Sacrifice for the Greater Good: Welfare and Distributional Impacts of Flood Detention Basins in China

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Abstract

Since 2000, China has implemented the Flood Detention Basin (FDB) policy as a mechanism to mitigate its substantial flood risks. This approach entails the strategic use of designated basins to capture excess water during flood periods to safeguard areas of higher economic or political importance. Our research uncovers a dual impact of this policy: it enhances economic resilience against floods, but also perpetuates regional economic inequalities. Specifically, the persistent threat of flooding in counties with FDBs deters investment, thereby hindering local structural transformation—a mechanism we term the 'firm-adaptation effect.' We employed spatial regression discontinuity and synthetic difference-in-difference approaches, supplemented by a dynamic economic geography model. Our analysis reveals a significant 9.5% reduction in individual savings following a county's designation as an FDB-county. In understanding the mechanism, we report the 'firm-adaptation effect' that the likelihood of manufacturing firm investments in FDB counties decreased by approximately 8% after the FDB

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designation. While current government compensation policies in China address direct flood damages in FDB counties, our results highlight the need to also compensate the prolonged and indirect economic costs of FDB counties.

Keywords: Natural Disaster Policy, Flood, Inequality, Economic Geography Model

1 Introduction

In dealing with the intensifying challenges of climate change, a pivotal question emerges: how can we devise environmental policies that effectively reduce social and economic losses from natural disasters? While such policies universally impact populations, their distributional consequences often result in uneven outcomes. Empirical evidence, as highlighted by Duflo and Pande (2007), indicates that individuals living upstream of a dam experience increased economic mobility constraints compared to their downstream counterparts. The intricacies of policy formulation are further amplified when policymakers must prioritize actions to minimize overall damage from natural catastrophes. Although a substantial body of research has investigated the economic ramifications of natural disasters (e.g., Cavallo et al. 2013 and Borensztein et al. 2017), there is a notable gap in understanding the effects of natural disaster management policies, with some recent progress made by Taylor and Druckenmiller 2022). This paper aims to contribute to bridging this gap by examining the welfare and economic impacts of China's Flood Detention Basin policy.

Flood Detention Basins (FDBs) play a crucial role in China's flood management strategy. An FDB, typically located in low-lying wetland areas, is designed to temporarily store excessive floodwater. The strategic placement of FDBs is a proactive measure to enhance flood resilience by attenuating flood surges that might otherwise impact downstream areas. These basins act as a buffer during high flood events, where the government diverts excess water to prevent inundation of more economically or politically important areas. While this means periodic flooding of the basins themselves, it is a calculated trade-off to protect key areas. As of now, China has 98 FDBs located in major river basins: 44 in the Yangtze

River basin, 2 in the Huang River, 28 in the Hai River, and 21 in the Huai River, and 2 in others. Together, they cover 11 provinces, 44 cities and 106 counties. The significance of FDBs in China's flood risk management is underscored by their repeated use in mitigating floods, with notable deployments during the major flood events of 1998, 2003, 2007, 2020, and 2023.

Flood Detention Basins (FDBs) play a crucial role in flood risk management, yet their implementation can exacerbate regional inequalities. Take Anhui and Jiangsu provinces, both prone to severe flooding along the Huai River. Anhui contains 18 FDBs, compared to just 3 in Jiangsu. In flood seasons, Anhui's FDB counties are deliberately flooded to mitigate risk, often to protect areas in Jiangsu. The impact of the strategy is clear in the stark economic differences between the two provinces. Anhui's GDP stands at only 30% of Jiangsu's, highlighting the economic cost of such flood management practices.

The mechanisms through which FDBs contribute to regional inequality can be understood in two dimensions. The first is the immediate economic cost. Channeling floodwaters into FDBs leads to the inundation of land, directly causing tangible economic losses in the affected counties. The second dimension is the longer-term, indirect effect on these regions. The expectation that FDB areas will consistently bear the brunt of seasonal floods can significantly dampen investment incentives and hinder structural transformation. This 'anticipation effect' discourages residents from investing in physical capital. Additionally, constraints on inter-regional labor mobility in China, as exemplified by the Hukou system, limit the ability of individuals to relocate away from flood-prone areas. This exacerbates existing regional disparities, creating a complex challenge. While the overall welfare effects of FDBs might be positive in terms of flood mitigation, they inadvertently contribute to a persistent inequality between regions.

Our empirical analysis supports the hypothesized mechanisms regarding the economic impact of Flood Detention Basins (FDBs). Initially, using a fixed effects regression model, we observe that GDP per capita is about 12.9% lower in FDB counties. This decline is mainly in the industrial sector, with a 20% gap in industrial development covering market entry, production, and productivity, while the agricultural sector shows no significant differences. However, there are concerns of endogeneity in this approach, as the selection of FDB locations could be influenced by government decisions to protect economically vital counties, often choosing less developed areas for FDBs.

To address these endogeneity issues, we implement a spatial regression discontinuity design. By comparing economic outcomes of FDB counties with neighboring areas, we find that FDB regions tend to have lower fixed assets and decreased sales, with both per-employee fixed assets and output being lower. Further, we assess the impact of the 2010 policy change on FDB designations using a synthetic difference-in-differences approach. The results show a significant decline in income for residents in newly designated FDB counties. This is attributed to a dual channel mechanism: a shift towards de-industrialization, marked by increased agricultural activities and fewer new manufacturing firm establishments, and a reduction in governmental expenditure, indicating less policy focus post-FDB designation.

In summation, our empirical findings robustly support the existence of the 'anticipation effect', which we identify as a key driver of the persistent economic disparities observed between FDB and non-FDB counties.

Informed by the frameworks of , our dynamic economic geography model incorporates elements such as imperfect labor mobility and physical capital accumulation, which are vulnerable to flooding events. It also encompasses an industry entry and exit dynamic, reflecting the challenges of industrialization in FDB regions. Our objective is to causally discern both the direct and indirect impacts of flooding on economic activities, calibrating the model parameters based on our empirical findings. Utilizing this calibrated model enables us to, firstly, quantify the welfare implications in different regions arising from the introduction of FDB measures. This includes an analysis of potential escalations in regional inequality triggered by FDB policies. Secondly, the model facilitates a discussion on the extent to which FDB initiatives might bolster resilience against future climate extremes and elevated flood risks. Furthermore, we explore how ancillary public policies, such as financial transfers to FDB regions and measures to reduce labor mobility costs, could augment overall welfare.

We also critically examine the current compensation policies in FDB regions, which are predominantly contingent on the occurrence of flooding events. Our analysis suggests that this approach might be insufficient, considering the anticipatory effects of establishing FDBs. Such measures can have a lasting impact on local economies and livelihoods, extending beyond the immediate aftermath of flood incidents.

Informed by the frameworks of Desmet and Rossi-Hansberg (2014), Balboni (2019), and Jia et al. (2022), our dynamic economic geography model integrates elements such as imperfect labor mobility and physical capital accumulation, which are susceptible to flooding events. It also addresses the industry entry and exit dynamics, reflecting industrialization challenges in Flood-Disaster-Buffer (FDB) regions. Our aim is to causally dissect both the direct and indirect impacts of flooding on economic activities, calibrating our model parameters based on empirical evidence. To enrich our analysis, we introduce a counterfactual examination, comparing the actual scenario with two counterfactual situations: (1) a scenario where the ratio of FDB counties to non-FDB counties is equalized at 1 and (2) a scenario where the risk ratio associated with FDB is reduced to zero. This counterfactual approach allows us to explore the implications of different levels of flood protection and risk mitigation strategies. Utilizing this calibrated model, we first quantify the regional inequality resulting from FDB implementation. Secondly, the model provides insights into how FDB policies might enhance resilience against future climate extremes. Further, we investigate the role of policies in making sufficient compensations.

In addressing the policy implications of our findings, it is crucial to consider the Chinese government's current approach to managing the economic impact of the Flood Detention Basin (FDB) policy. Since 2010, the government has been compensating residents in FDB counties for their direct losses. However, our research indicates that these direct costs represent only a small proportion of the total economic damages. More substantial are the long-term economic costs stemming from a reduced willingness for manufacturing firms to invest in these counties, a consequence of the persistent flood risk. This reduced investment willingness leads to a downgrade of structural transformation. Therefore, we advocate for a more comprehensive compensation policy that accounts for these indirect and long-term economic effects. The government's policy should aim not only to address immediate losses but also to mitigate the presistent economic impact.

2 Research Background

In this study, we focus on flood detention basins in China, which are key for managing flood risks. We will first discuss river flood risks in the country. Then, we will explain what flood detention basins are, how they are chosen, how the related policies are implemented, and the compensation policy associated with them.

2.1 River Flood Risks in China

China's susceptibility to flood risks arises from a combination of several factors: its large land area, intricate topographical variances, substantial population density, and rapid urban development. Internationally, analyses related to flood risks frequently underscore China's heightened vulnerability. Several global indices assess the degree of flood risk across nations, and within these assessments, China invariably emerges as a nation of paramount concern. As a case in point, the "Aqueduct Floods Tool", an initiative of the World Resources Institute, ranks China third in terms of population exposure to river floods. Their 2015 assessment indicated that, on an annual average, river floods affect a population exceeding 3 million in China, only surpassed by India (4,835,259) and Bangladesh (3,477,315). This assessment finds resonance with findings from the Center for Research on the Epidemiology of Disasters (CRED), which has documented myriad flood incidents in China over recent decades, each event leaving a large impact on millions and exacting considerable economic costs. The combination of these assessments emphasizes the importance of setting up robust flood mitigation mechanisms in China especially in the context of climate change.

