The Agricultural and Economic Impacts of Massive Water Diversion*

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Abstract

We investigate the agricultural and economic impacts of China's South-North Water Diversion Project, a massive initiative that channels water from the abundant southern regions to the drier north. Using a difference-in-differences approach, we find the project leads to an 8.2% increase in total grain output and a 4.7% boost in agricultural productivity for water-receiving counties. Additionally, the project mitigates the adverse effects of drought shocks, resulting in modest increases in local incomes. We find no evidence that areas providing water experience significant losses. Back-of-the-envelope calculations indicate an internal rate of return of 6.4%, highlighting the project's economic viability.

JEL Codes: O13, O18, Q15, Q25, Q28
Keywords: water scarcity, China's South-North Water Diversion Project, agricultural productivity, regional development, drought conditions

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1 Introduction

Water is a fundamental input to all economic activities. Yet, it remains scarce for billions worldwide. The UN World Water Development Report 2023 highlights that an estimated two to three billion individuals globally grapple with water shortages. As climate change accelerates and population surges, these shortages are poised to intensify, potentially hampering the economic progress of numerous nations (Damania et al., 2017; World Bank, 2016).[1] To mitigate this crisis, governments have implemented various hydrological interventions, such as dams, reservoirs, and irrigation systems, to improve water management and allocative efficiency. While these projects play a pivotal role in directing water to areas of greater need and value, they often operate within specific river basins or localized regions, limiting their reach and impact. Furthermore, while certain regions or communities benefit from these interventions, others might incur substantial costs, resulting in limited net gains from such infrastructure (Dillon and Fishman, 2019; Duflo and Pande, 2007; Howe and Goemans, 2003; Strobl and Strobl, 2011).

In response to these challenges, governments around the world are increasingly considering large-scale, long-distance water diversion projects as potential solutions.[2] For instance, the proposed "North American Water and Power Alliance" (NAWAPA) in the U.S. aims to transfer water over thousands of kilometers from the Great Lakes to the country's southern regions (Macfarlane, 2023; Tockner et al., 2016). Similarly, India's ambitious "National River Linking Project", currently under construction, is designed to connect various rivers to redistribute water across multiple states (Misra et al., 2007). All these initiatives seek to move substantial volumes of water from water-abundant basins to areas parched by scarcity, offering the potential to significantly improve water distribution. Furthermore, due to the ample water endowment in the source regions, such projects are anticipated to have minimal adverse impacts on the areas from which water is diverted.

Despite their significant potential benefits, these projects are often perceived as high-risk endeavors, primarily due to their substantial financial requirements, extensive construction periods, and potential environmental ramifications (Shumilova et al., 2018). These factors lead to reservations among policymakers and other stakeholders, who question whether the benefits derived from these

[1] According to the Water Resources Group, under a business-as-usual scenario, the world is projected to face a 40 percent shortfall between water supply and demand in 2030. Further, the World Bank estimates that by 2050, there will be a 30-50 percent increase in water demand due to factors such as population growth and urban expansion.

[2] Large-scale water diversion projects, or water transfer megaprojects, are typically defined as interventions involving water transfers over distances greater than 190 kilometers, construction costs above 1 billion USD, or annual water transfers exceeding 0.23 billion cubic meters. For a more detailed classification and overview of these projects, see Shumilova et al. (2018).

megaprojects will sufficiently outweigh their costs. As a result, while many of these projects have been proposed, the majority remain in deliberation or early planning phases, witnessing limited progress.[3]

Central to the discussions and decision-making around large-scale water diversion projects are several crucial questions: How do these projects impact productivity and income in the areas that receive water? Can the economic benefits they deliver justify the substantial costs involved? And importantly, what consequences might be felt in source regions that provide their water? Despite the significance of these questions, empirical evidence on such projects remains scarce, primarily due to the rarity of water diversion megaprojects as well as challenges related to data and methodology. This study seeks to address this gap by examining the South-North Water Diversion Project (SNWDP) in China, the world's largest initiative of its kind. The two primary routes of the SNWDP began operations in late 2013 and 2014, respectively. Since then, they have been consistently diverting water from the Yangtze River to the northern regions, benefiting over 140 million people across six provinces (Ministry of Water Resources of China, 2020). Employing a difference-in-differences approach and detailed data on project implementation, agricultural production, and local income, we investigate the impacts of the SNWDP on both the regions receiving water and those from which water is sourced.

Our estimation strategy starts by comparing agricultural and economic outcomes between the water-receiving counties and their geographically proximate counterparts, before and after the initiation of water diversion. Leveraging county-level panel data from 2008 to 2019, we first analyze the impact of this project on agricultural outcomes. Our focus on the agricultural impacts is motivated by the pivotal role of water in agricultural production, as evidenced in various studies (Asher et al., 2023; Blakeslee et al., 2023; Hornbeck and Keskin, 2014; Jain et al., 2021), and aligns with the SNWDP's stated goals of replenishing agricultural water supplies and restoring ecological conditions (The State Council of China, 2014). In additional analyses, we also explore the effects on non-agricultural sectors and broader economic outcomes.

Our findings indicate that the SNWDP has significantly improved agricultural productivity in water-receiving counties. Specifically, these counties experienced an 8.2 percent increase in total grain output. The estimate is statistically significant, with a p-value below 0.01. These estimates

[3]For instance, the "North American Water and Power Alliance" (NAWAPA) megaproject in the US has encountered repeated setbacks since its proposal in the 1950s, only gaining renewed attention in the 2010s. Similarly, the Sibaral Project, conceived during the Soviet Union era to divert water from Siberian rivers to the Aral Sea, has recently seen a revival in discussions among stakeholders in Central Asia and Russia.

are also robust to the control of province-by-year fixed effects, which ensures that the effects are identified exclusively from cross-county variations within the same province and year. After the inclusion of additional climatic variables, the estimated effects remain consistent, both in terms of magnitude and significance. Turning to agricultural inputs, we find that both land and machinery usage responded to the initiation of water diversion. The data show a 6.2 percent increase in sown area and an 8.6 percent rise in machinery power, suggesting that the observed increase in output is partially driven by the expanded utilization of these inputs. However, no significant effects are observed on labor and fertilizer usage; both estimates are minimal and not statistically distinguishable from zero. Using the Total Factor Productivity (TFP) derived from a Cobb-Douglas production model, we provide evidence that the SNWDP has improved agricultural productivity by 4.7 percent. We conduct a battery of checks to validate our findings. We show that the potential bias due to geographical spillovers from water-receiving onto non-receiving counties are likely minimal, the main findings are robust to the exclusion of outlier counties, and there are parallel trends in the main outcome variables before the initiation of water diversion.

We perform several additional analyses to explore potential mechanisms behind our findings. Using data from over 1,000 national groundwater stations, we assess the impact of the SNWDP on groundwater levels. Our findings suggest that the SNWDP has increased groundwater levels in receiving counties by an average of 4.4 meters, approximately 3.5 percent of the sample mean. This substantial elevation in groundwater levels indicates that the project has effectively improved water availability and relieved scarcity in targeted regions. Moreover, our heterogeneity analysis shows that the positive effects of the SNWDP are more pronounced in regions experiencing higher levels of aridity, particularly those stricken by drought conditions. This finding suggests that the key mechanism through which the SNWDP achieves its effects is by alleviating water shortages. Such findings also highlight the project's capacity to effectively mitigate the detrimental impacts of extreme weather events. These insights are consistent with the findings of recent studies, including those documented by Duflo and Pande (2007) and Hornbeck and Keskin (2014).

