Sacrifice for the Greater Good?
Benefits and Costs of Flood Detention Basins

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July 25, 2024

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Abstract

Should we intentionally expose certain areas to higher risks to protect broader regions from disasters? Policymakers often face a winner-loser dilemma when making such decisions. In 2000, the Chinese government officially implemented the Flood Detention Basin (FDB) policy, where FDB counties are more frequently inundated to absorb excess floodwater, thereby protecting larger regions, particularly urban cities. Our analysis reveals that the flood inundation area in FDB counties tends to be about 50% higher than in comparable non-FDB counties. We then evaluate the benefits and costs of this flood risk redistribution policy. Event-study analysis indicates that FDB counties suffer an annual real GDP loss of approximately $10 billion. Firms' reluctance to enter and invest in FDB counties explains this economic underdevelopment. Selection into the FDB list leads to an average of 15.9% decrease in firm entry into FDB counties. Spatial regression discontinuity analysis also shows a 19.7% reduction in firm-level fixed asset investments in FDB counties. Using a spatial general equilibrium framework, we construct a counterfactual scenario where FDB counties absorb less floodwater. Integrating a hydrodynamic engineering model, we find the actual benefit-to-cost ratio in total output to be around 3.5. Another counterfactual analysis suggests that urban cities may be overprotected, as similar output gains could be achieved by removing higher productivity counties from the FDB list.

JEL classification: Q54, Q56, R58, R13

Keywords: Natural Disasters, Environment and Development, Regional Development Policy, General Equilibrium and Welfare Analysis

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1 Introduction

> *What is it which prompts the generous to sacrifice their own interests to the greater interests of others? ... It is the love of the grandeur who shows us the propriety of resigning the greatest interests of our own, for the yet greater interests of others; and the deformity of doing the smallest injury to another, in order to obtain the greatest benefit to ourselves.*
>
> — The Theory of Moral Sentiments*, Adam Smith*

The long-term global climate change has increased flood risks. According to the EM-DAT International Disaster Database, floods have caused over $550 billion in damages since 2000. The population in flood-prone areas has also risen substantially by 34.1% from 2000 to 2018, markedly higher than the global population growth of 18.6% over the same period (Tellman et al. 2021). For centuries, we have taken precautionary actions, such as constructing levees and dams (Duflo and Pande 2007) and protecting wetlands (Taylor and Druckenmiller 2022), to manage floods. However, as the threat of extreme floods intensifies, policymakers may also face extreme decisions. A crucial question in flood management is whether to deliberately expose certain areas to higher risks, such as through flood water diversion, to protect broader regions from severe flood damage. These decisions are difficult, as environmental policies often result in uneven impacts (e.g., He et al. 2020), creating potential winners and losers, necessitating policymakers to carefully consider the trade-offs between equity and efficiency.

This study focuses on the Flood Detention Basin (FDB) policy in China, a country with the most severe river flood risk in the world.[1] In 2000, the Chinese government officially implemented the FDB policy, which clearly designated areas to bear higher flood risks. According to the Ministry of Water Resources in China, "residents in FDB counties make significant sacrifices to protect the collective social welfare and enhance overall economic resilience against floods." Under this policy, some pre-designated rural counties will be intentionally flooded in severe flood events to protect broader areas, particularly major cities, from inundation. In 2000, the government designated 98 low-lying wetlands as flood

[1]According to the EM-DAT International Disaster Database, China ranks first in the number of total river flood events from 2000 to 2017. The EM-DAT International Disaster Database also records 4,066 disaster events that occurred between 2000 and 2024, with damage data available for 1,155 of these events. The total recorded damage amounts to US$736 billion, of which US$555 billion pertains to developing countries. Specifically, China accounts for US$211 billion, and India for US$77 billion.

detention basins, covering over 30,000 km^2 and directly affecting more than 15 million residents across 96 FDB counties. Since its implementation, floodwaters have been diverted to FDB counties more than 100 times to manage excess water. Using a flood proxy constructed from the Global Flood Database (Tellman et al. 2021), we find that flood inundation areas in FDB counties are over 50% larger than in other counties, holding key geographical attributes constant.

To the best of our knowledge, this study is the first to examine the impact of a risk-redistribution disaster management policy that deliberately expose certain regions to higher risks to protect others. Given the deliberate design of risk redistribution and explicit designation of winners and losers in this policy, we believe the benefit and cost analysis of FDB policy would offer reference for managing floods globally. Our research also contributes to the early body of work on flooding in China.

In this research, our first goal is to quantify the cost of the policy on FDB counties so that we can understand the extent to which those counties have sacrificed for the greater good. Our second goal is to evaluate whether the policy has resulted in a net gain in total output by extending our investigation to a general equilibrium context.

There are three primary findings. First, being selected into the FDB list has caused persistent negative impacts on the economic development of FDB counties. Based on the difference-in-differences approach, we find that the nighttime light intensity in counties included in the 2000 FDB list has decreased by approximately 10% over a decade. Drawing on the work of Henderson et al. (2012) and Martinez (2022), which estimate the elasticity of GDP to nighttime light at approximately 0.3, we translate the reduction in light intensity to an annual GDP loss of around US$10 billion in FDB counties. This cost estimation also aligns with that by hydrologists (Wang et al. 2021).

Second, in studying the mechanism, we find that the 'firm response effect' is the major reason causing economic underdevelopment in FDB counties.[2] To be more specific, firms have less incentives to enter and invest in FDB counties due to their increased flood risks. By identifying the causal impact of the 2010 policy change, where the Chinese government

[2]In Section 6, we also study three other mechanisms: the migration channel, the direct flood inundation channel, and the agricultural channel. We then provide empirical evidence to rule out those channels.

added 20 counties to the FDB list and removed 10, we provide empirical evidence supporting this mechanism:

(i) The difference-in-differences analysis using synthetic weights (Arkhangelsky et al. 2021) shows that, on average, the number of new firm entries declines by 15.9% in the newly selected FDB counties following the 2010 policy change;

(ii) Spatial regression discontinuity (Imbens and Wager 2019) analysis indicates a 19.7% gap in fixed asset investment between FDB counties and their neighboring counties, and this gap only emerged after the 2010 policy change;

(iii) The hesitance of firms to enter and invest in FDB counties leads to a lag in manufacturing. Annual manufacturing output, on average, has reduced by 18.2% in newly listed FDB counties;

(iv) In contrast, counties that were removed from the 2010 FDB list experience a significant has increased in the number of new firm entry and investment in fixed assets. We view this balanced and symmetrical result as compelling evidence that highlights the important influence of the FDB policy on firm decision-making.

Third, based on a spatial general equilibrium model, we conduct two counterfactual practices to (i) assess whether the FDB policy has yielded an overall increase in total output; (ii) and assess whether the policy is optimally designed in terms of the number of FDB counties. Inspired by the research of Desmet and Rossi-Hansberg (2014), Balboni (2019), and Jia et al. (2022), our model allows the flow of tradable manufacturing goods between FDB counties and other counties. The key parameter for our counterfactual practice is the flood exposure redistribution rate between FDB counties and non-FDB counties. In the absence of FDB counties absorbing excessive water, flood exposure in FDB counties would decrease, while exposure in protected areas would increase. We then use hydro-dynamic engineering model to determine the actual exposure distribution rate to be 45%. Based on that, we find the benefit to cost ratio in output is 3.5, and the net output gain is \$3.03 billion. In our second counterfactual practice, we successively remove FDB counties of higher productivity from the FDB list. Results indicate that counties of higher productivity do not contribute much to the output gain, which implies that the Chinese government may overprotect urban cities from floods as similar output gains can be gained from removing FDB counties of higher productivity from the FDB list.

Our research resonates with existing research on floods (e.g., Kocornik-Mina et al. 2020, Rentschler et al. 2022, and Patel 2023) and are important for three reasons. First, we introduce another dimension to the discussion of costs of disasters by showing that policies designed to manage disasters can also generate costs. Previous literature (e.g., Kahn 2005, Weitzman 2009, Strobl 2011, Hsiang and Jina 2014, Felbermayr and Gröschl 2014, Elliott et al. 2015, Shah and Steinberg 2017, and Desmet et al. 2018) mainly focuses on the short-term or long-term costs of disasters. Our research indicates that policies aiming to enhance economic resilience against natural disasters could also lead to long-term expenses due to the redistribution of risk. This aspect has received less attention in the existing literature.

Second, our study contributes to the strand of literature examining the adaptation of individuals and firms to natural disasters (e.g., Boustan et al. 2012, Barone and Mocetti 2014, Gibson and Mullins 2020, Bakkensen and Ma 2020, Gandhi et al. 2022, Balboni et al. 2023). Barone and Mocetti (2014) documents the long-term market distortions induced by earthquakes. Balboni et al. (2023) reveals a tendency among firms to relocate from flood-affected zones to less flood-prone areas. Jia et al. (2022) investigates how flood risk influence firm location decisions within the United States and its impact on long run economic cost. Our work is consistent with the previous research in finding the reluctance of firms to invest in areas of higher natural disaster risks. Moreover, we use this mechanism as a foundation to investigate the general welfare implication of a natural disaster management policy. Also, we help to explain why urban cities in China recover quickly from floods, as suggested by Kocornik-Mina et al. 2020.

Third, our research contributes to the discussion on the impact of environmental policies, highlighting the distributional impacts and welfare gain caused by such policies. Duflo and Pande (2007) reveals that residents situated upstream of dams in India face significant limitations in economic mobility relative to those living downstream. Similarly, He et al. (2020) documents that upstream polluting firms near monitoring stations in China undergo greater reductions in TFP compared to their downstream counterparts. Taylor and Druckenmiller (2022) finds spatial heterogeneity in benefiting from the Clean Water Act in the United States. Consistent with their work, we also find that environmental policy would cause unequal outcomes to different groups of people. In terms of flood management policy, existing literature mainly focuses on the flood insurance programs in the United State (e.g., Gallagher 2014, Mulder 2021, Georgic and Klaiber 2022) or approaches to mitigate coastal flood risks in developing countries (e.g., Balboni 2019 and Hsiao 2023). Our study extends the discussion to examine the impacts of a unique flood risk management strategy, the FDB policy, that involves clear design of flood risk redistribution.

Section 2 provides an overview of the institutional background. Section 3 introduces the data used in the study and presents descriptive statistics. Section 4 introduces the identification methods employed to determine the economic costs incurred by FDB policy. In Section 6, we discuss the mechanisms driving these costs. Subsequently, Section 7 estimates the net output gain using a spatial general equilibrium and hydro-dynamic model so that we can estimate the benefit to cost ratio of the FDB policy. Section 8 concludes.

2 Research Background

2.1 Substantial Flood Damage in China

Based on the estimation of the EM-DAT database, from 2000 to 2017, China suffered from 135 river floods, causing a damage of 150 billions USD and affecting 74 million people. According to the EM-DAT International Disaster Database, China ranks No.1 in terms of total river flood events, total river flood damages, and total affected populations from 2000-2017. 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. An important feature of China floods is that floods disproportionately affect the country's economically important regions as indicated in Figure 1, leading to substantial threats to the economy. For example, Huai River basin is identified as a high-risk flood zone, according to hydrological studies (e.g., Zhang and Song (2014)). However, some of China's economically important provinces, including Jiangsu Province, are also located in this river basin. Flooding those richer regions could hinder overall economic growth. And that is the reason why addressing floods is a critical concern for the Chinese government.

2.2 Flood Detention Basin Policy

The Flood Control Law of the People's Republic of China, implemented in 2000, stands as China's first legislation governing flood management. It is also the first law that officially designates Flood Detention Basins (FDBs). According to the law, FDBs refer to the flood storage and detention basins that are low-lying lands and lakes used for temporary storage of floods. Chinese government then builds dams and dikes in those Flood Detention Basin (FDB) counties so that the government can successfully divert flood water to FDBs during floods. 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. As shown in Figure 2, FDB counties in Huai River Basin are protecting downstream urban districts from severe flood damages.

As highlighted in Table 1, the FDB policy directly affects about 1.1% of China's total population. The aggregate area of FDBs is 30,443 km^2 (0.3% of China's total land), which is comparable to the territories of Switzerland. To illustrate how FDB is used to store excessive flood water, we provide an example of Mengwa Flood Detention Basin, the most frequent used FDB in China, in Appendix A.1.

2.3 2000 and 2010 Policy Change

According to the 2000 Flood Control Law, 96 counties were designated as Flood Detention Basin (FDB) counties, marking the first time in the history of the People's Republic of China that the locations of flood detention basins were officially confirmed. In 2010, Ministry of Water Resources revised the previous regulation in the *National Flood Detention Basin Construction and Management Plan*. As indicated in Table 2, under this new plan, 13 FDBs were added and 12 were removed. Consequently, the number of counties classified as FDB counties changed. 20 counties were newly selected into the FDB list, while 10 were removed from this list. Table 1 and Table 2 offer an overview of the Flood Detention Basins (FDB) in China's major river basins in 2000 and 2010.

3 Data and Descriptive Results

3.1 Data

FDB List - The Ministry of Water Resources officially announced the list of Flood Detention Basins (FDB) in 2000 and 2010. We then define counties that hold flood detention basins as FDB counties.

Data on Floods - We gathered data on each flood event from the Global Flood Database (GFD), which provides comprehensive tracking of floods in China from 2000 to 2018. This database documents a total of 189 flood events within China. Using GFD, we are able to construct proxies of flood exposures. Given GFD offers satellite maps that record flood events for every county (see (Figure A3), we are able to collect data regarding the length of flooding experienced by each pixel (30m $\times$ 30m). Additionally, the database allows us to identify whether a pixel includes permanent water bodies, which "are consistently identified with the presence of surface water for the majority of observations in two time periods (1984-1999 and 200-2018) at 30m resolution which was resampled to 250m resolution in Google Earth Engine using nearest neighbor resampling.", according to GFD. We then proxy flood exposure using pixel-adjusted flood duration, which is calculated following three steps for each county.

First, we identify all the pixels within a county that are not occupied by permanent water bodies. Next, we look at every flood event individually, adding together the duration of flooding for each non-permanent water pixel to get the county's total flood duration for each flood event. Finally, to proxy flood risk of each county, we divide the county's flood duration by the count of non-permanent water pixels. We believe that this index provides a nuanced quantification of flood risk, adjusted for the spatial extent of the county's land area susceptible to flooding.

Following this thought, we define the size-adjusted flood duration as

$$AdjustedFloodExposure_{ift} = \frac{\sum_{j \in A_i} FloodDuration_{fjt}}{|A_i|}$$

where $AdjustedFloodExposure_{ift}$ indicates the size-adjusted flood exposure at flood event f that happened at time t. A_i represents pixels that have not contained permanent water in county i. $FloodDuration_{fjt}$ is the number of flooded days experienced by non-permanent water pixel j at the flood event f of time t. It will be 0 if the non-permanent water pixel has not been flooded at the flood event. And it will take a positive value if that non-permanent water pixel has been flooded at the flood event. Here, we define a pixel as a flood-pixel at a flood event f if that pixel: (i) has not contained permanent water previously, which means $j \in A_i$; (ii) but has been marked as flooded by Global Flood Database in the flood event f of time t. Hence, $\sum_{j \in A_i} FloodDuration_{fjt}$ measures the total sum of flood duration experienced by non-permanent water pixels in county i at flood event f of time t. By dividing this sum by total number of non-permanent water pixels $|A_i|$, we adjust the total sum of flood duration by the size of non-permanent water in county i.

Data on Light - Given possible threats to GDP estimation in datasets provided by the National Bureau of Statistics (NBS), as suggested by Martinez (2022), we use nighttime light data as a proxy of economic activity. Specifically, we use the 1984-2020 'Prolonged Artificial Nighttime-light Dataset of China' data by Zhang et al. (2024).

Data on Firm-level Outcomes - Firm-level data is collected from National Enterprise Credit Information Publicity System (NECIPS) and Annual Survey of Industrial Enterprises (ASIE). NECIPS, administered by China's State Administration for Market Regulation (SAMR), provides annual registration records for all Chinese enterprises spanning from 1960 to 2023. This dataset is rich in detail, encompassing key information such as the date of establishment, ownership type, and geographical location of each firm. Using the geo-located data within this resource, we are able to accurately track the entry of firms in counties and towns designated as Flood Detention Basins (FDB). The firm-level data derived from ASIE spans from 1998 to 2014. ASIE encompasses private industrial enterprises with annual sales exceeding 5 million RMB (approximately 0.7 million USD) and all state-owned industrial enterprises (SOEs). Compiled and maintained by the National Bureau of Statistics (NBS), this dataset offers an extensive array of information sourced from the accounting records of these firms. It includes data on inputs, outputs, sales, taxes, and profits. This dataset contrasts with the National Enterprise Credit Information Publicity System (NECIPS) in two key aspects. Firstly, ASIE's temporal scope is confined to the period between 1998 and 2014, whereas NECIPS provides a wider temporal range for analysis (1960 to 2023). Secondly, ASIE primarily concentrates on collecting comprehensive details about firm activities, whereas NECIPS is oriented towards the registration of new firms.

Data on Other Socio-economic Outcomes - Other county level data is collected from the County-level Statistical Annual Yearbooks from 1999 to 2022. The National Bureau of Statistics (NBS) conducts county-level survey each year. It is a longitudinal survey that collects county-level socio-economic data for all counties in China. County-level variables include local output (disaggregated by sector), number of firms, fiscal income, fiscal expenditure, savings and etc.

Geographical Data - Elevation and gradient information is obtained from the NASA ASTER Global Digital Elevation Model (GDEM). The GDEM, with its extensive coverage from 83 degrees north to 83 degrees south latitude, encompasses 99 percent of the Earth's landmass. This comprehensive database enabled us to gather detailed elevation and gradient data for all counties and towns across China. For precipitation data, we turned to the Global Surface Summary of the Day (GSOD), sourced from the Integrated Surface Hourly (ISH) dataset. GSOD provides daily summaries typically within 1-2 days of the observation date. It encompasses data from over 9,000 stations worldwide, offering historical records from 1929 onwards, with the period from 1973 to the present being the most complete. Utilizing this resource, we calculated the mean monthly precipitation for each village and town in China.

3.2 Descriptive Statistics

In Table 3, we compare several descriptive statistics of FDB counties and non-FDB counties. FDB counties, compared to non-FDB counties, exhibit differences in geographical, flood, and socio-economic characteristics. Geographically, FDB counties have lower elevations and slopes but more permanent water pixels. This is consistent with the government claim that flood detention basins are typically low-lying lands and lakes used for temporary storage of floods. In descriptive results, we find that FDB counties experience higher flood exposure and larger areas of flood inundation. Contrary to the claim that FDB counties should hold less population and be poorer, the data demonstrates that FDB counties actually have larger populations and higher nighttime light intensity, which is often an indicator of greater economic activity. Additionally, FDB counties have a slightly greater number of firms compared to non-FDB counties. These socio-economic indicators suggest that FDB counties are not poorer; rather, they have significant economic activities. This evidence contradicts the assumption that FDB counties are less populated and economically disadvantaged.

Figure 3 demonstrates that size-adjusted flood exposure is higher in FDB counties compared to non-FDB counties. From 2000 to 2018, FDB counties consistently experience higher levels of flood exposure. Notably, the peaks in the graph around 2003, 2006, 2010, and 2014 highlight periods where FDB counties face substantially increased flood risks, possibly due to flood water detention. This elevated flood exposure in FDB counties imply the policy's deliberate design to absorb excess floodwater in designated areas. We quantify the impact of FDB policy on flood exposure in Section 5.1.

4 Empirical Strategies

4.1 Identification Challenge: FDB Location Choice

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).

However, potentially non-random FDB location choice remains the major challenge in identifying the effects of the Flood Detention Basin (FDB) policy. The selection or removal of counties from the FDB list is likely influenced by factors other than geographical factors. For instance, the government may designate less economically developed counties to host those basins, or conversely, remove a county from the FDB list due to its better economic performance.

In Table 4, we apply a logit regression model to identify the determinants influencing the selection of Flood Detention Basins (FDB) locations. Our findings suggest that the choice of FDB sites is predominantly influenced by geographical characteristics. This aligns with the official stance of the Chinese government, which defines FDBs as 'low-lying lands and lakes situated beyond the back scarps of dikes, inclusive of flood diversion outfalls, utilized for the temporary storage of floodwaters.' Our analysis corroborates this definition, revealing a significant tendency for counties with lower elevation levels to be selected as FDBs. We do not find empirical evidence to claim that the Chinese government intentionally selected relatively poorer counties as FDBs.

4.2 Identification Strategy

Our analysis, employing logit regression as shown in Table 4, reveals no significant correlation between a county's FDB status and its GDP, which suggests that FDB policy implementation may not directly hinge on economic output. However, this does not entirely rule out the possibility that socioeconomic factors influence FDB selection decisions.To address the endogeneity concern, we use three identification strategies: traditional TWFE Difference-in-Differences, the Synthetic Difference-In-Differences (SDID) and spatial regression discontinuity (SRD).