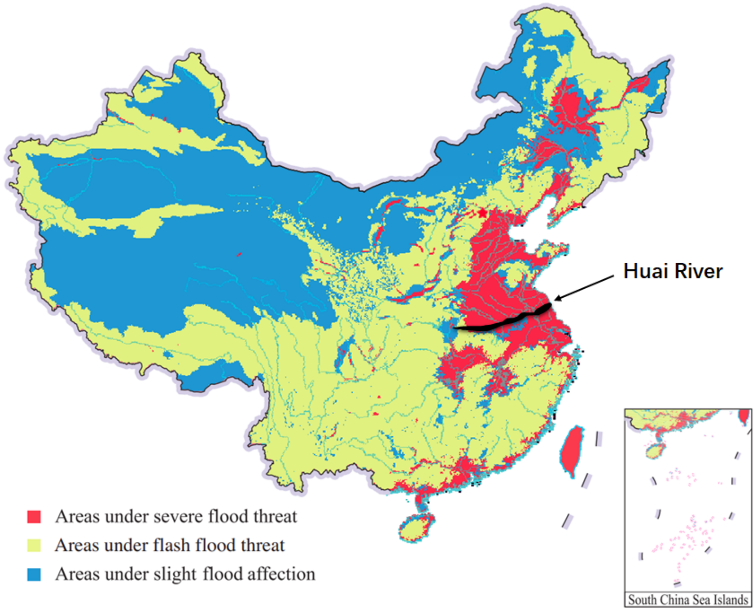


Figure 1: Flood Risk in China (Source: Zhang and Song 2014)

2.2 Flood Detention Basins in China

2.2.1 Definition of Flood Detention Basins

The Flood Control Law of the People's Republic of China, established in 1997 and enacted in 1998, stands as China's premier legislation governing flood management. Under this law, "flood control zones" denote areas vulnerable to flooding. These zones comprise three categories:

1. Flood Basins (FBs): The flood basins are areas that are subjected to inundation and are not yet protected by any projects or facilities.

2. Flood Detention Basins (FDBs): The flood storage and detention basins are the low-lying lands and lakes beyond the back scarps of the dikes, including the flood diversion outfalls, used for temporary storage of floods.

3. Flood Protected Areas (FPAs): The areas protected against floods are areas protected by projects and facilities for flood control in conformity with standards for flood control.

In 2009, Ministry of Water Resources implemented the *National Flood Detention Basin Construction and Management Plan*. According to this plan, the goal of establishing flood detention basins is to "safeguard the interests of pivotal regions and the whole watershed". The government also claims that residents within these basins make substantial sacrifices to protect the collective social welfare.

Table 1: Flood Detention Basins in the Main River Basins of China (2000)

River Basin	Number of FDBs	Affected Population (million)	Total Area (Km^2)	Storage Capacity (billion m^3)
Yangtze	40	6.12	11959	63.6
Yellow	5	3.18	5212	12.9
Hai	26	4.40	9597	17.2
Huai	26	1.61	3674	14.1
Total	97	15.3	30443	107.7

Note: The data is extracted from Huang (2003).

Table 2: Number of FDBs under 2000 and 2010 Policy

		FDBs Located in:			
Rivers	N(FDBs)	N(Provinces)	N(Municipalities*)	N(Cities)	N(Counties)
2000 Policy					
Yangtze	40	4	0	10	28
Hai	26	3	2	11	37
Huai	26	2	0	9	19
Yellow	5	2	0	6	12
Total	*97*	*8*	*2*	*36*	*96*
2010 Policy					
Yangtze	44	5	0	11	31
Hai	28	3	2	11	39
Huai	21	3	0	14	24
Yellow	2	2	0	5	8
Songhua	2	1	0	2	3
Zhu	1	1	0	1	1
Total	*98*	*11*	*2*	*44*	*106*
Δ(*2010-2000*)	*1*	*3*	*0*	*8*	*10*

Note: (1) The term '2000 Policy' refers to the National Flood Control Law issued by China's Ministry of Water Resources in 2000, and '2010 Policy' to its subsequent update in 2010; (2) The 'Total' number of flood detention basins might differ from the sum of basins across various rivers. This discrepancy arises because some basins span multiple provinces, cities, or counties; (3) The term 'Municipalities*' denotes municipalities directly governed by China's Central Government, specifically Beijing and Tianjin in this study; (4) Under the 2000 Policy, the provinces designated as Flood Detention Basin (FDB) regions included Hunan, Hubei, Anhui, Henan, Hebei, Shandong, Jiangxi, and Jiangsu. The 2010 Policy expanded this list to include Heilongjiang, Jilin, and Guangdong; (5) More details are included in the appendix.

2.2.2 Selection of Flood Detention Basin

In determining the locations for Flood Detention Basins, the Chinese government incorporates a blend of geographical and political-economic considerations.

Geographical Factors

From a geographical perspective, detention basins are typically placed in topographically low areas conducive to floodwater containment. The field of hydrology has provided a wealth of research on optimizing the selection of flood detention basins. Mays and Bedient (1982) developed an optimal model based on dynamic programming, aiming to determine the ideal size and location of detention basins, with the goal of minimizing system construction expenditures. This model was further refined by Bennett and Mays (1985) by incorporating the cost implications of detention basin structures and downstream channel designs. Utilizing this evolved model, Taur et al. (1987) optimized the detention basin system in Austin, Texas. Travis and Mays and Bedient (1982) advanced this line of research by optimizing the placement and sizing of retention basins in a watershed, targeting the reduction of aggregated costs encompassing construction, maintenance, and sediment removal. Subsequent studies have integrated various optimization techniques, such as genetic algorithms and simulated annealing, and incorporated detailed engineering cost assessments into the design frameworks for detention basin-river-protected region systems (e.g., Perez-Pedini et al. 2005; Park et al. 2014).

Political and Economic Factors

While contemporary research has proffered instrumental methodologies and insights for designing detention basins, it is essential to recognize the distinct factors distinguishing China from other nations. Globally, flood detention basins predominantly serve the single function of flood mitigation. However, in China, demographic growth and economic developments within flood detention areas necessitate a more complicated approach. Decisions regarding flood diversion location and management strategies must consider the equilibrium between flood control benefits for downstream areas, potential flood-related damages within the detention basins, and the infrastructural costs associated with flood diversion controls.

Institutionally, the Ministry of Water Resources emphasizes the relative importance of urban cities over counties. Cities, particularly those with populations exceeding 1.5 million, are designated as "Megacities". To safeguard these urban centers, the government uses Flood Detention Basins to ensure that these megacities are equipped to manage floods with return periods exceeding 200 years.

Table 3: Grade of Flood Protection (City)

Classification	Population (in 10 thousands)	Equivalent Economic Scale (in 10 thousands)	Expected Flood Return Period (years)
I.Megacity	>150	>300	>200
II.Large city	>150, >50	<300, >100	100-200
III.Medium city	<50, <20	<100, <40	100-50
IV.Small city	<20	<40	50-20

Note: The classification of city size is based on the city's GDP and population, with GDP being the primary indicator and population as the secondary one.

Table 4: Grade of Flood Protection (County)

Classification	Population (in 10 thousands)	Arable Land Size (in 10 thousands acre)	Expected Flood Return Period (years)
I	>150	>300	50-100
II	>150, >50	>300, >100	30-50
III	<50, <20	<100, >30	20-30
IV	<20	<30	10-20

Note: The classification of city size is based on the city's GDP and population, with GDP being the primary indicator and population as the secondary one.

2.2.3 Policy Implementation (Mengwa Flood Detention Basin as an Example)

Extreme floods in primary river basins like the Changjiang, Yellow, Huai, and Hai Rivers have effectively utilized flood basins to mitigate damage either wholly or in part. These Flood Detention Basins have been employed to accommodate floodwaters, thereby lowering peak flood levels. The success in flood alleviation using these detention areas establishes this method as a central strategy for flood risk reduction in China.

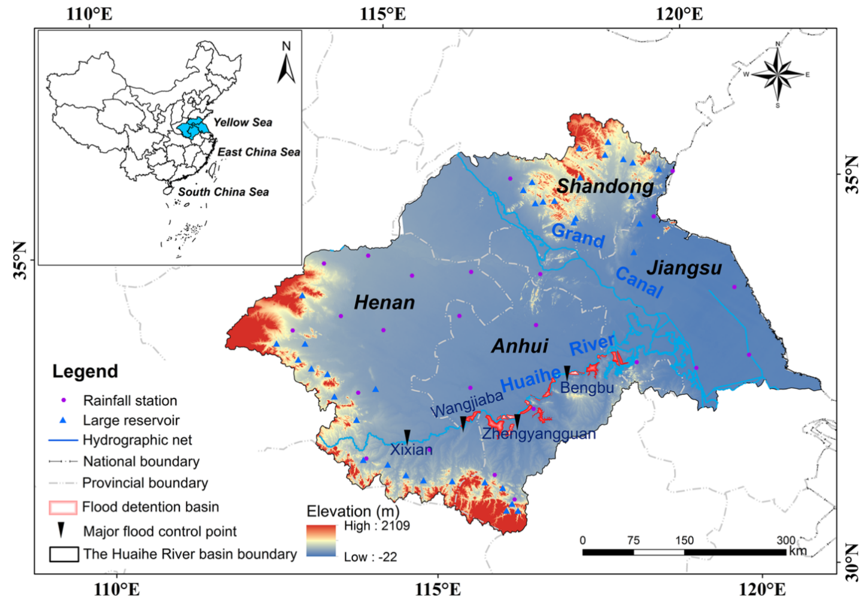


Figure 2: Wangjiaba Location (Source: Zhang and Song 2014)

In scenarios where river or lake water levels surpass state-defined flood diversion benchmarks, necessitating the use of flood storage basins, specific governmental and flood control entities are authorized to make decisions in line with approved flood control plans. Any interference or delays in the activation of these basins are prohibited, with local governments having the authority to enforce their usage.

