBRE model. The estimated coefficients are reported in Table B.6. First stage coefficients and the corresponding statistics are in

Table B.7-B.8. Including the abatement technology variable in equation B.3 that introduces an additional endogenous variable and complicates the model. I use the control function approach to estimate the corresponding model. Table B.9 provides the corresponding estimated coefficients.

Comparisons of the coefficients of the locational impacts to a firm's pollution level and the scale of installed abatement technology among the WBRE models that are adopted in the paper suggest that the magnitudes of the coefficients are very similar as well. First stage estimates suggest that the chosen instrumental variables: firm distances to the closest road; railroad; industrial park; and commercial center, are strongly correlated to a firm's location along river networks and residential areas.[1] The estimated coefficients using a control function approach, which includes another endogenous variable (abatement technology installation), are reported in Table B.9.

[1] Sargan-Hensen statistics suggests that they are valid instruments. And the Kleibergen-Paap Wald statistics for each regression have passed the Stock-Yogo weak identification test critical values (Stock and Yogo, 2005). Angrist and Pischke first-stage F statistics are also reported to guarantee each of the endogenous regressors is not weakly identified (Angrist and Pischke, 2009).

		Power	Steel	Cement	Paper	Clothing/Dyeing	Food/Bev
Distance in km to	quarter 1	-109.8***	-98.64***	-86.77***	-60.96***	-55.69***	-46.45***
Downstream estuary		(1.843)	(6.456)	(9.236)	(0.604)	(1.483)	(0.610)
	quarter 2	-107.4***	-98.53***	-86.95***	-60.98***	-55.75***	-46.46***
		(1.883)	(6.457)	(9.272)	(0.605)	(1.506)	(0.612)
	quarter 3	-110.0***	-97.87***	-86.80***	-61.03***	-55.46***	-46.46***
		(1.877)	(6.916)	(9.300)	(0.605)	(1.497)	(0.610)
	quarter 4	-107.7***	-97.23***	-86.70***	-60.77***	-55.17***	-46.35***
		(1.870)	(7.045)	(9.486)	(0.605)	(1.549)	(0.610)
	quarter 5	-108.9***	-98.99***	-86.95***	-60.84***	-55.42***	-46.19***
		(1.886)	(6.940)	(8.980)	(0.603)	(1.523)	(0.612)
	quarter 6	-108.4***	-98.56***	-87.20***	-60.78***	-55.36***	-46.37***
		(1.861)	(6.860)	(8.813)	(0.603)	(1.521)	(0.608)
	quarter 7	-109.7***	-98.26***	-87.03***	-60.81***	-55.50***	-46.37***
		(1.848)	(6.876)	(8.864)	(0.604)	(1.534)	(0.612)
	quarter 8	-106.0***	-97.02***	-86.71***	-60.71***	-55.32***	-46.67***
		(1.860)	(6.887)	(9.013)	(0.602)	(1.536)	(0.612)
	quarter 9	-116.6***	-98.42***	-87.56***	-61.18***	-55.43***	-45.71***
		(1.841)	(6.876)	(8.427)	(0.602)	(1.505)	(0.613)
	quarter 10	-111.5***	-98.08***	-87.72***	-60.77***	-55.53***	-46.27***
		(1.841)	(6.811)	(8.360)	(0.602)	(1.503)	(0.610)
	quarter 11	-111.7***	-97.48***	-87.01***	-60.82***	-55.36***	-45.70***
		(1.820)	(6.805)	(8.890)	(0.601)	(1.506)	(0.609)
	quarter 12	-111.0***	-96.67***	-86.56***	-60.85***	-55.38***	-46.07***
		(1.825)	(6.562)	(9.336)	(0.601)	(1.516)	(0.606)
	quarter 13	-113.0***	-99.51***	-87.38***	-60.91***	-55.36***	-46.24***
		(1.829)	(5.672)	(7.828)	(0.603)	(1.532)	(0.608)
	quarter 14	-112.1***	-97.21***	-87.23***	-60.67***	-55.24***	-46.04***
		(1.858)	(5.983)	(8.088)	(0.602)	(1.530)	(0.610)
	quarter 15	-114.3***	-97.35***	-87.15***	-60.71***	-55.26***	-46.13***
		(1.893)	(6.181)	(8.423)	(0.602)	(1.548)	(0.610)
	quarter 16	-111.9***	-97.14***	-86.93***	-60.46***	-55.45***	-46.29***
		(1.965)	(6.120)	(8.973)	(0.603)	(1.655)	(0.604)
	quarter 17	-110.2***	-97.13***	-86.57***	-61.29***	-55.62***	-45.89***
		(2.072)	(6.431)	(9.305)	(0.603)	(1.719)	(0.610)
	quarter 18	-106.9***	-97.89***	-86.97***	-60.97***	-55.38***	-46.02***
		(2.064)	(6.411)	(9.218)	(0.603)	(1.716)	(0.605)
	quarter 19	-103.4***	-97.22***	-87.16***	-60.98***	-55.35***	-46.12***
		(1.861)	(6.437)	(9.299)	(0.602)	(1.723)	(0.606)
	quarter 20	-103.6***	-96.78***	-87.11***	-60.73***	-55.22***	-46.29***
		(2.054)	(6.493)	(9.357)	(0.602)	(1.721)	(0.605)