Two-Way-Fixed-Effects (TWFE) Difference-In-Differences

We first use the most traditional Two-Way-Fixed-Effects (TWFE) Difference-In-Differences approach to investigate the imapct of FDB policy. The regression specification takes the form of:

$$ln(Y)_{it} = \alpha + \beta_1 FDB_{it} + \gamma_i + \lambda_t + \epsilon_i$$

where Y_{it} measures the outcome of interest of county i in year t, FDB_{it} is a dummy variable that equals 1 if the county i is an FDB county in year t, and 0 if not. γ_i, and λ_t indicate county and year fixed effects, respectively. Standard errors are clustered at the county level. In this regression specification, β_1 is the difference-in-difference estimate that measures the impact of FDB policy on outcomes of interests.

Synthetic Difference-In-Differences (SDID)

Considering recent discussions on the properties of the staggered Difference-in-Differences (DID) approach, particularly regarding potential biases stemming from the weighting problem as highlighted by Borusyak et al. (2024), we argue that the Synthetic Difference-in-Differences (SDID) method, proposed by Arkhangelsky et al. (2021). 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 controls. We argue that SDID is well-suited for our empirical setting for several reasons.

First, constructing a counterfactual group using synthetic weights, as proposed by Abadie et al. (2010), effectively addresses concerns about the weighting problem inherent in traditional TWFE DID. SDID ensures that the synthetic control group closely mirrors the treatment group's pre-treatment characteristics, thereby enhancing the validity of causal inferences.

Second, Roth et al. (2023) suggest that clustering at the unit level is inappropriate when the number of treated groups is small. In our context, the 2010 policy change by the Chinese government, which added 20 new counties to the list and removed 10, involves a limited number of treated clusters. Given this small sample size, employing bootstrap standard errors, as facilitated by the SDID approach, provides a more reliable measure.

Third, the construction of synthetic weights mitigates potential threats to exogeneity by ensuring that the counterfactual group exhibits pre-treatment outcomes that are parallel to those of the treatment group. This parallel trend assumption is crucial for the validity of DID estimates, and the SDID method's ability to create a closely matched synthetic control group strengthens this assumption.

In summary, the SDID approach offers a robust solution to the potential biases associated with traditional DID methods, particularly in settings with small numbers of treated units and concerns about weighting and exogeneity. This makes it a particularly suitable choice for our analysis of the economic impacts of the 2010 policy change in China. Following Arkhangelsky et al. (2021), the average treatment effect on the treated, or ATT, is denoted as τ. Estimation of the ATT proceeds as follows:

$$\left(\widehat{\tau}^{sdid}, \widehat{\mu}, \widehat{\alpha}, \widehat{\beta}\right) = \underset{\tau,\mu,\alpha,\beta}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau\right)^2 \widehat{\omega}_i^{sdid} \widehat{\lambda}_t^{sdid} \right\}$$

weights $\hat{\omega}_i^{\text{sdid}}$ and $\widehat{\lambda}_t^{\text{sdid}}$ are optimally chosen given the design by Arkhangelsky et al. (2021). Time fixed effects are denoted by β_t and unit fixed effects are denoted by α_i. Y_{it} is the outcome of a county i at year t. W_{it} is the treatment dummy that equals 1 if county i is treated in year t, and 0 if not. μ is the constant term.

Spatial Regression Discontinuity (SRD)

We also employ a spatial regression discontinuity design based on a firm-level dataset, the Annual Survey of Industrial Enterprises (ASIE). Both parametric and nonparametric methods can estimate the discontinuity. Imbens and Wager (2019) demonstrated that the parametric RD method, employing a polynomial function of the running variable as a regression control, often produces RD estimates sensitive to the polynomial's degree and exhibits several other unfavorable statistical characteristics. Consequently, we adopt the advised local linear method and proceed to estimate the equation below.:

$$\begin{aligned} Y_{ij} = \alpha_1 \text{ FDB }_{ij} + \alpha_2 \text{ Dist }_{ij} + \alpha_3 \text{ FDB }_{ij} \cdot \text{ Dist }_{ij} \\ +\varepsilon_{ij} \quad \text{ s.t. } -h \leqslant \text{ Dist }_{ij} \leqslant h, \end{aligned}$$

where Y_{ij} is the assets per worker of firm i in county j. FDB $_{ij}$ is an indicator variable that equals 1 if firm i is treated by policy shock (in the new FDB region or in the newly abolished FDB region), and 0 otherwise. Dist $_{ij}$ measures the distance between firm i and new FDB county border (or abolished FDB county border) j (negative if outside the county and positive within the county), and h is the estimated MSE-optimal bandwidth following Calonico, Cattaneo, and Farrell (2018). The standard error is clustered at the county level to deal with the potential spatial correlation of the error term, as suggested by Cameron and Miller (2015).

4.3 Counties as the Unit of Analysis

In this study, we concentrate on the county level rather than the town level within China's administrative hierarchy. Counties, situated between prefectures and townships, form the third tier of the administrative structure. Mainland China comprises 2,851 county-level divisions. According to 2000 and 2010 FDB policy, in total, 96 and 106 counties could be identified as a FDB county, respectively. We focus on counties for two reasons. First, county-level data is more comprehensive. The National Bureau of Statistics (NBS) provides the most extensive collection of socioeconomic variables at the county level. By focusing our analysis here, we can more effectively examine the impact of policies on crucial socioeconomic indicators, such as the output of various sectors. Second, flood detention typically will impact most towns in a county. Although dams are situated in towns, we observed that in the event of a flood, the impact typically extends to encompass the entire county.

5 Economic Costs on FDB Counties

5.1 FDB Policy and Flood Risk Redistribution

Figure 3 straightforwardly demonstrates that the size-adjusted flood exposure is much higher in FDB counties, compared to non-FDB counties. We then use the following specification to determine whether the flood exposure in FDB counties is significantly higher than non-FDB counties.

$$ln(Exposure_{ijt}) = \alpha + \beta_1 FDB_{ijt} + \beta_2 X_{ijt} + \gamma_j + \theta_t + \epsilon_i$$

where $ln(Exposure_{ijt})$ is the proxy of flood risk in county i, city j, at year t. In our setting, we use two proxies to investigate the impact of FDB policy on flood exposure. The first proxy is the size of inundation area. And the second one is the size-adjusted flood exposure (detailed explanation can be found in Section 3.1), which measures the average days of flood inundation of a county in a flood event. FDB_{ijt} is a dummy that equals 1 if the county i is a FDB county, and 0 if not. γ_j represents the city fixed effect, and θ_t represents time fixed effect. ϵ_i is the standard error that is clustered at city level. X_{ijt} contains geographical controls (precipitation, elevation and slope), which are important determinants of floods. β_1 then measures whether FDB counties have a higher flood exposure than other counties in a given city, holding geographical factors constant.

As indicated in Column (1) and (2) of Table 5, we find that after controlling for important geographical controls, the size of flood inundation area in FDB counties is more than 50% higher in FDB counties than other counties in the same city. Column (3) and (4) also suggest that the size-adjusted flood exposure is 5% higher in FDB counties, compared to other counties in the same city. This empirical evidence supports the claim that FDB policy induces flood risk redistribution across different regions. In other words, FDB counties tend to absorb more flood water according to the policy design.

In Figure 4, we examine the impact of being selected for the 2010 FDB list on the size of flood inundation. By controlling for county and time fixed effects, we find that selection into the 2010 FDB list tends to increase flood inundation size by 48.59%, which is consistent with resutls in Table 5. Notably, in 2013, a year of severe floods, the inundation size increased by over 200% in the FDB counties. However, since only 20 counties were newly added to the 2010 FDB list, and not all of them were utilized for floodwater diversion post-2010, the results in Figure 4 are relatively noisier compared to those presented in Table 5.

5.2 Main Result: Nighttime Light

To quantify the economic costs on FDB counties, we examine the impact of the FDB policy on nighttime light intensity. We choose nighttime light as a proxy for economic activity over GDP for two reasons. First, GDP data before 2000 is unavailable, preventing us from analyzing the impact of the 2000 policy change. Second, nighttime light is a more credible indicator of economic activity in China in that Chinese GDP figures are likely to be exaggerated (Martinez 2022). Moreover, the level of exaggeration differs across time because of incentive changes (Zeng and Zhou 2024).

Table 6 summarizes the impact of the FDB policy on nighttime light intensity. Panel A presents results using traditional two-way fixed-effect difference-in-differences (TWFE DID) estimates without any controls. In Column (1), we find that a county being selected into the FDB list leads to an average decrease of 17.6% in nighttime light intensity. Considering recent discussions on the properties of the staggered DID approach (e.g., Borusyak et al. 2024), potential biases may arise from the weighting problem. Therefore, we separately investigate the impacts of the 2000 and 2010 policy changes in Columns (2) and (3). Column (2) shows that selection into the 2000 FDB list leads to a 13.7% decrease in nighttime light intensity, while Column (3) indicates a 7.8% decrease for the 2010 FDB list.

Panel B reports results using the synthetic difference-in-differences (SDID) approach proposed by Arkhangelsky et al. (2021). We believe SDID is appropriate for our empirical setting for three reasons. First, constructing a counterfactual group using synthetic weights (Abadie et al. 2010) addresses concerns about the weighting problem in traditional TWFE DID. Second, as suggested by Roth et al. (2023), clustering at the unit level is not suitable when the number of treated groups is small. In the 2010 policy change, the Chinese government selected 20 new counties and removed 10 from the list. Given the small size of treated clusters, using bootstrap standard errors offered by the SDID approach is more appropriate. Third, synthetic weight construction helps mitigate potential threats to exogeneity by creating a counterfactual whose pre-treatment outcomes are parallel to the treatment group. Results in Panel B are robust and indicate a negative impact of being selected into the FDB list on nighttime light intensity, with magnitudes similar to those in Panel A.

In Column (4) of both Panels A and B, we focus on the impact of removal from the FDB list in 2000. The results in both panels are not significant, indicating that being removed from the FDB list does not lead to significant economic recovery. We interpret this as a 'scarring effect,' where counties once selected into the FDB list struggle to recover even after removal. We consider the result in Column (4) of Panel B to be more credible than that in Panel A, given the small number of counties removed from the list, making SDID more appropriate than TWFE.

Figure 5 illustrates the dynamic impacts of the FDB policy on nighttime light intensity using an event-study approach. Before the treatment, there is no significant difference between the treated and control groups. This suggests that the treated and control groups followed similar trends in nighttime light intensity prior to the policy intervention, validating the parallel trend assumption. Immediately after the implementation of the FDB policy, we observe a noticeable and persistent decline in nighttime light intensity for the treated counties. This indicatres both immediate and lasting adverse effects of the FDB policy on economic activity as proxied by nighttime light intensity. We present the SDID event-study results in Figure 6.

5.3 Interpreting Effect Size: from Light to GDP

According to column (2) in Panel B of Table 6, being selected into the FDB list in 2000 results in a 10.7% decrease in nighttime light intensity. Various studies have examined the elasticity between nighttime light intensity and GDP, allowing us to translate this reduction into a loss in real GDP. Henderson et al. (2012) find that the elasticity of GDP with respect to nighttime lights is 0.277, which is supported by Martinez (2022), who finds an elasticity of 0.296. Additionally, Martinez (2022) notes that elasticity is higher in non-democratic regimes, estimating an elasticity of 0.312 for China. This translates into an annual GDP loss of 2.96%, 3.17%, and 3.34%, respectively. Using real GDP data from Chen et al. (2022), we estimate the GDP loss to be $9.84 billion, $10.54 billion, and $11.13 billion, respectively, based on the elasticities from Henderson et al. (2012) and Martinez (2022). On average, an FDB county tends to lose $0.10-0.12 billion per year due to being selected into the FDB list. To validate these findings, we conducted an interdisciplinary cross-check. Our results align with a hydrological case study by Wang et al. (2021), published in the leading hydrological journal *Journal of Hydrology*, which also reports an annual economic loss of \$0.1 billion for an FDB county in Yangtze River.

5.4 Robustness and Placebo

In Figure 7 and Table 7, we report our results using other difference-in-differences methods. Although we believe that synthetic difference-in-differences (Arkhangelsky et al. 2021) is the most suitable method in our setting, we report the event-study results using different methods proposed by De Chaisemartin and d'Haultfoeuille (2020), Gardner (2022), and Callaway and Sant'Anna (2021). The robustness checks demonstrate that our main findings are consistent across these alternative methodologies. Specifically, the results in Table 6 are robust in terms of both statistical significance and magnitude when using other difference-in-differences approaches. Overall, the consistency of our findings across multiple methodologies underscores the validity of our results and the robustness of our conclusions.

In Figure 8, we conduct three distinct types of placebo tests: the in-time placebo test, the in-space placebo test, and the mixed placebo test. In the in-time placebo tests, we forward the treatment time by several years, using fake treatment times to assess if our results are driven by temporal trends rather than the actual intervention. For the in-space placebo tests, we assign treatment to randomly selected units that did not receive the intervention, testing the robustness of our findings against spatial confounding factors. Lastly, the mixed placebo tests combine both approaches by randomly assigning fake treatment units and times. The results shown in Figure 8 indicate that our main findings hold up under these placebo tests, as the estimated effects do not show significant deviations from zero, thus confirming the robustness and validity of our original results.

6 Mechanisms

6.1 Migration Channel

A natural hypothesis is that rational agents will leave FDB counties, leading to a loss of labor which results in economic underdevelopment. However, as shown in Figure 9, we do not find significant evidence of people leaving FDB counties. Although there is a downward (upward) trend of registered population after counties being selected (removed) from the FDB list, we do not find the estimate being neither economically significant nor statistically significant, indicating that migration decision is not sensitive to FDB policy. We do not find this result surprising because extensive literature has demonstrated the difficulty of individuals in developing countries to make rational migration decisions, as summarized in Lagakos (2020). For China specific studies, we would like to propose several possible reasons that people do not migrate in response to FDB policy.

First, according to the seminal work of Zhao (1999), the existing arrangement of land management is a major reason why rural people in China choose not to migrate in spite of the incentive and ability to migrate. In the early 1980s, the Chinese government introduced the Household Responsibility System that grants rural households land use rights and income rights over lands. Although land belongs to the village, land allocation within villages was highly egalitarian, resulting in minimal per capita differences in landholdings among households within a village. A recent paper by Adamopoulos et al. (2024) also indicates that the land system is a major friction of rural-urban migration.

Second, the Chinese government has not designed a suitable incentive scheme to motivate FDB residents to leave. According to the latest migration subsidy plan in 2017, the government compensates \$2.4k per person, which is significantly less than the \$8.1k per person provided under *the Relocation for Poverty Alleviation* program and is insufficient to cover migration costs. According to a survey conducted by *the Huai River Regulation Commission of the Ministry of Water Resources*, 93% of residents in the Mengwa Flood Detention Basin are dissatisfied with the migration subsidy provided by the government, and 94% are unhappy with the proposed migration destinations. This dissatisfaction reflects broader issues in the policy's design, including inadequate financial support and poorly planned relocation sites, which fail to meet the needs and preferences of the affected residents. Consequently, the lack of proper incentives and satisfactory relocation plans has resulted in non-optimal migration from FDB counties.

6.2 Direct Flood Inundation Channel

To determine whether the economic cost in FDB counties is primarily due to direct flood inundation or policy effects, we analyze the heterogeneous impacts of FDB policy on night-time light intensity. The Chinese government classifies FDB counties into three categories: Important FDB counties, General FDB counties, and Reserved FDB counties. These classifications reflect the varying likelihood of these counties being used for flood water diversion both before and after the official FDB implementation. For example, most important FDB counties have served for flood water diversion even befor the official implementation of the FDB policy.

Our findings in Figure 10 and Table 11 reveal a striking pattern: nighttime light intensity decreases the least in Important FDB counties (11.6%). On the other hand, light has decreased by 30.8% and 16.6% in Reserved and General FDB counties. This initially counter-intuitive result suggests that these counties, which are historically more exposed to frequent flooding and flood water detention, have developed better expectations for floods. This anticipation mitigates the adverse economic impacts of the FDB policy. Consequently, although there is a reduction in nighttime light intensity in Important FDB counties, the decrease is less pronounced compared to other FDB categories.

In contrast, counties classified under General and Reserved FDBs, which lack a historical precedence of frequent flooding, experience a more severe reduction in nighttime light intensity. For these regions, the FDB designation introduces an unexpected shock. The sudden imposition of flood designation leaves these areas more vulnerable and less prepared for the economic constraints imposed by the policy. This results in a more substantial negative impact on economic activities in these regions.

The critical distinction lies in the anticipation effect. Important FDB counties, with their established flood expectations and adaptive measures, experience a moderated impact on economic activity. On the other hand, General and Reserved FDB counties face heightened economic challenges due to the policy-induced risks, leading to a more pronounced decline in light intensity.

Overall, these findings indicate that the economic cost associated with FDB policies is not primarily due to direct flood inundation. Instead, the anticipation effect of policy implementation plays a more significant role in affecting economic development. The unexpected designation shocks in General and Reserved FDB counties exacerbate economic underperformance. Thus, the economic underdevelopment observed in these regions is largely a result of the policy itself rather than direct flooding events.

6.3 Loss in Agriculture or Manufacturing?

We also investigate whether the costs associated with flooding are predominantly caused by its impact on agriculture. Given that FDB counties primarily depend on agriculture, it is plausible that floods would incur significant costs by damaging agricultural crops. However, our findings (Figure 11) do not show significant evidence of a decline in agricultural output, with the observed change being minimal (0.3%). This resilience in agricultural output could be possibly attributed to the geographical conditions of China's agricultural land. For instance, in Hunan Province, the quality of arable land tends to improve after floods, which may mitigate the adverse effects. Additionally, farmers in the southern region can harvest three times a year, so even if they suffer flood damage during the rainy season, they can partially compensate for the losses through winter crops.

In contrast, manufacturing output experiences a substantial and significant decrease of 18.2%. Specifically, there was a sustained output reduction of about 20% during the initial five years (2010-2015), which widened to approximately 40% post-2016. This suggests that the FDB policy has a lasting negative impact on manufacturing activities within FDB counties. This stark decline underscores the lag in structural transformation within FDB counties. While farmers adapt to new policies, they remain largely confined to agriculture due to limited opportunities for transitioning into the manufacturing sector.

6.4 Firm Response Effect

We propose the 'firm response effect,' suggesting that firms have less incentive to enter and invest in counties with higher flood risk, leading to an underdeveloped manufacturing sector in FDB counties. This hypothesis has two empirical implications. First, when a county is added to the FDB list, firms are less likely to enter and invest in that county. Second, when a county is removed from the FDB list, firms begin to reenter and invest. In 2010, the Chinese government added 20 counties to the FDB list and removed 10 counties from it, allowing us to empirically test the 'firm response effect' hypothesis.

In this section, we present balanced and symmetric results of three different outcomes that show both the impact of being added to the FDB list and the impact of being removed from the list. By comparing these two scenarios, we can confirm that the FDB policy significantly influences firms' entry and investment decisions. Specifically, we find a decline in firm entry and investment in counties added to the list, and an increase in firm entry and investment in counties removed from the list. These balanced and symmetric findings serve as strong evidence to rule out other possible mechanisms and underscore the exclusive impact of FDB policy on firms' decision making.

It would be ideal for us to study the causal impact of both 2000 policy and 2010 policy, especially the 2000 policy given its importance. However, the unavailability of firm-level data prior to 2000 makes us impossible to construct pre-treatment counterfactual control groups. Hence, we have to restrict our examination to the causal impacts of 2010 policy on various firm level outcome variables.

Firm Entry - The increased flood risk in FDB counties necessitates higher expected returns on investment for firms considering entry into these areas. Consequently, firms have less incentive to enter FDB counties. In other words, the increase in flood risk acts as a deterrent for new firm entry. To explore this intuition, we examine the impact of the 2010 FDB policy change on firm entry using the Annual Registration Data of Chinese Enterprises from 2000 to 2020. In Panel A of Figure 12, we find balanced and symmetric impacts of selection into and removal from the FDB list. Each dot in the figure represents a point estimate, showing the difference between actual FDB counties and their synthetic counterparts. Prior to 2010, the proximity of these estimates to zero, coupled with their statistical insignificance, confirms that our synthetic group effectively mirrors the counterfactual FDB counties.

The negative impact on firm entry in these counties is immediate and persists over a decade, as evidenced by the consistently negative and significant coefficients observed even in 2020. One year after the policy implementation, in 2011, firm entry in FDB counties decreased by approximately 10.9%. In 2012, this decrease grew to around 25.2%. The negative impact then persists from 2013 to 2021, stabilizing at around 15%. This empirical evidence supports our theory that firms lack incentives to enter counties newly designated as FDB-county. Conversely, we also find that firms begin to reenter counties removed from the FDB list. Although the impact is not immediate, by 2013 we observe a significant increase in firm entry, with a magnitude of 29.2%. This positive impact persists until 2020.