To illustrate the function of FDBs, we look at flood management in the Huai River Basin (HRB). Located in the transition zone between the southern and northern climates of China, the Huai River Basin experiences dramatic climate changes, resulting in precipitation that varies both spatially and temporally. 70% of the precipitation is concentrated in the flood season from June to September. Due to the unique geographical condition of the HRB, flooding is frequent. For example, the HRB has seen floods in six years in the 1990s.

In 2007, a high-intensity rainfall hit the HRB and the average rainfall reached 465 mm. The precipitation led to multi-peak flooding in the Huaihe River and threatened the downstream areas of the Flood Detention Basin. When the water level reached 29.3m on July 10, the government raised the flood severity level to the highest and operated the Wangjiaba Dentention Basin. The basin diverted water for 46 hours and stored flood with a volume of

250 million cubic meters. Even though the downstream land is protected, the use of Mengwa resulted in a forced migration of more than 3,000 people, an inundation of more than 12,000 hectares of farmland, and destruction of all Wangjiaba infrastructure. According to Chinese government, the 2007 flood affected around 2.5 million hectares of crops and caused a direct economic loss of around 2.5 billion USD, which is around 50 % less than the flood loss in 1991. The decrease in economic loss is largely contributed to the operation of FDBs.

Figure 3: Pre and Post Operation of Wangjiaba (Source: NetEase Media)

2.2.4 Compensation Policy

This legislation mandates local governments to draft safety plans for flood basins, control population growth in flood storage zones, relocate residents from high-risk areas, and implement other essential safety measures. Moreover, it is the responsibility of regions benefiting from flood storage basins to compensate and support these areas, as per state regulations. The State Council and provincial governments are also tasked with establishing systems for flood basin safety and compensation.

Since 2003, the Chinese government has started to compensate residents of FDBs who have suffered crop losses and property damage. However, the amount of compensation is inadequate. On the one hand, the task of auditing assets and verifying damage has proven cumbersome for local government administrations, resulting in a lengthy compensation process. On the other hand, residents of a FDB will only receive a one-time compensation if the government operates the FDB during a flood, but will not receive any reimbursement for long-term loss.

2.3 Counties as the Unit of Analysis

We will estimate the distributional and welfare impacts of flood detention basin at the county level, which is the lowest level of disaggregation for which data is available. Counties are found in the third level of the administrative hierarchy in provinces and autonomous regions and the second level in municipalities. In total, there are total of 2,851 county-level divisions in mainland China.

3 Data

In this project, we aim to quantitatively assess both the short term and long term impacts of Flood Detention Basin (FDB) establishment on multifarious socio-economic outcomes, notably nighttime light, firm entry and exit, labor mobility patterns, and poverty status. Our primary dataset, focused on flood detention basins, has been constructed through an exhaustive search of governmental documents and media reports, enabling us to collect implementation details for each FDB spanning the 1950-2020. This breadth of variation is enough for us to implement the identification strategy.

3.1 County-Level Datasets

At the county level, we collect relevant variables from the county statistical yearbooks spanning 1999 to 2002. County level variables include local GDP (disaggregated by sector), demographic density, government income, government expenditure, investment, and tax revenue streams.

3.2 Firm-Level Datasets

Firm-level variables are obtained from two repositories: The National Enterprise Credit Information Publicity System and the Annual Survey of Industrial Enterprises (ASIE). The former offers a comprehensive log of daily registration data for firms, tracing back to the inception of the People's Republic of China. This includes firm geolocation, business status, inception date, extant operational status, and labor force count. The ASIE, by contrast, is more circumscribed, focusing on enterprises with an annual turnover more than 5 million RMB — predominantly within the manufacturing sector. It includes data of enterprise-level production and investment from 1998 to 2014. To provide a complementary understanding on regional economic outcomes, we also use nighttime light data, a proxy often lauded for its immunity to traditional data manipulation challenges. Sourced from the National Science and Technology Infrastructure, this dataset provides the 'Prolonged Artificial Nighttime-light Dataset of China' spanning 1984-2020, arguably the most extensive luminosity dataset specific to China.

4 Empirical Results

In this section, we present our empirical findings based on three identification strategies: (i) baseline fixed effects regression; (ii) geographical regression discontinuity; and (iii) synthetic difference-in-differences (DiD). Our baseline fixed effects analysis offers preliminary evidence suggesting a lack of economic vigor in FDB counties relative to their non-FDB counterparts. However, the baseline fixed effects regression may suffer from potential endogeneity issues stemming from non-randomized assignment of FDB designations. To solve this problem, we use two identification strategies.

Firstly, we leverage a geographical regression discontinuity design, contrasting economic outcomes of FDB counties with their neighboring counties. This approach shows that manufacturing in FDB counties is less developed compared to nearby non-FDB areas. Our secondary identification hinges on a synthetic difference-in-differences framework. Based on a 2010 policy initiative wherein an additional 20 counties were designated as FDBs, we use this quasi-experimental variation to discern the potential impact of such designations. Our findings from this technique are similar from both fixed effects and geographical regression discontinuity analyses. To sum up, the collective empirical evidence converge on the conclusion that manufacturing in FDB counties is less developed, potentially attributable to diminished investment incentives and a perceived lack of governmental prioritization of these regions.

4.1 Descriptive Results

In total, there are 81 FDB counties distributed across 36 cities within 9 provinces. A detailed comparison between non-FDB and FDB counties is described in Table 5.Within this table, Panel A derives from a subset of county-level data, while Panel B derives from the more exhaustive nighttime light datasets. Table 5 straightforwardly suggests the economic disparity between FDB counties and non-FDB counties that FDB counties manifesting discernible economic disadvantages. An exception to this general trend is the larger agricultural production in FDB counties relative to their non-FDB counterparts. This indicates the heavier reliance of FDB counties on agricultural activities. Furthermore, Figure 4 chronologically maps the mean nighttime light patterns of non-FDB and FDB counties. As can be seen in this figure, the intensity of nighttime light in FDB counties is much weaker than that in non-FDB counties.

Table 5: Descriptive Statistics

Counties	**Non FDB**	**FDB**	**Δ(nonFDB-FDB)**	**Δ/FDB**
Panel A: County-Level Dataset				
Number of Counties	$1,777$	67		
Number of Cities	309	36		
Number of Provinces	27	9		
Population(k)	506.59	778.04		
per capita:				
GDP	$23,849.42$	$20,601.93$	$3,247.49$	15.76%
Industrial Production	$11,449.88$	$10,138.16$	$1,311.72$	6.37%
Agricultural Production	$4,843.94$	$6,474.55$	$-1,630.61$	-25.18%
Individual Saving	$15,170.07$	$13,369.88$	$1,800.19$	13.46%
Fiscal Income	$1,539.01$	$1,061.86$	477.15	44.94%
Fiscal Expenditure	$4,337.45$	$2,779.75$	$1,557.7$	56.04%
N(obs)	30,722	1,124		
Panel B: Nighttime Light Data				
Number of Counties	$2,484$	81		
Number of Cities	310	36		
Number of Provinces	27	9		
Mean	1.97	0.54	1.43	264.81%
Sum	$3,099.77$	$2,450.23$	649.54	26.51%
Min	0.20	0.00		
Max	32.80	24.42	8.38	34.32%
N(obs)	52,584	1,701		

Note: (1) Panel A uses the incomprehensive county-level dataset, and Panel B uses the comprehensive nighttime light dataset; (2) FDB_i is a dummy that equals 1 if the county i has a Flood Detention Basin, and equals 0 if not.