While the SNWDP has led to notable improvements in productivity and output, this does not necessarily translate into a commensurate increase in income due to potential rises in input costs and possible price reductions within a general equilibrium context. To conduct a more informed cost-benefit analysis, we turn to evaluate the effects of the project on local income levels. Our results show a moderate improvement in rural income, with the project contributing to an approximately 2 percent increase in per capita annual income for rural residents in water-receiving counties. In addition, both the industrial and tertiary sectors experienced positive growth effects as a result of the SNWDP, which could be driven by spillovers from improved agricultural productivity or increased water availability for non-agricultural activities. Accordingly, per capita urban income in receiving regions also saw a modest increase, estimated at around 1.5 percent.

Finally, we examine the potential distributional effects of the SNWDP. Given that water is diverted from the Yangtze River in the south, it is plausible that source areas along the river might suffer from reduced water, leading to lower productivity and income. To investigate this, we employ a similar estimation strategy, contrasting the outcomes of counties providing water with those situated within a 200-kilometer radius. Our findings reveal no significant adverse effects on the source regions. This suggests that the benefits accruing to water-receiving counties do not come at the expense of significant losses in the source areas. This finding aligns with the fact that the annual volume of water diverted northward is less than 2 percent of the Yangtze River's runoff. The absence of notable distributional effects underscores a key advantage of large-scale, long-distance water diversion from abundant river basins, that is, significantly benefiting receiving areas without detrimentally impacting source regions. Moreover, using the estimated income effects and detailed project investment data, our cost-benefit analysis indicates an internal rate of return of 6.4 percent for the SNWDP. This rate surpasses the returns on Chinese highways and other large infrastructure projects, which typically have a rate of return between 4 and 6 percent (Shirley and Winston, 2004; Wu et al., 2021). Such a favorable return underscores the financial viability of the project.

Our work contributes to the literature on water management strategies, a crucial component in addressing the global challenge of water scarcity. A significant body of research has already explored the impact of water shortages on economic growth, poverty, and household well-being (Blakeslee et al., 2020; Damania et al., 2017; Jain et al., 2021; Sekhri, 2014), highlighting the urgent need for strategic and effective solutions. Recent studies have shown that hydrological infrastructures, along with innovations in water technology (Hornbeck and Keskin, 2014; Meeks, 2017), are instrumental in improving water allocative efficiency and boosting economic productivity. However, these studies have primarily focused on localized interventions, such as dams and irrigation systems (Blakeslee et al., 2023; Dillon and Fishman, 2019; Duflo and Pande, 2007; Senaratna Sellamuttu et al., 2014). The broader implications of inter-basin water diversion initiatives, despite their prominence in global policy discourses, remain insufficiently examined. Our research addresses this gap by providing a thorough assessment of the impacts of the world's largest water diversion project. We present evidence that this project not only achieves considerable benefits but also does so in a manner that justifies its significant investments, contributing valuable insights to the ongoing debate and policymaking concerning such large-scale initiatives.[4]

This study also contributes to the broader research aimed at identifying factors crucial for agricultural productivity and addressing barriers to its growth. Sustainable agricultural growth is vital for food security, poverty reduction, and economic transformation (Foster and Rosenzweig, 2004; Gollin et al., 2002). Extensive research has highlighted the importance of investments in research, the use of fertilizers, and the adoption of high-yield varieties in boosting agricultural productivity (Duflo et al., 2011; Evenson and Gollin, 2003; Kantor and Whalley, 2019; Suri, 2011). Our findings complement recent studies that underscore the benefits of water diversion for agriculture in receiving regions (Asher et al., 2023; Blakeslee et al., 2023). Unlike prior studies that focus solely on regions receiving water, our analysis also assesses the potential impacts on areas providing water. We find that the regions from which water is diverted do not experience significant adverse effects, demonstrating the project's ability to enhance efficiency on a broad scale without imposing undue burdens on source areas.

Lastly, our paper aligns with the emerging body of research on the detrimental impacts of extreme weather events in the context of global climate change (Chen et al., 2016; Dell et al., 2012; Deschênes and Greenstone, 2007; Schlenker et al., 2006). Our analysis provides additional quasi-experimental evidence demonstrating how extreme weather events, like droughts, can significantly diminish agricultural output and productivity. Yet, it also shows that large-scale hydrological interventions can effectively counter these adverse effects, thereby boosting productivity and income for a wide population base.

2 Context

China is endowed with approximately 6% of the world's total water resources, yet its per capita availability is strikingly less than a third of the global average (World Bank, 2013). According to the United Nations Commission on Sustainable Development, which examined 153 nations and territories, China ranks among the 13 countries facing severe water scarcity. This issue is intensified

[4]This study adds to concurrent research that identifies positive effects of the SNWDP on land prices (Yang, 2024) and a Chinese paper documenting positive effects on local economic growth (Xie et al., 2023). Our study differs from these two studies in terms of both the outcomes of interest and the research design. Unlike Yang (2024), which assumes that areas closer to the SNWDP's trunk canal (e.g., within 5 km) are more affected than those farther away, we utilize precise information on each county's water recipient status. Additionally, while both of these studies focus solely on the Central Route, our research employs a more comprehensive dataset that includes both the Central and Eastern Routes, covering all affected areas. Moreover, our cost-benefit analysis accounts for potential spillovers to nearby regions and potential losses to source areas, offering more nuanced and relevant policy implications.

by a pronounced spatial imbalance in water distribution across the country; while the south enjoys an abundance, the north faces a significant shortage. While the northern regions cover 63% of China's total land area and are home to 40% of the population, they possess only 19% of the nation's water resources (Zhang et al., 2009). This imbalance has severely constrained the development of the northern regions, exacerbating regional economic disparities.

The genesis of the South-North Water Diversion Project (SNWDP) can be traced back to 1952, when Chairman Mao Zedong, during a visit to the Yellow River, was struck by the significant disparity in water resources between the north and south of China. He put forth a solution that has since echoed through the decades: "The south has abundant water, while the north faces scarcity. If possible, the north should borrow a little from the south." This idea, though revisited intermittently by policymakers and experts from the 1950s through the 1980s, saw little progress due to technological and financial constraints. It was not until 1995, after the project's inclusion in the Eighth Five-Year Plan, that the Chinese government began a comprehensive feasibility assessment. The SNWDP was officially launched in 2002 when the State Council approved its construction plan (People's Daily, 2014b).

The primary objective of the South-North Water Diversion Project (SNWDP) is to transfer water from the Yangtze River to China's arid northern provinces. This initiative aims to alleviate water shortages, foster economic growth, and improve ecological conditions in these regions. While the majority of the diverted water is allocated to industrial and residential uses, significant benefits are also expected for the agricultural sector. This expectation stems from China's "urban-biased resource allocation system" (Lin and Yang, 2000), where urban and industrial sectors typically receive priority access to scarce resources, often leading to the over-extraction of groundwater and the reallocation of agricultural water for urban consumption. Consequently, one of the SNWDP's key goals is to replenish and substitute the agricultural water that was previously redirected to urban areas, thereby restoring agricultural productivity and ecological conditions (The State Council of China, 2014). Given the existing competition for limited water resources between rural and urban sectors and the urban-prioritized allocation system, the influx of water from the SNWDP could significantly ease constraints on rural areas, potentially yielding substantial impacts on agriculture in water-receiving regions.

