Government and Nature: Evidence from the Distribution of Flood Damages in China

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Abstract

Can governments address climate threats by deliberately redistributing damages across space? We study the world's largest flood-damage reallocation program, the Flood Detention Basins (FDB) policy in China, which designates over 30,000 km^2 of rural land as temporary flood storage zones. During severe floods, the government can deliberately divert excess floodwater through gates and dams into FDBs to protect downstream cities. Combining a difference-in-differences design with a spatial general equilibrium model, we quantify both local and aggregate effects. FDB policy causes persistent local economic losses in FDB-designated counties: an 11 percent decline in firm entry and an approximately 10 percent reduction in nighttime light intensity. Using a spatial model with trade linkages among FDB-designated counties, FDB-protected cities, and other regions, we find that the policy increases total output by 0.24 percent (equivalent to 15 billion USD). When migration frictions are relaxed, aggregate gains double but inequality between rural FDB areas and protected cities widens. Our results reveal the trade-off between efficiency and equity in deliberate damage reallocation.

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1 Introduction

You are to bring into the Ark two of every kind...to keep them alive with you.

— Genesis 6:20

The story of Noah's Ark marks humanity's earliest attempt to make decisions in the face of catastrophic flooding and the inevitable choice of who will be saved and who will suffer. That ancient dilemma has now become central to modern disaster management. As climate change intensifies, governments confront a similar challenge: how to distribute environmental damages when universal protection is not feasible.

Floods already threaten more than 1.8 billion people worldwide, and the frequency of severe floods is projected to double across about 40 percent of the Earth's land surface by 2050 (Arnell and Gosling 2016; Tellman et al. 2021). A key lesson from the disaster literature is that losses are shaped not only by hazard exposure but also by institutions and policies (Kahn 2005). As with many environmental policies that create winners and losers (e.g., He et al. 2020; Taylor and Druckenmiller 2022), flood management interventions have uneven distributional effects. Dams and levees, for example, generate asymmetric impacts on upstream and downstream regions along a river (Duflo and Pande 2007). In managing floods, governments face the challenge of whether to concentrate damages in less economically productive areas in order to protect larger populations or key centers of economic activity. Such spatial redistribution of damages raises important trade-offs between efficiency and equity.

In this paper, we study a flood management policy that redistributes flood risk and damage and thus creates both winners and losers: Flood Detention Basins (FDBs), the last-resort instrument in flood control. During severe floods, when reservoirs reach capacity, governments divert floods into FDBs, typically located in low-lying areas, to protect broader regions from catastrophic damage. Outside of flood events, these FDB areas revert to regular economic activities. An example of an FDB is the Birds Point-New Madrid Floodway in Missouri, the United States, which is designed to "lower flood stages upstream and adjacent to the floodway during major flood events", according to the Army Corps of Engineers.[1]

[1]The Birds Point-New Madrid Floodway in Missouri is engineered to divert up to 550,000 cubic feet per second from the Mississippi River during an extreme flood event.

China operates the world's largest Flood Detention Basin (FDB) program. In 2000, the central government launched the national *Flood Control Law* and designated 98 basins, which are largely located in rural counties, to protect downstream urban areas during severe floods. These designated FDBs cover more than 30,000 km^2 and house a resident population of over 15 million. Since the policy announcement, FDBs have been activated nine times to absorb excess floodwater. Using a satellite-based flood dataset (Tellman et al. 2021), we construct county-level proxies to measure flood exposure and find that the size of flood inundation in counties with FDBs is over 45 percent larger compared to protected counties.

Two features make China an especially compelling case for analysis. First, the country faces exceptionally high flood exposure: more than 395 million people are at risk, and a substantial share of economic activity is concentrated in flood-prone regions. As a result, floods generate considerable and persistent economic losses (Kocornik-Mina et al. 2020). Second, the FDB program is a large-scale, nationally coordinated policy that has been in place for more than two decades. This provides a unique opportunity to assess the long-term consequences of systematically redistributing floods across space and populations. Taken together, China's flood-management experience offers a reference point for other countries confronting the challenge of addressing floods in economically important regions.

This paper examines both the local and aggregate impacts of China's Flood Detention Basin (FDB) program by combining reduced-form evidence with a quantitative spatial model. Using a difference-in-differences design, we first estimate the economic losses experienced by FDB-designated counties. This approach allows us to measure the extent to which rural and economically vulnerable counties have been designated to bear disproportionate costs following the implementation of the FDB policy. We then develop a quantitative spatial model that captures trade linkages between FDB-designated, FDB-protected, and other counties. This framework allows us to quantify the benefits to protected regions and evaluate whether the redistribution of flood damages may yield a net gain in total output.

We find that FDB designation has a negative and persistent effect on local economic development. On average, designation significantly reduces annual nighttime light intensity by approximately 10 percent. Based on the estimated elasticity of GDP with respect to night-

https://www.mvm.usace.army.mil/Missions/Emergency-Operations/Birds-Point-New-Madrid-Floodway/

time lights (around 0.3; Henderson et al. 2012, Martinez 2022), this corresponds to an annual GDP loss of roughly 3 percent. Our results are also robust to alternative control groups and alternative difference-in-differences estimators (De Chaisemartin and d'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021; Gardner, 2022), and the estimate is consistent with findings from hydrological studies (e.g., Wang et al. 2021). Event studies confirm parallel pre-trends and document lasting post-treatment declines. Similar to Assunção et al. (2022), we also detect spillover impacts beyond the direct policy effect: neighboring counties bordering FDB-designated counties experience significant output losses, with the magnitude of the effect diminishing with distance from the basin boundary. Together, these findings indicate that the FDB policy imposes not only persistent costs on designated counties but also spillover costs on their contiguous neighbors.

A key challenge in interpreting these results is the potential endogeneity of FDB site selection. One might worry that counties with weaker economic prospects were chosen to host basins. To address this concern, we exploit the fact that the *Flood Control Law* emphasizes only geographical criteria for site selection and suggests that FDBs should be located in low-lying areas hydrologically suited for absorbing floodwater. Our linear probability model further supports the government's claim and shows that FDB designation is significantly associated with geographical factors but not with economic characteristics.

To investigate the mechanism behind the observed declines in local economic activity, we exploit the 2010 policy change in which the government added 20 counties to the FDB list. This policy change provides a quasi-experimental setting to examine how newly designated areas respond to increased flood risk. We find strong evidence that increased flood risk discourages investment. Following designation, total firm entry in newly added counties has declined by about 11.5 percent, with a larger decline of 14.3 percent among large manufacturing firms (turnover above 3 million RMB). These results are consistent with Jia et al. (2022) and Balboni et al. (2023) who show that firms adjust location choices in response to flood risk. We then turn to migration as another possible channel. Unlike prior studies that document migration responses to flooding (e.g., Hornbeck and Naidu 2014), we find no evidence of significant outflows from FDB counties after designation, likely due to mobility restrictions in China. Taken together, the evidence indicates that firm responses are the

primary driver of the persistent economic costs caused by FDB designation.

We then develop a spatial general equilibrium model to quantify the broader consequences of the FDB policy. Following Fajgelbaum et al. (2019) and Jia et al. (2022), we model manufacturing goods as tradable across regions, with firms making entry decisions based on ex-ante flood-risk expectations. When floods occur, firms experience productivity losses. The model captures three key mechanisms: (1) *the sacrifice effect*, which refers to direct economic losses borne by FDB-designated counties; (2) *the protection effect*, which refers to flood protection benefits accruing to downstream urban centers; and (3) *market-based spillover effects*, which refers to the general equilibrium effects across all regions through trade linkages. For the quantitative implementation, we calibrate the model to match county-level economic characteristics between 2000 and 2010. The model successfully replicates untargeted moments such as capital investment and employment for manufacturing firms. We then construct counterfactual scenarios in which FDBs are absent. Based on our empirical estimates and hydrological simulations, we reallocate approximately 45 percent of the additional floodwater absorbed by FDB-designated counties to downstream FDB-protected counties, primarily located in urban areas. The spatial redistribution of floods changes the output in FDB-designated and FDB-protected through productivity effects. These output changes then propagate through trade linkages and leads to general equilibrium effects across other counties. We compare the equilibrium output under the actual FDB policy with that in a counterfactual scenario without FDBs.

We obtain four main findings. First, our quantitative results indicate that the FDB policy yields positive aggregate gains: total output increases by approximately 0.24 percent, equivalent to about 15 billion USD in 2010. Second, despite these aggregate gains, the policy produces pronounced distributional effects. FDB-designated counties experience output losses of nearly 1 percent (*the sacrifice effect*), while FDB-protected counties enjoy gains exceeding 2.5 percent (*the protection effect*). Other regions, although not directly exposed to flooding, experience modest negative spillovers due to business-stealing effects from urban centers (*the market-based spillover effect*). Third, when migration frictions are relaxed, workers reallocate from flood-prone basins to safer and more productive urban areas. As a result, the aggregate output gain doubles, reaching roughly 37 billion USD in 2010. However,

greater labor mobility also exacerbates rural–urban inequality, as the output gap between protected and basin counties widens further. Fourth, when we incorporate projected increases in flood risk driven by climate change, the aggregate benefits of the FDB policy rise sharply with risk intensity. This finding suggests that China's FDB system plays an important role in strengthening economic resilience to future floods.

This paper makes three contributions. First, we identify a previously less studied source of disaster-related costs. Paradoxically, a policy designed to reduce aggregate flood damage may itself impose substantial economic losses on particular regions. We find that the costs borne by FDB-designated counties are comparable to, or even exceed, those caused by major hurricanes in the United States (Strobl 2011; Hsiang and Jina 2014). While previous studies have primarily examined the realized impacts of natural disasters in both developing and developed settings (Strobl 2011; Cavallo et al. 2013; Hsiang and Jina 2014; Elliott et al. 2015; Desmet et al. 2021; Patel 2023; Balboni et al. 2025; Ficarra and Mari 2025), we show that the government's deliberate redistribution of flood damages can itself generate large and persistent economic costs.

Second, our analysis contributes to the literature on adaptation to climate change (e.g., Fried 2022; Cruz and Rossi-Hansberg 2024) by providing causal evidence on adaptation to climate risk and by quantitatively assessing the resulting general equilibrium effects. Exploiting the quasi-experimental variation generated by the FDB policy, we show that greater flood risk discourages investment and firm entry, particularly among large manufacturing firms, consistent with Jia et al. (2022) and Balboni et al. (2023). We also find little evidence of population migration, which reflects how China's institutional mobility constraints limit household adaptation (Boustan et al. 2012; Hornbeck and Naidu 2014; Gröger and Zylberberg 2016; Boustan et al. 2020). In our counterfactual analysis, we show that the net output gain increases when migration constraints are relaxed. This finding is consistent with Au and Henderson (2006), Tombe and Zhu (2019), and Ma and Tang (2020), who demonstrate that easing migration restrictions raises aggregate output and facilitates the reallocation of labor toward more productive urban centers.

Finally, our work connects the study of disaster management to the broader discussion on the distributional and aggregate effects of environmental and infrastructure policies. Prior

research shows that such interventions often generate spatially heterogeneous impacts: upstream versus downstream (He et al. 2020), within watersheds (Taylor and Druckenmiller 2022), or between regions affected by dams and sea walls (Duflo and Pande 2007; Hsiao 2023; Balboni 2025). We extend this literature by quantifying both the local trade-offs and the general equilibrium consequences of redistributing flood damages. Our findings reveal that while the FDB policy enhances aggregate output, it widens inequality between protected urban centers and rural counties, consistent with evidence that adaptation infrastructure and environmental regulation can produce uneven regional outcomes. The FDB policy provides new evidence about flood management from a developing economy and illustrates the fundamental trade-off between efficiency and equity in disaster management.

This paper is structured as follows. Section 2 provides an overview of the research background and introduces the data. Section 3 uses a difference-in-differences approach to investigate economic costs for FDB counties. Section 4 estimates the aggregate impacts of the FDB policy using a spatial general equilibrium model, and Section 5 concludes.

2 Background and Data

2.1 Flood Detention Basins

Flood Detention Basins (FDBs) function as last-resort mechanisms to absorb excess water once reservoirs and levees reach capacity. During severe flood events, water is deliberately diverted into these designated basins to mitigate downstream flooding and protect urban areas. When upstream flooding threatens to cause significant damage downstream, the government activates FDBs to temporarily store surplus water. In this process, floodwater is released into the basins through control gates and dams. After the flood peak passes, the retained water is gradually discharged back into river channels.

A well-known example is the Birds Point–New Madrid Floodway in Missouri, authorized under the *Flood Control Act of 1928* to divert water from the Mississippi River during major floods.[2] Comparable systems also exist in Europe. The Odenkirchen flood retention basin on

[2]https://www.mvm.usace.army.mil/Missions/Emergency-Operations/Birds-Point-New-Madrid-Floodway/

the River Niers in Germany was built approximately six decades ago in response to a severe flood event (Haselsteiner and Mottner 2022), and the Jonenbach flood protection project in Switzerland was launched in 2004 as a response to repeated flooding in the region[3]. These examples demonstrate how detention, diversion, and controlled flooding are integrated into broader flood management strategies alongside conventional levees and reservoirs.

2.2 China's Flood Detention Basin Policy

China is among the countries most exposed to flooding worldwide, with nearly 400 million people at risk annually. (World Bank 2021; Rentschler et al. 2022). From 2000 to 2017, floods caused over USD 150 billion in economic losses, according to EM-DAT. Severe flood events are expected to become more frequent in China (Arnell and Gosling 2016). Importantly, China's most economically significant regions, such as the Yangtze and Huai River basins, face severe and recurrent flood risk.

China's Flood Detention Basin (FDB) program is the largest and most systematic of its kind worldwide. Its scale and scope make it a unique case for understanding how active flood management strategies shape local economies as well as national aggregate development. Table B2 offers an overview of the FDBs in China's major river basins in 2000 and 2010. In 2000, the Chinese government passed the *Flood Control Law of the People's Republic of China*, its first legislation dedicated to flood management. The law designated 98 detention basins in 96 counties, covering over 30,000 km^2 (about 0.3% of China's land area) and directly affecting more than 15 million residents. The stated purpose was to "safeguard the interests of pivotal regions." In 2010, the Ministry of Water Resources revised the earlier law in the *National Flood Detention Basin Construction and Management Plan*. Under this new plan, 13 FDBs were added and 12 were removed. Consequently, the specific counties classified as FDB counties changed, with 20 new additions to the list and 10 removed.

[3]https://www.zh.ch/de/news-uebersicht/medienmitteilungen/2004/06/146_spatenstich_jonenbach.html

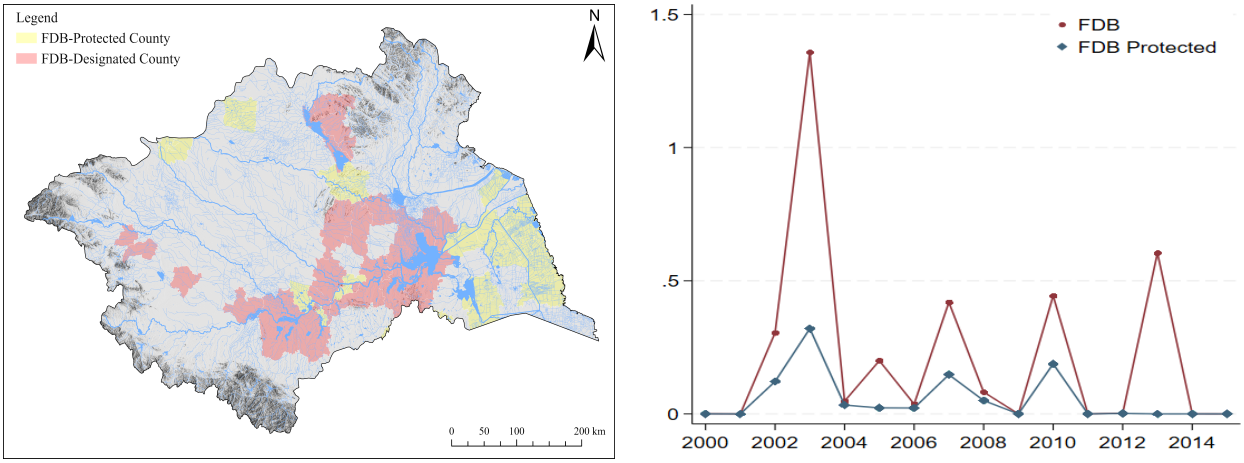
Selection of FDBs

The selection of FDBs is determined by the central government and is guided primarily by geographical indicators, making the policy plausibly exogenous to local economic conditions and alleviating concerns about local political selection. According to the 2000 *Flood Control Law* launched by the Ministry of Water Resources, FDBs must be located in "low-lying lands that are hydrologically suitable for temporary storage of floodwater." Hydrology research similarly emphasizes the role of elevation and topography in optimizing basin placement (e.g., Mays and Bedient 1982; Bennett and Mays 1985; Taur et al. 1987). In Table B4, we examine the determinants of FDB designation using a linear probability model. The results indicate that hydrological and geographical factors are strong predictors of selection, with lower-lying counties significantly more likely to host an FDB. By contrast, proxies for local socioeconomic development, such as average nighttime lights in 1995-2000, are not significantly related to FDB designation. In Table B3, we show the descriptive statistics of FDB-designated counties, FDB-protected counties, and other counties. We find that, while FDB-designated counties are less populated and host fewer firm activities than FDB-protected counties, they are more populated and exhibit comparable levels of firm activity relative to other counties. This pattern is not surprising. FDB-designated counties are typically located along major rivers and benefit from lower transportation and trade costs. Many of them are also situated in historically wealthier regions (e.g., southern China) with higher levels of economic development and better infrastructure. Nonetheless, unobserved factors beyond our data may also have influenced the government's decisions. We will return to this concern when we discuss our identification strategy in Section 3.3.

Redistributing Floods under the FDB Policy

To illustrate how the FDB system operates in practice, we begin with the Huai River Basin, one of the regions in China most prone to flooding and with a long history of flood management interventions. As shown in Panel A of Figure 1, FDB counties are located upstream, while downstream urban areas are designated as FDB-protected counties. During severe floods, water can be diverted into FDB counties, thereby protecting downstream

urban areas from extensive inundation. This institutional design explicitly creates winners (protected cities) and losers (FDB counties).



(a) FDB-designated Counties and FDB-protected Counties in Huai River Basin

(b) Flood Exposure (unit: days) in FDB-designated and FDB-protected Counties

Figure 1: FDB and FDB Protected Counties

Note: (1) An FDB-designated county refers to a county that contains a government-designated Flood Detention Basin (FDB), whereas an FDB-protected county is one that receives flood protection from its upstream FDB county during severe flood events; (2) Panel A illustrates the spatial distribution of FDB counties and FDB-protected counties in the Huai River Basin, while Panel B compares the flood exposure of all FDB counties and all FDB-protected counties across China; (3) Flood exposure refers to the average number of flooding days experienced by non-permanent water pixels within a county; (4) Flood data are sourced from Tellman et al. (2021), and the detailed construction of the flood exposure measure is described in Appendix A.1.

We then turn to validation exercises to show that this institutional logic is reflected in the data. Panel B of Figure 1 shows that flood exposure is substantially higher in FDB counties than in protected counties. In years with little or no flooding, exposure levels are similar across the two groups, but during major flood years the gap widens sharply, consistent with the policy's design to divert water only in severe events as a measure of last resort. Table B5 confirms this pattern: fixed-effects regressions show that the total size of flood inundation is about 45% larger in FDB counties than in protected counties. Consistent with these results, Table B.4 presents simulations from a hydrodynamic engineering model that also show greater exposure in FDB counties. The magnitude is also similar to what we estimate using fixed-effects regressions.

Implications for Local Residents

During the flood detention period, residents are temporarily relocated to neighboring counties. Unlike the case of building reservoirs, the government does not force residents in FDB counties to leave. Although the government may encourage local residents to relocate, the financial incentives provided are limited. According to a survey conducted in a Flood Detention Basin, 73% of local residents are dissatisfied with the current migration incentive scheme. We present more empirical findings about migration in Section 3.

Compensation for households in FDB counties during flood activation is limited. *The 2000 Temporary Measures for the Use of Compensation in Flood Storage and Detention Areas* suggested that up to 70% of losses from flood detention should be reimbursed, but the rules for eligibility are vague. In practice, compensation is uneven: households receive no reimbursement for livelihood losses if assets are deemed "relocatable," yet the criteria for what counts as relocatable remain undefined. In a recent example, when Zhuozhou was used for flood storage in 2023, families of victims received about $3,000 per fatality, compared to an estimated statistical value of life in China of roughly $690,000 in 2019 (Cao et al. 2023).

