Three Papers on Environment-related Decision-Making and Development in China

Xiaojia Bao

Submitted in partial fulfillment of the
requirements for the degree
of Doctor of Philosophy
in the Graduate School of Arts and Sciences

COLUMBIA UNIVERSITY

2013

ABSTRACT

Three Papers on Environment-related Decision-Making and Development in China

Xiaojia Bao

Abstract

Environment related decision making in developing countries has been widely concerned because of the weak institution and high vulnerability to environmental risks and changes. However, empirical studies on these perspectives, especially quantitative analysis, are still quite limited due to data limitations. This dissertation empirically explore both governmental and households behaviors in a series of environmental decisions: dam construction, typhoon relief, water and electricity consumption in China, using both officially reported data and micro-level data collected in the field. In general, both governments and households respond to internal and external environmental shocks using their own tools, by adjusting governmental transfers or water and electricity consumptions. The last chapter discusses what are the implications of these findings on environment management and sustainable development.

Table of Contents

List of Figures

List of Tables

Acknowledgments

I would like to sincerely thank my advisors Suresh Naidu, Upmanu Lall and Wolfram Schlenker.

I am especially grateful to my teachers Douglas Almond, Jushan Bai, Scott Barrett, Pierre-André Chiappori, Macartan N. Humphreys, John Mutter, Serena Ng, Cristian Kiki Pop-Eleches, Jeffrey Sachs, Bhaven Sampat, Paolo Siconolfi, Gregory Yetman.

I also thank to those who make this doctoral program possible, Mona Khalidi, Geoffrey Heal, Joseph Stiglitz, John Coatsworth as well as faculties and colleagues who helped me along the way: Navin Kartik, Zhong Ma, Malgosia Madajewicz, Massimo Morelli, Shangjin Wei, Li An, Prabhat Barnwal, Kayleigh Campbell, Jon von der Goltz, Amir Jina, Tao Li, Huijie Lu, Geoffrey McCarney, Gordon McCord, Daiju Narita, Andrew Neal, Matthew Notowidigdo, Anisa Khadem Nwachuku, James Rising, Anna Tompsett, Marta Vicarelli, Liangzhi You, Nan Zhong.

I thank Jesse Anttila-Hughes, Geoffrey Chi-Johnston, Ram Fishman, Solomon Hsiang, Chandra Kiran Krishnamurthy, Kyle Meng and Nicole Ngo for inspiration and support.

I thank my parents and my brother for everything.

Finally, I thank Columbia University, especially Weatherhead East Asian Institute and Center for International Conflict Resolution, for funding my study and research.

Dissertation Committee

Upmanu Lall
Columbia University
Department of Earth & Environmental Engineering
Department of Civil Engineering & Engineering Mechanics

John Mutter
Columbia University
Department of International & Public Affairs
Department of Earth & Environmental Sciences

Suresh Naidu
Columbia University
Department of Economics
Department of International & Public Affairs

Wolfram Schlenker
Columbia University
Department of Economics
Department of International & Public Affairs

Matthew Turner
University of Toronto
Department of Economics

Chapter 1

Introduction

1.1 Background

Decision making related to natural environment is complex due to externalities and uncertainties associated with the environment system. Besides quantifying the externality and uncertainty of environmental elements (such as ground water depletion, climate change and natural disasters etc), it is also key to understand how externalities and uncertainties interact with the behaviors of various decision makers. This is especially true in the context of developing countries, because not only they are more vulnerable to environmental changes due to the low income level and weak institutions, but also they may impact the environment more for future economic growth expectations.

Governments, enterprises and individuals are the three main types of decision makers in the economy and environment system. Comparing to governments and individuals, enterprises make decisions more straightforwardly and just maximize profits under the price signal which may be comprehensively decided by governments and the market. The objective functions of governments and individuals are less clear, varying over institutional, social, cultural and economic contexts.

Studies on governmental decision behaviors on environment related perspectives have focused a lot on bottom-up decision systems, which are widely adopted by developed countries. In this type of systems, governments make decisions on regulation setting, public good and service provision and income redistribution after incorporating environment factors. Governments face incentives of direct voting or voting with feet by individuals. There have been many empirical studies evaluating governments' decisions and individual response to these decisions, such as pollution regulation, environmental tax and relief transfers (Besley and Rosen, 1998;Eisensee and Strömberg, 2007).

However, studies on governmental decision making for environment are still quite limited in top-down systems (Burgess *et al.*, 2012). In this type of systems, governments face an additional incentive to "impress" the upper-level governments. Even though the wellbeing of local individuals are included in the performance evaluation, information asymmetry makes the system easy to be sabotaged by corruption, bureaucracy and many unobservable factors such as governors' preferences and social network. To understand the system well, a lot of empirical studies on governmental decisions are needed to provide basic knowledge and information on the "gray-box" of governmental decision system. One main challenge for these studies is to identify an exogenous change which triggers the governmental decision system and then evaluate the social, economic and environmental impacts of these changes.

Equity and efficiency have been widely agreed to be the main rules evaluating governmental decisions. This requires the incorporation of individual preference, which needs a lot of inputs on basic knowledge about individual preferences and behaviors. This dissertation aims to provide basic empirical supports of governmental decision evaluation by observing both governmental and individual behaviors on a series of decision making problems. Specifically, it includes two studies on governmental decision making on public projects and disaster relief and one study on individual behaviors (Chapter 2 & 3) of water and electricity consumption (Chapter 4) in the context of China.

1.2 Approach

The papers in this dissertation are all empirical studies. Chapter 2 studies how hydropower dam projects impact local counties and how the central government use intergovernmental transfers to balance uneven impacts across regions. Chapter 3 also studies the intergovernmental transfer behavior, but focusing on a different type of environment problems: typhoons. It estimates the efforts of the central government using intergovernmental transfers to help local disaster relief. These two papers represent the main functions of intergovernmental transfers: public investment, fiscal equalization and risk sharing. Two types of fiscal federalism models are built separately to explain governmental responsiveness to internally initiated projects and external natural shocks. Chapter 4 is a micro-level study on household water and electricity consumption behaviors in rural China. It especially explores how local households adjust their consumption in face of weather variabilities.

A variety of data from different sources are used for the empirical analysis, including officially reported data, manually collected data through internet resources and field collected data . The first two studies use a combination of governmental reported economic and fiscal data and remote sensing satellite data at county level. A complete list of all dams above 100 meters in China are manually collected based on internet resources. The third study uses household data on water and electricity bills in a rural village of Northern China. Basic econometric approaches, including difference-in-difference, first-difference and fixed effects regressions are used to analyze data.

In the dissertation, the two governmental studies and the household study are not directly linked to each other. To meet the goal of evaluating governmental decisions comprehensively by incorporating governmental and households behaviors together, future research on wider range of governmental policies and household behaviors are needed to bridge the gap.

1.3 Chapter summaries

Chapter 2: Dams and Intergovernmental Transfer: Are Dam Projects Pareto Improving in China? In Chapter 2, using the geographic variation of dam impacts based on distances to the river and distances to dams, I use difference-in-difference approach to estimate dam impacts at county level in China from 1996 to 2010. The results indicate that dam-site counties significantly benefit from dam projects, while upstream counties significantly get harmed. A large-scale dam increases the revenue in dam-site counties by 13-20%, and decreases the revenue in upstream counties to 7-16% after the projects begins. Further downstream counties suffer from rice yield decrease by more than 5%, even though their overall economy are not significantly impacted. The central government increases transfers to upstream counties by 7-13%, which compensates the revenue losses quite well. Both the revenue and transfer impact estimates show geographic heterogeneities. The closer a county is to a dam, the larger the impacts will be. When combining the changes in governmental revenue and net transfers, the results indicate that large-scale dam projects in China are close to the Pareto improvement outcomes in the perspective of governmental economic performance. One concern of this study is that ecosystem impacts are not included in the analysis. The results are only based on the balance sheets of governments. It should be cautious to apply the conclusions to the whole macro economy.

Chapter 3: Transfer for Disasters: Governmental Responsiveness to Typhoon Risks in China (with Solomon Hsiang and Daiju Narita). In Chapter 3, Solomon Hsiang, Daiju Narita and I examine central government's efforts of making transfers to help typhoon relief in local governments. Local macroeconomic performance measured by per capita GDP is not significantly damaged by typhoon exposures. The central government increases special transfer with targeted purposes to local regions for the current year typhoon exposure. On average, local regions receive 5% more special transfers when the average maximum wind speed increases by 10m/s. However, general transfers which are non-targeting transfers, barely change along with typhoon exposures. Transfers respond to local vulnerability prioritively. The increasing transfer efforts target mainly at poor regions and regions suffered from severe typhoons with high average maximum wind speed. Transfer responsiveness is not significantly associated with population density, ethnicity group composition and number of peer competing counties within the same prefecture. Neither the “province manages county" reform nor political connection impact special transfer responsiveness. One thing to note is that the estimate in this paper might be a lower bound of the actual disaster transfer responsiveness, because disaster transfer is only a small part of total special transfer which is analyzed in the paper.

Chapter 4: Water, Electricity and Weather Variability in Rural Northern China. In Chapter 4, I examine household water and electricity use behaviors, especially the impacts of weather variabilities on these behaviors, using household data in a water-scarce rural village in Northern China. I find that smaller families tend to increase per capita water and electricity consumptions by more than 20% for one less family member. Households with more women in the family have higher water and electricity consumptions even when controlling the family size. Both water and electricity consumptions increase in hotter or drier months. Smaller households are more sensitive to weather variabilities by increasing water use more in face of temperature increases. One concern of the study is that local households occasionally use ground water as an alternative of the metered pipe water. The estimates derived in this paper for weather responsiveness of water use should be interpreted as a lower bound of the true water responses.

Chapter 2

Dams and Intergovernmental Transfer: Are Dam Projects Pareto Improving in China?

Abstract

Large-scale dams are controversial public infrastructure projects due to the unevenly distributed benefits and losses to local regions. The central government can make redistributive fiscal transfers to attenuate the impacts and reduce the inequality among local governments, but whether large-scale dam projects are Pareto improving is still a question. Using the geographic variation of dam impacts based on distances to the river and distances to dams, this paper adopts a difference-in-difference approach to estimate dam impacts at county level in China from 1996 to 2010. I find that a large-scale dam reduces local revenue in upstream counties significantly by 16%, while increasing local revenue by similar magnitude in dam-site counties. The negative revenue impacts in upstream counties are mitigated by intergovernmental transfers from the central government, with an increase rate around 13% during the dam construction and operation periods. No significant revenue and transfer impacts are found in downstream counties, except counties far downstream. These results suggest that dam-site counties benefit from dam projects the most, and intergovernmental transfers help to balance the negative impacts of dams in upstream counties correspondingly, making large-scale dam projects close to Pareto improving outcomes in China.

2.1 Introduction

Many countries invest heavily on infrastructure projects to stimulate economic development and reduce poverty. The annual infrastructure investment in China amounted to more than 20% of national gross domestic product (GDP) in the past decade, covering public and private infrastructure projects on energy, transportation, primary natural resources, public facilities, hydrological and agricultural infrastructures. These projects bring uneven impacts to local regions, with benefits like economic production, increasing employment, lower transaction and transportation cost for the society and spillover benefits to other industries[1] and losses like involuntary migration, crowding-out traditional industries and social structure change[2] etc. Governments use redistributive intergovernmental transfers to balance the economic impacts of large projects on local governments. Given the coexistence of benefits and losses caused by the infrastructure projects, is the governmental redistribution system effective to mitigate the negative impacts? Are infrastructure projects Pareto improving under the governmental redistribution system? Are regions equally benefitting from the infrastructure projects?

I particularly focus on large-scale dams in China, i.e. dams with height above 100 meters to answer the above questions, for three considerations. First, large-scale dams bring huge economic impacts to a wide range of areas. There are 142 large-scale dams, i.e. dams with height above 100 meters in China by 2010, contributing to 40% of total hydropower generation capacity and 44% of water storage capacity [3]. Second, dam impacts show significant geographic characteristics. Once the dam wall divides a river basin into three sections, up-

[1] See Aschauer (1989), Munnell (1990), Haughwout (1998) , Fernald (1999) and Banerjee *et al.* (2012) for transportation infrastructures, Greenstein and Spiller (1995) and Nadiri *et al.* (2009) for telecommunication infrastructures, De Long and Summers (1991) for other types of infrastructures.

[2] See Brocker *et al.* (2010) and Meijers *et al.* (2012) for related researches.

[3] Hydropower contributes to around 16% of total power generation in 2010 in China.

stream, dam-site and downstream regions, each region will be exposed to different benefits and risks from the same dam project, making the uneven impacts observable at the administrative government level. Third, most large-scale dam projects are approved by the central government (Ministry of Water Resources) in China, which provides a social and economic context with more concentrated governmental involvement in the dam decision making and intergovernmental redistribution.

To analyze the governmental redistributive system, I first introduce a simple fiscal federalism model representing the multi-level governments' decision making process on intergovernmental transfers and infrastructure approvals, following the model setup for intergovernmental fiscal relationship by Zou (2012) and Slack (1980). The model implies that no region should be worse-off from a publicly approved dam project and negative revenue impacts will be mitigated by intergovernmental transfers if the redistribution system is effective. Total economic impacts of dam projects on a local government are composed by the local revenue impacts and external transfers impacts. Following this framework, I also provide the first empirical analysis on governmental redistribution mechanism reflected from the fiscal transaction for large-scale dam projects, with analysis unit at county level in China. Most of the current literatures on empirical economic impact estimates of dam projects are about the overall economic impacts in terms of economic production or income to a region(Duflo and Pande, 2007, Strobl and Strobl, 2011, Hansen *et al.*, 2009, Chakravarty, 2011 and Lipscomb *et al.*, 2011). This paper takes an additional step to separate the local revenue and external transfer effects from dam projects, besides the overall economic impacts.

The paper covers 136 large-scale dams after the crosscheck of officially reported dam locations and Google Earth images. These dams normally serve multiple functions, including hydropower generation, flood control, irrigation, navigation, water supply and tourism. The overall economic impact of a dam on a specific region depends strongly on the relative distance between the region and the dam and the perpendicular distance between the region and the river. Upstream areas are subject to inundation risks and water use restrictions, as well as irrigation, navigation and tourism benefits. Dam-site areas where the dam is located are subject to electricity generation benefits, inundation and pollution risks. Downstream areas benefit from reduced flooding risks and irrigations, while they are also subject to reduced water flow and higher drought risks. The perpendicular distance to the river also matters for dam impacts on a specific region. Most of impacts, such as irrigation, flood control, hydropower generation and inundation, rely on the water flow[4]. Areas located close to the river will be impacted by the hydrological changes more than areas further away.

Using geographic variation of dam impacts, I adopt a difference-in-difference(DID) approach to explore the differences between counties directly impacted by dams as the treatment counties and similar counties not impacted by dams as the control counties, before and after the dam construction to get unbiased estimates of dam impacts in the construction and operation periods. I obtain estimates separately for three main areas along the river: upstream, dam-site and downstream regions. Because the DID approach uses the information of existing distribution of dam locations, estimates of dam impacts are robust to the fact that dam locations may be not exogenous to the economic performance.

I define treatment counties as counties with geographic centroids located within 20km away from the river, and control counties as counties with geographic centroids located slightly further away. Because upstream counties are normally wider and larger than downstream counties, upstream control counties are defined as these located in the band of 20km to 100km away from the river, while downstream control counties are defined as these located in the band of 20km to 50km away from the river. Considering that the average size of counties in China is around 400 square kilometers, treatment counties are almost the closest

[4]The paper doesn't include the analysis on power supply beyonds electricity generation. Because the electricity supply destination are mostly large regions, such as East China or North China, depending on contracts for individual dams, control and treat counties are likely to enjoy similar electricity supply benefits. the difference-in-difference estimates will not capture the electricity supply benefits.

layer of counties along the river, while control counties are counties located close to treatment counties, but slightly away from the river. To link counties and dams, I assume that the nearest dam impacts treatment counties the most, which is empirically verified. Control counties are used repeatedly for multiple dams. This categorization on countries also provides a group of treatment and control counties linking to the same dam for all locations. Following this definition, treatment and control counties show similar pre-dam trends for most economic and demographic variables, meeting the assumption for DID estimation.

The first set of results is on governmental fiscal revenues, which covers tax and fee revenue collected from the local administrative region. The results indicate that dam-site counties significantly benefit from dam projects, while upstream counties significantly get harmed. The revenue impacts of dam operation is larger than that of dam construction, considering that dam only functions partially in the construction period. A large-scale dam increases the revenue in the dam-site counties by 12.9% during the dam construction period and 19.9% during the dam operation period. Upstream counties, however, suffer a 16.5% decrease in per capita governmental revenue during the operation period and 7.5% decrease during the construction period. Downstream counties are not significantly impacted. Negative impacts in the upstream counties are not all from inundation and resettlement losses, but also potentially from other changes, such as long-term social and economic disruptions and water use restriction in the upstream. Most of the revenue impacts to the dam-site counties are from hydropower generation benefits.

The second set of results is on net intergovernmental transfers received by local county governments. Both the upstream and dam-site counties receive more transfer. However, the transfer effect is much larger in the dam construction period than that in the dam operation period. Per capita transfer into upstream counties increases by 13.6% during the construction period and 6.7% insignificantly during the operation period. The transfer to dam-site counties increase by more than 16% in both periods. The transfer effect in downstream counties is not significant. Increases in net transfers into upstream counties sufficiently mitigate the negative revenue impacts in the upstream counties.

Both the revenue and transfer impact estimates show geographic heterogeneities. The closer a county is to a dam, the larger the impacts will be. Counties located within 200km away from the dam along the river are subject to the largest distributive impacts. Counties in the far downstream suffer a loss in total revenue and agricultural yield. The impacts are also heterogeneous for the designed purposes of dams. Hydropower dams bring larger distributive impacts than irrigational dams.

When combining dam impacts on governmental revenue and net transfers, the result indicates that large-scale dam projects in China are close to the Pareto improvement outcomes in the perspective of governmental economic performance. However, the benefits distribute unevenly. Local dam-site counties capture most of the benefits. Downstream counties get slightly worse off, but the impact estimates are not statistically significant. The results on the macro economic performance of GDP show similar patterns, except that upstream counties also getting worse off. This indicates that even though the transfers attenuate the negative impacts to a certain extent, the magnitude of transfers to the upstream and downstream counties are smaller than the optimal level. The uneven economic impacts on different regions imply that the central government put a larger decision weight on the dam-site counties comparing to others when making fiscal redistributions. It reveals that counties with the geography suitable for building dams have larger decision weights.

The above results are robust to subsample analysis and other estimate specifications. Falsification tests verify the credibility of the classification of treatment and control counties, and classification of time periods to capture the impacts. The main results on dam-site county benefits and upstream compensations are robust to the data collapse methodology proposed by Bertrand *et al.* (2004) to correct the serial correlation concerns caused by DID analysis using long time series data

To my knowledge this is the first paper not only studying economic impacts of large-scale projects, but also exploring the governmental redistributive efforts for economic impacts of projects, by separating the internal governmental revenue and external governmental redistribution impacts for large projects in China. It contributes to the large literatures on dam impacts (Duflo and Pande, 2007, Strobl and Strobl, 2011, Hansen *et al.*, 2009, Chakravarty, 2011 and Lipscomb *et al.*, 2011), infrastructure and development (Aschauer, 1989 and Banerjee *et al.*, 2012) and intergovernmental transfers (Sole-Olle and Sorribas-Navarro, 2008 and Zou, 2012). The findings can provide policy implications on the welfare impacts of hydropower dams and intergovernmental redistribution decision making in China.

The following part begins with an introduction on dams and intergovernmental transfers in China. Section III shows a theoretical model for intergovernmental transfer decision process of infrastructure projects. Section IV discusses the data collection for empirical analysis. Section V introduced the DID approach. Section VI presents the results, robustness analysis and policy implications of the results. Section VII concludes.

2.2 Dams and Intergovernmental Transfer in China

There have been 24,119 dams built in China by 2008, accounting to more than 50% of total dams in the world. Even though the overall dam construction speed has slowed down since the 1990s', the speed of large-scale dam construction, i.e. dams with height above 100 meters has accelerated[5](see Table 2.1). On average, there were 1.3 large-scale dams built every year before 1988. The number rose to 4.8 between 1989 and 2005 (CHINCOLD, 2008). More large dams will be built in the next 10 years[6]. Large-scale dams are strategically important

[5]The technology development in arch and buttress dams makes it possible to use less concrete and soil for construction of larger and taller dams.

[6]The installed hydropower capacity is expected to reach 320 GW in 2020, doubling the 2008 level according to the midterm and longterm development plan for renewable energy (NDRC, 2007). More than 100 GW

for renewable energy generation and water regulation in China.

In the following section, I first introduce large-scale dam projects in China. Then I explain potential economic benefits and losses related to these dams. Following that, I describe the intergovernmental transfer system in China.

2.2.1 Large-scale Dams in China

In China, dams are classified into 6 categories, large I, large II, medium, small I, small II and others[7] based to the scale of the reservoir. The decision making process differentiates for dams of different categories. Higher-ranked dams require approval from higher level of governments. 98% of dams with height above 100 meters are classified as large I hydrological projects, which need the approval from the central government. Dams with lower heights and smaller reservoirs are more likely to be approved by provincial or prefectural governments. Besides that, dam above 100 meters is a category routinely reported in dam statistics and local economic reports, even though there is no specific technical differences between dams above 100 meters and those slightly below the bar. This may provide a small nudging effect for the decision makers to propose dam projects with height above 100 meters instead of projects below the bar when they have the option to built dams with heights close to 100 meters. This phenomenon may occur when local governments use dam projects to signal local governor performances. Figure 2.4 plots the distribution of dam heights for new dams above 30 meters from 1996 to 2003. It shows that when the dam height is close to 100 meters, they are more likely to exceed 100 meters than below it. In the rest of the paper, dams above 100 meters will be called as large-scale dams. By focusing on this specific category of dams,

will be from dams above 100 meters.

[7]Large I projects: reservoir> 1 billion cubic meters; Large II projects: 0.1-1 billion cubic meters; Medium projects: 10-100 million cubic meters; Small I projects: 1-10 million cubic meters; Small II projects: 0.1-1 million cubic meters; and others.

the analysis can provide implications on redistribution mechanisms of central-approved large dam projects.

Large-scale dams normally serve multiple functions, including hydropower generation, irrigation, flood control, water supply, navigation and tourism. To meet these functions, a dam wall is built on the river, storing water in the reservoir behind the wall and releasing water downstream for specific purposes. The main dam operation scheme is to decide when and how much to store and release water. Most dams have a net storage in the dry winter and early spring, and then a net release in the late spring and early summer to prepare for summer floods.

On average, a large-scale dam costs around 1 billion CNY (140 million US Dollar) in the 2002 price level. The average dam construction period is around 7 years. These dams are mostly co-financed by the state-owned electricity company, financial institutions, the central government and local governments, with most of the investments from companies and financial institutions[8].

The approval process of large-scale dam projects follows a bottom-up structure, requiring proposals from local governments and approval by the central government. First, regional governments or river basin committees frame the five-year plan about hydropower development in the river basin, under the guidance of national hydrological infrastructure development plan released by the central government. The national hydropower development plan includes expected goals of hydropower capacity and renewable energy capacity. Once the regional five-year plan is approved by the state council, local electricity companies, mostly state-owned, will submit project proposals, including the information of dam site choice,

[8]For example, Ertan Dam located in the upstream of Yangtze was financed by State Development Investment Corp and Sichuan Investment Energy Corp at the proportion of 52:48. Three Gorges Dam was financed by the Three Gorges Construction Fund sponsored by the central government, Three Gorges Company and the electricity revenue after 2003, loans from China Development Bank and the Three Gorges Bond.

technological and initial feasibility study reports. Third, the central government approves the project proposal, and then the construction work can begin[9]. Local governments have limited decision power on the location and design of dams.

In addition to the governments' direct involvement in approving and investing on dam projects, they also have the administrative authority to make regulations and policy guidelines, such as environmental protection regulations on water use distribution. There have been environmental regulations restricting polluting industry development in the upstream to protect the water quality in reservoir, and guidelines on water use privilege if there were droughts or floods(MEP, 2008 and MWR, 2005). Even though I will not specifically estimate specific economic impacts of these regulations separately, I expect to capture their overall economics impacts from the macro economic performance outcomes.

2.2.2 Benefits and Losses from Large-scale Dams

By changing the hydrological cycle of the river, dams impact areas along the river differently depending on the relative location of the local county and the dam. A dam wall divides the whole river basin into three sections, upstream, dam-site and downstream regions. Upstream regions are areas behind the dam wall. It is also called the catchment region, where the reservoir will be located and where the storage water will be originated from. Dam-site regions are areas where the dam is located and where construction activities occur. Downstream regions are areas where the reservoir water flow to. They are also called as command regions of the dam. Large-scale dams often serve multiple economics and service functions, including hydropower generation, water supply, irrigation and flood control.

Hydropower generation is one of the main functions from large-scale dams. Dam-site regions capture most of the direct revenues from electricity generation, including tax revenue

[9]Yangliuhu Dam is the only one that was disapproved by the central government.

increase and potential increased job opportunities. Local regions may also benefit from other indirect revenue impacts. For example, dam construction work can bring infrastructure improvement benefits, such as roads, telecommunication, sanitation accesses. Even though electricity provision is believed to be one of the social benefits due to the low hydropower costs[10], it will not be included in the benefit analysis of this paper. One reason is that the specific benefiting region of power provision is difficult to be identified. Electricity benefits can spread to the whole nation or a major part of the nation through the grid system. Most of the large-scale power plants in West China[11] are now contracted to serve East China[12] under the national policy of "West-East Electricity Transfer" since 2001[13]. Electricity supply benefits spread quite evenly in the hydropower serving region. So the power provision benefits are not included in this paper, since it mainly targets on the unevenly distributed benefits from dams.

Water supply is another important function for dams, including water supply for irrigation, industrial and household uses. Irrigational benefits can extend to nearby downstream regions and nearby upstream regions following the canal system. Around 20% of the total irrigational regions are irrigated by dams and reservoirs in China (Zhou, 1997). Most of the main dam-irrigated cropped regions are in Yellow River and Yangtze River basins close to the dam sites. Duflo and Pande (2007) and Hansen *et al.* (2009) reported positive impacts on downstream agricultural yield from dam irrigation in India and US.

Flood control is also a main dam function, but mainly benefiting downstream regions.

[10]Hydropower electricity is generally cheaper than electricity generated from coal plants. So areas served with hydropower electricity benefit from lower energy cost.

[11]Around 60% of large-scale dams are located in the western provinces, like Guizhou, Sichuan, Yunnan and Guangxi.

[12]This is the region with most economic activities in China. Power shortage generally exists in this region.

[13]For example, Longtan Dam provides 30% of the electricity generated to the local grid system and 70% to Eastern China, while the Three Gorges Dam provides all the electricity generated to Eastern China.

By regulating water flow through dam storage and release, dams can reduce flooding risk of the whole downstream regions in flooding seasons. Other benefits of dam projects include navigation in the dam-site and upstream region, and tourism development in the local and upstream region. By lifting water level in the reservoir, the vast water body can support longer navigation route, reducing navigation risks.

Dams projects are also associated with negative impacts, including inundation, involuntary-migration, water flow change and stricter water regulations. Due to water storage in the reservoir, areas closely behind the dam are subject to inundations. People in dam-site counties suffer from involuntary migration and asset losses. There have been more than 10 million people affected by involuntary resettlement caused by dams since 1950s. For Three Gorges Dam specifically, around 1.4 million people migrated because of the dam impacts according to official reports (Heming *et al.*, 2001). Even though people are compensated fully or partially for the assets losses and livelihood changes, social and non-monetary environmental impacts are rarely compensated, such as damages to the social network and social capital accumulation(Cernea, 2000).

Large-scale dam projects can also bring environmental, hydrological and social changes. Hydrological cycle in the river basin will be disrupted, reflected from decreased water speed, shrinking water flow and decreased sediment delivery in downstream regions. But whether these impacts are benefits or damages for macro-economic performance, or for agriculture specifically, is ambiguous, especially when environmental impacts occur simultaneously with irrigation and inundation functions(Yang *et al.*, 2008). Disease burden may increase due to the change of landscapes caused by the inundation. The large reservoir surface in the dam-site and upstream region may increase the spread of mosquito-borne infectious disease, such as malaria (Chakravarty, 2011). There are also concerns about water pollution in the upstream and dam-site areas due to the accumulated wastes behind the dam wall. Large-scale dams may impact the spawning and growth of fisheries in the downstream regions, due to changes in water flow, changes in water temperature and species migration disruption(Xie *et al.*, 2007).

Besides geographic heterogeneity on upstream, dam-site and local regions, dam impacts also show temporal heterogeneity, since the dam construction periods range more than several years. Dam construction and operation may cause different impacts. Dam construction bring negative impacts such as displacement and inundation, and positive impacts such as dam-related infrastructure construction and part of the dam functions. However, the main benefits from dam functions happen in the dam operation periods, including power generation, irrigation, flood control, water supply, navigation, tourism and fishing. Dam operation may bring negative impacts such as hydrological and fishery changes in the river. Some impacts occur both in the construction and operation periods, including pollution control and land conservation in upstream regions, social capital loss from involuntary migrations. By analyzing dam impacts in two periods separately, the temporal heterogeneity will be captured.

2.2.3 Intergovernmental Transfer in China

The current intergovernmental transfer system in China formed in 1994 under the Tax Sharing Scheme (TSS), which shaped the vertical fiscal relationship between the central and local governments. It empowers the central government to collect certain categories of taxes or share several tax revenues with the local governments. The central government can make fiscal intergovernmental transfers to local governments for economic development and revenue redistribution purposes. Transfers often take the forms of tax return, subsidy, general transfer and special transfer for specific projects. Tax return is used to encourage investment in certain region or certain industry, for example, special development zones. General transfer is used to narrow down the gap between local expenditure and fiscal capacity. There are also transfers targeting at specific projects on infrastructure investment, agriculture, science and technology development, education and subsidy transfers for poor regions, minority ethnic regions, urban areas and natural disaster relief.

The magnitudes of transfers to a county differentiate for various types of transfers. Most transfers follow implicit formulas, mostly based on the population needing the service, fiscal deficits of local governments or ethnical composition. For instance, transfer for agriculture and rural tax reform was distributed according to the reported number of rural people and agricultural cropping areas. However, some other special transfers are more flexible, largely depending on the local needs, instead of a constant pre-defined formula, such as transfers for infrastructure construction and disaster relief. These transfers are more likely to be impacted by the local governments' project proposals, political bargaining power and historical transfer magnitudes.

For dam projects specifically, related intergovernmental transfers include tax return, special transfer for dam project construction, special transfer for reservoir protection, special transfer for water source protection, special transfer for strategically important geographic regions, special transfer for infrastructure construction besides dams, general transfer and subsidies for fiscal deficits caused by involuntary migration, agricultural impacts or other economic impacts. New dam projects may change the intergovernmental transfer amount through multiple ways. First, general transfers may change due to dams revenue impacts and population changes, since the formula for general transfers includes elements such as fiscal deficit ratio, population size and population with special demands. Second, special transfers may be impacted due to dam related economic activities, such as dam-related infrastructure construction, reservoir protection, upstream soil and land conservation, agricultural irrigations and fisheries etc.

For local governments, total fiscal resources are composed by the internal tax revenue and external transfers. Intergovernmental transfers reflect the fiscal redistribution from upper-level governments. The transfer here are mainly governmental fiscal transfers to balance fiscal capacity of local governments. Even though they play a role of attenuating the revenue losses of local governments, private compensations made by dam companies [14] for asset loss, resettlement and migrations are not included in the transfers. So the separation of internal and external revenue sources makes it possible have a better understanding of the governments' decision making process on dams and to distinguish the direct economic impacts and fiscal redistribution by local governments.

2.3 Theoretical Model

The following is a simple fiscal federalism model explaining governments' decision process for large infrastructures approved by the central government. The basic model setup is that there are two local governments (1,2) under the governance of the same central government. Each local government makes expenditures and provides public service to maximize social utility in the administrative region under a fiscal budget constraint independently, while the central government maximizes the weighted sum of utility in two localities. The main model structure follows the basic model setup on intergovernmental transfers proposed by Slack (1980) and Zou (2012). Local governments keep a vertical fiscal relationship with the central government, i.e. central government collects a certain share of tax revenues generated from the local governments and makes fiscal transfers down to local governments. The optimization problem is a typical Stackelberg game, with equilibrium solved by backward induction.

Assume that the decision on dam construction and dam impacts are exogenous for local governments. The central government has the final approval authority, while local governments have limited bargaining power about the location and approval of the dam projects

[14] The direct compensation for asset loss and alternative livelihood is done by the dam construction companies following the national compensation rule. This private compensations are included in the cost-benefit analysis of the dam projects and borne by the dam companies.

ex ante. Once the project is approved, the impacts will be exogenous for local governments [15].

The fiscal relationship between central and local governments follows the fiscal federalism structure. The central government collects taxes from two localities to support its expenditure, and also makes intergovernmental transfers to localities for efficiency and equity considerations. Localities share fiscal tax revenues with the central government following the ratio of ρ: $(1-\rho)$, with local governments sharing ρ percent of total tax and central government sharing the rest[16]. The intergovernmental transfers from central government to local governments are reframed as the net transfer amount into local governments, because empirically there are transfers in both directions between local and central governments. The intergovernmental transfers are simplified to only one block transfer [17], which means the transfer amount is independent of local expenditure behavior [18].

2.3.1 Assumptions

The main assumptions for the model are the following.

1. There is no borrowing or saving for local governments across time periods. This is a static model for a one-shot game.

---

[15]Empirically, the decision on location and design of large-scale dam projects are mostly proposed by the river basin committee and Ministry of Water Resources under the help of research institutes affiliated to water resource department. Local county governments have little bargaining power on the location choices. But they *ex post* can raise project or program proposals and apply for the intergovernmental transfers from the central government.

[16]The tax sharing proportion is the same across the country. But different ratios may be applied for different taxes. For instance, valued-added tax is shared at 75:25 by the central and local governments. Income tax is shared at the ratio of 60:40.

[17]In reality, there are two types of intergovernmental transfers: block transfer and matching transfer. Block transfer is the transfer independent of the local expenditure size and fields, while the matching transfer is the transfer correlated with local expenditures.

[18]If the transfers are specified as block and matching transfers. The main analysis results do not change much, because the matching factor for central governmental transfers are normally constant across regions.

2. Government's utility function meets Inana conditions, i.e. (1) $U(0) = 0$; (2) $U' > 0$ and $U'' < 0$; (3) $\lim_{x \to +\infty} U(x) = 0$, $\lim_{x \to 0} U(x) = +\infty$.

3. There are no horizontal transfers directly among local governments.

4. The decision of dam construction and economic impacts of dam projects are exogenous to local governments.

Applying backward induction, the Subgame Nash Equilibrium (SGNE) can be solved by solving local optimization problem first and central optimization problem second as the following.

2.3.2 Local Government Optimization

Assuming two local governments make decisions simultaneously, i.e. one cannot observe another's action *ex ante*. Each government maximizes the utility of the presentative agent, subject to a budget constraint in the administrative region.

$$\begin{aligned} \max_{g_i} \quad & U_i(g_i)(i = 1, 2) \\ \text{s.t.} \quad & g_i \leq \rho t Y_i + f_i \end{aligned}$$

where U_i is the utility function of the representative individual as a function of public service provided by local government (g_i). The public service is assumed to be rival but non-exclusive. So g_i here is the per capita public service provided by the local government. t is the average tax rate. $\rho t Y_i$ represents the total tax revenue generated by the locality, as ρ being share held by the local government and t as the average tax rate. $(1 - \rho) t Y_i$ is tax revenue collected by central government that is from locality i. f_i is the block transfer which is independent to local expenditure amount g_i. The expenditure or public service provided by local government is constrained by the total fiscal revenue, which is the sum of local tax revenue and transfer from the central government.

The utility is framed to be depending on public expenditure, because local governors can signal economic performance to upper-level governments for promotion or evaluation(Li and Zhou, 2005). Tax rate is assumed to be constant here, because the whole country adopts the same tax rate structure except special development zones or poor regions with preferential tax rates. Most types of taxes apply an uniform tax rate, with exceptions for progressive tax rates applied on income taxes.

Solving the above problem using Lagrangian approach, the optimal local investment of locality i and j are:

$$g_i^* = \rho t Y_i + f_i \tag{2.1}$$

This is the static optimal result, meaning that local governments will spend out the available fiscal resource to maximize the public service provision utility. If a dam project brings local revenue impacts (ΔY_i) and external redistribution impacts (Δf_i), the change of local expenditure will be $\Delta g_i = \rho t \Delta Y_i + \Delta f_i$.