Table B.1: Firm's Locational Impact on Water Pollution: 2011-2015

		Power	Steel	Cement	Paper	Clothing/Dyeing	Food/Bev
Distance in km to Residential area	quarter 1	84.39***	78.58***	66.12*	54.62***	41.94***	39.92***
		(4.347)	(0.456)	(28.24)	(0.556)	(0.614)	(1.505)
	quarter 2	83.52***	78.59***	65.83*	54.90***	42.04***	40.10***
		(4.488)	(0.456)	(28.37)	(0.560)	(0.621)	(1.491)
	quarter 3	83.74***	78.60***	65.41*	54.98***	41.95***	39.99***
		(4.765)	(0.456)	(28.46)	(0.559)	(0.617)	(1.494)
	quarter 4	82.99***	78.68***	65.47*	54.83***	42.06***	40.61***
		(4.788)	(0.457)	(28.33)	(0.560)	(0.617)	(1.458)
	quarter 5	83.69***	78.44***	66.04*	54.90***	42.11***	39.17***
		(4.469)	(0.456)	(28.27)	(0.555)	(0.621)	(1.507)
	quarter 6	82.70***	78.35***	65.82*	55.12***	43.19***	38.99***
		(4.549)	(0.455)	(28.49)	(0.558)	(0.607)	(1.490)
	quarter 7	83.57***	78.47***	65.39*	55.29***	41.67***	38.99***
		(4.572)	(0.456)	(28.49)	(0.558)	(0.611)	(1.502)
	quarter 8	82.97***	78.62***	65.96*	54.60***	41.46***	39.17***
		(4.488)	(0.457)	(28.56)	(0.554)	(0.617)	(1.482)
	quarter 9	83.74***	78.49***	67.36*	56.06***	42.46***	39.29***
		(4.636)	(0.454)	(28.47)	(0.553)	(0.621)	(1.261)
	quarter 10	82.92***	78.62***	66.23*	54.84***	43.16***	39.29***
		(4.743)	(0.457)	(28.33)	(0.554)	(0.608)	(1.253)
	quarter 11	83.26***	78.57***	65.91*	54.82***	41.90***	39.18***
		(4.612)	(0.457)	(28.31)	(0.554)	(0.608)	(1.253)
	quarter 12	81.77***	78.63***	65.73*	54.80***	41.87***	40.67***
		(5.868)	(0.458)	(28.10)	(0.551)	(0.616)	(1.255)
	quarter 13	83.42***	78.47***	64.83*	55.15***	42.91***	39.82***
		(6.164)	(0.456)	(29.38)	(0.550)	(0.609)	(1.376)
	quarter 14	81.82***	78.67***	65.22*	54.99***	41.93***	40.26***
		(6.196)	(0.457)	(29.32)	(0.553)	(0.606)	(1.361)
	quarter 15	81.64***	78.64***	65.25*	54.93***	42.51***	39.62***
		(6.048)	(0.457)	(29.20)	(0.553)	(0.606)	(1.984)
	quarter 16	81.47***	78.63***	65.27*	54.80***	42.24***	41.76***
		(6.871)	(0.457)	(28.84)	(0.553)	(0.618)	(2.648)
	quarter 17	82.26***	78.65***	65.91*	55.17***	43.28***	39.68***
		(7.347)	(0.457)	(28.41)	(0.549)	(0.608)	(2.722)
	quarter 18	82.09***	78.54***	65.40*	55.11***	42.86***	39.79***
		(7.433)	(0.457)	(28.66)	(0.552)	(0.602)	(2.667)
	quarter 19	81.34***	78.50***	65.77*	54.89***	43.10***	40.03***
		(7.397)	(0.457)	(28.59)	(0.553)	(0.606)	(2.115)
	quarter 20	80.21***	78.51***	65.42*	55.04***	42.54***	39.01***
		(7.329)	(0.457)	(28.74)	(0.554)	(0.603)	(2.709)
Technology Capacity (in ton)		-2130.9***	-1960.9***	-1490.0***	-725.3***	-1951.7**	-2327.5**
		(219.9)	(205.6)	(300.8)	(192.7)	(696.5)	(729.0)
	N	70572	75628	21552	39860	29444	32636

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Abatement technology is production capacity (tons) installed with denitrification technology for Cement, Paper, and Food Sectors, and with desulfurization technology for Power, Steel, and Clothing/Dyeing Sectors.