Regarding the average treatment effect, we find that firm entry tends to significantly decrease by 15.9% after a county is selected into the FDB list. This indicates that selection into the FDB list diminishes the county's attractiveness for the entry of manufacturing firms. On the other hand, firm entry tends to significantly increase by 16.8% after a county is removed from the FDB list. The balanced and symmetric result indicate the importance of FDB policy in affecting firms' entry decisions.

Number of Large Manufacturing Firms - In Panel B of Figure 12, we present robust evidence that the FDB policy influences firm entry decisions, focusing specifically on the number of larger manufacturing firms. Using county-level statistical yearbook data from 2000 to 2010, we find that the average number of larger manufacturing firms in a county significantly decreases by 21.7% after the county is included in the FDB list in 2010. Conversely, when a county is removed from the FDB list, the number of larger manufacturing firms increases by 14.1%, although this change is not statistically significant. Comparing the results of Panel B with those of Panel A, we observe that the impact of being added to the FDB list is more pronounced for larger manufacturing firms compared to all firms. However, when a county is removed from the FDB list, larger manufacturing firms show more hesitation in re-entering these counties, while all firms tend to respond more sensitively to the policy change. This suggests that larger manufacturing firms are more cautious in their entry decisions, possibly due to their higher position in fixed asset investments.

Combining the findings from Panel A and Panel B, we conclude that: (i) being included in the FDB list tends to decrease a county's attractiveness for firm entry, whereas removal from the list tends to increase it; (ii) larger manufacturing firms, compared to other firms, are more cautious in their entry decisions.

Fixed Assets Investment - By using spatial Regression Discontinuity (SRD), we provide evidence to indicate that the FDB policy affects firms' investment decision. We specifically focus on fixed assets investment because fixed assets are especially prone to suffering from flood damage because they are either immovable or it is highly challenging to relocate them. Given the data availability constraints that prevent tracking post-2013 data, we concentrate on outcomes likely to be immediately influenced by the FDB policy. We hypothesize that the considerable financial costs associated with either repairing or replacing these assets makes entrepreneurs hesitate to invest in fixed assets situated in FDB counties with higher flood risk.

Figure 13 displays the logarithm of fixed asset investment, adjusting for both county fixed effects and industry fixed effects, plotted against the distance to the corresponding FDB county boundary. Each point on the graph represents the average logarithmic fixed asset investment for firms within specific distance intervals. And the 95% confidence intervals for these averages are also indicated in the figure. To highlight the policy's impact at the FDB county boundary, a curve fitting these data points is presented on the plot, clearly demonstrating the discontinuity at the boundary of FDB counties.

Panel A of Figure 13 presents a regression discontinuity (RD) plot of the residual logarithm of fixed asset investment. In the left sub-figure of Panel A, we explore how being designated as an FDB county influences fixed asset investment. This plot reveals a pronounced decline in fixed asset investment exactly at the boundary of counties newly included in the FDB list. This observation implies that within firms of these newly designated FDB counties, fixed asset investment is substantially lower compared to firms in adjacent counties. Conversely, the right sub-figure of Panel A in Figure 13 examines the effects on fixed asset investment following a county's removal from the FDB list. Contrary to Panel A, we observe a significant jump in fixed asset investment right at the boundary of counties recently excluded from the FDB list. This suggests that after being removed from the FDB list, firms in these counties exhibit considerably higher fixed asset investment relative to those in neighboring counties.

Following the work by He et al. (2020), we investigate the dynamics in fixed assets investment in Panel B of Figure 13. This SRD approach hinges on comparing firms located within FDB-designated areas to those in geographically adjacent but non-FDB counties. A critical assumption of SRD is the similarity in pre-treatment outcomes between neighboring FDB and non-FDB counties. For newly-selected FDB counties, we find that the fixed assets discontinuity was close to zero before 2010, but became significantly larger in 2011.[3] This negligible and insignificant effect prior to 2010 supports our foundational assumption: absent the FDB policy, manufacturing firms in FDB and non-FDB counties would have similar trends for fixed asset investment.

Table 12 quantifies the graphical evidence depicted in Figure 13, examining the impact of counties entering and exiting the FDB list. Panel A presents the SRD analysis without control variables. Columns (1) to (3) show that firms in counties newly included in the FDB list exhibit lower levels of fixed asset investment compared to firms in geographically adjacent counties. Conversely, columns (4) to (6) indicate that firms in counties recently removed from the FDB list demonstrate higher fixed asset investments than their counterparts in neighboring counties. To further validate our findings, we conduct robustness tests in Panel B, incorporating both county and industry fixed effects, and in Panel C, incorporating county-by-industry fixed effects. Panel B assesses differences in fixed asset investment across counties and industries, while Panel C provides a more detailed comparison by evaluating firms within the same industries but located in proximate geographical areas, thus eliminating potential industry-specific confounding factors. Our analyses yield significant results across Panels A, B, and C, with consistent effect sizes in Panels B and C. Additionally, the SRD estimates exhibit strong robustness across various kernel function selections. Findings from Panels B and C underscore the significant influence of the FDB policy on firms' investment decisions.

[3]Due to data availability, unfortunately, we can only track the impact to the year of 2013.

7 Spatial General Equilibrium: Assessing the Benefit to Cost Ratio of FDB Policy

7.1 An Illustrative Partial Equilibrium Model

We begin by concretizing the 'firm response effect' using an illustrative partial equilibrium model. While our comprehensive general equilibrium model accounts for interactions between different counties by including the flow of capital and manufacturing goods, this simpler model offers more straightforward economic intuitions regarding the trade-off between equality and efficiency in designing this flood risk redistribution policy. We then extend our analysis to the full general equilibrium model, which we use for counterfactual scenarios and to assess the benefit to cost ratio of FDB policies.

Flood Risk and Firm Investment Decision

In a two-period model, we assume that there are two types of counties, $i = s, p$. County s represents FDB counties that are sacrificed for protecting other counties, county p represents counties that are protected by FDB counties.

In period 1, the risk-neutral investor is endowed with an initial wealth, W, that can be used for consumption, investments in different counties, and investment in bonds. In period 2, investors consume the investment returns from the first period. The optimization problem is characterized below.

$$
\begin{aligned}
& \max_{c_0, c_1, a_s, a_p, b} c_0 + \beta \mathbb{E}_\mu c_1 \\
s.t. \quad & c_0 + \sum_{i=s,p} a_i + b = W \\
& c_1 = \sum_{i=s,p} (1 + r_i) a_i + (1 + r_f) b
\end{aligned}
$$

Here, c_0 and c_1 represent the consumption at period 1 and period 2, respectively. a_s and a_p represent investors' period-one investment in sacrificed county and in protected county. b represents the bond investment. r_i is the return of assets, or the marginal benefit of investing in assets. r_f is the risk-free interest rate.

The production problem is characterized as:

$$\max_{k_i} \quad z_i k_i^{\alpha} - \bar{r}_i k_i$$

Here, k_i is the capital input in county i. z_i represents the productivity in county i. $\bar{r}_i$ represents the effective cost of investment in county i.

At each flood event, $\mu = \{\tau_s, \tau_p\}$, where τ_i is a dummy that equals 1 if the county is flooded at the flood event, and 0 if not. We consider flood as independent event in two types of counties. The flood probability of each county is $Pr(\tau_i = 1) = p_i$. Flood event will create a wedge between return of asset, r_i, and effective cost of investment, $\bar{r}_i$ such that

$$r_i = \bar{r}_i - \tau_i d$$

where d is the damage per asset caused by flood. Here, we assume that flood will cause proportional damages per asset that are identical across sacrificed and protected county.

The market clearing condition requires $r_{i,t}$ to clear the local capital market such that:

$$k_i = a_i$$

Following the above conditions, the optimal investment can be characterized as below:

$$\alpha z_i a_i^{\alpha-1} - r_f = p_i d$$

We can also consider the optimally condition as the characterization of flood risk premium. Here, the marginal product of capital is $MPK_i = \alpha z_i a_i^{\alpha-1}$. Hence, the difference between MPK_i and r_f can be interpreted as the flood risk premium, which equals the expected damage caused to the county i. Hence, the optimal investment a_i is determined by the flood probability p_i. Specifically, when flood probability increases, the amount of investment will decrease.

Impact of FDB Policy

We believe that the key function of FDB policy is to redistribute flood risk. To be more specific, the FDB policy aims to increase the flood risk in sacrificed county by Δp and decrease the flood risk in protected county by Δp. Hence, in sacrificed county, the FDB-adjusted flood probability will be $p_s' = p_s + \Delta p$. And in protected county, In protected county, the FDB-adjusted flood probability will be: $p_p' = p_p - \Delta p$. In Section 5.1, we find empirical evidence to confirm the validity of this assumption. Holding geographical conditions constant, we find that flood inundation area in sacrificed FDB counties is more than 50% higher, and the size adjusted flood exposure is around 5% higher in FDB counties (see Table 5).

Proposition 1 (Trade-off in Equality and Efficiency) *Assume* $\frac{z_p}{(p_p d + r_f)^{2-\alpha}} > \frac{z_s}{(p_s d + r_f)^{2-\alpha}}$, *then we have:* $\frac{d(a_p + a_s)}{dp} > 0$ *and* $\frac{d(a_p - a_s)}{dp} < 0$.

$\frac{z_p}{(p_p d + r_f)^{2-\alpha}} > \frac{z_s}{(p_s d + r_f)^{2-\alpha}}$ indicates that the damage standardized productivity in protected county is higher than that in sacrificed county. In other words, it specifies that a government that prioritizes efficiency has correctly identified counties worth to be protected.

The implication of this proposition are twofolds. First, FDB policy will bring an increase in total investment and will improve the economic resilience towards floods. The flood risk redistribution from protected to sacrificed counties will increase the total investment $a_p + a_s$. Second, FDB policy will also bring the inequality between sacrificed counties and protected counties because the investment gap $a_p - a_s$ will increase as well. We provide proof of this proposition in the Appendix A.3.

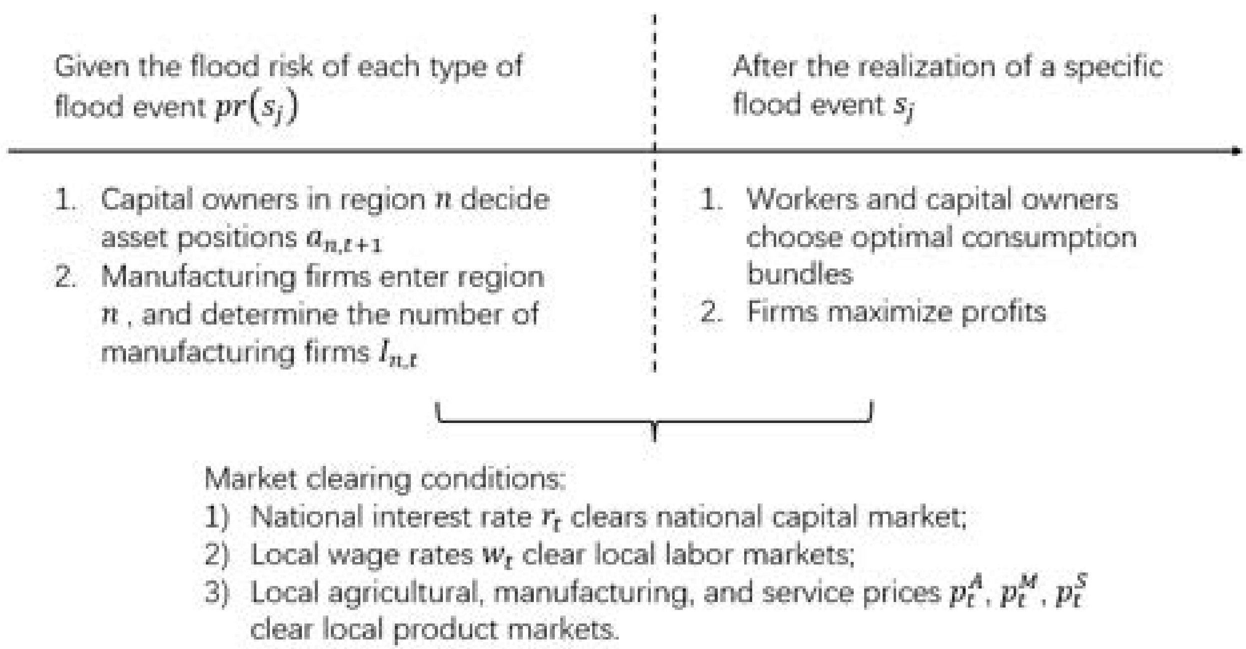
7.2 Model Environment and Equilibrium Conditions

Model Framework

Consider an economy with N regions, each indexed by $n \in N$. There is a unit mass of hand-to-mouth workers in the economy. In this general equilibrium model, worker cannot migrate across regions, which is consistent with our empirical evidence showing no evidence of migration (Section 6.1). Each region has one representative capital owner who cannot move across regions and makes optimal investment decision to determine asset positions. Manufacturing goods are traded between region n and region i, which is subject to iceberg trade cost. For example, d_{ni} measures the trade cost of shipping one unit of goods from region n to destination region i. Agricultural and service goods are not tradable across different regions.

Before the realization of each type of flood events s_j, capital owners in region n decide their optimal asset positions $a_{n,t+1}$, and manufacturing firms decide entering the region n, thus determining the number of manufacturing firms $I_{n,t}$. The manufacturing firm count satisfies the free entry condition. After the flood realization, workers and capital owners choose optimal consumption bundles, and firms maximize their profits accordingly. Finally, factor prices clear the national capital market, local labor markets, and local product markets.

The figure below provides an illustration of the model's timeline. It shows the sequence of events and decisions made by capital owners, manufacturing firms, and workers, both before and after the realization of a specific flood event. It also outlines the market clearing conditions for national capital market, local labor markets, and local product markets.



Floods

Considering the varying damage level of flood events from 2000 to 2010, we define $S = \{s_1, s_2, ..., s_j\}$, where each s_j corresponds to a unique type of flood event, categorized by its severity.[4] For each type of flood event s_j, it happens with a probability of $pr(s_j)$. The collective flood risk is then characterized by a vector of flood probability $Pr = \{pr(s_1), pr(s_2), ..., pr(s_J)\}$. For each flood type j, region n is either flooded or not. Hence, flood event s_j consists of a vector of region-specific flood events, $\{f_{n,j}\}$, that $s_j = \{f_{1,j}, f_{2,j}, ..., f_{N,j}\}$. Here, $f_{n,j}$ is a dummy variable that takes the value of 1 if region n is flooded in this type of flood, and 0 if not.

We assume that a flood event s_j affects the economy by decreasing the productivity of each sector. Specifically, floods negatively affect the region-specific manufacturing productivity $z_n^M(s_j)$. We model the productivity as:

$$z_n^M(s_j) = \bar{z_n^M} exp(-\epsilon_M f_{n,j}) \tag{1}$$

where $\bar{z_n^M}$ denote the region-specific productivity during non-flooding time; ϵ_M denotes the magnitude of region-specific percentage productivity loss during flooding seasons $f_{n,t} = 1$.

From 2000 to 2010, we believe that each flood event at time t represents a specific type of flood event because of their different levels of severity. Hence, we can also denote s_j as s_t. We will use s_t, instead of s_j, in the following description.

Workers

There is a unit mass of hand-to-mouth workers living in N regions, denoted by L_n, who are immobile across regions ($\sum_{n=1}^{N} L_n = 1$). Workers are assumed to be hand-to-mouth and supply one unit labor inelastically in the region they live in. After the actualization of each flood event, workers then optimize their consumption bundles given flood event s_t.

[4] No flood is still considered as a type of flood, though the induced damage is 0 in this case.

Specifically, workers maximize their utility function, according to the budget constraint.

$$\begin{aligned}
&\max_{\{C_n^A(s_t),C_n^M(s_t),C_n^S(s_t)\}} && U(C_n^A(s_t),C_n^M(s_t),C_n^S(s_t)) \\
&s.t. && P_n^A(s_t)C_n^A(s_t)+P_n^M(s_t)C_n^M(s_t)+P_n^S(s_t)C_n^S(s_t)=w_n(s_t)
\end{aligned} \tag{2}$$

where $U(C_n^A(s_t),C_n^M(s_t),C_n^S(s_t))$ takes a Cobb-Douglas form such that $U(C_n^A(s_t),C_n^M(s_t),C_n^S(s_t)) = \xi_A log(C_n^A(s_t)) + (1-\xi_A-\xi_S)log(C_n^M(s_t)) + \xi_S log(C_n^S(s_t))$, $w_n(s_t)$ is the wage rate in region n given flood event s_t, P_n^A, P_n^M and P_n^S represent the prices of agricultural goods, manufacturing goods, and service goods, respectively, in region n.

Capital Owners

During time period t, capital owners in region n decide the asset positions, $a_{n,t+1}$, before the actualization of flood event s_t. Hence, the asset position decision is independent of s_t. After the realization of the flood event, capital owners optimize their consumption bundles given event-specific prices. Capital owners' preferences are identical to those of the workers. Capital owners maximize their utility given budget constraint:

$$\begin{aligned}
V_n^s(a_{n,t}) = &\max_{\{C_n^A(s_t),C_n^M(s_t),C_n^S(s_t),a_{n,t+1}\}} && \mathbb{E}_{s_t}U(C_n^A(s_t),C_n^M(s_t),C_n^S(s_t))+\beta V_n^s(a_{n,t+1}) \\
&s.t. && P_n^A(s_t)C_n^A(s_t)+P_n^M(s_t)C_n^M(s_t)+P_n^S(s_t)C_n^S(s_t)+a_{n,t+1}=(1+r(s_t))a_{n,t}+I_{n,t}\pi_n(s_t)
\end{aligned} \tag{3}$$

where national interest rate is given by $r(s_t)$. $\pi_n(s_t)$ represents the average profit of manufacturing firms in region n. $U(C_n^A(s_t),C_n^M(s_t),C_n^S(s_t))$ takes a Cobb-Douglas form such that $U(C_n^A(s_t),C_n^M(s_t),C_n^S(s_t)) = \xi_A log(C_n^A(s_t)) + (1-\xi_A-\xi_S)log(C_n^M(s_t)) + \xi_S log(C_n^S(s_t))$. P_n^A, P_n^M and P_n^S represents the price of agricultural goods, manufacturing goods, and service goods, respectively, in region n.

Production

In our model, we have three sectors: the primary (agricultural) sector, the manufacturing sector, and the service sector. Agricultural sector, manufacturing firms, and service sector produce three types of goods: agricultural goods $Y_n^A(s_t)$, manufacturing goods $Y_n^M(s_t)$, and service goods $Y_n^S(s_t)$. The primary sectors supply non-tradable agriculture goods in the local market in a perfectly competitive way and produce with a linear production technology. The profit maximization problem for the primary sector in flood event s_t is given by:

$$\begin{aligned} \max_{\{l_n^A(s_t)\}} \quad & P_n^A(s_t)Y_n^A(s_t) - w_n(s_t)l_n^A(s_t) \\ s.t. \quad & Y_n^A(s_t) = z_n^A(s_t)l_n^A(s_t) \end{aligned} \tag{4}$$

We assume the tertiary sectors also supply non-tradable service goods in the local market in a perfectly competitive way. The difference from the primary sector is that the tertiary sectors produce with both labor and capital in a Cobb-Douglas way. For the service sector, the maximization problem in flood event s_t is given by:

$$\begin{aligned} \max_{\{l_n^S(s_t),k_n^S(s_t)\}} \quad & P_n^S(s_t)Y_n^S(s_t) - w_n(s_t)l_n^S(s_t) - r_n(s_t)k_n^S(s_t) \\ s.t. \quad & Y_n^S(s_t) = z_n^S(s_t)l_n^S(s_t)^\alpha k_n^S(s_t)^{1-\alpha} \end{aligned} \tag{5}$$

We assume that firms in the secondary sector supply tradable manufacturing goods in a monopolistically competitive way. More specifically, consumers in region n consume heterogeneous manufacturing goods produced by firms in different regions $i \in \{1, 2, ..., N\}$ based on a CES aggregate function:

$$Y_n^M(s_t) = \left[\sum_{i=1}^{N} I_{i,t} y_{in}^M(s_t)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{6}$$

where σ measures the level of elasticity of substitution across manufacturing goods produced by different regions, $Y_{in}^M(s_t)$ is the output of manufacturing good produced by region i and sold to region n, and $I_{i,t}$ denotes the number of manufacturing firms in region n. Denote $P_{in}^M(s_t)$ as the price of manufacturing good produced by region i and sold to region n, then one can easily show that the price index of manufacturing goods sold in region n is $P_n^M(s_t) = \left[\sum_{i=1}^N I_{i,t} P_{in}^M(s_t)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$.