2.3.3 Central Government Optimization

Once predicting the optimal decision of local governments, the central government maximizes the weighted sum of utilities from two local governments, subject to the fiscal budget constraint.

$$\begin{aligned} \max_{f_1, f_2} \quad & \alpha U_1(g_1^*) + (1-\alpha) U_2(g_2^*) \\ \text{s.t.} \quad & f_1 + f_2 \leq (1-\rho) t (Y_1 + Y_2) \end{aligned}$$

Here α represents the constant weight that central government puts on locality 1, and $1-\alpha$ is the weight on locality 2. In addition, the central government is restricted by the budget constraint that total transfer should be no more than the tax revenue available to the central government, which is $(1-\rho)$ share of total tax revenue. So $(1-\rho)t(Y_1+Y_2)$ is the tax revenue shared by the central government.

Substituting g_1^* and g_2^* using the local optimization solution of equation (1), the central government's optimization problem can be solved using Lagrangian approach.

$$L = \alpha U_1(g_1^*) + (1-\alpha)U_2(g_2^*) + \lambda[(1-\rho)t(Y_1+Y_2) - f_1 - f_2]$$

FOC:

$$\begin{aligned}\frac{\partial L}{\partial f_1} &= \alpha U_g' g_1^{*\prime} - \lambda = 0\\ \frac{\partial L}{\partial f_2} &= (1-\alpha)U_g' g_2^{*\prime} - \lambda = 0\\ \frac{\partial L}{\partial \lambda} &= (1-\rho)t(Y_1+Y_2) - f_1 - f_2 = 0\end{aligned}$$

If the utility function is assumed as $U(g) = ln(g)$, the optimal transfer amount can be solved as the following.

$$\begin{aligned}f_1^* &= \alpha t(Y_1+Y_2) - \rho t Y_1\\ f_2^* &= (1-\alpha)t(Y_1+Y_2) - \rho t Y_2\end{aligned} \tag{2.2}$$

The optimal governmental expenditure or governmental service to be provided will be solved.

$$\begin{aligned}g_1^* &= \alpha t(Y_1+Y_2)\\ g_2^* &= (1-\alpha)t(Y_1+Y_2)\end{aligned}$$

The result indicates that the optimal governmental public service is a share of the total tax revenues from all localities. The share depends on the decision weight central government putting on local regions. Assume that a dam project brings net benefit ΔY to the country, the model implies that both governments will a proportion of the benefits from the project. However, the benefit proportions will be different for local governments depending on the decision weight and total population.

2.3.4 Propositions

Based on the above optimization results, we can derive three propositions related to the governmental fiscal transfer decision.

Proposition 1: *If local revenue decreases because of the infrastructure project, the transfer will increase. If local revenue increases, the change in transfer is uncertain.*

$$\Delta f_i^* | (Y_i < 0) > 0$$

This proposition can be derived from Equation(2.2) of the optimal transfer results. This proposition indicates that transfers can mitigate the negative revenue impacts.

Proposition 2: *The change in governmental economic performance or public good provision is equivalent to the sum of changes of local tax revenue and total received transfers.*

$$\Delta g_i^* = \rho t \Delta Y_i + \Delta f_i^*$$

Proposition 3: *The change in governmental fiscal resources is equivalent to the decision weight α.*

$$\Delta g_i^* = \alpha t (Y_1 + Y_2)$$

This proposition means that governmental economic performance can reveal information on the relative decision weight of local governments. There have been a lot of researches studying why the central government weigh local regions differently. The potential impacting factors include population of local region, iinequality aversion of the central government(Behrman and Craig, 1987), economic strength of local regions(Huang and Chen 2012 and Shih *et al.*), electoral productivity and partisanship(Castells and Sole-Olle, 2005), other political influence factors such as seats in the Political Bureau (Huang and Chen, 2012), media (Besley and Burgess, 2002) and ethnical composition. However, this paper only reveal the relative decision weights across different locations. The specific mechanisms why a certain region has higher or lower weights will not be verified.

2.3.5 Graphic Interpretation

To interpret the results graphically, the change in local tax revenue and change in intergovernmental transfer of one region can be plotted on a Cartesian Plane as shown in Figure(2.12). If we draw diagonal line passing original point O, it represents the original economic condition without infrastructure projects. Local revenue impacts of dam projects will push the outcome point away from the original point along the horizontal axis. The fiscal redistributive impacts from intergovernmental transfers will push the point away from the horizontal axis. The sum of horizontal and vertical values represents the change in governmental performance (Δg) under the internal and external revenue impacts from an infrastructure. The grey area below the diagonal line represents the worse-off outcomes, meaning that governmental performance is worse than the outcome without dam projects. Area above the diagonal line is the better-off zone for local governments.

If the dam project brings outcomes A and B as shown in Figure (2.12), it indicates that the project decreases the governmental revenue of A and increases the transfer to A, while increasing the governmental revenue of B and decreases the transfer to B. Combining the revenue and redistribution results together, the project is Pareto improving since both A and B are above the diagonal line. Proposition 3 from the theoretical model indicated that the relative location of A and B from the diagonal line may imply the decision weight of each local government, i.e α. The intercept of 45 degree line passing the point represents the governmental performance of that local government. We can call these 45 degree lines iso-wellbeing lines, because any point moving along the line generates the same governmental utility. The further the iso-wellbeing line is away from the diagonal line, the better-off the local government will be, and the higher the decision weight will be for that government.

In the following section, I use empirical data to estimate revenue and redistribution impacts of large dam projects on local governments in China. The estimates will be plotted on the Cartesian Plane to determine whether the dam projects are governmental Pareto improving or not.

2.4 Data and Summary Statistics

2.4.1 Dam and Hydrological data

Dam data was obtained from China Large Dam Management Committee(China ICOLD), covering all dams above 100 meters finished or under construction by 2003. I manually updated the dataset with newer dams based on China ICOLD report in 2008 and annual hydropower reports after 2008(CHINCOLD, 2008). In all, there are 143 dams above 100 meters by 2010. The dataset includes dam characteristics such as the official construction begin and finish year, dam location, reservoir volume, reservoir storage level, hydropower capacity, dam designed purposes and dam height. Dams were manually georeferenced based on the crosscheck of registered administrative location and Google Earth image location. The following analysis focuses on 136 Dams in mainland China[19].

The river stream network and basin information are from USGS Hydro1K dataset, which records detailed information on river streams, including stream length, river gradient, distance to the water head and distance to the water end. Each stream within the dataset is coded by a 6-digit Pfafstetter number, from which the related upstream and downstream streams can be identified[20]. Due to the limitation of Pfafstetter basin coding that it can

[19]The rest 7 dams are in Taiwan.

[20]Each region was codes from large numbers to small numbers following the river flow direction, with odd number representing the interbasin or stem river, and even number representing the sub-stream river. The

only divide a basin into 9 sub basins in maximum, Pfafstetter basins might be inconsistent with empirically reported river basins. So I matched the Pfafstetter basin with real basin division to define the boundaries of basins. There are 25 major basins in China. A lot of the dams are located in Yangtze and Yellow river basins.

2.4.2 Economic Data

The economic and demographic data were reported by National Bureau of Statistics in the Annual County Statistics Yearbook. The annual reports cover 2086 counties from 1996 to 2010, with information in economic, social and demographic perspectives. Main variables include GDP, population, consumption price index, total governmental revenue and total governmental expenditure. Population here refers to the reported population registered in the local county based on the Hukou system in China. So population changes mainly capture changes involving Hukou changes, such as project-induced migrations, job-related migrations, births and deaths in the local region. Typical migrant workers, as rural labor force working in the urban areas, will not be included in the population of their working location, because most of migrant workers still keep their original household registration.

Besides the above economic data, I also use local fiscal information, which were reported by Ministry of Finance annually on *China County-Level Fiscal Statistic Report*. Fiscal data are available from 1994 to 2006. It covers detailed categories of governmental fiscal activities, including local fiscal revenue, fiscal expenditure, and intergovernmental transfer from central government to local government, and transfer from local government to central government. I use net intergovernmental transfer, i.e. the transfer from central to local government minus the transfer from local to central government to represent the net transfer flow from central government to local governments.

specific method to trace the upstream and downstream regions can be found at Furnans & Olivera (2001).

Real economic and fiscal data are calculated at the price level in 2000, by adjusting the nominal values by annual consumption price index of local counties. On average, the population of a county is around 400,000. Mean GDP per person was around 12,000 CNY (around 1,700 US dollars) in 2006 using the 2000 price level. Governmental revenue per person was around 630 CNY and net intergovernmental transfer per person was around 930 CNY in 2006.

2.4.3 Agricultural Data

To explore dam impacts on agriculture production, I use the agricultural production data provided by International Food Policy and Research Institute (IFPRI), covering agricultural yields and cropping areas of three crops (rice, wheat and maize) at county level in China from 1980 to 2000. Yields have increased significantly in the past several decades. The average yield for rice is around 6 tons per hectare. I drop yield and area outliers with value beyond three standard deviation from the annual average value for each county.

2.4.4 Weather Data

Because the operation and function of dams are closely linked to the weather condition in the basin or local region, In order to control other types of weather disasters, I also collect temperature and precipitation data from 1980 to 2010, with temperature records from CRU(Climate Research Unit in University of East Angolia) database and precipitation records from National Centers for Environmental Prediction, NOAA(National Oceanic and Atmospheric Administration). Annual average temperature and precipitation at county level were derived from monthly temperature records at the 0.5*0.5 grid level and monthly precipitation observations at the 2.5*2.5 grid level. The drought index was built based on the deviation of annual precipitation from historical average precipitation. A year was defined as drought year if the annual precipitation in a region is 0.7 standard deviation lower than the historical average.

2.5 Empirical Analysis

I use difference-in-difference approach to estimate the dam impacts, by comparing control and treatment counties before and after the dam construction. Ordinary least square (OLS) estimates will be biased because dam location may be impacted by local economic performance. The central government may distribute dam projects to a rich or poor region for promoting economic development and reducing inequality among regions. Many researchers used the instrument variable (IV) approach to estimate the causal effect of dam projects on different outcome variables, with river gradient as an instrument for geographic variations of dam locations (Duflo and Pande 2007, Strobl and Strobl 2011, Chakravarty 2011, Hansen *et al.* 2009, Lipscomb *et al.* 2011). A possible concern about the IV approach is exclusion restriction violation. River gradient can impact economic performance through other ways besides dam locations. For example, empirical data indicated that river gradient may impact highway and railway construction, since river gradient might be correlated with land steepness. Table(2.13) indicated that both railway and highway constructions are most frequent for environments with medium gradient, which is similar for dam projects(Duflo and Pande 2007).

2.5.1 Difference-in-Difference Approach

I define the control and treatment county groups based on the geographic variations of dam impacts from variations on distance to river and distance to the dam. Control and treatment counties are separately defined in upstream, dam-site and downstream regions. Most of the positive and negative impacts from dam projects rely on the natural water flow directly, such as flood control, irrigational water supply, power generation, navigation and tourism, dam-induced migration and water use restrictions. So regions closer to the river are exposed to more impacts comparing to regions further away.

Treatment counties are defined as counties with geographic centroids located within the 20km neighborhood [21]near the dammed-river. Control counties are defined as counties located next to the treated counties but further away from the river. So the control and treat counties have similar geographic topography such as slope and elevation, weather, ethnical composition, provincial governance, except the only difference in distances to river. Control counties are defined slightly differently in upstream and downstream regions. Because downstream counties are normally flatter and smaller in size than upstream counties in China, upstream control counties are defined in a broader scale than downstream control counties. Upstream and dam-site control counties are counties with centroids located more than 20km but within 100km neighborhood of the river. Downstream control counties are these with centroids located between 20 and 50km away from the river. In addition, based on the inundation and dam construction records of each dam, counties directly involved in the land inundation and displacement records were marked as treatment counties. In this way, each dam has its corresponding upstream control, dam-site control, downstream control and treatment groups.

Besides defining the comparable control and treatment counties, the temporal periods area divided into three categories, before dam construction, during dam construction and after dam being constructed. “Before" periods are defined as two years before the official dam construction begin year, because there are preparatory construction[22] and anticipatory

[21]The average width/length of the county polygons is around 40km. This means that counties with river pass through will most likely be included in the treatment group. Counties close enough to the river, even with the river not directly passing through, will be also included in the treatment group, because they bear impacts from the dams, like water supply by canal network, and dam-related construction activities.

[22]Regulations in China requires that large-scale infrastructures should finish “San Tong Yi Ping" (access to water, electricity, road and land leveling) before the official construction.

economic activities before the official dam construction year. “During" periods are defined as one year before construction and years with actual construction work. “After" periods are defined as years after the official dam construction finish year.

The dam treatment is defined as the dam impacts from the nearest large-scale dam project. Since a county can be subject to the impacts of multiple dams, here I assume the nearest dam matters most for the economic condition of a region. Each treatment county is linked to the nearest dam based on distance between the county and dams along the river. The control counties can be used as multiple controls for different dams. The validity of nearest dam assumption here will be verified using the second closest dam as a sensitivity test in the following analysis.

The main assumption for DID estimation is that control and treatment counties should follow the same trend before dam construction, so that the growth in control and treatment counties would be the same if dams were never built. Table(2.3) plots the trend difference of treatment and control counties in upstream, dam-site and downstream regions. It indicates that treatment and control counties in three regions follow similar trends for most variables before dam construction periods. The smaller pre-trend of dam-site treatment counties on net transfers and the larger pre-trend of upstream treatment counties on precipitation may imply that the DID estimates might be downward biased. The larger pre-trend of upstream treatment counties on transfer is not robust on weather control.

In addition to the homogenous pretrend assumption, there are concerns about the uncertainty of DID estimators from panel data with long time series. Because the treatment status changes very little in the long time series and the dependent variable will be highly serial correlated, the standard error of estimates will be underestimated using typical DID approaches. A potential solution to the problem is to ignore the time series information and collapse data into two periods, before and after the treatment. The regression estimates based on the collapsed data will be unbiased (Bertrand *et al.* 2004, Donald and Lang 2007).

In the result reporting part, I report both the simple DID estimates and DID estimates using collapsed data.

2.5.2 Empirical Approach

In the following section, I use two specifications to estimate the average impacts of dam projects and the temporal heterogeneity of dam impacts for each location group separately.

The regression specification for estimating average impacts of dam impacts is:

$$\begin{aligned} y_{idpt} &= \beta_0 + \beta_1(\mathrm{Up}_i * \mathrm{T}_{id} * \mathrm{P1}_{idt}) + \beta_2(\mathrm{Up}_i * \mathrm{T}_{id} * \mathrm{P2}_{idt}) + \beta_3(\mathrm{Vicinity}_i * \mathrm{T}_{id} * \mathrm{P1}_{idt}) \\ &+ \beta_4(\mathrm{Vicinity}_i * \mathrm{T}_{id} * \mathrm{P2}_{idt}) + \beta_5(\mathrm{T}_{id} * \mathrm{P1}_{idt}) + \beta_6(\mathrm{T}_{id} * \mathrm{P2}_{idt}) + \gamma M_{idt} + \delta X_{it} \\ &+ \rho_t + \lambda_i + \zeta_p t + \epsilon_{idt} \end{aligned} \tag{2.3}$$

where T_{id} is a dummy variable indicating whether i is a treatment or control county for dam d. $\mathrm{P1}_{idt}$ and $\mathrm{P2}_{idt}$ are dummy variables showing whether county i in year t is in the dam construction or operation periods of dam d. Up_i and $\mathrm{Vicinity}_i$ are dummy variables indicating whether i is in the upstream or dam-site region of dam d, the default group is set as "downstream". M_{idt} are the interactions between location and treatment status, and interactions between location and dam periods. $\hat{\beta}_5$ and $\hat{\beta}_6$ are the estimates for average treatment effect(ATE) for downstream counties. $\hat{\beta}_1 + \hat{\beta}_5$ and $\hat{\beta}_2 + \hat{\beta}_6$ are the ATE estimates for upstream counties. $\hat{\beta}_3 + \hat{\beta}_5$ and $\hat{\beta}_4 + \hat{\beta}_6$ are the ATE estimates for dam-site counties. The above specification provides similar results as DID estimates for each location separately.

X_{it} are temperature and precipitation controls for i in province p in year t. The regression includes county fixed effect (λ_i), year fixed effect (ρ_t) and provincial trend ($\zeta_p t$) to capture the impacts of geographic endowment, annual variation and different provincial growth trends on outcome variables. Errors are clustered at dam level to correct correlations among counties linked to the same dam in the same basin, considering that dam operation impacts counties in the basin coherently and the dam construction decision involves basin level integrated planning.

Besides the static estimates of dam effects in the dam construction and operation period, I also estimate the temporal variation of dam effects at different years, using the following specification at upstream, dam-site and downstream regions separately.

$$y_{idpt} = \sum_{t=-8...16} \beta_t \text{treat}_i * \text{Dyear}_{it} + \delta X_{it} + \rho_t + \lambda_i + \zeta_p t + \epsilon_{idt} \tag{2.4}$$

where Dyear is the normalized year relevant to the official dam construction year. The regression included 25 years, ranging from 8 years before dam construction to 16 years after the official dam construction year. The default group is set at 2 years before the official dam construction year. The regression includes year fixed effect, county fixed effects and provincial trend. The errors are clustered at dam level.

2.6 Results

The following section reports the estimates of average dam impacts on governmental revenue, net transfer, economic and agricultural outcomes in upstream, dam-site and downstream regions. The spatial and temporal heterogeneity are also explored. One thing to be noticed is that here Iï¿œm only estimating the impacts of large-scale dams on upstream, dam-site and downstream administrative regions, instead of the actual geographic upstream and downstream regions, considering that a local administrative region may spread across the geographic upstream and downstream areas simultaneously.

2.6.1 Governmental Revenue

Table(2.4) provides the DID estimates for local governmental revenue impacts of large-scale dams from Equation (2.3), with logarithm of per capita governmental revenue as the dependent variable. The first column reports governmental revenue impact estimates using all county samples. The "treat*during" coefficient captures dam construction impacts, and the "treat*after" coefficient captures dam operation impacts. The estimate for upstream construction effect is the linear combination of $\beta_1 + \beta_5$. Similarly. the estimates for upstream operation and dam-site regions are also linear combination results. Column (1) indicates that upstream counties suffer a 16.5% decrease in governmental revenue during operation periods and an 7.5% decrease insignificantly during dam construction periods. Dam-site counties benefit in both dam construction and dam operation periods. But the magnitude of dam operation benefit is much larger than that of dam construction benefit, with revenue increasing by almost 20% in the operation periods. This is consistent with the previous evidence that local counties benefit from increased economic activities in the dam construction periods and increased tax revenue from electricity sell from hydropower generation. Nevertheless, downstream counties show insignificant and negative coefficients in both periods, implying slight economic worse-off results. There are worries that the results might be driven by specific county group, specific dams and provinces. The rest of the table reports various of sensitivity checks. Column (2) reports the results using counties located within 1000km away from the day. Coefficients are almost the same as the full sample results. Column (3) reports the results by dropping top invested dams with investment larger than 20 Billion CNY. It shows that the uneven revenue impacts are not dominated by heavily invested large-scale infrastructure projects. Due to the geographic conditions for dam projects, dams tend to be concentrated in several provinces, such as Sichuan, Hubei and Guizhou. To verify that the estimates are not driven by the changes of governmental revenue in these provinces, Column (4) reports the results by dropping the top 4 provinces with most counties connected to dams. Column (5) is an additional sensitivity check on the estimates by dropping weather controls. It indicates that the main results remain robust. To correct the serial correlation concerns caused by a few treatment status in the long times series, Column (6) reports the results using Duflo and Pande (2007) data collapsing approach, to collapse all periods into three time points (before, during and after) for each county. It shows that the revenue impact estimates for dam-site regions remain robust, while the upstream revenue effects are not significant.

Dam impacts on local governmental revenue show great geographic heterogeneities. Figure(2.5) shows estimates in different distance bins in upstream, dam-site and downstream regions. The closer a county is to a dam, the larger the impacts are. Most of the negative revenue impacts occur in upstream counties located within 200km away from the dam, which is the same for both dam construction and dam operation, with revenue decreased by more than 20%. This region is also the area exposed to direct inundation, migration, social structure disruption and water quality regulations.

In addition to the different impacts from dam construction and dam operation, temporal heterogeneity of dam impacts are analyzed following regression Equation(2.4). Considering that counties within 200km away from the nearest dams are exposed to the largest impacts, Figure(2.6) plots out the annual estimates for dam impacts on governmental revenue in upstream, dam-site. downstream and all three regions, with upstream and downstream counties located within 200km away from the nearest dam. Because there are quite few treatment status changes in a given year, there might be serial correlation concerns for the annual estimates. The negative impacts of upstream region are not quite significant. For the dam-site regions, the positive impacts on governmental revenue begin from the 1 year before the official dam begin year and becoming larger gradually. The largest revenue effect is observed 7-8 years after the dam construction, which is also the beginning period of full dam operation, considering that a dam takes 6-7 years to be built on average. If the analysis is done in all three regions, there are no significant dam impacts on the governmental revenue. but the direction of the estimates are positive.

Both the geographic and temporal heterogeneities of dam impacts imply that dam operation causes much larger uneven impacts than dam construction in both upstream and dam-site regions. This is different from the usual arguments about negative dam impacts in the construction periods on upstream regions. There are several potential reasons. One is that actual inundation only begins a few years before the full operation time, even though population migration may occur in the whole construction periods. Dam construction itself doesn't change the hydrological cycle to upstream regions much, because the river will be diverted to an alternative path. The revenue base in upstream will not be impacted much during most of the construction periods. Another reason might be that dam construction has a lag effect on the governmental revenue, considering that the economic, social and environment disruption may take time to be reflected into economic performances. Even though the migrants are compensated directly for the damages they suffer, the social impacts or other indirect social costs are not compensated.

2.6.2 Intergovernmental Transfer

The second set of results is on the external revenue source of local governments, net intergovernmental transfers. Table (2.5) reports the estimates for changes in per capita net transfer due to dam projects. The general structure is the same as that for governmental revenue. Column (1) reports the estimates using the whole sample. Column (2)-(5) report the estimates using nearby county samples, non-heavily-invested dams, provinces less concentrated with dams, and regression without weather controls. Upstream and dam-site regions receive higher transfers from dam projects. The net transfer into upstream counties increases by 13.6% from construction and less from dam operation. Dam construction and operation increases net transfer into dam-site counties by more than 16.6%. For both the upstream and dam-site transfer effects, dam construction brings a larger transfer effect than operation. This is different from the temporal pattern of local governmental revenue impact, which is larger in dam operation periods. The net transfer to downstream regions shows insignificant deceases in both the operation and construction periods. The results are robust for counties located within 1000km away from the nearest dam, dams with less fixed investment and provinces less concentrated with dams. So dams with large investment bring almost the same transfer increase to dam-site counties, implying that transfers are not fully for dam investments. The transfer increases are not restricted to dam-concentrated provinces.

The transfer impacts also show geographic heterogeneities, as plotted in Figure(2.7). Upstream counties located closer to the dam have an increase in net transfers, especially counties located within 200km away from the nearest dam. For counties located further away in the upstream, the positive transfer effects are smaller. Transfers into downstream counties within 200km away from the day decrease slightly, even though the decrease is not statistically significant. Figure(2.8) plots the temporal heterogeneities of transfer impacts for upstream and downstream counties located within 200km away from the dam, since counties in this distance are subject to larger impacts on transfers. The top-left graph of temporal heterogeneities of dam impacts in the upstream shows similar pattern as the construction and operation estimations. Transfers increase significantly from the official construction year and 6 years after the official construction year. Then the transfer increases become much smaller after 7 years. The top-right graph in Figure(2.8) shows that the transfer into dam-site counties increase slightly but not statistically significant, potentially due to linear correlation among year dummies or the lower pre-trend in treatment counties before the dam construction period. Table(2.3) shows that treatment counties in the dam-site region have a smaller growth rate than dam-site control counties. However, the above estimates result reveal that dam bring a positive transfer effect to dam-site regions. So the negative pre-trend difference in the dam-site region works favoring my estimation. Net transfer in downstream regions are not significantly impacted.

The geographic heterogeneity of dam impacts in different distance bins on governmental revenue and intergovernmental transfer implies that governmental transfers change in the opposite direction of governmental revenues in upstream and downstream regions, verifying the first proposition in the theoretical model. Even though there is no explicit regulations or policies regulating that the net transfers are used to compensate the governmental revenues in the upstream regions, the opposite movement of external net governmental transfer and internal governmental revenues indicates that intergovernmental transfers redistribute some of the uneven impacts of large-scale dams in different regions and balance the revenue sources of local county governments. However, the temporal pattern of transfer impacts in two dam periods are not coherent to the temporal pattern of revenue impacts. Dam construction brings larger transfer effects and smaller revenue effects than dam operation.

2.6.3 Economic Production GDP

Table (2.6) lists the regression results for dam impacts on logarithm of per capita GDP. It indicates that dam projects reduce per capita GDP in the upstream counties with a small decrease during the dam construction period and 6.5% decrease in dam operation period. Downstream regions also experience small decreases in logarithm of per capita GDP. Dam-site regions experience increase in per capita GDP, by around 3% in both dam construction and operation periods. If the county samples are restricted to upstream and downstream counties located within 1000 km away from the nearest dam, as shown in column (2), the negative impacts of downstream regions are not statistically significant any more while the operation negative impacts on upstream counties remain significant at 90% confidence level. Column (3) and column(4) show that the different GDP impacts in upstream, dam-site and downstream regions are not dominated by dams with large investment costs and provinces concentrated with dams. The consistent negative impacts from dam operation reinsure that there might be lagging social impacts caused by the migration and other social costs due to water use restriction to the upstream regions besides the immediate economic impacts from dam-driven migration. Using data collapsing approach to deal with the serial correlation concerns of county GDP, column (6) shows that the estimates for dam-site regions remain robust, while the estimates for upstream regions switch direction, potentially because of the smaller observations in upstream regions reflecting from the larger magnitude of estimates and large standard errors.

The distributive impacts of dam projects on logarithm per capita GDP also shows geographic heterogeneities, as reported in Figure (2.11). Counties located within 200km upstream of the dam suffer from larger GDP losses in the operation period, while counties farther away in the upstream are barely impacted. The impacts of dam projects on downstream regions are more complex. Downstream counties closely nearby (within 200km away from the dam site)benefit from an increase in per capita GDP, while downstream counties farther away (more than 200km) suffer from a drop in per capita GDP. This pattern is consistent with Chakravarty (2011) findings for dam impacts on child mortality for downstream benefits for nearby regions and losses for far downstream counties. Potential reasons for the different impacts to downstream regions are that nearby downstream counties benefit from water supply and irrigation, while further downstream regions may suffer from reduced water because of the water storage in the upstream. Figure(2.10) plots the temporal heterogeneities of GDP impacts of upstream and downstream counties located within 200km away from the nearest dam. The top-left subplot shows similar patterns as Table (2.6). Dam construction brings much larger GDP loss than dam construction.

In 2003, China changed the GDP calculation methods from production/expenditure accounting to a combination of census and production/expenditure accounting. The adjustment was believed to enhance the accounting for small-scale industries and enterprises. Subsample analysis for periods before and after 2003 in Table (2.6) show estimates with similar directions with average estimates.

2.6.4 Pareto Improvement Analysis

According to proposition 2 of the theoretical model, the sum of governmental revenue and intergovernmental transfers represent the overall governmental economic performance. Different from GDP and income as the macroeconomic performance variables, the combination of governmental revenue and transfers emphasizes the governmental performance and the separation of internal and external sources of total fiscal revenue. In the governor promotion social contexts of China, governmental performance can be a strong motivation for governors to make investment decisions and signal their performances. In the following section, I will compare the governmental performance and overall economic performances for Pareto efficiency analysis.

Figure (2.13) and Figure (2.14) plot the estimated changes of local governmental revenue and intergovernmental transfers caused by large-scale dams in upstream, dam-site and downstream regions. Because the above regression specification use logarithm values as the dependent variables, the estimates are interpreted as percentages changes. Multiplying the estimates with mean values of the control counties before dam construction, we can get the value changes of each outcome variables using control counties before dam construction as the benchmark value. Both figures also plot the 95% confidence interval of the value changes.

Figure (2.13) shows that upstream and dam-site counties benefit from dam construction in the perspective of governmental fiscal capacity, while dam construction barely impacts downstream counties. dam-site counties benefit from a 23 CNY increase in local revenue and 52 CNY increase in received transfers per person. Upstream counties suffer from revenue loss amounting around 10 CNY, but receive an increase of transfer amounting around 50 CNY. Figure (2.14) shows that dam-site counties consistently benefit from dam operation. Upstream and downstream counties are close to the diagonal line, with governmental performance similar to the no-dam performance. For upstream counties in the dam operation period, governmental revenue decrease by 22 CNY per person, while the transfer increase in a smaller magnitude than that of dam construction period, at around 25 CNY per person just compensating the revenue loss. So dam projects are generally Pareto improving for different regions. No region get statistically worse off in governmental economic performance. Considering that counties located within 200km away from the dam are subject to the largest impacts, the outcomes for these counties are plotted in Figure (2.15) and Figure (2.16). Both figures imply that nearby counties show similar pattern as that of the whole sample.

The macroeconomic variable GDP result shows similar patterns for dam-site benefits. But upstream and downstream regions suffer from decreases in GDP, even though the effects are not statistically significant, except dam operation for upstream counties. Since total GDP is composed by economic performance of private sector, governmental sector and international trade sector, the difference between overall economic performance and governmental performance results reveals that private sector in the upstream region get slightly worse-off from dam construction. The negative impacts on private sector are not redistributed well through market mechanisms.

Applying proposition 3 of the theoretical model, the Pareto efficiency analysis results indicate that the central government put a higher decision weight on dam-site counties in the utility function for public service provision in face of dam projects. Upstream and downstream regions are barely considered, with the decision weights of both regions close to zero, except upstream counties in the dam construction period. In the whole process of dam construction and dam operation, dam-site counties are highly weighed by the central government. While upstream counties are only weighted in a small magnitude in the dam construction period, potentially due to the attention on migration, inundation and social structure disruption. But the weight becomes much smaller in the dam operation period, even though the negative revenue and GDP impacts are much larger.

2.6.5 Demographic and Agricultural Yields

Involuntary migration and agricultural impacts of dam projects have been widely studied as potential mechanisms leading to economic losses and benefits. Table(2.7) reports the dam impacts on level value of population, logarithm of population, average yield and planting areas of rice.

Total population are not significantly impacted by large-scale dam projects, even though upstream counties show a decrease in total population level value. However, the estimates on logarithm population in upstream counties show opposite direction with that of level values, potentially caused by the fact that dams cause migrations to population in a specific area instead of a proportion of the total population of the county. This results is consistent with involuntary migration in upstream regions. For most counties, dam normally inundates part of the administrative county. The migration policy prioritize local migration to external migration. However, the impacts on per capita governmental revenue reported in the above tables imply that the total upstream revenue decreases considering that population also decreases. The losses might be due to damage to social structure and social capital in the region.

Even though irrigational dam projects was believed to increase the downstream agricultural production significantly in India and Africa (Duflo and Pande 2007, Strobl and Strobl 2011), the analysis on agricultural impacts of hydropower dams in China indicates that upstream counties benefit from an insignificant increase in rice yield, while downstream counties suffer from rice yield drop, with a 5.4% decrease in dam construction period and 7.6% in dam operation period. The main downstream regions suffering from rice yield drop are counties located more than 200km away from the dam site, which is consistent to the negative GDP impacts in these regions. Rice planting areas show similar patterns as rice yields. The decrease of rice yield and area in the downstream regions corresponds to the reduced GDP and revenue found previously in downstream regions. One potential reason is the reduced water flow because of water storage in the upstream areas.

2.6.6 Dam Functions

As mentioned in the background section, dams with different designed functions operate differently. Hydropower dams store water in dry season to fill the reservoir and release water prior the flooding season to save space for flooding water storage. However, irrigational dams need to release water in dry season to downstream region and other agricultural service regions to provide irrigational water. There have been studies found that irrigational dams reduce weather variability in downstream significantly (Hansen *et al.* 2009, Duflo and Pande 2007). In the following section, I separately analyze the revenue and transfer impacts of hydropower and irrigational dams.

Table (2.8) lists the estimates for governmental revenue and transfer separately from two types of dams. An dam is classified as a hydropower or irrigational dam as long as hydropower generation or irrigation is listed as one of the main functions. From the governmental revenue results in column 2 and 3, hydropower dams contribute to more revenue than irrigational dams in dam-site counties, but also bringing more revenue loss to upstream counties. Hydropower dams increase revenue in dam-site counties by 17.2% in the operation period, while irrigational dams almost bring no significant revenue contribution to local dam-site counties. The result verifies that the revenue benefits in dam-site counties are mainly from electricity generation. The differences on revenue impacts are not because of the size or height of dams, because there are no significant differences between the heights of two types of dams, considering that most dams includes both functions as the designed purposes. From intergovernmental transfer results in column 4 and 5, dam functions do not have big impacts on the transfers to local dam-site counties. But upstream counties receive more transfers from hydropower dams than irrigational dams.

2.6.7 Falsification Tests

To verify that the main results I obtained are not because of factors correlated with the way I define the treatment and control groups, or factors correlated with the way to link treat counties to the nearest dam, I run two falsification tests. The first falsification test is to test the validity of dam treatment. I randomly assign treatment status to counties following the proportion of treatment and control counties in the analysis, keeping the linkage of counties and dams as they are. The governmental revenue estimates from this falsification test is reported in column (2) in Panel A of Table (2.10). The estimates for upstream and dam-site counties in both the dam construction and dam operation periods are not significant. The magnitudes of the coefficients are also quite different from the original DID results as in column (1). The intergovernmental transfer outcome from this falsification is reported in column (2) in Panel B of Table (2.10). None of the estimates for upstream and local regions are significant. This convinces us that the original definition of treat and control groups is crucial for the estimate results.

The second falsification test is to test the temporal dependence of the estimate results. Here I randomly assign the dam construction year to each dam, maintaining the dam construction length and linkage between counties and dams. The dam construction begin year is assumed to follow a truncated normal distribution between 1980 and 2010, with the mean and standard deviation the same as the original begin year. So the dam construction period will still be the same length, but with different construction begin year and finish year. This falsification test can verify how strong the result relies on the correct identification of dam construction and dam operation period. The result was listed in column(3) of Table (2.10) for governmental revenue and intergovernmental transfers. The estimates for local and upstream counties are not significant any more for both the governmental revenues and net intergovernmental transfer. However, the pattern of stronger dam operation effects than dam construction effects is observed in this falsification test, because the dam construction and dam operation in the falsification test follow similar orders as the original.

The comparison between the original results and results from two falsification tests indicates that correctly specifying the treatment and control status and dam construction begin year is crucial to estimate the distributive and redistributive impacts of dam projects. The estimates on revenue and transfer impacts are not caused by other variations beyond the treatment status and different periods.

Because there are concerns about using the nearest dam only to estimate the dam impacts on counties, I checked the impacts of second-layer dams, i.e. the second closest dam to a county to see how excluding the second layer or farther dams impacts the dam estimates. The results are listed in Table (2.11). The second layer dams do not impact the net governmental transfer significantly in the upstream and downstream regions. However, the second closest dam still decreases governmental revenue in the dam operation periods to upstream regions significantly. This may imply that the actual economic impacts of counties from dam projects may be underestimated using only the nearest dam.

2.6.8 Discussion

The impact estimates are different from the results obtained by Duflo and Pande (2007) and Strobl and Strobl (2011), where they found positive agricultural benefits to downstream regions from irrigational dams in India and Africa. One potential reason is that the operation scheme of hydropower dams differs from that of irrigational dams, which was illustrated from the comparison of hydropower and irrigational dams in the previous section. For hydropower dams, the primary purpose is power generation, which requires storing water in the dry autumn season and releasing water for water generation. While for irrigational dams, the primary purpose is to provide irrigational water use to the downstream regions, which requires the dam to release water in the dry season. The water storage in dry season for hydropower dams may severe the drought condition in downstream regions, while the irrigation services of irrigational dams can relieve the drought condition in downstream regions. Another possible reason is that the outcome variables are different. I mainly analyze the impacts on governmental revenue and GDP, which include other non-agricultural impacts, such as construction work, tourism and other economic impacts beyond agriculture. Even though dam projects may decrease agricultural production due to water seepage or inundation, they also bring a lot of other economic activities, such as road construction, infrastructure improvement and increasing job opportunities.