2.3 Data

Flood Detention Basins and Protected Regions. The Ministry of Water Resources announced the official list of FDBs in 2000 and revised it in 2010. We define counties containing these basins as FDB-designated counties, with the original policy documents provided in Online Appendix B.1. According to the *Flood Control Law*, FDBs are intended to safeguard large and economically important regions by diverting floodwater into designated basins. Since no official list of protected counties exists, we construct one based on government guidelines. Specifically, we identify all counties neighboring an FDB-designated county and overlay them with river networks and flow directions to determine which are downstream. The *Standard for Flood Control*, issued by the Ministry of Housing and Urban-Rural Development, outlines the criteria for cities to qualify for protection from severe floods (e.g., those with a 100-year return period), including requirements related to population size and economic level. Using these criteria, we can identify the counties that are protected under

the FDB policy.

Nighttime Light Intensity. A key input for our analysis is a consistent measure of local economic activity. We rely on nighttime light intensity from PANDA-China as the primary proxy because it offers broad spatial coverage, a long-run time series, and alleviates concerns about the reliability of official GDP statistics from the National Bureau of Statistics (NBS) (Martinez, 2022; Gong et al., 2025). Compared to other nighttime light datasets such as DMSP-OLS (available only from 1992 to 2013, with saturation and blooming problems) and VIIRS (available only since 2012), PANDA-China offers three advantages. First, it provides the longest consistent annual series for China, spanning nearly four decades, which is crucial for analyzing both the 2000 and 2010 FDB reforms. Second, the data are temporally consistent and overcome sensor breaks that cause spurious fluctuations in earlier products. Third, validation exercises show that PANDA-China exhibits stronger correlations with socioeconomic indicators such as GDP and built-up areas than alternative nightlight datasets, while maintaining high accuracy.

Floods. We use a global flood dataset from Tellman et al. (2021), which comprehensively tracks floods worldwide from 2000 to 2018, and we restrict the sample to events occurring within China. The database records 189 flood events in China and provides pixel-level information (30m $\times$ 30m) on the number of days each pixel is flooded. It also identifies permanent-water pixels, defined as areas with persistent surface water presence.

Using these data, we construct a county-level measure of size-adjusted flood exposure. We first exclude permanent-water pixels, and then for each flood event we record the number of days that each pixel within a county was inundated.[4] Summing these flooded days across all non-permanent water pixels gives the total flood duration for the county. Finally, we divide this by the number of non-permanent water pixels in the county to obtain a size-adjusted flood exposure. This captures the average flood duration per pixel and allows us to compare counties with different land areas at risk. Full details of the construction are provided in Appendix A.1.

Firm-level Outcomes. Firm-level data come from the National Enterprise Credit In-

[4]Floods in the Global Flood Database are reported as event periods; to translate these into flood days at the pixel level, we use the duration information that records how many days each pixel was flooded during a given event.

formation Publicity System (NECIPS). NECIPS, administered by the State Administration for Market Regulation (SAMR), provides annual registration records for all Chinese enterprises from 1960 to 2023. It reports key information such as establishment date, ownership type, and geographical location, which allows us to track firm entry at the county level, including in counties designated as Flood Detention Basins (FDBs).

Population Data. We use two proxies to measure population: county-level registered population and county-level floating migration. The county-level registered population refers to individuals officially recorded under a county's household registration system, regardless of their actual residence. These data are sourced from the County Statistical Yearbooks of the National Bureau of Statistics (NBS). Additionally, we follow the approach outlined in Chen et al. (2022b) to construct the county-level floating migration population. We use individual-level micro census data drawn randomly from the 2000, 2005, 2010, and 2015 census, specifically using 1%, 20%, 3.30%, and 1% samples, respectively. Details on how we construct the county-level outmigration ratio can be found in Appendix A.2.

Other Socio-economic Outcomes. Other county-level data are collected from the County-level Statistical Annual Yearbooks from 1999 to 2022. The National Bureau of Statistics (NBS) conducts a 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 county-level output disaggregated by agriculture, manufacturing, and services, as well as indicators such as the number of large manufacturing firms and their aggregate revenue.

Geographical Data. Elevation and slope data are drawn from the NASA ASTER Global Digital Elevation Model (GDEM), which covers 99% of the Earth's landmass between 83°N and 83°S. This allows us to compile detailed elevation measures for all counties and towns in China. Precipitation data come from the Global Surface Summary of the Day (GSOD), based on the Integrated Surface Hourly (ISH) dataset. GSOD provides daily records from more than 9,000 stations worldwide, with comprehensive coverage since 1973. From these data, we construct mean monthly precipitation at the county level. River data are from the National Fundamental Geographic Information System (NFGIS).

3 Evaluating Local Costs for FDB-designated Counties

The FDB policy simultaneously creates both winners and losers. FDB-protected counties benefit from reduced exposure to severe flooding, whereas counties hosting FDBs (FDB-designated counties) face heightened flood risk. Quantifying the local costs borne by FDB-designated counties is central to evaluating the overall efficiency and equity implications of the policy. Before turning to the aggregate effects in our general equilibrium model, we begin by quantifying the direct economic impact of FDB designation on FDB-designated counties.

Our empirical analysis proceeds in two steps. We first estimate the causal impacts of FDB designation on local economic activity using a difference-in-differences design. This approach allows us to compare outcomes in designated FDB counties with those in otherwise similar counties that were not selected into the FDB list. We then examine the channels through which these effects take place. Specifically, we focus on sectoral composition, firm entry, and population dynamics to understand how increased flood exposure in FDB counties translates into persistent economic losses.

3.1 Empirical Strategy

Empirical Strategy. We first employ a traditional two-way fixed-effects (TWFE) approach to estimate the impact of the policy on FDB counties. The treatment is defined as a county being designated by the government to host an FDB. In 2000, 98 basins were designated as FDBs across 96 counties, and in 2010, an additional 20 counties were added to the list.[5] Accordingly, a county is considered treated from the year it was designated as an FDB county. We first use the standard Two-Way-Fixed-Effects (TWFE) approach to investigate the impact of FDB policy. The regression specification takes the form of:

$$Y_{ikt} = \alpha + \beta \times FDB_{ikt} + \gamma_i + \lambda_{kt} + \epsilon_{ikt},$$

[5]There are 20 counties that were designated as FDBs in 2000 but removed from the policy list after 2010. We exclude these counties so that, in our analysis, all remaining FDB counties are consistently designated as FDB counties over time.

where Y_{ikt} measures the outcome of interest in county i, province k, and year t, the treatment variable FDB_{ikt} is a dummy variable that equals one if county i has been designated as a FDB county before year t, and 0 otherwise. The coefficient β measures the impact of FDB designation on county-level outcomes. We include county fixed effects γ_i and year fixed effects in all regressions, and we show that our results are robust when including province-by-year fixed effects λ_{kt}. We cluster standard errors at the county level.

To test whether FDB-designated counties and our control counties have similar trends prior to the FDB designation, we estimate event studies of the form:

$$Y_{ikt} = \alpha + \sum_{\tau=-10, \tau \neq -1}^{10} \beta_\tau \times 1[t = \tau + T_{ik}^{FDB}] + \gamma_i + \lambda_{kt} + \epsilon_{ikt}.$$

In this specification, T_{ik}^{FDB} denotes the calendar year when county i was designated as an FDB county for the first time. β_τ represents differences in the outcome variables between the FDB counties and control counties in each year.

A few potential concerns arise in the standard TWFE approach. The first is that FDB designation may not be random, which could bias our estimates. As discussed in Section 2.2, although the government suggests that the FDB selection is decided by the geographical factors and our empirical results in Table B4 confirm the government's claim, there may exist unobserved selection criteria. For example, if governments are intentionally selecting counties of lower economic growth potential, we might expect a naive comparison between FDB and control counties would result in an upward bias of β. To address this concern, we use the DID estimator with matching weights (Arkhangelsky et al., 2021), which combines attractive features of traditional difference-in-differences (DID) with the method of synthetic control (SC) (Abadie et al., 2010). As in the SC approach, this approach balances treated and control units on pre-treatment outcomes and limits researcher discretion in estimating pre-trends (e.g., the choice of covariates, time periods, or deliberate choice of control units). This approach mitigates possible concerns noted by Roth et al. (2023) and generally outperforms standard DID in avoiding spurious significance (Arkhangelsky et al., 2021). We also implement alternative difference-in-differences estimators proposed by De Chaisemartin and d'Haultfoeuille (2020), Callaway and Sant'Anna (2021), and Gardner (2022). Our results

remain robust across specifications.

Constructing the Control Group. To avoid contamination of the control group, we impose several restrictions to ensure that the control group is comparable to FDB-designated counties. First, we exclude FDB-protected counties because they receive an opposite type of treatment: rather than facing policy-induced increases in flood exposure, they benefit from reductions in flood risk due to the protection provided by the FDB system.

Second, we address the concern that flood diversion may generate spatial spillovers. Neighboring counties can be indirectly affected if floodwater extends beyond FDB boundaries during detention periods. To mitigate potential bias arising from these spillovers, we exclude two additional groups of counties: (1) those adjacent to FDB counties, which may experience overflow flooding when basins are activated; and (2) those adjacent to protected urban areas, which may receive implicit protection. Figure 2 provides an illustrative example of the different categories of counties, while Figure 3 shows their actual geographical distribution.

After excluding these three types of counties in the first two steps, the remaining counties, which are neither directly targeted by the FDB policy nor exposed to potential flood spillovers, serve as our control group in the two-way fixed-effects (TWFE) analysis.

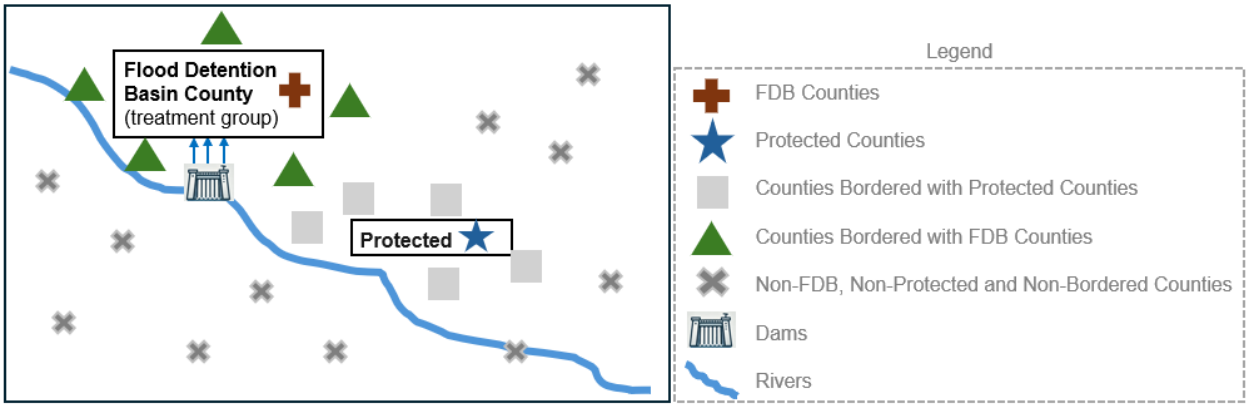


Figure 2: Illustrating the Control Group Design

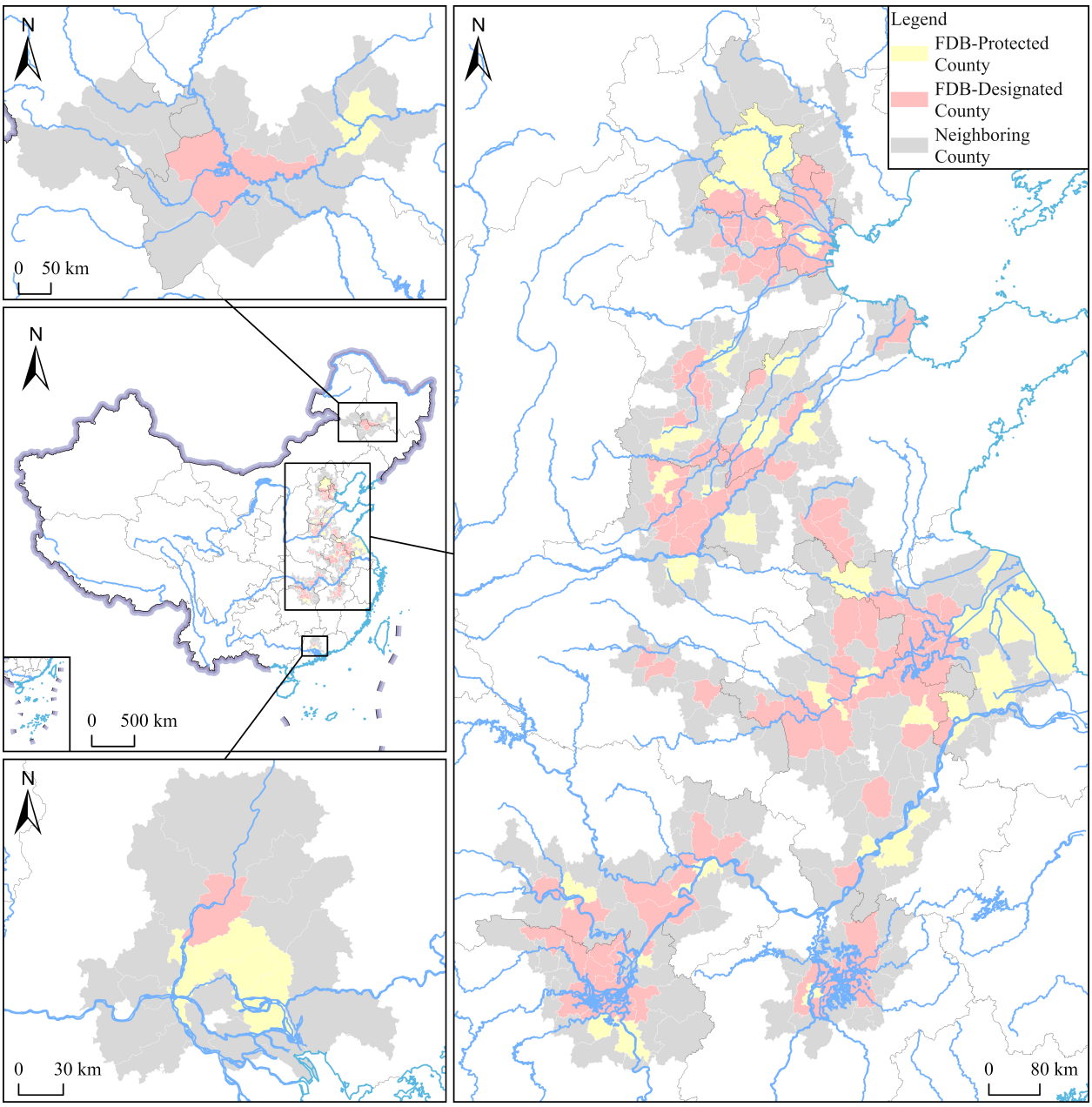


Figure 3: FDB-designated, FDB-protected, and Their Neighboring Counties

Note: An FDB-designated county (marked in color red) refers to a county that contains a government-designated Flood Detention Basin (FDB), an FDB-protected county (marked in color yellow) is one that receives flood protection from its upstream FDB county during severe flood events, while neighboring counties (marked in gray) are those bordered with FDB-designated or FDB-protected counties.

The first two steps yield a potential pool of comparable control counties. In the third step, we further weight the control group to ensure that the control group shares similar pre-treatment trends in the outcome variables. Differential pre-trends between FDB-designated

and control counties pose an important threat to identification, as the two groups might differ systematically in their baseline characteristics. To address this, we incorporate synthetic weights into the difference-in-differences design following Abadie et al. (2010) and Arkhangelsky et al. (2021), which balances pre-treatment outcomes between treated and control counties. In our main DID specification, we employ all three of these steps to the control group. Also, as shown in Section 3.2, our results remain robust when we redefine the control group using alternative sample constructions.

3.2 Main Results: Impacts on Nighttime Light

To quantify the economic impact on FDB counties, we examine the policy's effect on nighttime light intensity. We use nighttime lights as a proxy for economic activity for two reasons. First, high-quality county-level economic data are largely unavailable before 2000, which limits us to directly compare pre- and post-treatment outcomes. Second, satellite-based measures of nighttime luminosity provide a more reliable indicator of local economic activity in China, as shown in recent studies (e.g., Martinez, 2022; Gong et al., 2025).

Figure 4 presents the dynamic effects of the FDB policy on nighttime light intensity, estimated using both the standard TWFE model and the DID estimator with matching weights (Arkhangelsky et al., 2021). Before treatment, there is no statistically significant difference between treated and control counties, which suggests that treatment group and control group have similar trends before the FDB policy treatment. After the policy implementation, nighttime light intensity in FDB-designated counties declines persistently. Both TWFE and DID estimators show similar magnitudes and trajectories. And the consistency between the TWFE and DID estimates supports the robustness of our findings.

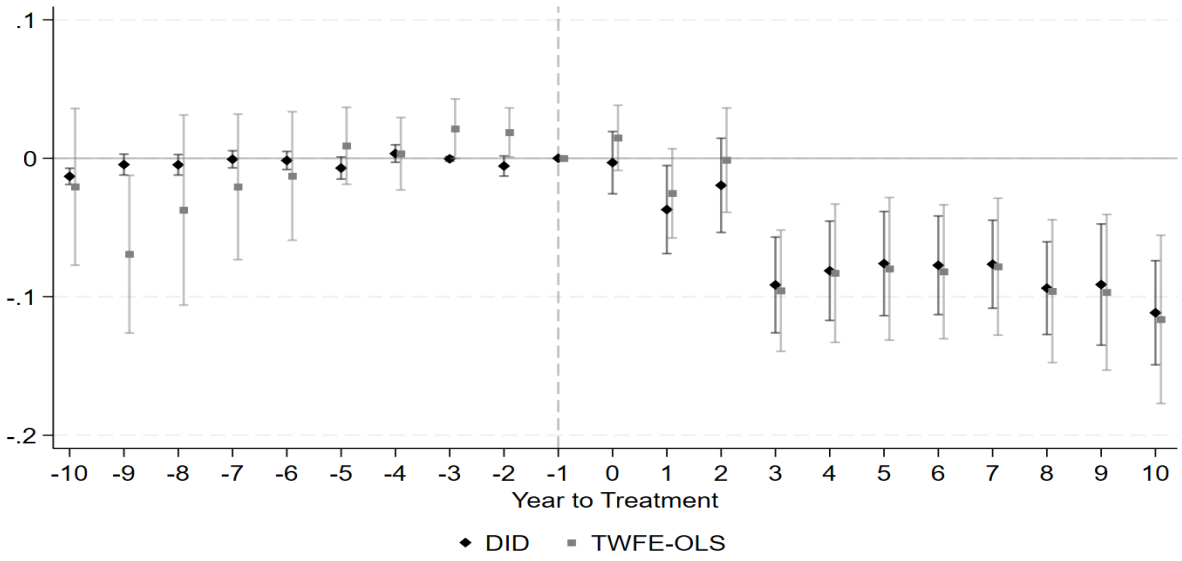


Figure 4: Effects of the Policy on Nighttime Light Intensity

Note: (1) The figure depicts the event study coefficients from TWFE and DID approach as described in Section 3.1; (2) Data: 1990-2020 Nighttime Light Intensity; (3) Outcome variable is the nighttime light intensity with Inverse Hyperbolic Sine (IHS) transformation; (4) Treatment is FDB designation: 96 counties were selected into the FDB list in 2000, while 20 counties were selected into the FDB list in 2010; (5) The construction of the control group is discussed in Section 3.1; FDB-protected counties and neighboring counties of FDB-designated and FDB-protected counties are excluded from the control group; (6) All regressions include county, year, and province-by-year fixed effects; (7) Standard errors are clustered at the county level; (8) 95% confidence intervals are plotted around point estimates.

In Table 1, we use both the TWFE approach and the Difference-in-Differences (DID) with synthetic matching weights to estimate the impact of the FDB policy on nighttime light intensity. In Panel B, we present our main results based on DID approach. Column (4) of Panel B in Table 1 suggests that, on average, the nighttime light intensity in FDB-designated counties decreases by 9.4 percent after the policy implementation. Based on elasticities of GDP with respect to nighttime lights (0.277 in Henderson et al. 2012, 0.296 in Martinez 2022, and 0.312 for China in Martinez 2022), this corresponds to an implied GDP decline of roughly 2.6-2.9 percent. These results align with hydrological simulations by Wang et al. (2021), which estimate comparable output losses in FDB-designated counties. We further demonstrate robustness to alternative control group selections and DID methods in Online Appendix C.1. Column (4) in Panel B of Table 1 presents a conservative estimate. Compared with Columns (1) and (3), the magnitude declines once we include province-

by-year fixed effects, which absorb province-specific time-varying shocks. Because FDB designations cluster within particular river basins and provinces (e.g., many FDBs located in Anhui Province are designed to protect downstream areas in Jiangsu Province), province-by-year dummies may absorb cross-province variation attributable to the policy and yield more conservative estimates of the policy's impact.