Firms in the secondary industry produce manufacturing goods with a Cobb-Douglas production function. The transportation of goods across regions is subject to iceberg cost d_{ni}. Denote l_{ni}^M and k_{ni}^M as the labour and capital inputs of producing manufacturing goods supplied from region n to region i. The maximization problem for each firm in region n in flood event s_t is given by:

$$\begin{aligned} \pi_n(s_t) = \max_{\{l_{ni}^M(s_t), k_{ni}^M(s_t)\}_{i=1}^N} \sum_{i=1}^{N} \left[P_{ni}^M(s_t) y_{ni}^M(s_t) - w_n(s_t) l_{ni}^M(s_t) - r(s_t) k_{ni}^M(s_t) \right] \\ s.t. \qquad d_{ni} y_{ni}^M(s_t) = z_n^M(s_t) l_{ni}^M(s_t)^{\alpha} k_{ni}^M(s_t)^{1-\alpha} \qquad \forall i \end{aligned} \tag{7}$$

During time period t, manufacturing firms decide whether to enter region n, before the actualization of flood event s_t. In each period, there is a probability of η that the manufacturing firm will exit the market. The value function of the manufacturing firm in region n could be written as:

$$V_{n,t}^s = \mathbb{E}_{s_t} \pi_n(s_t) + \beta(1-\eta) V_{n,t+1}^s \tag{8}$$

The free entry condition requires that the value function of manufacturing firms should equal to the entry cost c_n^s.

$$V_{n,t}^s = c_n^s \tag{9}$$

Market Clearing Conditions

There are three sets of market clearing conditions.

1. National capital market: The flood-event-specific interest rate $r(s_t)$ require asset positions equal flood-event-specific capital demands in all regions:

$$\sum_{n=1}^{N} I_n \sum_{i=1}^{N} k_{ni}^M(s_t) + \sum_{n=1}^{N} k_n^S(s_t) = \sum_{n=1}^{N} a_{n,t} \tag{10}$$

2. Local labour markets: The flood-event-specific wage rates $w_n(s_t)$ require labour supply equal flood-event-specific labour demands in all regions:

$$l_n^A(s_t) + \sum_{i=1}^{N} l_{ni}^M(s_t) di + l_n^S(s_t) = L_n \qquad \forall n \tag{11}$$

3. Local final good markets: The final good markets are assumed to be perfectly com-

petitive, so prices $P_n^A(s_t)$, $P_{ni}^M(s_t)$ and $P_n^S(s_t)$ satisfy that the final good demands and supplies are equalized in all regions:

$$L_n C_n^{w,A}(s_t) + C_n^{s,A}(s_t) = Y_n^A(s_t) \qquad \forall n \tag{12}$$

$$L_n C_n^{w,S}(s_t) + C_n^{s,S}(s_t) = Y_n^S(s_t) \qquad \forall n \tag{13}$$

$$P_{ni}^M(s_t) = \left[L_i C_i^{w,M}(s_t) + C_i^{s,M}(s_t)\right]^{\frac{1}{\sigma}} P_i^M(s_t) y_{ni}^M(s_t)^{-\frac{1}{\sigma}} \qquad \forall i, n \tag{14}$$

$$P_n^M(s_t) = \left[\sum_{i=1}^{N} I_{i,t} P_{in}^M(s_t)^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \qquad \forall n \tag{15}$$

Equilibrium

The spatial general equilibrium consists of capital owners' asset positions $\{a_{n,t}\}$ and consumption bundles $\{C_n^{o,A}(s_t), C_n^{o,M}(s_t), C_n^{o,S}(s_t)\}$, workers' consumption bundles $\{C_n^{w,A}(s_t), C_n^{w,M}(s_t), C_n^{w,S}(s_t)\}$, sector-specific factor demands and outputs $\{l_n^A(s_t), l_n^M(s_t), l_n^S(s_t), k_n^M(s_t), k_n^S(s_t), Y_n^A(s_t), Y_n^M(s_t), Y_n^S(s_t)\}$, manufacturing firms counts $\{I_{n,t}\}$, and prices $\{w_n(s_t), r(s_t), P_n^A(s_t), P_n^M(s_t), P_n^S(s_t)\}$, such that given the distribution of workers $\{L_n\}$

1. Before the realization of flood events s_t
   - (i) $\{a_{n,t}\}$ satisfy capital owners' optimal investment decisions in Equation 3;
   - (ii) $\{I_{n,t}\}$ satisfy the free entry condition in Equation 9;
2. After the realization of flood event s_t
   - (i) $\{C_n^{o,A}(s_t), C_n^{o,M}(s_t), C_n^{o,S}(s_t)\}$ and $\{C_n^{w,A}(s_t), C_n^{w,M}(s_t), C_n^{w,S}(s_t)\}$ satisfy capital owners' and workers' utility maximization problems in Equation 2 and 3;
   - (ii) $\{l_n^A(s_t), l_n^M(s_t), l_n^S(s_t), k_n^M(s_t), k_n^S(s_t), Y_n^A(s_t), Y_n^M(s_t), Y_n^S(s_t)\}$ satisfy sectors' profit maximization problems in Equation 4, 5, and 7;
   - (iii) $\{w_n(s_t), r(s_t), P_n^A(s_t), P_n^M(s_t), P_n^S(s_t)\}$ clear the factor and product markets in Equation 10 - 15.

7.3 Calibration and Simulation

In this section, we calibrate our model to match Chinese counties in Huai River Basin, the basin with the highest river flood risk, between 2000 and 2010.

Exogenously Calibrated Parameters

Panel A of Table 13 shows parameter values obtained directly from literature and data. We treat each region as a county, and there are $N = 176$ counties in Huai River Area. We standardize labour force $\bar{L}$ to be 1,000. Following previous literature (Head et al. 2014 & Jia et al. 2022), we set the elasticity of substitution across varieties, σ, as 5. We choose a discount factor, β, to be 0.95 to generate an aggregate steady-state interest of 5%. Shares of sector-specific consumption match the real data provided by 2000-2010 Chinese National Bureau of Statistics. To be specific, the share of agricultural consumption, ξ_1, is 11.7%, and the share of service consumption, ξ_3, is 42.2%. 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 Chinese input and output tables and national accounts, sourced from Chinese National Bureau of Statistics.

Transportation Cost - 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 2006, 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.

Probability of Each Flood Type - In 2000 and 2010, there were 5 major floods in Huai River Basin, which happened in 2002, 2003, 2005, 2007, and 2010, respectively. Those flood events inundated different counties in Huai River Basin 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 precipitation, we divide the monthly-averaged precipitation during flood seasons (June to September) into two categories: (i) < 120 mm; (ii) > 120 mm. We then calculated the region-specific flooding probability based on both historical data on monthly precipitation and actual flood event.

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

$$Y_{sicjt} = \alpha + \beta_1 Flooded_{icjt} + \gamma_{jt} + \lambda_t + \eta_c + \epsilon_c$$

In this estimation, $s(s = 1, 2, 3)$ represents primary, secondary (manufacturing), and tertiary industry, respectively. i, c, j represent county, city, province, respectively. t represents year. Y_{sicjt} refers to the labor productivity of different sectors in a county, which is measured by dividing output by number of employees in an industry. $FloodExposure_{icjt}$ indicates the inundation size of county i in year t. γ_{jt}, λ_t, and η_t represent Province $\times$ Year, Year, and Time fixed effects. α is the constant term. Standard errors are clustered at city level. Reduced form results suggest that secondary (manufacturing) sector, estimation results suggest a productivity loss of 5.9%. Productivity loss in primary and service sector are not significant.

Internally Calibrated Parameters

In Panel B of Table 13, we calibrate the region-specific total factor productivity (TFP) of primary, secondary and tertiary industry in different counties. The target is to match data on county-level sector specific real outputs and labor force share. Although we estimate all parameters together, we can pinpoint which parameter influences a specific outcome. For instance, sector-specific real outputs at the county level are influenced by sector-specific productivity, while regional amenities are determined by the labor force in each area. To maintain consistency, we standardize the total national GDP and population to 1,000 in our base calibration, as these factors do not impact our baseline calibration.

7.4 Model Prediction

In this section, we conduct a comparative analysis to illustrate the consistency between the empirical findings and the predictions of our general equilibrium model. Our objective, as displayed in Table 15, is to validate the model's capability to accurately reflect the reality of FDB counties. This comparative approach demonstrates the robustness and reliability of our model as a tool for simulating the real-world economic scenarios. Table 15 offers a comparison of the actual empirical results and model-predicted outcomes. Column 1 in Table 15 reports the spatial regression discontinuity result we gained in Table 12, while Column 2 reports the result we gain based on model simulation. Since the magnitude does not differ a lot, we believe that our analysis reveals a close alignment between the model predictions and the empirical data, which underscores the validity of our general equilibrium model.

7.5 Counterfactual Practice 1: FDB-induced Net Output Gain

In this section, we quantify three different effects: (1) sacrifice effect, which is the cost caused to FDB counties due to the FDB policy. We could compare this with our reduced-form results; (2) protection effect, which is the benefit brought to FDB-protected counties due to the FDB policy; (3) the effect on total output, which is the net output gain to the whole society due to the FDB policy. The key parameter for us to construct the counterfactual scenario is the flood exposure in FDB counties and FDB-protected counties. In the coutnerfactual scenario in the absence of FDB policy, flood exposure in FDB counties would decrease, while flood exposure in protected aresa would increase.

Constructing the Counterfactual Practice

We construct the counterfactual scenario based on three steps. In the first step, we identify flooded counties in each flood event. For each flood event, we calculate the flood exposure, as measured by the average number of flooded days, of each county. In the second step, for each flood event, we adjust the flood exposure distribution between FDB counties and FDB-protected counties by redistributing flood exposure. We calculate the net output change in different counterfactual scenarios in which the flood exposure in FDB county decreases by 10% - 90%. Figure 14 presents a mind map to illustrate how we construct the counterfactual. To put it simply, without flood water diversion, flooded days in FDB counties would decrease, and the amount of reduced days will be evenly distributed to downstream urban cities. Based on Table 14, we have estimates of flood exposure on productivity. Hence, we can then transform the increased flood exposure in protected areas to the increased negative impacts on those areas. An illustrative graph is also presented in Figure 14. In the actual case, we find that flood exposure decreased sharply in neighboring protected counties. However, in the counterfactual case, the disparity is not evident. Finally, we are able to construct a set of counterfactual flood events $S' = \{s'_1, s'_2, ..., s'_J\}$ based on the counterfactual distribution of flood risk.

Using Hydro-dynamic Model to Determine the Actual Redistribution Rate

Although we are able to quantify the net output change given different exposure redistribution rate, we cannot use economics knowledge to determine the *actual* flood exposure redistribution rate. According to a hydro-logical research by Mingkai and Kai 2017, "inundated farmland in the downstream would be increased to 2530 hectares, with an increased area of 1340 hectares more than the use of the Mengwa Detention Basin." This indicates that inundation in protected areas would have increased by 50% if without flood water diversion to FDB counties. However, we cannot translate it into the flood exposure decrease in FDB counties.

To solve this issue, under the supervision of Danish Hydraulic Institute (DHI), we use a hydro-dynamic engineering model to measure the flood exposure redistribution rate in a real flood event. As shown in Figure 15, the inundation area of an important intended-to-protect city, Wuhan, would increase by 45% if without flood water diversion. We specifically choose Wuhan for analysis because we could directly transform the change in protected city to the change in FDB counties given their similar sizes.

Based on our hydrological practice, we set the actual flood exposure redistribution rate as 45%. Given this estimation, in the actual case, we assume flooded days in FDB counties would decrease by 45%.

Sacrifice Effect

In Table 16, we quantify the sacrifice effect on FDB counties by collecting β_{FDB} in the calibrated case and the counterfactual case from running the regression

$$lnY_{icpt} = \alpha + \beta_{FDB} * \text{FDB}_{icpt} + \gamma_{pt} + \eta_t + \lambda_c + \epsilon_c$$

where FDB_{icpt} is a dummy variable that equals 1 if the county i in city c, province p, at time t, is an FDB-county, and 0 if not. γ_{pt} is province-year fixed effect, η_t is time fixed effect, and λ_c is city fixed effect. ϵ_c is the standard error, which is clustered at the city level.

Column 3 reports the magnitude of change in β_{FDB} in the calibrated case and counterfactual case (flood exposure redistribution rate: 45%). We compare the results on total output with the result presented in Table 6. As shown in column (3) in Table 6, the average treatment effect of FDB policy on nighttime light in FDB counties is around -10%. According to the work of Henderson et al. (2012) on estimating the elasticity between light and GDP, we can then translate this impact to around -3%, which is consistent with the result presented in Column 3 of Table 16. This consistency further validates our methods of constructing the counterfactual scenario.

Table 16 then helps us to overcome the limitation of data availability and provides us with more results on the sacrifice effect. We find that the manufacturing output, total capital, manufacturing capital, share of manufacturing labor, and wage decreases by 9.62%, 5.11%, 8.49%, 10.86%, and 3.76%, respectively, because of the policy given a flood exposure redistribution rate of 45%.

More results on sacrifice effect of different flood exposure redistribution rates are presented in Figure 16.

Protection Effect

When focusing on the impact of FDB policy on FDB-protected counties, we believe that the protection effect stems from two sources: (1) direct protection effect that protectd counties suffer from less damage when being hit by floods; (2) indirect protection effect that protected counties benefit from a reduced flood risk.

In Table 17, we first estimate the direct protection effect by running the regression

$$\text{lnLight}_{icpt} = \alpha + \beta_1 Flooded_{icpt} + \beta_2 Flooded \times FDB_{icpt} + \beta_3 Flooded \times Protected_{icpt} + X_{icpt} + \gamma_{pt} + \lambda_c + \epsilon_c$$

where $lnLight_{icpt}$ is the ln(nighttime light intensity) of county i in city c, province p, at time t. $Flooded_{icpt}$ is a dummy variable that equals 1 if the county is flooded in year t, and 0 if not. FDB_{icpt} is a dummy variable that equals 1 if the county is an FDB county, and 0 if not. $Protected_{icpt}$ is a dummy variable that equals 1 if the county is an FDB-protected county, and 0 if not. X_{icpt} are controls. γ_{pt} is province-year fixed effect, η_t is time fixed effect, and λ_c is city fixed effect. ϵ_c is the standard error, which is clustered at the city level.

Following this specification, β_2 measures the impact of a county being designated as FDB county, while β_3 measures the impact of a county being protected by FDB counties. As shown in Table 17, we find that a protected county tends to suffer around 10% less when being hit by floods. However, an FDB county tends to suffer around 18% more when being hit by floods. This results indicates that FDB-protected counties are *direct*ly protected in flood events.

However, in our general equilibrium setting, we are more interested in the *indirect* protection effect that those protected counties also benefit from a reduced flood risk that firms are more willing to enter those counties. To understand the magnitude of protection effect, in Table 18, we quantify the total protection effect on FDB-protected counties by collecting $\beta_{FDB_protected}$ in the calibrated case and the counterfactual case from running the regression

$$lnY_{icpt} = \alpha + \beta_{FDB} * \text{FDB\_Protected}_{icpt} + \gamma_{pt} + \eta_t + \lambda_c + \epsilon_c$$

where FDB_{icpt} is a dummy variable that equals 1 if the county i in city c, province p, at time t, is an FDB-protected county, and 0 if not. γ_{pt} is province-year fixed effect, η_t is time fixed effect, and λ_c is city fixed effect. ϵ_c is the standard error, which is clustered at the city level.

Table 18 provides us with the result on protection effect. We find that total output, manufacturing output, total capital, manufacturing capital, share of manufacturing labor, and wage increases by 1.74%, 3.92%, 2.51%, 3.30%, 4.40%, and 4.17%, respectively, because of the policy given a flood exposure redistribution rate of 45%.

More results on protection effect of different flood exposure redistribution rates are presented in Figure 16.

Benefit to Cost Ratio

Finally, in Table 19, we quantify the welfare implication of the FDB policy by comparing the total output in the calibrated case and the counterfactual scenario. Overall, we find a 0.06% increase in total output due to the FDB policy, which equates to an annual net increase in output of around US$3billion in Huai River Basin. According to EM-DAT International Disaster Database, the average flood damage in China is around US$8billion every year in China. Hence, we believe that the FDB policy has substantially addressed the economic threat imposed by floods.

We also examine the potential policy implications under two future scenarios characterized by heightened flood damages due to increasing risks associated with climate change. To explore these scenarios, we amplify the productivity decline in the manufacturing sector by 50% and 100%, respectively. In Table 13, the existing loss in the manufacturing sector stands at approximately 14.8%. Under the projected future scenarios, if the productivity decline due to floods escalates by 50% and 100%, respectively, the anticipated productivity losses will reach 24.2% and 29.6%. We observe that the overall total output would rise by 0.08% and 0.11%, respectively.

Figure 17 presents the benefit to cost ratio in other flood exposure redistribution rates. We find that the benefit to cost ratio is larger than 1, regardless of the redistribution rate. This indicates that flooding counties to protect urbans will always generate a net gain in output. However, as the redistribution rate increases, we also find that the benefit to cost ratio increases, indicating that the policy will be more effective if the ability of FDB counties absorbing flood water is stronger.

7.6 Counterfactual Practice 2: Is the current FDB policy optimal?

In the second counterfactual practice, we extend our discussion to think about whether the policy is optimal. It would be ideal for us to provide a list of counties that are most suitable for flood water detention. But we are not able to complete this task because of hydrological challenges. The optimal design given economic criteria may not be feasible if we take geographical factors into account. Consider an extreme example. Under economic criteria, we may assign a county far away from river as an FDB county. Even we incorporate some geographical factors (e.g., elevation) into an economic model, the result may not be hydrologically feasible.

Despite of the challenge, the discussion on policy optimality is intrinsically important. We take a second-best approach by considering whether the government is over-protecting urban cities by designating too many FDB counties. Among those 96 FDB counties, half of them were not used for flood water diversion. Given this fact, we ask whether it is necessary to include all of them into the FDB list. To answer this question, we follow three steps. In the first step, we rank FDB counties in terms of their exposure-standardized productivity, which is consistent with the proposition we have in Section 7.1. In the second step, we successively remove FDB counties of higher productivity from the FDB list and calculate the total output in each counterfactual scenario. In the third step, we calculate the relative contribution of each productivity group by comparing the counterfactual with the actual case.

In Figure 18, we present the net output gain of successively adding counties of higher productivity. Overall, we find that the net output gain increases as we add more counties to the list. However, according to Figure 19, we find that the relative contribution is much higher in lower productivity groups than in higher productivity groups. County groups ranking 0-10%, 10-20%, 25-40%, and 40-50% in terms of productivity contribute more than 10%. Specifically, county group with a rank of 10-25% and 25-40% contribute the most to the net output gain, all above 25%. However, we find that the relative contribution of higher productivity group is low. County group ranking 75-80% and 85-100% contribute 0% and 3%, respectively.

On the one hand, we do not find counter-evidence to indicate that the inclusion of higher productivity counties is imposing negative effects on total outputs as the net output gain is increasing with the number of included FDB counties. On the other hand, however, the relative contribution of adding higher productivity counties is small. In terms of total outputs, it may be cost beneift efficient. However, if considering other non-monetary costs, then it may not be efficient because those counties may experience other costs that we are not able to measure in this study.

Overall, we suggest that the Chinese government is over protecting urban areas from floods by designating too many counties as FDB counties. Removing counties of higher productivity will not cause significant losses in output, but may save those counties from suffering both monetary and non-monetary costs.

8 Conclusion

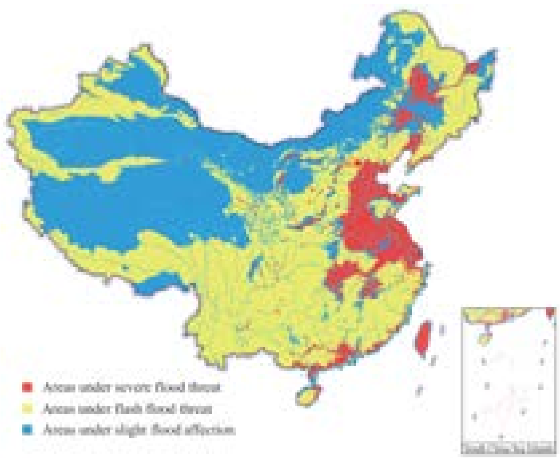
Flood disasters, especially prevalent in developing countries like China and India, significantly impact individuals, highlighting the critical need for effective flood management strategies. The construction of Flood Detention Basins (FDBs) is one such policy implemented to mitigate the severe effects of river floods in China. FDBs, strategically placed in low-lying areas, are designed to temporarily hold excess floodwaters, thus protecting downstream regions at the expense of increasing flood risks in the designated areas. This policy, while crucial for minimizing overall flood damage, prompts a reevaluation of the economic sacrifices made by communities within these basins, impacting over 15 million people across various provinces and municipalities.