2.7 Conclusions

Governments globally encourage infrastructure investment to promote economic development. However, a lot of the infrastructure projects may bring unevenly distributed impacts to different locations, with large-scale dams as one example. Dam projects have been controversial for the benefits on power generation, flood control and irrigation, and damages from environmental and social impacts of inundation and hydrological change. The benefits and damages are distributed geographically unevenly among different regions, depending on the location along a river. Are the negative impact caused by dam projects mitigated by the market and governmental mechanisms? Are the dam projects Pareto improving? This paper answers these questions in China, since more than half of the large-scale dam projects are located in China. The central decision making process of dam projects in China also makes it meaningful to answer these questions for policy perspectives.

Using variations of dam impacts from the distances to the dam and distances to the river, this paper adopts DID approach to estimate the dam impacts on fiscal, economic and agricultural outcomes. The governmental economic performance is evaluated for Pareto efficiency analysis, by separating the external and internal revenue sources of local county governments. Overall, large-dam projects are Pareto improving in the perspective of governmental economic performance, with no region getting significantly worse off. dam-site dam-site counties capture most of the economic benefits. Revenue losses in the upstream counties are mitigated by intergovernmental transfers, even though the transfer amounts are different in dam construction and operation periods.

Dam projects increase per capita governmental revenue to dam-site dam-site counties, with an average 13% increase during dam construction period and 20% increase during dam operation period from a dam above 100 meters. Upstream counties suffer a 16.5% decrease in per capita governmental revenue during dam operation period, while downstream counties are not significantly impacted, potentially due to the confronting impacts from flood control benefits and reduced water flow. Generally, dam operation brings larger distributive impacts than dam construction. The external intergovernmental transfers mitigate the negative revenue impacts sufficiently. Upstream counties receive an increase in transfers, with a 13.6% increase during dam construction period and a 6.7% increase during dam operation period. dam-site dam-site counties also receive more transfers, with an increase by more than 16% in both periods. Transfers to the downstream regions were not significantly observed. Unlike the large tax revenue impacts in dam operation periods, the redistributive transfers show a larger response to dam projects in dam construction period. The above results are not driven by top invested dams and big provinces. The main results are robust even when correcting the serial correlation concerns caused by too few treatment status in DID analysis with long time series.

Dam impact estimates show geographic and temporal heterogeneities, depending on the distance of a county to the dam. Counties which are located within 200km away from the dam-site are impacts more significantly than these further away. This confirms that the economic impacts on economic and fiscal performances in counties are associated with dam functions of power generation and reservoir storage. For other outcome variables beyonds governmental economic indicators, the estimates on logarithm population are not significant, potentially because the migration policy in China prioritize local resettlement. Rice yields in downstream regions are negatively impacted, potentially due to reduced water flow. Counies further downstream suffer a larger rice yield loss. These results are not consistent with the downstream agricultural benefits from irrigational dams observed by Duflo and Pande (2007) and Strobl and Strobl (2011). The reason may be due to the different design functions of dams. Hydropower dams tend to generate a larger uneven impacts across different regions, because of their special operation scheme to store water in the dry season.

By combining the fiscal distributive and redistributive impacts of dam projects, this paper provides an empirical approach to analyze the Pareto efficiency in the perspective of governmental economic performances in China. Even though estimates for GDP per capita also shows similar directions as the combination results of revenue and redistributive transfer outcomes, the separation of internal and external revenue sources provide a clearer view of the governmental redistributive mechanism in face of uneven impacts. It can shed some light on the policy implications on hydropower dam investment and intergovernmental redistribution decision making in China.

Tables and Figures

Table 2.1: Dam Construction History in China

		(≥100m)		Large Dams(≥30m)
Year	N	new dams per year	N	new dams per year
1973	21		1644	
1988	42	1.31	3768	132.75
2005	129	4.83	4839	59.5
2008	142	3.25	5191	88

Table 2.2: Descriptive Statistics of Upstream Areas in the Pre-dam Construction Period

		Up			Dam-site			Down		
Variable	Unit	Control	Treat	Diff	Control	Treat	Diff	Control	Treat	Diff
pop	10000	43.7	33.8	-10.0***	42.7	38.7	-4.03	53.9	55.7	1.8
GDP	Yuan/person	2909	3645	736*	3655	3566	-89.12	4312	5135	823***
GDP growth rate	%	0.1	0.1	-0.02+	0.1	0.1	-0.004	0.1	0.1	-0.006
yield(rice)	t/ha	5.2	5.1	-0.07	5.2	5.2	-0.03	5.6	5.7	0.078+
yield(wheat)	t/ha	2.1	2.2	0.05	2.0	2.1	0.10*	2.3	2.6	0.29***
yield(maize)	t/ha	3.3	3.2	-0.04	3.1	3.2	0.001	3.3	3.4	0.10*
rice area ratio	%	0.4	0.3	-0.006	0.4	0.4	-0.025+	0.5	0.5	-0.02**
temp	C degree	11.0	8.7	-2.31***	13.4	12.4	-1.03***	13.8	13.2	-0.57***
precip	mm/day	2.5	2.5	-0.06*	3.1	3.0	-0.14***	3.3	3.0	-0.23***
pc tax revenue	Yuan/person	131	201	70**	181	173	-8.04	163	189	26***
pc gov expenditure	Yuan/person	691	786	95	575	491	-84.31*	335	381	46*
pc transfer	Yuan/person	368	524	156***	281	249	-32	202	176	-26
lnpcgdp		7.8	7.9	0.09*	8.0	8.0	0.01	8.2	8.3	0.1***
lnpop		3.3	2.6	-0.71***	3.5	3.4	-0.09	3.7	3.8	0.05
lnpcgov revenue		4.7	4.8	0.17**	4.8	4.9	0.11	4.9	5.0	0.11**
lnpc transfer		5.3	5.7	0.4***	5.3	5.2	-0.1	4.8	4.7	-0.069
slope	0.01 Degree	362	424	62*	482	547	65	252	230	-23
dem	m	1479	1873	393.8**	1294	1420	125	535	507	-28
river flow		604	2693	2089**	1579	2763	1185	1124	7229	6104***

Notes: Diff is the difference between outcomes in the treatment and control counties. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2.3: Homogenous Trend Test Before Dam Construction

	Upstream	Dam-site	Downstream
pop	-0.01	0.11	-0.19
GDP	-31.92	21.03	8.17
GDP growth rate	0.011	-0.001	0.004
yield(rice)	0.001	-0.003	-0.005
yield(wheat)	-0.01	0.01	0.006
yield(maize)	-0.01	-0.02	-0.005
area(rice)	-28.57	-72.84+	49.07
area(wheat)	-20.58	-18.99	-95.05**
area(maize)	8.06	-35.27	-99.36
rice area ratio	-0.0003	0.00008	0.001+
temperature	-0.005	-0.002	0.003
precipitation	0.007*	0.002	0.00008
gov revenue	-4.76	3.13	2.88
gov expenditure	58.41	-5.19	-5.90
transfer	82.29+	-13.14*	-0.23

Notes: Economic variables of GDP, governmental revenue, governmental expenditure, transfer are in per capita terms. Coefficients are β estimates from $y_{ipt} = \beta \text{treat}_i * \text{year}_t + \alpha_p * \text{year}_t + \gamma_i + \rho_t + \epsilon_{ipt}$ for all upstream, dam-site and downstream regions separately two years before the official dam construction begin year. Standard errors were clustered at dam level. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.4: Impact of Dams on Governmental Revenue

Dependent Variable: Log per capita Governmental Revenue						
	(1) DID	(2) ≤1000km	(3) drop top invested dams	(4) drop top 4 provinces	(5)	(6) collapse
UP*treat*during	-0.075	0.006	-0.032	-0.164	-0.074	0.007
	(0.078)	(0.111)	(0.078)	(0.109)	(0.078)	(0.099)
UP*treat*after	-0.165+	-0.127	-0.093	-0.249*	-0.165+	0.039
	(0.089)	(0.122)	(0.093)	(0.118)	(0.089)	(0.133)
Dam-site*treat*during	0.129+	0.128+	0.137+	0.160*	0.129+	0.174*
	(0.074)	(0.075)	(0.078)	(0.077)	(0.075)	(0.084)
Dam-site*treat*after	0.199*	0.194*	0.218*	0.260*	0.199*	0.200+
	(0.084)	(0.085)	(0.087)	(0.098)	(0.084)	(0.111)
DOWN*treat*during	-0.044	-0.025	-0.047	-0.045	-0.044	-0.055
	(0.036)	(0.050)	(0.032)	(0.049)	(0.037)	(0.068)
DOWN*treat*after	-0.069	-0.031	-0.047	-0.129*	-0.070	-0.120
	(0.060)	(0.073)	(0.065)	(0.063)	(0.060)	(0.127)
N	13863	11526	10556	8912	13863	2245
Weather Controls	Y	Y	Y	Y	N	-
CFE	Y	Y	Y	Y	Y	Y
YFE	Y	Y	Y	Y	Y	-
Trend	province	province	province	province	province	-
Error Clustering	Dam	Dam	Dam	Dam	Dam	Dam

Notes: The coefficients of upstream and dam-site regions are the linear combination results from regressions with downstream set as the default group. Column (2) reports estimates for counties located within 1,000 km away from the dam.Column (3) reports the estimates dropping dams with investment larger than 20 Billion CNY. Column (4) reports estimates dropping the top 4 provinces (Sichuan, Hubei, Guizhou, Shaanxi) with counties linked to dams. Column (5) reports the estimates without weather controls. Column (6) reports estimates from collapsed data following BDM(2004) approach. Weather controls include annual average precipitation and temperature. All regressions include county fixed effects and year fixed effects. Standard errors clustered at dam level in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.5: Impact of Dams on Intergovernmental Transfers

Dependent Variable: Log per capita Net Transfer						
	(1)	(2)	(3)	(4)	(5)	(6)
	DID	≤1000km	drop top invested dams	drop top 4 provinces		collapse
UP*treat*during	0.136**	0.124*	0.126+	0.159*	0.125*	0.338
	(0.051)	(0.057)	(0.073)	(0.068)	(0.051)	(0.248)
UP*treat*after	0.067	0.095	-0.076	0.0002	0.058	0.373
	(0.093)	(0.098)	(0.072)	(0.080)	(0.094)	(0.244)
Dam-site*treat*during	0.185**	0.180**	0.199**	0.200***	0.183**	0.153
	(0.059)	(0.058)	(0.065)	(0.057)	(0.059)	(0.107)
Dam-site*treat*after	0.166+	0.165+	0.158	0.164+	0.167+	0.166
	(0.092)	(0.090)	(0.098)	(0.095)	(0.094)	(0.148)
DOWN*treat*during	0.007	-0.023	0.022	0.006	0.008	0.032
	(0.054)	(0.059)	(0.051)	(0.069)	(0.053)	(0.084)
DOWN*treat*after	0.007	-0.027	0.071	-0.037	0.010	0.211
	(0.072)	(0.080)	(0.069)	(0.073)	(0.071)	(0.177)
N	9688	8067	7468	6158	9688	1947
Weather Controls	Y	Y	Y	Y	N	-
CFE	Y	Y	Y	Y	Y	Y
YFE	Y	Y	Y	Y	Y	-
Province Trend	province	province	province	province	province	-
Error Clustering	Dam	Dam	Dam	Dam	Dam	Dam

Notes: The coefficients of upstream and dam-site regions are the linear combination results from regressions with downstream set as the default group. Column (2) reports estimates for counties located within 1,000 km away from the dam.Column (3) reports the estimates dropping dams with investment larger than 20 Billion CNY. Column (4) reports estimates dropping the top 4 provinces (Sichuan, Hubei, Guizhou, Shaanxi) with counties linked to dams. Column (5) reports the estimates without weather controls. Column (6) reports estimates from collapsed data following BDM(2004) approach. Weather controls include annual average precipitation and temperature. All regressions include county fixed effects and year fixed effects. Standard errors clustered at dam level in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.6: Impact of Dams on GDP

Dependent Variable: Log per capita GDP								
	(1) DID	(2) ≤1000km	(3) drop top invested dams	(4) drop top 4 provinces	(5)	(6) before 2003	(7) after 2003	(8) collapse
UP*treat*during	-0.035	-0.023	-0.032	-0.015	-0.039	-0.024	-0.042	0.192+
	(0.027)	(0.032)	(0.035)	(0.035)	(0.028)	(0.024)	(0.028)	(0.106)
UP*treat*after	-0.065*	-0.077+	-0.047	-0.042	-0.069*	-0.042	-0.008	0.226*
	(0.032)	(0.039)	(0.042)	(0.039)	(0.032)	(0.032)	(0.043)	(0.095)
LOCAL*treat*during	0.038	0.039	0.042	0.039	0.037	0.005	0.103+	0.053
	(0.046)	(0.046)	(0.049)	(0.042)	(0.046)	(0.032)	(0.058)	(0.052)
LOCAL*treat*after	0.033	0.035	0.035	0.077	0.033	0.019	0.109+	0.044
	(0.054)	(0.055)	(0.056)	(0.060)	(0.054)	(0.034)	(0.065)	(0.069)
DOWN*treat*during	-0.040+	-0.011	-0.042+	-0.030	-0.041+	-0.029+	-0.018	-0.033
	(0.022)	(0.032)	(0.021)	(0.032)	(0.022)	(0.015)	(0.024)	(0.045)
DOWN*treat*after	-0.068**	-0.037	-0.066*	-0.051	-0.068**	-0.036	-0.058*	0.033
	(0.025)	(0.034)	(0.028)	(0.033)	(0.025)	(0.026)	(0.028)	(0.069)
N	12319	10234	9380	7937	12319	5743	5108	2124
Weather Controls	Y	Y	Y	Y	N	Y	Y	-
CFE	Y	Y	Y	Y	Y	Y	Y	Y
YFE	Y	Y	Y	Y	Y	Y	Y	-
Trend	province	province	province	province	province	province	province	-
Error Clustering	Dam	Dam	Dam	Dam	Dam	Dam	Dam	Dam

Notes: The coefficients of upstream and dam-site regions are the linear combination results from regressions with downstream set as the default group. Column (2) reports estimates for counties located within 1,000 km away from the dam.Column (3) reports the estimates dropping dams with investment larger than 20 Billion CNY. Column (4) reports estimates dropping the top 4 provinces (Sichuan, Hubei, Guizhou, Shaanxi) with counties linked to dams. Column (5) reports the estimates without weather controls. Column (6) reports estimates before the 2000 GDP classification adjustment. Column (7) reports estimates after 2000 GDP classification adjustment. Column (8) reports estimates from collapsed data following BDM(2004) approach. Weather controls include annual average precipitation and temperature. All regressions include county fixed effects and year fixed effects. Standard errors clustered at dam level in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.7: Impacts of Dams on Demographic and Agricultural Variables

	pop	lnpop	yield rice	area rice
		Dam Construction(during)		
Upstream	-1.173+	0.012	0.027	0.023
	(0.671)	(0.012)	(0.038)	(0.123)
Dam-site	2.370	0.028	-0.014	-0.051
	(2.684)	(0.028)	(0.034)	(0.070)
Downstream	0.026	-0.003	-0.054**	-0.136
	(0.540)	(0.011)	(0.020)	(0.097)
		Dam Operation(after)		
Upstream	-1.286	0.003	0.055	0.125
	(0.797)	(0.012)	(0.044)	(0.143)
Dam-site	2.144	0.022	-0.021	-0.048
	(2.689)	(0.028)	(0.038)	(0.093)
Downstream	-0.405	-0.008	-0.076***	-0.118
	(0.862)	(0.018)	(0.018)	(0.078)
N	13931	13931	13833	13539

Notes: Each column is a separate regression for the dependent variable. Upstream and dam-site coefficients are the linear combination from the regression with downstream set as the default location group. All regressions include precipitation and temperature controls, year fixed effects, county fixed effects and provincial trend. Standard errors clustered at dam level in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.8: Impacts of Dams With Different Design Functions

	Gov. Revenue		Transfer	
	Hydropower	Irrigation	Hydropower	Irrigation
UP*treat*during	-0.132	0.024	0.129*	0.068
	(0.094)	(0.081)	(0.057)	(0.063)
UP*treat*after	-0.235*	-0.111	0.057	0.003
	(0.095)	(0.086)	(0.095)	(0.124)
Dam-site*treat*during	0.095	0.027	0.176**	0.193
	(0.076)	(0.132)	(0.060)	(0.115)
Dam-site*treat*after	0.173+	0.039	0.163+	0.163
	(0.087)	(0.159)	(0.093)	(0.161)
DOWN*treat*during	-0.020	-0.005	-0.031	0.015
	(0.039)	(0.057)	(0.056)	(0.054)
DOWN*treat*after	-0.038	0.002	-0.027	0.017
	(0.062)	(0.088)	(0.074)	(0.084)
N	12096	8229	8473	5673
Weather Controls	Y	Y	Y	Y
CFE	Y	Y	Y	Y
YFE	Y	Y	Y	Y
Province Trend	province	province	province	province
Error Clustering	Dam	Dam	Dam	Dam

Notes: Each column is a separate regression for the dependent variable using subsample counties which are linked to dams with one function or another. Hydropower dams are dams with hydropower generation listed as one of the functions. Irrigation dams are dams with irrigation listed as one of the functions. Upstream and dam-site coefficients are the linear combination from the regression with downstream set as the default location group. All regressions include precipitation and temperature controls, year fixed effects, county fixed effects and provincial trend. Standard errors clustered at dam level in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.9: Impacts of Dams of River Flow

	(1) flow January	(2) flow August
UP*treat*during	7.889*	0.917
	(3.251)	(0.998)
UP*treat*after	10.684**	-12.463***
	(3.873)	(2.102)
Dam-site*treat*during	-14.886	0.382
	(12.826)	(2.445)
Dam-site*treat*after	-14.726	-2.054
	(12.310)	(2.882)
DOWN*treat*during	-0.345	-1.791
	(0.957)	(1.477)
DOWN*treat*after	-2.526	-5.608+
	(2.555)	(3.185)
N	2817	1689

Notes: Hydropower dams are dams with hydropower generation listed as one of the functions. Irrigation dams are dams with irrigation listed as one of the functions. Upstream and dam-site coefficients are the linear combination from the regression with downstream set as the default location group. All regressions include precipitation and temperature controls, year fixed effects, county fixed effects and provincial trend. Standard errors clustered at dam level in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.10: Falsification Test of the DID results

	(1)	(2)	(3)
	original	randomize treatment county	randomize dam begin-year
Panel A: Log per capita Governmental Revenue			
UP*treat*during	-0.075	0.039	-0.107**
	(0.078)	(0.059)	(0.033)
UP*treat*after	-0.165+	-0.001	-0.180*
	(0.089)	(0.064)	(0.087)
Dam-site*treat*during	0.129+	-0.014	0.060
	(0.074)	(0.101)	(0.075)
Dam-site*treat*after	0.199*	-0.087	0.133
	(0.084)	(0.099)	(0.092)
DOWN*treat*during	-0.044	0.023	-0.005
	(0.036)	(0.029)	(0.046)
DOWN*treat*after	-0.069	0.024	-0.078
	(0.060)	(0.043)	(0.058)
N	13863	13863	13863
Panel B: Log per capita Net Transfers			
UP*treat*during	0.136**	-0.180***	0.018
	(0.051)	(0.047)	(0.066)
UP*treat*after	0.067	-0.046	0.109
	(0.093)	(0.068)	(0.090)
Dam-site*treat*during	0.185**	0.012	0.063
	(0.059)	(0.068)	(0.090)
Dam-site*treat*after	0.166+	0.093	0.105
	(0.092)	(0.100)	(0.108)
DOWN*treat*during	0.007	-0.036	-0.025
	(0.054)	(0.062)	(0.069)
DOWN*treat*after	0.007	-0.066	0.017
	(0.072)	(0.074)	(0.092)
N	9688	9688	9688

Notes: Each column is a separate regression for the dependent variable. Upstream and dam-site coefficients are the linear combination from the regression with downstream set as the default location group. Column (1) reports the original results. Column (2) reports the coefficients when the treatment status of each county were randomly assigned at probability 0.5. Column (3) reports the coefficients when the official dam construction year were randomly assigned following a truncated normal distribution, with the mean, standard deviation, lower and upper bounds set at the original level. All regressions include precipitation and temperature controls, year fixed effects, county fixed effects and provincial trend. Standard errors clustered at dam level in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.11: Impacts of Second Nearest Dams

	(1) GDP	(2) Gov. Rev	(3) Net Transfer	(4) Population
UP*treat*during	0.024	0.150	-0.067	-0.018*
	(0.036)	(0.102)	(0.042)	(0.006)
UP*treat*after	-0.067*	-0.143+	-0.068	-0.018*
	(0.030)	(0.076)	(0.108)	(0.006)
DOWN*treat*during	-0.017	0.074	-0.079	-0.003
	(0.031)	(0.080)	(0.047)	(0.010)
DOWN*treat*after	-0.058	-0.027	0.057	-0.014
	(0.034)	(0.087)	(0.084)	(0.022)
N	8440	9530	6753	9563
Weather Controls	Y	Y	Y	Y
CFE	Y	Y	Y	Y
YFE	Y	Y	Y	Y
Province Trend	Y	Y	Y	Y

Notes: The outcome variables are logarithm per capita GDP, logarithm per capita governmental revenue, logarithm per capita net transfer and logarithm population in each column. Here counties are matched to the second nearest dam. Downstream counties are included as default group in the regression. The coefficients reported here are the linear combination results for the specific location with downstream region. All regressions include precipitation and temperature controls, year fixed effects, county fixed effects and provincial trend. Standard errors clustered at river basin level in parentheses. Upstream and downstream samples here were restricted to these located within 1000 km away from the dam. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$.

Table 2.12: River Gradient With Railway and Highway Length

	(1) lnrail	(2) railway	(4) lnhighway	(3) highway
grad (0-1.5%)	0.00149**	0.000416*	0.00173+	0.0113+
	(0.000530)	(0.000156)	(0.000909)	(0.00591)
$\text{grad}_(1.5 - 3\%)$	0.0138	-0.000523	0.0495**	0.499***
	(0.0116)	(0.00288)	(0.0153)	(0.120)
$\text{grad}_(3 - 6\%)$	0.0806***	0.0156***	0.0227	-0.235
	(0.0187)	(0.00397)	(0.0229)	(0.174)
$\text{grad}_(> 6\%)$	-0.0480*	-0.0133*	-0.249***	-2.345***
	(0.0229)	(0.00634)	(0.0198)	(0.152)
constant	-1.855***	0.187***	1.873***	9.542***
	(0.203)	(0.0373)	(0.270)	(1.782)
N	31	31	31	31
F	10.91	10.40	416.2	161.0

Notes: The outcome variables are logarithm and level value of railway and highway lengths for each column. Each gradient category explanatory is the percentage of land in that category. The analysis was done for provinces of China in 2010. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$.

Table 2.13: Spatial Patterns for Residuals

	(1) lnpcgdp	(2) lnpcgov rev	(3) lnpcnet transfer
Upstream	-0.0106	-0.0135	0.00312
	(0.0111)	(0.0228)	(0.0183)
Local	-0.000101	-0.0417	0.0343
	(0.0130)	(0.0268)	(0.0213)
lon	-0.00158	0.00218	-0.00413**
	(0.000832)	(0.00171)	(0.00136)
lat	-0.00228*	-0.000670	-0.00262
	(0.000970)	(0.00200)	(0.00159)
N	952	952	922
F	2.500	1.417	10.25
df_m	6	6	6
df_r	945	945	915

Notes: The outcome variables are residuals in 2000 from regressions in the first columns of table 2.4 to table 2.6 for three different dependent variables. Similar results are got using residuals in other years. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, ***$p < 0.001$.

Figure 2.1: Map of Dams Above 100 meters in China Finished or Under Construction by 2010

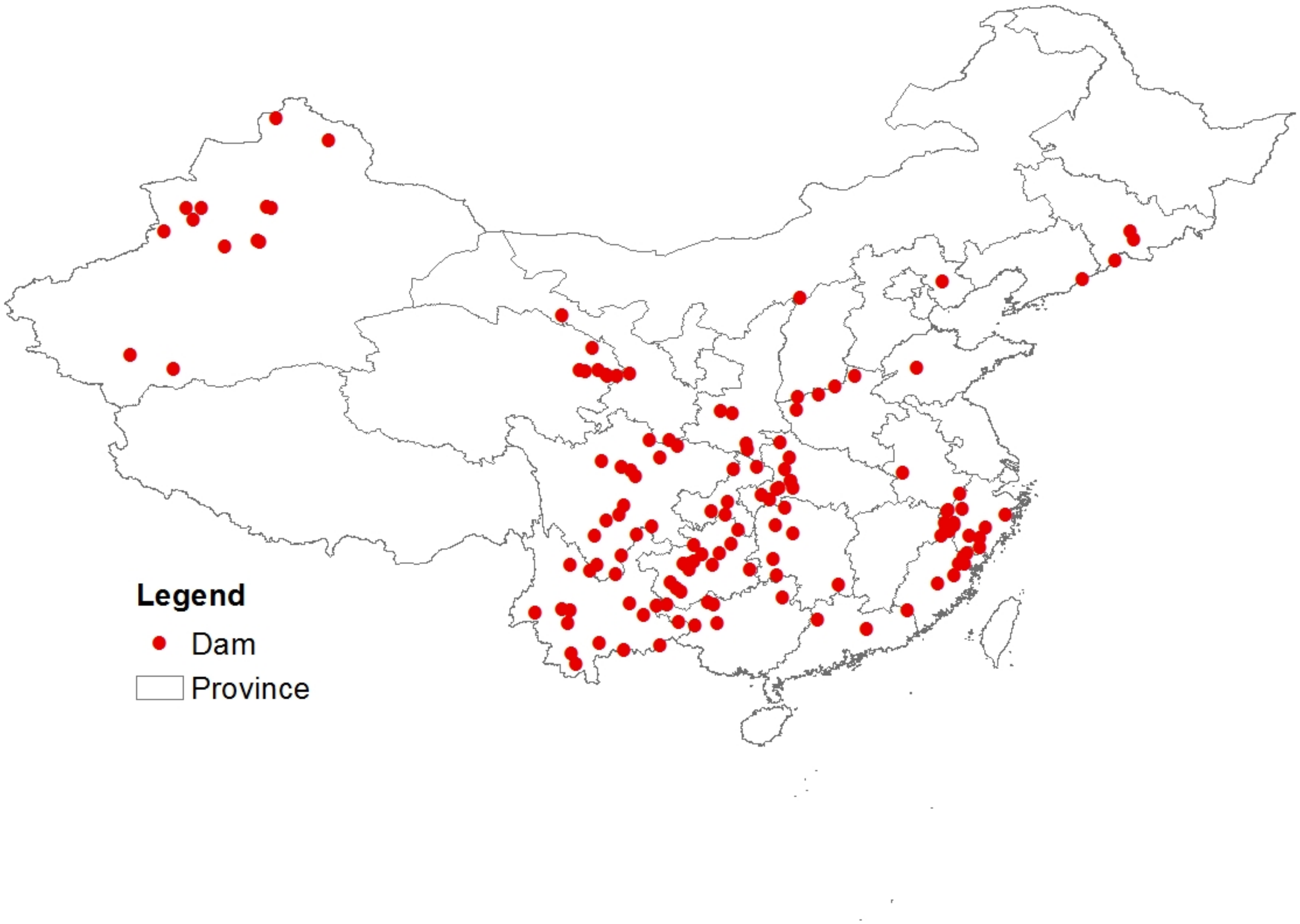
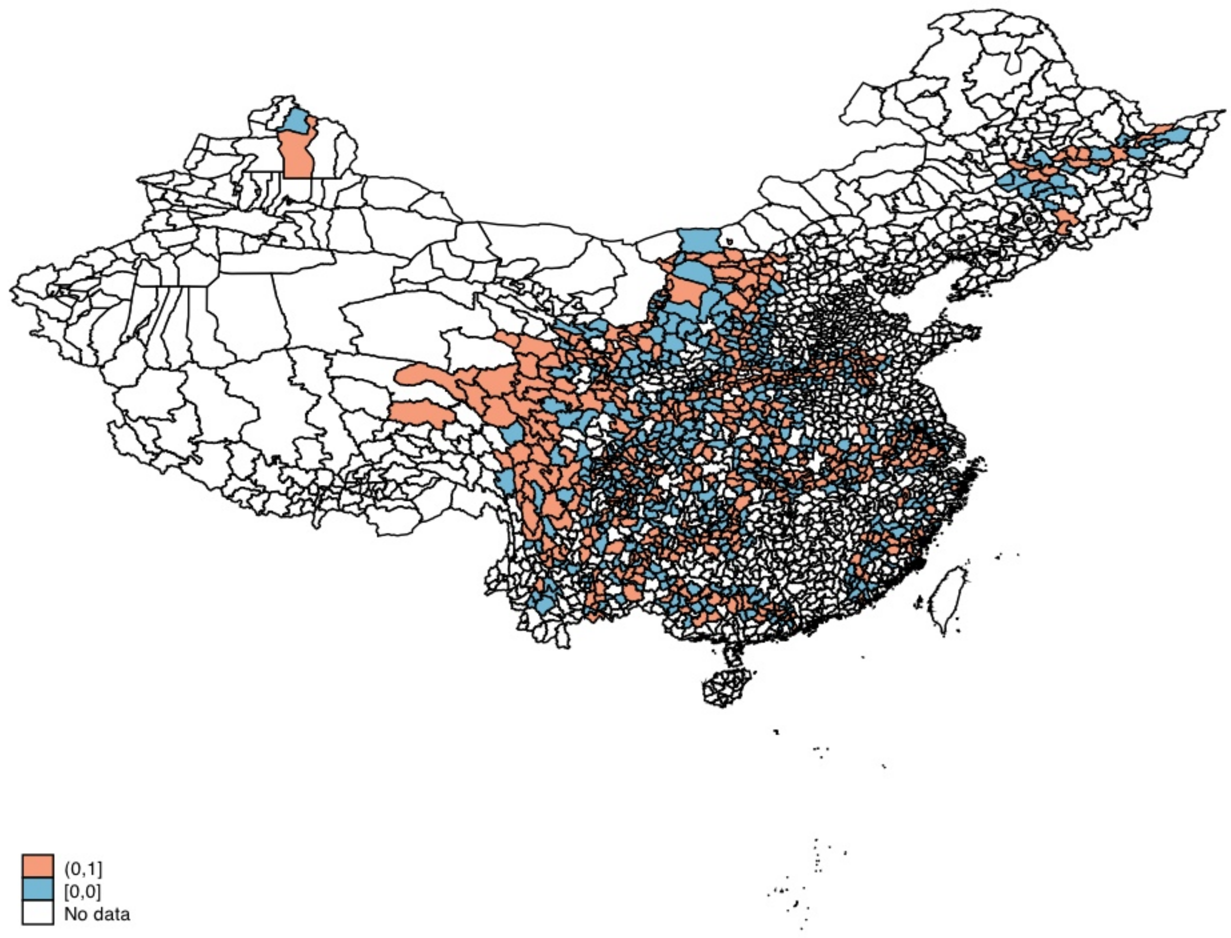
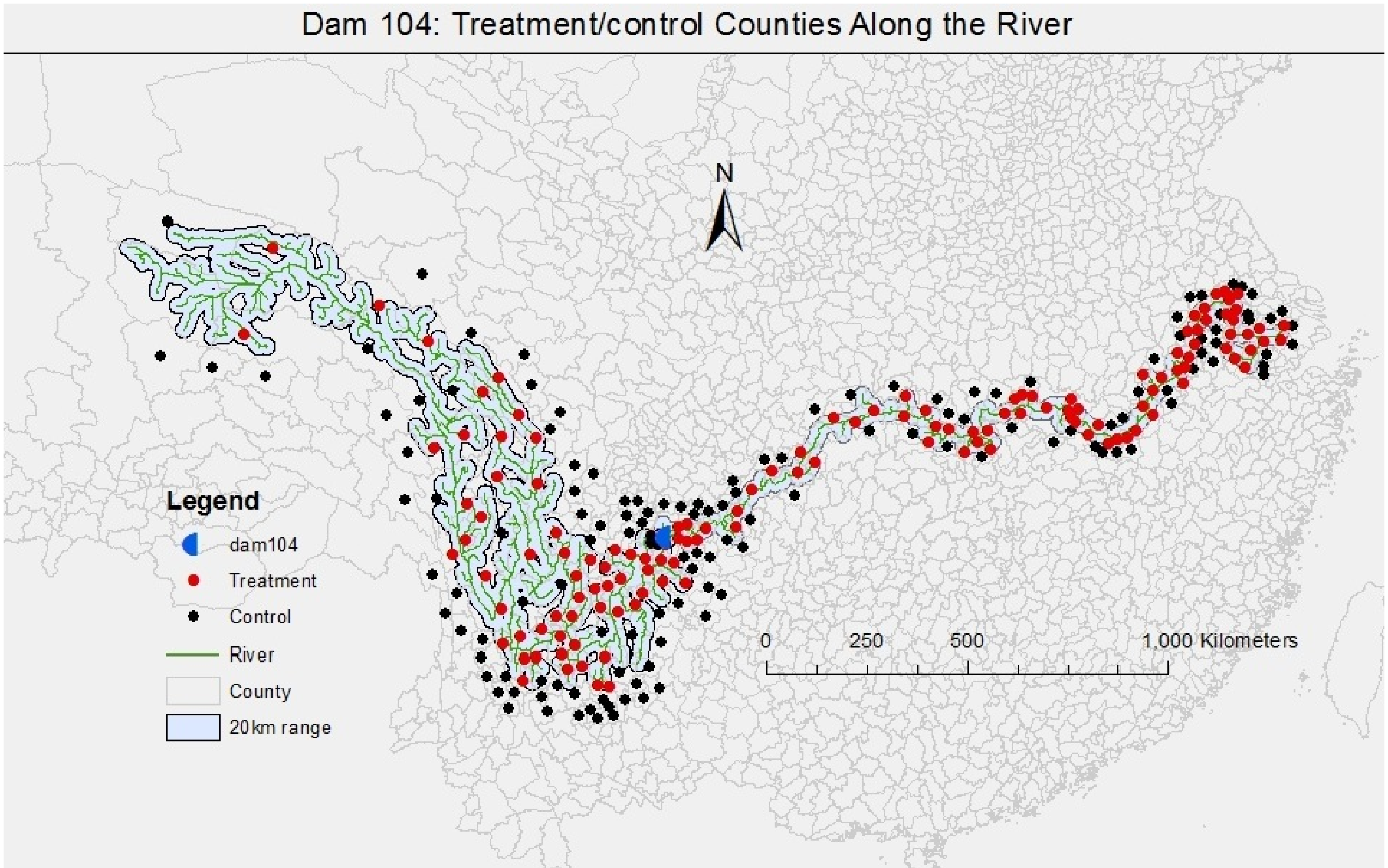


Figure 2.2: Map of Identified Treatment and Control Counties



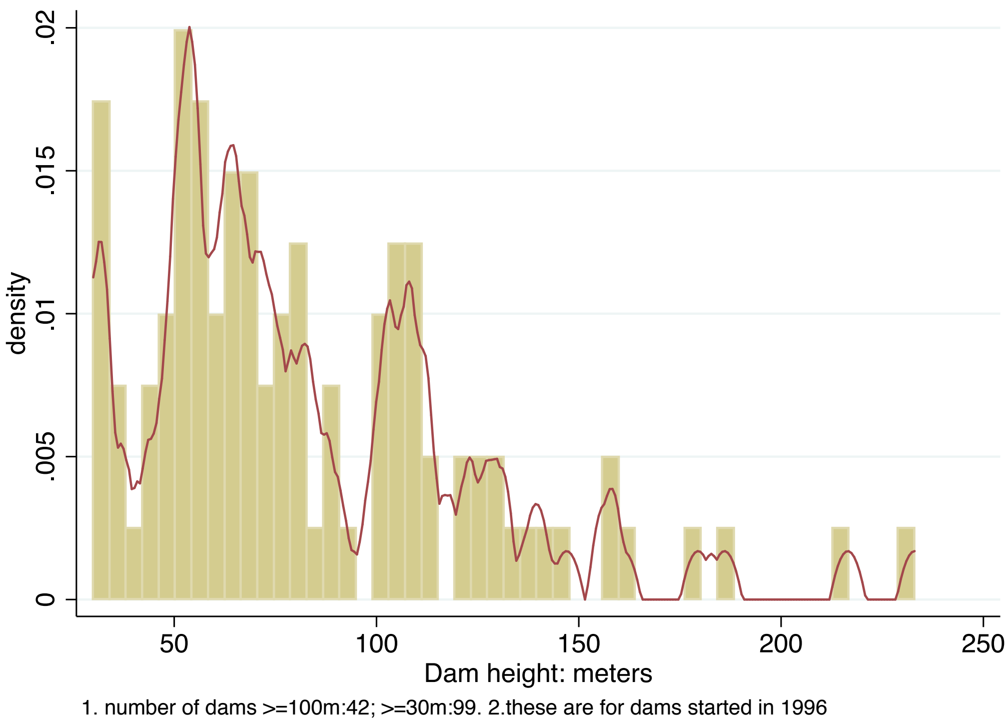
Notes: The orange polygons are treatment counties. The blue polygons are control counties.