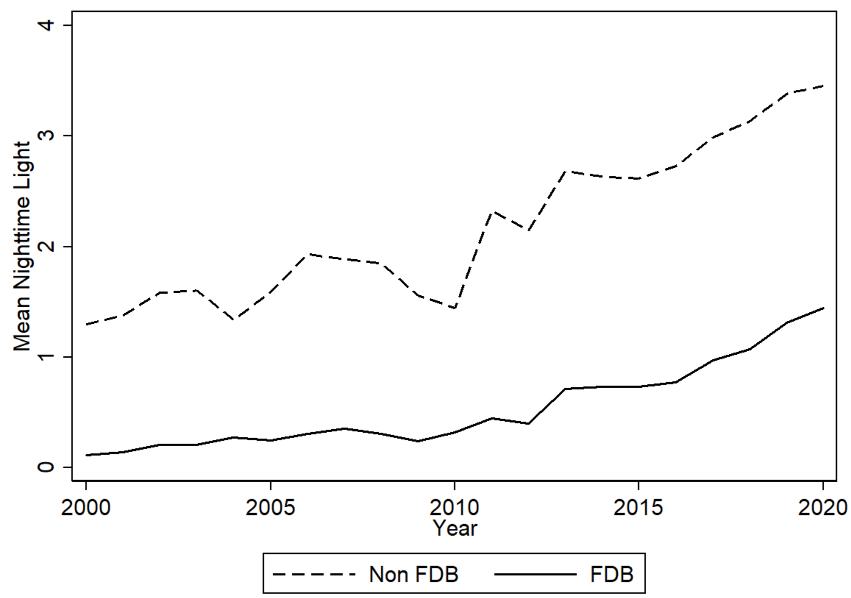


Figure 4: Nighttime Light in FDB and non-FDB Counties

4.2 Baseline Results

To investigate the impact of FDB on economic outcomes, we use the specification that takes the form of:

$$logY_{jcpt} = \alpha + \beta_1 FDB_j + \beta_2 Control_{jcpt} + \gamma_{pt} + \gamma_c + \epsilon_{jt}$$

where Y_{jcpt} is the log economic outcome of county j located in city i and province p in year t. FDB_j is a dummy that equals 1 if there is a FDB located in county j and equals 0 if not. $Control_{jcpt}$ include population, size, and the ratio between sector and first sector of county j. γ_{pt} is the province-by-year fixed effect and capture the province level fluctuations. γ_c captures any time-invariant county attributes. Standard errors are clustered at the county level. Table 6 offers an assessment of the impact of Flood Detention Basins (FDBs) on economic development through both direct and proxy indicators. Columns (1) to (6) report the relationship between FDBs and nighttime light intensity—a commonly employed proxy for economic activity. The consistently negative and statistically significant coefficients across these columns underscore a pronounced adverse impact of FDBs on regional economic vitality. In column (7), the analysis pivots to a more direct measure of economic well-being, using GDP per capita. The estimated coefficient here not only retains its negative sign but also exhibits a magnitude that is similar with the results obtained using nighttime light intensity. A synthesis of these findings suggests that economic development in FDB counties lags approximately 15% behind that observed in non-FDB counties, offering a potent testament to the challenges posed by FDBs to regional economic prospects.

Table 7 provides a detailed exploration of the impacts of Flood Detention Basins (FDBs) on diverse facts of regional economic performance. Focusing initially on the manufacturing sector in columns (1)-(3), the result reveals a discernible disadvantage across multiple outputs: firm entry, aggregate manufacturing output, and individual worker productivity, all of which indicate negative coefficients. Delving into the agricultural sector in column (4), there is a recorded decrease in agricultural production attributable to FDBs, although the coefficient remains not significant. Synthesizing these insights, it becomes evident that the establishment of FDBs correlates with suppressed economic activity predominantly within the manufacturing sector.

The empirical findings align well with our previous hypotheses. Primarily, it is worth to note that FDB zones, by virtue of their proximity to rivers, tend to inherit a richer, more fertile soil, rendering them more agriculturally productive than their non-FDB counterparts. Furthermore, post-2000 legislative enactments in China introduced compensations, extending subsidies to households in FDB regions in instances of agricultural losses due to flooding. Such a policy effectively mitigates the inherent agricultural risks associated with these areas. This can explain the non-significance of agriculture, as indicated by column (4) of the table. Looking into the fiscal landscape in columns (5) and (6), we observe a decrease in governmental income from FDB regions, attributable to the decline in production capacities and GDP contractions. Lastly, as suggested in column (7), household savings exhibit a downturn in FDB counties, which may be caused by poverty and low income in this area.

Table 6: Impact of Flood Detention Basin (FDB) on Economic Development: Fixed Effects Estimates

	Nighttime Light						GDP per capita
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(in logarithm)	Mean	Mean	Sum	Sum	Max	Max	
FDB	−0.716***	−0.175*	−0.235**	−0.166*	−0.225***	−0.133**	−0.129***
	(0.144)	(0.102)	(0.097)	(0.094)	(0.057)	(0.059)	(0.049)
N(obs)	54,164	31,844	54,164	31,844	54,164	31,844	31,844
R^2	0.616	0.805	0.654	0.759	0.514	0.565	0.850
Fixed Effects							
Province-Year	Y	Y	Y	Y	Y	Y	Y
City	Y	Y	Y	Y	Y	Y	Y
Control	N	Y	N	Y	N	Y	Y

Note: (1) Following other research on China, Tibet, Xinjiang, Qinghai, Taiwan, Macao, and Hongkong are excluded in the sample, but results are robust if including all provinces; (2) Regressions with controls use a county panel of 20 years (2000 - 2019) that includes 1,777 non-FDB counties and 67 FDB counties from 27 provinces in China, while regressions without controls use nighttime light data that includes 2,484 non-FDB counties and 81 FDB counties. The difference in the number of observation is because the county panel data is not comprehensive. (3) FDB_i is a dummy that equals 1 if the county i has a Flood Detention Basin, and equals 0 if not; (4) All regressions control for city fixed effects, province-by-year fixed effects, and a set of county-level controls; (5) Standard errors are clustered at the county level.

Table 7: Impact of Flood Detention Basin (FDB): Fixed Effects Estimates

	Industrial Sector			**Agriculture**	**Government Budget**		**Saving**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(in logarithm)	Firm Entry	Production	Productivity	Production	Income	Expenditure	
FDB	−0.180**	−0.220**	−0.141**	−0.058	−0.149**	−0.036	−0.081***
	(0.086)	(0.086)	(0.061)	(0.050)	(0.068)	(0.031)	(0.045)
N(obs)	31,844	31,844	31,470	31,844	31,792	31,830	31,648
R^2	0.793	0.803	0.608	0.855	0.814	0.948	0.866
Fixed Effects							
Province-Year	Y	Y	Y	Y	Y	Y	Y
City	Y	Y	Y	Y	Y	Y	Y
Control	Y	Y	Y	Y	Y	Y	Y

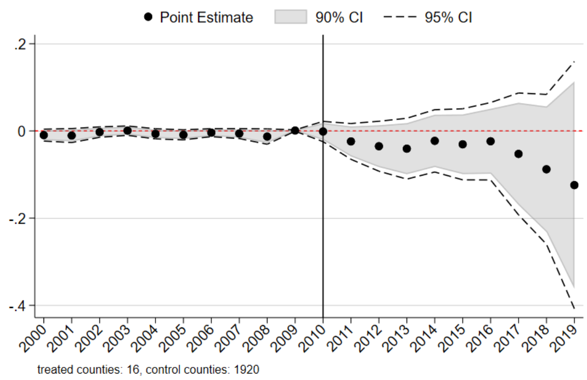
Note: (1) Following other research on China, Tibet, Xinjiang, Qinghai, Taiwan, Macao, and Hongkong are excluded in the sample, but results are robust if including all provinces; (2) We use a county panel of 20 years (2000 - 2019) that includes 1,777 non-FDB counties and 67 FDB counties from 27 provinces in China; (3) FDB_i is a dummy that equals 1 if the county i has a Flood Detention Basin, and equals 0 if not; (4) *Firm Entry* represents the number of new firms entering the county; *Manufacturing Production* represents the total production of the second sector; *Productivity* represents the production per worker; *Agricultural Production* represents the total production of the first sector; *Government Income* and *Government Expenditure* are outcomes per capita; *Saving* represents the individual saving; (5) All regressions control for city fixed effects, province-by-year fixed effects, and a set of county-level controls; (6) Standard errors are clustered at the county level.

4.3 Synthetic DiD results

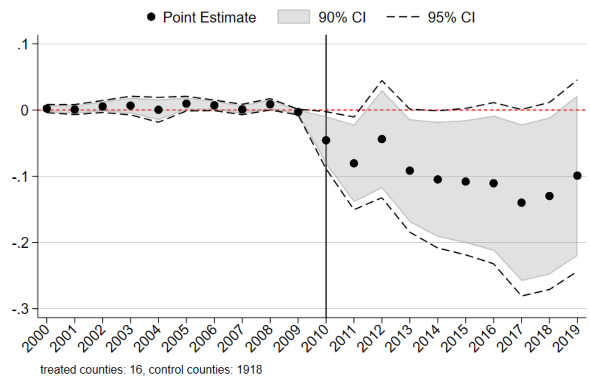
In 2010, the Chinese government removed 10 counties out of the Flood Detention Basin county, and added 20 counties to become the Flood Detention Basin county. This quasi-experimental policy setting offers us an opportunity to investigate the anticipation effect. To alleviate possible endogeneity challenges, we further apply a synthetic Difference-in-Difference (SDID) approach to study the impact of assigning one specific county as Flood Detention Basin county.

In our analytical context, there exists the possibility that interventions or treatments are non-randomly assigned. This non-random assignment poses challenges, especially with potential violations of the parallel trends assumption inherent in the conventional difference-in-differences approach. To address this methodological caveat, we adopt the Synthetic Difference-In-Differences (SDID) framework, as delineated by Arkhangelsky et al. (2021). This approach combines the core of the traditional difference-in-differences framework with the principles of the synthetic control method. Central to the SDID framework is its ability to derive a counterfactual for each treated entity by computing a weighted average from a comprehensive set of potential control units. A distinguishing feature of the SDID is its procedure to align pre-treatment trajectories between treated entities and their synthetic analogues. By fostering such congruence, the SDID approach ensures the validity of counterfactual constructs, enhancing the robustness of causal interpretations derived from our empirical inquiry. Utilizing the SDID methodology not only amplifies the methodological rigor but also enables a more granular exploration of the heterogeneous policy impacts.