Table B.1: Firm's Locational Impact on Water Pollution: 2011-2015 Continued

		Power	Steel	Cement	Paper	Clothing/Dyeing	Food/Bev
Governmental Expenditure		-1.69855***	-0.99198***	-1.31373***	-1.85743***	-1.51189***	-1.81193***
		(0.18542)	(0.28513)	(0.19465)	(0.18584)	(0.18529)	(0.1858)
Governmental Revenue		0.56006***	0.21141***	0.21516***	0.58095***	0.46282***	0.54722***
		(0.13862)	(0.0421)	(0.0421)	(0.13923)	(0.13821)	(0.13901)
Distance in km to Downstream estuary	quarter 1	0.00138***	0.00049***	0.00067**	0.00094***	0.00029***	0.00035***
		(0.00006)	(0.00008)	(0.00024)	(0.00027)	(0.00005)	(0.00008)
	quarter 2	0.00138***	0.00048***	0.0007**	0.00105***	0.0003***	0.00035***
		(0.00006)	(0.00008)	(0.00024)	(0.00027)	(0.00005)	(0.00007)
	quarter 3	0.00139***	0.00045***	0.00102***	0.00141***	0.00032***	0.00035***
		(0.00006)	(0.00008)	(0.00025)	(0.00028)	(0.00005)	(0.00007)
	quarter 4	0.00138***	0.00047***	0.00168***	0.00226***	0.00032***	0.00041***
		(0.00006)	(0.00009)	(0.00025)	(0.00028)	(0.00005)	(0.00007)
	quarter 5	0.00138***	0.0005***	0.002***	0.00265***	0.0003***	0.00049***
		(0.00006)	(0.00008)	(0.00023)	(0.00026)	(0.00005)	(0.00007)
	quarter 6	0.00139***	0.00052***	0.00201***	0.00273***	0.00031***	0.00048***
		(0.00006)	(0.00008)	(0.00023)	(0.00026)	(0.00005)	(0.00007)
	quarter 7	0.00139***	0.00052***	0.00198***	0.00272***	0.00031***	0.00048***
		(0.00006)	(0.00008)	(0.00024)	(0.00026)	(0.00005)	(0.00007)
	quarter 8	0.00139***	0.00054***	0.00206***	0.00281***	0.0003***	0.00048***
		(0.00006)	(0.00008)	(0.00024)	(0.00026)	(0.00005)	(0.00007)
	quarter 9	0.00139***	0.00053***	0.00212***	0.00277***	0.00031***	0.00051***
		(0.00006)	(0.00008)	(0.00023)	(0.00026)	(0.00005)	(0.00007)
	quarter 10	0.00138***	0.00052***	0.00224***	0.00299***	0.00032***	0.0005***
		(0.00006)	(0.00008)	(0.00023)	(0.00026)	(0.00005)	(0.00007)
	quarter 11	0.00138***	0.00057***	0.00253***	0.00325***	0.00031***	0.0005***
		(0.00006)	(0.00008)	(0.00023)	(0.00026)	(0.00005)	(0.00007)
	quarter 12	0.00137***	0.00065***	0.00264***	0.00342***	0.0004***	0.0005***
		(0.00006)	(0.00008)	(0.00023)	(0.00026)	(0.00005)	(0.00007)
	quarter 13	0.00143***	0.00065***	0.00308***	0.00375***	0.00042***	0.00052***
		(0.00006)	(0.00008)	(0.00023)	(0.00025)	(0.00005)	(0.00007)
	quarter 14	0.00143***	0.00065***	0.00328***	0.00403***	0.00043***	0.00051***
		(1.858)	(5.983)	(8.088)	(0.602)	(1.530)	(0.610)
	quarter 15	0.00143***	0.00072***	0.0035***	0.00426***	0.00042***	0.0005***
		(0.00006)	(0.00008)	(0.00023)	(0.00026)	(0.00005)	(0.00007)
	quarter 16	0.00141***	0.00094***	0.00383***	0.00461***	0.00048***	0.00051***
		(0.00006)	(0.00008)	(0.00023)	(0.00026)	(0.00005)	(0.00007)
	quarter 17	0.00139***	0.00096***	0.00375***	0.00445***	0.00051***	0.00052***
		(0.00006)	(0.00008)	(0.00023)	(0.00026)	(0.00005)	(0.00007)
	quarter 18	0.0014***	0.00096***	0.00389***	0.00463***	0.00052***	0.00051***
		(0.00006)	(0.00008)	(0.00022)	(0.00025)	(0.00005)	(0.00007)
	quarter 19	0.00139***	0.00095***	0.00396***	0.0047***	0.00052***	0.00049***
		(0.00006)	(0.00008)	(0.00023)	(0.00026)	(0.00005)	(0.00007)
	quarter 20	0.0014***	0.00096***	0.00387***	0.00457***	0.00051***	0.00052***
		(0.00006)	(0.00008)	(0.00023)	(0.00026)	(0.00005)	(0.00007)

Table B.2: Water-Polluting Firm's Locational Impact on Installed Abatement Technology: 2011-2015