Table 1: Impacts of FDB Designation on Nighttime Light Intensity

Variables (in IHS)	Nighttime Light Intensity			
Panel A. Baseline Result	(1)	(2)	(3)	(4)
FDB	−0.197***	−0.068***	−0.215***	−0.077***
	(0.038)	(0.029)	(0.038)	(0.031)
Method	TWFE	TWFE	TWFE	TWFE
Variables (in IHS)	Nighttime Light Intensity			
Panel B. Main Result	(1)	(2)	(3)	(4)
FDB	−0.154***	−0.083***	−0.172***	−0.094***
	(0.023)	(0.017)	(0.022)	(0.019)
Method	DID	DID	DID	DID
For All Panels:				
Observations	72,943	72,943	65,038	65,038
Sample Period	1990-2020	1990-2020	1990-2020	1990-2020
Fixed Effects				
Year	Y	Y	Y	Y
County	Y	Y	Y	Y
Province × Year	N	Y	N	Y
Control Group	Baseline	Baseline	Neighbor Excluded	Neighbor Excluded

Note: (1) 'TWFE' represents the traditional two-way fixed effects estimation, while 'DID' represents the difference-in-differences estimation with synthetic matching weights (see Section 3.1 for detailed discussion); (2) Treatment is FDB designation: 96 counties were selected into the FDB list in 2000, while 20 counties were selected into the FDB list in 2010; (3) The 'Baseline' control group excludes protected urban areas, while the 'Neighbor Excluded' control group further excludes first-ring neighboring counties that border FDB counties and protected counties (see Section 3.1 for detailed discussion); (4) Outcome variables are with Inverse Hyperbolic Sine (IHS) transformation; (5) Standard errors are clustered at the county level; (6) *, **, and *** respectively indicates significance at the 10%, 5%, and 1% levels.

Overall, the costs borne by FDB counties are economically substantial. Paradoxically, this disaster-management policy, which is designed to mitigate flood damage, has generated economic losses comparable to, or even exceeding, those caused by major hurricanes in the United States (Strobl 2011; Hsiang and Jina 2014). This burden is particularly striking given that China as a whole grew at an average annual rate of around 10 percent between 2000 and 2010. During this decade of unprecedented national growth and rapid urbanization, FDB-designated counties, however, have been prevented from fully sharing in these gains. As these counties are intrinsically less developed, the FDB policy has further widened the inequality between urban and rural areas by concentrating the costs of national flood resilience on the most vulnerable regions.

Proximity-Based Spillover Effect. We next examine whether the FDB policy generates spillover effects on neighboring counties. During flood detention, diverted waters may extend beyond county boundaries and inundate nearby areas, creating what we term a proximity-based spillover effect. We test for this type of spillover for two reasons. First, if neighboring counties are affected, including them in the control group would bias our estimates, as discussed in Section 3.1. Second, we seek to identify the geographical range over which spillovers persist. If flood spillovers extend only to immediate neighbors, then we can safely exclude those counties and still have a valid control group. But if the spillover extends further, then our control group could be contaminated, because even those counties regarded as control units are partially affected.

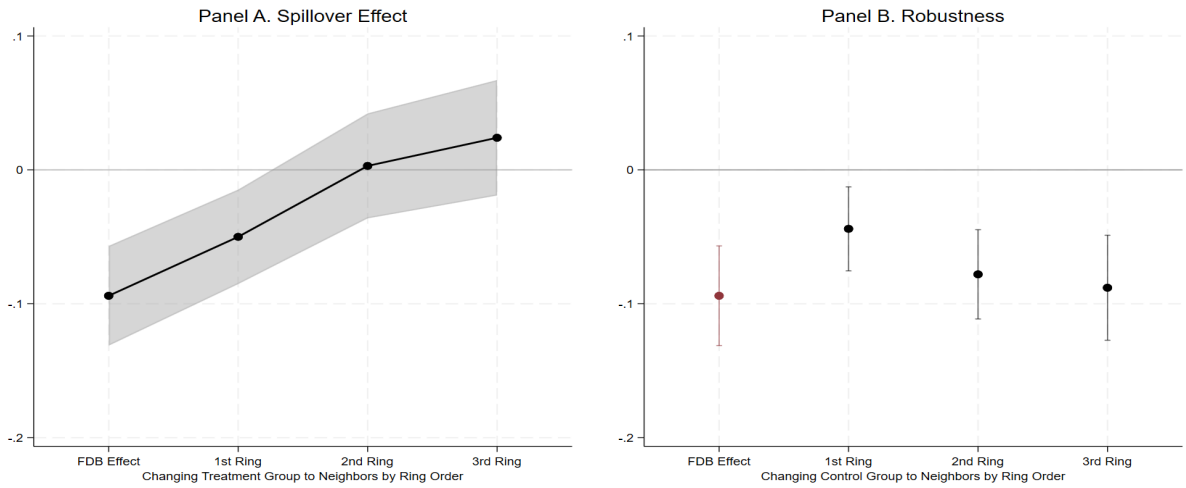


Figure 5: Proximity-Based Spillover Effects and Robustness with Alternative Control Groups

Note: (1) Panels A and B follow the same DID regression specification as Column (4) of Panel B in Table 1; (2) 'FDB Effect' represents the estimate from Column (4) of Panel B in Table 1; (3) '1st Ring' neighbors share a border with FDB counties, '2nd Ring' neighbors border the first ring, and '3rd Ring' neighbors border the second ring; (4) In Panel A, we test the proximity-based spillover effect by estimating the treatment effect of the FDB policy on neighboring counties of different ring orders; (5) In Panel B, we present robustness checks of the main analysis by changing the control group to first-, second-, and third-ring neighboring counties, respectively; (6) ATT of Panel A is reported in Table C5, and ATT of Panel B is reported in Table C1.

In Panel A of Figure 5, we classify counties into "rings" of proximity: first-ring neighbors share a border with FDB counties, second-ring neighbors border the first ring, and third-ring neighbors border the second ring. For each ring, we estimate the treatment effect of the FDB policy on those neighboring counties. The control group excludes FDB-designated counties, FDB-protected counties, and the corresponding ring(s) under analysis.[6]

Panel A of Figure 5 shows evidence of the proximity-based spillover effects: the FDB policy has a negative and statistically significant effect on first-ring neighboring counties. According to Column (2) of Table C5, nighttime light intensity in first-ring neighboring counties has decreased by about 5 percent following the policy implementation, which is roughly half the magnitude of the policy impact on FDB-designated counties. In contrast, the estimated effects for second- and third-ring neighbors are small and statistically insignifi-

[6]For example, when examining the impact on first-ring neighboring counties, second- and third-ring neighbors are excluded from the control group. Similarly, when examining the impact on second-ring neighbors, first- and third-ring neighbors are excluded.

cant. This pattern indicates that the FDB policy's adverse effects diminish with distance and already decays to non-significance for the second ring. Because first-ring neighbors are themselves negatively affected, they cannot serve as valid control units. Therefore, in Columns (2) and (4) of Table 1, we exclude first-ring neighbors from the control group. Table C3 reports the corresponding coefficients of Panel A in Figure 5.

Robustness. As an additional robustness check, we examine how alternative definitions of the control group affect our estimates. Neighboring counties of FDB-designated counties may be comparable in geography, natural endowments, and economic structure, and thus provide a possible counterfactual. We therefore replace the control group in Table 1 with counties belonging to different neighboring-ring orders. Panel B of Figure 5 reports these results. The first point estimate reproduces our main result from Column (4) of Panel B in Table 1, while the second restricts the control group to first-ring neighbors. As anticipated, the estimated effect becomes smaller. According to Column (2) in Panel B of Table C1, using first-ring neighboring counties as the control group yields a policy effect of –4.4 percent, which is roughly half the magnitude of our main estimate. That is because these counties themselves experience negative spillover effects, as we show in Panel A of Figure 5. When we instead use second- or third-ring neighbors as the control group, the results remain nearly identical to the baseline. These findings confirm that our estimates are robust to alternative control group definitions and that the spillover effects of the FDB policy are spatially limited.

We next assess robustness using alternative difference-in-differences estimators in Figure C2 and Table C2. While we view our preferred DID estimator with synthetic matching weights (Arkhangelsky et al., 2021) as best suited to our setting, we also apply the methods of De Chaisemartin and d'Haultfoeuille (2020), Callaway and Sant'Anna (2021), and Gardner (2022). Our results are robust across specifications.

Placebo Tests. In Figure C9, we implement three types of placebo tests: in-time, in-space, and mixed. In the in-time tests, we shift the treatment date forward by several years to assess whether our results are driven by temporal trends rather than the policy intervention. Consistent with the event-study analysis in Figure 4, we find no evidence that challenges the parallel trends assumption. In the in-space tests, we randomly assign treatment to units that are never treated, which allows us to evaluate robustness against spatial confounding.

The mixed placebo tests assign treatments to random units at random times. Across all specifications, the estimated effects are centered around zero, which indicates that the results are not driven by spurious temporal or spatial correlations.

3.3 Mechanisms

Having quantified the overall impact of the FDB policy on output in designated FDB counties, we next examine two potential mechanisms, changes in the composition of the local economy and population dynamics. These represent two key channels through which economies typically adjust to shocks. The first decade of the 21st century has witnessed rapid economic growth and structural transformation in China. We therefore investigate whether FDB counties have been constrained from fully participating in structural transformation and from shifting toward higher-value economic activities. We also examine population dynamics to assess whether individuals' location decisions respond to the FDB policy. Because detailed data are available only after 2000, our DID analysis focuses on the 2010 policy revision, which added 20 FDB-designated counties and provides a quasi-experimental setting for identifying these mechanisms.

Economic Activities

To assess whether FDB counties are hindered in achieving structural transformation from agriculture to manufacturing, we examine the policy's impact on output in those sectors.

Panel A of Figure 6 shows that manufacturing output in FDB-designated counties has declined within five years of the 2010 policy change, with the effect persisting over time and showing no signs of recovery. In contrast, agricultural output remains largely unaffected by the policy, as shown in Panel B of Figure 6. Columns (1) and (2) of Panel A in Table 2 report an economically significant decline in manufacturing output, ranging from approximately 10 to 20 percent across specifications. The effect remains economically large, though statistically weaker, when province-by-year fixed effects are included. This pattern aligns with the nighttime light results in Table 1 and confirms that the FDB designation leads to persistent and negative impacts on the manufacturing sector. Columns (3) and (4) of Panel

A in Table 2, however, show that the effect of the FDB policy on agricultural output is small and statistically insignificant. Anecdotal evidence in Online Appendix C.2.1 suggests that farmers have adapted to the FDB policy by cultivating more flood-resilient crops or relying on multiple harvests to offset temporary flood-induced losses.[7] Overall, these results indicate that the economic costs of the FDB policy are concentrated in the manufacturing sector and imply that FDB designation primarily constrains the manufacturing sector.

Given the larger decline observed in manufacturing output, we next examine firm dynamics to better understand the mechanisms behind this pattern. Columns (2) and (4) of Panel B in Table 2 show that FDB designation has significantly reduced new firm entry by 11.5 percent and the number of large manufacturing firms by 14.3 percent. Panels C and D of Figure 6 display a clear post-treatment downward trend, with no indication of pre-existing differences before the policy change. These results align with prior evidence that firms respond to heightened flood risk by changing their location decisions (e.g., Jia et al. 2022). Taken together, the evidence indicates that the FDB policy has led to a decline in the manufacturing sector in designated counties.

Discussions. While our baseline results attribute the decline in firm activity to the FDB policy, one potential concern is that other concurrent national or provincial initiatives could have contributed to similar trends. To strengthen the causal interpretation, we exploit the 2010 policy adjustment in which a small number of counties were removed from the FDB list. This policy change provides a useful validation test: if the observed effects indeed stem from FDB designation rather than from broader economic shocks, then counties removed from the list should experience opposite effects once the policy constraint is lifted.

Figure C10 reports the dynamic effects of FDB removal on firm activity. Panel A shows that the number of newly registered firms rises after removal, while Panel B shows a corresponding increase in the number of large manufacturing firms. In both cases, the patterns mirror those observed for newly designated counties in Table 2, with no visible pre-trends and persistent post-removal gains. This symmetry provides additional confidence that the

[7]Due to data limitations, we are unable to apply similar regression specifications to further decompose why the policy has no significant impact on the agricultural sector or to quantitatively assess farmers' adaptive responses. However, in Online Appendix C.2.1, we present supporting evidence from policy documents that outline government initiatives encouraging agricultural adaptation in FDB counties, as well as media reports confirming that farmers have indeed adjusted their production practices in response to the policy.

declines in manufacturing activity documented earlier are not driven by other contemporaneous policies, but are a direct consequence of FDB designation itself.

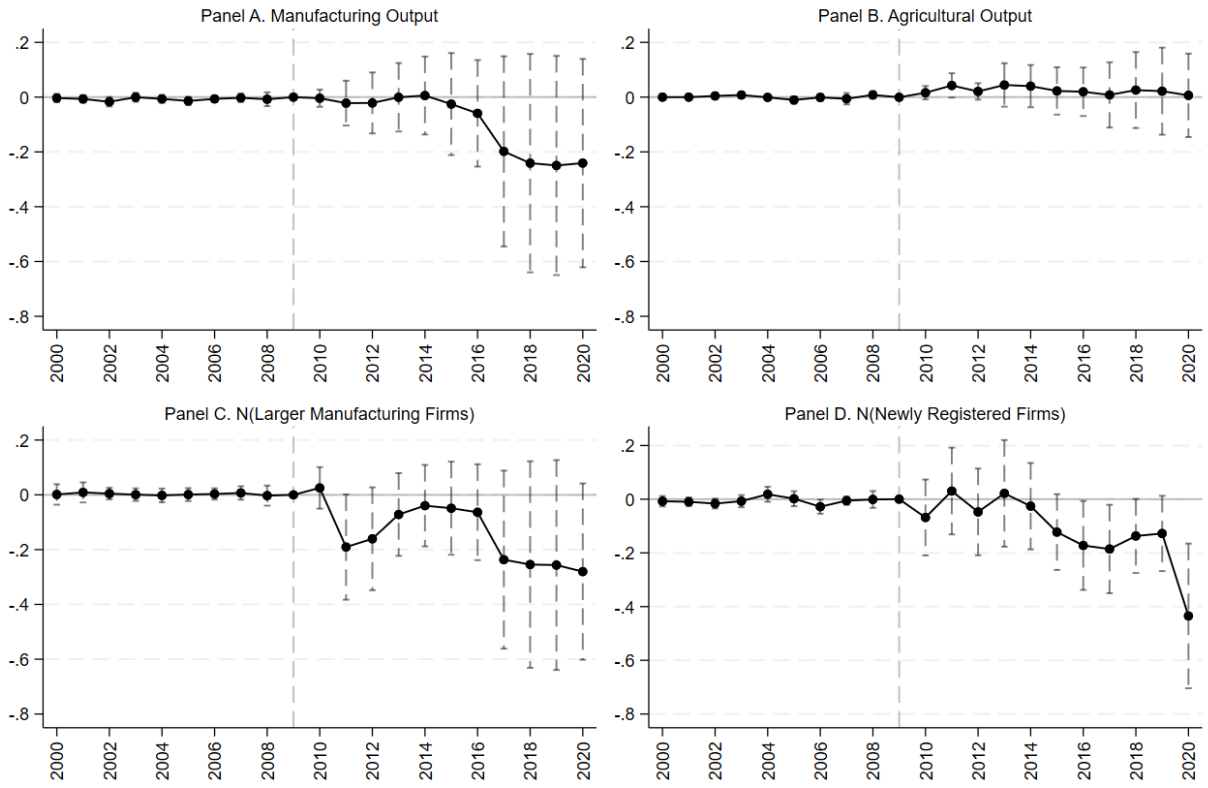


Figure 6: Effects of the Policy on Economic Activities

Note: (1) The figure depicts the event-study coefficients from the DID regression; (2) Data for Panels A-C are from the county-level statistical yearbook, and data for Panel D are from the National Enterprise Credit Information Publicity System (NECIPS); (3) Outcome variables are with Inverse Hyperbolic Sine (IHS) transformation; (4) Treatment is FDB designation in 2010: 20 counties were selected into the FDB list in 2010; (5) The construction of the control group is discussed in Section 3.1; FDB-protected counties and neighboring counties of FDB-designated and FDB-protected counties are excluded from the control group; (6) All regressions include county, year, and province-by-year fixed effects; (7) Standard errors are clustered at the county level; (8) 95% confidence intervals are plotted around point estimates.

Table 2: Impacts of FDB Designation on Economic Activities

Variables (in IHS)	Manufacturing Output		Agricultural Output	
Panel A. Output	(1)	(2)	(3)	(4)
FDB	−0.206*	−0.100	−0.036	0.024
	(0.108)	(0.092)	(0.047)	(0.037)
Observations	38,703	38,703	38,703	38,703
Variables (in IHS)	N (Registered Firms)		N (Larger Manufacturing Firms)	
Panel B. Firm Entry	(1)	(2)	(3)	(4)
FDB	−0.137***	−0.115***	−0.222***	−0.143*
	(0.041)	(0.037)	(0.081)	(0.076)
Observations	52,542	52,542	38,703	38,703
For All Panels:				
Sample Period	2000-2020	2000-2020	2000-2020	2000-2020
Fixed Effects				
Year	Y	Y	Y	Y
County	Y	Y	Y	Y
Province × Year	N	Y	N	Y
Control Group	Neighbor Excluded	Neighbor Excluded	Neighbor Excluded	Neighbor Excluded

Note: (1) We use the difference-in-differences estimation (see Section 3.1 for detailed discussion); (2) Treatment is FDB designation in 2010: 20 counties were selected into the FDB list in 2010; (3) Data of manufacturing output, agricultural output, the number of larger manufacturing firms is from the county-level statistical yearbook, and data of the number of registered firms is from the National Enterprise Credit Information Publicity System (NECIPS); (4) The 'Neighbor Excluded' control group excludes FDB-protected counties and first-ring neighboring counties that border FDB counties and protected counties (see Section 3.1 for detailed discussion); (5) Outcome variables are with Inverse Hyperbolic Sine (IHS) transformation; (6) Standard errors are clustered at the county level; (7) *, **, and *** respectively indicate significance at the 10%, 5%, and 1% levels.

Population

A natural hypothesis is that rational individuals would respond to higher flood risk by leaving FDB counties. To test this, we examine two population-related outcomes: the number of registered population and the net outmigration ratio. Columns (1) and (2) of

Table 3 show that FDB designation has no significant effect on the number of registered residents. This suggests that the number of individuals holding a local *Hukou*, which is the formal proof of residency, remains unchanged. However, registered population is not a perfect measure of migration because individuals may relocate without transferring their *Hukou* status.

To capture migration more accurately, we follow Chen et al. (2022b) and construct a county-level net outmigration ratio using micro Census data from 2000, 2005, 2010, and 2015. The construction of this proxy is described in Appendix A.2. This measure, commonly used in the migration literature (e.g., Boustan et al. 2012; Hornbeck and Naidu 2014), reflects the share of people leaving a county, net of arrivals and deaths, over a given period. A positive value indicates net population loss, while a negative value implies net inflow. Columns (3) and (4) of Table 3 show that although the estimated coefficients are positive, they are statistically insignificant, suggesting that FDB designation does not induce significant outmigration.

The absence of population movement is consistent with China's institutional constraints on mobility. First, China's land system creates substantial frictions to permanent relocation. Since the 1980s, the Household Responsibility System has granted rural households land-use and income rights tied to their place of registration (Adamopoulos et al., 2024). Because leaving an FDB county typically means forfeiting these rights, rural residents face strong disincentives to migrate. Second, the government provides only limited financial support for resettlement. Under the 2017 migration subsidy scheme, FDB residents received roughly \$2,400 per person, which is far below the \$8,100 provided under the *Relocation for Poverty Alleviation* program, a nationwide initiative designed to support permanent resettlement of rural populations from environmentally vulnerable areas. This gap suggests that FDB compensation is designed primarily as a temporary relief measure rather than a tool for long-term relocation. Survey evidence from the *Huai River Regulation Commission* further supports this interpretation: 93% of residents in the Mengwa FDB express dissatisfaction with the subsidy, and 94% are unhappy with designated relocation sites. Together, limited financial incentives and strong institutional frictions help explain why few residents move despite elevated flood risk.