The SNWDP comprises three distinct routes: the Central, Eastern, and Western, each illustrated in Figure 1. The Central Route, whose construction commenced in 2003, was designed to channel water from the middle reaches of the Yangtze River to the northern provinces of Henan and Hebei,

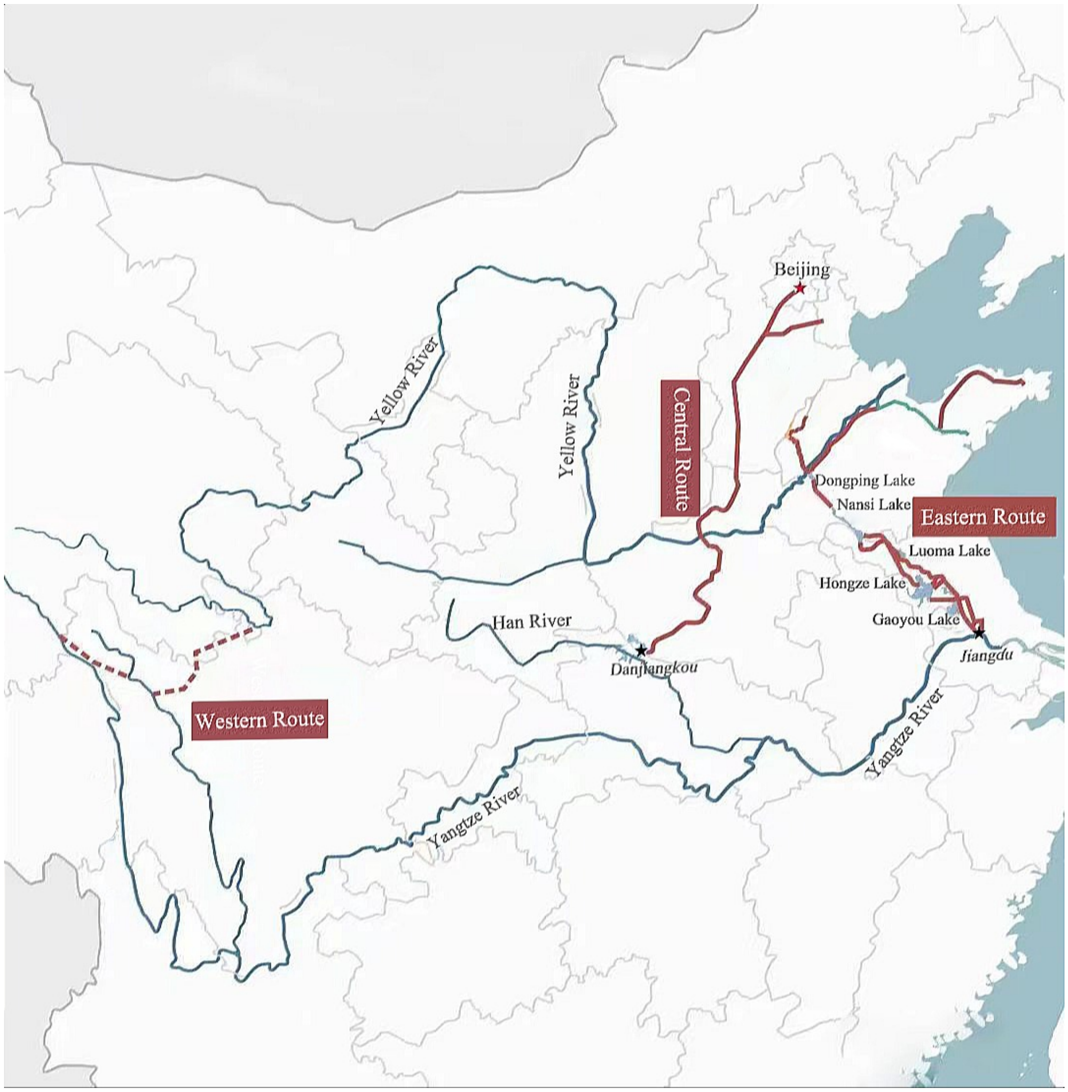


Figure 1: Geographic Layout of the Three Routes of the South-North Water Diversion Project

Notes: The Central and Eastern Routes of the SNWDP are depicted as two brown solid lines, with their starting points indicated by black stars. The Western Route remains in its conceptual phase, and water-receiving counties along that route have not yet been proposed.
Source: Department of South-to-North Water Diversion Project Management, Ministry of Water Resources of People's Republic of China.

as well as the municipalities of Beijing and Tianjin (Ministry of Water Resources of China, 2021). To achieve this, several dams were built or expanded along the Han River, a major tributary of the Yangtze, to amplify the water storage capacity of the *Danjiangkou* Reservoir. A canal system, spanning over 1400 kilometers in length, connects this reservoir to its final destination, Beijing. Given that the enhanced dams enable water storage up to an elevation of 176.6 meters – surpassing Beijing's elevation by about 100 meters – the water can travel by gravity towards the north (Ministry of Water Resources of China, 2005). Areas located near the primary canal can access the transferred water through an integrated network of pumps and extended canals, ensuring the benefits of the SNWDP are broadly disseminated. Appendix Figures A1 and A2 present illustrative images that give a direct insight into the projects' design and scale.

Construction of the Eastern Route commenced in 2002, intending to transfer water from the lower reaches of the Yangtze River to the Jiangsu and Shandong provinces. This route predominantly takes advantage of the historic Beijing-Hangzhou Grand Canal, directing water through existing pathways and infrastructures (Ministry of Water Resources of China, 2005). In particular, the Eastern Route sources water from the *Jiangdu* Water Conservancy Project, which is located near the junction of the Yangtze River and the East China Sea. A network of pump stations directs the water through several notable lakes including Hongze, Luoma, Nansi, and Dongping, extending from Jiangsu into Shangdong province. The route subsequently turns east and eventually reaches its destination, Qingdao, a major coastal city.

The Central Route began water diversion in December 2014 following successful trials, a year after the initiation of the Eastern Route in November 2013. Both routes have been operational since then, continuously transferring water from the Yangtze River to the designated northern areas. Appendix Figure A3 depicts the annual volume of water transferred by the Central and Eastern Routes. As can be seen, the diversion volume was minimal during the pre-operational trials, with less than 0.2 billion cubic meters being transferred in the 2013-2014 calendar year. However, this volume experienced a steady increase upon the formal operation of the Central Route at the end of 2014, peaking at 9.5 billion during the 2019-2020 period. Given that the project's blueprint outlines water diversion of 9.5 and 8.8 billion cubic meters for the Central and Eastern Route, respectively, the annual volumes are expected to be higher in subsequent years.[5] As of 2020, the continued operation of both routes had extended water supply to over 40 out of 341 prefectures, benefiting a population of 140 million (Ministry of Water Resources of China, 2020; People's Daily, 2021).

On the other hand, the Western Route, which was designed to channel water from the upper reaches of the Yangtze to six northwestern provinces (Qinghai, Gansu, Ningxia, Shaanxi, Shanxi, and Inner Mongolia), has encountered significant challenges. The targeted area for this route, the Tibetan Plateau, is characterized by its vulnerability to earthquakes and landslides, leading policymakers to reconsider the project's feasibility (Ministry of Water Resources of China, 2005; Xinhua News Agency, 2021). As of 2023, the Western Route remains in the conceptual stages, with

[5]With future phases of development, the project aims to redirect a yearly total of 44.8 billion cubic meters of water, with 27.8 billion from the Central and Eastern Routes.

no details released on potential water-receiving counties. Consequently, our analysis in this paper will be confined to the operational Central and Eastern Routes.