Chinese government states that residents living in FDB counties have made substantial sacrifice for the greater good. Our study quantitatively examines the economic costs and welfare gains of the FDB policy. We find that although the policy has improved the economic resilience against floods, it has also induced economic inequality between between FDB counties and their non-FDB counterparts. Firstly, our identification reveals that counties designated as FDB counties by the Chinese government in 2000 experience enduring negative effects on their economic development. On average, nighttime light intensity in FDB counties declined by roughly 9% annually over the long term. Based on our calculations, this translates to an annual GDP loss of around US$10 billion in FDB counties. Secondly, in studying the mechanism, we find that firms have less incentives to enter and invest in FDB counties due to their increased flood risks. Post-2010 FDB designation, our synthetic DiD estimates show a significant average annual decline in new manufacturing firm entries by 24.5%. Spatial regression discontinuity analysis indicates a roughly 20% gap in fixed asset investment between FDB counties and their neighboring counties, and this gap only emerged immediately after the 2010 policy change. Thirdly, our analysis employs a general equilibrium model to assess whether the FDB policy has yielded an overall increase in net output. Our counterfactual practice indicates that a benefit-to-cost ratio of around 3.5, based on estimation derived from hydro-dynamic engineering model.

Our research has two major policy implications. First, our research highlights a critical insufficiency in the Chinese government's compensation on FDB counties. Since 2000, many counties has started to absorb floodwaters, thereby protecting other regions from flood damage. However, the provision of governmental compensation for the affected counties began only 13 years later, in 2013. Moreover, the compensation focused solely on compensating for direct losses caused by flood inundation, such as damage to agricultural crops, and residential houses. Firms, however, are not compensated. Overall, the compensation could not account for 20% of the total loss. Our findings suggest that this compensation falls markedly short of addressing the full economic costs induced by the FDB policy. The substantial long-term economic costs have not been adequately compensated by the Chinese government. Based on our policy, we recommend Chinese government to provide adequate compensations to FDB counties.

Second, the findings of our study on China's Flood Detention Basin (FDB) policy offer insights for other nations contemplating similar flood risk management strategies. The evidence suggests that while such policies can provide broader regional protection from floods, they may come with significant long-term economic costs for the areas designated to absorb flood risks. For countries considering the adoption of analogous policies, it is crucial to recognize the potential for creating economic disparities and to weigh these against the intended benefits of reduced flood risk. Policymakers must ensure that robust compensatory mechanisms are in place to support affected regions, mitigating the economic sacrifices made by FDB-designated areas. In sum, while such policies can be an effective component of a comprehensive flood risk management strategy, they should be implemented with careful consideration of their distributional impacts.

9 Figures and Tables



(a) Flood Risk Distribution in China

(b) Nighttime Light in China

Figure 1: Richer regions in China face higher river flood risk.

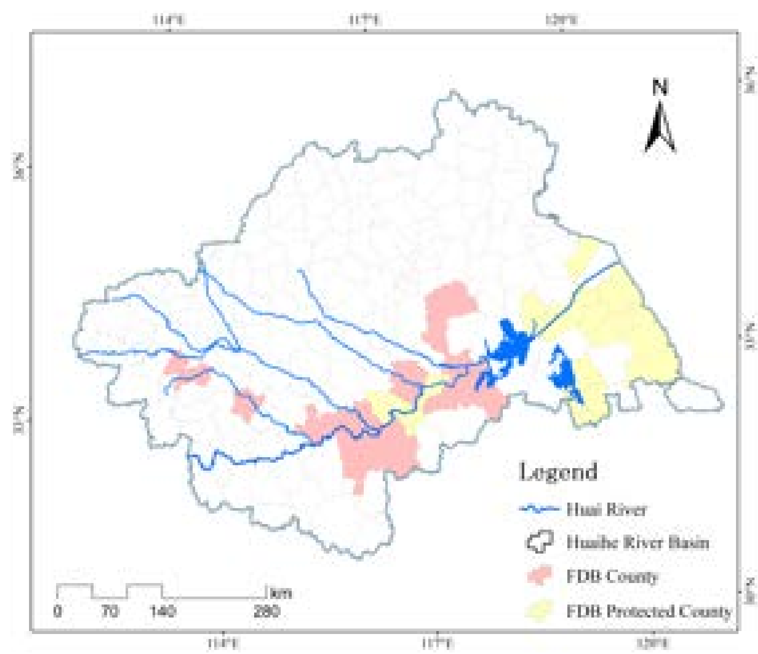


Figure 2: FDB Counties and FDB-Protected Districts in Huai River Basin

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	11,959	63.6
Yellow	5	3.18	5,212	12.9
Hai	26	4.40	9,597	17.2
Huai	26	1.61	3,674	14.1
Total	97	15.3	30,443	107.7
% of China		*1.1%*	*0.3%*	

Note: (1) This table reports the number of FDBs, affected population, total FDB areas, and the storage capacity of FDBs in 2003; (2) '% of China' refers to the percentage of affected population to the whole population in China and the percentage of total area to the total area of China.

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 implemented by China's Ministry of Water Resources in 2000, and '2010 Policy' to its subsequent update in 2010; (2) The 'Total' number might differ from the sum because some basins span multiple provinces, cities, and 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, 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.

Table 3: Descriptive Statistics: FDB Counties and non-FDB Counties

Mean	Unit	FDB Counties	non-FDB Counties
N(Counties)		116	2,363
N(obs)		2,709	55,729
Geographical Factors:			
Slope		6.14	12.46
Elevation		45.24	561.28
N(Permanent Water Pixels)		1136.33	388.77
Floods:			
Size-Adjusted Flood Exposure	days	0.126	0.020
Size of Flood Inundation	pixels	5,024.44	679.98
Socio-Economic Variables:			
Population	thousands	853.41	632.80
Nighttime Light Intensity		1,676,066	1,259,737
Number of Firms		5,669.49	5,496.63

Note: (1) We use a county panel of 20 years (2000 - 2020); (2) Detailed introduction of data used in this research can be found in Section 3.1; (3) From 2000 to 2020, a total of 116 counties have been designated as FDB counties. In 2000, the government selected 96 FDB counties. In 2010, the government selected another 20 counties into the FDB list, but removed 10 from the list.

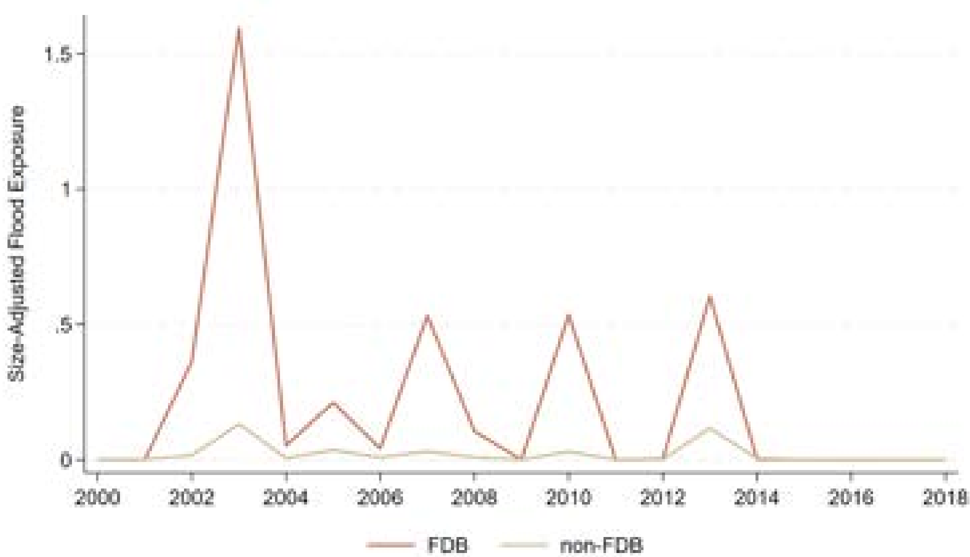


Figure 3: Size-Adjusted Flood Exposure in FDB and non-FDB Counties

Note: (1) The size-adjusted flood exposure is calculated using Global Flood Database. Detailed calculation procedure is introduced in Section 3.1; (2) 'Size-Adjusted Flood Exposure' measures the average days of inundation experienced by a non-permanent water pixel in a county.

Table 4: FDB Selection Criteria: Logit Model

(in logarithm)	(1)	(2)	(3)	(4)	(5)
Elevation	-1.377^{***}				-1.386^{***}
	(0.000)				(0.435)
Gradient		-2.301^{***}			0.013
		(0.000)			(0.866)
Precipitation			-0.155		0.016
			(0.176)		(0.933)
Manufacturing Output				0.059	0.080
				(0.071)	(0.076)
N(obs)	6,330	6,330	6,330	6,330	6,330
R^2	0.247	0.210	0.147	0.140	0.248
Fixed Effects					
Province-Year	Y	Y	Y	Y	Y
City	Y	Y	Y	Y	Y

Note: (1) We use a county panel of 20 years (2000 - 2019); (2) The dependent variable is a dummy FDB_i that equals 1 if the county i has a Flood Detention Basin, and equals 0 if not; (3) All regressions control for city fixed effects and province-by-year fixed effct; (4) Standard errors are clustered at the county level.

Table 5: Impacts of FDB Policy on Flood Exposure

	Flood Inundation Size		Size-Adjusted Flood Exposure	
Sample Period: 2000-2020	(1)	(2)	(3)	(4)
FDB	0.602***	0.547***	0.050***	0.043***
	(0.090)	(0.087)	(0.010)	(0.010)
N(obs)	52,307	52,307	52,307	52,307
Controls				
Precipitation	Y	N	Y	Y
Slope	Y	N	Y	Y
Elevation	Y	N	Y	Y
Fixed Effects				
Year	Y	Y	Y	Y
City	Y	Y	Y	Y

Note: (1) This table presents results of fixed-effect regression: $ln(Flood)_{ijt} = \alpha + \beta_1 FDB_{ijt} + \gamma_j + \lambda_t + \epsilon_j$, $ln(Flood)_{ijt}$ indicates flood-related outcomes in county i, city j, at year t, FDB_{ijt} is a dummy variable that equals 1 if the county i is an FDB county in year t, and 0 if not, γ_j is city fixed effect, λ_t is time fixed effect, standard errors are clustered at the county level; (2) We have two types of flood-related outcomes. 'Size of Flood Inundation' measures the area of flood inundation in each county, while 'Size-Adjusted Flood Exposure' measures the average days of flood inundation experienced by a non-permanent water pixel in a county. Detailed calculation is introduced in Section 3.1.

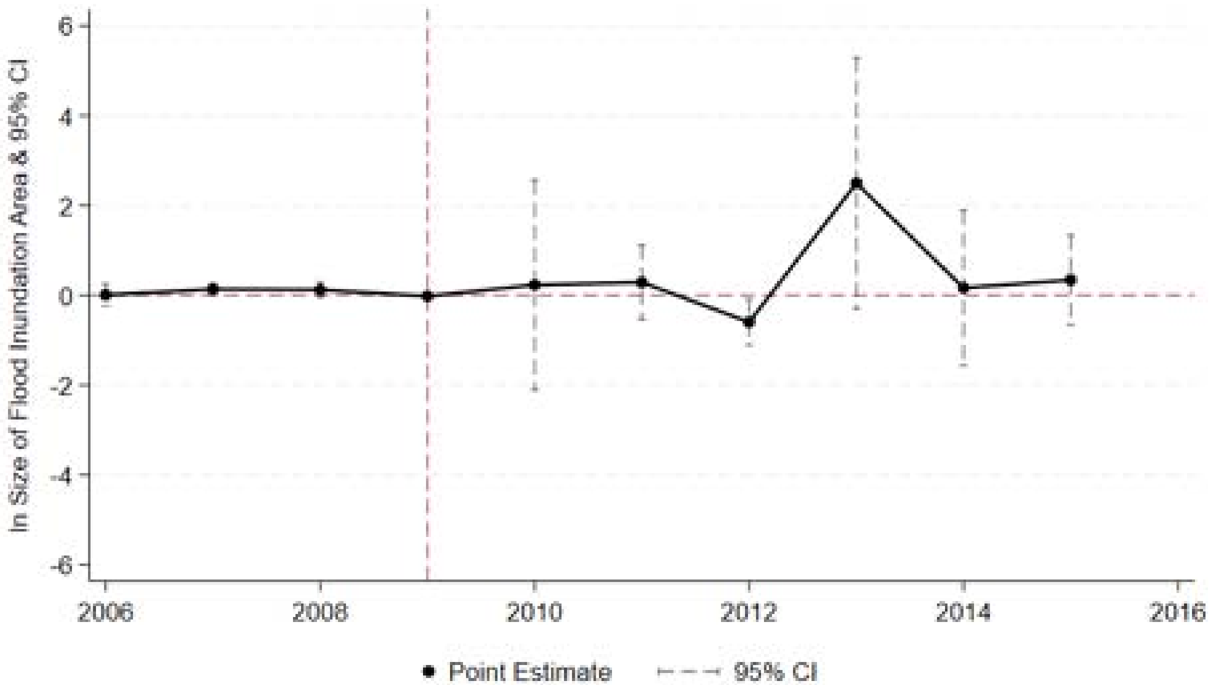


Figure 4: Dynamic Impacts of 2010 FDB Policy Change on Size of Flood Inundation

Note: (1) The event-study figure is based on SDID approach by Arkhangelsky et al. (2021); (2) The event-study regression includes county and year fixed effects; (3) Standard Error: Bootstrap; (4) 'Size of Flood Inundation' is calculated using the Global Flood Database (detailed calculation in Section 3.1), and it refers to the size of flood inundation area in a county; (5) In 2013, both northeast and southwest China have experienced sever floods.

Table 6: Main Results: Impacts of FDB on Nightime Light Intensity

	Selection into FDB			Removal from FDB
(ln)	All	2000 Cohort	2010 Cohort	
Panel A: Method - Traditional TWFE Difference-in-Differences				
	(1)	(2)	(3)	(4)
$\beta^{TWFE}_{Selection}$	−0.176***	−0.137***	−0.078*	
	(0.056)	(0.035)	(0.045)	
$\beta^{TWFE}_{Removal}$				−0.052
				(0.074)
R-squared	0.919	0.939	0.928	0.927
Sample Period	1990-2020	1990-2010	2000-2020	2000-2020
N(obs)	70,463	46,680	47,208	50,148
N(Treated Counties)	106	86	20	10
Panel B: Method - Synthetic Difference-in-Differences (Arkhangelsky et al. 2021)				
	(1)	(2)	(3)	(4)
$\beta^{SDID}_{Selection}$	−0.156***	−0.107***	−0.078**	
	(0.025)	(0.015)	(0.039)	
$\beta^{SDID}_{Removal}$				−0.003
				(0.064)
Sample Period	1990-2020	1990-2010	2000-2020	2000-2020
N(obs)	70,463	46,680	47,208	50,148
N(Treated Counties)	106	86	20	10
Control Group Selction				
Never Treated Counties	Y	Y	Y	Y
Spillover Counties	N	N	N	N
Always Treated Counties	/	/	N	N
2010 Selected FDB Counties	/	/	/	N
2010 Removed Counties	N	N	N	/
Fixed Effects				
Year	Y	Y	Y	Y
County	Y	Y	Y	Y

Note: (1) 'Selection into FDB' indicates the treatment of selecting counties into the FDB list in both 2000 and 2010, 'Removal from FDB' indicates the treatment of removing counties from the FDB list, solely in 2010; (2) All' includes two treated groups: counties selected into the FDB list in 2000, and in 2010, '2000 Cohort' focuses only on counties selected into the FDB list in 2000, '2010 Cohort' focuses only on counties selected into the FDB list in 2010; (3) We deliberately select control groups to remove possibly spillover groups and groups that receive other treatments.

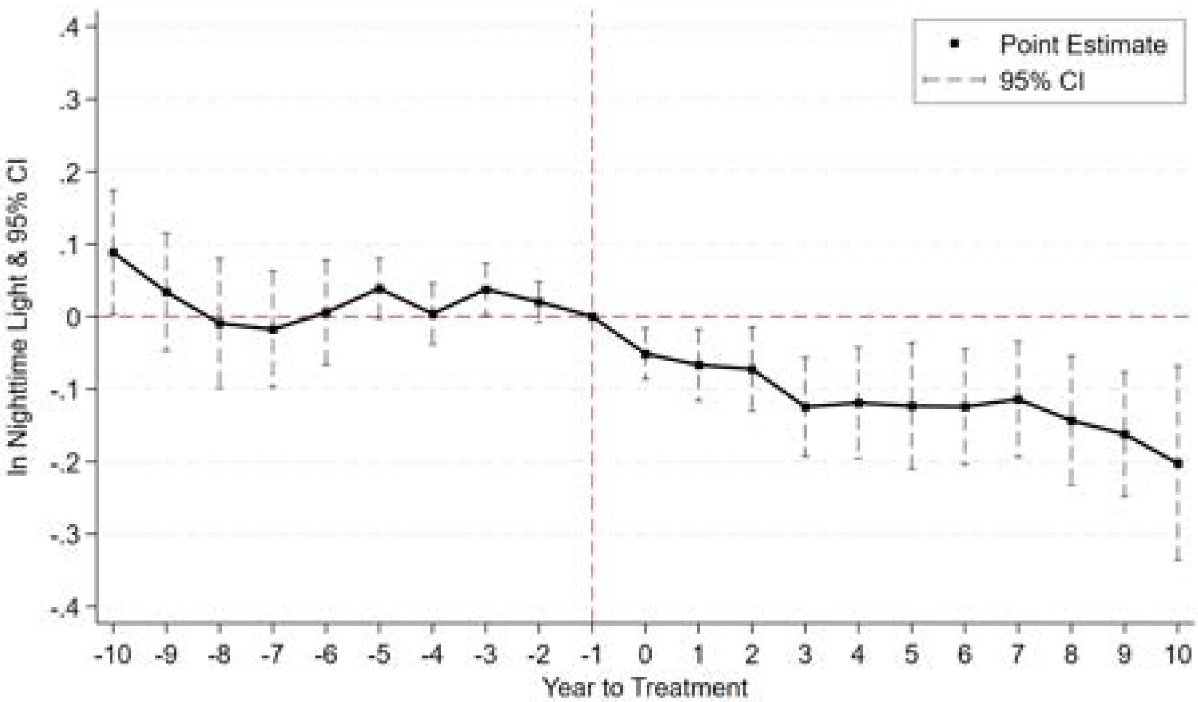


Figure 5: Dynamic Impacts of Selection into FDB List on Nighttime Light Intensity
Method: Traditional TWFE DID

Note: (1) Each dot represents the policy effect (ATT) estimated using the event-study approach; (2) Data: 1990-2020 Nighttime Light Intensity data; (3) 96 counties were selected into the FDB list in 2000, while 20 counties were selected into the FDB list in 2010; (3) The event-study regression includes county and year fixed effects, standard errors are clustered at county level; (4) We report the confidence interval at 95% confidence level.

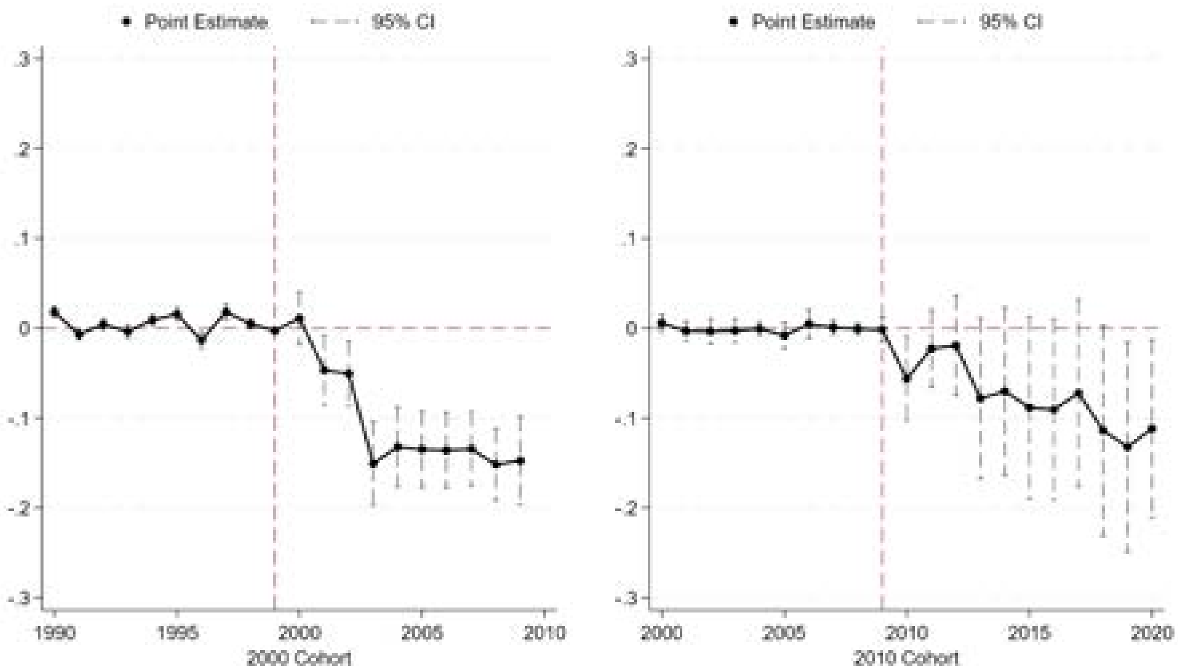


Figure 6: Dynamic Impacts of 2000 and 2010 FDB Policy Change on Light Intensity

Note: (1) Each dot represents the policy effect (ATT) estimated using the SDID event-study approach by Arkhangelsky et al. (2021)); (2) Data: 1990-2020 Nighttime Light Intensity data; (3) 96 counties were selected into the FDB list in 2000, while 20 counties were selected into the FDB list in 2010; (3) The event-study regression includes county and year fixed effects; (4) Standard Error: Bootstrap.