Table 3: Impacts of 2010 FDB Policy Change on Population

Variables	ln(Registered Population)		Net Outmigration Ratio (%)	
	(1)	(2)	(3)	(4)
FDB	−0.020	−0.023	0.070	0.143
	(0.047)	(0.044)	(0.117)	(0.118)
Sample Period	2000-2020	2000-2020	2000-2020	2000-2020
Observations	38,703	38,703	4,749	4,749
Fixed Effects				
Year	Y	Y	Y	Y
County	Y	Y	Y	Y
Province × Year	N	Y	N	Y
Control Group	Neighbor Excluded	Neighbor Excluded	Neighbor Excluded	Neighbor Excluded

Note: (1) We use the difference-in-differences approach (see Section 3.1 for detailed discussion); (2) Treatment is a county being selected into the 2010 FDB list: 20 counties were selected into the FDB list in 2010; (3) The 'Neighbor Excluded' control group excludes FDB-protected counties and first-ring neighboring counties that border FDB counties and protected counties (see Section 3.1 for detailed discussion); (4) Data of 'Registered Population' is from the county-level statistical yearbook, and data of the net outmigration ratio is from individual-level micro census data and we introduce how we construct the net outmigration ratio in Online Appendix A.2.

Summary

Taken together, the evidence highlights a sharp asymmetry between firms and individuals in their responses to FDB designation. On the one hand, firms are mobile and adjust their location decisions to avoid flood risk in FDB counties. As a result, there are significant declines in new firm entry and manufacturing output in FDB counties. By contrast, agriculture shows little adjustment and population remains relatively immobile due to migration frictions. As a result, FDB counties are trapped: people remain in place, but firms and investment do not. These patterns motivate our model, in which firms rather than households play the central role in shaping the long-run consequences of the FDB policy.

4 Quantification of the General Equilibrium Effect

In Section 3, we find that FDB designation results in sizable declines in local economic activity, primarily driven by reductions in manufacturing output. In Section D.1, we build a partial equilibrium model to illustrate the underlying tradeoffs of the policy. Then, we extend our analysis to the general equilibrium framework to include three forces simultaneously: the *sacrifice effect*, the *protection effect*, and the *market-based spillover effect*. Our reduced form analysis in Section 3 provides evidence of the *sacrifice effect* borne by FDB-designated counties. But at the same time, the institutional design of the policy generates the *protection effect* for downstream urban centers. It is difficult to isolate this effect solely using reduced form estimations because important urban cities are treated by various favorable policies simultaneously. Beyond these two effects, there is also a *market-based spillover effect*: changes in production and prices in both FDB and protected counties transmit to other regions through trade linkages. To quantify the aggregate impacts of FDB policy on outputs, in this section, we embed flood-induced productivity shocks and endogenous manufacturing firm entry into a spatial general equilibrium model.

4.1 Model Setup

Consider an economy with N counties subject to regional flood shocks.

Floods

We assume that at each time t, a flood event s_t happens, which can be described by a vector of county-specific flood exposure $s_t = \{f_{1,t}, f_{2,t}, \ldots, f_{N,t}\}$. We define S as the set of all possible flood events s_t, with each flood event occurring with a probability $pr(s_t)$.[8]

We assume that, in a flood event s_t, if region n is flooded, the flooding will negatively affect the productivity of local manufacturing firms. Following Jia et al. (2022), we model

[8]In theory, the cardinality of the set is 2^N. However, many flood events are naturally impossible. For example, it is unlikely to have floods in regions located in deserts. Therefore, in the calibration and counterfactual sections, we only consider flood events observed in historical data.

the flood-contingent productivity $z_n^M(s_t)$ as:

$$z_n^M(s_t) = \bar{z}_n^M \exp(-\epsilon_M f_{n,t}), \tag{1}$$

where $\bar{z}_n^M$ denotes the region-specific productivity during non-flooding times ($f_{n,t} = 0$), and ϵ_M denotes the percentage productivity loss with respect to flood exposure $f_{n,t}$.

Workers

In each region n, there is a unit mass of hand-to-mouth workers L_n, who are immobile across regions.[9] Workers supply one unit of labor inelastically in the region where they live. After observing the flood event s_t, workers choose their consumption on agricultural goods, $C_n^{w,A}(s_t)$, manufacturing goods, $C_n^{w,M}(s_t)$, and service goods, $C_n^{w,S}(s_t)$, to maximize their utility, subject to the budget constraint:

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

The utility $U(\cdot)$ takes a Cobb-Douglas form such that $U(\cdot) = \xi_A \log(C_n^{w,A}) + (1 - \xi_A - \xi_S)\log(C_n^{w,M}) + \xi_S \log(C_n^{w,S})$, where ξ_A is the share of income spent on agricultural goods, ξ_S is the share of income spent on service goods, and $1 - \xi_A - \xi_S$ is the share of income spent on manufacturing goods. $w_n(s_t)$ is the wage rate in region n, and $P_n^A(s_t)$, $P_n^M(s_t)$, and $P_n^S(s_t)$ represent the prices of agricultural goods, manufacturing goods, and service goods, respectively, in region n. All wages w_n, prices P_n, and consumptions C_n^w are contingent on flood event s_t because, in different flood events, the equilibrium wage, prices, and people's optimal consumption could change in response to floods.

[9] The assumption of abstracting from migratory response of labor is consistent with our empirical evidence showing no significant migration (Section 3.3). In the extension section we consider a setting where we allow for migration.

Capital Owners

During time period t, capital owners in region n maximize their expected life-time discounted utility by deciding how much to invest for the next period, $a_{n,t+1}$, before the realization of the flood event s_t. Hence, the asset position decision is independent of s_t, reflecting the fact that investment choices are forward-looking and adjust only to long-term changes in flood risk, rather than to the realization of a single-period flood event.

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

The income of capital owners comes from two sources. First, they get their return from the last period investment $[1 + r(s_t)]a_{n,t}$, where $r(s_t)$ is the national interest rate. Second, capital owners obtain all the profits of manufacturing firms $I_{n,t}\pi_n(s_t)$, where $I_{n,t}$ is the number of manufacturing firms and $\pi_n(s_t)$ is the average profit of manufacturing firms in region n. After the realization of the flood event s_t, capital owners optimize their consumption bundles subject to the budget constraint, and their preferences are identical to those of the workers, such that $U(\cdot) = \xi_A \log(C_n^{o,A}) + (1 - \xi_A - \xi_S) \log(C_n^{o,M}) + \xi_S \log(C_n^{o,S})$.

Production

In this economy, there are three sectors producing distinct consumption goods: agriculture $Y_n^A(s_t)$, manufacturing $Y_n^M(s_t)$, and services $Y_n^S(s_t)$. The agricultural sector uses labor $l_n^A(s_t)$ as the only input, supplying non-tradable agricultural goods with linear production technology to the local market. It operates in a perfectly competitive way, so the price of agricultural goods is determined by the local wage and agricultural productivity. The profit maximization problem for the agricultural sector during flood event s_t is given by:

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

We assume the service sector also supplies non-tradable goods in the local market in a perfectly competitive way. However, unlike the agricultural sector, the service sectors use both labor $l_n^S(s_t)$ and capital $k_n^S(s_t)$ in a Cobb-Douglas production technology, with the factor share of labor denoted by α. The maximization problem for the service sector is given by:

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

The manufacturing sector is the key focus of this paper, and therefore, we model this sector in greater detail to better capture the mechanisms identified in the empirical results. Firstly, we describe the demand for manufacturing goods and model consumers in region n as consuming a variety of manufacturing goods produced by heterogeneous firms from different regions, using a CES aggregator:

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

where σ measures the elasticity of substitution across manufacturing goods produced by different firms, $y_{in}^M(s_t)$ is the quantity of manufacturing goods produced in region i and sold to region n, and $I_{i,t}$ is the number of manufacturing firms in region i. Denote $P_{in}^M(s_t)$ as the price of manufacturing goods 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 $P_n^M(s_t) = \left[\sum_{i=1}^{N} I_{i,t} P_{in}^M(s_t)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$.

On the supply side, firms in region n hire labor $l_{ni}^M(s_t)$ and capital $k_{ni}^M(s_t)$ to produce manufacturing goods y_{ni} using a Cobb-Douglas technology with productivity $z_n^M(s_t)$. Manufacturing goods can be traded from region n to region i, subject to the iceberg cost d_{ni}, meaning that to ship one unit of goods, firms need to produce d_{ni} units. The profit for each firm in region n is given by:

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

To operate and earn profit $\pi_n(s_t)$ at time t, manufacturing firms must first decide whether to enter the market before the realization of the flood event s_t. We also assume there is a probability η that the manufacturing firm will exit the market in the next period. Therefore, the value of a manufacturing firm in region n, $V^s_{n,t}$, is the expected profit in period t plus the discounted value of the firm in the next period, conditional on survival:

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

Then the free entry condition requires that the value of manufacturing firms should equal to the entry cost c^f_n.

$$V^s_{n,t} = c^f_n. \tag{9}$$

Market Clearing Conditions

There are three sets of market clearing conditions.

1. National capital market: The flood-event-specific interest rate $r(s_t)$ equalizes the aggregate flood-event-specific capital demands and the aggregate asset holdings:

$$\sum_{n=1}^{N} I_n \sum_{i=1}^{N} k^M_{ni}(s_t) + \sum_{n=1}^{N} k^S_n(s_t) = \sum_{n=1}^{N} a_{n,t}. \tag{10}$$

2. Local labor markets: The flood-event-specific wage rates $w_n(s_t)$ equalize flood-event-specific labor demands to labor supply in each region:

$$l^A_n(s_t) + \sum_{i=1}^{N} l^M_{ni}(s_t) + l^S_n(s_t) = L_n. \tag{11}$$

3. Local final good markets: The final good markets are assumed to be perfectly competitive, so prices $P^A_n(s_t)$, $P^M_{in}(s_t)$ and $P^S_n(s_t)$ satisfy that the final good demands and supplies are equalized in all regions:

$$L_n C^{w,A}_n(s_t) + C^{o,A}_n(s_t) = Y^A_n(s_t), \tag{12}$$

$$L_n C_n^{w,S}(s_t) + C_n^{o,S}(s_t) = Y_n^S(s_t), \tag{13}$$

$$L_n C_n^{w,M}(s_t) + C_n^{o,M}(s_t) = \left[\frac{P_{in}^M(s_t)}{P_n^M(s_t)}\right]^{\sigma} y_{in}^M(s_t). \tag{14}$$

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 $\{l_n^A(s_t),\ l_{in}^M(s_t),\ l_n^S(s_t),\ k_{in}^M(s_t),\ k_n^S(s_t)\}$ and outputs $\{Y_n^A(s_t),\ y_{in}^M(s_t),\ Y_n^S(s_t)\}$, manufacturing firm counts $\{I_{n,t}\}$, and prices $\{w_n(s_t),\ r(s_t),\ P_n^A(s_t),\ P_{in}^M(s_t),\ P_n^S(s_t)\}$, 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) $\{l_n^A(s_t),\ l_{in}^M(s_t),\ l_n^S(s_t),\ k_{in}^M(s_t),\ k_n^S(s_t)\}$ and $\{Y_n^A(s_t),\ y_{in}^M(s_t),\ Y_n^S(s_t)\}$ satisfy sectors' profit maximization problems in Equation 4, 5, and 7;

   (iii) $\{w_n(s_t),\ r(s_t),\ P_n^A(s_t),\ P_{in}^M(s_t),\ P_n^S(s_t)\}$ clear the factor and product markets in Equation 10 - 14.

4.2 Calibration

In this section, we calibrate our model to match the county-level characteristics of Chinese counties averaged over the period between 2000 and 2010.

Externally Calibrated Parameters

Panel A of Table 4 shows parameter values obtained directly from literature and data. We treat each region as a county, and there are $N = 2072$ counties in the calibration[10]. We standardize labor 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 rate of 5%. We further match the shares of sector-specific consumption with the real data provided by 2000-2010 Chinese NBS. To be specific, the share of agricultural consumption, ξ_A, is 11.7%, and the share of service consumption, ξ_S, is 42.2%. We choose a factor share of capital, $1-\alpha$, to be 0.5 for both the manufacturing and service industry. This is consistent with the national-level sector specific factor share in China, calculated by Chinese input and output tables and national accounts, sourced from Chinese NBS.

Transportation Cost. The calculation of transportation costs, d_{ni}, is based on geodesic distances τ_{ni} (in kilometers) between counties n and i. For within-county transportation, we follow Redding and Venables (2004), Au and Henderson (2006), and Balboni (2025), and calculate the average distance from evenly distributed points within a circle (with the same area as the county) to its center, given by $\frac{2}{3}(\text{area}/\pi)^{1/2}$. Transportation costs are then specified as $d_{ni} = \exp(\phi\tau_{ni})$, with the minimum transportation cost being normalized to one. We set $\phi = 0.362$ so that the average implied trade cost in our data matches the calibration in Egger et al. (2023)[11].

Probability of Each Flood Type. Precipitation is a primary determinant of flooding: extreme rainfall is strongly predictive of flood occurrence, particularly in river basins with limited storage capacity. Prior work in hydrology and climate science has shown that precipitation anomalies are reliable predictors of flood risk (e.g., Houze Jr 2012; Hirabayashi et al. 2013; Kundzewicz et al. 2014). Building on this insight, we estimate flood probabilities

[10]The total number of counties in China is 2,846. However, to calibrate each county's local productivity, we need information about labor and output from county level statistics, which is only available for 2,072 counties during this period. The 2,072 counties account for 97.0% of China's total GDP, so the missing counties will have limited impact on our final results.

[11]Egger et al. (2023) estimate trade costs at the city level using a gravity model based on inter-city trade flows and travel times. Because our analysis is at the county level, their calibrated trade costs cannot be directly applied. We therefore follow their calibration logic and adjust ϕ to match their average trade cost in our setting.

$pr(s_t)$ by linking observed flood events to the historical distribution of precipitation.

Specifically, we use county-level precipitation data for the flood season (June–September) from 1980–1999 to estimate the distribution of rainfall, thereby constructing an empirical probability density function $\Pr(Prec_t)$. Each year from 2000-2010 is then classified into one of these precipitation intervals[12]. Within each interval, we compute the conditional probability of a flood event, $\Pr(s_t \mid Prec_t)$, by dividing evenly across the number of observed flood years that fall into that range. Finally, by the law of total probability, the unconditional probability of a flood event is $pr(s_t) = \Pr(s_t \mid Prec_t) \cdot \Pr(Prec_t)$[13].

Productivity Loss. We estimate the flood-induced productivity loss in the manufacturing sector by regressing the log of labor productivity on flood exposure. Reduced form results suggest that when the average days of flood in a county increases by one day, then the productivity in manufacturing sector would decrease by 5.9% (Table E2). This estimate aligns closely with prior evidence from China's manufacturing sector. Li et al. (2018) find that production capacity losses from an extreme storm flood in Shanghai amounted to 5.3% of annual industrial output (about US$23 billion). Likewise, Hu et al. (2019) report that large flood events have a lagged effect on labor productivity around 5.4%.

Internally Calibrated Parameters

We internally calibrate the remaining parameters $\{\bar{z_n^A}, \bar{z_n^M}, \bar{z_n^S}, c_n^f\}$ to match county-level data. Specifically, we calibrate sectoral productivity $\{\bar{z_n^A}, \bar{z_n^M}, \bar{z_n^S}\}$ so that the model reproduces county-level real outputs in agriculture, manufacturing, and services.[14] We then calibrate county-level firm entry costs c_n^f to match county-level manufacturing firm counts. The resulting parameters are reported in Panel B of Table 4.

[12]This procedure yields probabilities that incorporate both the climatological likelihood of heavy rainfall and the conditional likelihood of flooding given rainfall levels. We assume precipitation in 2000-2010 is drawn independently from the same distribution as in 1980-1999, abstracting from potential changes due to climate change.

[13]Here, we assume that if flood event s_t happened in a year with precipitation $Prec_t$, then the conditional probability $\Pr(s_t|\text{not } Prec_t) = 0$ for any other precipitation scenario.

[14]We normalize total national GDP and firm counts to 1,000 in the baseline calibration. The calibration uses the 2006 distribution as the reference year, but the results are unaffected as long as the cross-county distribution remains stable.

Table 4: Calibration Targets

Parameter	Numbers	Value	Source/Targeted Moments
Panel A: Exogenously Calibrated Parameters			**Source:**
N - Number of regions	1	2072	Number of counties
σ - Elasticity of substitution across varieties	1	5	Head et al. (2014)
β - Discount factor	1	0.95	Steady-state interest of 5%
ξ_A - Share of agricultural consumption	1	0.117	Chinese National Bureau of Statistics
ξ_S - Share of service consumption	1	0.422	Chinese National Bureau of Statistics
$pr(s_t)$ - Flooding event probability	11	0.09(0.04)	Precipitation and flood event (2000-2010)
d_{ni} - Transportation costs	N^2	1.57(0.41)	Geodesic distances
α - Factor share of labor	1	0.5	Factor shares of different sectors
η - Exit Rate of Firms	1	0.05	Standard Calibration
ϵ_M - Flood-induced productivity loss	1	-0.059	Estimation (Table E2)
Panel B: Internally Calibrated Parameters			**Targeted Moments:**
$\bar{z_n^A}$ - County-level agriculture productivity	N	0.52(0.52)	County-level agriculture outputs
$\bar{z_n^M}$ - County-level manufacturing productivity	N	0.15(0.11)	County-level manufacturing outputs
$\bar{z_n^S}$ - County-level service productivity	N	0.09(0.11)	County-level service outputs
c_n^f - Firm entry cost	N	33.08(73.65)	County-level manufacturing firm counts

Note: for flooding event probability, transportation costs, internally calibrated productivity and firm entry cost, the value in the table indicates the average value across all regions, and the standard error is in the parenthesis.

Model Fit

To evaluate the model's ability to replicate observed patterns, we compare its simulated outcomes with actual data. For the manufacturing sector, we first examine county-level fixed assets. Figure 7 shows data points clustered around the 45-degree line, suggesting that the model aligns well with the empirical distribution. A regression of model-generated values on the actual data in Table E3 yields a coefficient of 0.804 and an R^2 of 0.718. We conduct a similar exercise for the number of manufacturing workers and again find a close correspondence: the regression in Table E3 reports a coefficient of 1.292 with an R^2 of 0.678.

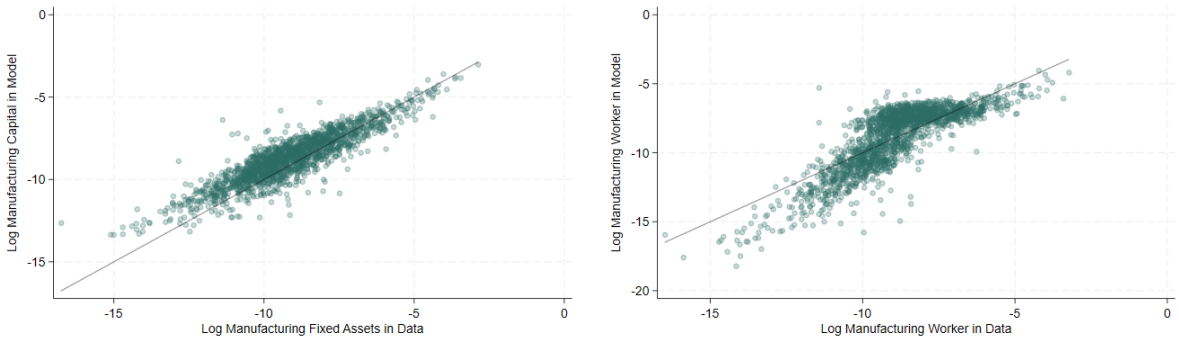


Figure 7: Model Fit

Note: The capital and worker variables measure average values across all years, both in the data and in the model. Both variables have been normalized so that aggregate capital and aggregate workers equal 1. The figure plots the log values of these normalized variables. Each emerald dot represents one county, and the gray line indicates the 45-degree line.

4.3 Simulation and Counterfactual Practices

In this section, we evaluate how economic outcomes would differ under alternative scenarios. We begin by asking what output would have been in the absence of the FDB policy, which allows us to benchmark its overall impact. We then relax the migration constraint by considering a setting without the Hukou system, shedding light on the role of labor mobility in shaping regional adjustment. Finally, we examine how future climate change scenarios might alter the policy's consequences. Together, these exercises provide insight into both the historical importance of the FDB program and its implications under changing institutional and environmental conditions.