		Power	Steel	Cement	Paper	Clothing/Dyeing	Food/Bev
Distance in km to	quarter 1	-0.00025***	-0.00111***	-0.00305***	-0.00468***	-0.0004***	-0.0004***
Residential area		(0.00007)	(0.00008)	(0.00028)	(0.00032)	(0.00005)	(0.00007)
	quarter 2	-0.00026***	-0.00103***	-0.00283***	-0.00422***	-0.0004***	-0.0004***
		(0.00007)	(0.00008)	(0.00028)	(0.00032)	(0.00005)	(0.00007)
	quarter 3	-0.00026***	-0.00096***	-0.0028***	-0.00418***	-0.00043***	-0.0004***
		(0.00007)	(0.00008)	(0.00028)	(0.00032)	(0.00005)	(0.00007)
	quarter 4	-0.00026***	-0.00097***	-0.00272***	-0.00388***	-0.00044***	-0.0004***
		(0.00007)	(0.00008)	(0.00028)	(0.00031)	(0.00005)	(0.00007)
	quarter 5	-0.00025***	-0.00093***	-0.00279***	-0.00392***	-0.00044***	-0.00041***
		(0.00007)	(0.00008)	(0.00028)	(0.00031)	(0.00005)	(0.00007)
	quarter 6	-0.00024***	-0.00095***	-0.00301***	-0.00405***	-0.00043***	-0.00041***
		(0.00007)	(0.00008)	(0.00028)	(0.00031)	(0.00005)	(0.00007)
	quarter 7	-0.00024***	-0.00095***	-0.00312***	-0.00416***	-0.00043***	-0.00041***
		(0.00007)	(0.00008)	(0.00028)	(0.00031)	(0.00005)	(0.00007)
	quarter 8	-0.00025***	-0.00096***	-0.00305***	-0.00393***	-0.00043***	-0.00041***
		(0.00007)	(0.00008)	(0.00028)	(0.00031)	(0.00005)	(0.00007)
	quarter 9	-0.00023***	-0.00096***	-0.00319***	-0.00423***	-0.00043***	-0.00044***
		(0.00007)	(0.00008)	(0.00028)	(0.00031)	(0.00005)	(0.00007)
	quarter 10	-0.00023***	-0.00096***	-0.00322***	-0.00417***	-0.00043***	-0.00043***
		(0.00007)	(0.00008)	(0.00028)	(0.00031)	(0.00005)	(0.00007)
	quarter 11	-0.00024***	-0.00096***	-0.00316***	-0.00401***	-0.00043***	-0.00044***
		(0.00007)	(0.00008)	(0.00028)	(0.00031)	(0.00005)	(0.00007)
	quarter 12	-0.00026***	-0.00096***	-0.00346***	-0.00424***	-0.00041***	-0.00044***
		(0.00007)	(0.00008)	(0.00028)	(0.00031)	(0.00005)	(0.00007)
	quarter 13	-0.00021***	-0.00096***	-0.00339***	-0.00427***	-0.00036***	-0.00045***
		(0.00007)	(0.00008)	(0.00027)	(0.00031)	(0.00005)	(0.00007)
	quarter 14	-0.00022***	-0.00096***	-0.0036***	-0.00444***	-0.00038***	-0.00044***
		(0.00007)	(0.00008)	(0.00028)	(0.00031)	(0.00005)	(0.00007)
	quarter 15	-0.00023***	-0.001***	-0.00367***	-0.0045***	-0.00039***	-0.00045***
		(0.00007)	(0.00008)	(0.00027)	(0.00031)	(0.00005)	(0.00007)
	quarter 16	-0.00025***	-0.00104***	-0.00361***	-0.00436***	-0.00039***	-0.00044***
		(0.00007)	(0.00008)	(0.00027)	(0.00031)	(0.00005)	(0.00007)
	quarter 17	-0.00026***	-0.00106***	-0.00428***	-0.0051***	-0.0004***	-0.00044***
		(0.00007)	(0.00008)	(0.00027)	(0.00031)	(0.00005)	(0.00007)
	quarter 18	-0.00025***	-0.00106***	-0.00427***	-0.00506***	-0.0004***	-0.00043***
		(0.00007)	(0.00008)	(0.00027)	(0.0003)	(0.00005)	(0.00007)
	quarter 19	-0.00026***	-0.00106***	-0.00425***	-0.00505***	-0.0004***	-0.00041***
		(0.00007)	(0.00008)	(0.00027)	(0.0003)	(0.00005)	(0.00007)
	quarter 20	-0.00026***	-0.00106***	-0.00423***	-0.00502***	-0.00041***	-0.00043***
		(0.00007)	(0.00008)	(0.00027)	(0.0003)	(0.00005)	(0.00007)
† *Kleibergen-Paap rk Wald F*		21.736	33.015	20.351	46.605	27.166	49.104
Sargan-Hansen Stat		0.005	0.044	0.456	0.29	0.428	0.449
p-val		0.9426	0.8341	0.4995	0.5903	0.5127	0.503
N		70572	75628	21552	39860	29444	32636

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Abatement technology is production capacity (tons) installed with denitrification technology for Cement, Paper, and Food Sectors, and with desulfurization technology for Power, Steel, and Clothing/Dyeing Sectors.