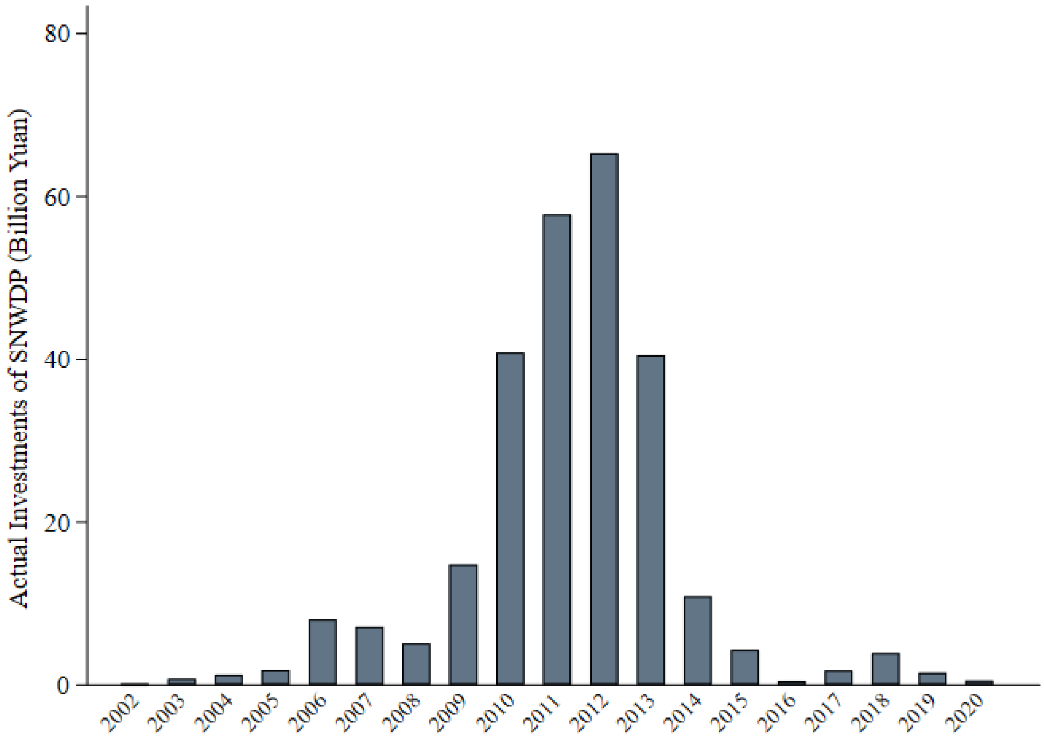


Figure 2: Annual Investment of the SNWDP from 2001 to 2020

Source: China South-to-North Water Diversion Project Construction Yearbook.

The SNWDP, recognized as the world's most extensive water diversion project, has incurred significant investment. Costs are not only associated with the construction but also the relocation of communities affected by the project. Figure 2 provides a yearly breakdown of these investments from 2002 to 2020. In the initial years, funding tended to be modest, with less than 2 billion CNY allocated annually. However, investments accelerated during the "11th Five-Year Plan", peaking in 2011 and 2012 as the Eastern and Central Routes approached completion. After both routes became operational, there was a notable reduction in investment in 2015. By 2020, with most of the extension works completed, expenditure declined to 0.5 billion CNY, primarily designated for maintenance and operational costs. In sum, the SNWDP has incurred 266 billion CNY in costs.[6]

Finally, the SNWDP is not without its controversies. On the one hand, the Chinese government

[6]Local governments contributed 7.6% of this expense, bank loans accounted for 19%, and the Central government financed the remaining 73.4% (People's Daily, 2014a; The State Council of China, 2004).

reports paint a positive picture, crediting the project with significant alleviation of water shortages, bolstered agricultural productivity and economic growth, and improved ecological conditions in the northern regions (Ministry of Water Resources of China, 2020; People's Daily, 2021). These reports, however, often rely on time-series comparisons and could potentially be confounded by macroeconomic trends and fluctuations. In contrast, a number of international media outlets are skeptical. They view the SNWDP more as a display of national power than a pragmatic solution, casting doubts on whether its benefits justify the substantial costs.[7] These critiques, however, often lack empirical grounding and are largely based on anecdotal evidence or isolated case studies. These conflicting narratives highlight the necessity for comprehensive and rigorous empirical evaluations of the SNWDP's impact, a gap the present study seeks to fill.

3 Hypotheses, Data and Empirical Strategy

3.1 Hypotheses

In our conceptual framework, water is a key determinant of productivity, especially for water-intensive sectors such as agriculture. The water-receiving counties were severely constrained by water scarcity prior to the diversion, facing barriers to productivity growth. The SNWDP, which channels substantial volumes of water from the abundant south, will alleviate this constraint and consequently enhance productivity. Since the industrial and residential sectors were prioritized in China's water allocation system, surface water and groundwater were over-extracted to satisfy their needs, leaving insufficient amounts for irrigation. Therefore, a stated purpose of the SNWDP is to replenish agricultural water supplies and restore ecological conditions by substituting water previously appropriated by industry and households.

According to the Ministry of Water Resources of China, 1.5 billion cubic meters of water previously occupied by urban sectors were returned to agriculture as a result of the SNWDP (Li et al., 2022). Additionally, 1.6 billion cubic meters of water from industry were returned to rivers to replenish the ecological system, indirectly benefiting agricultural production. Consistent with this, Ma et al. (2023) document that the volume of groundwater used for industry and households decreased in water-receiving regions due to the SNWDP, and the area of irrigated

[7] For instance, a Bloomberg article claimed, "World's largest water diversion plan won't quench China's thirst," `https://www.bloomberg.com/news/articles/2017-12-10/world-s-largest-water-diversion-plan-won-t-slake-china-s-thirst`, and The Economist suggested that the project might create more problems than it solves, `https://www.economist.com/china/2018/04/05/china-has-built-the-worlds-largest-water-diversion-project`.

farmland increased. For these reasons, we expect the productivity of the agricultural sector to be positively affected by the SNWDP. With improved water availability, other agricultural inputs may also expand, leading to higher output levels. Additionally, improvements in agricultural productivity might spill over to urban economic sectors. Since agricultural output constitutes key industrial inputs, increased productivity and output in agriculture might reduce material costs for industrial production. Furthermore, increased productivity in agriculture might raise the opportunity costs of migration, potentially elevating urban wages.

On the other hand, counties from which water is diverted may experience decreases in productivity. However, if the volume of diverted water is small relative to the water endowments in these source areas, the adverse impact may be limited. To test these hypotheses and explore the underlying mechanisms, we compile a comprehensive dataset from a variety of sources. This dataset contains information regarding each county's water-recipient status, as well as agricultural production, socioeconomic statistics, groundwater levels, geographic characteristics, and climatic conditions.

3.2 Data Sources and Variable Construction

3.2.1 Project Implementation Data

We leverage multiple data sources to identify counties and districts directly receiving water from the SNWDP. We began with the *China South-to-North Water Diversion Project Construction Yearbooks*, published by the State Council's SNWD Construction Committee. These publications provide detailed information about each construction segment of the SNWDP and their respective administrative regions, allowing us to pinpoint counties equipped with the necessary canal infrastructure to receive diverted water. However, canal access alone does not ensure actual water reception, as some counties may function only as "pass-through" areas. To address this, we supplement the yearbook data with records from provincial water resource bureaus and local official news outlets.

For regions along the Central Route, we obtain additional information from the *Construction Report on the Central Route of the South-to-North Water Diversion Project*. These reports, compiled by the provincial SNWD Construction Committees, feature maps that highlight designated water-receiving counties. We cross-verify the information from both sources and resolve a small number of discrepancies through detailed reviews of local official news reports. Regarding the Eastern Route, the data for Jiangsu Province is obtained from its Provincial Bureau of Water Resources. For Shandong Province, due to the absence of a standardized secondary source, we solely rely on local government announcements and media coverage for verification. Despite potential limitations, we anticipate this method to yield reliable data. The significance of the SNWDP's water delivery ensures that such events are consistently and comprehensively documented on official platforms and through media outlets, mitigating the risk of measurement errors or biased sampling. In supplementary analyses, we also demonstrate the robustness of our results by excluding Shandong from our sample. Finally, this process yields a list of 284 receiving counties and districts. This figure aligns closely with the Ministry of Water Resources of China's statement of "280+" beneficiary counties (Ministry of Water Resources of China, 2020), lending credibility to our assembled data (see Figure 3).