Net Output Change from FDB Policy

To quantify output in a scenario where FDB-designated counties no longer protect downstream urban areas, we proceed in two steps (Table E1 provides a road map of how we construct the counterfactual scenario). First, we construct counterfactual flood exposure across counties by redistributing water that would otherwise be detained.[15] Empirically, we find that FDB-designated counties experience about 45% higher flood exposure after the imple-

[15]See Online Appendix B.4 for details of the hydrological simulations and econometric estimates underlying this redistribution.

mentation of the policy (see Online Appendix B.3). In the counterfactual scenario without the FDB system, we therefore reallocate this 45% of floodwater from each FDB county to the counties it protects, distributing the inflow evenly across protected counties.[16] This procedure yields a set of counterfactual flood events, $S' = \{s'_1, s'_2, \ldots, s'_J\}$. In the second step, we map these counterfactual exposures into manufacturing outcomes: since flood exposure reduces productivity, lower exposure in FDB-designated counties increases their output, while higher exposure in protected counties reduces theirs. This allows us to quantify aggregate output in the absence of the FDB policy.[17]

In Figure 9, we compare simulated output under the actual FDB policy with the counterfactual output without the policy, respectively for FDB-designated counties, FDB-protected counties, and all other counties as defined in Section 3. These comparisons capture the total impact of the policy in each group, combining both its direct effect and the general equilibrium effect transmitted through trade and capital markets. Panel A reports average output per county, while Panel B aggregates total output across counties within each group.

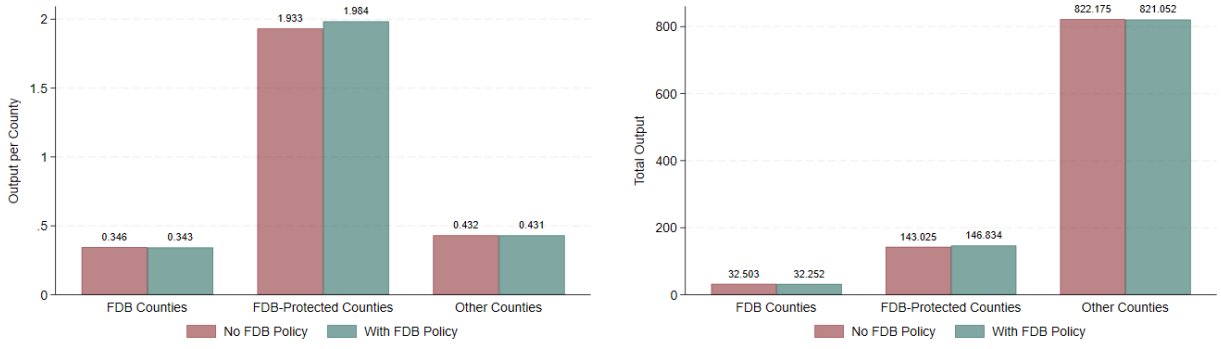
For FDB-designated counties, the policy reduces average output per county from 0.346 to 0.343 (-0.87%). While this decline reflects the *sacrifice effect* emphasized in Section 3.2, it also incorporates business stealing as protected urban areas gain from enhanced protection. For FDB-protected counties, output per county rises from 1.933 to 1.984 (+2.57%), driven by the *protection effect* – lower local flood exposure – together with additional agglomeration effects through increasing return to scale and love-of-variety preferences. For all other counties, average output falls slightly by 0.21%. This small decline reflects a *market-based spillover effects*, primarily business stealing transmitted through goods and capital markets, though the magnitude is modest. Taken together, Panel B of Figure 9 shows that total output across all counties increases from 997.70 to 1000.00, a net gain of 0.24% as a result of the FDB policy. Using China's 2010 GDP (6.19 trillion USD) as a reference, this corresponds to

[16] Alternative allocation rules, such as distributing water proportional to county size or population, yield quantitatively similar results. Moreover, this redistribution approach is consistent with both observed patterns in the hydrological data and the stated policy design. This method also maintains the empirical intuition that FDB-designated counties remain naturally more flood-prone even after redistribution. Our main results are robust to varying the redistribution rate.

[17] Please note that, in the following analysis, we focus specifically on output as our key result, which is measured as the absolute value averaged over the period between 2000 and 2010, with the national aggregate standardized to 1,000.

an output gain of roughly 15 billion USD.

These results highlight several important insights. First, the aggregate gain of 0.24% indicates that the FDB policy does generate a net positive effect on output by redistributing flood risk and limiting damage in urban centers. Yet the benefits are highly uneven. The largest gains accrue to FDB-protected counties, where output rises by 2.67%, reinforcing the advantages of already more developed urban regions. By contrast, FDB-designated counties bear output losses, and other counties outside the system experience only small negative spillovers, leaving them without meaningful gains. In practice, this means that the aggregate improvement comes almost entirely from urban areas, amplifying existing disparities between protected cities and vulnerable rural regions. This outcome is consistent with China's broader development strategy in the early 2000s, which prioritized safeguarding urban centers during rapid urbanization, even at the cost of widening urban-rural inequality.



(a) Output per County

(b) Total Output

Figure 8: Output of FDB-designated, FDB-protected, and Other Counties in Actual and Counterfactual Scenarios

Note: The maroon bars represent the counterfactual scenario without the FDB policy, while the emerald bars represent the simulated outcomes under the actual implementation of the FDB policy. Output is calculated separately for FDB-designated counties, FDB-protected counties, and other counties.

Relaxing the Migration Constraint

Migration is a potentially important adjustment channel in the presence of natural disaster shocks, as it allows individuals to move away from high-risk areas and reallocate toward regions with better economic opportunities. We then examine how limited mobility shapes

the distributional and aggregate effects of the FDB policy, and how relaxing these constraints might enhance its economic benefits.[18]

First, we examine full mobility, where residents face no migration restrictions. To implement this, we follow Artuç et al. (2010) and Balboni (2025) and incorporate a dynamic migration decision into the workers' problem.[19] Specifically, the workers' Bellman equation can be described by:

$$v_n^w = \max_{\{C_n^A(s_t), C_n^M(s_t), C_n^S(s_t), n' \in N\}} \mathbb{E}_{s_t} U(C_n^{w,A}(s_t), C_n^{w,M}(s_t), C_n^{w,S}(s_t)) + \{\beta v_{n'}^w + B_{n'} + b_{n',t}\}, \quad (15)$$

where B_n denotes the amenity of county n, and $b_{n,t}$ denotes the idiosyncratic preference shocks that are assumed to follow a Gumbel distribution with parameters $(-\gamma\upsilon, \upsilon)$. Taking expectation with respect to $b_{n,t}$ yields the following expression:

$$V_n^w = \max_{\{C_n^A(s_t), C_n^M(s_t), C_n^S(s_t)\}} \mathbb{E}_{s_t} U(C_n^{w,A}(s_t), C_n^{w,M}(s_t), C_n^{w,S}(s_t)) + \upsilon \log \sum_{n' \in N} [\exp(\beta V_{n'}^w + B_{n'})^{\frac{1}{\upsilon}}]. \quad (16)$$

We use the pre-FDB population distribution to calibrate implied amenities $\{B_n\}$. Holding these amenities fixed, we then simulate the full equilibrium by feeding the FDB-induced flood damage redistribution to the economy, allowing workers to adjust their migration decisions. Figure E2 shows that under free migration, population in FDB-designated counties falls by 1.63 percent, population in protected counties rises by 15.20 percent, and population in other regions declines slightly by 1.31 percent. Residents leave flood-prone FDB-designated counties for protected urban areas with better economic opportunities, and agglomeration forces further attract workers in other counties into these FDB-protected urban centers.

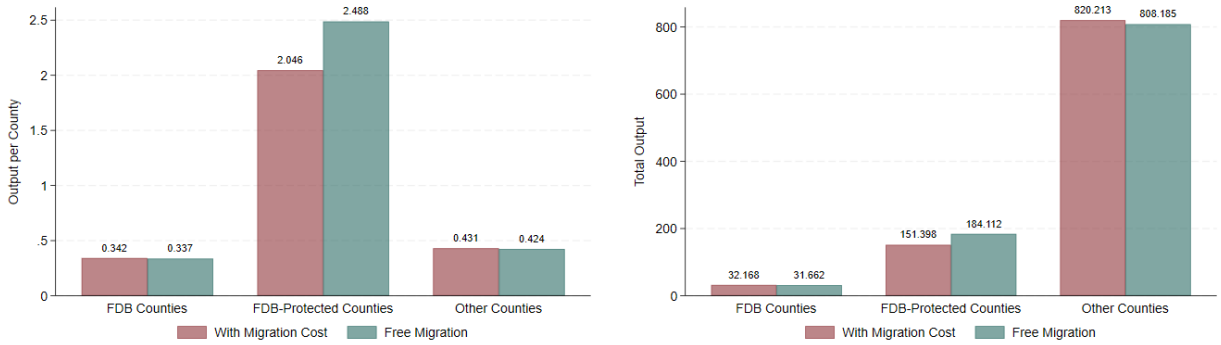
This reallocation substantially magnifies the aggregate gains of the FDB policy. Total output rises from 997.70 in the no-FDB, no-migration baseline to 1023.96 under free migration, a 2.63 percent increase. Using China's 2010 GDP as a benchmark, this corresponds

[18] In practice, however, Table 3 shows little evidence of actual migration in response to FDB designation. This reflects institutional frictions: residents of FDB-designated counties face strict restrictions on mobility, as the government neither permits free out-migration under the Hukou system nor provides strong incentives for relocation. To evaluate the potential role of migration absent these frictions, we conduct counterfactual exercises that relax the constraint in this section.

[19] Here, we assume the workers make their migration decisions before the realization of the flood event s_t to capture the idea that direct floods have limited long-run impacts on the economy (Jia et al., 2022).

to an output gain of roughly 163 billion USD, and it is over ten times larger than the 15 billion USD gain under baseline. These results highlight how complementary policy bundles can generate multiplier effects, but also reveal how the *Hukou* system sharply limits the effectiveness of the FDB policy. At the same time, free mobility exacerbates existing inequalities. Rural FDB-designated counties lose population as residents relocate to safe urban protected counties. Agglomeration forces further reinforce this divergence, as protected counties attract both migrants from FDBs and workers from other regions. As a result, the average output of FDB-protected counties becomes 6.39 times that of FDB-designated counties under free migration, compared to 4.78 times larger in the baseline scenario with migration frictions.

Second, recognizing that full mobility is not always a feasible policy option, we consider partial mobility following Tombe and Zhu (2019) who find that around 12% of the population is able to move despite institutional frictions. Figure E2 reports the resulting population distribution and implications for output distribution. As expected, the aggregate effects lie between the extremes of no migration and full migration. Specifically, total output increases by 0.61% (approximately 37 billion USD), doubling the gain in the baseline with migration frictions. In this scenario, the average output of FDB-protected counties is 4.97 times that of FDB-designated counties, compared to 4.78 in the baseline. Taken together, these results suggest that even partial relaxation of mobility constraints can substantially amplify the aggregate benefits of the FDB policy, though at the cost of greater rural-urban inequality.



(a) Average Output per County

(b) Total Output

Figure 9: Output of FDB-designated, FDB-protected, and Other Counties in Free Migration and Limited Migration Scenarios

Note: The maroon bars represent the counterfactual scenario without the FDB policy, while the emerald bars represent the simulated outcomes under the actual implementation of the FDB policy. Output is calculated separately for FDB countries, FDB-protected counties, and other counties.

Future Climate Change

In the face of climate change, future flood risk and flood damage are expected to rise substantially relative to current levels. To examine this, we scale our model's flood damage (measured by the flood exposure) using projections from the World Resources Institute's Aqueduct Floods[20], which reports annual expected urban damage as a percentage of urban asset value. For 2030, 2050, and 2080, we compute the ratio of expected damage relative to the 2010 baseline and apply this ratio to rescale our flood exposure parameters. The results show that the output gains from the FDB policy increase as flood risk intensifies: without the policy, total output is 1000.55 under the mild-risk 2030 scenario, 992.18 under the medium-risk 2050 scenario, and 968.27 under the severe-risk 2080 scenario; with the policy in place, output rises by 0.41%, 0.49%, and 1.24%, respectively. The implied gains grow with risk severity, indicating that the effectiveness of the FDB policy is magnified in higher-risk environments and underscoring its role in strengthening economic resilience under climate change.

[20] `https://www.wri.org/applications/aqueduct/floods/`, which reports that the percentage of annual expected urban damage is 0.22% in 2010, 0.23% in 2030, 0.37% in 2050, and 0.81% in 2080.

Discussions

We next turn to the question of whether the FDB policy is optimally designed. However, such optimization is not feasible at this stage due to our constraints in hydrological knowledge. An economically optimal design may not be geographically or hydrologically viable. For instance, assigning an inland county far from major rivers as an FDB area would be implausible. And simulating where water would go in the absence of FDBs requires substantial hydrological knowledge. Despite these challenges, assessing policy optimality remains important. We adopt a second-best approach to evaluate whether the government has over-protected urban centers by designating an excessive number of FDB-designated counties.

First, we rank FDB-designated counties by their exposure-standardized productivity. Second, we progressively remove higher-productivity counties from the FDB list and compute total output in each counterfactual scenario. Third, we measure the relative contribution of each productivity group by comparing its counterfactual output with the actual case. Figure E3 presents the net output gains from successively adding counties of higher productivity. While total output increases monotonically with the inclusion of more counties, the marginal contributions decline sharply at the upper end of the productivity distribution. Counties in the 10–40% productivity range contribute over 25% to net output gains, whereas those in the top 20% contribute little—0–3%. These results suggest that, although expanding the FDB list does not reduce total output, the additional benefits from including high-productivity counties are minimal. It implies that the government may be over-protecting urban areas by designating too many FDB-designated counties and excluding higher-productivity counties from the FDB list would yield negligible output losses.

5 Conclusion

Flood disasters, especially common in developing countries like China, India and Bangladesh, have profound impacts on the overall economy. In China, one approach to mitigating severe river floods is the construction of Flood Detention Basins (FDBs). Strategically located in low-lying areas, FDBs are designed to temporarily hold excess floodwaters, thereby pro-

tecting downstream regions but also increasing flood risk for those within the designated basins. While this policy may increase economic resilience against floods, it requires a closer examination of the economic costs and its uneven distributional impacts.

The Chinese government states that residents living in FDB-designated counties have made substantial sacrifices for the greater good. Our study quantitatively examines the economic costs and output gains of the FDB policy. We find that although the policy has improved the economic resilience to floods, it has also induced economic inequality between FDB-designated counties and their non-FDB counterparts. Firstly, our empirical results show that FDB-designated counties experience persistent negative policy effects on their economic development. On average, nighttime light intensity in FDB-designated counties declines by roughly 10 percent annually over the long term. Secondly, in studying the mechanism, we find that firms have fewer incentives to enter and invest in FDB-designated counties due to their increased flood risk. Thirdly, our general equilibrium model shows that the FDB policy has yielded an overall increase in net output, though at the cost of widening inequality between FDB and protected urban areas.

Our research has two major policy implications. First, our research highlights a critical insufficiency in the Chinese government's compensation for FDB-designated counties. Since 2000, many counties have started to absorb floodwaters, thereby protecting other regions from flood damage. The compensation, however, focuses solely on compensating direct flood losses, such as damage to agricultural crops. Our findings suggest that this compensation falls markedly short of addressing the total economic costs induced by the FDB policy. The substantial long-term economic costs have not been adequately compensated by the Chinese government.

Second, the findings of our study on China's Flood Detention Basin (FDB) policy offer insights for other nations considering 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 areas designated to absorb more flood risk. For countries considering the adoption of similar policies, it is crucial to recognize the potential for creating economic inequalities and to weigh these against the intended benefits of reducing overall flood damage. Policymakers should ensure that compensatory

mechanisms are in place to support regions that take more damage. 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 the trade-off between equality and efficiency.

References

Abadie, A., Diamond, A., and Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of california's tobacco control program. *Journal of American Statistical Association*, 105(490):493–505.

Adamopoulos, T., Brandt, L., Chen, C., Restuccia, D., and Wei, X. (2024). Land security and mobility frictions*. *The Quarterly Journal of Economics*, 139(3):1941–1987.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., and others (2021). Synthetic difference-in-differences. *American Economic Review*.

Arnell, N. W. and Gosling, S. N. (2016). The impacts of climate change on river flood risk at the global scale. *Climatic Change*, 134:387–401.

Artuç, E., Chaudhuri, S., and McLaren, J. (2010). Trade shocks and labor adjustment: A structural empirical approach. *American Economic Review*, 100(3):1008–1045.

Assunção, J., McMillan, R., Murphy, J., and Souza-Rodrigues, E. (2022). Optimal environmental targeting in the amazon rainforest. *The Review of Economic Studies*, 90(4):1608–1641.

Au, C.-C. and Henderson, J. V. (2006). Are chinese cities too small? *The Review of Economic Studies*, 73(3):549–576.

Balboni, C. (2025). In harm's way? infrastructure investments and the persistence of coastal cities. *American Economic Review*, 115(1):77–116.

Balboni, C., Bandiera, O., Burgess, R., Heil, A., Mazet-Sonilhac, C., Sulaiman, M., and Wang, Y. (2025). Weathering poverty. Working paper.

Balboni, C., Boehm, J., and Waseem, M. (2023). Firm adaptation in production networks: Evidence from extreme weather events in pakistan. Technical report, Working Paper.

Bennett, M. S. and Mays, L. W. (1985). Optimal design of detention and drainage channel systems. *Journal of Water Resources Planning and Management*, 111(1):99–112.

Boustan, L. P., Kahn, M. E., and Rhode, P. W. (2012). Moving to higher ground: Migration response to natural disasters in the early twentieth century. *American Economic Review*, 102(3):238–244.

Boustan, L. P., Kahn, M. E., Rhode, P. W., and Yanguas, M. L. (2020). The effect of natural disasters on economic activity in us counties: A century of data. *Journal of Urban Economics*, 118:103257.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230.

Cao, C., Song, X., Cai, W., Li, Y., Cong, J., Yu, X., Gao, M., and Wang, C. (2023). Estimating the value of a statistical life in china: A contingent valuation study in six representative cities. *Chinese Journal of Population, Resources and Environment*, 21(4):269–278.

Cavallo, E., Galiani, S., Noy, I., and Pantano, J. (2013). Catastrophic natural disasters and economic growth. *Review of Economics and Statistics*, 95(5):1549–1561.

Chen, J., Gao, M., Cheng, S., Hou, W., Song, M., Liu, X., and Liu, Y. (2022a). Global 1 km× 1 km gridded revised real gross domestic product and electricity consumption during 1992–2019 based on calibrated nighttime light data. *Scientific Data*, 9(1):202.

Chen, S., Oliva, P., and Zhang, P. (2022b). The effect of air pollution on migration: Evidence from china. *Journal of Development Economics*, 156:102833.

Cruz, J.-L. and Rossi-Hansberg, E. (2024). The economic geography of global warming. *Review of Economic Studies*, 91(2):899–939.

De Chaisemartin, C. and d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–2996.

Desmet, K., Kopp, R. E., Kulp, S. A., Nagy, D. K., Oppenheimer, M., Rossi-Hansberg, E., and Strauss, B. H. (2021). Evaluating the economic cost of coastal flooding. *American Economic Journal: Macroeconomics*, 13(2):444–86.

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

Egger, P. H., Loumeau, G., and Loumeau, N. (2023). China's dazzling transport-infrastructure growth: Measurement and effects. *Journal of International Economics*, 142:103734.

Elliott, R. J., Strobl, E., and Sun, P. (2015). The local impact of typhoons on economic activity in china: A view from outer space. *Journal of Urban Economics*, 88:50–66.

Fajgelbaum, P. D., Morales, E., Suárez Serrato, J. C., and Zidar, O. (2019). State taxes and spatial misallocation. *The Review of Economic Studies*, 86(1):333–376.

Ficarra, M. and Mari, R. (2025). Weathering the storm: sectoral economic and inflationary effects of floods and the role of adaptation.

Fried, S. (2022). Seawalls and stilts: A quantitative macro study of climate adaptation. *The Review of Economic Studies*, 89(6):3303–3344.

Gardner, J. (2022). Two-stage differences in differences. *arXiv preprint arXiv:2207.05943*.

Gong, B., Shen, Y., and Chen, S. (2025). Target-based gdp manipulation: Evidence from china. *Journal of Public Economics*, 244:105349.

Gröger, A. and Zylberberg, Y. (2016). Internal labor migration as a shock coping strategy: Evidence from a typhoon. *American Economic Journal: Applied Economics*, 8(2):123–53.

Haselsteiner, R. and Mottner, M. (2022). Upgrading of the flood retention basin odenkirchen in germany. In *E3S Web of Conferences*, volume 346, page 01025. EDP Sciences.

He, G., Wang, S., and Zhang, B. (2020). Watering down environmental regulation in china. *The Quarterly Journal of Economics*, 135(4):2135–2185.

Head, K., Mayer, T., and Thoenig, M. (2014). Welfare and trade without pareto. *American Economic Review*, 104(5):310–316.