† Stock-Yogo weak ID test critical values (maximal IV size): *10%* 19.93, *15%* 11.59, *20%* 8.75, *25%* 7.25. Source: Stock-Yogo (2005)

Table B.2: Water-Polluting Firm's Locational Impact on Installed Abatement Technology: 2011-2015 Continued

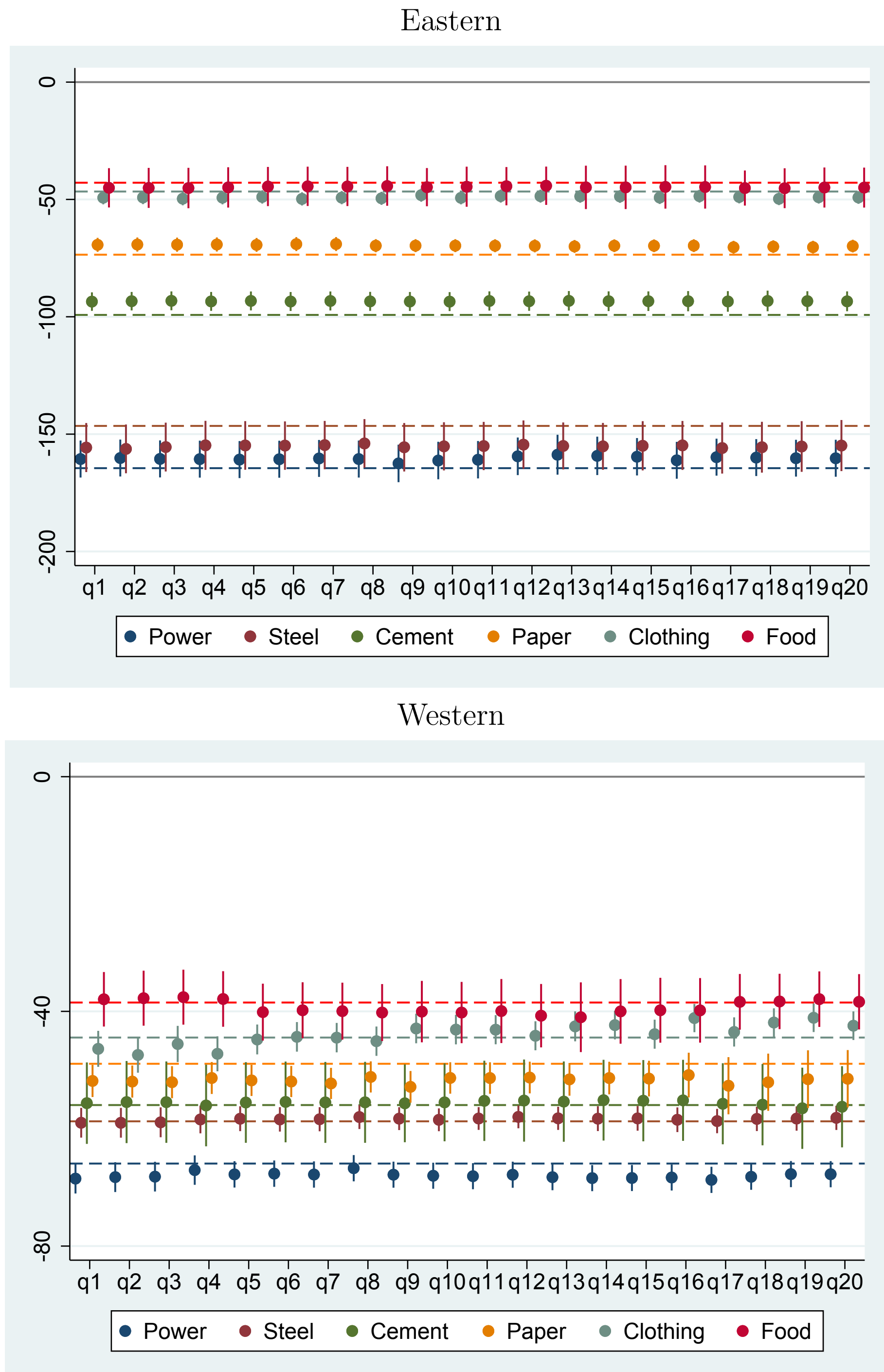

Figure B.1: Regional Comparisons: Coefficients of Distance to Downstream Variables by Sector