Based on these data, we construct a treatment indicator for each county and year, which takes the value of one if a county has begun to receive diverted water by that year, and zero if not. For water-receiving counties along the Eastern Route, this indicator is set to one for years following 2013. Similarly, for most receiving counties along the Central Route, the indicator is one for years after 2014.[8]

3.2.2 Agricultural and Socioeconomic Data

Since the water recipient status is defined at the county level, we utilize detailed agricultural and socioeconomic data corresponding to this granularity for the empirical analysis. The use of county-level data closely aligns with existing studies that explore environmental and technological determinants of agricultural development (Hornbeck, 2010; Hornbeck and Keskin, 2014; Kantor and Whalley, 2019; Kline and Moretti, 2014).

Our dataset spans from 2008 to 2019, a period for which comprehensive data are largely available. We obtain county-level agricultural production data from the China County Statistical Yearbooks and Provincial Statistical Yearbooks. These data include total grain output, sown area, labor, fertilizer, and machinery. Employing these data, we calculate agricultural Total Factor Productivity (TFP) using a Cobb-Douglas production function, in line with methodologies adopted in recent studies (Chen and Gong, 2021; Kantor and Whalley, 2019). Particularly, we regress total grain output on sown area, fertilizer, labor, and machinery inputs — each transformed into logarithmic form — while controlling for county and year-fixed effects. The resulting residuals from this

[8]During our verification process, we noted two exceptions: the prefectures of Cangzhou and Hengshui in Hebei Province. Compared with their Central Route counterparts, counties in these prefectures experienced construction delays and started receiving water in 2016 and 2017, respectively. In the main analysis, we use the actual years in which water diversion began to define their treatment status. As part of our robustness checks, we exclude the two prefectures from our sample and show that our results remain consistent.

regression are interpreted as the logarithm of TFP, which allows us to gauge the productivity change due to increased water resources from the SNWDP. We also gather additional socioeconomic data, including per capita rural and urban incomes, GDP, sectoral GDP, and population, from the aforementioned statistical yearbooks.

3.2.3 Weather, Groundwater, and Geographical Data

To account for time-variant weather influences, we collect geo-referenced climatic data such as precipitation, temperature, evaporation, and sunshine hours from the National Earth System Science Data Center, part of China's National Science & Technology Infrastructure. These data are provided at a fine resolution of 0.5 by 0.5-degree grids, and are aggregated to the county level by averaging the values of all grid points within each county. To shed light on potential mechanisms underlying the main results, we also collect groundwater level data from over 1,100 national monitoring stations. These data are detailed in the *China Geological Environment Monitoring Groundwater Level Yearbooks*, published by the China Geological Environment Monitoring Institute.[9] To understand the geographic differences between counties that do and do not receive diverted water, we also calculate the average elevation and slope for each county, based on the 30-meter spatial resolution DEM data from the 2011 ASTER GDEM, accessible at *yceo.yale.edu/aster-gdem-global-elevation-data.* Data on county boundaries are obtained from the China Data Center at the University of Michigan.

3.3 Empirical Strategy

To assess the impact of the SNWDP on agricultural and economic outcomes in water-receiving counties, we use a difference-in-differences strategy, comparing the water-receiving counties with the non-receiving ones before and after the initiation of water diversion. To ensure comparability between the treatment and control groups, we follow Hornbeck and Keskin (2014) and employ the nearby non-receiving counties as the control group. In particular, we define the control group as non-receiving counties within a 200-kilometer radius of those receiving water from the project.

It is worth mentioning that there could be a tradeoff in selecting the radius for defining the

[9] Precise geographic coordinates for each monitoring station are obtained using Baidu Maps' Application Programming Interface (API)—China's equivalent to Google. Utilizing an Inverse Distance Weighting (IDW) approach, we then convert the station data into a county-year panel. Particularly, this method calculates a weighted average of groundwater levels at all stations within a 200-kilometer radius of a county's centroid, assigning weights inversely proportional to their distances. Compared with the agricultural and socioeconomic data, the groundwater data are slightly shorter in timeframe, spanning from 2008 to 2017.

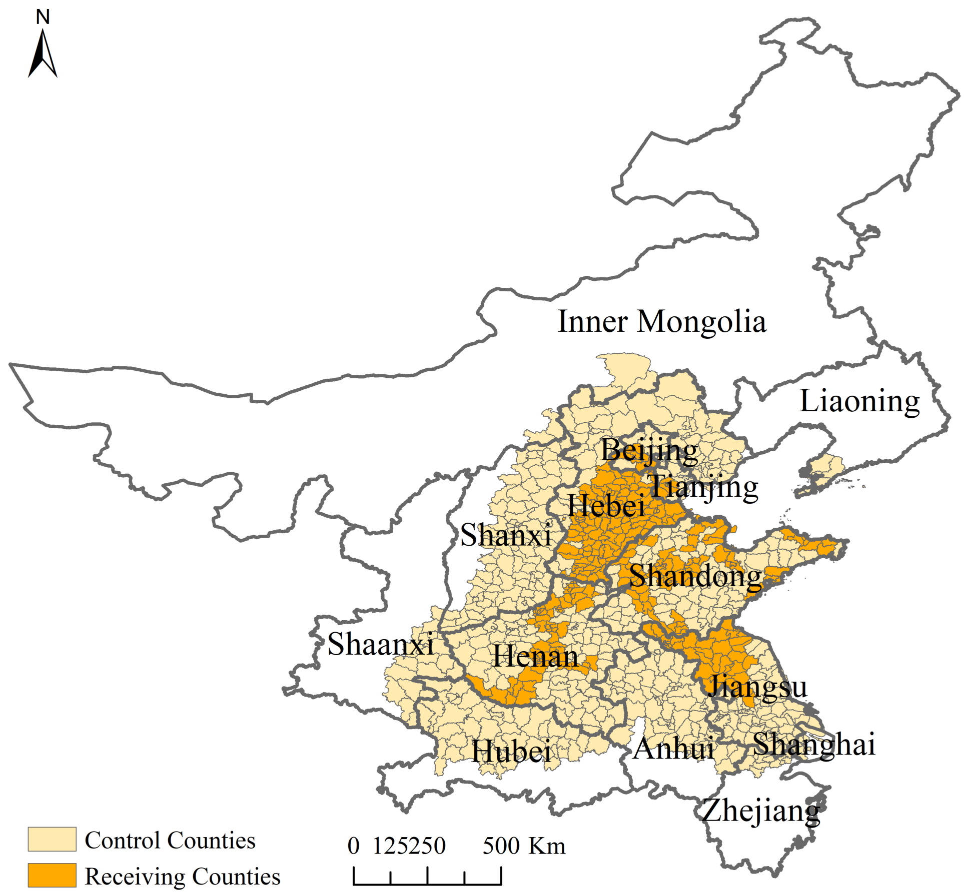


Figure 3: Illustration of Treatment and Control Counties Associated with the SNWDP

Notes: This figure depicts the geographical layout of the treatment and control counties associated with the SNWDP. Counties that directly receive water from the project are marked with a darker shade. The control group counties, located within a 200-kilometer radius of the treatment areas, are indicated in a lighter shade.

control group. A larger radius increases the sample size, allowing for higher statistical power and estimation precision. However, it also includes more distant counties in the control group, which may have different socioeconomic trends due to distinct market conditions, public policies, or climatic variations. In our main analysis, we adopt a 200-kilometer radius to define the control group. In subsequent analysis, we check the robustness of our main results using different radius choices. Additionally, an event-study model is employed to test for pre-trends. Figure 3 depicts the geographical layout of the treatment (darker shade) and control areas. The difference-in-differences strategy is summarized in the estimation equation below:

$$Y_{ct} = \beta \times \text{Treatment}_{ct} + \gamma \text{X}_{ct} + \lambda_c + \mu_t + \epsilon_{ct}, \tag{1}$$

where Y_{ct} represents an agricultural or economic outcome for county c in year t; $Treatment_{ct}$ is our key explanatory variable, an indicator for the treatment status. It is set to one for counties that have begun to receive water by year t, and zero otherwise. Note that once activated for a county, the treatment indicator remains on throughout the study period.[10] We use a treatment dummy as our explanatory variable as opposed to time-varying water volume data for two key reasons. First, detailed data on the volume of water diverted to each county and year are not available. Moreover, the actual volume of water diverted to a county typically depends on its needs and socioeconomic conditions for a given year, which could introduce endogeneity concerns.[11] In all regression models, we include county fixed effects, λ_c, to absorb any time-invariant determinants of economic outcomes in each county. Year fixed effects, μ_t, are also incorporated to control for macroeconomic trends and fluctuations common to all regions. We cluster standard errors at the county level to account for within-county correlation over time.