Figure 2.3: Illustration of Treatment and Control County Identification



Notes: This figure illustrates how the treatment and control counties are identified using Dam 104 (Xiangjia Ba Dam) as an example. Black dots are control counties. Red dots are treatment counties. Treatment counties are defined as counties with centroids located within 20km away from the river. Upstream control counties are defined as counties with centroids located between 20 and 100km away from the river. Downstream control counties are those with centroids located between 20 and 50km away from the river.

Figure 2.4: Distribution for All Dams (with construction starting from 1996) Above 30 Meters in China by 2010



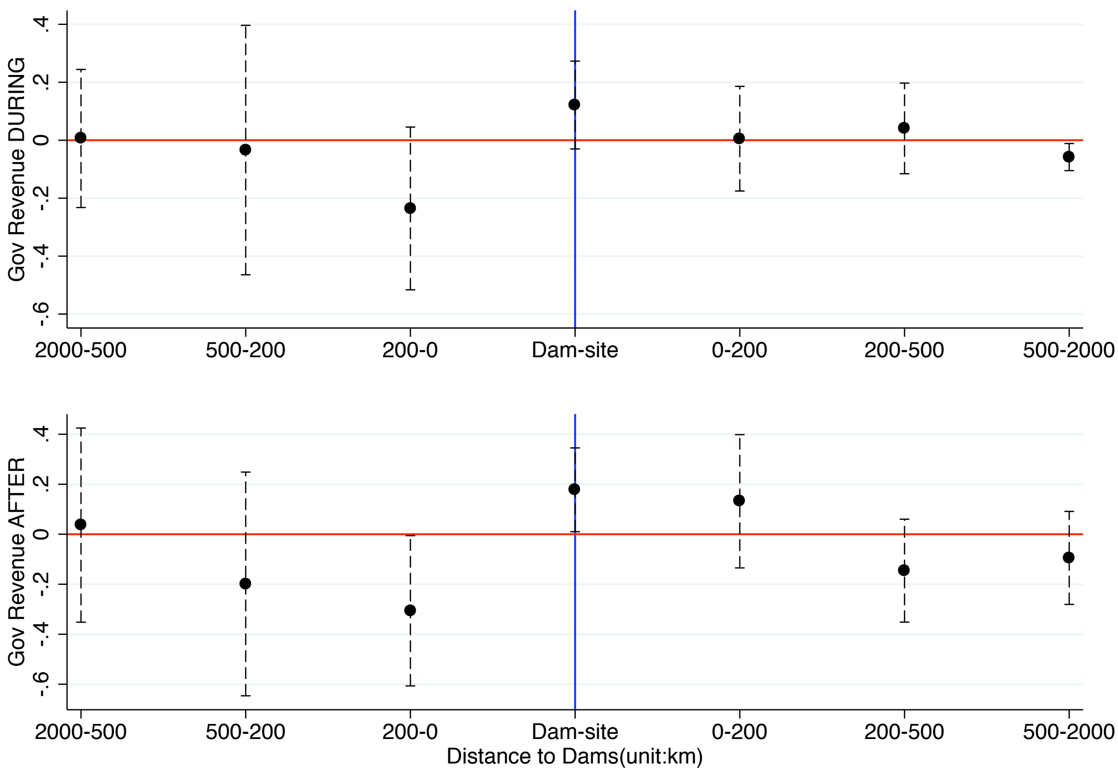


Figure 2.5: Estimates for Dam Impacts at Various Distance Bins for Governmental Revenue

Notes: The dependent variable is logarithm of per capita governmental revenue. The graph plots out the DID estimates and the 95% confidence interval for governmental revenue at each distance bin. The bins in the left of the "dam-site" regions are upstream counties, while bins in the right of the "dam-site" regions are downstream areas. The top plot reports the estimation results in dam construction periods. The bottom plot reports the estimation results in dam operation periods. The regression model in each distance bin includes provincial year trend, year fixed effects and county fixed effects, with error clustered at dam level.

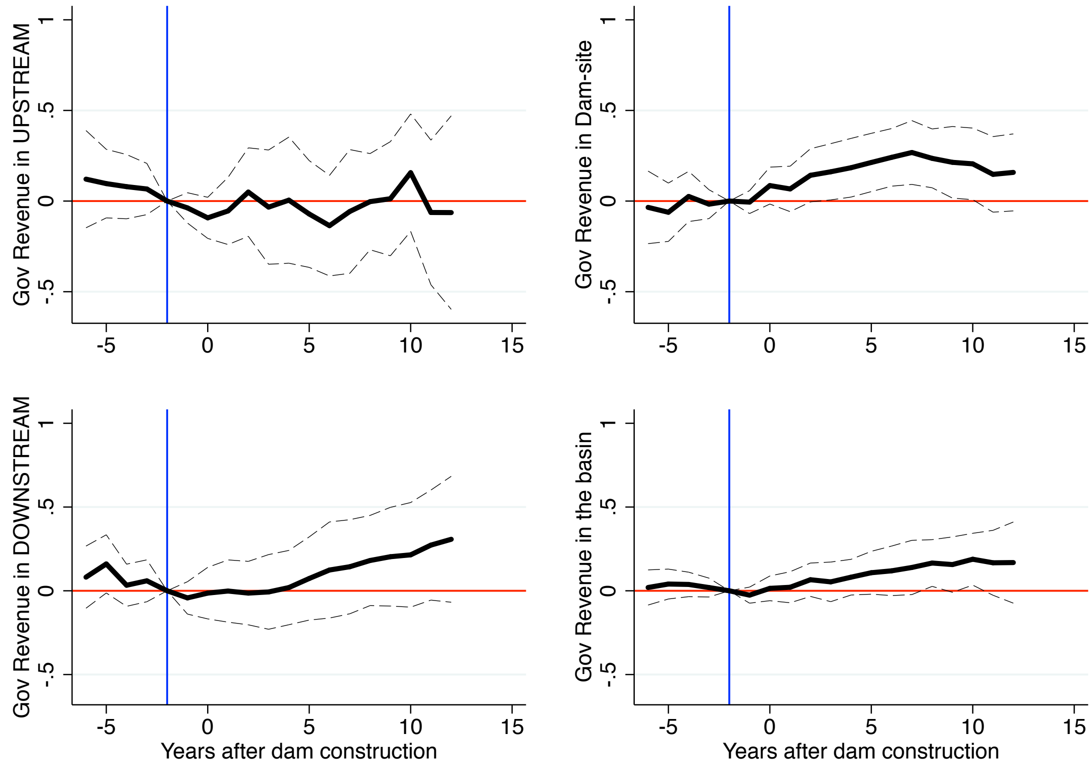


Figure 2.6: Dam Estimates Over Time for Governmental Revenue

Notes: The dependent variable is logarithm of per capita governmental revenue. The graph plots out β estimates and the 95% confidence interval from the regression equation of $y_{ipt} = \sum_{t=-9...16} \beta_t \text{treat}_i * \text{Dyear}_{it} + \delta X_{ipt} + \rho_t + \lambda_i + \zeta_p t + \epsilon_{ipt}$. Dyear is the normalized year relevant to official dam begin year. In the clockwise direction from the up-left graph, each graph is a separate regression showing the pattern for Upstream, dam-site, The whole Basin and Downstream. Two years before the official dam begin year were used as the default group. Upstream and downstream samples here were restricted to these located within 200 km away from the dam. Standard errors are clustered at dam level.

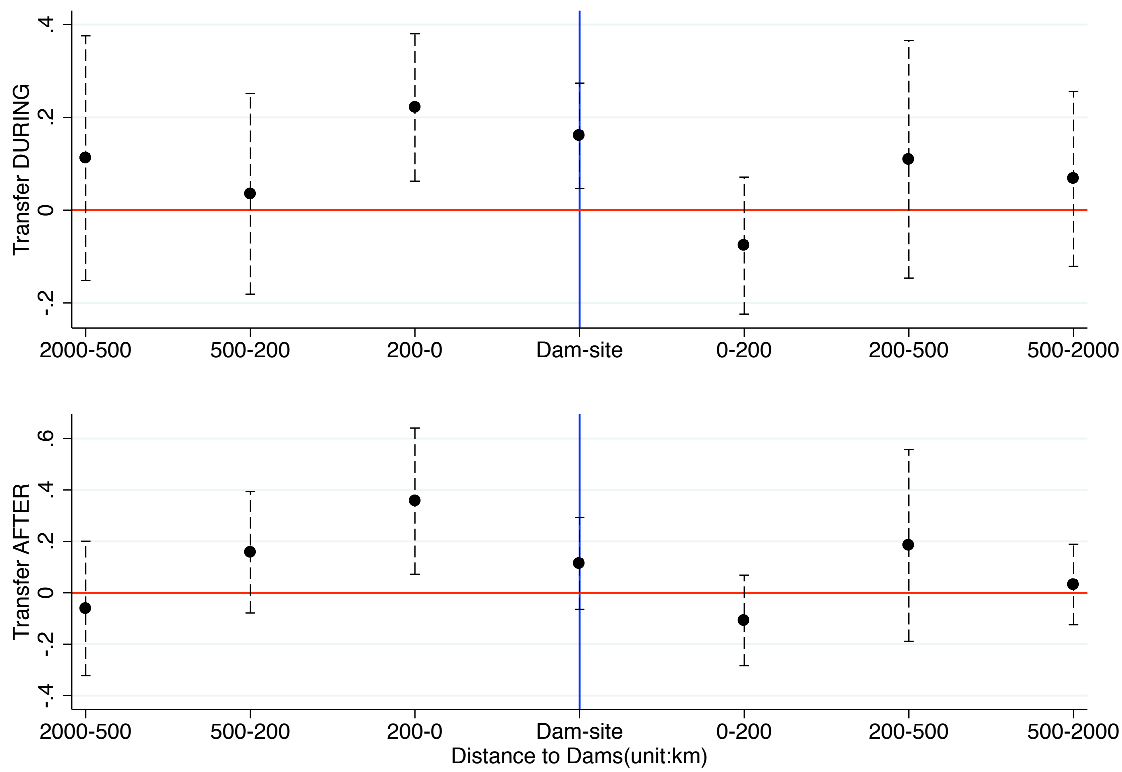


Figure 2.7: Estimates for Dam Impacts at Various Distance Bins for Net Transfer

Notes: The dependent variable is logarithm of per capita net intergovernmental transfers. The graph plots out the DID estimates and the 95% confidence interval for governmental revenue at each distance bin. The bins in the left of the "dam-site" regions are upstream counties, while bins in the right of the "dam-site" regions are downstream areas. The top plot reports the estimation results in dam construction periods. The bottom plot reports the estimation results in dam operation periods. The regression model in each distance bin includes provincial year trend, year fixed effects and county fixed effects, with error clustered at dam level.

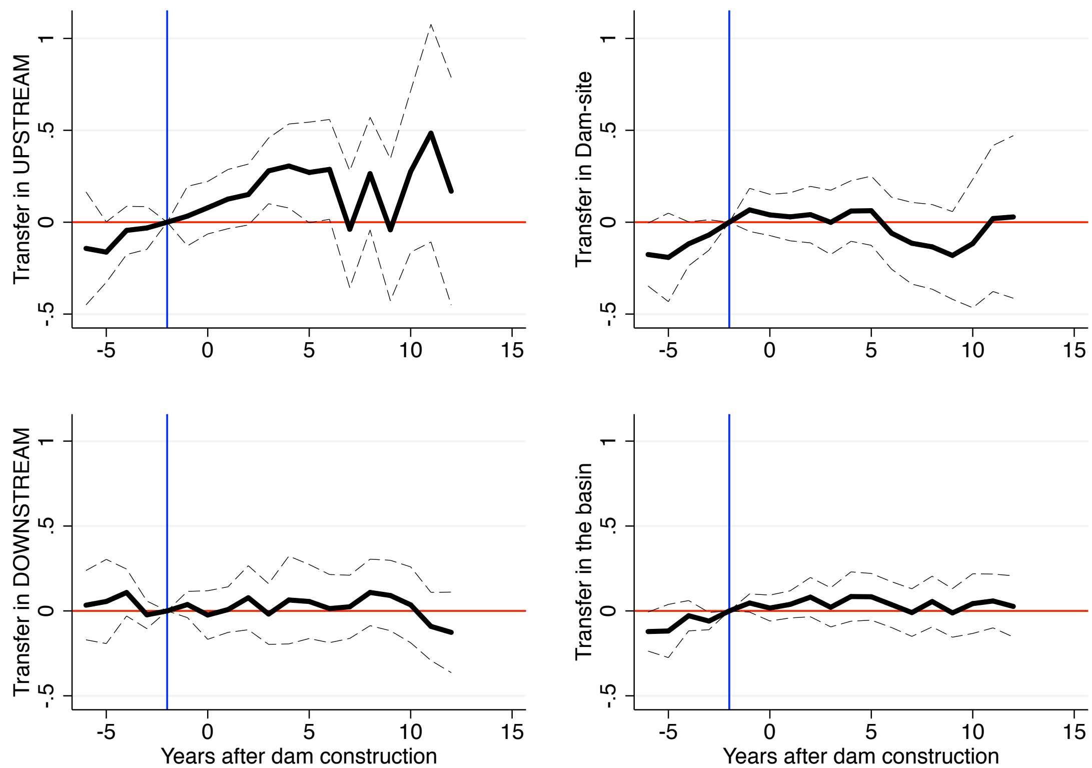


Figure 2.8: Dam Estimates Over Time for Intergovernmental Transfers

Notes: The dependent variable is logarithm of per capita net intergovernmental transfer. The graph plots out β estimates and the 95% confidence interval from the regression equation of $y_{ipt} = \sum_{t=-9...16} \beta_t \text{treat}_i * \text{Dyear}_{it} + \delta X_{ipt} + \rho_t + \lambda_i + \zeta_p t + \epsilon_{ipt}$. Dyear is the normalized year relevant to official dam begin year. In the clockwise direction from the up-left graph, each graph is a separate regression showing the pattern for Upstream, dam-site, The whole Basin and Downstream. Two years before the official dam begin year were used as the default group. Upstream and downstream samples here were restricted to these located within 200 km away from the dam. Standard errors are clustered at dam level.

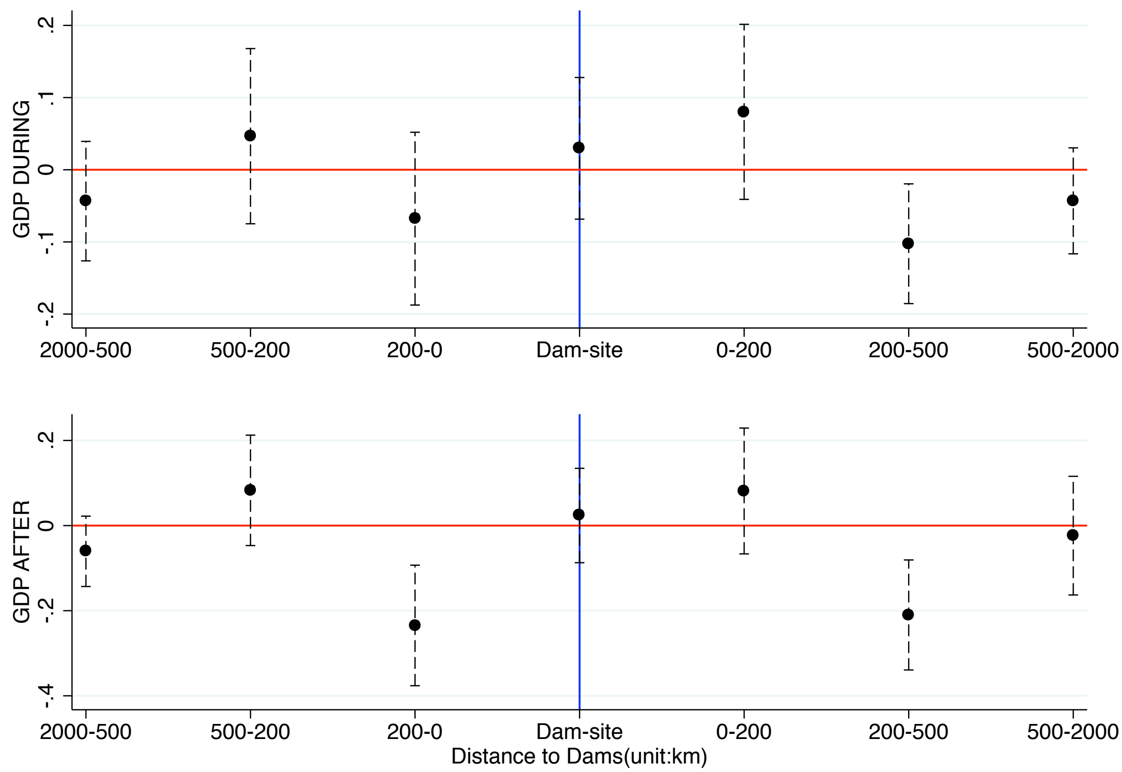


Figure 2.9: Estimates for Dam Impacts at Various Distance Bins for GDP

Notes: The dependent variable is logarithm of per capita GDP. The graph plots out the DID estimates and the 95% confidence interval for governmental revenue at each distance bin. The bins in the left of the "dam-site" regions are upstream counties, while bins in the right of the "dam-site" regions are downstream areas. The top plot reports the estimation results in dam construction periods. The bottom plot reports the estimation results in dam operation periods. The regression model in each distance bin includes provincial year trend, year fixed effects and county fixed effects, with error clustered at dam level.

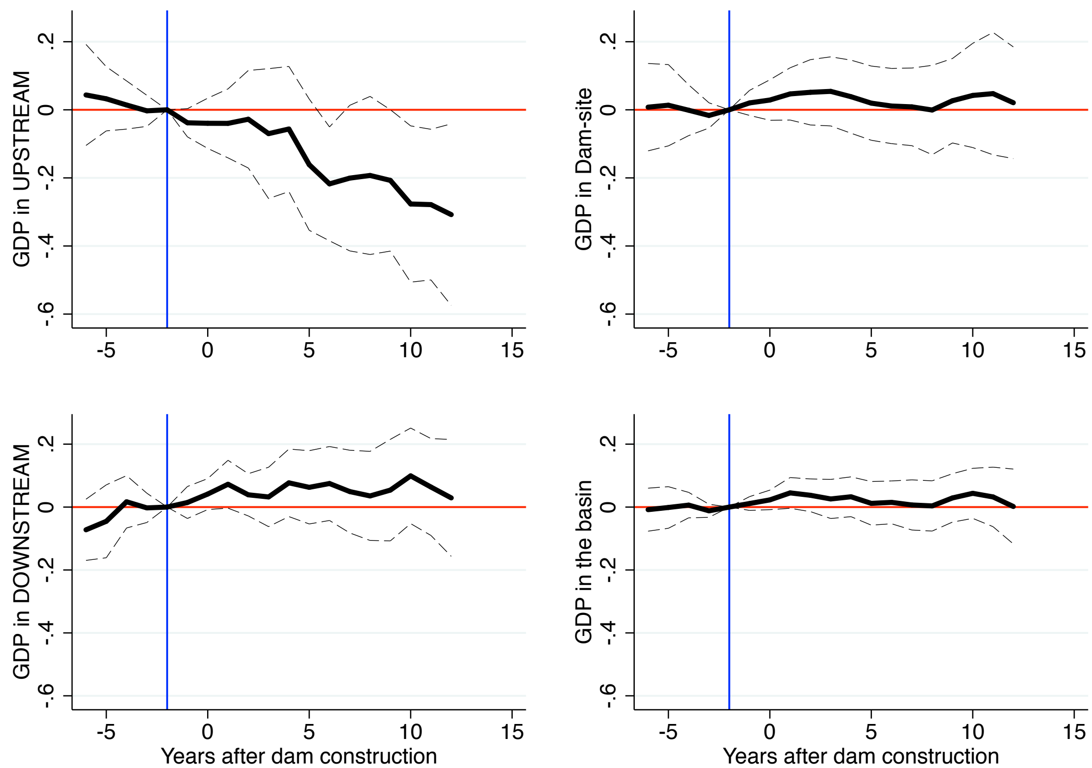


Figure 2.10: Dam Estimates Over Time for GDP

Notes: The dependent variable is logarithm of per capita GDP. The graph plots out β estimates and the 95% confidence interval from the regression equation of $y_{ipt} = \sum_{t=-9...16} \beta_t \text{treat}_i * \text{Dyear}_{it} + \delta X_{ipt} + \rho_t + \lambda_i + \zeta_p t + \epsilon_{ipt}$. Dyear is the normalized year relevant to official dam begin year. In the clockwise direction from the up-left graph, each graph is a separate regression showing the pattern for Upstream, dam-site, The whole Basin and Downstream. Two years before the official dam begin year were used as the default group. Upstream and downstream samples here were restricted to these located within 200 km away from the dam. Standard errors are clustered at dam level.

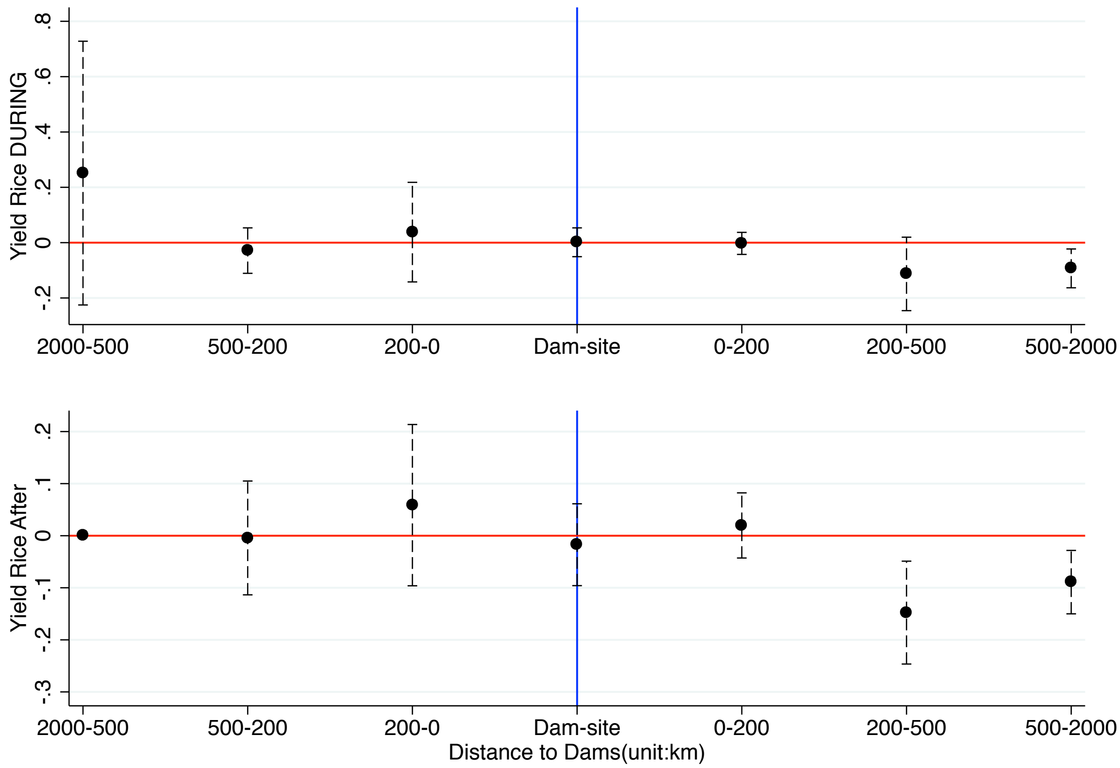
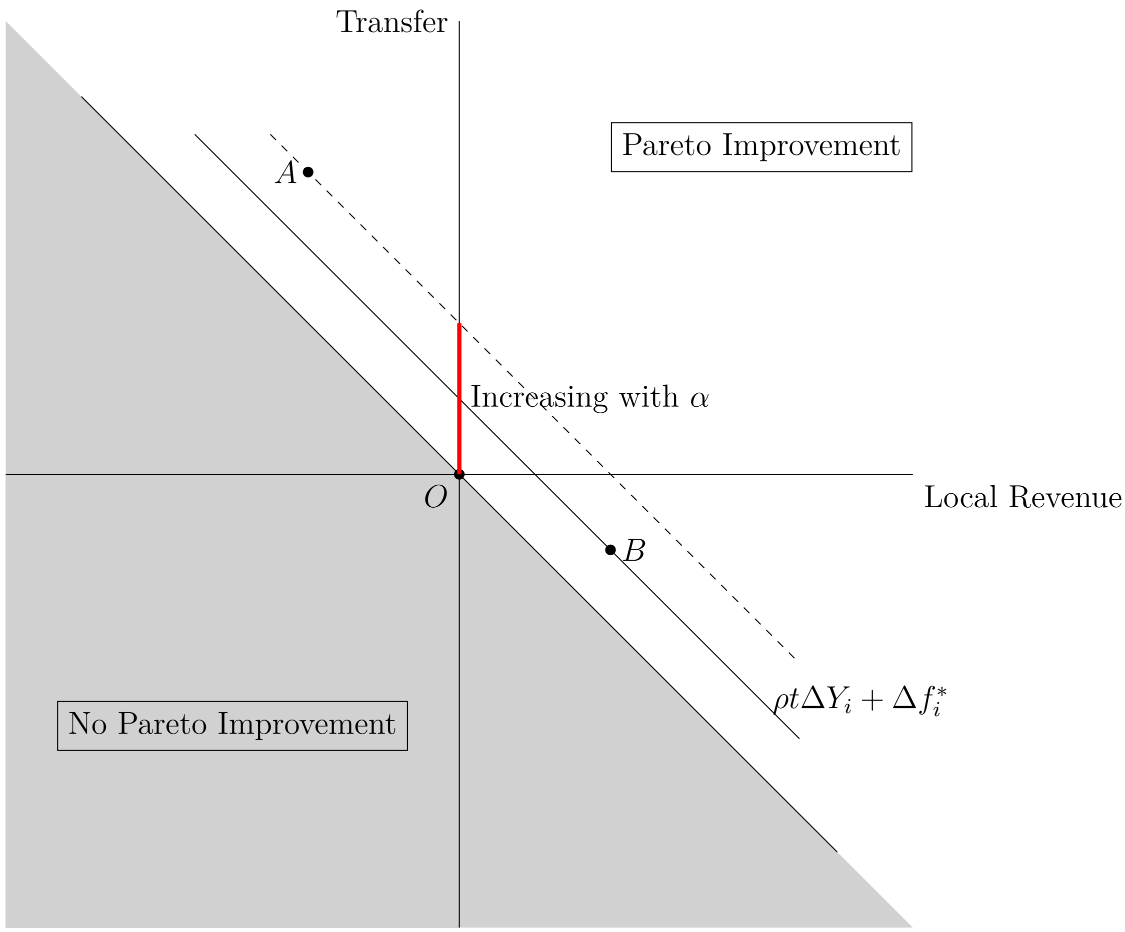


Figure 2.11: Estimates for Dam Impacts at Various Distance Bins for Rice Yield

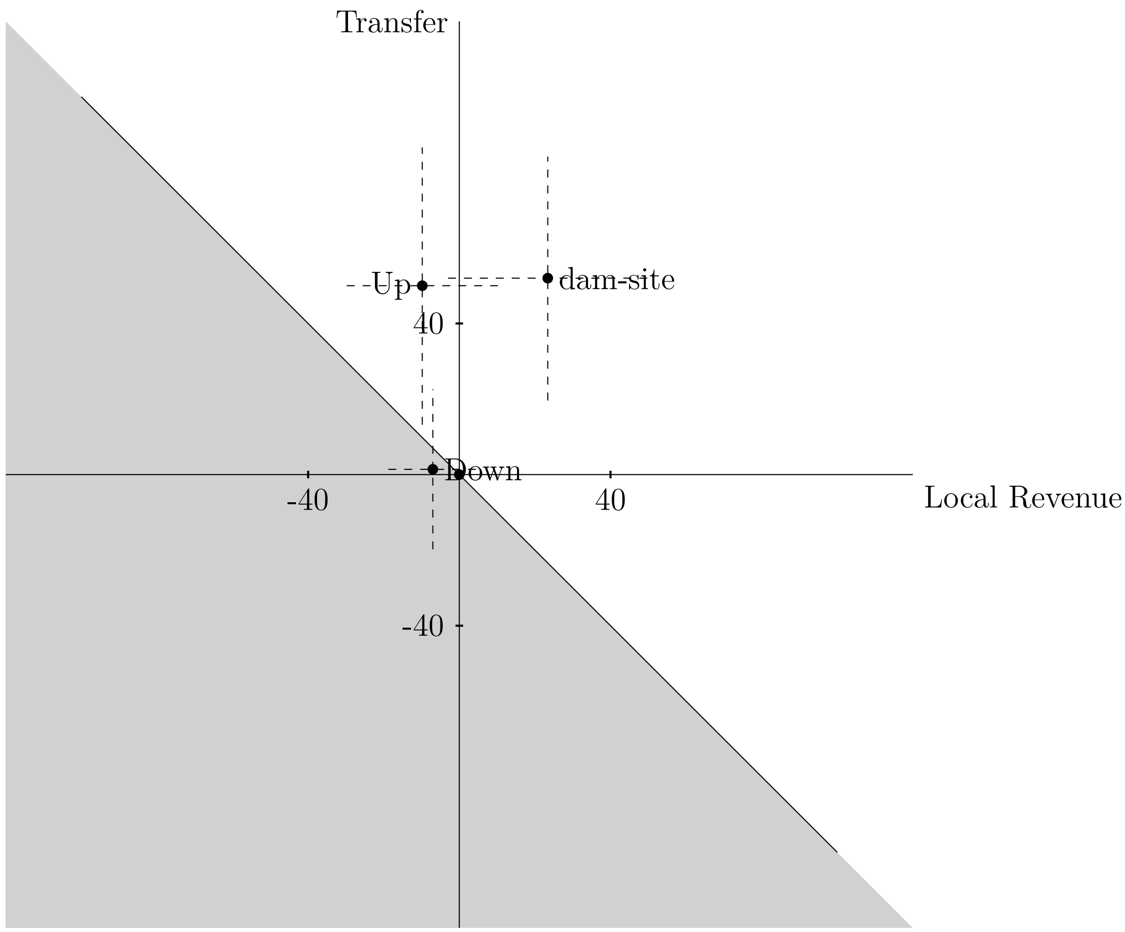
Notes: The dependent variable is logarithm of rice yield. The graph plots out the DID estimates and the 95% confidence interval for governmental revenue at each distance bin. The bins in the left of the "dam-site" regions are upstream counties, while bins in the right of the "dam-site" regions are downstream areas. The top plot reports the estimation results in dam construction periods. The bottom plot reports the estimation results in dam operation periods. The regression model in each distance bin includes provincial year trend, year fixed effects and county fixed effects, with error clustered at dam level.

Figure 2.12: Graphic Explanation of the Theoretical Model



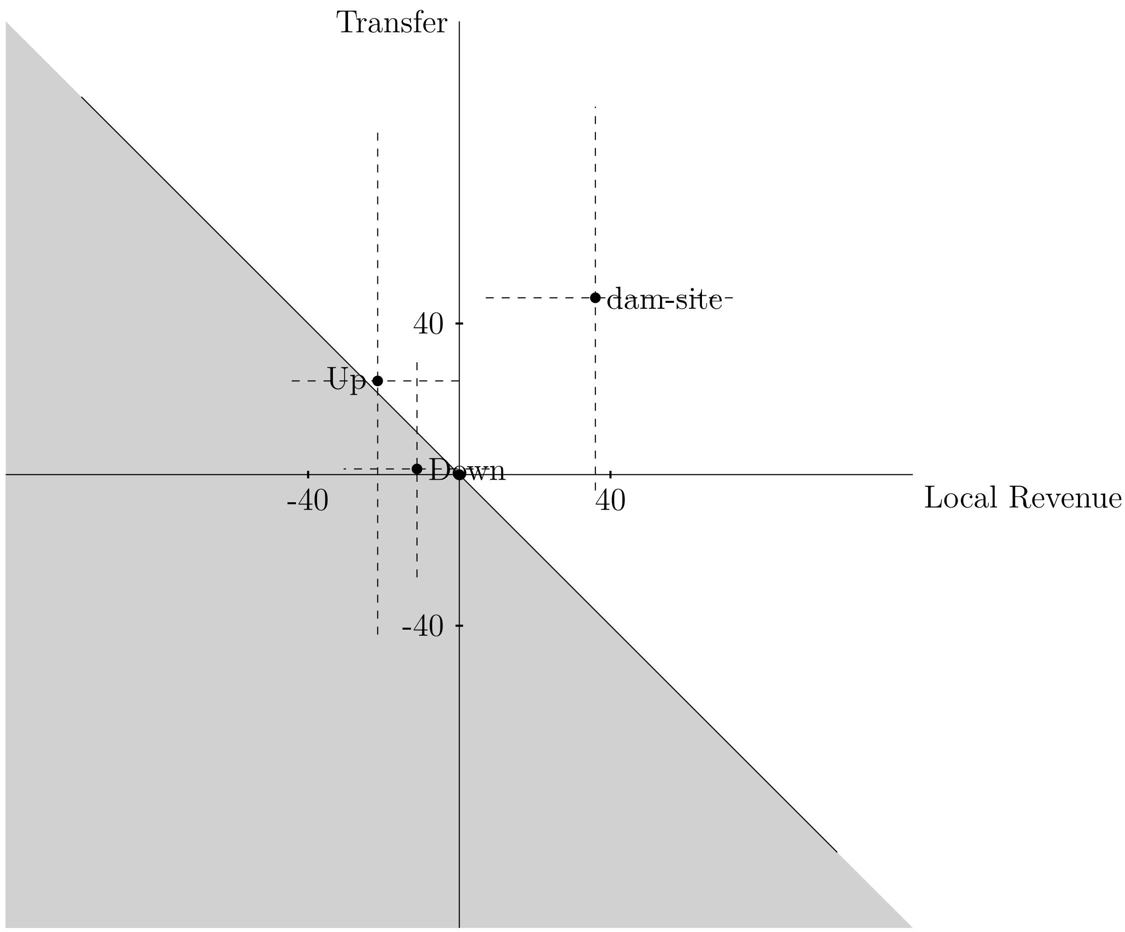
Notes: The comprehensive impacts of dams can push the outcome points away from the original point O to any points in the four quadrants, depending on the combination of changes in governmental revenue and changes in intergovernmental transfer. Points below the diagonal line passing through Quadrant II and Quadrant IV are worse-off outcomes. Above the diagonal line, the farther away a point is from the diagonal line, the better off it will be. The relative distance to the diagonal line represents the wellbeing of local governmental performance. The distance also represents the relative weight of a region in the central decision making process for fiscal resource distribution.