Henderson, J. V., Storeygard, A., and Weil, D. N. (2012). Measuring economic growth from outer space. *American Economic Review*, 102(2):994–1028.

Hirabayashi, Y., Mahendran, R., Koirala, S., Konoshima, L., Yamazaki, D., Watanabe, S., Kim, H., and Kanae, S. (2013). Global flood risk under climate change. *Nature Climate Change*, 3(9):816–821.

Hornbeck, R. and Naidu, S. (2014). When the levee breaks: Black migration and economic development in the american south. *American Economic Review*, 104(3):963–90.

Houze Jr, R. A. (2012). Orographic effects on precipitating clouds. *Reviews of Geophysics*, 50(1).

Hsiang, S. M. and Jina, A. S. (2014). The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones. Technical report, National Bureau of Economic Research.

Hsiao, A. (2023). Sea level rise and urban adaptation in jakarta. *Technical Report*.

Hu, X., Pant, R., Hall, J. W., Surminski, S., and Huang, J. (2019). Multi-scale assessment of the economic impacts of flooding: evidence from firm to macro-level analysis in the chinese manufacturing sector. *Sustainability*, 11(7):1933.

Jia, R., Ma, X., and Xie, V. W. (2022). Expecting floods: Firm entry, employment, and aggregate implications. *NBER Working Paper 30250, https://doi.org/10.3386/w30250.*

Kahn, M. E. (2005). The death toll from natural disasters: the role of income, geography, and institutions. *Review of economics and statistics*, 87(2):271–284.

Kocornik-Mina, A., McDermott, T. K., Michaels, G., and Rauch, F. (2020). Flooded cities. *American Economic Journal: Applied Economics*, 12(2):35–66.

Kundzewicz, Z. W., Kanae, S., Seneviratne, S. I., Handmer, J., Nicholls, N., Peduzzi, P., Mechler, R., Bouwer, L. M., Arnell, N., Mach, K., et al. (2014). Flood risk and climate change: global and regional perspectives. *Hydrological Sciences Journal*, 59(1):1–28.

Li, W., Wen, J., Xu, B., Li, X., and Du, S. (2018). Integrated assessment of economic losses in manufacturing industry in shanghai metropolitan area under an extreme storm flood scenario. *Sustainability*, 11(1):126.

Ma, L. and Tang, Y. (2020). Geography, trade, and internal migration in china. *Journal of Urban Economics*, 115:103181. Cities in China.

Martinez, L. R. (2022). How much should we trust the dictator's gdp growth estimates? *Journal of Political Economy*, 130(10):2731–2769.

Mays, L. W. and Bedient, P. B. (1982). Model for optimal size and location of detention. *Journal of the Water Resources Planning and Management Division*, 108(3):270–285.

Mingkai, Q. and Kai, W. (2017). Flood management in china: The huaihe river basin as a case study. *Flood Risk Management*, pages 129–152.

Patel, D. (2023). Floods. *Available at SSRN 4636828*.

Redding, S. and Venables, A. J. (2004). Economic geography and international inequality. *Journal of International Economics*, 62(1):53–82.

Rentschler, J., Salhab, M., and Jafino, B. A. (2022). Flood exposure and poverty in 188 countries. *Nature Communications*, 13(1):3527.

Roth, J., Sant'Anna, P. H., Bilinski, A., and Poe, J. (2023). What's trending in difference-in-differences? a synthesis of the recent econometrics literature. *Journal of Econometrics*, 235(2):2218–2244.

Strobl, E. (2011). The economic growth impact of hurricanes: Evidence from us coastal counties. *Review of Economics and Statistics*, 93(2):575–589.

Taur, C.-K., Toth, G., Oswald, G. E., and Mays, L. W. (1987). Austin detention basin optimization model. *Journal of Hydraulic Engineering*, 113(7):860–878.

Taylor, C. A. and Druckenmiller, H. (2022). Wetlands, flooding, and the clean water act. *American Economic Review*, 112(4):1334–1363.

Tellman, B., Sullivan, J. A., Kuhn, C., Kettner, A. J., Doyle, C. S., Brakenridge, G. R., Erickson, T. A., and Slayback, D. A. (2021). Satellite imaging reveals increased proportion of population exposed to floods. *Nature*, 596(7870):80–86.

Tombe, T. and Zhu, X. (2019). Trade, migration, and productivity: A quantitative analysis of china. *American Economic Review*, 109(5):1843–72.

Wang, K., Wang, Z., Liu, K., Cheng, L., Bai, Y., and Jin, G. (2021). Optimizing flood diversion siting and its control strategy of detention basins: A case study of the yangtze river, china. *Journal of Hydrology*, 597:126201.

World Bank (2021). Climate risk country profile: China. https://climateknowledgeportal.worldbank.org/sites/default/files/2021-05/15395A-WB_China%20Country%20Profile-WEB_0.pdf.

Online Appendix

A Supplementary Materials of Data

A.1 Data about Floods

To measure floods, we use the Global Flood Database (GFD) by Tellman et al. (2021), which is a comprehensive dataset offering high-resolution data on flood events worldwide from 2000 to 2018. Using satellite imagery and machine learning, it captures over 900 flood events with a spatial resolution of 30 meters, allowing for detailed analysis of flood exposure and impacts at localized levels. For China, it documents a total of 189 flood events within China. Given GFD offers satellite maps that record flood events for every county (see Figure A1), we 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 2000-2018 at 30 meter resolution which was resampled to 250m resolution in Google Earth Engine using nearest neighbor resampling.", according to GFD. We then construct three county-level proxies of flood exposures.

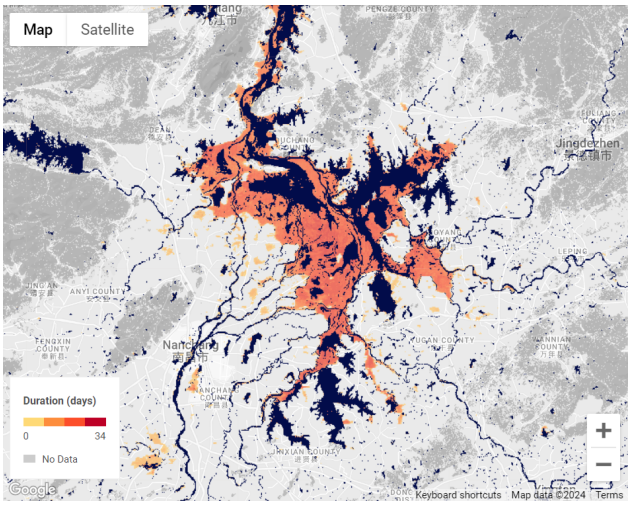


Figure A1: An Illustrative Example of Global Flood Database

Note: Blue areas indicate permanent water bodies, while red areas represent flooded regions. The intensity of the red color reflects the degree of flood inundation.

Size of Flood Inundation (total size of inundation in a flood event in a county)

$$\text{Size of Inundation}_{ift} = \sum_{j \in A_i} I(\text{Flood Duration}_{jft}) > 0$$

where A_i represents pixels that have not contained permanent water in county i, $\text{Flood Duration}_{jft}$ indicates the flood duration in a non-permanent water pixel j in flood event f at time t.

Flood Duration (total flood duration experienced by all non-permanent water pixels in a flood event in a county)

$$\text{Total Flood Duration}_{ift} = \sum_{j \in A_i} \text{Flood Duration}_{jft}$$

Size-Adjusted Flood Exposure (average flood duration of each non-permanent water pixel in a flood event in a 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. Panel B of Figure 1 demonstrates that size-adjusted flood exposure is higher in 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 risk, due to flood water detention.

A.2 Data about Population

We follow the approach by Chen et al. (2022b) to construct the county-level net outmigration ratio that we use in Section 3.3. In the work of Chen et al. (2022b), they distinguish two types of migrants in China: those who migrate to an new county but do not possess the local household registration (floating migrants), and those who migrate and possess the local household registration (registered migrants). In our paper, we only construct the floating migrants. We then use 1%, 20%, 3.30%, and 1% individual-level data randomly drawn from the 2000, 2005, 2010, and 2015 census, respectively. We calculate the net outmigration ration following the equation below:

$$\text{NetOutmig}_{[15,60]_{ct}} = \frac{\text{Pop}_{[15,60]_{ct}} - \text{Pop}_{[20,65]_{c,t+5}} - \hat{D}_{[15,60]_{c,t}}}{\text{Pop}_{[15,60]_{c,t}}} \times 100$$

where $\text{NetOutmig}_{c,t}$ represents the net-outmigration ratio for individuals aged $[15, 60]$ over the five-year period starting from year t in county c; $\text{Pop}_{[15,60]_{c,t}}$ denotes the total population aged $[15, 60]$ in county c at the beginning of the five-year interval that begins in year t, while $\text{Pop}_{[20,65]_{c,t+5}}$ refers to the population of the same cohort five years later, and $\hat{D}_{[15,60]_{c,t}}$ provides an approximation of deaths in that population during the five-year period. Additionally, we adopt the method from Chen et al. (2022b) to approximate the death count for each county.

B Supplementary Materials of Research Background in Section 2

B.1 Supplementary Materials of the FDB Policy



Figure B1: Before and After Flood Detention in an FDB County

Table B1: 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 B2: 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 simple 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.



Figure B2: Flood Detention Basins in 2000 (Original Policy Document)

索 引 号: 111000/2010-00628 信息所属单位: 防御司

发布机构: 水利部 成文日期: 2010年01月07日

名 称: 国家蓄滞洪区修订名录

文 号: 水汛[2010]14号 发布日期: 2010年01月12日

国家蓄滞洪区修订名录

Revised List of Flood Detention Basins (2010)

根据《蓄滞洪区运用补偿暂行办法》（2000年5月27日中华人民共和国国务院令第286号发布）规定,我部商财政部提出了国家蓄滞洪区名录修订意见并上报国务院。经国务院同意，现将《国家蓄滞洪区修订名录（2010年1月7日）》予以公布。

请你省（直辖市）和流域管理机构按照《蓄滞洪区运用补偿暂行办法》和有关规定，认真做好蓄滞洪区运用补偿的各项工作。

附件:

国家蓄滞洪区修订名录

(2010年1月7日)

长江流域：围堤湖、六角山、九垸、西官垸、安澧垸、澧南垸、安昌垸、安化垸、南顶垸、和康垸、南汉垸、民主垸、共双茶、城西垸、屈原农场、义和垸、北湖垸、集成安合、钱粮湖、建设垸、建新农场、君山农场、大通湖东、江南陆城、荆江分洪区、宛市扩大区、虎西备蓄区、人民大垸、洪湖分洪区、杜家台、西凉湖、东西湖、武湖、张渡湖、白潭湖、康山圩、珠湖圩、黄湖圩、方洲斜塘、华阳河、荒草二圩、荒草三圩、汪波东荡、蒿子圩。（共44处）

Figure B3: Flood Detention Basins in 2010 (Original Policy Document)



长江流域：围堤湖、六角山、九垸、西官垸、安澧垸、澧南垸、安昌垸、安化垸、南顶垸、和康垸、南汉垸、民主垸、共双茶、城西垸、屈原农场、义和垸、北湖垸、集成安合、钱粮湖、建设垸、建新农场、君山农场、大通湖东、江南陆城、荆江分洪区、宛市扩大区、虎西备蓄区、人民大垸、洪湖分洪区、杜家台、西凉湖、东西湖、武湖、张渡湖、白潭湖、康山圩、珠湖圩、黄湖圩、方洲斜塘、华阳河、荒草二圩、荒草三圩、汪波东荡、蒿子圩。（共44处）

黄河流域：北金堤、东平湖。（共2处）

淮河流域：蒙洼、城西湖、城东湖、瓦埠湖、老汪湖、泥河洼、老王坡、蛟停湖、黄墩湖、南润段、邱家湖、姜唐湖、寿西湖、董峰湖、汤渔湖、荆山湖、花园湖、杨庄、洪泽湖周边(含鲍集圩）、南四湖湖东、大道遥。（共21处）

海河流域：永定河泛区、小清河分洪区、东淀、文安洼、贾口洼、兰沟洼、宁晋泊、大陆泽、良相坡、长虹渠、柳围坡、白寺坡、大名泛区、恩县洼、盛庄洼、青甸洼、黄庄洼、大黄铺洼、三角淀、白洋淀、小滩坡、任固坡、共渠西、广润坡、团泊洼、永年洼、献县泛区、崔家桥。（共28处）

松花江流域：月亮泡、胖头泡。（共2处）

珠江流域：潖江。（1处）

以上合计共98处。

此外，淮河流域的上六坊堤、下六坊堤、石姚湾、洛河洼、方邱湖、临北段、香浮段、潘村洼等8处蓄滞洪区虽不再列入国家蓄滞洪区名录，但在规划工程完工前，遇大洪水时若分洪运用，仍参照《蓄滞洪区运用补偿暂行办法》给予补偿。

Figure B4: Flood Detention Basins in 2010 (Original Policy Document), continued

B.2 FDB Selection Criteria

According to the Chinese government, FDBs are located in low-lying lands that are hydrologically feasible to collect flood water. Table B3 presents summary statistics comparing FDB counties, protected counties, and other counties. FDB counties are, on average, located at substantially lower elevations and have gentler slopes than other counties. In contrast, nighttime light intensity in 1999 is similar between FDB and protected counties and moderately higher than in other counties.

Table B3: Descriptive Statistics of FDB-Designated, FDB-Protected, and Other Counties

	Types of Counties:		
(in logarithm)	FDB-Designated (1)	FDB-Protected (2)	Others (3)
Economic Characteristics:			
1999 Nighttime Light	13.359	13.369	12.510
	(0.808)	(0.801)	(1.299)
2000 Population	6.281	7.303	5.319
	(0.555)	(1.145)	(1.693)
2000 N(Firms)	6.484	7.336	6.532
	(1.608)	(1.556)	(1.661)
2000 N(Larger Manufacturing Firms)	3.734	4.266	3.262
	(0.756)	(0.841)	(1.033)
Geographical Characteristics:			
Elevation	3.396	3.641	5.785
	(0.793)	(1.067)	(1.597)
Slope	1.748	1.865	2.428
	(0.267)	(0.368)	(0.545)
Observations	97	131	2,612

Note: (1) Means are reported with standard deviations in parentheses. All variables are in natural logarithms; (2) Nighttime light intensity data is from Chen et al. (2022a), population, number of firms, and number of larger manufacturing firms data is from the 2000 county-level statistical yearbook, geographical data is from the NASA ASTER Global Digital Elevation Model (GDEM).

To formally examine these patterns, we estimate the following cross-sectional linear probability model:

$$FDB_{ic} = \alpha + \beta_1 Elevation_{ic} + \beta_2 Slope_{ic} + \beta_3 Light_{ic}^{95-00} + \gamma_c + \epsilon_{ic}$$

where FDB_{ic} is a dummy variable that equals 1 if the county i in city c is designated as an FDB county in 2000, and 0 otherwise. $Elevation_{ic}$ and $Slope_{ic}$ represents the elevation and slope of county i, respectively. $Light_{ic}^{95-00}$ measures the 1995-2000 average nighttime light intensity of county i. γ_c refers to the city fixed effects. Standard errors are clustered at the county level. The regression results in Table B4 confirm that elevation is a strong predictor of FDB designation: counties with higher elevation are significantly less likely to be chosen as FDBs, even after controlling for slope, light intensity, and city fixed effects.

In contrast, slope and nighttime light intensity are not statistically significant predictors. The empirical results confirm that hydrological suitability is the primary criterion in FDB designation decisions.

Table B4: FDB Selection Criteria: Linear Probability Model

Variables	Selection into 2000 FDB List		
(in logarithm)	(1)	(2)	(3)
Elevation	−0.071***	−0.075***	−0.075***
	(0.013)	(0.019)	(0.019)
Slope		0.011	0.010
		(0.029)	(0.030)
95-00 Average Light			−0.002
			(0.004)
N(obs)	1,873	1,873	1,873
Fixed Effects			
City	Y	Y	Y

Note: (1) The dependent variable is a dummy FDB_{ic} that equals 1 if the county i in city c has been designated to host a Flood Detention Basin in 2000, and equals 0 if not; (2) Standard errors are clustered at the city level; (3) *, **, and *** respectively indicates 10%, 5%, and 1% significance level.

B.3 FDB Policy and Flood Redistribution

Panel B of Figure 1 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 FDB-Protected and other 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 exposure 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 A.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.

Table B5: FDB and Flood Risk Redistribution

Variables (in IHS)	Number of Flooded Pixels			
Panel A. Flood Size	(1)	(2)	(3)	(4)
FDB	0.583***	0.530***	0.460***	0.460***
	(0.096)	(0.093)	(0.116)	(0.116)
Observations	47,367	47,367	4,674	4,674
Variables (in IHS)	Number of Flooded Days			
Panel B. Flood Exposure	(1)	(2)	(3)	(4)
FDB	0.049***	0.043***	0.025*	0.025*
	(0.011)	(0.010)	(0.013)	(0.013)
Observations	47,367	47,367	4,674	4,674
For All Panels:				
Sample Period	2000-2020	2000-2020	2000-2020	2000-2020
Sample	All	All	FDB+Protected	FDB+Protected
Controls	N	Y	N	Y
Fixed Effects				
Year	Y	Y	Y	Y
City	Y	Y	Y	Y

Note: (1) We introduce how we measure flood size and flood exposure in Section A.1; (2) 'All' represents that our samples include all types of counties, while 'FDB+Protected' represents that our sample only includes FDB-designated and FDB-protected counties; (3) controls include precipitation, elevation, and slope; (4) 'FDB' is a dummy variable that equals one if the county is an FDB-designated county; (5) Since flood data are unavailable before 2000, we cannot employ a difference-in-differences approach to estimate the impact of the 2000 FDB implementation on flood exposure. Instead, this table presents a cross-sectional comparison of flood size and exposure between FDB-designated counties and other counties within the same city.

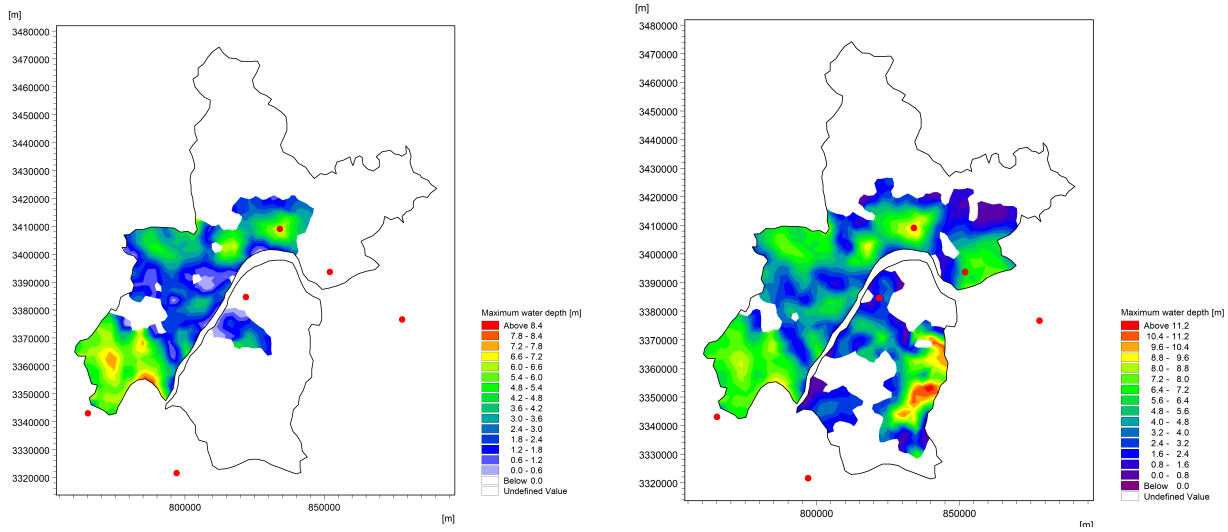
As indicated in Column (1) and (2) of Panel A in Table B5, we find that after controlling for important geographical controls, the size of flood inundation area in FDB counties is more than 50% higher in FDB counties than other counties in the same city. Column (1) and (2) of Panel B also suggest that the size-adjusted flood exposure is around 2.5-4.9% 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.

B.4 Hydrological Analysis based on Hydro-Dynamic Model

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." To rigorously quantify the level of floodwater redistribution, we incorporate an interdisciplinary approach and employ a hydro-dynamic engineering model developed under the supervision of the Danish Hydraulic Institute (DHI) to measure the flood exposure redistribution rate during a real flood event. The hydro-dynamic model is a sophisticated tool used for simulating water flow, particularly in river basins and floodplain areas. It accounts for variables such as topography, water velocity, flow rates, and human interventions, making it highly suitable for assessing the impacts of floodwater management policies like the Flood Detention Basin (FDB) policy. We specifically choose Wuhan for this analysis because of its economic importance, and its size is comparable to that of the FDB counties. This makes it easier to translate the flood protection benefits observed in Wuhan to the flood water absorbed by the FDB regions.