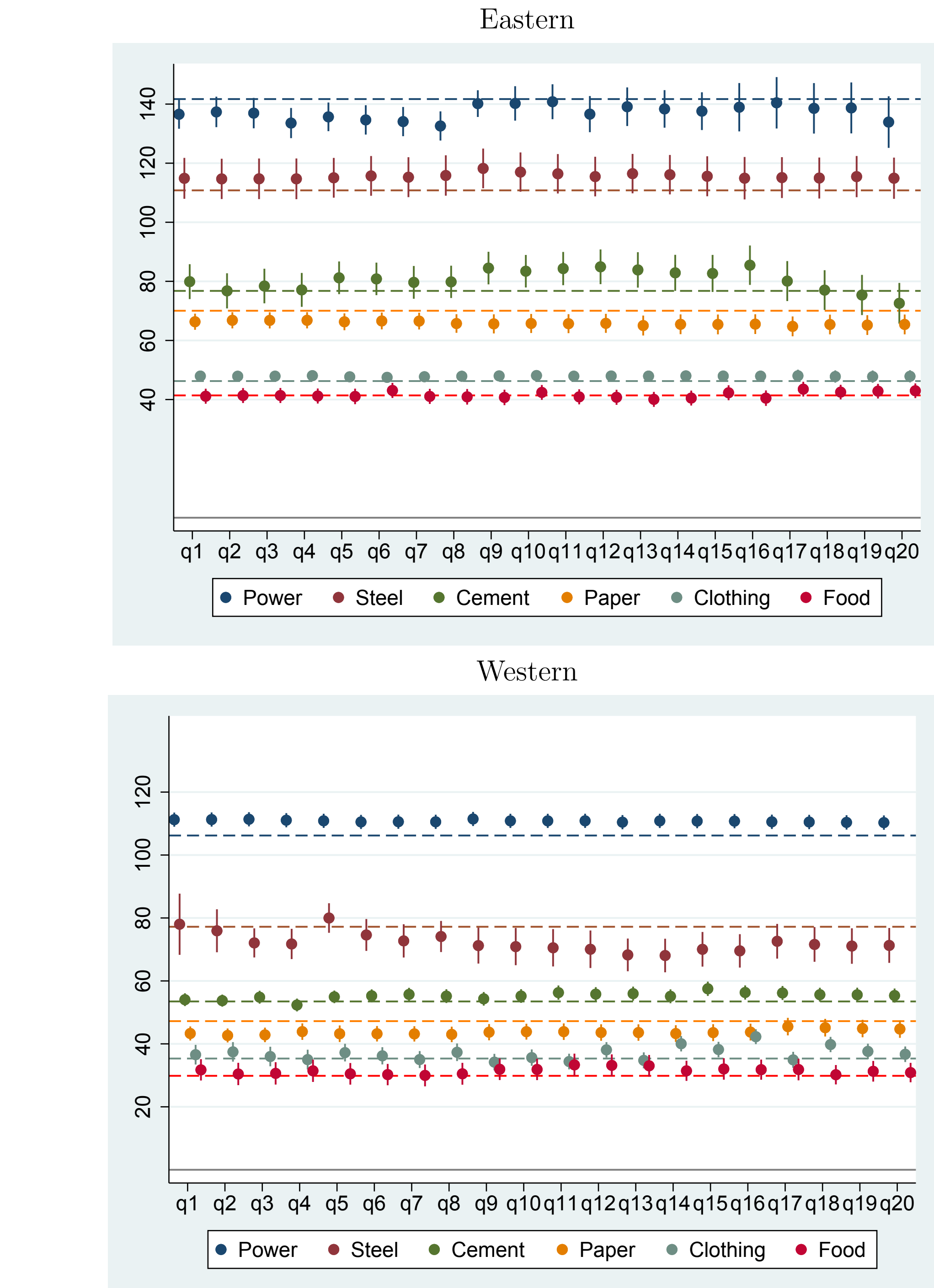

Figure B.2: Regional Comparisons: Coefficients of Distance to Residential Area Variables by Sector

dep. var.	Without Plant-level Control	Power	Steel	Cement	Paper	Clothing/Dyeing	Food
Pollution (COD in kg)	Distance in km to	-91.31***	-78.68***	-70.53***	-59.32***	-53.95***	-34.82***
	Downstream estuary	(2.272)	(2.778)	(2.012)	(2.203)	(1.283)	(0.936)
	Distance in km to	75.03***	60.91***	52.94***	43.62***	31.65***	27.34***
	Residential area	(1.819)	(2.287)	(1.277)	(1.040)	(1.010)	(2.114)
dep. var.	With Plant-level Control	Power	Steel	Cement	Paper	Clothing/Dyeing	Food
Pollution (COD in kg)	Distance in km to	-92.62***	-72.12***	-67.46***	-51.96***	-50.02***	-29.53***
	Downstream estuary	(7.807)	(7.347)	(4.500)	(7.807)	(2.771)	(2.775)
	Distance in km to	78.09***	63.18***	50.34***	39.67***	31.26***	27.71***
	Residential area	(7.578)	(5.059)	(2.981)	(3.413)	(2.726)	(2.057)
	N	19008	13992	4464	5824	4996	2592

Cluster robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.3: Firm's Locational Impact 2011-2015 (Additional Plant Control)

dep. var.	River Length $\leq$ *mean*	Power	Steel	Cement	Paper	Clothing	Food
Pollution (COD)	Distance in km to	-102.1***	-101.2***	-97.04***	-52.60***	-46.58***	-31.84***
(in kg)	Downstream estuary	(1.185)	(1.697)	(1.540)	(1.255)	(0.837)	(0.592)
	Distance in km to	98.83***	79.92***	78.25***	58.55***	50.14***	33.13***
	Residential area	(1.154)	(1.463)	(1.337)	(1.328)	(0.739)	(0.740)
	N	41384	41236	10684	17980	18696	15580
dep. var.	River Length $>$ *mean*	Power	Steel	Cement	Paper	Clothing	Food
Pollution (COD)	Distance in km to	-76.37***	-58.20***	-41.14***	-38.05***	-31.84***	-22.66***
(in kg)	Downstream estuary	(1.372)	(1.018)	(0.763)	(0.761)	(0.683)	(0.608)
	Distance in km to	70.57***	57.76***	51.86***	40.69***	23.26***	20.85***
	Residential area	(1.111)	(1.136)	(1.042)	(0.798)	(0.629)	(0.499)
	N	29188	34392	10868	21880	10748	17056

Cluster robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.4: Heterogeneity due to Jurisdictional River Length