4.3.1 The Impact of FDB on Overall Economy



(a) GDP per capita

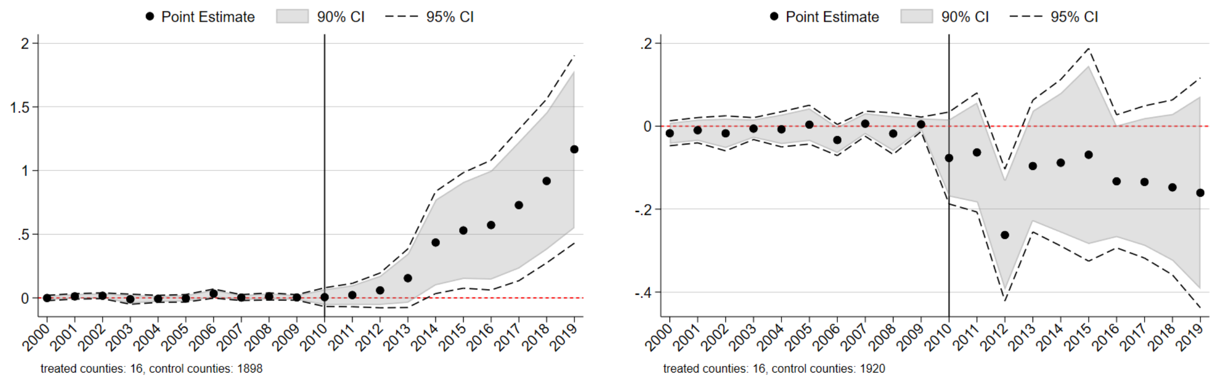


(b) Individual Saving

Figure 5: Policy Impact on Individual Income Level

The classification of a county as a Flood Detention Basin (FDB) marks a critical juncture in its economic trajectory, as illustrated in Figure 5. GDP per capita, a crucial indicator of a region's economic condition, is observed to undergo a significant decline in these FDB-designated counties. This downward trend in GDP per capita signals a potential deterioration in the economic opportunities available to residents. Complementing this is a notable decrease in savings levels, an important measure of disposable income. The reduction in savings implies not just a possible impact on income post-FDB designation, but also a weakening in the financial resilience of the community. Collectively, these patterns present a compelling picture of increasing economic inequality, as newly designated FDB counties appear to suffer setbacks compared to their non-FDB counterparts.

4.3.2 Anticipation Effect: the Impact of FDB on Different Sectors



(a) Agricultural Production

(b) New Manufacturing Firm Entry

Figure 6: Policy Impact on Agriculture and Manufacturing

Our analysis of Figure 6 reveals a significant economic transition in counties designated as Flood Detention Basins (FDBs). This transition is characterized by a structural shift from manufacturing industries to agriculture, a change that is both noteworthy and unexpected. In FDB counties, there is a discernible increase in agricultural activity, as evidenced by a surge in agricultural output and a higher propensity for new firm entry in this sector. These observations are juxtaposed against the counterfactual group, which does not exhibit a similar trend.

This shift can be attributed, at least in part, to the 'anticipation effect' of heightened flood risks associated with FDB designation. Our theoretical framework posits that the perceived or actual increase in flood risk acts as a deterrent for new firms considering entry into the manufacturing sector, which is typically more capital-intensive and risk-averse compared to agriculture. This deterrent effect likely stems from the higher vulnerability of manufacturing infrastructure and investments to flood-related disruptions.

Moreover, this transformation has broader economic implications. The move towards agriculture in FDB counties might reflect an adaptive response to environmental risks, but it also raises concerns about economic diversification and resilience. A heavy reliance on agriculture, especially in areas prone to flooding, could expose these regions to significant economic vulnerabilities, including market fluctuations and climate-related impacts.

Furthermore, this structural shift may also have implications for employment and income levels in these regions. The manufacturing sector is often associated with higher wages and more stable employment compared to agriculture, which is typically more labor-intensive and subject to seasonal variations. The transition to agriculture in FDB counties could therefore have a cascading effect on household incomes and local economies, as we can see in Figure 5.

4.3.3 Impact of FDB on Fiscal Income and Expenditure

(a) Fiscal Expenditure

(b) Fiscal Income

Figure 7: Policy Impact on Fiscal Income and Fiscal Expenditure

In our analysis of Figure 7, we find a pronounced decrease in government expenditure in counties following their designation as Flood Detention Basins (FDBs). Intriguingly, despite this reduction in spending, the governmental revenue in these FDB-designated counties does not show a commensurate decline. This suggests a fiscal imbalance where revenue streams remain relatively stable while expenditure contracts. Notably, this decrease in government spending tends to intensify over time, suggesting a persistent or growing fiscal restraint in these areas.

The paradox of maintained revenue alongside decreased expenditure raises important questions. It could indicate a shift in fiscal priorities or a reallocation of funds within these counties. One possible explanation is the increased allocation of funds towards flood management and mitigation efforts, which may divert resources from other public services. Alternatively, it could reflect a cautious fiscal approach adopted by local governments in response to the uncertainties and risks associated with the FDB status.

We believe that this would be another channel of exacerbating economic inequality. Lower expenditure on public services and infrastructure could hinder economic growth and development, exacerbating socio-economic disparities between FDB and non-FDB jurisdictions. Essential services such as education, healthcare, and transportation, which are pivotal for community well-being and economic activity, might be particularly affected. Moreover, the long-term effects of such fiscal policies merit consideration. Persistent underinvestment in critical public services can lead to a degradation of infrastructure and human capital, potentially locking these regions into a cycle of reduced economic vitality and increased vulnerability. This attenuated fiscal emphasis could therefore be a significant factor driving the widening socio-economic gap.

4.3.4 Summary

The regression results presented in Table 8 reveal economic impacts of Flood Detention Basin (FDB) designation, with two key mechanisms explaining these outcomes. Overall, there is a negative but statistically insignificant effect of FDB status on GDP per capita, indicating a marginal decline in economic output per person in these counties. This is paralleled by a significant decrease in individual savings, suggesting financial strain on residents in FDB areas. A primary mechanism behind these trends is the 'anticipation effect': agricultural output in FDB counties increases significantly while new firm entry, particularly in industrial sectors, decreases substantially. This points to a shift from manufacturing to agriculture, likely driven by the anticipation of heightened flood risks and its economic repercussions. Second, the fiscal dynamics in FDB counties provide further insight. Despite stable governmental income, there is a significant reduction in government expenditure, indicating a decreasing emphasis on these areas by local authorities. This constrained fiscal situation could be contributing to the reduced economic activity and financial security in FDB counties. These mechanisms together paint a picture of economic shifts and fiscal restraints in FDB-designated areas, leading to a worsening economic condition.

Table 8: Synthetid DiD Results: Economic Impact of FDB Policy

			Production		Fiscal	
	GDP p.c. (1)	Individual Saving (2)	Agricultural (3)	New Firm Entry (4)	Income (5)	Expenditure (5)
FDB	−0.035	−0.095**	0.375**	−0.078***	−0.054	−0.0895*
	(0.033)	(0.039)	(0.162)	(0.069)	(0.038)	(0.090)
N(obs)	36,784	36,784	36,784	36,784	36,784	36,784

Note: (1) * 0.1 ** 0.05 *** 0.01; (2) In 2010, 20 counties were newly selected into Flood Detention Basins; (3) Time: 2010-2022; (4) Each column reports a synthetic difference in difference regression; (5) The coefficient represents the Average Treatment Effect of the Treated (ATET), or the average of the staggered treatment effect; (5) All regressions are without controls.

4.4 Regression Discontinuity Results

4.4.1 Assumption

The Fixed Effects regression model serves as an initial empirical exploration. Yet, there exists a major identification challenge. Specifically, policy makers may exhibit a predisposition towards designating basins in economic disadvantaged regions as flood detention basins. This strategic selection, grounded in the rationale of minimizing aggregate economic costs, might bias the fixed-effect results. If such pre-existing economic conditions are indeed the primary determinants, then attributing the economic lag of FDB counties solely to the FDB intervention becomes less convincing. To circumnavigate this endogeneity issue, we employ a spatial regression discontinuity design. The RD identification takes the form of:

$$Y_{i,t} = \beta_0 + \beta_1 \text{FDB}_j + \beta_2 Controls_{j,t} + \beta_3 Controls_{i,j,t} + f(\cdot) + \epsilon_{i,t}$$

Following Ambrus et al. (2020) and let $f(\cdot) = f(\mathrm{d}_i)$ where d_i is the distance between the firm and the FDB-county border. We use a parametric specification to estimate the $f(d_i) = \sum_{k=1}^{K} \delta_k d_i^k$, where the optimal choice of K is determined using Akaike's criterion as in Black et al. (2007) and suggested in Lee and Lemieux (2010)[1]. $Controls_{j,t}$ include a list of county level control variables for county j at year t, including the nighttime light and population. $Controls_{i,j,t}$ include the firm specific control variables, such as the opening year, the industry type and also the ownership type. $Y_{i,t}$ is the firm level outcome such as the total fixed capital in year t for firm i. The coefficient of interest is β_1, which captures the effects of setting an area to be a FDB on the firm activities.