Figure 2.13: Governmental Pareto Improvement Outcome for Dam Construction



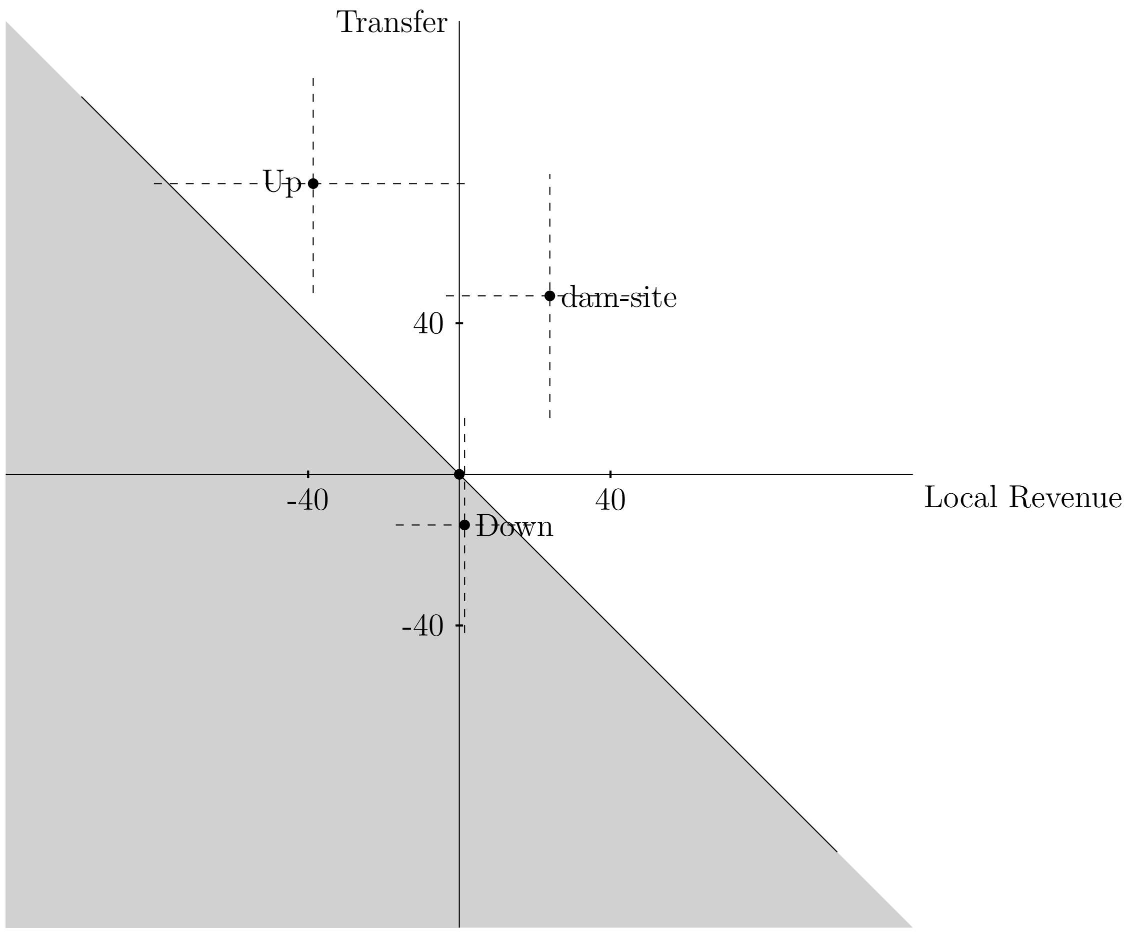
Notes: This figure plots the estimated dam construction impacts on governmental revenue and net transfer for counties at three locations. The value change in revenue and transfer are calculated by multiplying the estimates with the mean value of outcome variables for control counties before dam construction. The horizontal axis represents the changes in governmental revenue, while the vertical axis represents the changes in governmental transfer. The crosses at each point represent the 95% interval for both estimates. The further away the point is from the diagonal axis, the better off a county is.

Figure 2.14: Governmental Pareto Improvement Outcome for Dam Operation



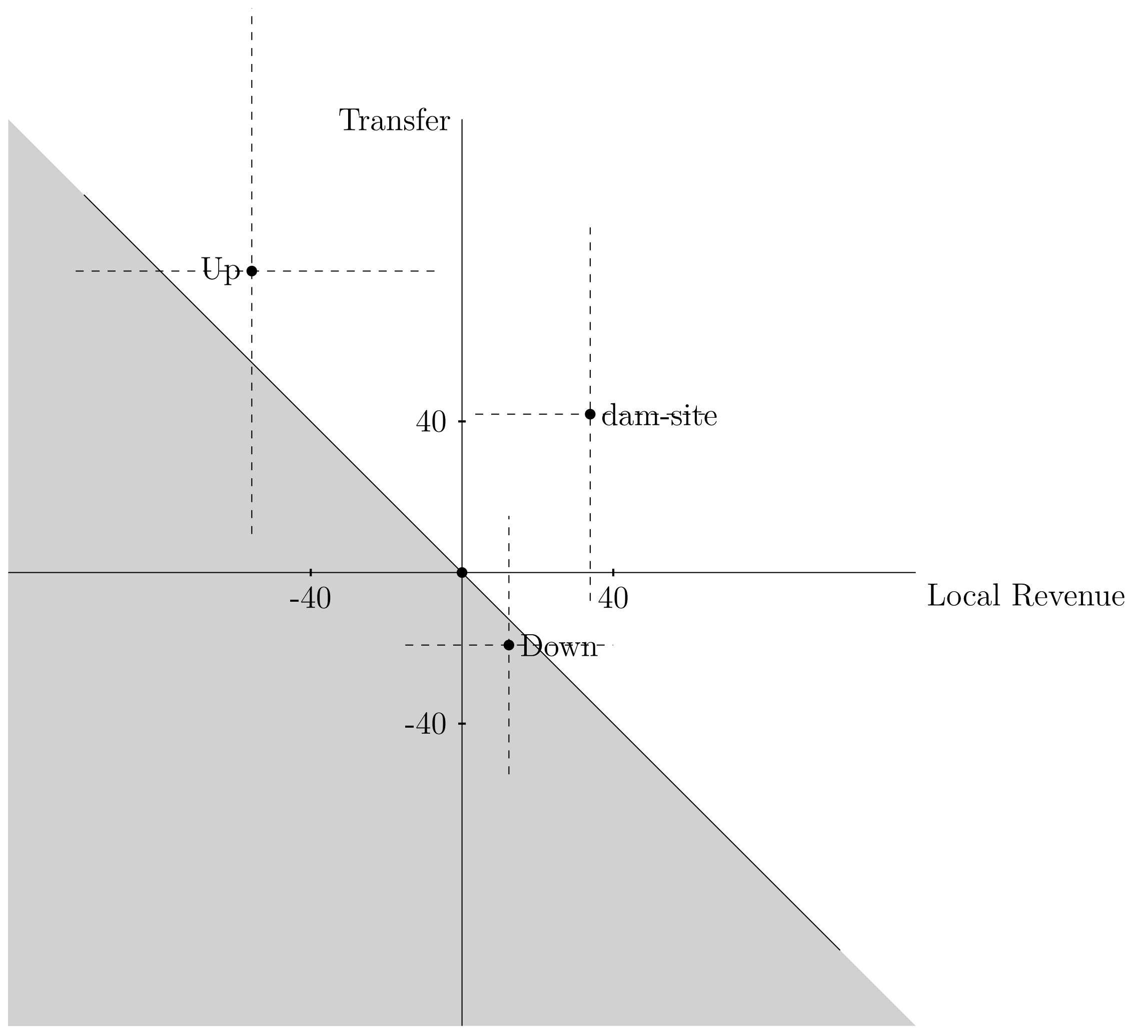
Notes: This figure plots the estimated dam operation impacts on governmental revenue and net transfer for counties at three locations. The horizontal axis represents the changes in governmental revenue, while the vertical axis represents the changes in governmental transfer. The crosses at each point represent the 95% interval for both estimates. The further away the point is from the diagonal axis, the better off a county is.

Figure 2.15: Governmental Pareto Improvement Outcome for Dam Construction (within 200km)



Notes: This figure plots the estimated dam construction impacts on governmental revenue and net transfer for counties within 200km away from the dam site, based on the estimated results from logarithm outcome variables and the mean values of dam-treated counties in the three locations. The horizontal axis represents the percentage changes in governmental revenue, while the vertical axis represents the percentage changes in governmental transfer. The crosses at each point represent the 95% interval for both variables. The farther away the point is from the diagonal axis, the better off a county is.

Figure 2.16: Governmental Pareto Improvement Outcome for Dam Operation (within 200km)



Notes: This figure plots the estimated dam operation impacts on governmental revenue and net transfer for counties within 200km away from the dam site, based on the estimated results from logarithm outcome variables and the mean values of dam-treated counties in the three locations. The horizontal axis represents the percentage changes in governmental revenue, while the vertical axis represents the percentage changes in governmental transfer. The crosses at each point represent the 95% interval for both variables. The farther away the point is from the diagonal axis, the better off a county is.

Chapter 3

Transfer for Disasters: Governmental Responsiveness to Typhoon Risks in China

Abstract

Natural disasters bring significant economic damages globally. Governmental-initiated disaster reliefs, especially disaster relief transfers from the central government to local regions, play an important role of reducing damage and help economic recovery for local regions. We use typhoon disaster in China as an example to analyze the responsiveness of central government for local disaster exposures and potential factors impacting central government's transfer efforts. By exploiting both geographic and year-to-year variations of typhoon exposure at the county level, we find that the central government responds to the current year typhoon exposure by increasing targeting transfers to local regions. Transfer efforts seem to be driven by local vulnerability, instead of political connection and governmental efficiency.

3.1 Introduction

About 75% of global population live in areas exposed to at least one type of natural disasters, like flood, drought, earthquake and typhoon etc (UNDP, 2012). These natural disasters bring significant asset loss, economic damage and death to vulnerable areas (Barro, 2006; Barro, 2009). Governmental-initiated disaster relief plays a key role to reduce physical and economic damages and help disaster recovery. Besides local disaster relief efforts, the central or federal government regularly provides disaster relief aid to local regions through the intergovernmental transfer system. This fiscal structure provides a risk sharing mechanism among multiple levels of governments. However, the capacity of local regions to attract central transfers may vary, depending on local vulnerability, geographic importance and other factors (Cole *et al.*, 2012; Albouy, 2012).

Most of studies on transfer across jurisdictions so far are about international aid transfers. International disaster relief aids are driven not only by local needs and vulnerability, but also by news coverage, governmental efficiency, strategic importance of receiver country and relative closeness between donor and receiver countries (Strömberg, 2007; Besley and Burgess, 2002). The closeness includes geographic, cultural and historical closeness, such as language similarity and colonial connection with the donor countries. Studies on transfers in the domestic context are still limited. This paper aims to study intergovernmental transfer responses to natural disasters using typhoon in China as a special case.

Typhoon, also called hurricane or tropical cyclones in other regions, make frequent landfalls to east coastal China, bringing severe economic damages every year. The central government arranges and delivers special transfers for disaster relief purposes to local governments, following the hierarchical fiscal federalism structure including province, prefecture and local county or city from top to bottom. Ever since the 1990s, China has been experiencing a fiscal reform called "province manages counties", which aims to remove the prefecture level for fiscal transactions between the province and county governments. Total governmental transfers for natural disaster relief purposes reached 8.64 billion CNY in 2011 (MCA, 2011).

To explore the transfer responsiveness to typhoon disasters, we first build a simple theoretical model about central government resource distribution to local governments. The model shows that disaster relief transfer depends on both the vulnerability or economic impacts of typhoon exposure and the decision weight or relative importance of local regions in the central government decision making process. These two claims are verified by empirical analysis, using a self-built dataset on typhoon exposure over all counties and cities in China from 1980 to 2008. We apply both fixed-effects and first-difference estimation methods to study the average transfer responsiveness to typhoon disasters and heterogeneities in the responsiveness. There are concerns that typhoon exposure may be not completely exogenous, and that it may be serially correlated or following certain unobserved climate patterns. First-difference estimation can provide unbiased estimates for the average responsiveness by using only the variation of differences of typhoon and outcome variables over time. We generate four sets of results about the average governmental responsiveness, heterogeneity of responsiveness, impacting factors for responsiveness and implications of the recent fiscal reform on governmental responsiveness.

The first set of results is about the average responsiveness of all local regions in China. Local macroeconomic performance measured by per capita GDP is not significantly damaged by typhoon exposures. This confirms the ambiguous macroeconomic impacts of typhoon disasters found in the Caribbean region (Hsiang, 2010). For intergovernmental transfers, the central government increases special transfer with targeted purposes to local regions for the current year typhoon exposure. On average, local regions receive 5% more special transfers when the average maximum wind speed increases by 10m/s. However, general transfers which are non-targeting transfers, barely change along with typhoon exposures. We also find that there is a delay in the expenditure of local governments relative to disaster exposure. Local regions tend to increase expenditures targeting at social welfares, such as social security, health expenditures one year after the typhoon disaster. This may imply ex-post disaster preventive efforts or the bureaucracy of governmental decisions.

The second set of results is about heterogeneities of governmental responsiveness. Responding to typhoon exposure, the central government increases special transfers mainly to poor regions and regions suffered from severe typhoons with high average maximum wind speed. This confirms the theoretical claim that more transfers go to regions with larger vulnerabilities.

The third set of results is about factors impacting central governmental responsiveness to local typhoon exposures. We obtain the average changes of GDP and special transfer to typhoon exposure for each local county and city separately. Regions experienced large GDP losses or benefits tend to be inland areas. The macroeconomy in coastal regions have adapted to frequent typhoon exposure very well. Special transfer responsiveness is lower in regions hit by typhoon every year. This supports the adaption behavior in high typhoon exposure regions found by Hsiang and Narita (2012). Special transfer responsiveness is also higher in more populated regions. However, special transfer responsiveness is not significantly associated with population density, ethnicity group composition and number of peer competitor counties within the same prefecture.

The fourth set of the results is about whether the “province manages county" reform and political connection impact special transfer responsiveness or not. Both the reform and connection between provincial governors with the political bureau members bring insignificant and positive impacts on the special transfer responsiveness. After the reform, local regions don’t receive more special transfers for the disaster relief. This may corresponds to one of the obstacles of the reform that the administrative structure didn’t reform simultaneously with the fiscal system. Local regions are still subject to the administration of prefectural governments, such as performance evaluation, project approval, officer promotion and designation etc (Wang *et al.*, 2011) .

One thing to note is that the estimate in this paper might be a lower bound of the actual disaster transfer responsiveness, because disaster transfer is only a small part of total special transfer which is analyzed in the paper. Here we assume that other terms of special transfer, such as education, technology development and infrastructure transfers[1], aren't correlated with the variation of typhoon exposures. To our knowledge, this is the first paper exploiting intergovernmental transfer responsiveness to natural disasters. It contributes to the large literature on disaster impacts, disaster relief and political economy of intergovernmental transfers.

The paper is organized as follows. Section 2 shows the background of typhoon exposure and intergovernmental fiscal structure in China. Section 3 builds an intergovernmental transfer model to show how disaster transfer responsiveness be impacted by local vulnerability and the importance weight of a region in the central decision process. Section 4 describes the dataset and empirical specification. Section 5 shows the empirical analysis results on average responsiveness and heterogenous responsiveness. Section 6 concludes.

3.2 Theoretical Model

To illustrate how the intergovernmental transfers respond to local typhoon risks, here is a simple federalism model including local natural disaster shock. The framework of this model is simplified from the intergovernmental transfer decision model by Zou (2012). Beyond that, this model also extend the typical intergovernmental transfer model by including local disaster shocks following similar structure as the model Persson and Tabellini (1996) developed for cross country risk sharing models.

[1]Infrastructure transfers here are transfers for general infrastructure constructions. Disaster related infrastructure maintenance and investment are funded by disaster transfer under special transfers.

Assume that there are two local governments $i = 1$ and $i = 2$ under the same central government. Both regions face the the same typhoon risk h with probability of π. However, they suffer different losses $L_1(h)$ and $L_2(h)$. In the no-typhoon state at the probability of $1 - \pi$, both regions have private good production level X_1 and X_2. The central government makes transfers G_1 and G_2 ex post to both regions for disaster relief purposes, subject to the budget constraint of $G_1 + G_2 = W$. Here W is the total available fiscal resource for disaster relief in the central government. Here we assume W is constant[2].

The central government faces the following optimization problem of maximizing the weighted sum of wellbeing in local governments, with decision weight denoted asα_1 and α_2 .

$$\begin{aligned} \max_{G_i} \quad & \pi \sum_{i=1,2} \alpha_i W_i(X_i - L_i(h) + G_i) + (1-\pi) \sum_{i=1,2} \alpha_i W_i(X_i) \\ \text{s.t.} \quad & G_1 + G_2 = W \end{aligned}$$

Solving it using Lagrangian approach, we can get:

$$\alpha_1 W_1'(X_1 - L_1(h) + G_1) = \alpha_2 W_2'(X_2 - L_2(h) + W - G_1) \tag{3.1}$$

Assume $W(x) = ln(x)$, the optimal transfer amount can be written as[3]:

$$G_1* = \frac{\alpha_1}{\alpha_1 + \alpha_2}(W - L_2(h)) + \frac{\alpha_2}{\alpha_1 + \alpha_2} L_1(h) \tag{3.2}$$

From the optimization results, it is intuitive to see that disaster relief into one region is positively correlated with local economic loss $L(h)$. Another finding is that the net change

[2]Considering that typhoon relief transfer is only a small part of the total intergovernmental transfer, it is reasonable to assume that total typhoon relief transfer resource is exogenous to the local disaster exposures.

[3]Here we need to plug in the condition that X_i endowment is efficient if there is no typhoon. $\alpha_1 W_1'(X_1) = \alpha_2 W_2'(X_2)$

of economic production $(G_i - L_i)$ is proportional to the decision weight α_i. So generally, regions suffered more economic losses and regions with larger decision weight receive more transfers from the central government.

3.3 Background

3.3.1 Typhoon Risks and Impacts

Around 1/3 of local counties, mostly in coastal regions area, are exposed to frequent typhoon hits in China. Figure (3.2) plots the average maximum wind speed of typhoon exposure across China. It shows that there are a lot of variations in the typhoon exposures across local regions. Typhoons in China mostly form in Western North Pacific sea (Wang *et al.*, 2007). Then they gear power over water surface following the track. After they make landfalls, wind speed and energy power will decrease along the way. The frequency of typhoon hits and vast geographic regions in China provide a chance to study the variations of typhoon exposures in lower administrative levels. According to the report of China Meteorological Administration, on average there were 9 typhoon hits in China annually from 1951 to 2008(MCA, 2011). Most of the typhoon events concentrate in the summer and early autumn season between June and October.

Typhoon events bring heavy rainfall and winds. However, the damages of typhoon can take multiple forms, such as heavy wind damaging infrastructure and crops, inundation induced by heavy rains and storm surge in coastal regions due to the combination of rainfall and wind push. The strength of typhoon exposure is normally measured by the maximum 1-minute sustained wind speed[4]. Even though wind-induced damages only contribute to part of total damages, rainfall and storm surges are also partially correlated with wind speeds.

[4] NOAA (2005)

The association between rainfall and wind speeds may depend on local topographic and landscape structure (Jiang *et al.*, 2008).

The combination of wind, flooding and storm surge bring significant economic damages and asset losses. Nordhaus (2010) studied economic impacts of hurricanes in coastal US and concluded that economic damages as percentage of GDP rose at the ninth power of hurricane wind speed. Other negative impacts confirmed in the empirical studies include slow down of output growth (Strobl, 2012), significant physical and human capital losses (Anttila-Hughes and Hsiang, 2013) and decrease in output of agricultural and tourism sectors[5] (Hsiang, 2010; Mohan and Strobl, 2013). For China specifically, total direct economic losses from typhoon reached 629.2 billion CNY, amounting to 24.2 billion CNY per year from 1983 to 2008 (Fengjin and Ziniu, 2010). There has been an increasing trend in typhoon-induced economic damages in the past decade in China.

The long-run and macroeconomic impacts of typhoon disasters are more complex (McComb *et al.*, 2011). Local regions may result into economic decline or recovery depending greatly on the social, political and institutional factors, such as governmental efficiency, literacy, openness and media coverage etc (Toya and Skidmore, 2007; Noy, 2009; Eisensee and Strömberg, 2007; Garrett and Sobel, 2003).

3.3.2 Disaster Relief Resources

Governmental-initiated disaster relief play an important role to reduce typhoon-induced damages. Special fiscal resources for disaster relief purposes are arranged by governments, targeting at both infrastructure maintenance, recovery and reconstruction and household level special aids for food, housing and health services. The funding of local disaster relief are mostly from special transfers from upper-level governments and special arranged disaster

[5] Hurricanes create output losses to agriculture industry, wholesale, restaurants and hotels industry and mining and utilities industry, and bring output increases to construction industry.

relief expenditure in local governments. Total governmental transfers for natural disaster relief reached 8.64 billion CNY in 2011. Even though it is only a small proportion (2.8%) of the total economic losses amounting to 309.6 billion CNY from all natural disasters(MCA, 2011), intergovernmental transfers are key for disaster relief in rural regions, where the private insurance coverage is limited[6].

Due to widespread typhoon risks, the central government needs to respond to disaster relief in multiple local regions. The transfer aid decision process from central government to local governments is still quite obscure. How large the transfer should be and where the transfer should go not only depend on the local vulnerabilities and local needs, but also on other social and political factors, such as governance efficiency, media coverage, ethnical composition, importance of local regions and the connection between local and central governments (Besley and Burgess, 2002; Cole *et al.*, 2012; Albouy, 2012).

3.3.3 Intergovernmental Transfers in China

This section provides a more detailed look into the fiscal transfer system in China. There are 4 fiscal jurisdiction levels with fiscal capacities of revenue collection and expenditure spending, including the central government, province, prefecture and county. Most of the central-local fiscal transferred went through this 4-layer transfer route: central-province-prefecture-county/city. In 2003, provinces passed 70.8 % of total fiscal resource to prefectures and prefectures passed 75.4% to county governments. China have been going through the “province manage county" fiscal reform ever since 1990s, which aims to flatten the fiscal hierarchical structure by removing prefecture inventions in fiscal activities between provinces and counties. The reform was initially planned to be complete by 2012, with all counties in

[6]The current disaster-related insurance type is mainly typical asset loss insurance. So far there is no special agricultural insurance for natural disasters in the whole nation. The asset insurance paid 112.97 billion CNY in 2005 for natural disasters (Wenhui, 2007), corresponding to the total economic losses of 252.8 billion CNY and 5.1 billion CNY disaster transfers (MCA, 2007).

China under the direct fiscal governance of corresponding provinces (Qinghai, 2009). However, the goal wasn't reached. It is generally believed that the reform has slowed down in many local regions. One of the largest obstacles is that the reform is only targeting at the fiscal relationship, instead of the administrative relationship. Even though local counties are relatively independent from the prefectural governments for fiscal activities, they are still under the administration of prefectural governments, which includes governance evaluation, regional development plan, evaluation and promotion for local governors. Another concern is that the relative independence of local counties in terms of fiscal activities may reduce spendings on long-term public services like education while increasing more short-term "promotion driven" expenditures such as infrastructure investments (Wang *et al.*, 2011).

Intergovernmental transfers include two types of transfers: special and general transfers. Special transfers are targeting transfers with usage specified by the central government. Examples of special transfers include infrastructure transfer, forest conservation transfer, land-for-green transfer, disaster relief transfer and education transfer to poor regions. General transfers used in this paper represents all other transfers except special transfers[7]. General transfers are non-targeting transfers that local governments have a lot of freedom to decide the usage[8]. Examples of general transfers include ethnicity minority region transfer, rural transfer and 9-year compulsory education transfer. Comparing to special transfers, general transfers tend to follow explicit formulas, normally based on population, rural ratio, ethnical composition and economic development level of regions. For example, there are 700 counties eligible for a special transfer to increase wage of civil servants. Agriculture and rural tax reform transfers are distributed based on the reported number of rural people

[7]In the fiscal reports, there is a specific category called "general transfers". It is not equivalent to general transfer used in this paper.

[8]For some general transfers, the usage was also restricted. For example, transfer to subsidize teacher salaries in rural regions has the usage specified clearly, even though it is categorized under general transfers.

and agricultural cropping areas. Special transfers are more subjective, depending on the local projects proposals, policy or development plans for the central government. It is also believed to be more subject to bargaining and political connection distortions (Huang and Chen, 2012). Figure(3.3) plots the growth trend of governmental transfers in the past two decades. Reliance on transfers for local governments has increased dramatically, with transfers contributing to more than 60% of local revenue in 2010. The composition of transfers also changed a lot. Local governments obtained more fiscal independence over the usage of transfers. Ratio of special transfers with designated purposes has decreased to around 50% in 2010[9].

Related to natural disasters, there is a "Natural Disaster Relief Fund" under the category of special transfers. The general process for intergovernmental relief fund distribution followed a path as "upward report and downward transfer". Once a disaster hit a local region, the local government needs to report damages to the upper level government. Then each upper-level government needs to report upwardly following the administrative hierarchy. After the report reached the central government, expert committees will evaluate the severity and decide whether to declare it "severe disaster" or not. Once a disaster is classified as a severe disaster, the central government will arrange transfers based on damage evaluations (MOF, 2011).

3.4 Data

This paper uses typhoon exposure, fiscal and economic data at county level from 1996 to 2008, with summary statistics reported in Table (4.1). More than 500 counties were excluded because they were not exposed to any typhoon shock during this period. As a result, around

[9] This is the national trend. For analysis in this paper, we only focus on counties and county-level cities, excluding a lot of prefectural cities. So the trend for counties and county-level cities is different.

1600 counties or county-level cities are included in the analysis.

3.4.1 Typhoon Data

We initiatively built a dataset on typhoon exposure covering all counties and cities in China by reconstructing the path and wind field for each West Pacific cyclones recorded in the International Best Track Archive for Climate Stewardship (IBTrACS) using Limited Information Cyclone Reconstruction and Integration for Climate and Economics (LICRICE) model [10]. After reconstruction for each cyclone separately, we can obtain two main indictors to describe the exposure of each cyclone: wind speed and energy dissipation index for each pixel by interpolation. County-level typhoon exposures were calculated by using information of all pixels within the geographic location. Annual indicators for typhoon exposures were derived using the information of all typhoons passing through a certain location in that specific year. This paper uses Average Maximum Wind Speed (maxs) to represent typhoon exposure for each county from 1980 to 2008[11]. One potential concern is that wind speed cannot account for all of typhoon impacts, since it doesn't take into complete consideration of storm surge and flooding. The latter two impacts depend more on the combination of local topographic condition and typhoon characteristics. So typhoon risks in the paper mainly refer to risks associated with maximum wind speed.

Figure (3.2) plots the distribution of average typhoon exposure to local counties in China. Coastal provinces, like Guangdong, Fujian and Zhejiang, are subject to larger typhoon risks than inland regions. There is a clear gradual decrease for typhoon risks from the coastal to inland areas as wind speed decrease after typhoon landfalls. Figure(3.1) plots the annual

[10]More detailed methodology of the wind field reconstruction can be found at Hsiang (2010)

[11]We also used Power Dissipation Density Index as typhoon measures and got estimates with similar directions and significance. We only include results for wind speed results here for ease of result comparison with other studies on typhoon studies (Nordhaus, 2010; Emanuel, 2005; Hsiang, 2010).

variation of typhoon risks for all local regions exposed to typhoon risks from 1980 to 2008. It shows that typhoon risks varied greatly from year to year. The largest exposure was observed in 1994, when a series of typhoon hit China in August and September. The average maximum wind speed across all regions with typhoon histories reached more than 13m/s[12] in 1994. Comparing to typhoon exposure of other Asian regions, coastal regions in China are considered to be high risky regions. The average maximum wind speed of Philippine provinces between 1979 and 2008 was 16.9m/s(Anttila-Hughes and Hsiang, 2013), while the average maximum wind speed of Japan between 1950 and 2008 was 3.39m/s (Hsiang and Narita, 2012).

3.4.2 Fiscal and Economic Data

Annual local fiscal information was obtained from Ministry of Finance from 1996 to 2006 (MOF, 1994-2006). It covers detailed categories of governmental fiscal activities, including local fiscal revenue and fiscal expenditure, and intergovernmental transfer from the central government to local governments. However, we don't have transfer data on natural disaster relief specifically. The economic and demographic data were obtained from National Bureau of Statistics in the County Statistics Yearbook from 1996 to 2010, covering 2086 counties and county-level cities(NBS, 2006-2010). Main variables include GDP, population, consumption price index, total governmental revenue and total governmental expenditure. Population here refers to the reported population registered in the local county based on the Hukou system in China. So population changes mainly capture changes involving Hukou changes, such as project-induced migrations, job-related migrations, births and deaths in the local region. Typical migrant workers, as rural labor force working in the urban areas, will not be included in the population of their working location, because most of migrant workers still

[12] 1m/s=3.6km/h$\approx 2.24 mile/h$

keep their original household registration.

Real economic and fiscal data are calculated at the price level in 2000, by adjusting the nominal values by annual consumption price index of local counties. Table (4.1) reports the summary statistics of county-level fiscal data. The average special transfer was 127 Yuan per capita during 1996 and 2006. The average population of local counties and county-level cities was around 460,000. Mean GDP per person was around 12,000 Yuan (around 1,700 US dollars) in 2006 using the 2000 price level. Governmental revenue per person was around 630 Yuan and net intergovernmental transfer per person was around 930 Yuan in 2006.

3.4.3 Agricultural Data

To explore typhoon impacts on agriculture production, we use the agricultural production data provided by International Food Policy and Research Institute (IFPRI), covering agricultural yields and cropping areas of three crops (rice, wheat and maize) at county level in China from 1980 to 2000. Rice yield increased significantly in the past several decades. The average yield for rice is around 6 tons per hectare. I drop yield and area outliers with value beyond three standard deviation from the annual average value for each county.

3.4.4 Weather Data

In order to control other types of weather disasters, we also collect temperature and precipitation data from 1980 to 2010, with temperature records from CRU(Climate Research Unit in University of East Angolia) database and precipitation records from National Centers for Environmental Prediction, NOAA(National Oceanic and Atmospheric Administration). Annual average temperature and precipitation at county level were derived from monthly temperature records at the 0.5*0.5 grid level and monthly precipitation observations at the 2.5*2.5 grid level.

3.5 Empirical Strategy

To empirically estimate governmental responsiveness to typhoon exposure, we exploit the year-to-year and geographic variations of typhoon exposure, measured by average maximum wind speed. Because typhoon exposure has strong geographic patterns, with certain regions getting more frequent exposures than others, simple cross-section analysis on typhoon exposure and transfer is not sufficient due to missing-variables, like geoeconomic importance and regional transfer policies. We explore the year-to-year variation of typhoon exposure for each location, by including county fixed effects, which can take into account of any regional fixed factors, such as geographic location. Year fixed effects are included to control any annual factors across the whole nation, such as big social and natural events like big earthquakes and annual policies like the adjustment of transfer categories or terms in specific years.

The exogenous variations of typhoon strength and landfall location provide strong causal implications on the relationship between governmental responsiveness and typhoon exposure. It is generally agreed by scientists that the annual year-to-year prediction of typhoon exposure to a specific local region is still quite difficult (Emanuel, 2005). Most of the current typhoon predications are very short-term, like daily and weekly predictions. So for outcome variables at the annual level, the variation of typhoon exposure is quite exogenous. There are also concerns that local typhoon exposure may be associated with the general weather or climate trends of El Niï¿œo-Southern Oscillation (ENSO) phenomenon and global warming(Goh and Chan, 2012), which may correlate with the economic development trend. For example, global warming may increase local typhoon exposure while local transfers also follow an increasing trend, the estimate for governmental responsiveness will be overestimated. To take care of this concern, two methods are adopted. First, we include prefectural trends in the specification model. Prefectural trends can capture the general typhoon exposure trend and transfer decision trend, because counties within a prefecture are more likely to be exposed to similar climate pattern due to geographic closeness. In addition, the prefectural trend can capture any transfer trend at prefecture level, such increasing or decreasing transfer efficiency, because prefectures are the lowest administrative level executing transfer money to local counties. Second, we use first-difference (FD) estimation to take care of the year-to-year trend of both typhoon and outcome variables at county level. By differencing out both outcome variables and typhoon exposure variable (maxs), we can remove the serial correlation concerns of outcome variables and typhoon risks and get unbiased estimates.

3.5.1 Fixed Effects Model Specification

We use the following model specification for Fixed Effects (FE) estimation.

$$Y_{ift} = \beta_0 + \beta_1 \mathrm{maxs}_{ift} + \alpha X_{ift} + \mu_i + \theta_t + \gamma_f t + \epsilon_{ift} \tag{3.3}$$

Where Y_{ifpt} is the dependent variable for county i in prefecture f of year t. We check typhoon impacts on multiple dependent variables separately: logarithm of per capita transfer, logarithm of per capita GDP and logarithm of per capita expenditure. $maxs_{ift}$ is the maximum wind speed of typhoon for county i in year t. X_{ift} are temperature and precipitation controls of county i in prefecture f of year t. μ_i is the county fixed effect. θ_t is year fixed effect. $\gamma_f t$ is the prefecture trend for each county i. Because transfer decision might be impacted by the typhoon risk of neighboring counties as well, we cluster errors at the prefecture level, which is one level higher than county to take account of correlations of counties within the same prefecture.

3.5.2 First-Difference Model Specification

We use the following model specification for First-Difference (FD) estimation.

$$\Delta Y_{ift} = \beta_0 + \beta_1 \Delta \text{maxs}_{ift} + \alpha \Delta X_{ift} + \mu_i + \theta_t + \epsilon_{ift} \tag{3.4}$$

Where $\Delta Y_{ift} = Y_{ift} - Y_{if(t-1)}$ is the first difference of current year value and last year value for outcome variables. Δmaxs_{ift} and ΔX_{ift} are the first difference results of typhoon exposure variables and weather control variables. The FD estimation structure can automatically remove effects of county fixed effect factors in the fixed effects model specification, because these terms will be dropped out after first differencing. μ_i in this specification model is similar to the county specific trend in the FE model. Year fixed effects in the FE model will be included in the constant terms of this model. Similar to the FE model, errors here will also be clustered at the prefecture level.

For $T = 2$, the FE and FD estimators are numerically equivalent. However for panel data with longer time periods, FE and FD estimators have their own advantages with respect to different model assumptions. If the error structure follows a random walk, the FD estimator is more efficient than FE estimator because the differential removes serial correlation perfectly. Under the assumption of strong exogeneity of homoscedasticity and no serial correlation in the errors, the FE estimator is more efficient than the FD estimator. In the following section, we use two types of model specifications and report results of both methods (Wooldridge, 2001).

3.6 Results

All results are presented in four parts. We first show the average economic impacts of typhoon exposure and governmental fiscal responsiveness to typhoon risks in all counties exposed to typhoon disasters. Both the FE and FD estimators are included. Then we show the temporal heterogeneities of typhoon impacts on economic and fiscal outcomes by including both historical and future typhoon exposures. This not only provides us the temporal pattern of governmental responsiveness, but also helps to verify the validity of data and model specification since future typhoon exposures are difficult to be predicted by decision makers and hence to impact the fiscal decision making. In the third part, we show heterogeneities of governmental responsiveness among local regions, and explore potential factors related to governmental responsiveness. In the fourth part, we present the impacts of the "province manage county" fiscal reform and political connections on governmental responsiveness in China.

3.6.1 Average Governmental Responsiveness

This section mainly presents average impact estimates of typhoon exposure on economic outcomes of GDP and governmental revenue, and how intergovernmental transfers change with respect to typhoon risks. There have been many studies about the economic impacts of typhoon shocks. The findings vary over negative impacts (Strobl, 2012) and no impacts (Hallegatte *et al.*, 2007) of typhoon exposure in various locations and targeting at different scales of typhoon or hurricane events. However, the question on governmental responsiveness was rarely studied. Here for the first time, we explore how governments use intergovernmental transfers to help local governments cope with typhoon shocks.

GDP

In order to estimate the economic impacts of typhoon exposure, we use logarithm of per capita GDP as the dependent variable for Equation (3.3) and (3.4). Table (3.2) shows regression results of typhoon impacts on GDP. Column (1)-(4) report the FE estimates with year and county fixed effects and prefectural trends. Column(5)-(8) report the FD estimates with county and year fixed effects. Both two methods confirm that typhoon exposure measured by average maximum wind speed didn't bring significant negative impacts to macroeconomic performance of per capita GDP. In stead, we found a positive impact of typhoon on GDP. The significances of estimates for current year typhoon exposure of "maxs" are not stable when including historical and future exposures. The FE effects estimates are at the edge of being significant at 90% confidence. The coefficient of current year exposure is around 0.3-0.7%, meaning that typhoon exposure with average maximum wind speed increasing by 10m/s may bring a 0.3-0.7% increase to per capita GDP to local regions in China. In addition, only the current year typhoon exposure matters for the GDP change. Neither past nor future exposures affect per capita GDP significantly. The positive impacts may be associated with the increased rainfall associated with typhoon exposures for inland regions of China, while coastal regions already have good adaptive capacity and disaster relief ability to reduce the economic impacts to local regions. We provide more evidence for this claim using the results for other outcome variables and heterogeneity analysis for typhoon impacts.