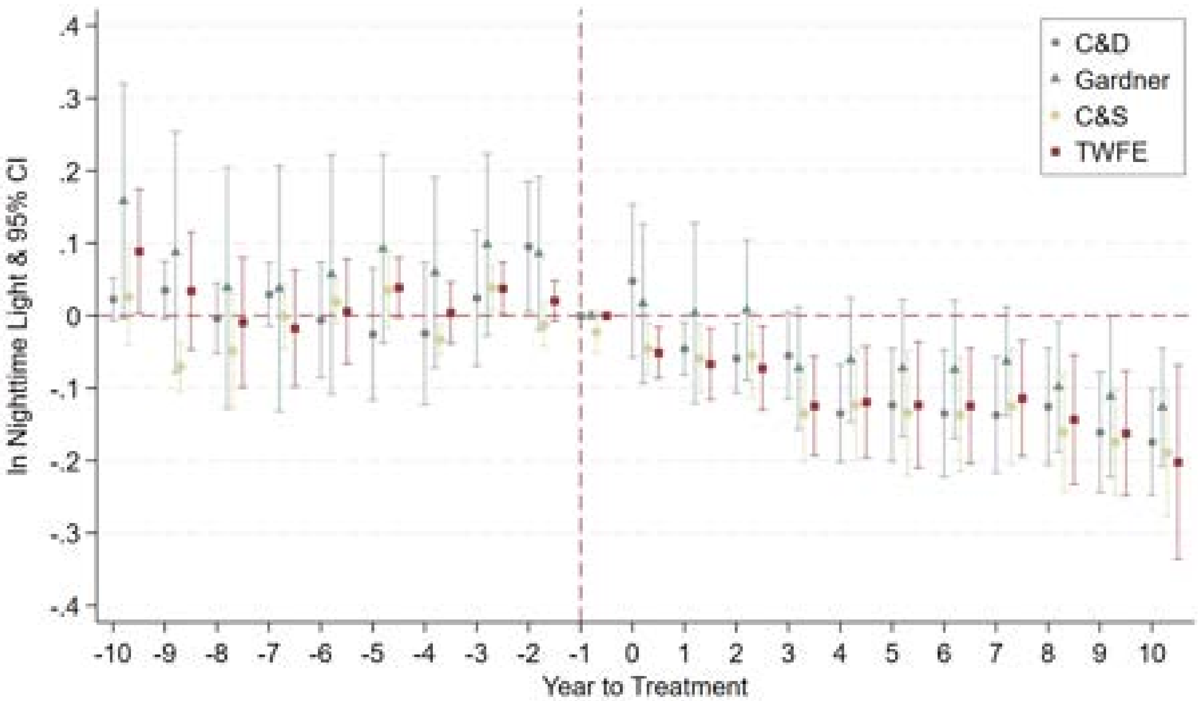


Figure 7: Event Study Robustness Check

Note: (1) Each dot represents the policy effect (ATT) estimated using different event-study approach; (2) 'TWFE' represents the traditional two-way-fixed-effects approach, 'C&D' refers to the two-way fixed effects estimators with heterogeneous treatment effects proposed by de Chaisemartin and D'Haultfœuille (2020), 'Gardner' refers to the two-stage DID approach by Gardner (2022), 'C&S' refers to the DID with multiple time periods by Callaway and Sant'Anna (2021); (3) Data: 1990-2020 Nighttime Light Intensity data; (4) 96 counties were selected into the FDB list in 2000, while 20 counties were selected into the FDB list in 2010; (5) The event-study regression includes county and year fixed effects, standard errors are clustered at county level; (6) We report the confidence interval at 95% confidence level.

Table 7: Robustness Check using Different DID Methods

	TWFE (1)	SDID (2)	C&D (3)	Gardner (4)	C&S (5)
FDB	-0.176^{***}	-0.156^{***}	-0.115^{***}	-0.182^{***}	-0.147^{***}
	(0.056)	(0.025)	(0.030)	(0.064)	(0.040)
N(obs)	70,463	70,463	70,463	70,463	70,463
Fixed Effects					
Year	Y	Y	Y	Y	Y
County	Y	Y	Y	Y	Y

Note: (1) Each point estimate represents the policy effect (ATT) estimated using different difference-in-differences (DID) approach, 'TWFE' represents the traditional two-way-fixed-effects approach, 'SDID' refers to the synthetic DID proposed by Arkhangelsky et al. (2021), 'C&D' refers to the two-way fixed effects estimators with heterogeneous treatment effects proposed by de Chaisemartin and D'Haultfœuille (2020), 'Gardner' refers to the two-stage DID approach by Gardner (2022), 'C&S' refers to the DID with multiple time periods by Callaway and Sant'Anna (2021); (2) Data: 1990-2020 Nighttime Light Intensity data; (3) 96 counties were selected into the FDB list in 2000, while 20 counties were selected into the FDB list in 2010; (3) All regressions includes county and year fixed effects, standard errors are clustered at county level in Column (1), and (3) - (5), standard errors in Column (2) is set to be bootstrap; (4) The selection of control group is consistent with Column (1) in Table 6.

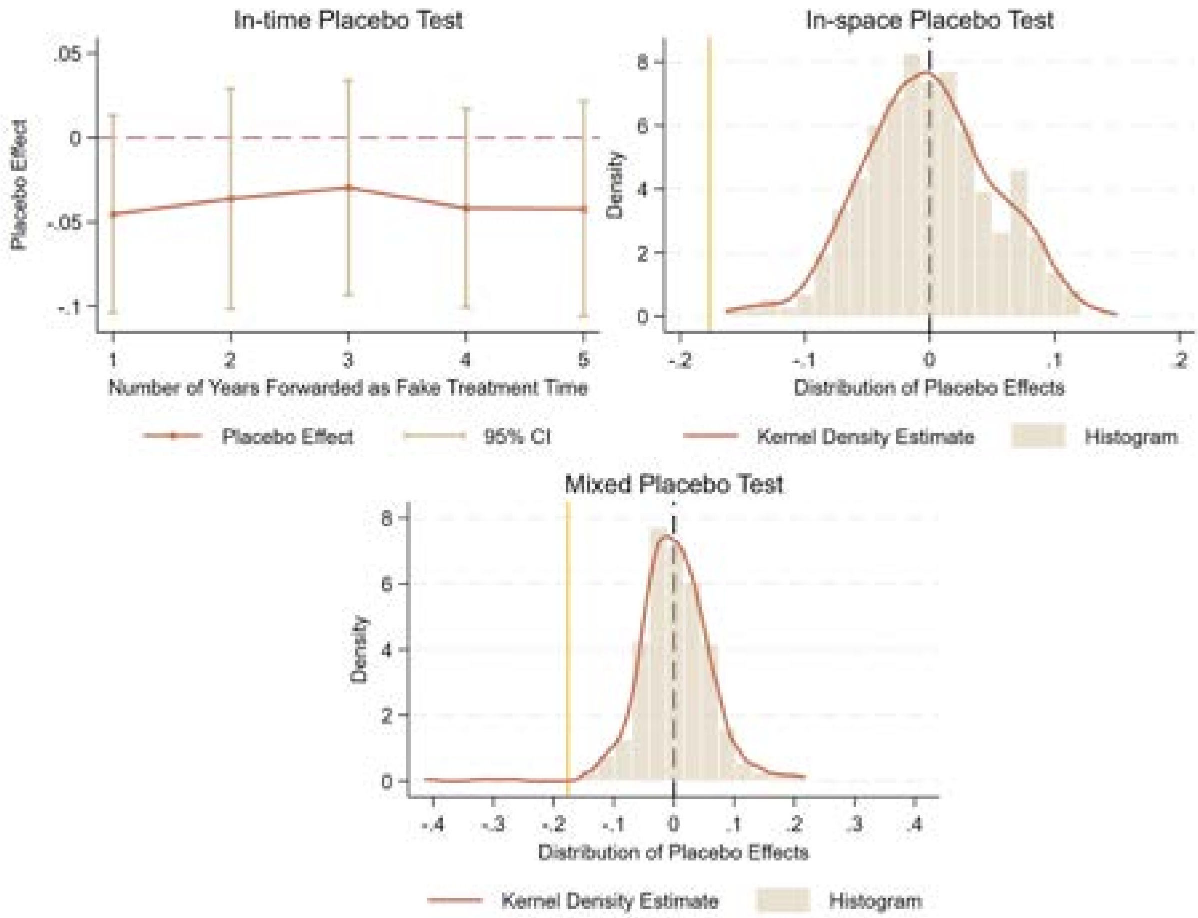


Figure 8: Placebo Test

Note: (1) This figure presents results of three distinct types of placebo tests of the traditional TWFE DID: the in-time placebo test, the in-space placebo test, and the mixed placebo test; (2) In the in-time placebo tests, we forward the treatment time by several years, using fake treatment times to assess if our results are driven by temporal trends rather than the actual intervention; (3) For the in-space placebo tests, we assign treatment to randomly selected units that did not receive the intervention, testing the robustness of our findings against spatial confounding factors; (4) The mixed placebo tests combine both approaches by randomly assigning fake treatment units and times.

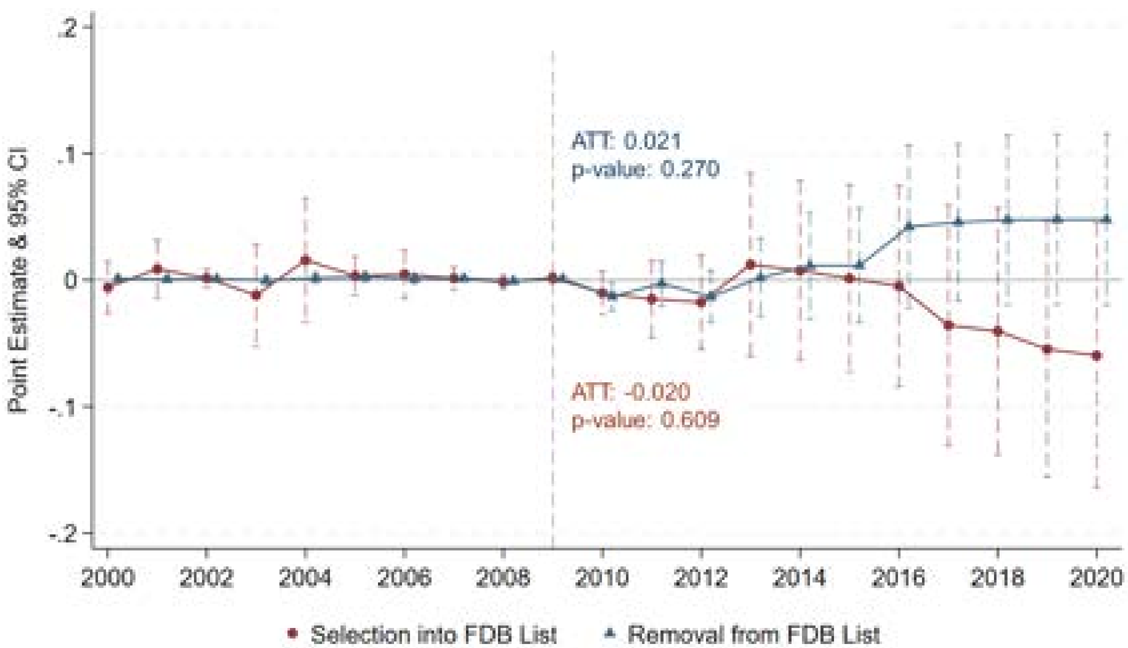


Figure 9: Dynamic Impacts of 2010 FDB Policy Change on Registered Population

Note: (1) Each dot represents the policy effect (ATT) estimated using the SDID event-study approach by Arkhangelsky et al. (2021)); (2) Data: 2000-2020 county-level statistical yearbook; (3) 20 counties were selected into the FDB list in 2010, while 10 counties were removed from the FDB list in 2010; (3) The event-study regression includes county and year fixed effects; (4) Standard Error: Bootstrap; (5) 'Registered population' refers to the population who registers as the official resident of the county.

Table 8: Impacts of 2010 FDB Policy Change on Registered Population

	Selection into FDB List		Removal from FDB List	
Sample Period: 2000-2020	(1)	(2)	(3)	(4)
$\beta^{SDID}_{Selection}$	−0.020	−0.020		
	(0.039)	(0.030)		
$\beta^{SDID}_{Removal}$			0.021	0.021
			(0.019)	(0.052)
Standard Error	Bootstrap	Placebo	Bootstrap	Placebo
N(obs)	43,050	43,050	43,050	43,050
N(Treated Counties)	20	20	10	10
Fixed Effects				
Year	Y	Y	Y	Y
County	Y	Y	Y	Y

Note: (1) We use SDID approach by Arkhangelsky et al. (2021); (2) Data: 2000-2020 county-level statistical yearbook; (3) 20 counties were selected into the FDB list in 2010, while 10 counties were removed from the FDB list in 2010; (3) We use two types of standard errors (bootstrap and placebo), county and year fixed effects are included; (4) 'Registered population' refers to the population who registers as the official resident of the county.

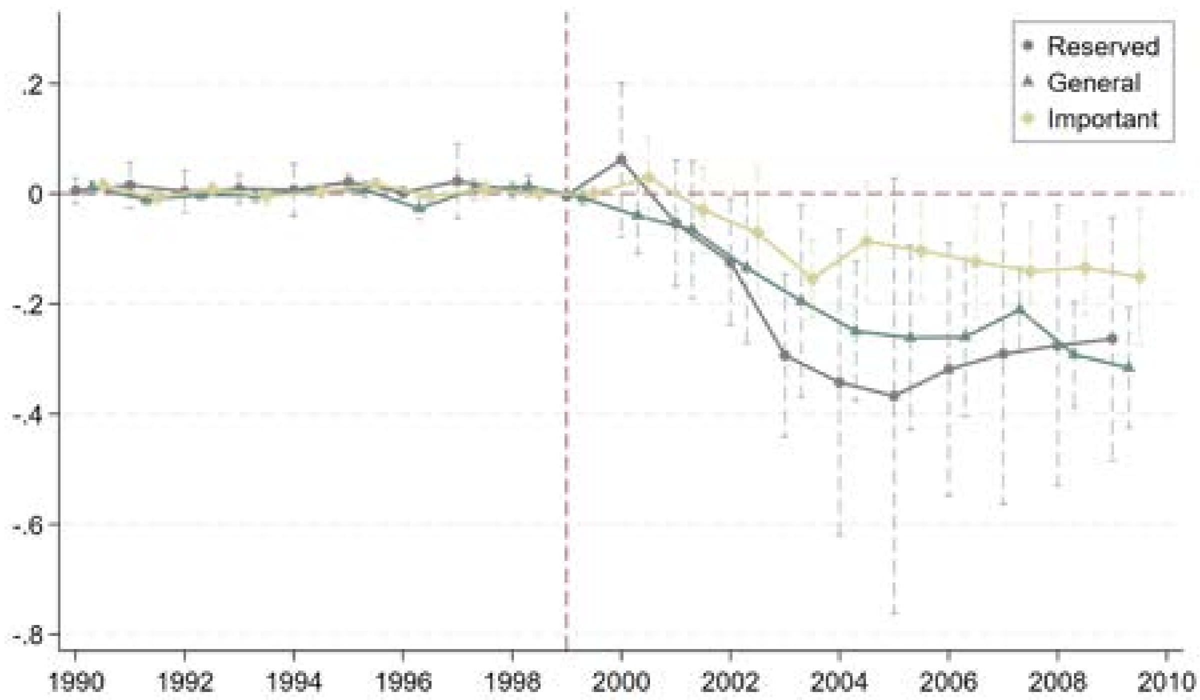


Figure 10: Heterogeneous Impact of 2010 Policy Change on Nighttime Light Intensity
Method: SDID (Arkhangelsky et al. 2021)

Note: (1) Each dot represents the policy effect (ATT) estimated using the event-study approach; (2) Data: 1990-2020 Nighttime Light Intensity data; (3) 96 counties were selected into the FDB list in 2000, while 20 counties were selected into the FDB list in 2010; (3) The event-study regression includes county and year fixed effects, standard errors are clustered at county level; (4) We report the confidence interval at 95% confidence level; (5) We classify FDB counties into three categories: Important, General, and Reserved according to the government classification. The likelihood of being flooded is the highest for Important FDBs, and the lowest for Reserved FDBs.

Table 9: Heterogeneous Impacts of FDB on Nightime Light Intensity

		Type of FDBs		
Sample Period: 1900-2020	All Sample (1)	Reserved FDB (2)	General FDB (3)	Important FDB (4)
$\beta^{SDID}_{Selection}$	-0.156^{***}	-0.308^{***}	-0.166^{***}	-0.116^{***}
	(0.025)	(0.079)	(0.043)	(0.043)
N(obs)	70,463	69,316	69,998	69,657
N(Treated Counties)	106	16	46	44
Fixed Effects				
Year	Y	Y	Y	Y
County	Y	Y	Y	Y

Note: (1) We use the SDID appraoch proposed by Arkhangelsky et al. (2021); (2) Data: 1990-2020 Nighttime Light Intensity data; (3) 96 counties were selected into the FDB list in 2000; (3) The event-study regression includes county and year fixed effects; (4) Standard Error: Bootstrap; (5) We also report the confidence interval at 95% confidence level; (6) We classify FDB counties into three categories: Important, General, and Reserved according to the government classification. The likelihood of being flooded is the highest for Important FDBs, and the lowest for Reserved FDBs.

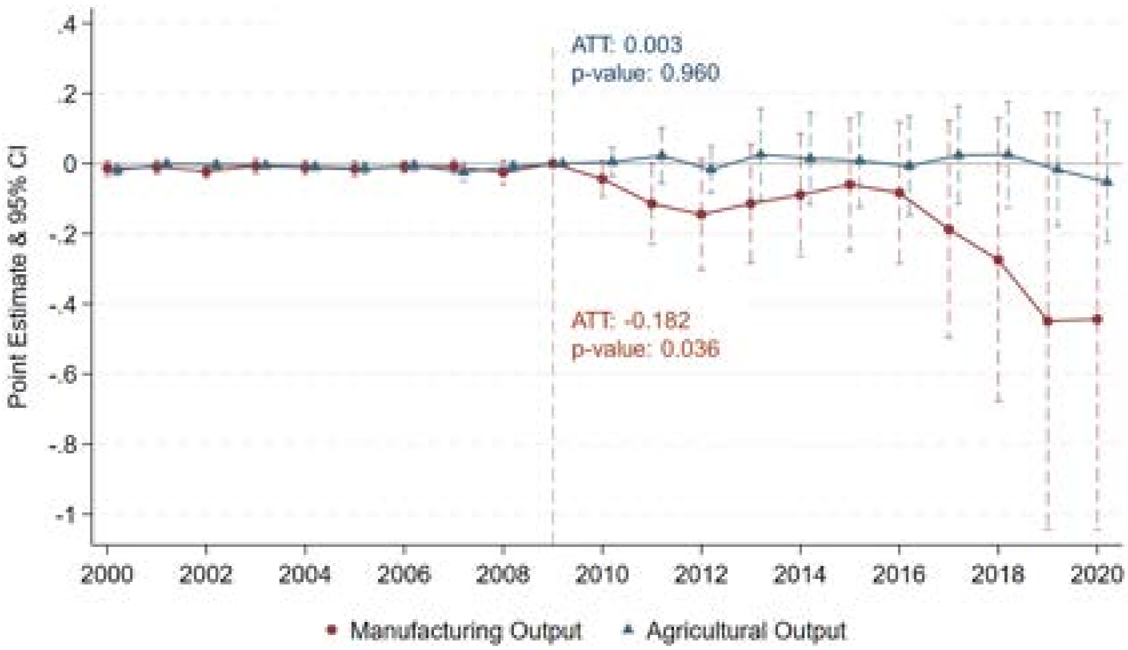


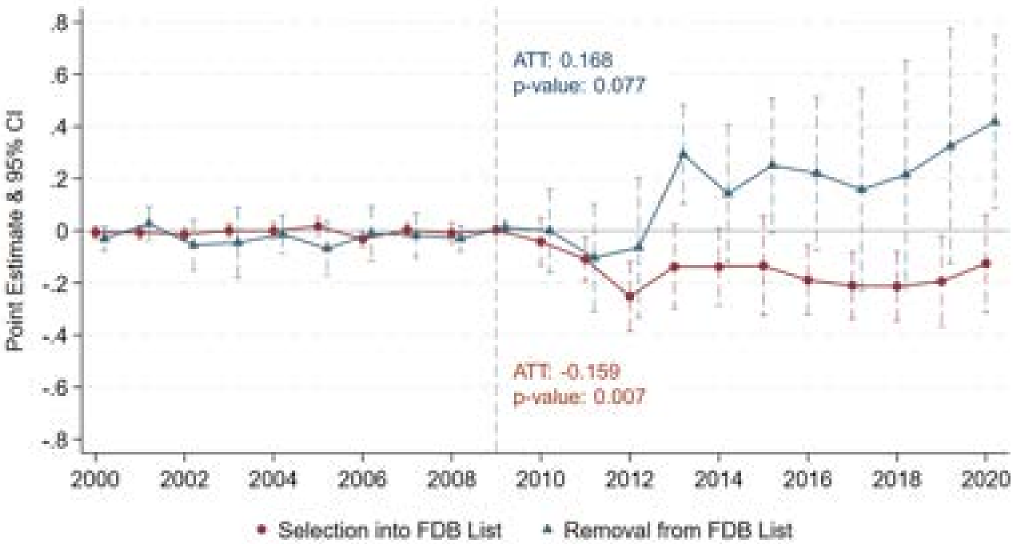
Figure 11: Dynamic Impacts of 2010 FDB Policy Change on Manufacturing and Agricultural Output

Note: (1) Each dot represents the policy effect (ATT) estimated using the SDID event-study approach by Arkhangelsky et al. (2021); (2) Data: 2000-2020 county-level statistical yearbook; (3) 20 counties were selected into the FDB list in 2010; (3) The event-study regression includes county and year fixed effects; (4) Standard Error: Bootstrap.