The process of implementing the model consists of several key steps. First, we collect high-resolution geographical shape data, river runoff data, and detailed policy information on floodwater diversion. These inputs are essential to build an accurate representation of the river system and floodplain in question, including the areas designated as FDB zones. The geographical data defines the physical characteristics of the region, while the runoff data provides insight into how much water the rivers and floodplains can handle during heavy rainfall or extreme flood events. The FDB policy details, on the other hand, establish the parameters of water diversion in our model. Next, we calibrate the model using histori-

cal flood data to ensure its accuracy. This involves adjusting model parameters until the simulated outcomes closely match the observed data from past flood events. Calibration is a crucial step because it ensures that the model is reliable and that its predictions reflect real-world conditions. By checking the consistency of model predictions with actual flood patterns, we validate the model's capacity to predict the effects of floodwater redistribution accurately. After calibration, we simulate a counterfactual scenario where the floodwater are not diverted to the FDB areas. This simulation allows us to assess what would happen in the absence of the flood diversion policy. The model predicts how floodwater would behave if allowed to flow freely without the designated intervention, providing us with a comparison between the actual and hypothetical scenarios. Finally, we compare the size of the inundation area in Wuhan City between the actual scenario, where floodwater are diverted into the FDB regions, and the counterfactual scenario without diversion. As shown in Figure B5, the inundation area in Wuhan, an important city intended to be protected by the FDB policy, increases by 45% in the absence of floodwater diversion.



(a) Actual Case: with FDB (b) Counterfactual Case: without FDB

Figure B5: 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.

C Supplementary Materials of Cost Estimation in Section 3

C.1 Robustness Check

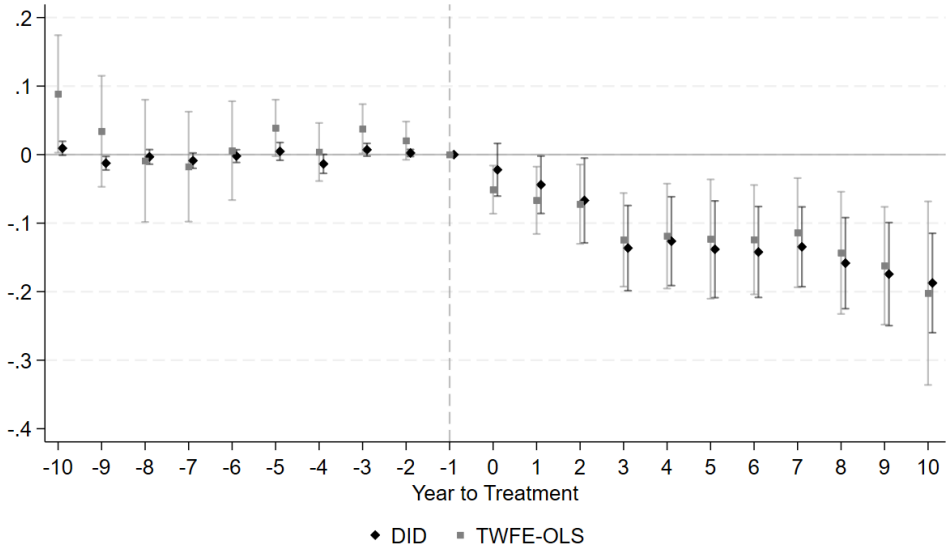
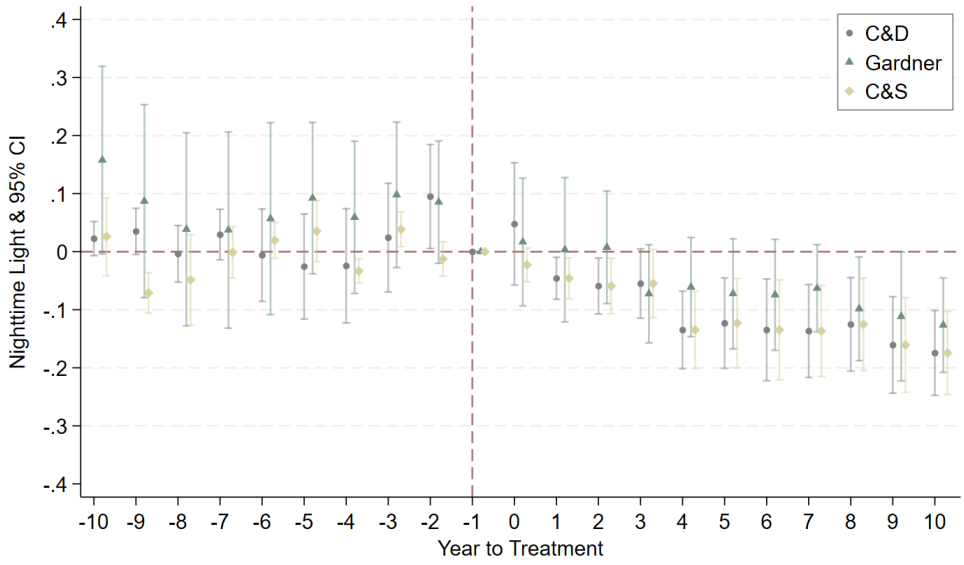
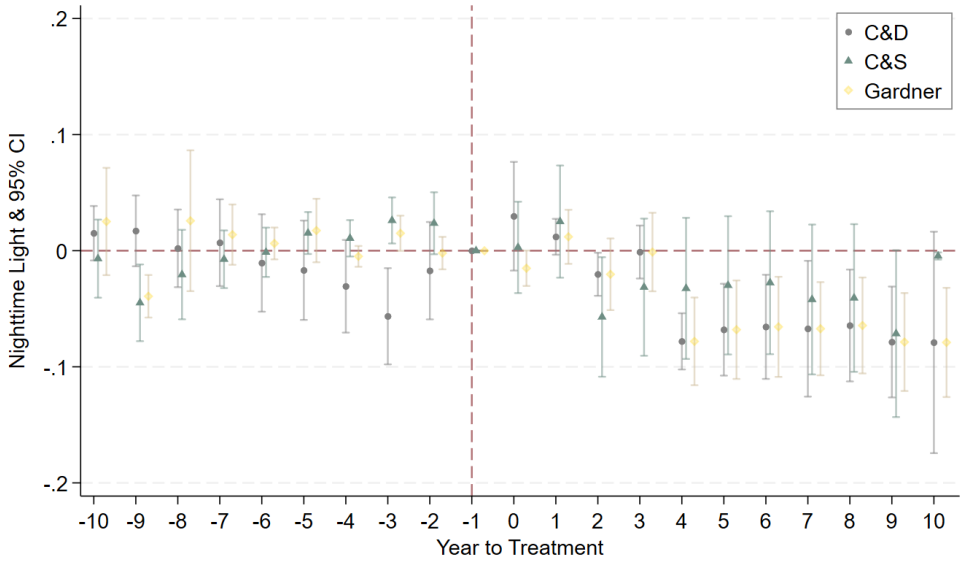


Figure C1: Robustness Check of Figure 4
(FE: County FE and Year FE)

Note: (1) This figure serves as a robustness check of Figure 4, re-estimating the difference-in-differences model with only county and year fixed effects included (see Section 3.1 for details); (2) All other details remain the same as in Figure 4.



(a) Panel A: FE - County FE and Year FE



(b) Panel B: FE - County FE, Year FE, and Province by Year FE

Figure C2: Robustness Check of Figure 4
(Alternative DID Approaches)

Note: (1) This figure serves as a robustness check of Figure 4, re-estimating the difference-in-differences model using alternative DID approaches; (2) 'C&D' refers to the two-way fixed effects estimators with heterogeneous treatment effects proposed by De Chaisemartin and d'Haultfoeuille (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) Panel A includes county FE and year FE, Panel B includes county FE, year FE, and province by year FE; (4) All other details remain the same as in Figure 4.

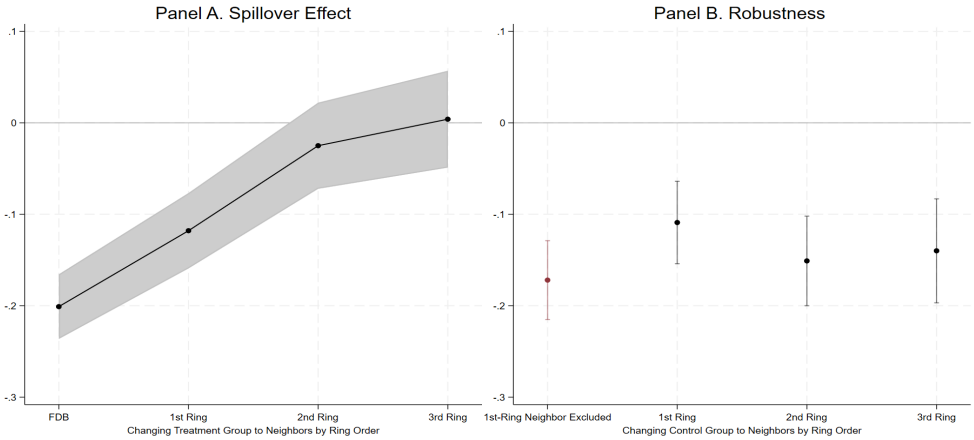


Figure C3: Robustness Check of Figure 5
(FE: County FE and Year FE)

Note: (1) This figure serves as a robustness check of Figure 5, re-estimating the difference-in-differences model with only county and year fixed effects included (see Section 3.1 for details); (2) ATT is reported in Table C1; (3) All other details remain the same as in Figure 5.

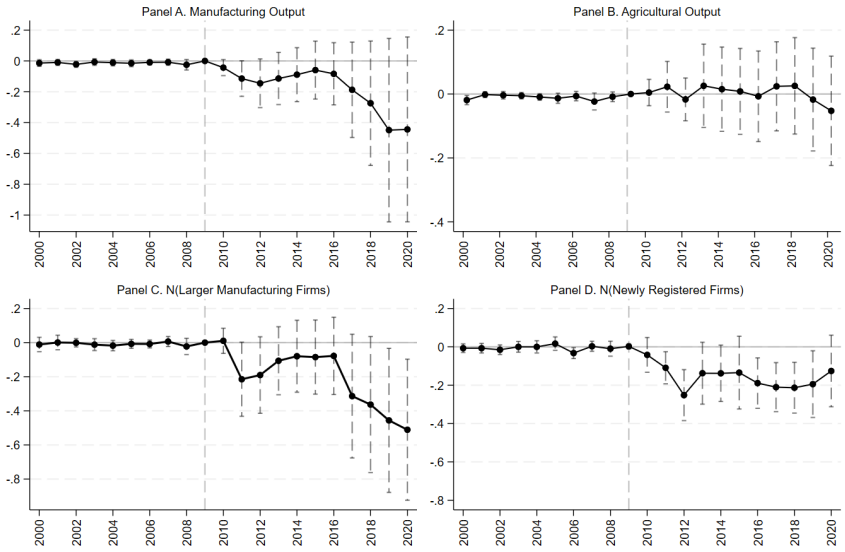


Figure C4: Robustness Check of Figure 6
(FE: County FE and Year FE)

Note: (1) This figure serves as a robustness check of Figure 6, re-estimating the difference-in-differences model with only county and year fixed effects included (see Section 3.1 for details); (2) All other details remain the same as in Figure 6.

Table C1: Robustness Check of Table 1 (Changing Control Group)

Variables (in IHS)	Nighttime Light Intensity					
Panel A. Method - TWFE	(1)	(2)	(3)	(4)	(5)	(6)
FDB	-0.148***	-0.077**	-0.185***	-0.107***	-0.119***	-0.083*
	(0.041)	(0.035)	(0.042)	(0.037)	(0.043)	(0.043)
Variables (in IHS)	Nighttime Light Intensity					
Panel B. Method - DID	(1)	(2)	(3)	(4)	(5)	(6)
FDB	-0.109***	-0.044***	-0.151***	-0.078***	-0.140***	-0.088***
	(0.023)	(0.016)	(0.035)	(0.017)	(0.025)	(0.029)
For All Panels:						
Observations	8,184	8,184	9,052	9,052	9,021	9,021
Sample Period	1990-2020	1990-2020	1990-2020	1990-2020	1990-2020	1990-2020
Fixed Effects						
Year	Y	Y	Y	Y	Y	Y
County	Y	Y	Y	Y	Y	Y
Province × Year	N	Y	N	Y	N	Y
Control Group	1st-Ring Neighbor	1st-Ring Neighbor	2nd-Ring Neighbor	2nd-Ring Neighbor	3rd-Ring Neighbor	3rd-Ring Neighbor

Note: (1) This table serves as a robustness check of Figure 1, re-estimating the difference-in-differences model by changing the control group (see Section 3.1 for details); (2) '1st Ring' neighbors share a border with FDB counties, '2nd Ring' neighbors border the first ring, and '3rd Ring' neighbors border the second ring; (3) All other details remain the same as in Table 1.

Table C2: Robustness Check of Table 1 using Alternative DID Methods

	C&D		Gardner		C&S	
	(1)	(2)	(3)	(4)	(5)	(6)
FDB	-0.115***	-0.051***	-0.182***	-0.063**	-0.147***	-0.081***
	(0.030)	(0.016)	(0.064)	(0.032)	(0.040)	(0.020)
Observations	65,038	65,038	65,038	65,038	65,038	65,038
Sample Period	1990-2020	1990-2020	1990-2020	1990-2020	1990-2020	1990-2020
Fixed Effects						
Year	Y	Y	Y	Y	Y	Y
County	Y	Y	Y	Y	Y	Y
Province × Year	N	Y	N	Y	N	Y
Control Group	Neighbor Excluded	Neighbor Excluded	Neighbor Excluded	Neighbor Excluded	Neighbor Excluded	Neighbor Excluded

Note: (1) This figure serves as a robustness check of Table 1, re-estimating the difference-in-differences model using alternative DID approaches; (2) 'C&D' refers to the two-way fixed effects estimators with heterogeneous treatment effects proposed by De Chaisemartin and d'Haultfoeuille (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); (4) All other details remain the same as in Table 1.

Table C3: Robustness Check of Table 2 Changing Control Group

Variables (in IHS)	Manufacturing Output		Agricultural Output	
Panel A. Output	(1)	(2)	(3)	(4)
FDB	−0.198*	−0.100	−0.025	0.033
	(0.110)	(0.079)	(0.047)	(0.040)
Observations	43,050	43,050	43,050	43,050
Variables (in IHS)	N (Newly Registered Firms)		N (Larger Manufacturing Firms)	
Panel B. Firm Entry	(1)	(2)	(3)	(4)
FDB	−0.142***	−0.131***	−0.218***	−0.126*
	(0.041)	(0.049)	(0.081)	(0.073)
Observations	57,876	57,876	43,050	43,050
For All Panels:				
Sample Period	2000-2020	2000-2020	2000-2020	2000-2020
Control Group	Baseline	Baseline	Baseline	Baseline
Fixed Effects				
Year	Y	Y	Y	Y
County	Y	Y	Y	Y
Province × Year	N	Y	N	Y

Note: (1) This figure serves as a robustness check of Table 2, re-estimating the difference-in-differences model using alternative control group; (2) The 'Baseline' control group excludes protected urban areas but does not exclude neighboring counties (see Section 3.1 for detailed discussion); (3) All other details remain the same as in Table 2.

Table C4: Robustness Check of Table 3 Changing Control Group

Variables	ln(Registered Population)		Net Outmigration Ratio (%)	
	(1)	(2)	(3)	(4)
FDB	−0.020	−0.017	0.074	0.205*
	(0.039)	(0.036)	(0.117)	(0.116)
Observations	43,050	43,050	5,340	5,340
Sample Period	2000-2020	2000-2020	2000-2020	2000-2020
Fixed Effects				
Year	Y	Y	Y	Y
County	Y	Y	Y	Y
Province × Year	N	Y	N	Y
Control Group	Baseline	Baseline	Baseline	Baseline

Note: (1) This figure serves as a robustness check of Table 3, re-estimating the difference-in-differences model using alternative control group; (2) The 'Baseline' control group excludes protected urban areas but does not exclude neighboring counties (see Section 3.1 for detailed discussion); (3) All other details remain the same as in Table 3.