	Power	Steel	Cement	Paper	Clothing	Food
$\frac{\beta_1 \cdot river\_length_i}{average\_river\_length}$	-92.95	-93.89	-97.80	-46.21	-31.81	-27.49
N	70572	75628	21552	39860	29444	32636

Table B.5: Heterogeneity due to Jurisdictional River Length (Percentage Model)

dep. var.		Power	Steel	Cement	Paper	Clothing/Dyeing	Food/Bev
Pollution (COD)	Distance in km to	-138.9***	-75.12***	-69.83***	-63.05***	-63.51***	-46.08***
	Downstream estuary	(13.82)	(11.88)	(1.803)	(2.591)	(2.128)	(3.504)
	Distance in km to	121.2***	106.2***	52.23***	50.92***	52.47***	32.40***
	Residential area	(15.27)	(9.876)	(2.668)	(3.669)	(2.072)	(5.084)
Abatement Tech.	Distance in km to	0.00532***	0.00031**	0.00062***	0.00102***	0.00663***	0.00014**
	Downstream estuary	(0.00027)	(0.00010)	(0.00009)	(0.00008)	(0.00030)	(0.00005)
	Distance in km to	-0.00577***	-0.000278**	-0.000542***	-0.000972***	-0.00730***	-0.000135**
	Residential area	(0.00029)	(0.00009)	(0.00009)	(0.00008)	(0.00032)	(0.00005)
	N	70572	75628	21552	39860	29444	32636

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Abatement technology is production capacity (tons) installed with denitrification technology for Cement, Paper, and Food Sectors, and with desulfurization technology for Power, Cement, and Clothing/Dyeing Sectors.

Table B.6: Firm's Locational Impact on Water Pollution and Installed Abatement Technology: 2011-2015 Mundlak-RE with IV for Location

Dis. in km to	Power	Cement	Steel	Paper	Clothing/Dyeing	Food/Bev
First Stage of the Instrumented Variable: Distance in km to the Downstream Estuary						
Closest	-0.1291***	-0.0479***	-0.05***	-0.0601***	0.0867***	-0.0392***
Railroad	(0.0021)	(0.0068)	(0.0014)	(0.0017)	(0.0087)	(0.0017)
Closest	-0.0261***	0.0311***	-0.0346***	0.0361***	-0.0309***	-0.0118***
Main road	(0.001)	(0.0082)	(0.0015)	(0.0027)	(0.0013)	(0.0009)
Closest	0.0858***	0.1524***	0.0531***	0.0415***	0.0008	0.0408***
Industr. park	(0.0016)	(0.0047)	(0.0011)	(0.0024)	(0.0073)	(0.0016)
Commercial	-0.018***	0.2476***	-0.0265***	-0.0085***	0.1038***	-0.0186***
Center	(0.0012)	(0.0145)	(0.0016)	(0.0025)	(0.0099)	(0.0042)
First Stage of the Instrumented Variable: Distance in km to the Closest Residential Area						
Closest	-0.0226***	0.0546***	-0.0288***	-0.007**	0.02*	-0.0347***
Railroad	(0.0046)	(0.0063)	(0.0022)	(0.0024)	(0.0101)	(0.0071)
Closest	-0.0279***	0.012***	-0.0528***	0.0476***	-0.0119***	-0.0417***
Main road	(0.0017)	(0.0034)	(0.0028)	(0.0032)	(0.0014)	(0.002)
Closest	-0.0088***	-0.1162***	0.0048**	-0.0015	-0.0541***	-0.0152***
Industr. park	(0.0027)	(0.0042)	(0.0016)	(0.0027)	(0.0068)	(0.0042)
Commercial	0.0338***	0.1767***	0.064***	-0.1219***	-0.1011***	0.2751***
Center	(0.0018)	(0.0116)	(0.0027)	(0.0027)	(0.006)	(0.0215)
Underidentification & Overidentification Test						
Kleibergen-Paap rk LM stat	106.44***	63.65***	170.45***	57.95***	38.38***	62.59***
Sargan-Hansen Stat	1.372	1.491	3.876	1.856	0.301	2.584
p-val	0.5035	0.4745	0.144	0.3953	0.8603	0.2747
Weak Identification Test						
† *Kleibergen-Paap rk Wald F*	22.18	29.47	26.08	19.88	19.18	20.11
‡ *AP F-val* downstream	271.79	69.06	124.2	26.5	33.64	27.2
AP F-val resi. area	31.84	37.82	33.1	52.26	27.31	40.24
N	70572	21552	75628	39860	29444	32636

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

† Stock-Yogo weak ID test critical values (maximal IV relative bias): *5%* 11.04, *10%* 7.56, *20%* 5.57, *30%* 4.73.
critical values (maximal IV size): *10%* 16.87, *15%* 9.93, *20%* 7.54, *25%* 6.28. Source: Stock-Yogo (2005)

‡ Critical values for single endog. regressor (maximal IV relative bias): *5%* 16.85, *10%* 9.08, *20%* 6.46, *30%* 5.39.
critical values (maximal IV size): *10%* 22.30, *15%* 12.83, *20%* 9.54, *25%* 7.80. Source: Stock-Yogo (2005).