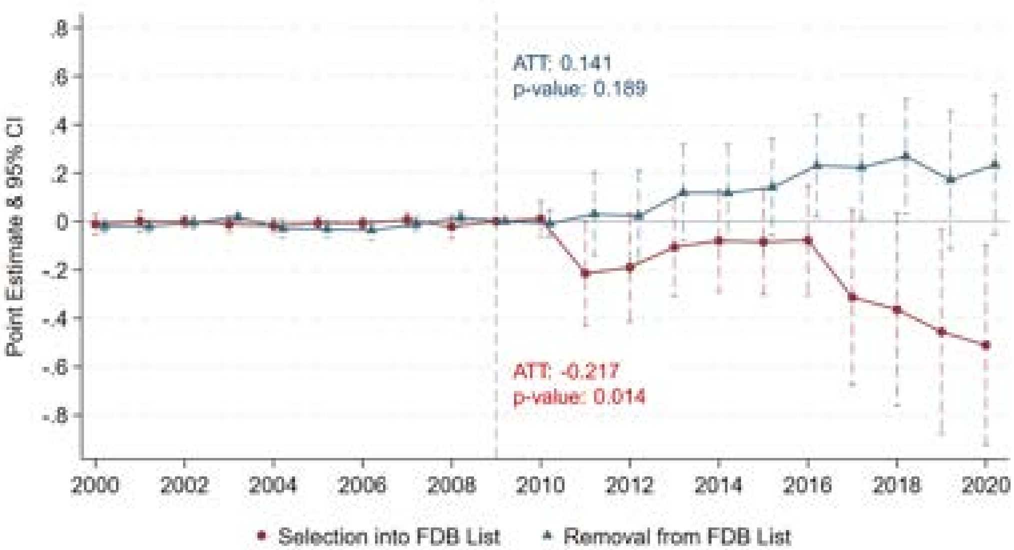
Table 10: Impacts of 2010 FDB Policy Change on Agricultural and Manufacturing Output

	ln(Agricultural Output)		ln(Manufacturing Output)	
Sample Period: 2000-2020	(1)	(2)	(3)	(4)
$\beta^{SDID}_{Selection}$	0.003	0.003	-0.182***	-0.182***
	(0.059)	(0.054)	(0.087)	(0.081)
Standard Error	Bootstrap	Placebo	Bootstrap	Placebo
N(obs)	39,354	39,354	39,354	39,354
N(Treated Counties)	20	20	20	20
Fixed Effects				
Year	Y	Y	Y	Y
County	Y	Y	Y	Y

Note: (1) We use SDID approach by Arkhangelsky et al. (2021); (2) Data: 2000-2020 county-level statistical yearbook; (3) 20 counties were selected into the FDB list in 2010; (3) We use two types of standard errors (bootstrap and placebo), county and year fixed effects are included.



(a) Outcome: ln(Number of Registered Firms)



(b) Outcome: ln(Number of Large Manufacturing Firms)

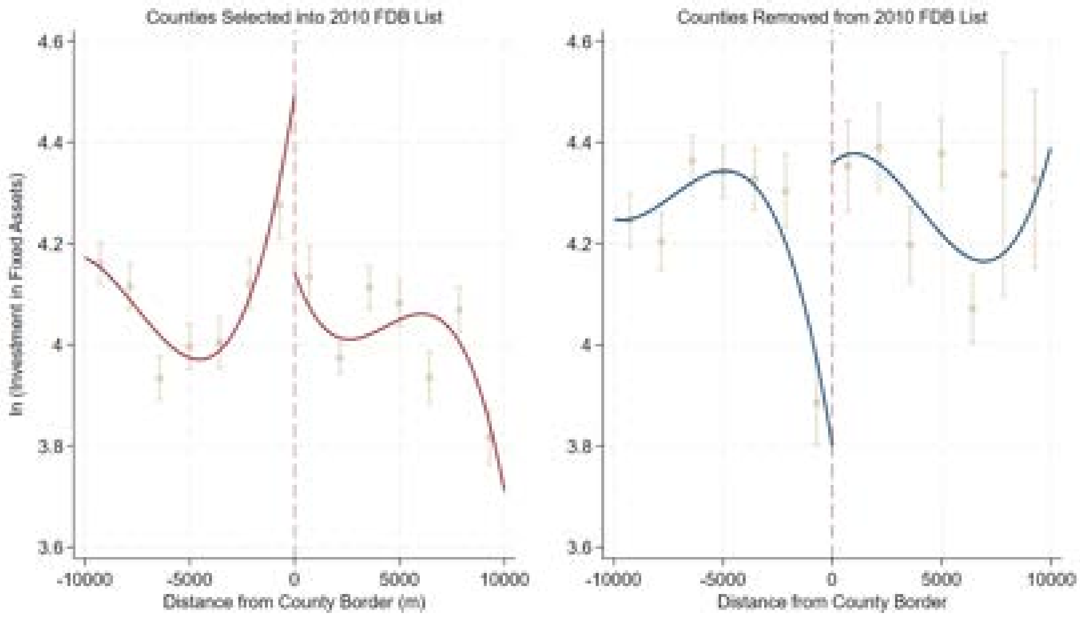
Figure 12: Dynamic Impacts of 2010 FDB Policy Change on Firm Entry

Note: (1) Each dot represents the policy effect (ATT) estimated using the SDID event-study approach by Arkhangelsky et al. (2021)); (2) Panel A Data: 2000-2020 NECIPS; Panel B data: 2000-2020 county level statistical yearbooks; (3) 20 counties were selected into the FDB list in 2010, while 10 counties were removed from the FDB list in 2010; (3) The event-study regression includes county and year fixed effects; (4) Standard Error: Bootstrap; (5) Larger Manufacturing Firms refer to firms whose annual revenue exceeds US$ 3million.

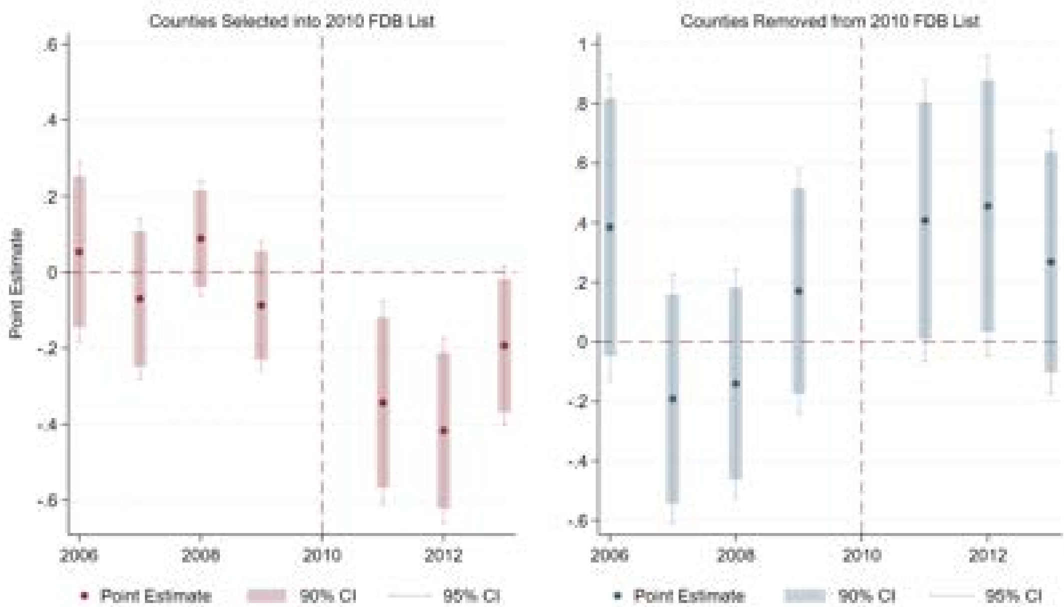
Table 11: Impacts of 2010 FDB Policy Change on Firm Entry

	Selection into FDB List		Removal from FDB List	
Sample Period: 2000-2020	(1)	(2)	(3)	(4)
Panel A: Outcome - ln(Number of Registered Firms)				
$\beta^{SDID}_{Selection}$	-0.159***	-0.159***		
	(0.059)	(0.071)		
$\beta^{SDID}_{Removal}$			0.168*	0.168
			(0.095)	(0.138)
Standard Error	Bootstrap	Placebo	Bootstrap	Placebo
N(obs)	58,191	58,191	58,191	58,191
N(Treated Counties)	20	20	10	10
Panel B: Outcome - ln(Number of Larger Manufacturing Firms)				
$\beta^{SDID}_{Selection}$	-0.217***	-0.217***		
	(0.088)	(0.117)		
$\beta^{SDID}_{Removal}$			0.141	0.141
			(0.107)	(0.116)
Standard Error	Bootstrap	Placebo	Bootstrap	Placebo
N(obs)	41,160	41,160	41,160	41,160
N(Treated Counties)	20	20	10	10
Fixed Effects				
Year	Y	Y	Y	Y
County	Y	Y	Y	Y

Note: (1) We use SDID approach by Arkhangelsky et al. (2021); (2) Panel A Data: 2000-2020 National Enterprise Credit Information Public System (NECIPS); Panel B data: 2000-2020 county level statistical yearbooks; (3) 20 counties were selected into the FDB list in 2010, and 10 counties were removed from the FDB list in 2010; (3) We use two types of standard errors (bootstrap and placebo), county and year fixed effects are included.



(a) Spatial Regression Discontinuity (Imbens and Wager 2019)



(b) Dynamic Spatial Regression Discontinuity

Figure 13: FDB v.s. Neighboring non-FDB Counties: Firm-Level Fixed Assets Investment

Note: (1) A positive distance indicates firms located within FDB counties, while a negative distance indicates firms located outside the border of FDB counties; (2) Industry and county fixed effects are absorbed before plotting the regression discontinuities; (3) FDB counties refer to those selected into the FDB list in 2010.

Table 12: Spatial Regression Discontinuity: Fixed Assets Gap

	ln(Gap in Fixed Assets Investment)					
	Selection into FDB List:			Removal from FDB List:		
	(1)	(2)	(3)	(4)	(5)	(5)
Panel A: No Control						
RD	−0.403***	−0.315***	−0.368***	0.553***	0.593***	0.631***
	(0.100)	(0.111)	(0.126)	(0.146)	(0.147)	(0.149)
Bandwidth	4.387	3.707	2.863	4.751	4.435	3.894
Panel B: County FE + Industry FE Absorbed						
RD	−0.217***	−0.166**	−0.179*	0.279**	0.285**	0.257*
	(0.078)	(0.084)	(0.097)	(0.129)	(0.131)	(0.148)
Bandwidth	4.883	4.294	3.360	4.629	4.314	3.516
Panel C: County by Industry FE Absorbed						
RD	−0.190***	−0.203***	−0.197***	0.258**	0.271**	0.276**
	(0.065)	(0.071)	(0.077)	(0.124)	(0.124)	(0.127)
Bandwidth	5.933	5.155	4.189	4.659	4.405	3.834
N(obs)	46,044	46,044	46,044	16,759	16,759	16,759
Kernel	Triangle	Epanech	Uniform	Triangle	Epanech	Uniform

Note: (1) Each coefficient represents a separate RD regression; (2) The running variable is the distance between a firm and the border of a corresponding FDB county, where negative (positive) means firms are located outside (within) FDB counties; (3) Negative coefficients indicate a negative gap between newly selected FDB counties and neighboring counties, positive coefficients indicate a positive gap between newly delisted FDB counties and neighboring counties; (4) The discontinuities are estimated using local linear regressions and MSE-optimal bandwidth proposed by Calonico et al. (2014); (5) Standard errors are clustered at the county level.

Table 13: Calibration Targets

Parameter	Numbers	Value	Source/Targeted Moments
Panel A: Exogenously Calibrated Parameters			**Source:**
N - Number of regions	1	176	Number of counties in Huai River Basin
$\bar{L}$ - Labour force	1	1,000	Standardized to 1,000
σ - Elasticity of substitution across varieties	1	5	Head et al. (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
$pr(s_t)$ - Natural flooding event probability	7	0.12(0.21)	Precipitation and Flood Event (2000-2009)
d_{ni} - Transportation costs	N^2	1.23(0.04)	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	Estimation
ϵ_M - Secondary productivity loss	1	-0.059	Estimation
Panel B: Internally Calibrated Parameters			**Targeted Moments:**
$\bar{z_n^A}$ - Region-specific primary productivity	N	0.83(0.34)	County-level real primary outputs
$\bar{z_n^M}$ - Region-specific secondary productivity	N	0.29(0.12)	County-level real secondary outputs
$\bar{z_n^S}$ - Region-specific tertiary productivity	N	0.21(0.22)	County-level real tertiary outputs
B_n - Local amenity	N	5.05(0.23)	County-level labour force share

Note: (1) 'Estimation' refers to the regression: $Y_{sicjt} = \alpha + \beta_1 Flooded_{icjt} + \gamma_{jt} + \lambda_t + \eta_c + \epsilon_c$, where Y_{sicjt} refers to the productivity of sector s in county i, city c, province j and year t, $Flooded_{icjt}$ is the dummy variable that equals 1 if the county is flooded in year t, α is the constant term, γ_{jt}, λ_t, and η_t are Province $\times$ Year, Year, and Time fixed effects, standard errors are clustered at city level; (2) ϵ_A is set to 0 because of insignificant β_1.

Table 14: Flood Impact on Productivity

(ln)	Total Productivity	Manufacturing Productivity
Size-adjusted Flooded Days	−0.043**	−0.059*
	(0.021)	(0.032)
N(obs)	1,283	1,283
Fixed Effects		
Province	Y	Y
City	Y	Y

Note: (1) FDB is a dummy that equals 1 if the county i has once labeled as a Flood Detention Basin county, and equals 0 if not; (2) All regressions control for city fixed effects, province-by-year fixed effects, and a set of county-level controls (land area, population, and precipitation); (3) Standard errors are clustered at the county level.

Table 15: Comparison of Actual and Model-generated Regression Results

	Actual Data:	Model Simulation:
(in logarithm)	Fixed Assets/Worker	Capital/Worker
	(1)	(2)
FDB	-0.197***	-0.175***
	(0.077)	(0.036)
N(obs)	46,044	1,936

Note: (1) Column 1 is extracted from Column (3) in Panel C of our regression discontinuity regression in Table 12; (2) Column 2 is based on our model prediction; (3) The consistency between those two estimates indicate that our model can well predict the fixed assets per worker.

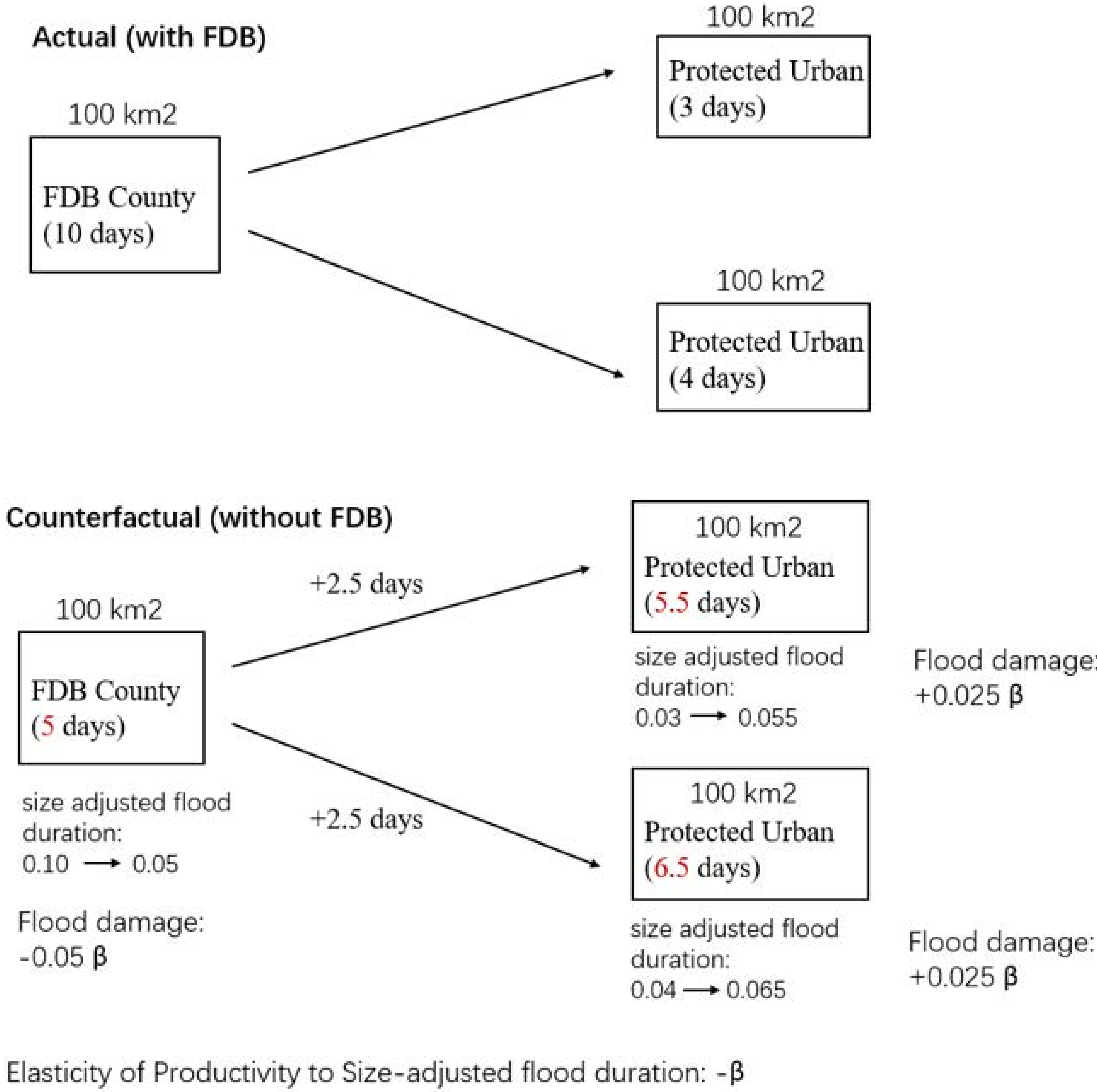
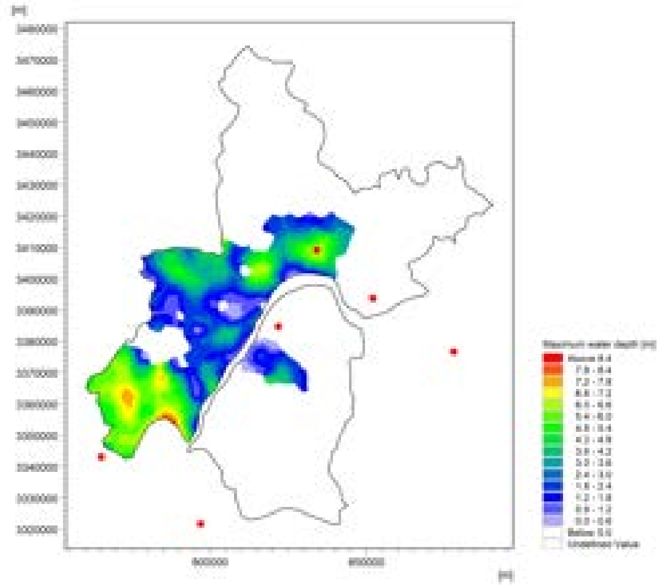
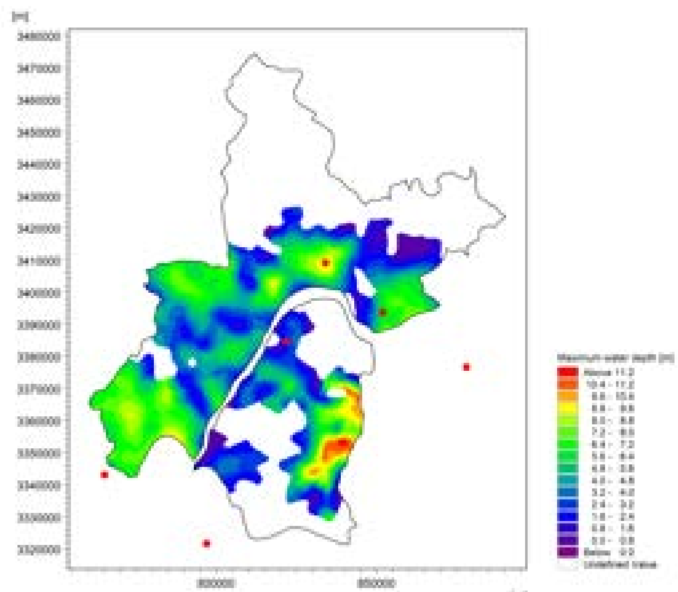


Figure 14: Mind Map



(a) Actual Case: Inundation in Wuhan City



(b) Counterfactual Case: Inundation in Wuhan City

Figure 15: Inundation Map in Wuhan City (Actual v.s. Counterfactual)

Note: (1) The map is drawn using MIKE hydrological modelling software launched by Danish Hydraulic Institute (DHI); (2) Model: hydro-dynamic model; (3) We select Wuhan city because this city is a major protected city by FDBs in Yangtze Rivers; (4) The flood exposure redistribution rate based on this estimation is 45%.