Special Transfers

Table(3.3) presents the estimation results of governmental transfer responsiveness to typhoon exposure. Special transfers increase by around 4-5%(from column (5)-(8)) on average for a 10m/s increase in average maximum wind speed in the current year. Both the FE and FD estimates are quite consistent over the significance and magnitude of the estimated coefficients. The results are also robust when controlling historical and future typhoon exposures. FD and FE estimates are different for the historical typhoon impacts, with FE estimates being significant and positive while FD estimates being insignificant and close to zero. The difference may rise because of the serial correlations of typhoon exposures of maxs, which can cause multi-linearity concerns using FE method. FD approach can help to solve the problem because it only uses the variation of annual differences of typhoon exposure after first differencing. This shows that the central government increases targeting aids to local regions for the current year exposure, comparing to the result of no changes for general transfer to be shown later.

One thing to be noticed is that we don't have data on intergovernmental transfers targeting at typhoon disaster relief specifically. Special transfers here are just general targeting transfers which include typhoon disaster relief transfer. In order to draw any claim about the change of typhoon relief specific transfers, we need to assume that other special transfer didn't change with typhoon risks. For example, transfers for disaster relief of other natural disasters like earthquake, non-typhoon induced flooding and droughts are included in the special transfer category. But here we assume these disasters are not directly related to typhoon risks.

In addition, because disaster relief transfer is only a small part of total special transfer, the actual change percentage of disaster relief transfers responding to typhoon risks should be larger than that of total special transfers. Estimate for total special transfer responsiveness also has larger noise than that for disaster relief transfer responsiveness to typhoon risks, if we assume other special transfers vary as well with the variation not related to typhoon risks.

Governmental Welfare Expenditure

Similar to the previous problem of data unavailability of transfers targeting at typhoon relief directly, we do not have governmental relief expenditure data. But we try to use a similar term called welfare expenditure to proxy the governmental relief expenditure. Welfare expenditure includes two types of governmental expenditures: expenditure for public health and expenditure for social welfare. Related to typhoon disasters, welfare expenditure includes all governmental expenses for disease treatment, medical service, aid to poor families and post-disaster relief expenditures related to typhoon shocks. Of course, welfare expenditure also include similar services for other types of natural disasters such as earthquake, flooding and droughts. As mentioned previously, here we assume these disasters are not related to typhoon risks directly.

Table (3.4) lists the FE and FD regression estimates for governmental welfare expenditure due to typhoon shocks. It shows that local regions increase welfare expenditure by 4-5% one year after the typhoon shock for a typhoon disaster with maximum wind speed increasing by 10m/s. Local governments don't response significantly to current year and future typhoon exposures. This may be because aid and relief targeting at individuals or families take a long time to be processed from individual level to the local governments. Or there might be concerns of administrative inefficiency in local county governments for disaster relief.

Other Outcome Variables

We also check the impacts of typhoon exposure on other outcome variables like general transfer, rice yield, governmental revenue, governmental expenditures and governmental infrastructure expenditures. Table(3.5) and Table (3.6) show the FE and FD estimates separately. Results from both methods are pretty consistent. Typhoon risks rarely impact general transfers. As mentioned in the background part, general transfers are non-targeting transfers which follow several routine formulas including elements like the ethnical composition, whether the local region is a designated poor region and population size etc. It is reasonable to believe that general transfers shouldn't vary together with typhoon risks. The impact of maximum wind speed of typhoon disasters on rice yield and governmental revenues are not significant. Total governmental expenditure increased in the typhoon hit year. Comparing the result with welfare expenditure response to past-year typhoon hit, it seems that local governments increase total expenditures but not on individual targeted welfare expenditures. Local governments respond faster to disaster relief for non-household or non-individual targeted purposes, such as infrastructure or public facility maintenance.

3.6.2 Heterogeneity of Governmental Responsiveness

The governmental responsiveness might be heterogenous for regions with different characteristics. As mentioned previously, literatures generally agree that local impacts from typhoon depend on many economic, cultural and social factors, such as income level, literary, governmental effectiveness and media coverage etc. Here we mainly focus on two factors: economic development level and background typhoon disaster strength.

Figure (3.4) shows the variability of typhoon impacts with respect to the historical typhoon exposure level. Regions benefit from typhoon exposure are mainly areas exposed to low level of typhoon shocks with average maximum wind speed below 10m/s. “High-Typhoon Risky" regions are barely impacted in macroeconomic performance by typhoon shocks. The benefits from typhoon might be regions benefiting from typhoon-induced rainfalls(Fumin *et al.*, 2002). However, special transfer increases are mainly observed in high risky regions. It shows that the central government indeed transferred more to regions with extremely high typhoon risks.

Figure (3.5) shows the variability of typhoon impacts with respect to economic development condition. Poor regions generally receive more special transfers and have larger governmental expenditures as responses to current year typhoon exposures. Especially for regions ranked in the lower 50 percentile in terms of per capita GDP, both special transfer and governmental expenditure increase significantly.

These two findings confirm the theoretical claims that transfers should respond to vulnerabilities, including natural vulnerability and economic vulnerability.

3.6.3 County Specific Transfer Responsiveness

In addition to the national average impacts of typhoon hits, we are more interested in the governmental responsiveness to typhoon in specific local regions. The central government may transfer different amounts to local regions even when they are exposed to the same level of typhoon risk. Here we define “transfer intensity index" as the average special transfer percentage change corresponding to a certain magnitude of typhoon risk shock, i.e. increase in average maximum wind speed by 10m/s. This index represents how strong the central government will respond to local disaster exposure. As claimed in the theoretical model, this index depends on two main factors: economic loss and decision weight of the local region. Conditional on the same economic losses, this index can provide some implication on the decision weight of local regions.

We use the following regression model to estimate the average economic and fiscal responsiveness to typhoon risks in local regions, i.e. β_i. By differencing both the dependent and explanatory variables, we can remove the serial correlation concerns of these variables and use purely the variation of differences. In this case, β_i estimates will be consistent and unbiased.

$$\Delta Y_{it} = \beta_0 + \beta_i \Delta \text{maxs}_{it} + \alpha \Delta X_{it} + \epsilon_{it} \tag{3.5}$$

Where ΔY_{it} is the first difference of dependent variables in the current year and that in the past year for county i of year t. Δmaxs is the first difference of average maximum wind speed of the current year and that of the past year. X_{it} includes precipitation and temperature controls.

Figure (3.7) maps the distribution of β_i estimates using logarithm per capita special transfer as the dependent variable. We can also call it transfer intensity index of local regions in China. Polygons with red and yellow color represent larger transfer intensity, meaning that these regions receive more transfers than other regions for the same amount of typhoon risks.

Figure (3.8) maps the distribution of β_i estimates using logarithm per capita GDP as the dependent variable. It shows that the macroeconomic performance of GDP were barely impacted by typhoon risks in the coastal regions. However, a lot of the benefiting (shown in red and yellow polygons) and damaged (shown in blue polygons) regions from typhoon shocks are located inland.

In order to find out what kind of factors are correlated with the transfer intensity and GDP impacts in local regions, we regress β_i with a lot of county characteristics, including average per capita GDP, population size, population density, ethnic minority, a dummy variable showing whether the region was hit by typhoon every year or not and the average maxs level for typhoon risks. Table (3.9) shows the β estimates for GDP, special transfer and general transfer. It shows that special transfer intensity for unit typhoon exposure change is larger for regions with larger population. A region with larger population receive not only more total special transfers, but also per capita special transfers. Regions frequently hit by typhoon receive lower special transfer. This reveals that the central government may expect local regions to develop certain adaptive capacity to typhoon risks. This is consistent with the finding by Hsiang and Narita (2012) of the adaption of regions constantly hit by tropical cyclone globally. Even though the linear estimate of GDP impacts on typhoon transfer intensity is insignificant, polynominal regression results indicated that poor regions has larger transfer intensity for unit typhoon risk change, as plotted in Figure(3.6).

3.6.4 Fiscal Reform and Political Connection

Besides the variability of governmental responsiveness to typhoon exposures related to local relief needs, such as economic level, population and frequency of typhoon exposure, governmental efficiency and political network connection may also impact the transfer responsiveness. The “province manages county" reform aims to increase efficiency of governmental fiscal activities by removing the prefecture governments. After the reform, local governments can receive transfers directly from the central government and provincial government. By reducing the “leakage" of transfer money in the prefecture level, local regions are expected to receive more transfers and respond to local demands faster. Column (1)-(2) in Table (3.11) list the regression results including interaction of reform status and typhoon exposure. Local regions receive more transfers after the reform, but the effect is not statistically significant.

How well local regions are connected to the central government, especially top leaders in the central bureau is another factor impacting resource distribution problems in China. There has been studies showing that better connection with the central government can lead to more capital investment and favoring aids to enterprises Qin (2011). Here we explore how provincial connections with the political bureau members impact governmental fiscal transfer for typhoon risks. We use the political connection data built by Victor Shih (Shih, 2004). Column(3)-(4) in Table (3.11) indicate better connection between the provincial governors and the central government has an insignificant and positive impacts on the special transfers for typhoon exposure.

3.7 Conclusion

Governmental disaster reliefs play an important role in reducing economic damages and helping post-disaster recovery in local regions. For regions in face of large-scale and severe disasters, intergovernmental transfers provide a potential risk-sharing mechanism across different governments. Is this system effective? Based on what considerations is the central government making transfer decisions? This is the first paper tries to answer these questions empirically. Using a self-built dataset on typhoon exposure over all counties and cities in China from 1980 to 2008, We apply both fixed-effects and first-difference estimation methods to estimate the average transfer responsiveness and heterogeneities in the responsiveness.

Results show that the central government do respond to the current-year local disasters, by increasing transfers to regions in face of increasing typhoon exposures. On average, local regions receive 5% more special transfers when the average maximum wind speed increases by 10m/s. The transfer increase only observed for special transfers, which are targeting transfers with usages restricted by the central government. Because we don't have data on disaster relief transfer, which is only part of special transfers, the result can be interpreted as a lower bound of disaster relief transfer changes. The estimates are very unlikely to be driven by other types of special transfers, considering the first-difference approach we use and the temporal pattern of estimates. Neither future nor historical exposures impact transfer responsiveness. We also find that local macroeconomic performance measured by per capita GDP is not significantly damaged by typhoon exposures, even though tend to increase expenditures targeting at social welfares, such as social security, health expenditures one year after the typhoon disaster.

Transfer responsiveness estimates show heterogeneities across local regions, with higher transfer efforts for more vulnerable regions: areas with low per capita GDP or high typhoon risks. County-specific estimates for economic impacts and governmental responsiveness show that regions experienced large GDP losses or benefits tend to be inland areas. The macroeconomy in coastal regions have adapted to frequent typhoon exposure very well. Special transfer responsiveness is lower in regions hit by typhoon every year. This supports climate adaption behavior in high typhoon exposure regions found by Hsiang and Narita (2012). Special transfer responsiveness is also higher in more populated regions. However, special transfer responsiveness is not significantly associated with population density, ethnicity group composition and number of peer competitor counties within the same prefecture. We also don't find significant impacts of political connection and the "province manages county" reform on transfer responsiveness. This coincides with the claim on obstacles of the reform(Wang *et al.*, 2011). The effectiveness might be low because it only targets at the vertical fiscal structure change while the vertical administrative structure remaining the same.

This paper contributes to the large literature on disaster relief, intergovernmental fiscal relationship and typhoon impacts. According to climate change predictions, local regions in China might be exposed to more frequent and more intensive typhoons. This research will be helpful for both governments and non-governmental agents to better prepare for natural disasters and establish more efficient and effective risk-sharing mechanisms.

Tables and Figures

Table 3.1: Summary Statistics

Variable	Unit	N	Mean	Standard Deviation	max	min	Begin-Year	End-Year
GDP	Yuan	25272	7960.805	9091.269	266.6667	209368.8	1996	2008
Governmental Revenue	Yuan	28663	380.7537	717.4942	5.060046	21581.81	1996	2008
General Transfer	Yuan	20706	262.8195	374.8532	-1099.234	10527.47	1996	2006
Special Transfer	Yuan	20659	127.0835	168.5602	-53.05914	5209.714	1996	2006
Governmental Expenditure	Yuan	28241	1103.346	1453.001	23.65073	30136.7	1996	2008
Expenditure on Welfare	Yuan	17289	40.34384	68.70531	-2860.227	1144.083	1996	2006
Population		28668	46.50446	34.18096	0.55	268.2	1996	2008
Average Max Wind Speed	m/s	83317	4.976622	7.879083	0	55.1928	1980	2008
Power Dissipation Index	$10^8 units$	83317	0.0100269	0.0329115	0	0.8575692	1980	2008
Temperature	C degree	61690	12.29147	6.302399	-12.43854	27.20333	1980	2008
Precipitation	mm/day	61690	2.818198	1.393159	0.0257652	8.614	1980	2008
Rice Yield	t/ha	26031	5.399468	1.734563	0.0019599	19.43125	1980	2000

Notes: “Net Revenue Flow In" is the net fiscal revenue flow into local regions. It equals total transfer plus tax return from the upper level governments minus remittance (submitted transfers from local governments to the central government).

Table 3.2: Impacts of Typhoon on GDP

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
maxs F2								0.291
								(0.311)
maxs F1				0.344			0.482	0.656
				(0.425)			(0.306)	(0.408)
maxs	0.679+	0.761+	0.719	0.760	0.298	0.455+	0.821*	0.950*
	(0.349)	(0.405)	(0.438)	(0.489)	(0.200)	(0.269)	(0.355)	(0.423)
maxs T-1		0.397	0.344	0.431		0.293	0.444	0.453
		(0.407)	(0.468)	(0.419)		(0.294)	(0.317)	(0.373)
maxs T-2			-0.194					
			(0.338)					
N	23325	23325	23325	21407	21026	21026	19116	17261
CFE	Y	Y	Y	Y	Y	Y	Y	Y
YFE	Y	Y	Y	Y	N	N	N	N
trend	pref	pref	pref	pref	FD	FD	FD	FD
cluster	pref	pref	pref	pref	pref	pref	pref	pref

Notes: This table reports regression results using GDP as the dependent variable. Both the fixed effects and first-differencing models include temperature and precipitation controls. Column (1)-(4) presents the results for typhoon exposure in the current year and past few years including county fixed effects, year fixed effects and prefectural trends. The unit of coefficient estimate for average maximum wind speed(maxs) is percentage dependent variable change for 10m/s increase in wind speed. Column(5)-(8) presents the first-differencing (FD) estimators for typhoon exposure in the current year, past year and future years. Standard errors clustered at prefecture level in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.3: Impacts of Typhoon on Special Transfers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
maxs F2								0.270
								(1.431)
maxs F1				1.349			-0.386	-0.177
				(1.312)			(1.427)	(1.597)
maxs	5.087***	5.677***	7.224***	6.020***	4.813***	4.652***	4.388**	4.526**
	(1.191)	(1.245)	(1.267)	(1.340)	(1.204)	(1.241)	(1.349)	(1.624)
maxs T-1		2.910*	4.660***	3.232**		-0.329	-0.472	-0.397
		(1.159)	(1.393)	(1.177)		(1.127)	(1.277)	(1.364)
maxs T-2			5.599***					
			(1.571)					
N	20605	20605	20605	20605	17948	17948	17948	17948
CFE	Y	Y	Y	Y	Y	Y	Y	Y
YFE	Y	Y	Y	Y	N	N	N	N
trend	pref	pref	pref	pref	FD	FD	FD	FD
cluster	pref	pref	pref	pref	pref	pref	pref	pref

Notes: This table reports regression results using special transfer as the dependent variable. Both the fixed effects and first-differencing models include temperature and precipitation controls. Column (1)-(4) presents the results for typhoon exposure in the current year and past few years including county fixed effects, year fixed effects and prefectural trends. The unit of coefficient estimate for average maximum wind speed(maxs) is percentage dependent variable change for 10m/s increase in wind speed. Column(5)-(8) presents the first-differencing (FD) estimators for typhoon exposure in the current year, past year and future years. Standard errors clustered at prefecture level in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.4: Impacts of Typhoon on Welfare Expenditure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
maxs F2								-2.849
								(2.134)
maxs F1				0.233			-0.854	-3.100
				(2.645)			(2.467)	(2.803)
maxs	-0.178	1.038	0.741	1.110	-1.074	0.939	0.342	-1.166
	(1.521)	(1.508)	(1.604)	(1.885)	(1.770)	(1.709)	(1.835)	(2.087)
maxs T-1		5.420*	5.084*	5.480*		4.430*	4.105*	3.326
		(2.154)	(2.355)	(2.407)		(1.813)	(2.054)	(2.235)
maxs T-2			-1.129					
			(2.093)					
N	17250	17250	17250	17250	15115	15115	15115	15115
CFE	Y	Y	Y	Y	Y	Y	Y	Y
YFE	Y	Y	Y	Y	N	N	N	N
trend	pref	pref	pref	pref	FD	FD	FD	FD
cluster	pref	pref	pref	pref	pref	pref	pref	pref

Notes: This table reports regression results using welfare transfer as the dependent variable. Both the fixed effects and first-differencing models include temperature and precipitation controls. Column (1)-(4) presents the results for typhoon exposure in the current year and past few years including county fixed effects, year fixed effects and prefectural trends. The unit of coefficient estimate for average maximum wind speed(maxs) is percentage dependent variable change for 10m/s increase in wind speed. Column(5)-(8) presents the first-differencing (FD) estimators for typhoon exposure in the current year, past year and future years. Standard errors clustered at prefecture level in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.5: Impacts of Typhoon on Other Outcome Variables Using FE Model

	Rice Yield	Gov. Revenue	Gov. Expenditure	General Transfer	Infrastructure Expenditure
maxs	-0.817	-1.046+	0.412	0.353	3.998
	(0.595)	(0.618)	(0.395)	(1.489)	(3.733)
maxs T-1	-0.472	0.0214	-0.557	-2.590	-4.167
	(0.441)	(0.622)	(0.409)	(1.643)	(3.637)
N	9710	21167	20749	19738	12988
CFE	Y	Y	Y	Y	Y
YFE	Y	Y	Y	Y	Y
trend	pref	pref	pref	pref	pref
cluster	pref	pref	pref	pref	pref

Notes: This table reports fixed effects estimators of typhoon impacts on several other outcome variables. Precipitation and temperature are controlled in the regression. County fixed effects, year fixed effects and prefectural trends are included. “maxs’ and “maxs T-1’ are separately typhoon exposures of the current year and past year. The unit of coefficient estimate for average maximum wind speed(maxs) is percentage dependent variable change for 10m/s increase in wind speed. Standard errors clustered at prefecture level in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.6: Impacts of Typhoon on Other Outcome Variables Using FD Model

	Rice Yield	Gov. Revenue	Gov. Expenditure	General Transfer	Infrastructure Expenditure
maxs	0.349	-0.927	0.753*	2.552	1.240
	(0.470)	(0.603)	(0.377)	(1.780)	(3.712)
maxs T-1	0.160	-0.192	-0.352	-2.476	-2.744
	(0.393)	(0.458)	(0.322)	(1.842)	(3.231)
N	21562	18990	18554	17052	10466
CFE	Y	Y	Y	Y	Y
YFE	N	N	N	N	N
trend	FD	FD	FD	FD	FD
cluster	pref	pref	pref	pref	pref

Notes: This table reports first-difference estimators of typhoon impacts on several other outcome variables. Precipitation and temperature are controlled in the regression. The model also includes county fixed effects. “Maxs’ and “maxs T-1’ are separately typhoon exposures of the current year and past year. The unit of coefficient estimate for average maximum wind speed(maxs) is percentage dependent variable change for 10m/s increase in wind speed. Standard errors clustered at prefecture level in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.7: Relationship Between Administration Level and Governmental Responsiveness (FE)

	GDP	Special Transfer	General Transfer	Welfare Expenditure	Gov. Revenue
maxs	-0.176	7.034**	-0.314	0.572	-1.991*
	(0.648)	(2.137)	(2.241)	(2.478)	(0.972)
countyXmaxs	1.348*	-2.037	0.903	0.700	1.239
	(0.643)	(2.049)	(2.314)	(2.565)	(1.012)
L.maxs	0.780	6.081**	-6.662**	4.703	-1.090
	(0.708)	(1.872)	(2.402)	(3.178)	(1.023)
countyXL.maxs	-0.404	-4.376*	5.020*	1.366	1.623
	(0.748)	(1.978)	(2.535)	(3.490)	(1.203)
N	19400	20541	19738	17213	21089
CFE	Y	Y	Y	Y	Y
YFE	Y	Y	Y	Y	Y
trend	pref	pref	pref	pref	pref
cluster	pref	pref	pref	pref	pref

Notes: This table reports FD estimation results for administration level and governmental responsiveness in local regions. Local regions are composed of two types, city and county. In the regression, city was set as the default group. The unit of coefficient estimate for average maximum wind speed(maxs) is percentage dependent variable change for 10m/s increase in wind speed. Standard errors clustered at prefecture level in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.8: Relationship Between Administration Level and Governmental Responsiveness (FD)

	GDP	Special Transfer	General Transfer	Welfare Expenditure	Gov. Revenue
maxs	-0.0499	3.646	4.259+	-8.621*	-1.621*
	(0.410)	(2.766)	(2.242)	(4.233)	(0.670)
countyXmaxs	1.019*	-0.248	3.733	10.51*	0.957
	(0.461)	(2.663)	(2.327)	(4.377)	(0.758)
L.maxs	0.856*	-3.799+	-5.271+	-14.95***	-0.273
	(0.425)	(2.005)	(3.032)	(3.442)	(0.603)
countyXL.maxs	-0.368	-2.073	8.028**	11.79**	0.363
	(0.476)	(2.112)	(3.033)	(4.064)	(0.693)
N	17219	17931	17035	15109	18937
CFE	Y	Y	Y	Y	Y
YFE	Y	Y	Y	Y	Y
trend	FD	FD	FD	FD	FD
cluster	pref	pref	pref	pref	pref

Notes: This table reports FD estimation results for administration level and governmental responsiveness in local regions. Local regions are composed of two types, city and county. In the regression, city was set as the default group. The unit of coefficient estimate for average maximum wind speed(maxs) is percentage dependent variable change for 10m/s increase in wind speed. Standard errors clustered at prefecture level in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.9: Factors Impacting Governmental Responsiveness

	(1) GDP	(2) Special Transfer	(3) General Transfer
Ln per capita GDP	-2.228*	1.448	3.884
	(1.022)	(2.284)	(2.361)
Ln pop	0.253	5.914**	1.565
	(0.871)	(1.945)	(2.237)
population density	0.00293	-0.00776	0.00107
	(0.00220)	(0.00696)	(0.00574)
Han ratio	-0.414	9.339	5.858
	(2.118)	(5.334)	(5.521)
Annually hit by typhoon	-2.550	-12.25**	-1.769
	(1.742)	(4.247)	(4.964)
Average maxs	0.0223	0.309	0.153
	(0.152)	(0.610)	(0.582)
#of county/cities within prefecture	0.00911	-0.0605	-0.0285
	(0.130)	(0.343)	(0.485)
N	1215	1151	1086
adj. R-sq	0.127	0.211	0.124

Notes: “Annually Hit by Typhoon" is a dummy variable, which equals to 1 if the region was hit annually by typhoon from 1996 to 2006, and 0 otherwise. “Han ratio" is the ratio of Han population in total population for each local region in 2000. Standard errors clustered at prefecture level in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.10: Correlation of County Specific Estimates for Fiscal and Economic Variables

	Special Transfer	General Transfer	GDP	Gov Revenue
General Transfer	-0.19***			
GDP	-0.19***	0.12***		
Gov Revenue	-0.03	-0.07**	-0.07**	
Gov Expenditure	0.14***	0.02	-0.84***	0.17***

Notes: This table reports the correlation of county specific estimates for the main fiscal and economic variables with respect to typhoon exposure which is measured by maxs, including special transfer, general transfer, GDP, governmental revenue and governmental expenditure.** $p < 0.01$, *** $p < 0.001$.

Table 3.11: Relationship Between Reform and Political Connections and Governmental Responsiveness

	(1)	(2)	(3)	(4)
maxs	4.791***	4.383**	2.517	5.912+
	(1.408)	(1.439)	(3.624)	(3.153)
reform*maxs	3.311	3.670		
	(2.170)	(2.640)		
connect*maxs			4.279	
			(3.479)	
#of connections*maxs				0.340
				(1.443)
Method	FE	FD	FE	FE
Trend	pref		pref	pref

Notes: "Reform" =1 if the region finishes "province manages county" reform. "Connect"=1 if the provincial governors is connected with the political bureau members by "Long March" experience, common working experience, education experience and birth province. The unit of coefficient estimate for average maximum wind speed(maxs) is percentage dependent variable change for 10m/s increase in wind speed. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

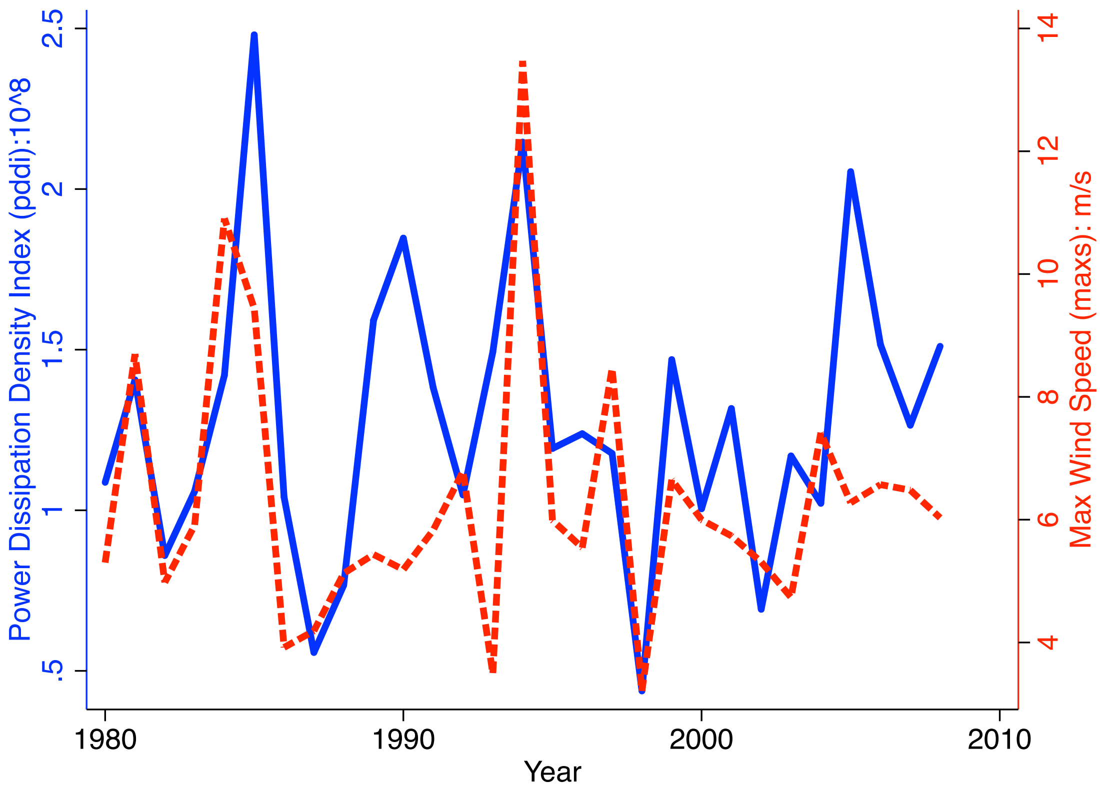


Figure 3.1: County Average Typhoon Exposure: 1980-2008

Notes: This graph plots the average typhoon exposure to all local regions each year. The red line represents average maximum wind speed. The blue line represents power dissipation density index.

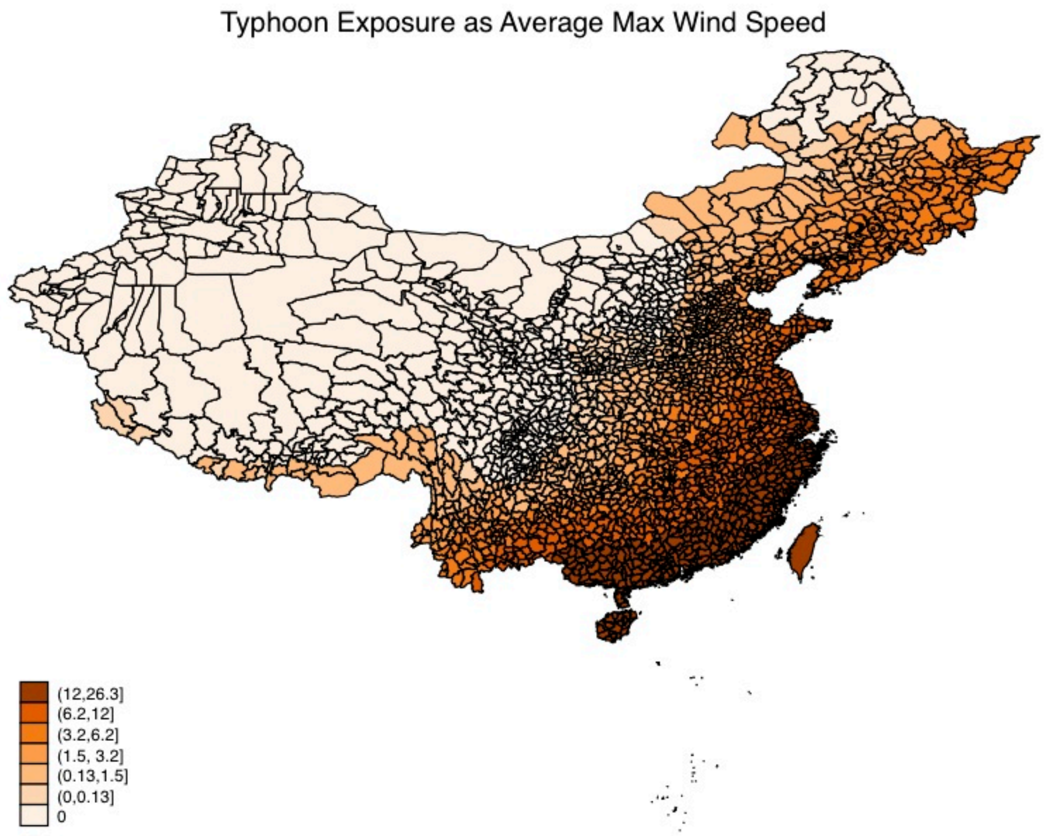


Figure 3.2: Map of Typhoon Exposure of Counties in China (Average Maximum Wind Speed:m/s)

Notes: This map plots the annual mean Average Maximum Wind Speed (maxs) from 1980 to 2008 for each county separately.

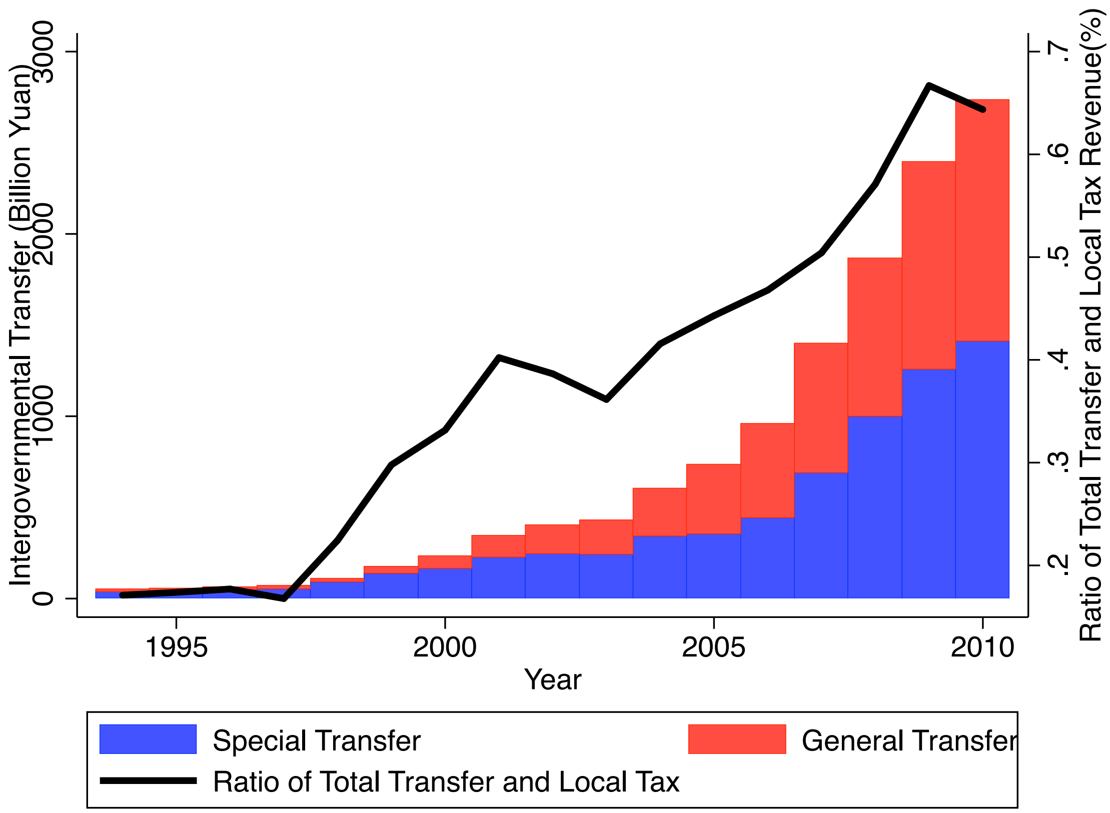


Figure 3.3: Trend of Intergovernmental Transfers in China (1993-2010)

Sources: Annual Data Report by Ministry of Finance (MOF, 1994-2010) and Liu (2010)

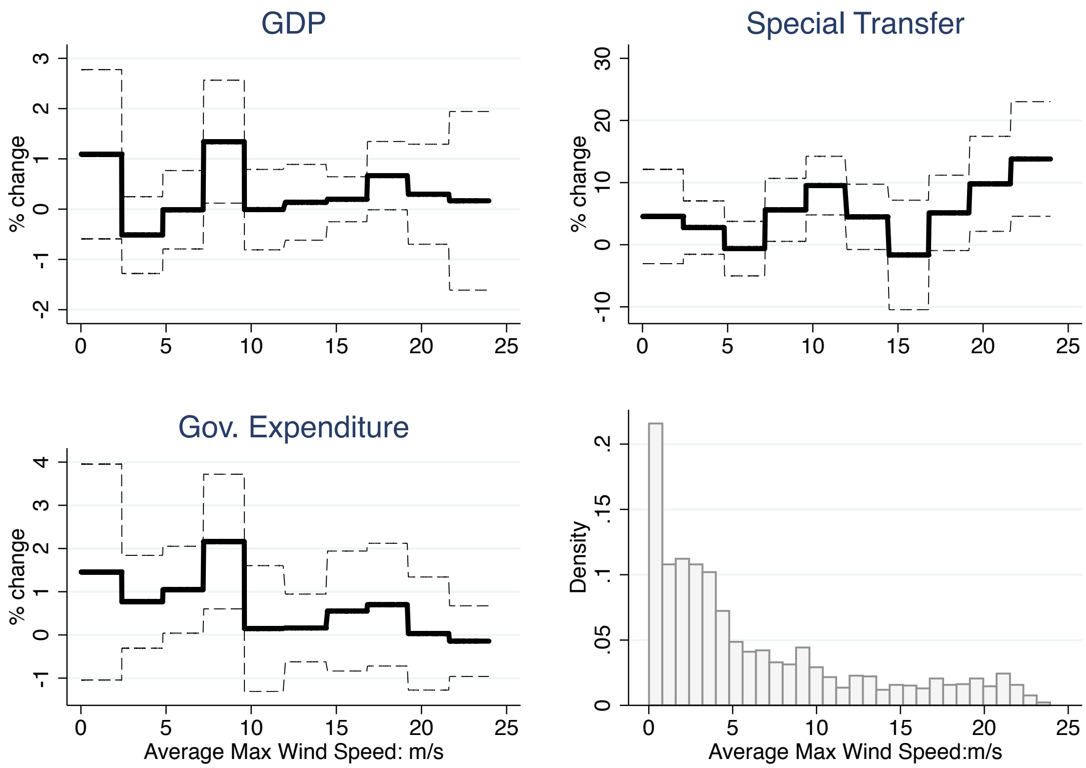


Figure 3.4: Heterogeneity of Typhoon Impacts With Respect to Local Typhoon Risks

Notes: Four graphs in this figure plot the estimates and 95% confidence intervals for typhoon impacts using sub-sample data of specific typhoon exposure bins, for three variables: GDP, Special Transfer and Governmental Expenditure from top left to bottom. Typhoon exposure bins are constructed based on the average historical typhoon exposure of local regions from 1980 to 2008. In all, we use 10 bins for typhoon exposure. The black solid line represents estimates. The dotted lines are 95% confidence intervals. The bottom right graph is the distribution histogram of historical average max wind speed. The unit of coefficient estimate for average maximum wind speed(maxs) is percentage dependent variable change for 10m/s increase in wind speed.