Given that our difference-in-differences strategy mainly relies on variation in the water-receiving status across counties, it is natural to ask what determines whether a county receives the diverted water. Although specifics of the policymaking process are not publicly available, certain patterns emerge from the data. As highlighted in Section 2, the Central Route, originating from the *Danjiangkou* Reservoir, primarily targets Beijing as its destination. Observing Figures 1 and 3, it becomes apparent that the actual route closely aligns with a straight line between its source and Beijing, with most water-receiving counties situated along this path. These patterns suggest that considerations of distance and cost minimization likely play an important role in determining which counties access water from the SNWDP. The Central Route is designed to minimize the distance, and only areas proximate to the main route could and did access the diverted water through extended canals and aqueducts. Similarly, since the Eastern Route leverages the Grand Canal and existing water infrastructure to bring down costs, regions situated near these facilities are more likely to be treated.

To shed more light on this aspect, Table 1 compares the geographic and socioeconomic characteristics (measured in 2008) between the treatment and control counties. The results show that,

[10]Since the treatment start time is not uniform across water-receiving counties, we address potential treatment effect heterogeneity by using the method proposed by Sun and Abraham (2021) in a robustness check in Section 4.1. Because there is only a one-year gap in the start time between the Central Route and the Eastern Route counties, we do not view this staggered nature of the treatment as a major threat to our identification. Our results also remain largely unaffected when we harmonize the treatment start year to 2014.

[11]Local governments negotiate with the SNWD administration regarding the annual volume of water diverted. The actual volume is influenced by factors such as the water availability in the Yangtze River and the specific demand of a county in a given year.

Table 1: Summary Statistics and Balance Check Results

VARIABLES	Control	Treatment	Difference
	(1)	(2)	(3)
Population	3.944	3.995	.051
	(.586)	(.439)	(.037)
Per Capita GDP	9.845	10.21	.364***
	(.797)	(.879)	(.064)
Grain Output	12.28	12.40	.113
	(1.149)	(1.168)	(.099)
Per Capita Grain Output	8.359	8.429	.070
	(.924)	(1.114)	(.090)
TFP	.010	.003	-.007
	(.152)	(.141)	(.014)
Altitude	.404	.083	-.322***
	(.472)	(.102)	(.022)
Slope	3.577	1.220	-2.356***
	(3.869)	(1.877)	(.209)
Observations	486	276	762

Notes: This table presents summary statistics comparing water-receiving counties (treatment group) to counties within a 200-km radius (control group). Population, GDP, and agricultural outcomes are based on data from 2008 or the earliest available year. Robust standard errors are reported in parentheses (***p<0.01, **p<0.05, *p<0.1).

compared to their neighboring counties, the treatment areas generally exhibit higher levels of economic development, as indicated by per capita GDP. However, there are no significant differences in their population, grain output, and agricultural TFP. Additionally, water-receiving counties are characterized by lower average altitudes and slopes, suggesting that regions with less rugged terrain, which pose fewer construction challenges, are more likely to be recipients of the diverted water. These findings further support the notion that cost considerations significantly influence the selection of water-receiving regions.

The observed disparities between the treatment and control groups raise concerns about whether their socioeconomic outcomes follow distinct trajectories, potentially violating the parallel trends assumption essential for the difference-in-differences estimation. To mitigate these concerns, our regression models incorporate linear year trends interacted with base-year geographic and economic characteristics. Furthermore, we employ an event-study approach to test for the pre-trends. To account for time-varying climatic variables that may affect productivity and economic performance, we also control for average monthly precipitation, temperature, and evaporation in certain specifications.

4 Results

In this section, we first discuss findings regarding the agricultural impacts of SNWDP in water-receiving counties, followed by an analysis of the impacts on a range of additional socioeconomic outcomes. We then investigate potential distribution consequences for the water source counties located in the downstream Yangtze River Basin. This section concludes with a cost-benefit analysis based on these estimates and project investments.

4.1 Main Results

Table 2 presents the results from Equation 1, focusing on various agricultural outcomes as the dependent variables. In Columns 1–2, we examine the impact on the log of total grain output and observe a significant increase in water-receiving counties as a result of the SNWDP. When we only control for county and year-fixed effects and linear trends interacted with baseline characteristics, the estimated coefficient is .081, indicating an 8.1 percent increase in grain output following water diversion. The estimate is statistically significant, with a p-value below .01. It also remains consistent both in magnitude and significance when we additionally include the climatic controls.

To understand the drivers behind the observed increase in output, Columns 3–6 of the table further examine the impact of water diversion on key agricultural inputs, including labor, machinery, fertilizer, and sown area. Theoretically, improvements in agricultural productivity due to increased water availability could lead to adjustments in input utilization. On one side, improved productivity could encourage farmers to expand production, thus increasing their use of input factors. Conversely, more accessible water resources, either directly provided by the government or through improved groundwater levels, could reduce the need for labor-intensive tasks like water extraction or competition for water resources, potentially leading to a decrease in labor input.

Our results reveal that water diversion indeed had significant impacts on certain input factors. Notably, machinery usage and sown area both experienced increases, by approximately 8.6 and 6.2 percent, respectively. In contrast, changes in labor and fertilizer usage were negligible; the estimated effects on these inputs are small in magnitude and statistically indistinguishable from zero.

Table 2: The Impact of SNWDP on Agricultural Production

VARIABLES	Grain Output		Labor	Machinery	Fertilizer	Land
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	.081***	.082***	-.018	.086***	-.005	.062***
	(.022)	(.022)	(.028)	(.021)	(.022)	(.021)
County & Year FE	Y	Y	Y	Y	Y	Y
Linear Trends	Y	Y	Y	Y	Y	Y
Weather Controls	N	Y	Y	Y	Y	Y
Mean of dep.	12.47	12.47	2.41	3.92	10.05	10.76
Observations	5,224	5,224	5,224	5,224	5,224	5,224

Notes: The dependent variables are as follows: the logarithm of total grain output in Columns 1–2, and the logarithms of labor, machinery, fertilizer, and sown area in Columns 3–6, respectively. All models include county and year-fixed effects, and linear trends interacted with 2008 GDP, total population, longitude, latitude, altitude, and slope. Columns 2–6 additionally adjust for time-varying weather conditions, including annual mean precipitation, temperature, and total sunshine hours. Robust standard errors, clustered at the county level, are reported in parentheses (***p<0.01, **p<0.05, *p<0.1).

The absence of a significant change in fertilizer usage might be attributed to financial constraints; fertilizer is a relatively costly input, and farmers may encounter challenges in accessing credit or other resources to scale up its usage. These results suggest that the observed increase in total output is partially driven by the expansion of certain inputs. However, the disproportionate increase in output relative to input changes implies that productivity improvements also play a crucial role. To quantify the impact of the SNWDP on productivity, we re-estimate our model with three different measures of productivity as outcome variables. The findings are detailed in Table 3.