Our empirical strategy leverages a comparison between firms situated within FDB-designated areas and those operating in geographically adjacent non-FDB locales. Central to this methodology is the foundational assumption that prior socioeconomic characteristics remain similar between neighboring FDB and non-FDB counties. Furthermore, it is imperative to ensure that inundations consequent to flooding remain confined to FDB regions without spillover effects on neighboring non-FDB areas. The validity of this assumption is grounded in the geographical conditions associated with Flood Detention Basins. Given data constraints, our analysis employs a county-level granularity, a spatial unit substantially larger than Flood Detention Basins. Given this, we believe that any immediate flooding impacts are localized within the FDB-designated areas, leaving geographically contiguous non-FDB counties unaffected. Additionally, given the limited spatial extent of FDBs within a county, we believe that even minor FDB-induced adversities possess the potency to exert a pronounced impact across the entirety of the county.[2]

4.4.2 Geographical Regression Discontinuity Results

In Table 10, an examination of firm behavior in proximity to FDB counties reveals discernible patterns in manufacturing. Specifically, firms situated within FDB counties exhibit a pronounced reduction in their holdings of fixed assets. Contrastingly, their current as-

[1] here we choose K to be 4

[2] We are still on the process of checking the validity. But we believe that this will not be a big issue.

sets appear to be less affected. Upon closer inspection of outcomes such as fixed assets per worker, output per worker, and aggregate sales, we find that the coefficient is negative and statistically significant. These patterns in firm behaviors underscore the weaker business vitality within FDB counties.

In FDB counties, the underinvestment in fixed assets can be attributed to two primary mechanisms: the immediate flood effect and long-term anticipation effect. Firstly, tangible assets such as machinery and infrastructure inherently bear a heightened risk of degradation during flood events. Unlike fixed assets, current assets—represented by financial instruments and inventories—either possess inherent resilience against flood-related adversities or benefit from the feasibility of relocation to mitigate exposure. Secondly, anticipation effect, given the augmented flood risks in FDB regions, invariably influences entrepreneurial decisions, rendering them more hesitate in investing in fixed asset within FDB counties.

Table 9: Impact of FDB on Firm Activities: Spatial Regression Discontinuity

	(1) Fixed Assets	(2) Current Assets	(3) Fixed assets/Worker	(4) Output/Worker	(5) Sales
FDB	−0.176***	−0.058	−0.079**	−0.092***	−0.103***
	(0.049)	(0.039)	(0.040)	(0.035)	(0.038)
N(obs)	382,858	385,564	380,469	354,868	387,402
R^2	0.747	0.791	0.719	0.753	0.769
Fixed Effects					
Firm	Y	Y	Y	Y	Y
City	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y
Control	Y	Y	Y	Y	Y

Note: (1) The sample is restricted to the group of firms whose distance to the FDB-county border is less than 30km. (2) The standard errors are clustered at the 1 longitude × 1 latitude cells level. (3) FDB_j is a dummy that equals 1 if the county j has a FDB, and equals 0 if not. (4) Outcome variables are all in logarithm.

5 Theoretical Framework

In this study, we establish a spatial equilibrium framework to rigorously evaluate the welfare and economic implications of Flood Detention Basins. Our model is designed with three primary objectives. Firstly, it employs a general equilibrium approach, allowing for the integration of calibration and simulation techniques. Hence, we could check whether the model's predictions are aligned with our empirical findings. Secondly, through counterfactual analysis, we aim to quantify the total welfare enhancement attributable to this policy. Specifically, we investigate the extent to which pre-flood loss allocation under this policy has augmented societal welfare. Lastly, we utilize counterfactual scenarios to assess the degree to which the Flood Detention Basin policy has influenced regional inequalities within China.

5.1 Model Set Up

Consider an economy with N number of regions, and each region is indexed by $n \in N$. Each location n is endowed with amenity value B_n. There is a measure of $\overline{L}$ of hand-to-mouth workers in the economy who can migrate across regions subject to migration cost μ_{ni} if they move from region n to region i. There is one representative saver in each region who cannot move across regions. Goods trade between region n and region i is subject to iceberg trade cost, i.e. d_{ni} must be shipped from region n in order for one unit of good to arrive in region i.

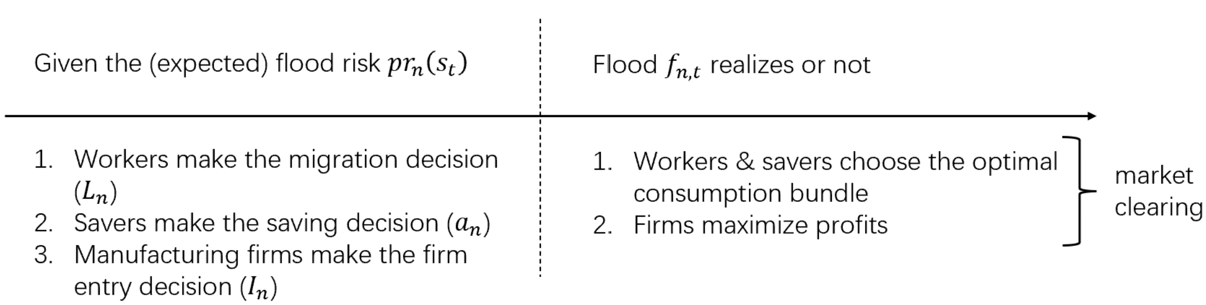


Figure 8: Timing in the Model

5.2 Flooding events

Denote $S = \{s_1, s_2, ..., s_J\}$ as the set of possible natural flood events. The region-specific flooding risk is characterized by a vector of flooding probability $Pr = \{pr(s_1), pr(s_2), ..., pr(s_J)\}$. Flood event s_t consists of a vector of region-specific flooding events $s_t = \{f_{1,t}, f_{2,t}, ..., f_{N,t}\}$. Flooding happens in region n at time t implies $f_{n,t} = 1$ and $f_{n,t} = 0$ otherwise.

A natural flood event s_t affects agents in the economy through the following channel. A realized flooding event negatively affect the region-specific agriculture productivity $z_n^A(s_t)$, manufacturing productivity $z_n^M(s_t)$ and service productivity $z_n^S(s_t)$. More specifically, we model the productivity as:

$$\begin{cases} z_n^A(s_t) = \bar{z_n^A} exp(-\epsilon_A f_{n,t}) \\ z_n^M(s_t) = \bar{z_n^M} exp(-\epsilon_M f_{n,t}) \\ z_n^S(s_t) = \bar{z_n^S} exp(-\epsilon_S f_{n,t}) \end{cases} \tag{1}$$

where $\bar{z_n^A}$, $\bar{z_n^M}$ and $\bar{z_n^S}$ denote the region-specific productivity during non-flooding time; ϵ_A, ϵ_M and ϵ_S denotes the region-specific percentage productivity losses during flooding seasons $f_{n,t} = 1$.

5.3 The workers' problem

We assume the consumers make the migration decisions n' before the realization of the flooding events s_t, so n' is independent of the flooding state s_t. After flooding events realize, workers optimize their consumption bundles given state s_t.

A worker in region n at time t consumes three types of goods: agricultural goods $C_n^A(s_t)$, service goods $C_n^S(s_t)$ and manufacturing goods $C_n^M(s_t)$, where the former two are non-tradable while the latter can be traded across regions. Further, we assume that there is an endogenous mass of I firms in the economy. The geographic distribution of the firms is characterized by $\{I_1, I_2, ..., I_n\}$. The consumers exhibit love of variety over the heterogeneous products produced by all firms $i \in \{1, 2, ..., N\}$. Hence, the optimization problem of a worker living in region n at time t over the composition of manufacturing goods is given by:

$$
\begin{aligned}
C_n^M(s_t) = \max_{C_{in}^M(s_t)} & \left[\int_N I_i C_{in}^M(s_t)^{\frac{\sigma-1}{\sigma}} di \right]^{\frac{\sigma}{\sigma-1}} \\
s.t. & \int_N I_i P_{in}^M(s_t) C_{in}^M(s_t) di \leq P_n^M(s_t) C_n^M(s_t)
\end{aligned} \tag{2}
$$

where $C_{in}^M(s_t)$ is the consumption of manufacturing good produced by a firm in region i and $P_{in}^M(s_t)$ is the price of the firm's good at region n. One can easily show that $P_n^M(s_t) = \left[\int_N I_i P_{in}^M(s_t)^{1-\sigma} di \right]^{\frac{1}{1-\sigma}}$

Workers' utility function is given by $U(C_n^A(s_t), C_n^M(s_t), C_n^S(s_t))$. Workers supply one unit labor inelastically in the region they live in.