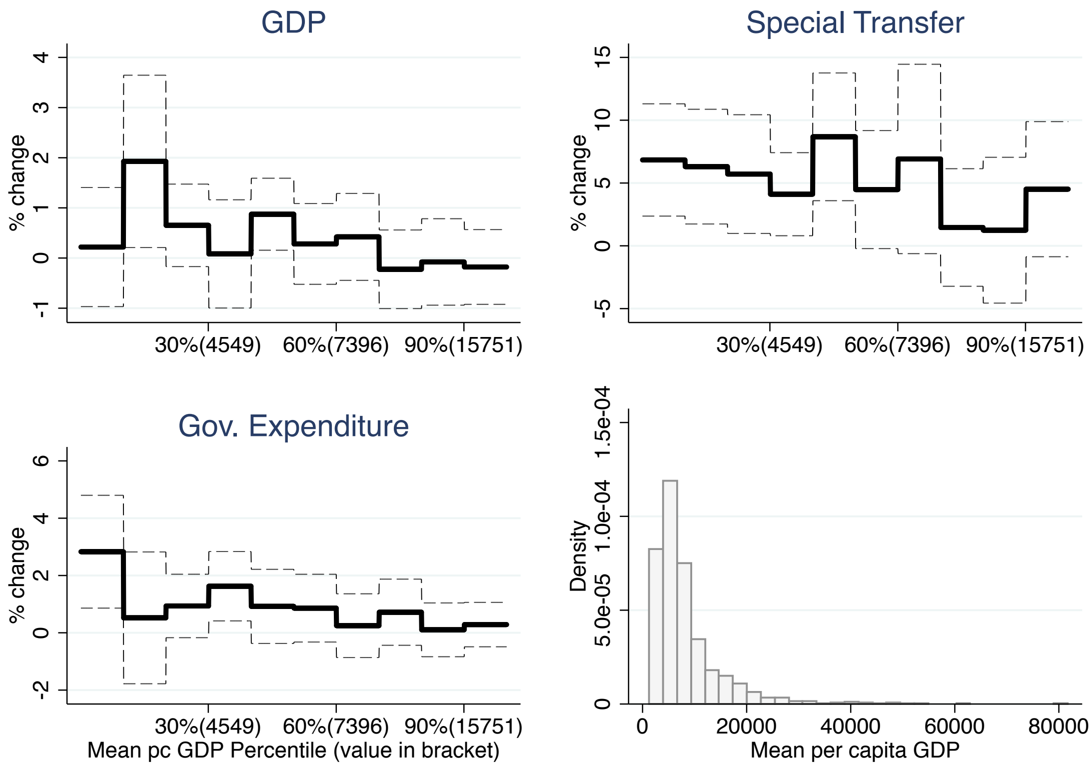


Figure 3.5: Heterogeneity of Typhoon Impacts With Respect to Local Economic Level

Notes: Four graphs in this figure plot the estimates and 95% confidence intervals for typhoon impacts using sub-sample data of specific per capita GDP bins, for three variables: GDP, Special Transfer and Governmental Expenditure from top left to bottom. Per capita GDP bins are constructed based on the average historical GDP level of local regions from 1996 to 2008. In all, we use 10 bins, with each bin representing a decile of per capita GDP. The black solid line represents estimates. The dotted lines are 95% confidence intervals. The bottom right graph is the distribution histogram of average per capita GDP of local regions. The unit of coefficient estimate for average maximum wind speed(maxs) is percentage dependent variable change for 10m/s increase in wind speed.

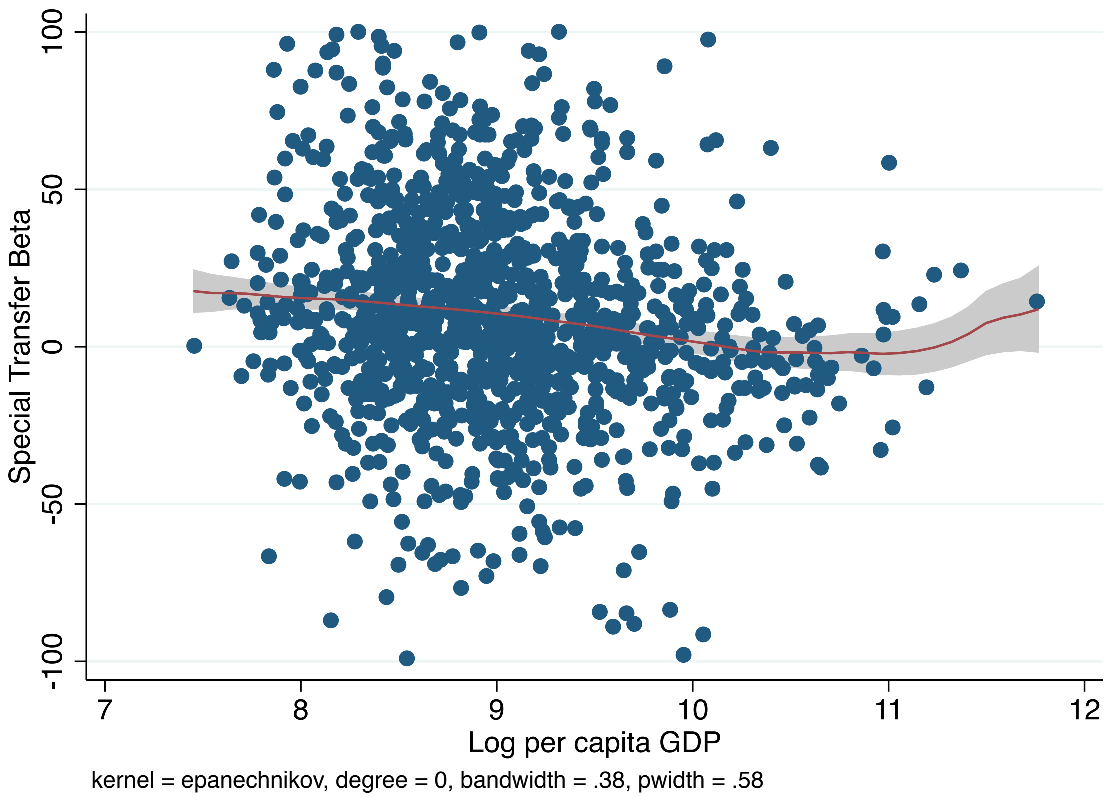


Figure 3.6: Scatter Plot of Transfer Intensity Estimates in Local Regions

Notes: This figure plots the β estimates for governmental special transfers using equation 3.5. A polynomial line with 95% confidence interval was fit on the scatter dots. The unit of coefficient estimate for average maximum wind speed(maxs) is percentage dependent variable change for 10m/s increase in wind speed.

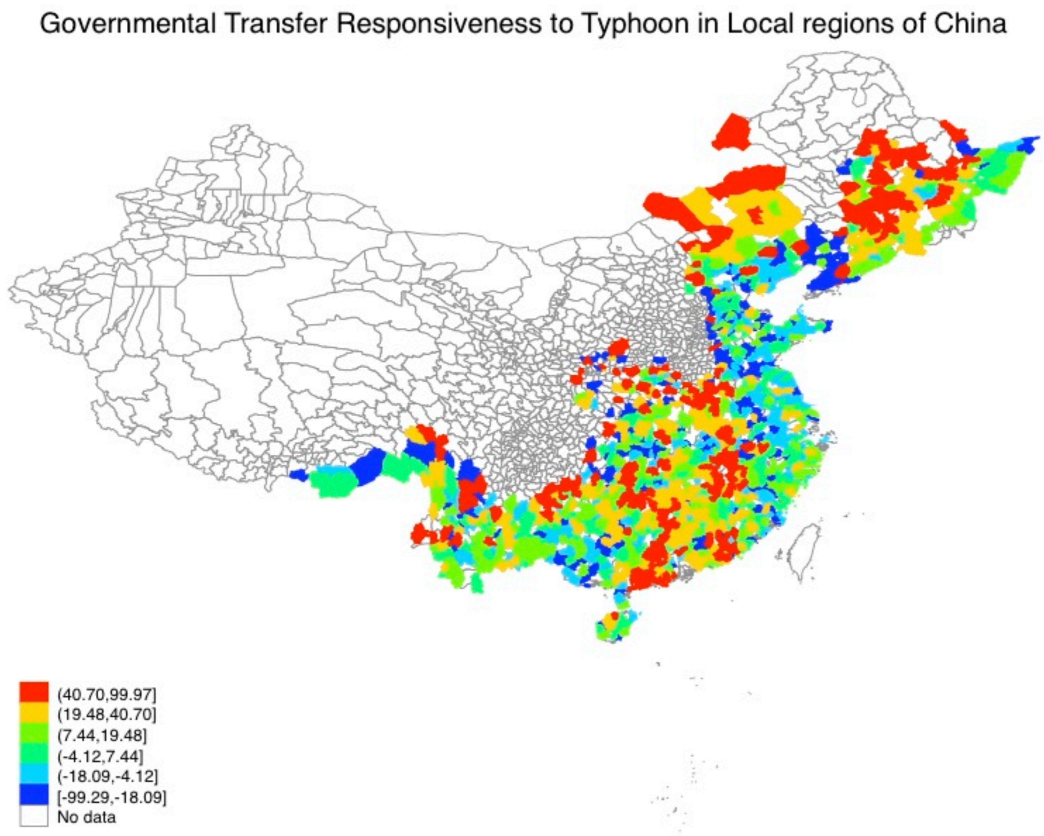


Figure 3.7: Governmental Responsiveness to Typhoon Exposure in Local Regions of China Measured by Special Transfers

Notes: This graph plots the average transfer responsiveness estimate to typhoon hits for each county separately. The estimated coefficients are obtained through β_i for each county i from equation 3.5, using logarithm of per capita transfer as the dependent variable. The unit of coefficient estimate for average maximum wind speed(maxs) is percentage dependent variable change for 10m/s increase in wind speed.

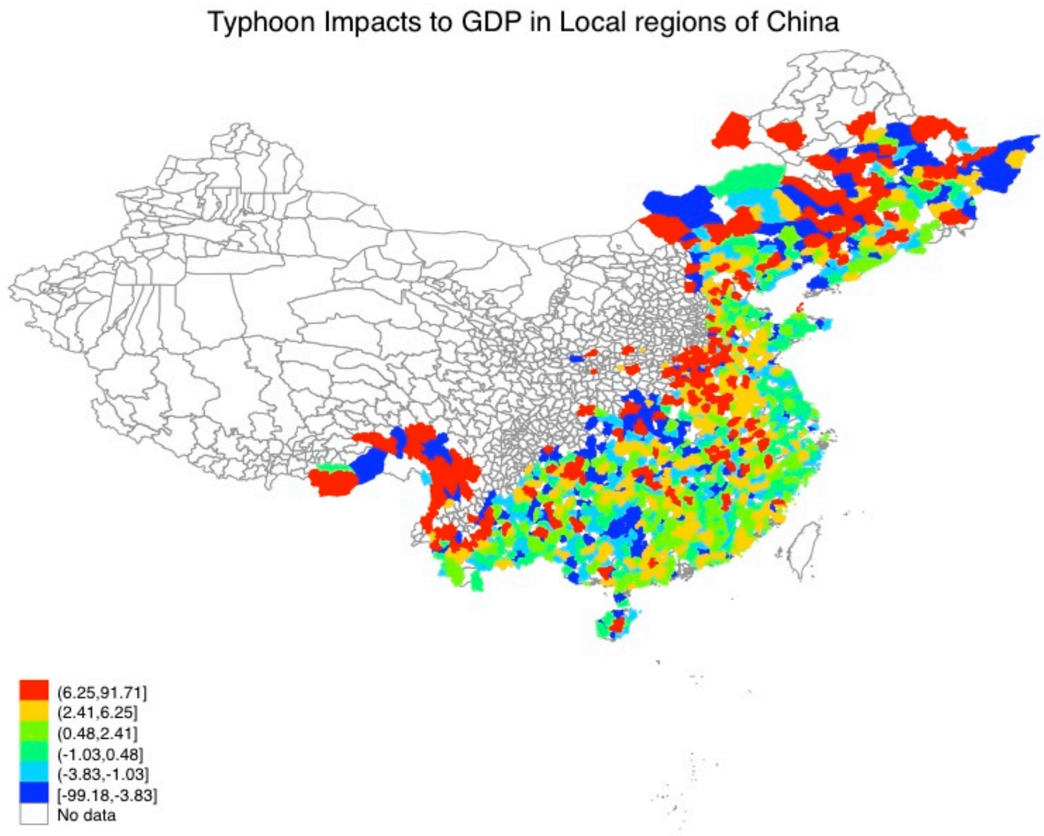


Figure 3.8: Average Impacts of Typhoon Hits on GDP in Local Counties of China

Notes: This graph plots the average impact of typhoon risks on GDP for each county separately. The estimated coefficients are obtained through β_i for each county i from equation 3.5, using logarithm of per capita GDP as the dependent variable. The unit of coefficient estimate for average maximum wind speed(maxs) is percentage dependent variable change for 10m/s increase in wind speed.

Chapter 4

Water, Electricity and Weather Variability in Rural Northern China

Abstract [1]

Economic growth has reshaped rural household characteristics dramatically in the past few decades in China. Families become richer, smaller and older. How do these changes impact household water and electricity demands? This paper answers the question using household data in a water-scarce rural village in Northern China. I find that smaller families tend to increase per capita water and electricity consumptions by more than 20% for one fewer family member. Households with more women in the family have higher water and electricity consumptions even when controlling the family size. Both water and electricity consumptions increase in hotter and drier months. Smaller households are more sensitive to weather variabilities by increasing water use more in face of temperature increases. These findings provide implications on rural water and electricity demand in the context of urbanization and larger weather variability for water-scarce regions in developing countries.

[1]This research was funded by the Doctoral Empedocle Maffia Fellowship by Center for International Conflict Resolution in Columbia University.

4.1 Introduction

Around 783 million people don't have access to safe drinking water globally. 80 percent of them live in rural areas (WBCSD, 2005). Around 1.3 billion people don't have access to electricity globally. 85 percent of them live in rural areas (IEA, 2009). There are a lot of stress to meet water and electricity demands in rural areas. Meanwhile, climate change, associated from weather variabilities, might bring pressure not only on water supplies, but also on water demands. So understanding household water and electricity consumption behavior in rural areas in development countries is very important for policy making on rural water and electricity supply.

For China specifically, around 300 million rural people don't have access to stable safe drinking water[2]. On one hand, the fast urbanization process in China has changed rural household structures significantly, with households becoming smaller, richer, older and occupied by children and women more. On the other hand, a large part of China faces increasing risks of extreme heat and droughts under the impact of climate change. Both household characteristic changes and climate change may impact local water and electricity demands and bring pressure on the supply side to meet these demands. This paper aims to study household water use and electricity consumption behavior and how weather variabilities change water and electricity demands in rural China.

I use Nanhe village as a special case to answer the above questions. Nanhe village is a typical rural village in northern China, with a total population around 3500. The average annual income per household is around 20,000 CNY in 2009. I collect water, electricity and household data from the village committee and local electricity authority for all households registered in the village. OLS (Ordinary Least Squares) approaches for cross-section and

[2]According to 12th Five-Year-Plan on Rural Safe Drinking Water Projects, by NDRC(National Development and Reform Committee)

panel data are used to estimate impacts of household characteristics and weather variables on water and electricity demands.

Household size shows a strong scale-economy effect for per capita water and electricity consumptions. An additional family member correlates with a 24% decrease in per capita water use. The results are consistent with findings in other papers (Schleich and Hillenbrand, 2009; Jorgensen *et al.*, 2009; Gaudin, 2006). Number of female members in the family is significantly correlated with per capita water and electricity consumption, with an estimated coefficient around 6-7%. Due to missing data on household income, I use electricity consumption in March 2009[3] as the proxy for household income for analysis about income impacts on water use. Result shows that water use is significantly correlated with electricity or income level. The energy elasticity for water use is around 0.136. This number is slightly smaller than other estimates for income elasticity (Zhang, 2005). Neither household head gender nor maximum age in the households are significantly correlated with per capita water use and electricity consumption.

Households tend to use more water and electricity in dry and hot months. Per capita water use decreases by 0.7% for 10mm increase in the monthly precipitation and increases by 2% for 1 Celsius degree increase in temperature. Per capita electricity consumption decreases by 4% for every 10mm increase in precipitation and increases by 2% for 1 Celsius increase in temperature. These results are consistent with studies done in other developed countries (Pint, 1999; Danielson, 1979). By checking impacts of household characteristics on water and electricity consumption change corresponding to weather variabilities, I find that local households are quite similar in the electricity adjustment behavior in face of temperature changes. However, for water use adjustment in face of temperature changes, smaller households tend to respond more and increase water consumption more. This confirms the

[3]The water use data are from April to August. The income proxy is the electricity consumption one month earlier.

claim that small households are more sensitive to external changes (Arbués *et al.*, 2010).

The above results are robust to cross-sectional, pooled OLS and fixed effects estimation specifications. One concern of the study is that local households occasionally use ground water as an alternative of the metered pipe water. Due to water deterioration, ground water are mainly used for washing and watering plants in the village. These water uses are more sensitive to temperature and precipitation changes. So the estimates derived in this paper for weather responsiveness of water use can be interpreted as a lower bound of the true water responses. Due to the short study period in this paper, the results mainly describe how households in the rural village vary their water and electricity use for seasonal variation of temperature and precipitation. For further implications of water and electricity use responses for climate change, longer time periods are needed. Northern China generally face teh challenges of increased temperature and increased rainfall (Piao *et al.*, 2010). The weather effects will be strengthened by the urbanization process. This puts huge pressure on water and electricity supply system to meet the increasing demands.

This is the first paper studying household water and electricity consumption behavior and responses to weather variabilities in rural China. The paper contributes to the large literature on water use, electricity consumption and weather variability. Results found in the paper have great policy implications on water and electricity supply in rural regions and water resource allocation in the context of urbanization and seasonal weather variations.

The paper is organized as follows. Section II introduces the background of this study. Section III shows the data used in this paper. Section IV covers the empirical model specification. Section V presents the results and Section VI concludes.

4.2 Background

Water and electricity are two basic needs in human daily life. Based on the destination, uses are categorized into agricultural, industrial, residential and commercial uses. Even though residential water and electricity consumptions only make a small proportion of their total uses, accounting for 8% of total water use (WBCSD, 2005) and 36% of total energy consumption (IEA, 2009), they are key for human health and basic living. Understanding the water and electricity consumption behaviors are crucial for sustainable water and electricity supply. It is generally agreed in literatures that water and electricity consumptions are impacted by price, income, household characteristics and weather comprehensively.

4.2.1 Water and Electricity Consumption

Price and Income

Price is the primary factor identified impacting water and electricity consumptions. Price elasticity estimation has been the research focus for a long time. For both water and electricity sectors, there are various price schemes applied globally, including unit price, increasing block price and decreasing block price. The main difficulty for estimating price elasticity is to choose an appropriate price variable. Several forms of prices have been used in different models, such as marginal price, average price or the combination of the two. Generally, the price elasticity estimate for water use ranges from -0.2 to -0.8 (Billings and Agthe, 1980; Nieswiadomy, 1992; Gaudin *et al.*, 2001). The price elasticity for electricity consumption ranges from -0.2 to -0.4(Filippini, 1995; Espey and Espey, 2004; Reiss and White, 2005).

Income is another factor that can impact water use directly and indirectly. The direct income effect is that higher income results into more water and electricity consumption because of higher purchasing power. But direct income effect is very small, considering that water and electricity fee takes a very small proportion of total household income (Gaudin *et al.*, 2001; Garcia and Reynaud, 2004). Indirect income effects refer to behavior changes due to income change. For example, households may install more water-using facilities, or purchase more water-saving and energy efficient appliances when there is an income increase. The combination of direction and indirect impacts makes the income elasticity on water and energy use quite non-linear and ambiguous (Campbell *et al.*, 2004). Estimates for income elasticity of electricity consumption have a mean value of 0.28 for short-run income elasticity and 0.97 for long-run income elasticity (Branch, 1993; Alberini *et al.*, 2011; Dergiades and Tsoulfidis, 2008; Espey and Espey, 2004). Estimates for income elasticity for water use have median around 0.35 and mean around 0.41 (Dalhuisen *et al.*, 2003).

Household Characteristics

Besides price and income, household characteristics are also correlated with household water and electricity consumption. These characteristics include household size, age structure, gender structure, educational level of household members, house type, house area, garden area, and building age etc.

Larger households tend to use more total water and energy and less in per capita terms. (Arbues *et al.*, 2003; Gregory and Leo, 2003; Reiss and White, 2005; Schleich and Hillenbrand, 2009). Most studies on water and electricity consumption find quite similar magnitudes for household size. One additional family member is estimated to increase total water use by 8% (Hoffmann *et al.*, 2006) and electricity consumption by 7% (Branch, 1993). The relationship of age and water and electricity consumption is more complex. Families with more young people and children may use more water because they have more outdoor activities (Gregory and Leo, 2003; Nauges, 2003). Also families with more elderly consume more water and electricity.

Among many household characteristics, the characteristics of the household head are also considered to be an important element. It was believed that household members tend to learn from the water and electricity consumption behavior of household head. For example, household with female household head might be more water saving (Campbell *et al.*, 2004).

Weather Variability

Both water and electricity consumption also respond to weather variabilities. Though residential water use is not as responsive to weather as agricultural water use, it does respond to a certain level. Typical weather elements impacting residential water use include precipitation, temperature, maximum daily temperature, and rainy days etc (Hoffmann *et al.*, 2006). People might shower more and wash more if temperature goes higher (Taylor *et al.*, 2004; Olmstead *et al.*, 2007). The impact of precipitation is ambiguous, because more precipitation may correspond not only to less plant-watering and outdoor activities, but also to higher need of washing due to stains or mud. Maidment and Miaou (1986) found that household water uses was correlated with both the occurrence and the magnitude of rainfall significantly.

The relationship between residential electricity consumption and temperature has been widely studied. Crowley (2003) claimed that total energy consumption would increase by 3.8% for every 2 Celsius degree increase. Deschenes (2011) find a U-shape curve for electricity consumption and temperature. Electricity increases in very cold and hot days. Auffhammer and Aroonruengsawat (2011) also studied the non-linear relationship between electricity consumption and temperature. Once temperature exceeds 80F (26.7 Celsius) degree, the average percentage change of electricity consumption is around 1-4% for unit F degree increase.

So far most of the studies were done in developed countries or urban regions in developing countries. Hoffmann *et al.* (2006) surveyed all published journal articles on residential water use since 1980 and found that 56% are sampled in US, 24% in Europe, 16% in Australia, and the other 4% from other regions. However, water use challenge is especially high in those less studied areas, where water use level is typically very lower, and households are more vulnerable to water shortages. Rural water and electricity consumptions in developing countries are still not well studied. However, these are the regions experiencing fast social and economic changes and suffering from water and electricity restraints. So studies focusing on water and electricity behaviors in rural regions in development countries have huge policy implications. This paper first time studies the water and electricity behaviors of rural households in a water scarce region of China.

4.2.2 Nanhe Village

The studied area in this paper is Nanhe Village in Northern China (shown in Figure (4.1)).Total population in the village is around 3500, with 880 households registered in the village in 2009. Average annual income per household is around 20,000 CNY (or 3000 US Dollar). Main income sources of Nanhe Village are agriculture crops, one iron mine and four livestock farms. Agricultural revenue contributes to around 40% of total household income. Pipe water system in Nanhe Village was built in 2007 and it has been serving the village since then. The water price structure follows the decreasing block rate at 3CNY/ton for the first 2 tons and 2.5Yuan/ton for further amount. Nanhe has a wet and hot summer season and a dry and cold winter season. Annual average precipitation is around 700mm, with most of the rain falling between May and September. Annual average temperature is around 15 Celsius Degree. For ease of management, the whole village is divided into 9 groups from east to west. Group 1, 2 and 3 are in the east part of village with low elevation (with an average at 3140 ft) and Group 8, 9 are in the west part of village with high elevation (with an average at 3180 ft). There are more ground water wells in the east part than the west part, because the ground water level is much lower in the east.

Pipe water and privately-own shallow ground water are the two main water sources for local villagers. Because of ground water deterioration and water level decline due to nearby minings, most people have already switched from ground water to pipe water. Currently, all of the drinking and cooking water are from pipe water, but occasionally ground water is still used for washing, cleaning and watering. This means that actual water use is higher than the metered water used in this paper. Because water used for washing, cleaning or watering is more sensitive to weather variability than water used for cooking, drinking or bathing, I believe the estimates on water use responses to weather variabilities in the following empirical analysis are lower bounds of the true values.

4.2.3 Data

I use three different datasets for the empirical analysis: water use data, electricity consumption data and household characteristic data.

Household water use data in the village were collected by the village committee. A water manager is assigned to record household water meter readings once every month. I obtained monthly accumulated water meter readings from March to August in 2009. Based on this, monthly household water use was calculated from April to August. Table (4.1) reports the summary statistics of monthly water uses. The monthly average household water use is around 1.7-2.4 m^3 for each household. The average water use per capita per day is 14-26 liters, which is very low comparing to the UN requirement of 20-50 liters for residential water use. Local households tend to use ground water occasionally for purposes of washing or watering plants. During the study period, average household water use increased from April to July, reaching maximum in July, and then decreased in August to a level a bit lower than that in April. Figure (4.2) plots the distribution of per capita water use in April and July. There is an obvious rightward shift in the distribution curve.

Household characteristics data in 2009 was obtained from the village committee. It covers characteristics like household size, gender and age composition of family members, household head and group belonging of each household. Local village committee updates the records every year take take account of population change and household structure changes[4]. Table (4.1) shows that most household heads are male. The average household has 4 members and 2 females. The average age of the oldest person within family is around 52 years old.

electricity consumption data was provided by the local electricity supply company. Electricity bills are paid every other month in the local village. I got electricity for the registered households from September 2007 to May 2009. Table (4.1) lists the average electricity consumption for every two months. The average electricity consumption is around 0.5-0.7 kwh per person per day, which is low comparing to the national average of 0.65 kwh in 2000 (Zhang, 2004) and 9 kwh in California in 1999 (Ito, 2012)

I also calculated the monthly average temperature and precipitation of local county based on temperature records from CRU(Climate Research Unit in University of East Angolia) database and precipitation records from National Centers for Environmental Prediction, NOAA(National Oceanic and Atmospheric Administration). Figure (4.3) plots the trend of monthly precipitation and temperature in 2009. Precipitation was the highest n August.

Because each dataset has different identifiers, some identified by household head name and some by the oldest member, I manually match the households based on names of family members for all three datasets. In all, I get 500 households after matching. Table (4.1) lists the summary statistics of variables before and after match. T-test results shows that there are no significant differences for household characteristics and electricity consumption variables before and after match. Water use in the matched households are slightly higher than that of all households. The reason for the discrepancy of data before and after match may be labor migration. Because of the increasing labor migration to urban areas in the village, many households live outside the village occasionally, like nearby cities or towns,

[4]For example, people tend to separate from their parents after marriage, even though they still live in the same village.

even though they are still registered in the village. So their water use in the village usually is lower than the village average. Due to mobility, these households are less likely to be matched across different datasets. In addition, The matched households represent those living a relatively stable life in the village. So it is reasonable to believe that analysis based on the matched households can represent the water use and electricity consumption condition of the whole village very well.

4.3 Empirical Strategy

I use OLS (Ordinary Least Squares) estimations for the empirical analysis on water use pattern and water use adjustments. For impacts of household characteristics on water use, I use both cross-section and pooled OLS estimations. Explanatory household characteristic variables include family size, # of females in the family, household head gender, age of the oldest family member and committee group to which the household belongs to. For impacts of weather variables on water use, I use fixed effects models, as specified here.

$$Y_{im} = \alpha_1 \text{Temperature}_m + \alpha_2 \text{Precipitation}_m + \gamma_i + \epsilon_{im} \tag{4.1}$$

where Y is the dependent variable for household i in month m. For electricity consumption analysis, I also include year fixed effects to control for annually fixed factors, such as local electricity facility maintenance.

Slightly different from other studies on water demand functions (Olmstead *et al.*, 2007), price is not included here. Since all households in this study are in the same village and exposed to the same price structure during the study period, there are not enough variations in exposed price. In addition, even if we can calculate the marginal price or average price based on the simple increasing block price structure, simple OLS regression will just generate a positive coefficient on price for water use, which cannot be interpreted as the price elasticity for water use.

There might be OVB (Omitted Variable Bias) concerns in this specification due to missing variables, especially income variables. For example, if household income is positively correlated with family size, considering that richer households can afford more children[5] and income is also positively correlated with water use, the coefficient estimate for household size might be biased upward if income is not controlled. To correct the OVB problem, household income was proxied by electricity in March 2009. There has been many studies found significant correlations of income and electricity consumption (Dergiades and Tsoulfidis, 2008; Alberini *et al.*, 2011; Branch, 1993). Of course, this is not a perfect proxy for income, because there are also factors impacting electricity consumption, like electricity price. In this paper, I mainly use it to verify the robustness of estimates for other household characteristics.

4.4 Results

The results are present in two sections separately: results on residential water use levels and changes.

4.4.1 Residential Water and Electricity Consumption

Table (4.2) reports the cross-section (column 1,2) and pooled OLS (column 3,4) estimation for household characteristics impacting household water use. Column(1) and (2) reports results using the April water use data only. Household size shows a strong scale-economy effect. An additional family member correlates with 24% decrease in per capita water use. This coefficient is smaller than results in Schleich and Hillenbrand (2009) and Jorgensen *et al.* (2009), which were between 0.4 and 0.5. But it is close to Gaudin (2006)'s result with

[5]Rural families in Shanxi Province are allowed to have a second child in 2009.

coefficient around 0.25. Number of female members in the family is significantly correlated with per capita water use in the pooled OLS results. One more female member increases the per capita water use by around 8.7%. Even though its significance disappear in the cross-section results, the estimate value remain around 6-7%. Water use is also significantly correlated with electricity or income level. The energy elasticity for water use is around 0.136. This number is slightly smaller than estimates from Zhang (2005). The potential reason is that households in local region occasionally use pumped water from shallow ground wells for some residential use purposes. The coefficient of electricity elasticity for water use here is the combination of income effects and substations between metered pipe water and ground water uses. Neither household head gender nor maximum age in the households are significantly correlated with household water use.

Besides household characteristics, weather variables also impact rural residential water use. Households tend to use more water in dry and hot months. Per capita water use decreases by 0.7% when the monthly precipitation increases by 10mm, while it increases by 2% for 1 degree increase in temperature. Theses results are quite robust for both fixed effects and other pooled OLS estimations. Similar responses to weather variabilities were also found in other studies on water use behaviors(Pint, 1999; Danielson, 1979). Figure(4.4) plots the estimate and confidence interval for each month of the pooled OLS model specification. Water uses increase significantly by more than 10% and 30% in June and July comparing to the level in April. Then in August, the water use level declines back to the April level. Comparing this pattern with the monthly temperature and precipitation pattern as shown in Figure (4.3), water use changes closely with the weather.

I also analyzed the relationship between total water use change with household characteristics. As shown in column(1) of Table (4.3), total water use are not correlated with family size anymore (Arbués *et al.*, 2010). This confirms the scale-effect findings that larger households are better for per capita water use by sharing certain water use facilities together. Similar to per capita water use results, number of females in the family and weather characteristics also impact total water use. Older family members tend do reduce water use. Analysis on electricity consumption show similar patterns for water use, with higher water uses in drier and hotter months. Estimates for weather variables are robust using both pooled OLS (in Table (4.3)) and fixed effects (in Table (4.4)) approaches. Both water and electricity consumption show similar percentage changes for one degree increase in temperature. Temperature estimates are also similar in magnitude as other findings on electricity consumption response to temperature (Auffhammer and Aroonruengsawat, 2011;Costa and Kahn, 2010; Deschenes, 2011). However, the response of electricity consumption to precipitation is much larger than that for water use. One potential reason is that local electricity supply is very unstable and vulnerable for lightning and rainfall events, which can cause blackouts frequently. In addition, local electricity manager will shut off power to avoid damages for heavy rainfalls.

4.4.2 Temperature Variability

As shown in the previous results, residential water use experiences gradual increases and decreases from April to May. Besides the average response to weather variability, another question is how household characteristics impact the water use adjustment behavior. In order to answer the question, I interact several household characteristics with temperature in the regression.

Table (4.5) reports results by including interactions of electricity consumption in May 2009, household head gender, number of females and family size with temperature. Larger families respond less to temperature changes. An additional member in the family can decrease the response to temperature by 0.4%. This corresponds to similar findings on the relationship between family size, water use adjustment and weather adaptions. Arbués *et al.* (2010) shows that small households are more sensitive to price changes for water use in

Spain. Deressa *et al.* (2009) finds that larger households are more open to weather adaptive technologies and practices. Neither income proxied by electricity consumption nor household gender structure impact water use responsiveness to temperature variations significantly.

I also checked impacts of household characteristics on water use adjustment during the water use increase (April-July) and decrease period (July-August). Cross-sectional analysis on the water use changes for these two periods are presented in Table (4.6). The findings confirms the previous results on the relationship between household size and water use changes. Larger households tend to adjust less. In addition, households with male household heads tend to adjust more, both in the water increasing and decreasing periods. Generally, water use adjustment moves in the opposite direction to water use level at the beginning period. Households use large amount of water tend to decrease water use in the future. This holds for both the water use increasing and decreasing period.

Table (4.7) reports results by including interactions of electricity consumption in May 2009, household head gender, number of females and family size with temperature. It shows that none of household characteristics impact electricity consumption response to temperature. Household income proxied by per capita electricity consumption in May 2009 has a significant negative coefficient. However, because the weakness of using part of the dependent variable as the proxy, the estimate for the interaction term might be biased.

4.5 Conclusions

Residential water and electricity demands have been reshaped by both household characteristics and weather variabilities. Understanding the connection between water, electricity and weather variability is important for water and electricity supply. This is especially true in rural regions of developing countries. I modeled household water and electricity demand model in a rural village in Northern China using household level panel data.

Both household size and number of females in the family impact water and electricity consumption significantly. Household size shows a strong scale-economy effect for per capita water and electricity consumptions. An additional family member correlates with 24% decrease in per capita water use. Women tend to use more water and electricity in the local village, with water use increasing by around 6-7% for one more woman in the family. Neither household head gender nor maximum age in the households are significantly correlated with per capita water use and electricity consumption. In addition, water and electricity consumptions are closely associated with weather variables. Households tend to use more water and electricity in dry and hot months. Per capita water use decreases by 0.7% when the monthly precipitation increases by 10mm, while it increases by 2% for 1 Celsius degree increase in temperature. Per capita electricity consumption decreases by 4% for every 10mm increase in precipitation and increases by 2% for 1 Celsius increase in temperature. For water use adjustment in face of temperature changes, smaller households tend to respond more and increase water consumption more.

The above results are robust to cross-sectional, pooled OLS and fixed effects estimation specifications. Due to exclusion of ground water in the analysis, the estimates derived in this paper for weather responsiveness of water use can be interpreted as a lower bound of the true water responses. Another finding is the high similarity between temperature response of water and electricity around 2% per one celsius degree change. The result is also similar to other studies done in development countries. This may imply that there are some generality among temperature responsiveness for basic water and electricity consumption beyond the social and economic contexts. Further studies might be needed to nail down potential specific factors driving the similar results.

This is the first paper studying household water and electricity consumption behavior and responses to weather variabilities in rural China. The results may provide policy implications on water and electricity supply in rural regions. Linking the estimated results with the weather predication of increased temperature and increased rainfall in Northern China (Piao *et al.*, 2010), water and electricity demands will increase in local regions. The effects might be strengthened by the urbanization process. This will put huge pressure on water and electricity supply system to meet the increasing demands. Of course, longer time series data are needed to provide more specific implications on the water and electricity use responses for climate change.