In Columns 1–2 where we examine the log of per worker output as the dependent variable, the point estimates of approximately 0.1 indicate a 10 percent increase in this measure in water-receiving counties following water diversion. These estimates are also statistically significant at conventional levels. In Columns 3–4 where per hectare output is used as the dependent variable, we find smaller and statistically less significant estimated effects, indicating an approximate 2 percent increase. This finding is probably not surprising, given our earlier observation of a substantial increase in land input. It is worth noting that while these productivity measures standardize total output by labor or land area, they do not account for the effects of changes in other inputs. Therefore, we estimate agricultural Total Factor Productivity (TFP) using a Cobb-Douglas production function, as detailed

Table 3: The Impact of SNWDP on Agricultural Productivity

VARIABLES	Per Worker Output		Per Hectare Output		TFP	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	.096***	.101***	.018*	.020*	.046***	.047***
	(.034)	(.034)	(.011)	(.011)	(.014)	(.014)
County & Year FE	Y	Y	Y	Y	Y	Y
Linear Trends	Y	Y	Y	Y	Y	Y
Weather Controls	N	Y	N	Y	N	Y
Mean of dep.	10.06	10.06	1.71	1.71	-.0004	-.0004
Observations	5,224	5,224	5,224	5,224	5,224	5,224

Notes: The dependent variables are as follows: the logarithm of per capita grain output in Columns 1–2, the logarithm of per hectare output in Columns 3–4, and the logarithm of agricultural TFP in Columns 5–6, respectively. All models include county and year-fixed effects, and linear trends interacted with 2008 GDP, total population, longitude, latitude, altitude, and slope. Even-numbered columns additionally adjust for time-varying weather conditions, including annual mean precipitation, temperature, and total sunshine hours. Robust standard errors, clustered at the county level, are reported in parentheses (***p<0.01, **p<0.05, *p<0.1).

in Section 3. This measure isolates the contribution of other inputs from the output increase, primarily reflecting productivity changes due to increased water availability from the SNWDP. The results, presented in Columns 5–6, consistently show a positive and statistically significant increase in agricultural productivity of 4.7 percent.

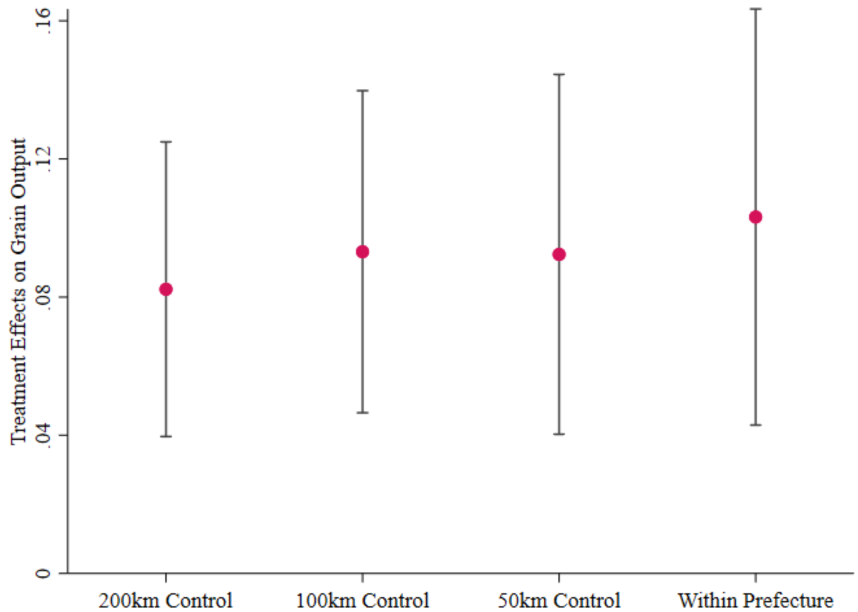
To account for potential spatial correlation in the model's error term, we use the Conley (1999)'s method to estimate the standard errors. Following existing studies, we assume that the spatial correlation between counties declines linearly up to a distance of 50 kilometers and is zero beyond this cutoff. The results, reported in Appendix A4, show that this adjustment barely affects the statistical significance of the estimated effects. The results are also similar when we use 100 km or 200 km as the distance cutoff. In addition to correcting for standard errors, we further validate our findings through a series of robustness checks below.

Testing Geographic Spillovers. A key concern in our analysis is the potential for geographic spillovers of the water diversion onto the control regions. Control counties situated near the treatment areas might indirectly benefit from the diverted water through connected river and groundwater networks, potentially causing a downward bias in our estimates. Conversely, if agricultural inputs such as capital and labor are reallocated from control areas to treatment counties, the treatment counties might show a larger agricultural output increase than the true effect of water diversion, thus overestimating the true effect. To address this concern, we check the robustness of our results using control groups defined within alternative radii: 100 km and 50 km, in addition to the 200 km radius in our main analysis. If geographic spillovers are present—whether positive or negative—counties closer to the treatment areas should be more affected. This means that any bias (upward or downward) resulting from geographic spillovers would be greater when using these closer counties as the control group. However, Figure 4 demonstrates that the estimated effects are fairly stable in terms of magnitude and significance across different radii of the control group. This pattern persists even when considering counties within the same prefecture as the treatment areas for comparison.[12]

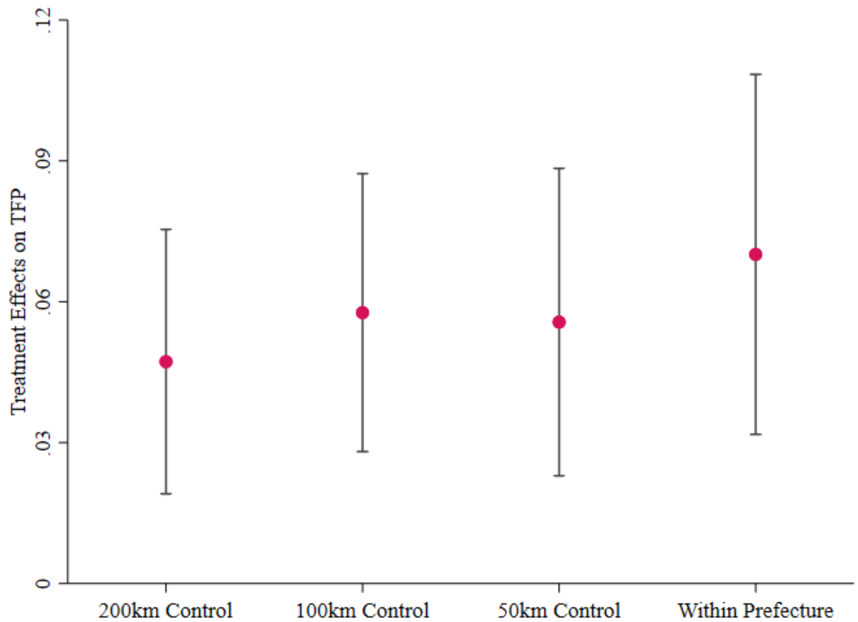
Furthermore, in Appendix Table A5, we restrict to the non-water receiving counties, and compare those located within 50 kilometers and those between 50 and 100 kilometers away from the receiving areas, before and after the initiation of water diversion. The results do not show statistically different impacts of the SNWDP on the nearer non-receiving counties. Collectively, these results suggest that geographical spillovers, if present, are likely minimal across county borders and do not significantly bias our estimates. This is probably because counties, averaging 1,390 km^2 in size in our sample, are large enough to internalize the impact of increased water resources. Additionally, each county functions as a relatively integrated labor market, with approximately 90 percent of workers commuting within its boundaries (Chen et al., 2023), as well as a highly independent administrative unit in local policy-making. This means that unlike recent studies examining the effects of irrigation among closely located villages and communities, our analysis might not capture fine-grained spillover effects on non-receiving locations.