Following Balboni (2021), the workers' Bellman equation could be written as

$$
v_n^w = \max_{C_n^A(s_t), C_n^M(s_t), C_n^S(s_t)} \mathbb{E}_{s_t} U(C_n^A(s_t), C_n^M(s_t), C_n^S(s_t)) + \max_{n' \in N} \{\beta v_{n'}^w - \mu_{nn'} + B_{n'} + b_{n',t}\} \tag{3}
$$

where $b_{i,t}$ is a idiosyncratic preference shock which is assumed to follow Gumbel distribution with parameter $(-\gamma\upsilon, \upsilon)$. Taking expectation over $b_{n',t}$ yields $\mathbb{E}_b v_n^w$:

$$
V_n^w = \max_{C_n^A(s_t), C_n^M(s_t), C_n^S(s_t)} \mathbb{E}_{s_t} U(C_n^A(s_t), C_n^M(s_t), C_n^S(s_t)) + \upsilon log \sum_{n' \in N} [exp(\beta V_{n'}^w - \mu_{nn'} + B_{n'})^{\frac{1}{\upsilon}}] \tag{4}
$$

The budget constraint is characterized by the following equation:

$$
P_n^A(s_t) C_n^A(s_t) + P_n^M(s_t) C_n^M(s_t) + P_n^S(s_t) C_n^S(s_t) = w_n(s_t) + \frac{I_n}{L_n} \pi_n(s_t) \qquad \forall s_t \tag{5}
$$

where $w_n(s_t)$ and $\pi_n(s_t)$ are the region-specific wage rate and manufacturing firm profits respectively under flooding state s_t.

Denote the m_{ni} as the fraction of population in region n that migrates to destination i in each period. One can show the origin-destination migration flows m_{ni} can be characterized by:

$$
m_{ni} = \frac{exp(\beta V_i^w - \mu_{ni} + B_i)^{\frac{1}{\upsilon}}}{\sum_{j \in N} [exp(\beta V_j^w - \mu_{nj} + B_j)^{\frac{1}{\upsilon}}]} \tag{6}
$$

Hence the population in region n is given by:

$$L_n = \sum_{i \in N} m_{in} L_i \tag{7}$$

5.4 The savers' problem

We assume that the savers make the saving decisions $a_{n,t+1}$ before the realization of the flooding events s_t, so $a_{n,t+1}$ is independent of s_t. After flooding events realize, the savers optimize their consumption bundles given state s_t.

The savers' preferences are identical to those of the workers. So the savers' Bellman equation could be written as

$$V_n^s(a_{n,t}) = \max_{C_n^{s,A}(s_t), C_n^{s,M}(s_t), C_n^{s,S}(s_t)} \mathbb{E}_{f_t} U(C_n^{s,A}(s_t), C_n^{s,M}(s_t), C_n^{s,S}(s_t)) + \beta V_n^s(a_{n,t+1}) \tag{8}$$

The budget constraint is characterized by the following equation:

$$P_n^A(s_t) C_n^{s,A}(s_t) + P_n^M(s_t) C_n^{s,M}(s_t) + P_n^S(s_t) C_n^{s,S}(s_t) + a_{n,t+1} = (1 + r(s_t)) a_{n,t} \qquad \forall s_t \tag{9}$$

5.5 Primary and tertiary industry

We assume there is a representative primary industry firm at each region n that produces non-tradable agriculture goods with a linear production function. The representative primary firm supplies good in a perfectly competitive way, so the maximization problem for $\forall s_t$ is given by:

$$\begin{aligned} &\max_{l_n^A(s_t)} P_n^A(s_t) y_n^A(s_t) - w_n(s_t) l_n^A(s_t) \\ &s.t.\ \ y_n^A(s_t) = z_n^A(s_t) l_n^A(s_t) \end{aligned} \tag{10}$$

We assume there is a representative tertiary industry firm at each region n that produces non-tradable service goods with a Cobb-Douglas production function. The representative tertiary firm supplies good in a perfectly competitive way, so the maximization problem for

$\forall s_t$ is given by:

$$\max_{l_n^S(s_t), k_n^S(s_t)} P_n^S(s_t) y_n^S(s_t) - w_n(s_t) l_n^S(s_t) - [r(s_t) + \delta] k_n^S(s_t)$$
$$s.t. \;\; y_n^S(s_t) = z_n^S(s_t) l_n^S(s_t)^\alpha k_n^S(s_t)^{1-\alpha} \tag{11}$$

5.6 Manufacturing firms

We assume that there is an endogenous mass of I manufacturing firms allocating across N regions. I_n are determined by endogenous entry and mechanical exit. We assume that firms make the entry decision before the realization of the flooding events, so I_n are independent of flooding state s_t. The expected value of establishing a firm is:

$$V_n^f = \mathbb{E}_{s_t} \pi_n(s_t) + \beta(1-\eta) V_n^f \tag{12}$$

where η is the time-invariant mechanical exit rate. Let c_n^f denote the region-specific entry cost, then free entry condition implies:

$$V_n^f = c_n^f \tag{13}$$

Provided the realization of flooding events s_t, manufacturing firms in region n follow identical Cobb-Douglas production function with labor and physical capital input. The manufacturing firms supply goods to all regions in a monopolistically competitive way, so the maximization problem is characterized by:

$$\pi_n(s_t) = \max_{k_{ni}(s_t), l_{ni}^M(s_t)} \int_N \left\{ P_{ni}^M(s_t) y_{ni}^M(s_t) - [r(s_t) + \delta] k_{ni}(s_t) - w_n(s_t) l_{ni}^M(s_t) \right\} di$$
$$s.t. \qquad d_{ni} y_{ni}^M(s_t) = z_n^M(s_t) k_{ni}(s_t)^\alpha l_{ni}^M(s_t)^{1-\alpha} \qquad \forall s_t \tag{14}$$

where $k_{ni}(s_t)$ and $l_{ni}^M(s_t)$ denote the factors invested by a firm in region n in producing goods supplied to consumers in region i; d_{ni} denotes the iceberg cost of transporting manufacturing goods from region n to region i; $P^M_{ni}(s_t)$ denotes the region i price of manufacturing goods supplied by a firm in region n.

5.7 General Equilibrium

The general equilibrium consists of local asset positions $\{a_n\}$, local firm counts $\{I_n\}$ and local labour supply $\{L_n\}$, and in each natural flooding event s_t, workers' and savers' consumption bundles $\{C^{w,i}_n(s_t), C^{s,i}_n(s_t)\}$, sector-specific factor demands and outputs $\{l^i_n(s_t), k^i_n(s_t), y^i_n(s_t)\}$, and prices $\{w_n(s_t), r(s_t), P^A_n(s_t), P^M_n(s_t), P^S_n(s_t)\}$ such that:

Before the realization of flood events:

1. Local labour supplies $\{L_n\}$ satisfy workers' optimal migration decisions;
2. Local asset positions $\{a_n\}$ satisfy savers' optimal saving decisions;
3. Local firm counts $\{I_n\}$ satisfy secondary firms' entry decisions;

After the realization of flood event s_t:

1. Workers' and savers' consumption bundles $\{C^{w,i}_n(s_t), C^{s,i}_n(s_t)\}$ satisfy agents' utility maximization problems;
2. Firms' factor demands and outputs $\{l^i_n(s_t), k^i_n(s_t), y^i_n(s_t)\}$ satisfy the firms' profit maximization problems;
3. Prices $\{w_n(s_t), r(s_t), P^A_n(s_t), P^M_n(s_t), P^S_n(s_t)\}$ clear the factor and product markets given quantities in (4) and (5);

5.8 Analytical Results

Proposition 1 (Immediate Flood Loss). *Realized flood events, $f_{n,t} = 1$, will cause immediate reductions in local manufacturing firms' profits π_n, wage rate w_n, and manufacturing industry labor share r^M_n.*

Proposition 1 addresses the immediate economic costs, specifically in the manufacturing sector, resulting from the implementation of the Flood Detention Basin (FDB) policy. It posits that FDB counties are likely to experience direct damage to their manufacturing industries due to the inundation in flood season.

Proposition 2 (Long-Term Anticipation Effect). *When flood risk $pr(f_n = 1)$ increases, the expected return of investment decreases. For fims, firm entry I_n decreases. For individuals, individual saving a_n decreases and the willingness to migrate $m_{n,-n}$ increases.*

Proposition 2 delves into the long-term economic impact on FDB counties, particularly focusing on their diminishing appeal to investors. This reduction in attractiveness is attributed to the heightened flood risk in these areas. Consequently, a lower number of firms are expected to establish their operations in FDB counties. This shift is anticipated to lead to a decrease in total individual income within these counties, subsequently diminishing personal savings. Another outcome of this economic downturn is an expected increase in the propensity of individuals to migrate, seeking more stable economic conditions.

6 Calibration and Simulation

In this section, we calibrate our model to match the characteristics of Chinese counties in Huai River Area between 2000 and 2010.