Tables and Figures

Table 4.1: Summary Statistics

	Variable	Before Merge			After Merge			T-test
		Mean	sd	obs	Mean	sd	obs	
Water use(unit: m^3)	April	1.7	2.0	797	1.8	1.6	550	0.28
	May	1.7	1.7	797	1.8	1.6	550	0.06+
	June	2.1	1.9	797	2.3	1.9	550	0.05+
	July	2.4	2.4	797	2.6	2.4	550	0.13
	August	1.5	1.5	797	1.7	1.5	550	0.02*
Household characteristics	Group	5.0	2.7	664	5.0	2.6	550	1.00
	HH Gender	1.0	0.1	664	1.0	0.1	550	0.23
	Family Size	4.0	1.4	664	4.0	1.3	550	0.84
	# of Females	1.9	0.9	664	1.9	0.9	550	0.91
	Max Age	52.1	10.5	664	51.8	10.5	550	0.51
electricity consumption(unit: kwh)	Jan	92.3	167.3	815	85.7	91.9	550	0.40
	Mar	130.4	229.6	816	123.2	138.7	550	0.51
	May	100.3	199.0	816	90.6	81.6	550	0.28

Notes: "Group" denotes the committee group a household belongs to."Before Merge" data are the raw balanced data sample for each separate dataset of water use, household characteristics and electricity consumption. "After Merge" data are the balanced dataset after merging three datasets. T-test results present the p-value of T-tests for equal mean for "before merge" and "after merge" data. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.2: Factors Impacting Residential Water Use

	(1)	(2)	(3)	(4)	(5)
Family Size	-0.240***	-0.244***	-0.294***	-0.295***	
	(0.0317)	(0.0311)	(0.0157)	(0.0155)	
# of Female	0.0722	0.0648	0.0874***	0.0882***	
	(0.0448)	(0.0443)	(0.0213)	(0.0211)	
Max age	-0.0166	-0.0124	-0.00155	-0.00107	
	(0.0247)	(0.0248)	(0.0124)	(0.0123)	
HH Gender	0.0158	-0.0105	0.0985	0.101	
	(0.321)	(0.297)	(0.163)	(0.170)	
		0.136***			
		(0.0401)			
Precipitation			-0.707***		-0.823***
			(0.165)		(0.123)
Temperature			0.0208***		0.0199***
			(0.00320)		(0.00229)
Constant	6.965***	6.383***	6.627***	6.955***	5.729***
	(0.373)	(0.388)	(0.201)	(0.197)	(0.0540)
Controls				Month Dummies	
Household FE					Y
N	512	508	2579	2579	2579
Adjusted R^2	0.168	0.186	0.213	0.226	0.585

Notes: The dependent variable is log per capita water use. Column(1)-(2) are cross-section estimation for water use in April. Column (3)-(4) are pooled regression results including weather control and monthly dummies separately. Column(5) presents fixed effects results. Unit of precipitation here is meter. The coefficient for max age is multiplied by 10. Household Head (HH) gender=1 for males. All the regressions also control group committee dummies. Robust errors in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.3: Household Characteristics and Total Water and electricity consumption

	(1) log (water)	(2) log (Electric.)	(3) log (per capita electric.)
Family Size	-0.00724	0.0582***	-0.230***
	(0.0156)	(0.0114)	(0.0115)
# of Female	0.0732***	0.0367*	0.0498**
	(0.0212)	(0.0153)	(0.0155)
Max age	-0.0311*	-0.0390***	-0.00939
	(0.0122)	(0.00904)	(0.00901)
HH Gender	0.117	0.0451	0.0196
	(0.173)	(0.0884)	(0.0965)
Precipitation	-0.706***	-4.973***	-4.977***
	(0.162)	(0.345)	(0.347)
Temperature	0.0206***	0.0223***	0.0224***
	(0.00316)	(0.00215)	(0.00216)
N	2579	5863	5863
Adjusted R^2	0.036	0.098	0.184

Notes: These are pooled OLS regression results. The time range of water is from April to August in 2009. The time range of electricity is from September 2007 to May 2009 (every other month). Unit of precipitation here is meter. The coefficient for max age is multiplied by 10. Household Head (HH) gender=1 for males. All the regressions also control group committee dummies. Robust errors in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.4: Fixed Effects Estimation of Water and electricity consumption Response to Weather Variability

	Log (Water)	Log(Electricity)	
Precipitation	-0.823***	-4.914***	-6.485***
	(0.123)	(0.231)	(0.680)
Temperature	0.0199***	0.0221***	0.248***
	(0.00229)	(0.00142)	(0.0184)
Household FE	Y	Y	Y
Year FE	-	Y	
Month FE	-		Y
N	2579	5863	5863
Adjusted R^2	0.480	0.636	0.088

Notes: The time range of water is from April to August in 2009. The time range of electricity is from September 2007 to May 2009 (every other month). Unit of precipitation here is meter. Standard errors in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.5: Household Characteristics and Water Use Response to Temperature (FE)

	(1)	(2)	(3)	(4)	(5)
Precipitation	-0.836***	-0.823***	-0.823***	-0.823***	-0.823***
	(0.124)	(0.123)	(0.123)	(0.123)	(0.123)
Temperature	0.0231*	-0.0127	0.0259***	0.0360***	0.0199***
	(0.00906)	(0.0286)	(0.00512)	(0.00711)	(0.00229)
Log (per capita electric.)	-0.000872				
*temperature	(0.00289)				
HH Gender*temperature		0.0328			
		(0.0286)			
# of Females*temperature			-0.00307		
			(0.00235)		
Family Size*temperature				-0.00399*	
				(0.00168)	
N	2558	2579	2579	2579	2579
Adjusted R^2	0.584	0.585	0.585	0.586	0.585

Notes: The dependent variable here is log per capita water use. Unit of precipitation here is meter. Household Head (HH) gender=1 for males. Standard errors in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.6: Cross-sectional Analysis on Water Use Adjustment

	(1)	(2)	(3)	(4)
	Water use change (April-July)		Water use change (July-August)	
log(per capita electricity)	-0.268+	-0.162	0.0133	0.0996
	(0.159)	(0.156)	(0.0953)	(0.0764)
Family Size	-0.236+	-0.132	-0.0506	-0.0732
	(0.133)	(0.130)	(0.0998)	(0.0778)
# of Female	0.0230	-0.0336	0.0681	0.183+
	(0.180)	(0.188)	(0.139)	(0.105)
Max age	-0.0224	-0.0763	0.0125	-0.0503
	(0.114)	(0.120)	(0.0884)	(0.0611)
HH Gender	1.380**	1.306***	-0.488*	0.457
	(0.451)	(0.324)	(0.235)	(0.342)
log water (April)		-0.758**		
		(0.256)		
log water(July)				-1.785***
				(0.164)
N	545	508	545	515
Adjusted R^2	0.024	0.069	0.023	0.456

Notes: The dependent variable for Column(1)-(2) is the difference between water use in July and April(increasing water use period). The dependent variable for Column(3)-(4) is the difference between water use in August and July (decreasing water use period). Unit of precipitation here is meter. Household Head (HH) gender=1 for males. All the regressions include household characteristics of HH gender, family size, # of females, max age and group belonging. Robust errors in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.7: Household Characteristics and Electricity Consumption Response to Temperature (FE)

	(1)	(2)	(3)	(4)	(5)
Precipitation	-4.308***	-4.246***	-4.247***	-4.247***	-4.246***
	(0.239)	(0.240)	(0.240)	(0.240)	(0.240)
Temperature	0.0324***	0.0121	0.0146***	0.0147***	0.0136***
	(0.00338)	(0.0100)	(0.00211)	(0.00268)	(0.00143)
Log (per capita electric.)	-0.00613***				
*temperature	(0.00101)				
HH Gender*temperature		0.00147			
		(0.01000)			
# of Females*temperature			-0.000547		
			(0.000800)		
Family Size*temperature				-0.000290	
				(0.000568)	
N	5831	5863	5863	5863	5863
Adjusted R^2	0.602	0.600	0.601	0.600	0.601

Notes: The dependent variable here is log per capita electricity consumption. Unit of precipitation here is meter. Household Head (HH) gender=1 for males. Standard errors in parentheses. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

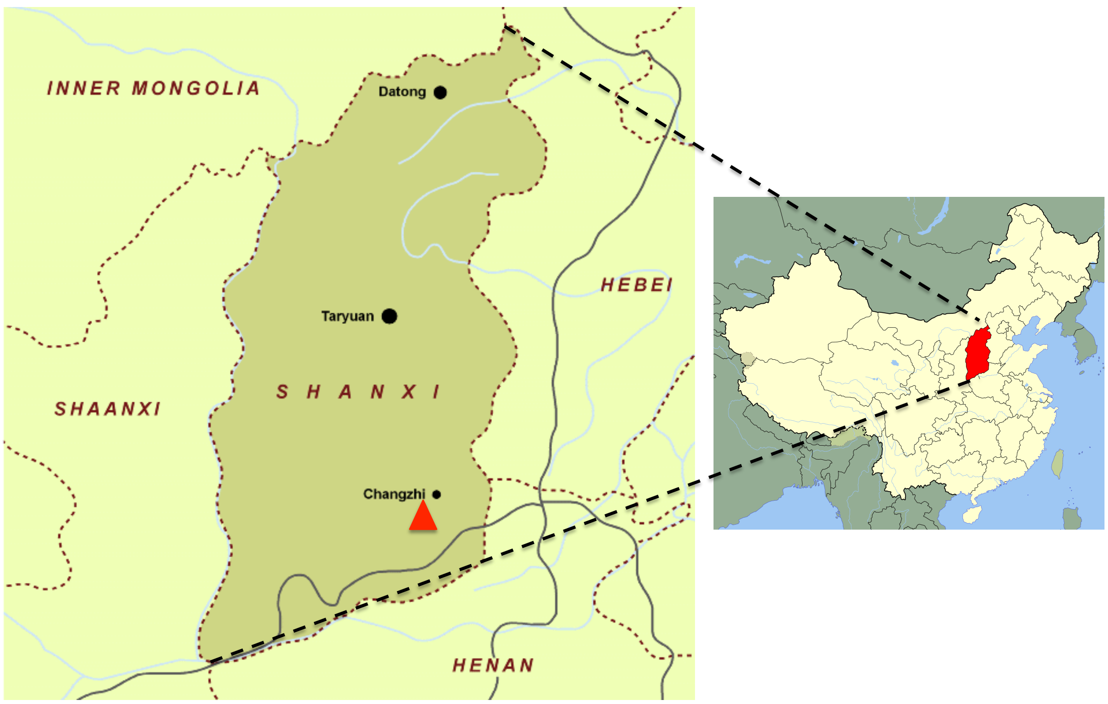


Figure 4.1: Location of Nanhe Village in China

Notes: The red triangle region is the studied village: Nanhe Village in Changzhi, Shanxi.

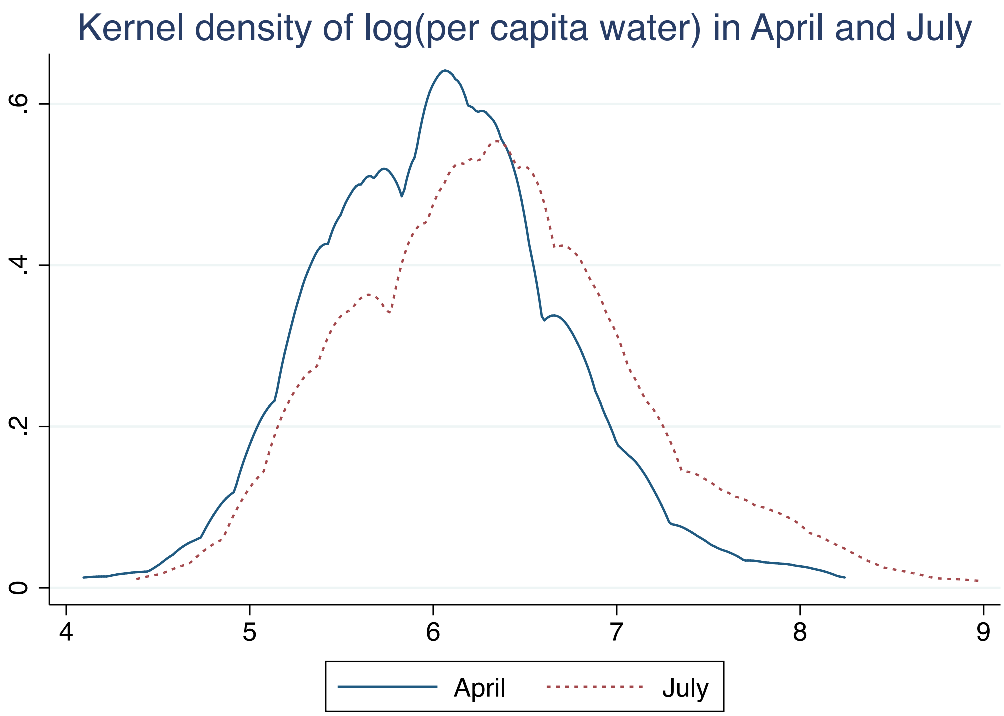


Figure 4.2: Distribution of per capita Water Use in April and July

Notes: The solid line represents water use in April, while the dotted line represents water use in July.

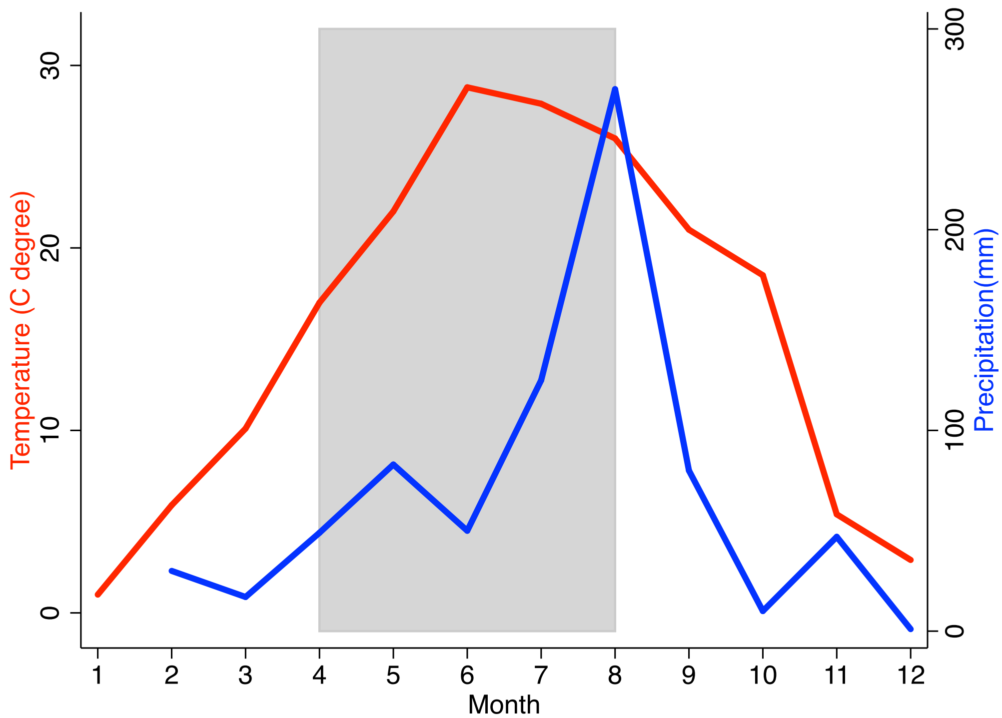


Figure 4.3: Monthly Temperature and Precipitation of Nanhe Village in 2009

Notes: This graph plots monthly average temperature and precipitation of Nanhe Village in 2009. Red line represents temperature and blue line represents precipitation. Shaded area is the study months: April to August.

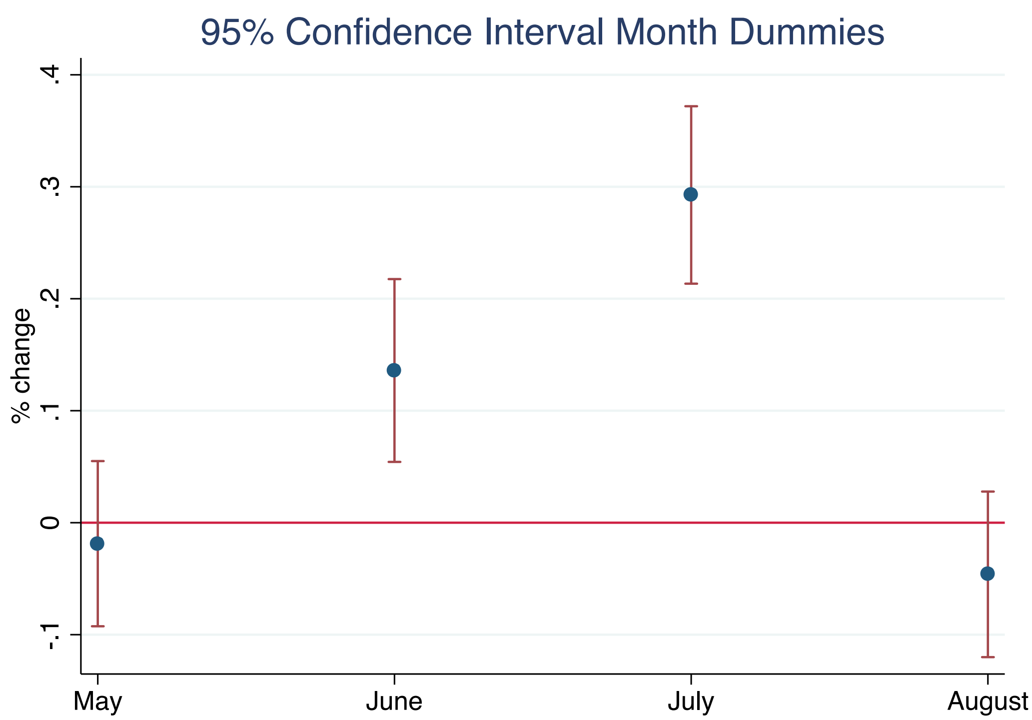


Figure 4.4: 95% Confidence Interval of Month Dummies For Per Capita Water Use

Notes: This graph plots the estimates and 95% confidence interval of month dummies using regression model in Column(4) of Table 4.2.

Chapter 5

Implications and future work

In general, these studies show that in the context of top-down decision system in China, both governments and households respond to environmental changes using their own resources in the decision making process. The responses are reflected from intergovernmental transfers response to revenue changes coupled with environmental changes caused by large hydropower dam projects, intergovernmental transfer increases for local typhoon disaster relief and individual adjustment on water and electricity use for weather variabilities. Especially, results on the governmental studies imply that the top-down decision system has its own advantage of redistributing impacts from large projects and sharing risks among many areas.

Globally there have been wide debates about whether or not and in which fields to increase or decrease decentralization. High decentralization has the advantage of smaller information costs and more flexible in locally-tailored decision making. However, relatively centralized system have the advantages of risk sharing, equalization redistribution and facilitating large scale projects. China has gone through a process of centralization in the 1960s-1970s, decentralization in the 1980s-early 1990s for the reform and development and re-centralization in the 1990s. In the recent few years, there have been a partial-decentralization trend represented by the "province manages county" reform promoted nationally. Besides the institutional structure, there are other factors, such as governmental evaluation system and environment right system, can be improved to increase the efficiency and equity of environmental decision makings. These are all potential study subjects following the line of environmental decision making.

One thing worth notice is that there are many other factors of environmental decision making not covered in this dissertation, such as environment property rights, information transparency and governor evaluation system. They all can potentially impact the equity and efficiency results for environmental decisions. China as an experience field provides many chances to study the impacts of these factors on environmental decisions of various decision makers, because there are a lot of cross-sectional and temporal variations of these factors in the local level.

Considering the increasing trend of both large projects and climate risks driven by economic development and climate change in the future, findings in this can provide basic knowledge understanding the environmental decision making in developing countries and have policy implications on improving the governmental institution structure and promoting sustainable development.

Bibliography

Alberini, A., Gans, W. and Velez-Lopez, D. (2011). Residential consumption of gas and electricity in the u.s.: The role of prices and income. *Energy Economics*, **33** (5), 870 – 881.

Albouy, D. (2012). Evaluating the efficiency and equity of federal fiscal equalization. *Journal of Public Economics*, **96** (9-10), 824–839.

Anttila-Hughes, J. K. and Hsiang, S. M. (2013). Destruction, disinvestment, and death: Economic and human losses following environmental disaster.

Arbues, F., Garcia-Valinas, M. A. and Martinez-Espineira, R. (2003). Estimation of residential water demand: a state-of-the-art review. *The Journal of Socio-Economics*, **32** (1), 81–102.

Arbués, F., Villanúa, I. and Barberán, R. (2010). Household size and residential water demand: an empirical approach. *Australian Journal of Agricultural and Resource Economics*, **54** (1), 61–80.

Aschauer, D. A. (1989). Is public expenditure productive? *Journal of Monetary Economics*, **23** (2), 177 – 200.

Auffhammer, M. and Aroonruengsawat, A. (2011). Simulating the impacts of climate change, prices and population on california's residential electricity consumption. *Climatic Change*, **109** (1), 191–210.

Banerjee, A., Duflo, E. and Qian, N. (2012). *On the Road: Access to Transportation Infrastructure and Economic Growth in China*. Working Paper 17897, National Bureau of Economic Research.

Barro, R. J. (2006). Rare disasters and asset markets in the twentieth century. *The Quarterly Journal of Economics*, **121** (3), 823–866.

— (2009). Rare disasters, asset prices, and welfare costs. *American Economic Review*, **99** (1), 243–64.

Behrman, J. R. and Craig, S. G. (1987). The distribution of public services: An exploration of local governmental preferences. *American Economic Review*, **77** (1), 37–49.

Bertrand, M., Duflo, E. and Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics*, **119** (1), 249–275.

Besley, T. and Burgess, R. (2002). The political economy of government responsiveness: Theory and evidence from india. *The Quarterly Journal of Economics*, **117** (4), 1415–1451.

Besley, T. J. and Rosen, H. S. (1998). *Sales Taxes and Prices: An Empirical Analysis*. NBER Working Papers 6667, National Bureau of Economic Research, Inc.

Billings, R. B. and Agthe, D. E. (1980). Price elasticities for water: A case of increasing block rates. *Land Economics*, **56** (1), pp. 73–84.

Branch, E. R. (1993). Short run income elasticity of demand for residential electricity using consumer expenditure survey data. *The Energy Journal*, **14** (4), pp. 111–121.

Brocker, J., Korzhenevych, A. and Schurmann, C. (2010). Assessing spatial equity and efficiency impacts of transport infrastructure projects. *Transportation Research Part B: Methodological*, **44** (7), 795–811.

Burgess, R., Hansen, M., Olken, B. A., Potapov, P. and Sieber, S. (2012). The political economy of deforestation in the tropics. *The Quarterly Journal of Economics*.

Campbell, H. E., Johnson, R. M. and Larson, E. H. (2004). Prices, devices, people, or rules: The relative effectiveness of policy instruments in water conservation1. *Review of Policy Research*, **21** (5), 637–662.

Castells, A. and Sole-Olle, A. (2005). The regional allocation of infrastructure investment: The role of equity, efficiency and political factors. *European Economic Review*, **49** (5), 1165–1205.

Cernea, M. M. (2000). Risks, safeguards and reconstruction: A model for population displacement and resettlement. *Economic and Political Weekly*, **35** (41), 3659–3678.

Chakravarty, A. (2011). *Dams and Infant Mortality in Africa*. Working paper.

CHINCOLD, C. C. o. L. D. (2008). *Recent reports on large dams in China*. Official report (chinese).

Cole, S., Healy, A. and Werker, E. (2012). Do voters demand responsive governments? evidence from indian disaster relief. *Journal of Development Economics*, **97** (2), 167 – 181.

Costa, D. L. and Kahn, M. E. (2010). *Why Has California's Residential Electricity Consumption Been So Flat since the 1980s: A Microeconometric Approach*. NBER Working Papers 15978, National Bureau of Economic Research, Inc.

Crowley, F., C.; Joutz (2003). *Hourly electricity loads: Temperature elasticities and climate change*. Tech. rep.

Dalhuisen, J. M., Florax, R. J. G. M., de Groot, H. L. F. and Nijkamp, P. (2003). Price and income elasticities of residential water demand: A meta-analysis. *Land Economics*, **79** (2), 292–308.

Danielson, L. E. (1979). An analysis of residential demand for water using micro time-series data. *Water Resources Research*, **15** (4), 763–767.

De Long, J. B. and Summers, L. H. (1991). Equipment investment and economic growth. *The Quarterly Journal of Economics*, **106** (2), 445–502.

Deressa, T. T., Hassan, R. M., Ringler, C., Alemu, T. and Yesuf, M. (2009). Determinants of farmers' choice of adaptation methods to climate change in the nile basin of ethiopia. *Global Environmental Change*, **19** (2), 248 – 255, traditional Peoples and Climate Change.

Dergiades, T. and Tsoulfidis, L. (2008). Estimating residential demand for electricity in the united states, 1965-2006. *Energy Economics*, **30** (5), 2722 – 2730.

Deschenes, M., Olivier; Greenstone (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the us. *American Economic Journal: Applied Economics*, **3** (4), 152–85.

Donald, S. G. and Lang, K. (2007). Inference with difference-in-differences and other panel data. *Review of Economics and Statistics*, **89** (2), 221–233.

Duflo, E. and Pande, R. (2007). Dams. *The Quarterly Journal of Economics*, **122** (2), 601–646.

Eisensee, T. and Strömberg, D. (2007). News droughts, news floods, and u. s. disaster relief. *The Quarterly Journal of Economics*, **122** (2), 693–728.

Emanuel, K. (2005). Increasing destructiveness of tropical cyclones over the past 30 years. *Nature*, **436**, 686+.

Espey, J. A. and Espey, M. (2004). Turning on the lights: A meta-analysis of residential electricity demand elasticities. *Journal of Agricultural and Applied Economics*, **36** (01).

Fengjin, X. and Ziniu, X. (2010). Characteristics of tropical cyclones in china and their impacts analysis. *Natural Hazards*, **54** (3), 827–837.

Fernald, J. G. (1999). Roads to prosperity? assessing the link between public capital and productivity. *The American Economic Review*, **89** (3), pp. 619–638.

FILIPPINI, M. (1995). Swiss residential demand for electricity by time-of-use. *Resource and Energy Economics*, **17** (3), 281 – 290.

FUMIN, R., GLEASON, B. and EASTERLING, D. (2002). Typhoon impacts on china's precipitation during 1957-1996. *Advances in Atmospheric Sciences*, **19** (5), 943–952.

GARCIA, S. and REYNAUD, A. (2004). Estimating the benefits of efficient water pricing in france. *Resource and Energy Economics*, **26** (1), 1 – 25.

GARRETT, T. A. and SOBEL, R. S. (2003). The political economy of fema disaster payments. *Economic Inquiry*, **41** (3), 496–509.

GAUDIN, S. (2006). Effect of price information on residential water demand. *Applied Economics*, **38** (4), 383–393.

—, GRIFFIN, R. C. and SICKLES, R. C. (2001). Demand specification for municipal water management: Evaluation of the stone-geary form. *Land Economics*, **77** (3), pp. 399–422.

GOH, A. Z.-C. and CHAN, J. C. L. (2012). Variations and prediction of the annual number of tropical cyclones affecting korea and japan. *International Journal of Climatology*, **32** (2), 178–189.

GREENSTEIN, S. M. and SPILLER, P. T. (1995). Modern telecommunications infrastructure and economic activity: An empirical investigation. *Industrial and Corporate Change*, **4** (4), 647–665.

GREGORY, G. D. and LEO, M. D. (2003). Repeated behavior and environmental psychology: The role of personal involvement and habit formation in explaining water consumption. *Journal of Applied Social Psychology*, **33** (6), 1261–1296.

HALLEGATTE, S., HOURCADE, J.-C. and DUMAS, P. (2007). Why economic dynamics matter in assessing climate change damages: Illustration on extreme events. *Ecological Economics*, **62** (2), 330–340.

HANSEN, Z. K., LIBECAP, G. D. and E., L. S. (2009). *Climate Variability and Water Infrastructure: Historical Experience in the Western United States*. Working Paper 15558, NBER.

HAUGHWOUT, A. F. (1998). Aggregate production functions, interregional equilibrium, and the measurement of infrastructure productivity. *Journal of Urban Economics*, **44** (2), 216–227.

HEMING, L., WALEY, P. and REES, P. (2001). Reservoir resettlement in china: past experience and the three gorges dam. *Geographical Journal*, **167** (3), 195–212.

Hoffmann, M., Worthington, A. and Higgs, H. (2006). Urban water demand with fixed volumetric charging in a large municipality: the case of brisbane, australia. *Australian Journal of Agricultural and Resource Economics*, **50** (3), 347–359.

Hsiang, S. M. (2010). Temperatures and cyclones strongly associated with economic production in the caribbean and central america. *Proceedings of the National Academy of Sciences*, **107** (35), 15367–15372.

— and Narita, D. (2012). Adaptation to cyclone risk: Evidence from the global cross-section. *Climate Change Economics*, **03** (02), 1250011.

Huang, B. and Chen, K. (2012). Are intergovernmental transfers in china equalizing? *China Economic Review*, **23** (3), 534 – 551.

IEA (2009). *World Energy Outlook*. Tech. rep.

Ito, K. (2012). *Do Consumers Respond to Marginal or Average Price? Evidence from Non-linear Electricity Pricing*. Working Paper 18533, National Bureau of Economic Research.

Jiang, H., Halverson, J. B., Simpson, J. and Zipser, E. J. (2008). Hurricane "Rainfall Potential" Derived from Satellite Observations Aids Overland Rainfall Prediction. *J. Appl. Meteor. Climatol.*, **47** (4), 944–959.

Jorgensen, B., Graymore, M. and O'Toole, K. (2009). Household water use behavior: An integrated model. *Journal of Environmental Management*, **91** (1), 227 – 236.

Li, H. and Zhou, L.-A. (2005). Political turnover and economic performance: the incentive role of personnel control in china. *Journal of Public Economics*, **89** (9-10), 1743 – 1762.

Lipscomb, M., Mushfiq, A. M. and Bahram, T. (2011). *Development Effects of Electrification:Evidence from the Geologic Placement of Hydropower Plants in Brazil*. Working paper, CAF.

Liu, Z. (2010). Study on sources and sizes of local fiscal revenue in china. *Local Fiscal Studies*, (4).

Maidment, D. R. and Miaou, S.-P. (1986). Daily water use in nine cities. *Water Resources Research*, **22** (6), 845–851.

MCA (2007). Summary report of losses from natural disasters in china in 2007 (chinese).

— (2011). Summary report of losses from natural disasters in china in 2011 (chinese).

McComb, R., Moh, Y.-K. and Schiller, A. (2011). Measuring long-run economic effects of natural hazard. *Natural Hazards*, **58** (1), 559–566.

Meijers, E., Hoekstra, J., Leijten, M., Louw, E. and Spaans, M. (2012). Connecting the periphery: distributive effects of new infrastructure. *Journal of Transport Geography*, **22** (0), 187 – 198.

MEP (2008). (ministry of environmental protection) water pollution control plan in the three gorges reservoir and upstream regions.

MOF (1994-2006). China fiscal statistical info in local regions.

— (1994-2010). China fiscal statistical yearbook.

— (2011). Regulation on natural disaster relief fund management.

Mohan, P. and Strobl, E. (2013). The Economic Impact of Hurricanes in History: Evidence from Sugar Exports in the Caribbean from 1700 to 1960. *Wea. Climate Soc.*, **5** (1), 5–13.

Munnell, A. H. (1990). How does public infrastructure affect regional economic performance? *Conference Series;[Proceedings]*, pp. 69–112.

MWR (2005). (ministry of environmental protection and ministry of water resources) water pollution control and land conservation in upstream danjiangkou reservoir.

Nadiri, M. I., Nandi, B. and Chakraborty, C. (2009). Telecommunications infrastructure, telecommunications intensity and productivity growth in us industries: a disaggregated approach. *International Journal of Management and Network Economics*, **1** (2), 186–210.

Nauges, A., Celine ; Thomas (2003). Long-run study of residential water consumption. *Environmental & Resource Economics*, **26** (1), 25–43.

NBS (2006-2010). County statistics yearbook.

NDRC (2007). Midterm and longterm development plan for renewable energy, (National Development and Reform Committee).

Nieswiadomy, M. L. (1992). Estimating urban residential water demand: Effects of price structure, conservation, and education. *Water Resources Research*, **28** (3), 609–615.

NOAA (2005). National hurricane center: Glossary of nhc/tpc terms.

Nordhaus, W. (2010). The economics of hurricanes and implications of global warming. *Climate Change Economics*, **01** (01), 1–20.

Noy, I. (2009). The macroeconomic consequences of disasters. *Journal of Development Economics*, **88** (2), 221–231.

Olmstead, S. M., Michael Hanemann, W. and Stavins, R. N. (2007). Water demand under alternative price structures. *Journal of Environmental Economics and Management*, **54** (2), 181–198.

Persson, T. and Tabellini, G. (1996). Federal fiscal constitutions: Risk sharing and moral hazard. *Econometrica*, **64** (3), pp. 623–646.

Piao, S., Ciais, P., Huang, Y., Shen, Z. and et al (2010). The impacts of climate change on water resources and agriculture in china. *Nature*, **467**.

Pint, E. M. (1999). Household responses to increased water rates during the california drought. *Land Economics*, **75** (2), pp. 246–266.

Qin, B. (2011). Political connection and government patronage: Evidence from chinese manufacturing firms.

Qinghai, C. (2009). *Research on the fiscal level of local government in China*. Beijing: Economic Science Press.

Reiss, P. C. and White, M. W. (2005). Household electricity demand, revisited. *The Review of Economic Studies*, **72** (3), 853–883.

Schleich, J. and Hillenbrand, T. (2009). Determinants of residential water demand in germany. *Ecological Economics*, **68** (6), 1756 – 1769.

Shih, V. (2004). Database on provincial factional affiliation with standing committee members of the chinese communist party: 1978-2004.

—, Zhang, L. Q. and Liu, M. (). When the autocrat gives: Determinants of fiscal transfers in china.

Slack, E. (1980). Local fiscal response to intergovernmental transfers. *The Review of Economics and Statistics*, **62** (3), pp. 364–370.

Sole-Olle, A. and Sorribas-Navarro, P. (2008). The effects of partisan alignment on the allocation of intergovernmental transfers. differences-in-differences estimates for spain. *Journal of Public Economics*, **92** (12), 2302 – 2319.

Strobl, E. (2012). The economic growth impact of natural disasters in developing countries: Evidence from hurricane strikes in the central american and caribbean regions. *Journal of Development Economics*, **97** (1), 130 – 141.

— and Strobl, R. O. (2011). The distributional impact of large dams: Evidence from cropland productivity in africa. *Journal of Development Economics*, **96** (2), 432–450.

Strömberg, D. (2007). Natural disasters, economic development, and humanitarian aid. *The Journal of Economic Perspectives*, **21** (3), pp. 199–222.

Taylor, R. G., McKean, J. R. and Young, R. A. (2004). Alternate price specifications for estimating residential water demand with fixed fees. *Land Economics*, **80** (3), pp. 463–475.

Toya, H. and Skidmore, M. (2007). Economic development and the impacts of natural disasters. *Economics Letters*, **94** (1), 20 – 25.

UNDP (2012). Reducing disaster risk: A challenge for development (a global report).

Wang, G., Su, J., Ding, Y. and Chen, D. (2007). Tropical cyclone genesis over the south china sea. *Journal of Marine Systems*, **68** (3-4), 318–326.

Wang, W., Zheng, X. and Zhao, Z. (2011). Fiscal reform and public education spending: A quasi-natural experiment of fiscal decentralization in china. *Publius: The Journal of Federalism*.

WBCSD (2005). *Water: Facts and Trends*. Tech. rep.

Wenhui, C. (2007). *Report on risk management in China*. China Public Finance and Economics Press.

Wooldridge, J. (2001). *Econometric Analysis of Cross Section and Panel Data*. MIT Press.

Xie, S., Li, Z., Liu, J., Xie, S., Wang, H. and Murphy, B. R. (2007). Fisheries of the yangtze river show immediate impacts of the three gorges dam. *Fisheries*, **32** (7), 343–344.

Yang, T., Zhang, Q., Chen, Y. D., Tao, X., Xu, C.-y. and Chen, X. (2008). A spatial assessment of hydrologic alteration caused by dam construction in the middle and lower yellow river, china. *Hydrological Processes*, **22** (18), 3829–3843.

Zhang, D., Henry; Brown (2005). Understanding urban residential water use in beijing and tianjin, china. *Habitat International*, **29**, 469–491.

Zhang, Q. (2004). Residential energy consumption in china and its comparison with japan, canada, and usa. *Energy and Buildings*, **36** (12), 1217 – 1225, energy and Environment of Residential Buildings in China.

Zhou, W. (1997). Review of the irrigation equipment manufacture and supply sector in china. *Water Reports*, (14), 139–148.

Zou, H. (2012). *Optimal Design of Intergovernmental Grants in a Dynamic Model*. Working Paper 37427, MPRA.