Table 16: Quantification of Sacrifice Effect (Actual v.s. Counterfactual)

	β_{FDB} :		
	A.Calibration	B.Counterfactual	|Diff/A|(%)
	(1)	(2)	(3)
Output: Total	−0.030***	−0.029***	3.46%
Output: Manufacturing	−0.468***	−0.427***	9.62%
Capital: Total	−0.251***	−0.239***	5.11%
Capital: Manufacturing	−0.373***	−0.344***	8.49%
Share of Manufacturing Labor	−0.052***	−0.048***	10.86%
Wage	−0.373***	−0.359***	3.76%

Note: (1) In the counterfactual case, we redistribute 45% of the flood risk to FDB-protected counties; (2) We collect β_{FDB} from running the regression $ln(Output)_{icpt} = \alpha + \beta_{FDB} * \text{FDB}_{icpt} + \gamma_{pt} + \eta_t + \lambda_c + \epsilon_{icpt}$, where FDB_{icpt} is a dummy that equals 1 if the county is an FDB-county, and 0 if not, γ_{pt} is province-year fixed effect, η_t is time fixed effect, and λ_c is city fixed effect; (3) The '|Diff/A|(%)' can be interpreted as the 'sacrifice effect', which is the impact of FDB policy on different outcomes in FDB counties.

Table 17: Reduced Form: Direct Protection Effect

	ln(Nighttime Light Intensity)			
Flooded	−0.053**	−0.048*	−0.055*	−0.059*
	(0.027)	(0.027)	(0.031)	(0.032)
Flooded × FDB			−0.177*	−0.180*
			(0.092)	(0.067)
Flooded × Protected			0.105*	0.104*
			(0.061)	(0.067)
N(obs)	5,242	5,242	5,242	5,242
R^2	0.888	0.887	0.887	0.888
Fixed Effects				
Province-Year	Y	Y	Y	Y
City	Y	Y	Y	Y
Controls				
Demographic	Y	Y	Y	Y
Geographical	Y	N	Y	N

Note: (1) FDB is a dummy that equals 1 if the county i has once labeled as a Flood Detention Basin county, and equals 0 if not; (2) All regressions control for city fixed effects, province-by-year fixed effects, and a set of county-level controls (land area, population, and precipitation); (3) Standard errors are clustered at the county level.

Table 18: Quantification of Protection Effect (Actual v.s. Counterfactual)

	$\beta_{FDB-Protected}$:		
	A.Calibration (1)	B.Counterfactual (2)	|Diff/A|(%) (3)
Output: Total	0.983***	0.967***	1.74%
Output: Manufacturing	1.304***	1.255***	3.92%
Capital: Total	0.750***	0.732***	2.51%
Capital: Manufacturing	1.044***	1.011***	3.30%
Share of Manufacturing Labor	0.138***	0.132***	4.40%
Wage	0.544***	0.522***	4.17%

Note: (1) In the counterfactual case, we redistribute 50% of the flood risk to FDB-protected counties; (2) We collect $\beta_{Protected}$ from running the regression $ln(Output)_{icpt} = \alpha + \beta_{Protected} *$ FDB-Protected$_{icpt} + \gamma_{pt} + \eta_t + \lambda_c + \epsilon_{icpt}$, where FDB-Protected$_{icpt}$ is a dummy that equals 1 if the county is an FDB-protected county, and 0 if not; (3) The '|Diff/A|(%)' can be interpreted as the 'protection effect', which is the impact of FDB policy on different outcomes in FDB-protected counties.

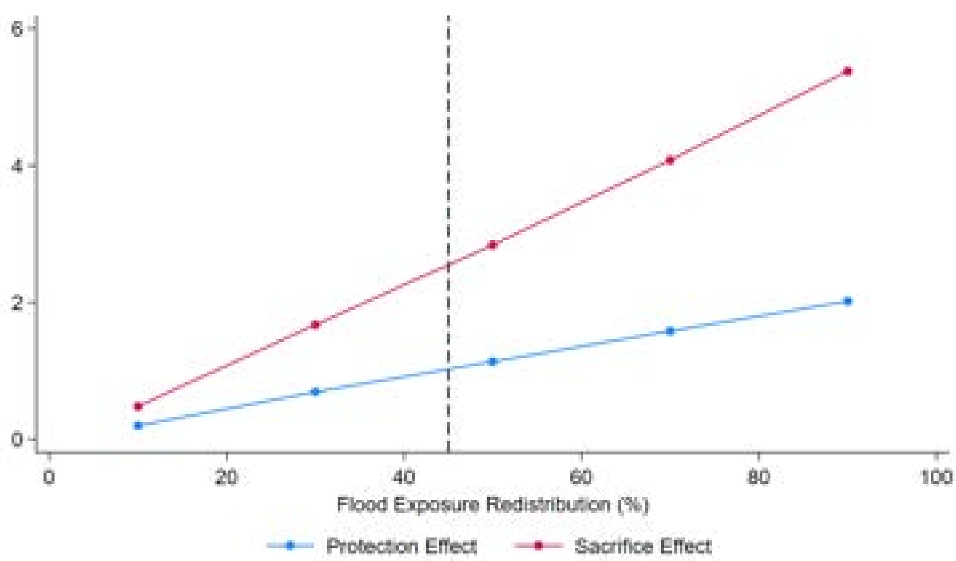


Figure 16: Sacrifice Effect and Protection Effect

Table 19: Total Output in Actual and Counterfactual Case

	Current Case:	Future Flood Risk Increases by:	
Actual - Counterfactual:		50%	100%
	(1)	(2)	(3)
Sacrifice Effect on FDB Counties ($\beta_{FDB} < 0$)			
$\Delta(\beta_{FDB})$	3.46%	4.79%	5.84%
Protection Effect on FDB-protected Counties ($\beta_{Protected} > 0$)			
$\Delta(\beta_{Protected})$	1.74%	2.51%	3.15%
Overall Economy:			
Δ(Total Output)	0.06%	0.08%	0.11%

Note: (1) We collect β_{FDB} from running the regression $ln(Output)_{icpt} = \alpha + \beta_{FDB} * \text{FDB}_{icpt} + \gamma_{pt} + \eta_t + \lambda_c + \epsilon_{icpt}$, where FDB_{icpt} is a dummy that equals 1 if the county is an FDB-county, and 0 if not, γ_{pt} is province-year fixed effect, η_t is time fixed effect, and λ_c is city fixed effect; (2) We collect $\beta_{Protected}$ from running the regression $ln(Output)_{icpt} = \alpha + \beta_{Protected} * \text{FDB-Protected}_{icpt} + \gamma_{pt} + \eta_t + \lambda_c + \epsilon_{icpt}$, where $\text{FDB-Protected}_{icpt}$ is a dummy that equals 1 if the county is an FDB-protected county, and 0 if not; (3) The coefficient in Column (1) is the same as the coefficient in Column (3) in Table 16 and Table 18.

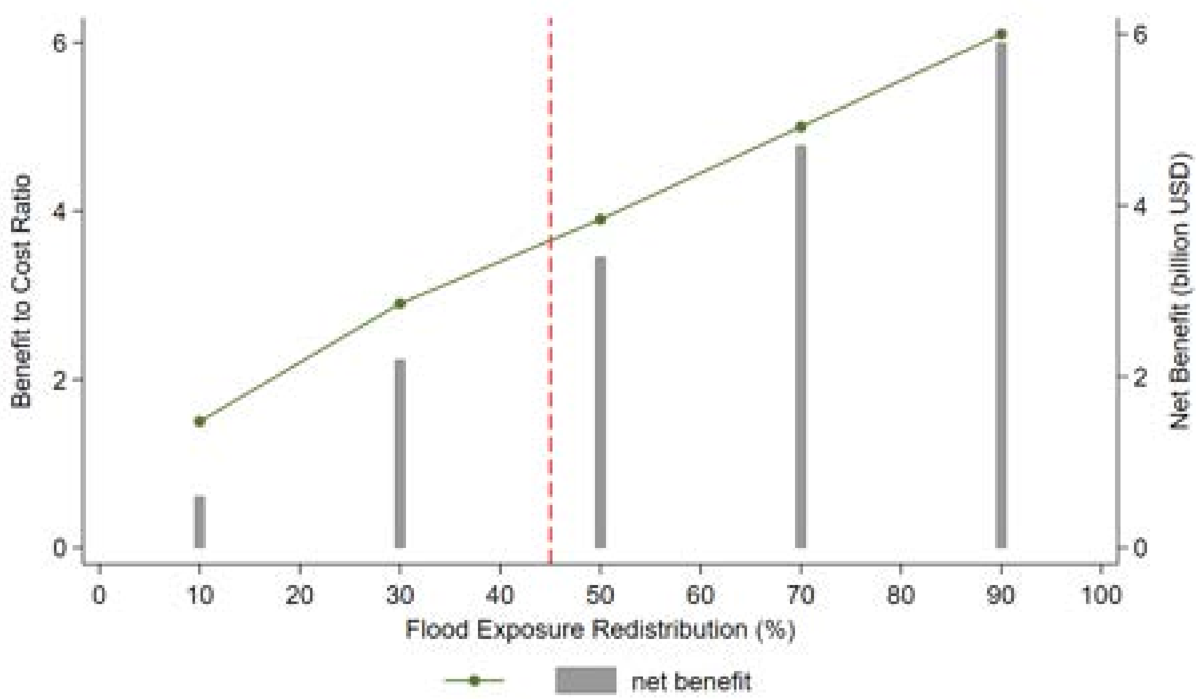


Figure 17: Benefit to Cost Ratio

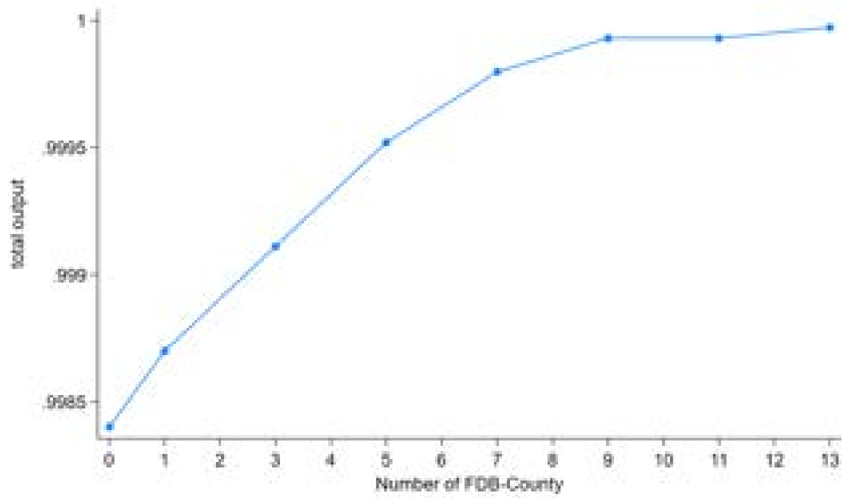


Figure 18: Counterfactual Practice: Successively Adding Counties

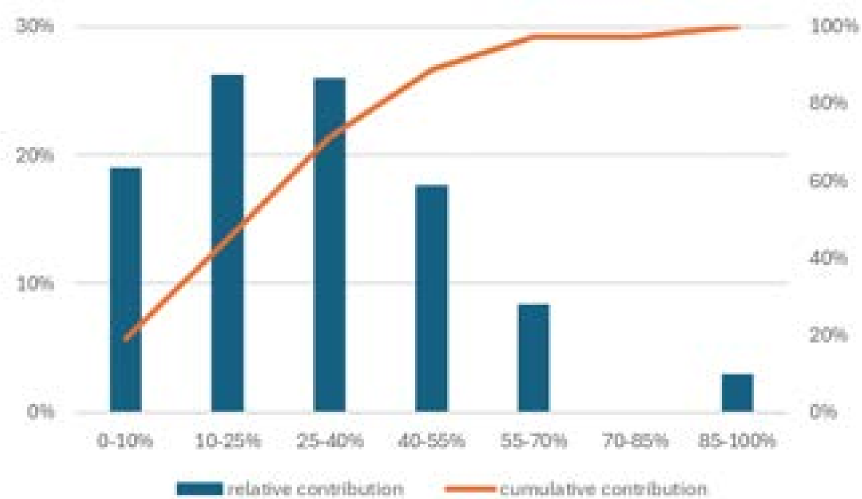


Figure 19: Relative Contribution of Different Productivity Groups

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A Appendix

A.1 Example of FDB Implementation (Mengwa FDB)

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.

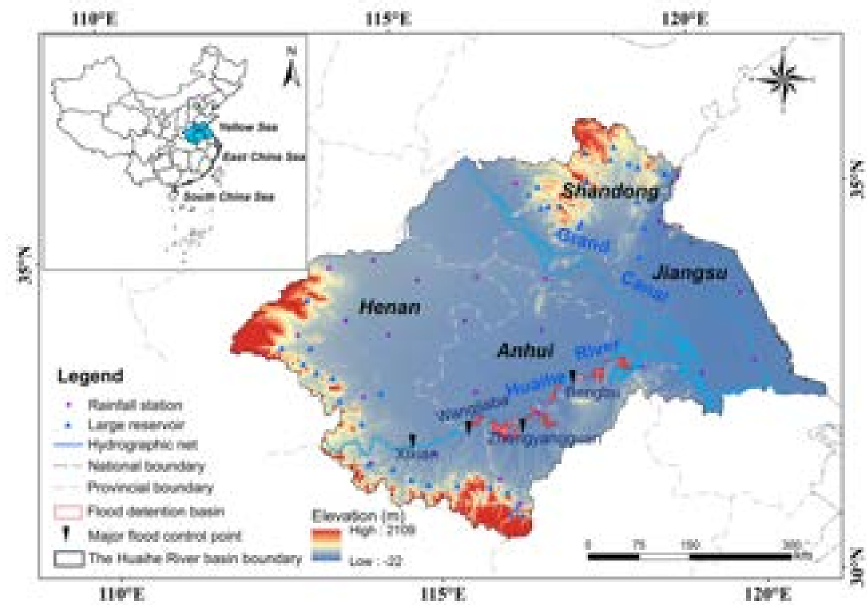

Figure A1: Wangjiaba Location (Source: Zhang and Song 2014)

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 A2: Pre and Post Detention of Wangjia Dam (Source: NetEase Media)

A.2 Global Flood Database

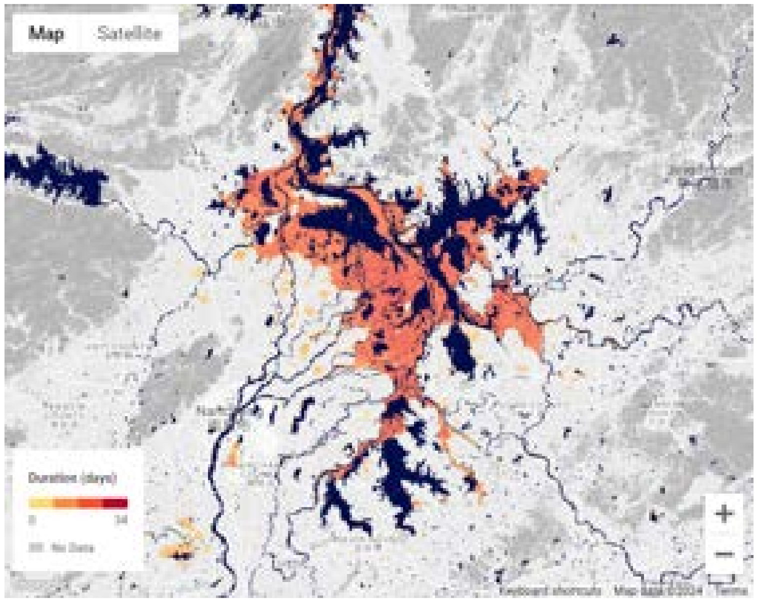

Figure A3: An Illustrative Example of Global Flood Database

A.3 Proof of Proposition 1

Given flood event $\mu = \{\tau_s, \tau_p\}$, we can rewrite the investor's optimization problem in state-contingent form:

$$\max_{c_0, a_s, a_p, b, c_1(\mu)} c_0 + \beta \mathbb{E}_\mu c_1(\mu)$$

$$s.t. \quad c_0 + \sum_{i=s,p} a_i + b = W$$

$$c_1(\mu) = \sum_{i=s,p} (1 + r_i(\mu)) a_i + (1 + r_f) b$$

The first-order conditions of the optimization problem yields the optimal asset positions $\{a_i\}_{i=s,p}$:

$$\sum_\mu Pr(\mu)[1 + r_i(\mu)] = 1 + r_f$$

where the actual investment returns $r_i(\mu)$ are determined by intrinsic capital productivity in the local area $\bar{r}_i$ and flood damage under event μ:

$$r_i(\mu) = \bar{r}_i - FloodDamage(\mu)$$

Plugging the actual investment return expressions into the Euler equation yields:

$$\bar{r}_i - r_f = \sum_{\mu} Pr(\mu) FloodDamage(\mu)$$

Assume that the county-specific events τ_i are independently distributed, then we get the pricing functions for county-specific assets $\{a_i\}_{i=s,p}$ are given by:

$$\bar{r}_i - r_f = p_i d \tag{16}$$

The intrinsic capital productivity of county i is given by the following optimization problem:

$$\max_{k_i} \quad z_i k_i^{\alpha} - \bar{r}_i k_i$$

Combined with market clearing conditions $k_i = a_i$, the intrinsic capital return $\bar{r}_i$ is given by:

$$\bar{r}_i = \alpha z_i a_i^{\alpha - 1}$$

Plugging it into equation (21), it yields:

$$a_i = \frac{\alpha z_i}{r_f + p_i d}^{\frac{1}{1-\alpha}}$$

Consider a FDB policy that reallocates $dp > 0$ flood risk from protected county $dp_p = -dp$ to sacrificed county $dp_s = dp$. Assume that $\frac{z_p}{(p_p d + r_f)^{2-\alpha}} > \frac{z_s}{(p_s d + r_f)^{2-\alpha}}$. The impacts on aggregate capital investments and investment gap can be described by:

$$\frac{d(a_p + a_s)}{dp} = \frac{d}{1-\alpha}\left[\frac{\alpha z_p}{(r_f + p_p d)^{2-\alpha}}^{\frac{1}{1-\alpha}} - \frac{\alpha z_s}{(r_f + p_s d)^{2-\alpha}}^{\frac{1}{1-\alpha}}\right] > 0$$

$$\frac{d|a_p - a_s|}{dp} = \frac{d}{1-\alpha}\left[\frac{\alpha z_p}{(r_f + p_p d)^{2-\alpha}}^{\frac{1}{1-\alpha}} + \frac{\alpha z_s}{(r_f + p_s d)^{2-\alpha}}^{\frac{1}{1-\alpha}}\right] > 0$$