Table B.7: First Stage Regression (Firm's Locational Impact on Water Pollution)

Dis. in km to	Power	Cement	Steel	Paper	Clothing/Dyeing	Food/Bev
First Stage of the Instrumented Variable: Distance in km to the Downstream Estuary						
Closest	-0.3039***	-0.0772***	-0.1054***	0.0008	-0.0793***	-0.012***
Railroad	(0.0051)	(0.0043)	(0.0034)	(0.0037)	(0.0132)	(0.0021)
Closest	-0.0792***	-0.0218***	-0.1073***	-0.0287***	0.0056	0.0256***
Main road	(0.0046)	(0.0035)	(0.0052)	(0.0026)	(0.0041)	(0.0035)
Closest	-0.0552***	-0.0104***	-0.0328***	0.011***	0.0002	0.0042
Industr. park	(0.0055)	(0.004)	(0.0027)	(0.0036)	(0.0046)	(0.0024)
Commercial	0.2301***	0.0057	0.1488***	-0.0807***	0.0281*	-0.0656***
Center	(0.0042)	(0.0051)	(0.0042)	(0.0045)	(0.0117)	(0.0031)
First Stage of the Instrumented Variable: Distance in km to the Closest Residential Area						
Closest	0.2353***	0.021***	0.0909***	-0.0316***	0.0788***	-0.0551***
Railroad	(0.004)	(0.0052)	(0.0033)	(0.0043)	(0.0114)	(0.0018)
Closest	0.0909***	0.0381***	0.1595***	0.0335***	0.0397***	0.0579***
Main road	(0.0039)	(0.0043)	(0.0054)	(0.0036)	(0.0047)	(0.003)
Closest	0.1037***	0.0572***	0.0917***	0.0639***	0.0134*	0.0357***
Industr. park	(0.0043)	(0.0046)	(0.0028)	(0.0049)	(0.0054)	(0.0019)
Commercial	-0.2606***	-0.0663***	-0.2131***	-0.0643***	-0.0382***	-0.0354***
Center	(0.0035)	(0.0053)	(0.0034)	(0.0045)	(0.0101)	(0.0025)
Underidentification & Overidentification Test						
Kleibergen-Paap rk LM stat	55.51***	63.09***	70.24***	77.83***	70.53***	63.28***
Sargan-Hansen Stat	2.783	1.388	4.505	0.169	0.492	4.063
p-val	0.2487	0.4997	0.1051	0.9189	0.7821	0.1311
Weak Identification Test						
† *Kleibergen-Paap rk Wald F*	21.93	19.26	17.87	25.45	18.05	19.25
‡ *AP F-val* downstream	29.49	78.81	31.12	35.27	31.05	25.09
AP F-val resi. area	45.47	22.29	22.84	35.08	23.11	79.05
N	70572	21552	75628	39860	29444	32636

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

† Stock-Yogo weak ID test critical values (maximal IV relative bias): *5%* 11.04, *10%* 7.56, *20%* 5.57, *30%* 4.73.

critical values (maximal IV size): *10%* 16.87, *15%* 9.93, *20%* 7.54, *25%* 6.28. Source: Stock-Yogo (2005)

‡ Critical values for single endog. regressor (maximal IV relative bias): *5%* 16.85, *10%* 9.08, *20%* 6.46, *30%* 5.39.

critical values (maximal IV size): *10%* 22.30, *15%* 12.83, *20%* 9.54, *25%* 7.80. Source: Stock-Yogo (2005).

Table B.8: First Stage Regression (Water-Polluting Firm's Locational Impact on Abatement Tech. Installation)

dep var Pollution (COD)	Power	Steel	Cement	Paper	Clothing/Dyeing	Food/Bev
Distance in km to	-134.0***	-114.0***	-108.6***	-56.92***	-27.04***	-27.85***
Downstream boundary	(7.463)	(7.658)	(8.592)	(5.500)	(6.162)	(6.370)
Distance in km to	138.6***	168.9***	91.62***	97.64***	42.72***	19.41**
Residential area	(9.440)	(12.23)	(28.74)	(4.908)	(11.713)	(6.667)
Abatement tech.	-1753.4***	-4473.7***	-3166.8***	-1224.4***	-3874.9***	-1654.8***
Capacity (tons)	(90.23)	(203.56)	(864.12)	(75.71)	(152.19)	(76.89)
Residual from	-133.8***	52.51***	-123.5***	-1.191	-78.18***	-128.5***
Downstream equation	(14.57)	(11.19)	(4.370)	(3.927)	(14.27)	(15.72)
Residual from	28.80***	56.31***	10.25***	13.90***	52.09***	30.15***
Residential equation	(1.711)	(1.535)	(0.688)	(0.657)	(0.785)	(1.890)
Residual from	2184.79***	15372.17***	-13221.06***	1490.21***	-4099.55**	-6829.00***
Technology equation	(127.95)	(576.52)	(1261.93)	(92.03)	(1310.18)	(481.74)
N	70572	75628	21552	39860	29444	32636

Robust standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Abatement technology is production capacity (tons) installed with denitrification technology for Cement, Paper, and Food Sectors, and with desulfurization technology for Power, Cement, and Clothing/Dyeing Sectors.

Table B.9: Firm's Locational Impact on Water Pollution: Control Function Approach 2011-2015

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