Table 10: Impact of FDB on Firm Activities: Spatial Regression Discontinuity

Parameter	Numbers	Value	Source/Targeted Moments
Exogenously Calibrated Parameters			
N - Number of regions	1	176	Number of counties in Huaihe River Area
$\bar{L}$ - Labour force	1	1	Standarized to one
σ - Elasticity of substitution across varieties	1	5	Head and Mayer (2014)
β - Discount factor	1	0.95	Steady-state interest of 5%
ξ_1 - Share of agricultural consumption	1	0.117	Chinese National Bureau of Statistics
ξ_3 - Share of service consumption	1	0.422	Chinese National Bureau of Statistics
υ - Gumbel distribution	1	0.33	Balboni (2021)
η - Firm exit rate	1	0.05	Qichacha firm exit rate
$pr(s_t)$ - Natural flooding event probability	7	0.14(0.15)	Precipitation and Flood Event (2000-2010)
d_{ni} - Transportation costs	N^2	3.57(0.64)	Geodesic distances
α - Factor share of capital	1	0.5	Factor shares of secondary and tertiary industries
Immediate Loss from Flood Inundation:			
ϵ_A - Primary productivity loss	1	0.076	Estimation
ϵ_M - Secondary productivity loss	1	-0.086	Estimation
ϵ_S - Tertiary productivity loss	1	-0.002	Estimation
Internally Calibrated Parameters			
$\bar{z}_n^A$ - Region-specific primary productivity	N	0.74(0.30)	County-level real primary outputs
$\bar{z}_n^M$ - Region-specific secondary productivity	N	0.72(0.24)	County-level real secondary outputs
$\bar{z}_n^S$ - Region-specific tertiary productivity	N	0.39(0.35)	County-level real tertiary outputs
B_n - Local amenity	N	0.00(0.18)	County-level labour force share
c_n^f - Region-specific firm entry costs	N	0.37(0.18)	County-level manufacturing firm counts

6.1 Exogenously Calibrated Parameters

Panel A of Table 9 shows the parameter values obtained directly from the literature and the data. We treat each region as a county, and there are M = 176 counties in Huai River Area. We standardize labour force $\bar{L}$ to be one. We set the elasticity of substitution across varieties $\sigma = 5$, which is the mean estimate in the trade literature (Head and Mayer 2014 & Jia et al. 2022). We choose a discount factor β to be 0.95 to generate an aggregate steady-state interest of 5%. We choose the shares of sector-specific consumption to match the real data provided by Chinese National Bureau of Statistics. For the Gumbel distribution, we follow Balboni (2019) and choose an elasticity of migration $\frac{1}{v}$ that equals 3. We choose a firm exit rate that matches the national actual rate provided by Qichacha, which is a universal business registration dataset in China. We choose a factor share of capital α that equals 0.5 for both the secondary and tertiary industry, and 0 for the primary industry. This is consistent of the national-level sector specific factor share in China, calculated by data from Chinese National Bureau of Statistics.

Transportation costs

The calculation of transportation costs d_{ni} is based on geodesic distances across different counties. For the transportation cost within a county, we adopt a similar approach as existing literature (e.g., Redding and Venables (2004), Au and Henderson (2006a), and Balboni 2019). Specifically, we calibrated trade costs by approximating intra-unit trade costs based on the average distance travelled to the centre of a circular unit of the same area from evenly-distributed points within the given by $\frac{2}{3}(\text{area}/\pi)^{1/2}$. We standardize the smallest transportation costs to be 1.

Region-specific flooding probability

In 2000 and 2010, there were 6 major floods (2002, 2003, 2005, 2007, 2008 and 2010) in Huai River. Those flood events inundated different counties in Huai River and caused damages of different levels. For example, the 2003 flood caused damages to 61 counties out of 176 counties in Huai river, while the 2010 flood caused damages to 25 counties. Based on the level of total precipitation, we divide the annual precipitation into three categories: (i) < 800 mm; (ii) 800 - 1,000 mm; (iii) $> 1,000$ mm. We then calculated the region-specific flooding probability based on both historical data on annual precipitation and actual flood event.

Table 11: Flood Events and Annual Precipitation in Huai River(2000-2010)

Annual Precipitation	Years	Flood	Average Number of Affected Counties
$<$ 800 mm	2001	N.A.	N.A.
800 - 1000 mm	2002, 2004, 2006, 2008 - 2010	2002, 2008, 2010	35
$>$ 1000 mm	2000, 2003, 2005, and 2007	2003, 2005, and 2007	70

Note: The annual preccipation is collected from xxx, and the flood event data is collected from xxx.

Productivity Losses

We estimate productivity losses in primary sector, secondary sector and tertiary sector based on the estimation below.

$$Y_{i,c,t} = \alpha + \beta_1 \times Flood_{c,t} + \gamma_c + \theta_t + \epsilon_c$$

In this estimation, $Y_{i,c,t}$ stands for the sector-specific productivity, as measured by real output divided by sector-specific employment, in sector $i(i = 1, 2, 3)$ in county c at year t. $Flood_{c,t}$ is a dummy variable that equals 1 if county c experienced flood at year t. We also control for county fixed effect γ_c and time fixed effect θ_t. The standard error is clustered at county level. The estimation results suggest that the primary sector did not suffer from flood loss. Instead, the productivity in primary sector increased after the flood event. The reasons are twofolds. First, although flood will fully inundate the agricultural land, the soil will become more futile after the flood. Second, there exists a de-industrialization process that residents in FDB counties rely more on agriculture instead of manufacturing due to the FDB designation. As we can see from our estimation results of productivity loss in second sector, manufacturing suffered approximately 8.6% loss due to the flood event. As for the tertiary sector, the loss is approximately 0.2%, which indicates the flood-resilience of tertiary sector.

6.2 Internally Calibrated Parameters

We calibrate four sets of region-specific parameters $\{\bar{z_n^A}, \bar{z_n^M}, \bar{z_n^S}, B_n, c_n^f\}$ such that our model generated moments match data on county-level sector specific real outputs, labour force share and manufacturing firm counts. Even though all of the parameters are jointly estimated, it is possible to isolate the parameter that drives identification of a given moment. Specifically, county-level sector specific real outputs drives identification of sector specific productivity in counties. Labour force in each region drives identification of region-specific amenities. Entry costs are informed by the amount of manufacturing firms in each region. Because units of GDP, population, and firm count do not affect our counterfactual results, we normalize the national total GDP, population and firm count to 1 in our baseline calibration.

6.3 Estimation Results

In this section, we conduct a comparative analysis to illustrate the consistency between the empirical findings from Flood Detention Basin (FDB) regions and the predictions of our economic model. Our objective, as displayed in Table 12, is to validate the model's capability to accurately reflect the economic realities of FDB areas. This comparative approach is pivotal in demonstrating the robustness and reliability of our model as a tool for replicating and understanding real-world economic scenarios.

Table 12 offers a comparison of the actual empirical results and model-predicted outcomes under analogous conditions. We focus on two key economic indicators: Fixed Assets per Worker and Capital per Worker. These metrics are essential for evaluating the impact of FDB policies on the allocation and productivity of labor and capital in these regions. Our analysis reveals a close alignment between the model predictions and the empirical data, which underscores the validity of our model.

Table 12: Comparison of Actual and Model-generated Regression Results

(in logarithm)	Actual Data Fixed Assets/Worker	Model Simulation Capital/Worker
FDB	-0.079**	-0.089**
	(0.040)	(0.032)
N(obs)	380,469	1,936
R^2	0.719	0.572

6.4 Counterfactual Practices

In this section, we present an empirical analysis aimed at understanding the impact of different levels of flood risk on Flood Detention Basin (FDB) counties compared to their non-FDB counterparts. Our primary focus is to evaluate the outcomes under various flood risk scenarios: calibrated flood risk scenario and two counterfactual scenarios (a reduced flood risk scenario, and a no flood risk scenario). The results of this analysis are encapsulated in Table 13, which illustrates the values for key economic indicators under these different scenarios.

To construct the counterfactuals, we first consider the current calibrated flood risk scenario, where the average flood risk in FDB counties is approximately double that of non-FDB counties. This scenario serves as our baseline for comparison. We then create two counterfactual scenarios. The first counterfactual scenario, termed 'Reduced Flood Risk', involves adjusting the average flood risk in FDB counties to match the average risk level of non-FDB counties. This allows us to examine the economic outcomes if the FDB counties were exposed to the same level of flood risk as non-FDB areas.

The second counterfactual, 'No Flood Risk', posits a scenario where the flood risk in FDB counties is entirely eliminated. This hypothetical scenario provides an extreme case for analysis, enabling us to isolate and understand the economic impacts solely attributable to the presence of flood risk.

In each scenario, we assess several key economic indicators, including Flood Probability, Expected Utility, Firm Count, Secondary Labour Share, and Real Wage. These indicators are crucial for evaluating the economic vitality and resilience of counties under different levels of flood risk exposure. By comparing the realized data with these counterfactual scenarios, we aim to elucidate the potential economic benefits that could arise from strategic flood risk management and policy interventions in FDB counties. In summary, our counterfactual practice provides a nuanced understanding of how varying levels of flood risk can differentially impact regions that are otherwise similar in non-risk characteristics.

Table 13: FDBs' values as percentages of Non-FDBs' values

	Flood Probability	Expected Utility	Firm Count	Secondary Labour Share	Real Wage
Calibrated Flood Risk	2.104	-0.076	-0.131	-0.032	-0.081
Reduced Flood Risk	1.000	-0.061	-0.070	-0.024	-0.068
		80.3%	53.4%	75.0%	84.0%
No Flood Risk	0	-0.046	-0.017	-0.017	-0.056
		60.5%	13.0%	53.1%	69.1%

Note: In the current calibrated flood risk scenario, the average flood risk in FDB counties is approximately double that of non-FDB counties.The first counterfactual scenario, termed 'Reduced Flood Risk', involves adjusting the average flood risk in FDB counties to match the average risk level of non-FDB counties. The second counterfactual, 'No Flood Risk', posits a scenario where the flood risk in FDB counties is entirely eliminated. This hypothetical scenario provides an extreme case for analysis, enabling us to isolate and understand the economic impacts solely attributable to the presence of flood risk.

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