C.2 Additional Results

C.2.1 Additional Anecdotal Evidence



Figure C5: Policy Document that Encourages Adaptation in the Agricultural Sector

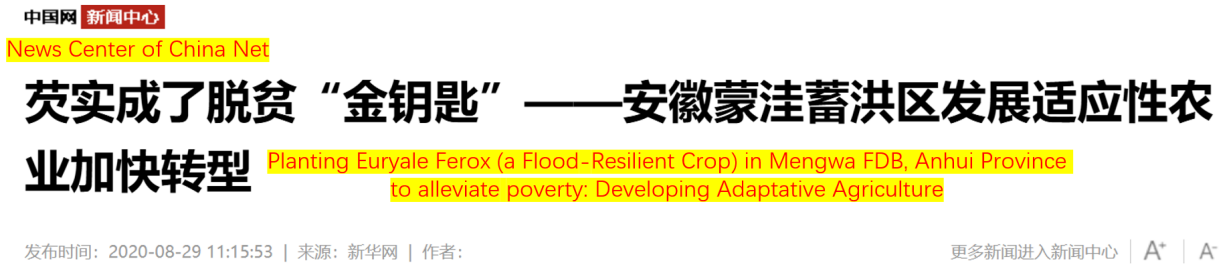


Figure C6: News Reports about Agricultural Adaption in FDB Counties

C.2.2 Additional Empirical Results

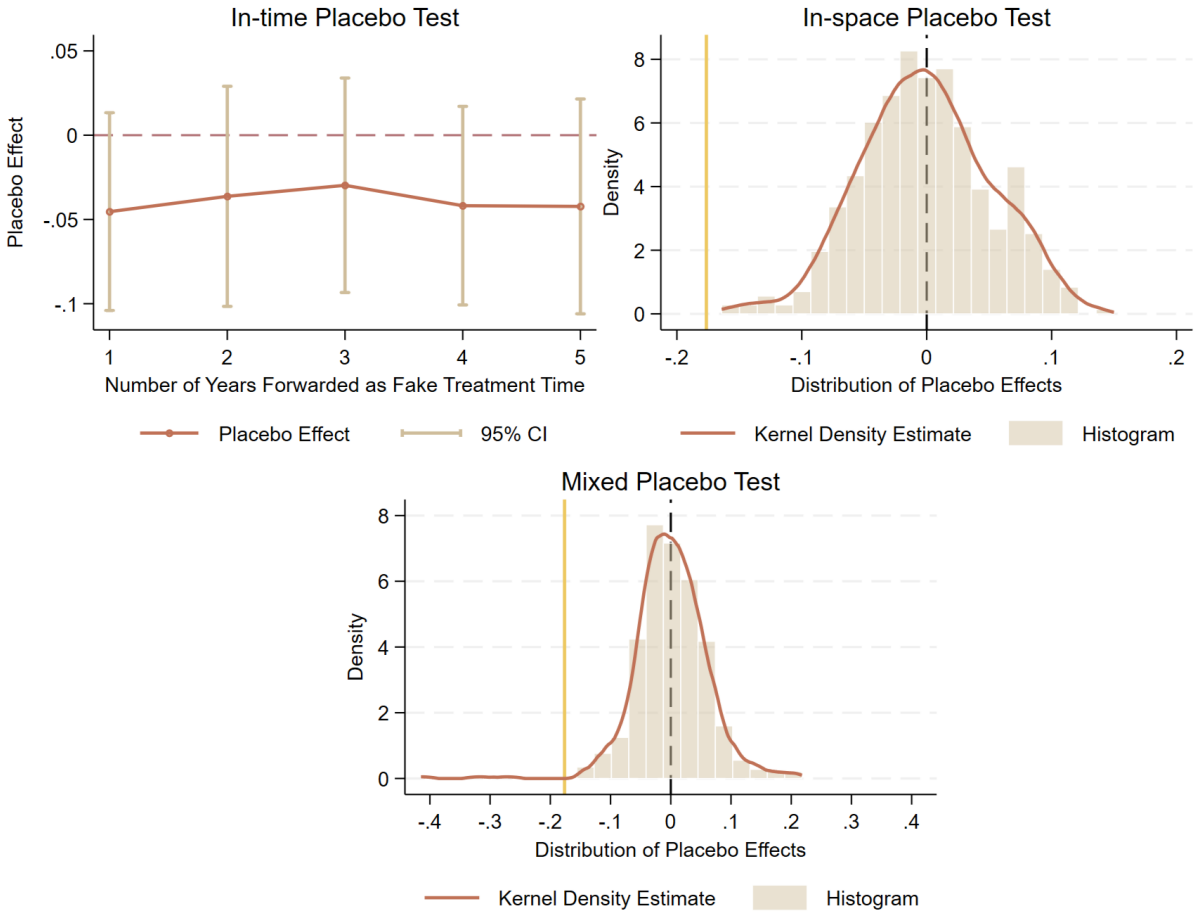
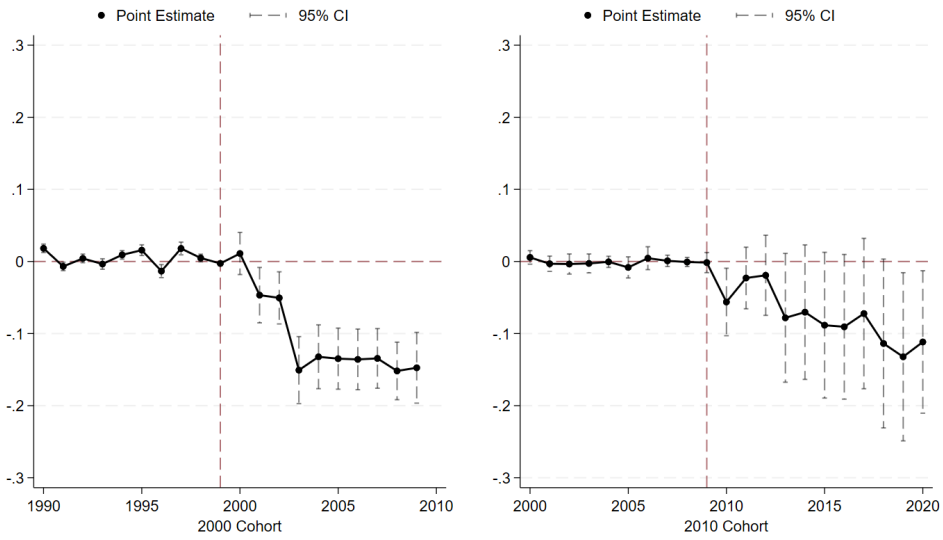
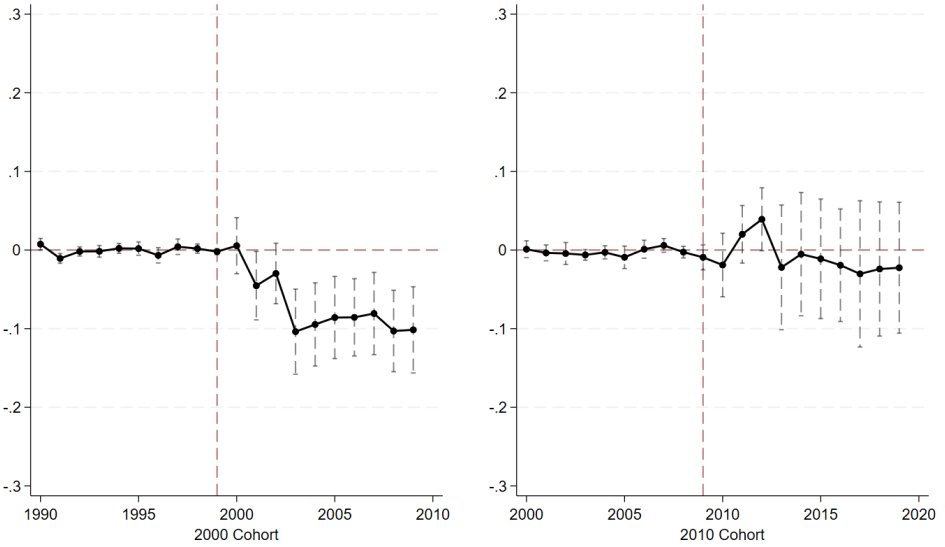


Figure C7: Placebo Test

Note: (1) This figure presents results of three distinct types of placebo tests of the TWFE: 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.



(a) Panel A: FE - County FE and year FE



(b) Panel B: FE - County FE, Year FE, and Province by Year FE

Figure C8: Dynamic Impacts of 2000 and 2010 FDB Policy on Nighttime Light Intensity

Note: (1) The figure depicts the event study coefficients from DID approach as described in Section 3.1; (2) Treatment is 2000 and 2010 FDB designation, respectively, for the left figure and for the right figure: 96 counties were selected into the FDB list in 2000, while 20 counties were selected into the FDB list in 2010; (3) Panel A adds county FE and year FE into the DID, while Panel B adds county FE, year FE, and province by year FE into the DID. (4) All other details remain the same as in Figure 4.

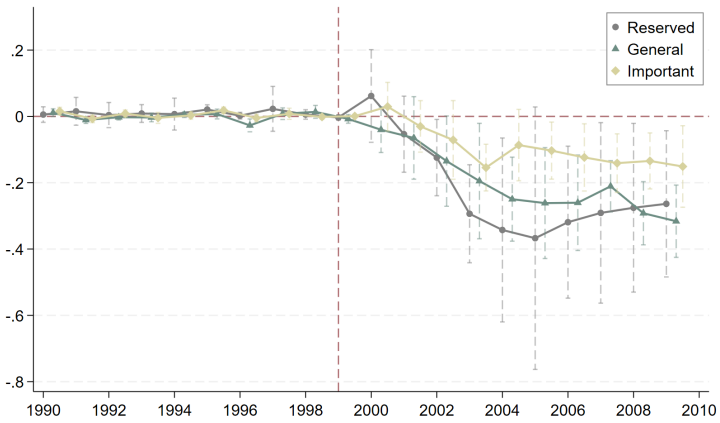


Figure C9: Heterogeneous Impact of FDB Policy on Nighttime Light Intensity

Note: (1) The figure depicts the event study coefficients from DID approach as described in Section 3.1; (2) 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; (3) All other details remain the same as in Figure 4.

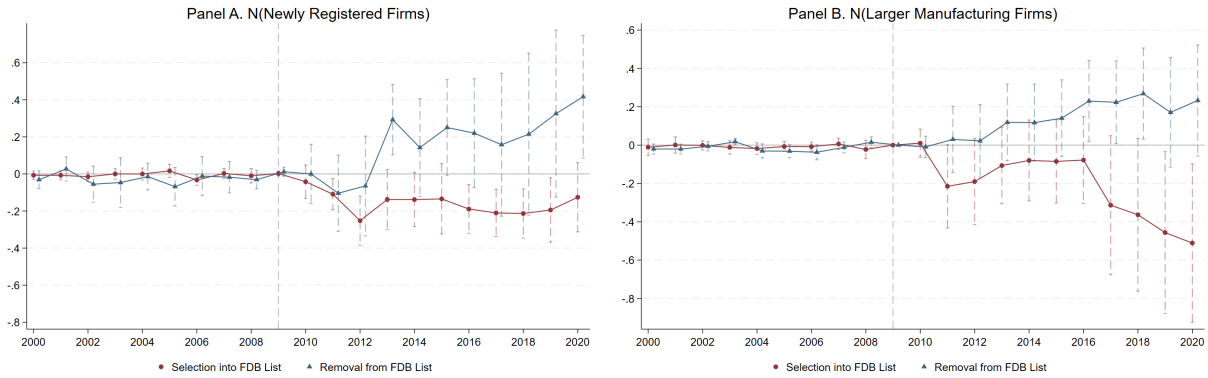


Figure C10: Impacts of FDB Selection and FDB Removal on Firm Entry

Note: (1) The figure depicts the event study coefficients from DID approach as described in Section 3.1; (2) In each figure, we present results of two treatments: selection into the 2010 FDB list, and removal from the 2010 FDB list. In 2010, 20 counties were designated as FDB counties, while 10 were removed from the list; (3) We include county FE and year FE into our regressions; (4) All other details remain the same as in Figure 6.

Table C5: Proximity-Based Spillover Test

Variables (in IHS)	Nighttime Light Intensity					
	(1)	(2)	(3)	(4)	(5)	(6)
1st-Ring × Post	-0.118***	-0.050***				
	(0.021)	(0.018)				
2nd-Ring × Post			-0.025	0.003		
			(0.024)	(0.020)		
3rd-Ring × Post					-0.004	0.024
					(0.027)	(0.022)
Observations	78,773	78,773	80,253	80,253	80,290	80,290
Fixed Effects						
Year	Y	Y	Y	Y	Y	Y
County	Y	Y	Y	Y	Y	Y
Province × Year	N	Y	N	Y	N	Y
Control Group	All-Neighbor Excluded	All-Neighbor Excluded	All-Neighbor Excluded	All-Neighbor Excluded	All-Neighbor Excluded	All-Neighbor Excluded

Note: (1) This table reports the ATT corresponding to Panel A of Figure 5 and replicates Table 1, redefining the treatment group as the neighboring counties of FDB-designated and FDB-protected counties. The objective is to examine the presence of proximity-based spillover effects; (2) '1st Ring' neighbors share a border with FDB counties, '2nd Ring' neighbors border the first ring, and '3rd Ring' neighbors border the second ring; (3) The 'All-Neighbor Excluded' control group excludes all FDB-designated, FDB-protected, and 1st/2nd/3rd-ring counties. For instance, in column (2), 2nd-ring and 3rd-ring neighboring counties are excluded from the control group; (4) All other details remain the same as in Table 1.

Table C6: Main Results: Impacts of FDB Designation on Nighttime Light Intensity

Variables (in IHS)	Nighttime Light Intensity			
Panel A. 2000 Policy Effect	(1)	(2)	(3)	(4)
2000 FDB	−0.159***	−0.056**	−0.121***	−0.094***
	(0.035)	(0.026)	(0.015)	(0.019
Sample Period	1990-2010	1990-2010	1990-2010	1990-2010
Observations	41,580	41,580	41,580	41,580
Variables (in IHS)	Nighttime Light Intensity			
Panel B. 2000 Policy Effect	(1)	(2)	(3)	(4)
2010 FDB	−0.083**	0.002	−0.064*	−0.009
	(0.043)	(0.036)	(0.038)	(0.038)
Sample Period	2010-2020	2010-2020	2010-2020	2010-2020
Observations	42,231	42,231	42,231	42,231
For All Panels:				
Method	TWFE	TWFE	DID	DID
Fixed Effects				
Year	Y	Y	Y	Y
County	Y	Y	Y	Y
Province × Year	N	Y	N	Y
Control Group	Neighbor Excluded	Neighbor Excluded	Neighbor Excluded	Neighbor Excluded

Note: (1) This table reports the ATT corresponding to Figure C8; (2) In Panel A, the treatment is defined as selection into the 2000 FDB list, while in Panel B, it is defined as selection into the 2010 FDB list; (3) All other details remain the same as in Table 1.

Table C7: Heterogeneous Impacts of FDB on Nightime Light Intensity

	Type of FDBs:					
	Reserved		General		Important	
	(1)	(2)	(3)	(4)	(5)	(6)
FDB	-0.308***	-0.231***	-0.166***	-0.084**	-0.116***	-0.047*
	(0.079)	(0.039)	(0.043)	(0.042)	(0.043)	(0.027)
Observations	69,316	69,316	69,998	69,998	69,657	69,657
Fixed Effects						
Year	Y	Y	Y	Y	Y	Y
County	Y	Y	Y	Y	Y	Y
Province-Year	N	Y	N	Y	N	Y
Control Group	Neighbor Excluded	Neighbor Excluded	Neighbor Excluded	Neighbor Excluded	Neighbor Excluded	Neighbor Excluded

Note: (1) We estimate the impact of FDB policy on three different types of FDB-designated counties: 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; (3) All other details are the same in Table 1.

D Additional Results of the General Equilibrium Model in Section 4

D.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.

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

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

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

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: $p'_p = p_p - \Delta p$.

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 D.2.

D.2 Proof of Proposition 1

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

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

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:

$$\bar{r}_i - r_f = p_i d \tag{17}$$

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:

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

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

E Additional Results

E.1 Direct Protection Effect

In Table E1, 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 E1, 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.

Table E1: 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)
Observations	5,242	5,242	5,242	5,242
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 is a FDB-Designated 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.

E.2 Elasticity between Flood and Productivity

Productivity Loss. We estimate productivity loss in manufacturing sector based on the estimation below:

$$Y_{it} = \alpha + \beta FloodExposure_{i,t} + \gamma_c + \lambda_t + \epsilon_{i,t}.$$

In this estimation, Y_{it} represents the log labor productivity in county i and year t, measured as output per worker in a given industry. $FloodExposure_{it}$ indicates the size-adjusted flood exposure, which is the average days of flood, as described in Section 2, in county i and year t. λ_c and η_t represent city and time fixed effects. Standard errors are clustered at city level.

Table E2: Flood Impact on Productivity

(ln)	Total Productivity	Manufacturing Productivity
Flood Exposure	−0.043**	−0.059*
	(0.021)	(0.032)
Observations	1,283	1,283
Fixed Effects		
Year	Y	Y
City	Y	Y

Note: (1) 'Flood Exposure' represents the size-adjusted flood exposure of a county at flood event that happened at time t, detailed construction is introduced in Appendix A.1; (2) 'Total Productivity' represents the total local output per worker, 'Manufacturing Productivity' represents the manufacturing output per worker; (3) All regressions control for city fixed effects and year fixed effects; (4) Standard errors are clustered at the county level.

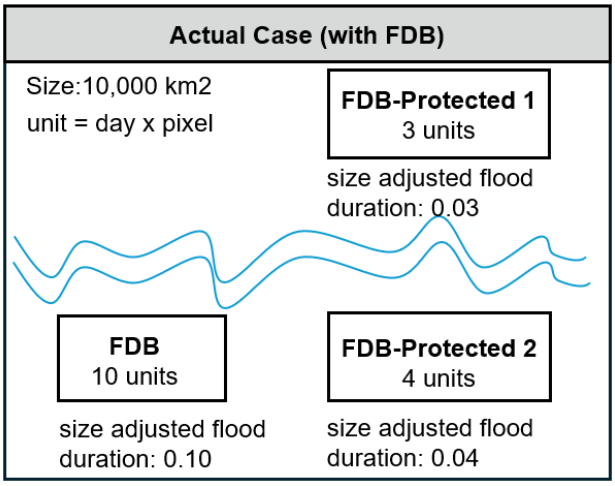
E.3 Model Fit: Comparing Data Outcomes and Data Generated Outcomes

Table E3: Model Fit

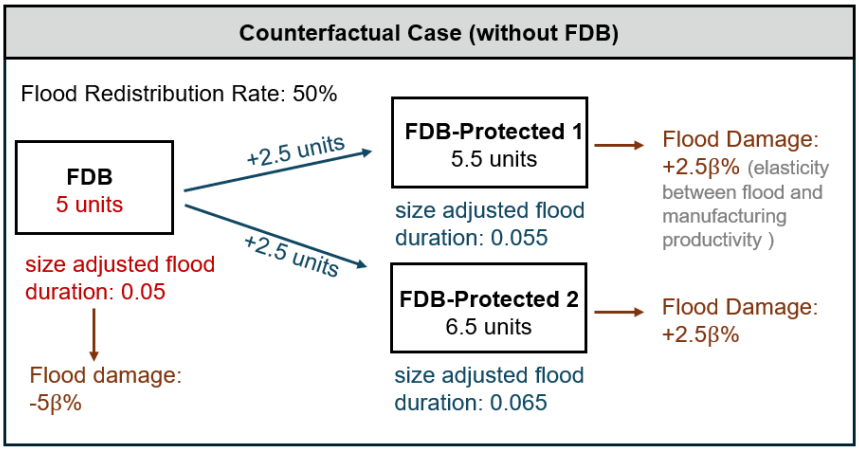
	(1)	(2)	(3)	(4)
Capital (Data)	0.784***	0.948***		
	(0.009)	(0.002)		
Labor (Data)			1.147***	1.001***
			(0.018)	(0.003)
Observations	1,827	1,827	1,827	1,827
Adjusted R-square	0.795	0.993	0.687	0.980
With Constant	*Y*	*N*	*Y*	*N*

Note: (1) The dependent variable is the model-generated outcome for capital (Column 1 and 2) or labor (Column 3 and 4), regressed on corresponding data outcomes; (2) Columns 1 and 3 include a constant term, while Columns 3 and 4 are estimated without a constant; (3) Both model-generated outcome and data outcomes are in log. (4) Standard errors are clustered at the county level.

E.4 Illustration of the Counterfactual Practice



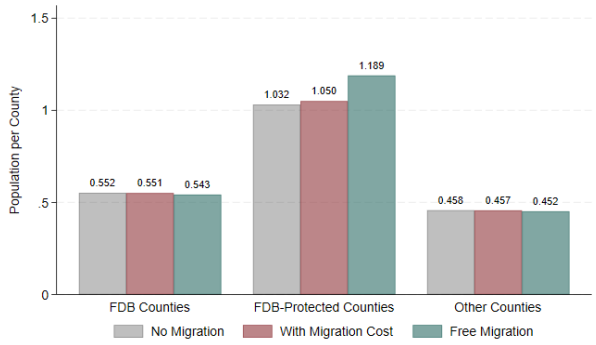
(a) Actual Case: With Flood Detention Basin



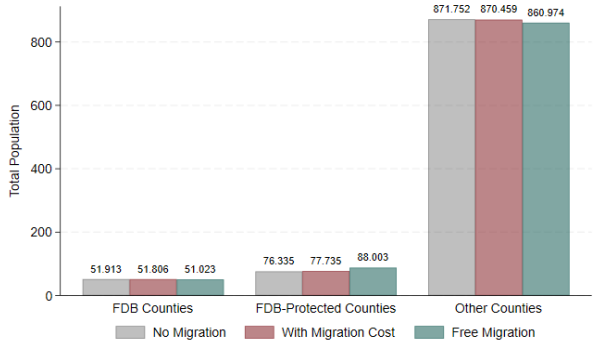
(b) Counterfactual Case: Without Flood Detention Basins

Figure E1: Mind Map: Constructing the Counterfactual Scenario

E.5 Alternative Counterfactual Practice: Migration



(a) Average Population per County



(b) Total Population

Figure E2: Population of FDB-Designated, FDB-Protected, and Other Counties in Actual and Counterfactual Scenarios

Note: The maroon bars represent the counterfactual scenario with the FDB policy in place, but with migration restricted such that only 12% of individuals who wish to migrate are ultimately able to migrate. The emerald bars represent the simulated outcomes under the FDB policy with free migration. Output is reported separately for FDB countries, FDB-Protected counties, and other counties.

E.6 Alternative Counterfactual Practice: Relative Contribution of Different FDB Counties

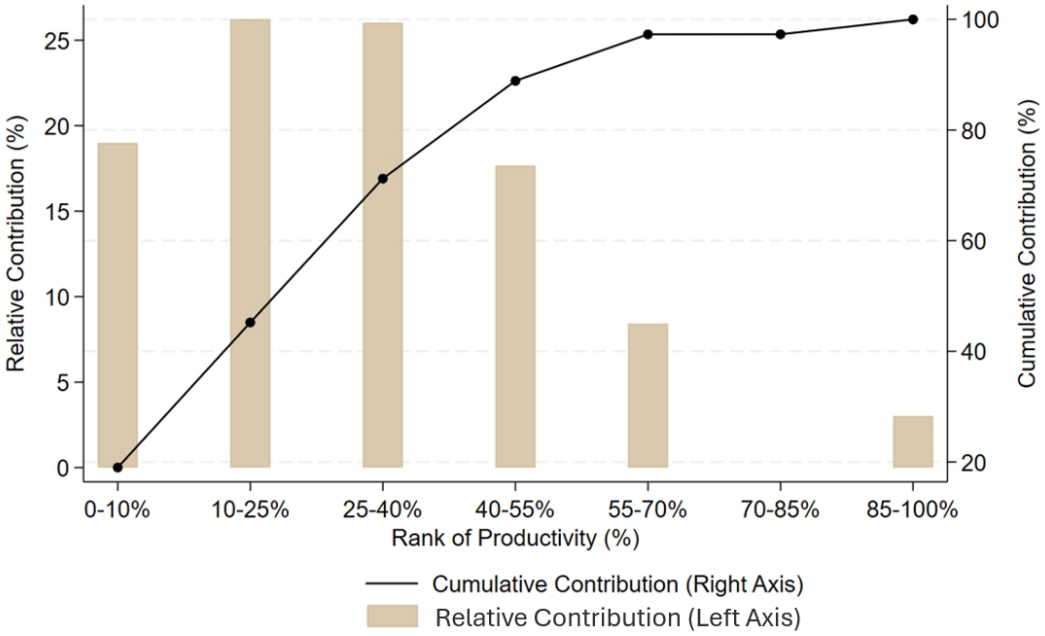


Figure E3: Relative Contribution of Different Productivity Groups