Alternative Specifications and Samples. An observation from Figure 3 is that some non-water receiving counties in the control group are located in different provinces than those in the treatment group. Given that provinces may have varying market conditions, government policies, and public services, one might be concerned about the comparability of these counties with the water-receiving areas. To mitigate this concern, we additionally include province-by-year fixed effects in our regression models. This specification ensures that our identification relies solely on cross-county variations within the same province and year. The results are detailed in Appendix Table A6. Reassuringly, they show that our main findings remain robust under this specification. Furthermore, we adopt a more general translog production function for estimating the agricultural

[12]The corresponding results are reported in Appendix Tables A2 and A3.



(a) Grain Output



(b) TFP

Figure 4: Estimated Treatment Effects of SNWDP Using Different Control Groups

Notes: This figure plots coefficient estimates and 95% confidence intervals for treatment effects of SNWDP from Equation 1, using counties within 200, 100, and 50 km, and the same prefecture of the treatment areas as the control groups, respectively. Robust standard errors are clustered by county.

TFP, which includes the second order of each input and their full interactions in the regressions (Chen and Gong, 2021; Christensen et al., 1973). The findings, as shown in Appendix Table A7, align closely with the previous ones.

As previously outlined in Section 3, Shandong Province presents a special case due to the absence of a systematic secondary data source for cross-verifying counties' water-recipient status. As a result, we have had to rely on local government announcements and media coverage for this verification. To test the robustness of our findings, in Columns 1–3 of Appendix Table A8, we exclude Shandong Province from our analysis. Our findings indicate that the exclusion of these counties does not qualitatively affect our estimated effects, reinforcing the credibility of our carefully compiled dataset. In Columns 4–6 of the same table, we omit counties in Cangzhou and Hengshui Prectures. These areas began receiving water later than their counterparts along the Central Routes, specifically starting in 2016 and 2017, as opposed to most Central Route counties which started in November 2014. Again, the results remain consistent after this adjustment. Finally, we separately analyze the impacts of the Central and Eastern Routes and present the findings in Table A11. The estimates show similar effects for both routes, though the impacts of the Eastern Route appear slightly more pronounced. Overall, these results corroborate the previous findings, suggesting that the estimated effects are not skewed by any single route, region, or data anomalies.

Placebo Assignment of Treatment. To further substantiate that the observed effects are indeed attributable to the initiation of water diversion, we conduct a placebo test, using the same specification as in Column 6 of Table 3. In this test, the water recipient status is randomly assigned across all sample counties. We repeat this process 1,000 times, and plot the distribution of the estimated effects on total grain output and agricultural TFP in two separate panels of Figure A4. The results reveal that the majority of these placebo estimates are concentrated around zero, with a significant skew to the left of the actual estimated coefficient, as indicated by the dashed lines. This placebo test further alleviates concerns about unobserved confounders and strengthens the robustness of our main results.[13]

Testing Pre-trends. To validate that our findings are not driven by pre-existing differential trends between the water-receiving and non-receiving counties and to study the dynamics of the treatment effect, we conduct an event-study analysis using a modified version of Equation 1. Specifically, we replace the treatment indicator with a series of dummies indicating years relative to

[13]We could not utilize the unimplemented Western Route as a placebo since the Western Route remains in an early phase, and water-receiving counties along that route have not yet been proposed. For more detailed discussions, see Section 2.

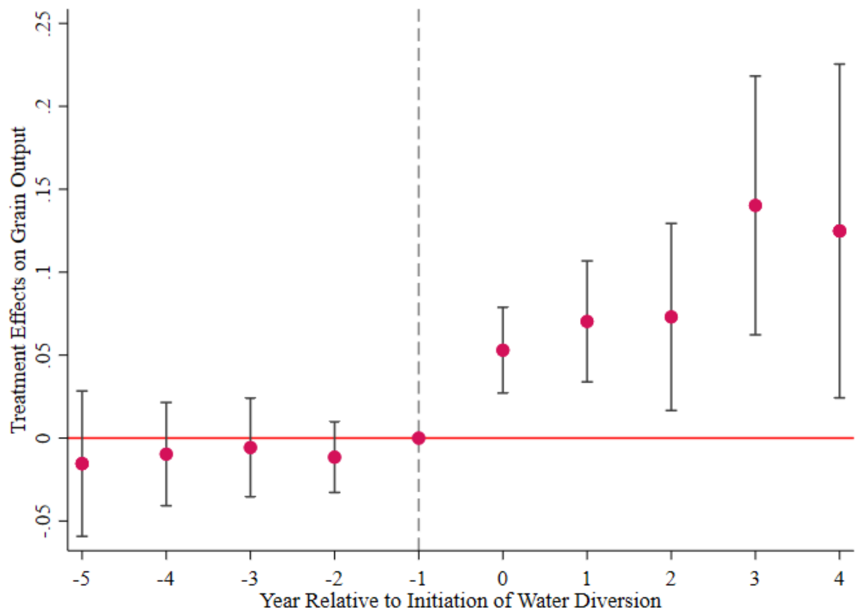
the initiation of water diversion:

$$Y_{ct} = \sum_{k=-5}^{4} \beta_k \times D_{k(ct)} + \gamma \mathrm{X}_{ct} + \lambda_c + \mu_t + \epsilon_{ct}, \tag{2}$$

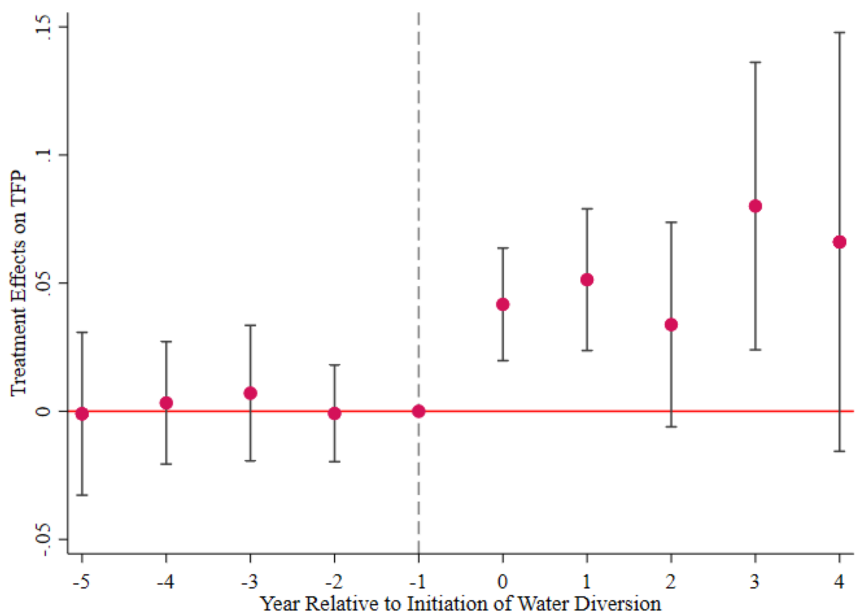
In this specification, $D_{k(ct)}$ is a binary variable that equals one if county c began receiving water from the SNWDP k years from the current year. For instance, $k = 2$ would represent two years after the water diversion began, while $k = -2$ would denote two years before it started. We use $k = -1$, the year immediately preceding the initiation of water diversion, as the reference group. Consequently, all estimated effects are relative to this baseline year. Other variables are defined consistently with those in Equation 1. The resulting event-study estimates are depicted in Figure 5.

The event-study graph reveals several key insights. First, the coefficients for the years leading up to the water diversion are all negligible and statistically indifferent from zero, indicating an absence of pre-trends and thus reinforcing the validity of our difference-in-differences approach. Second, the treatment effects emerge distinctly in the year water diversion begins, affirming the direct impact of the SNWDP. Additionally, the magnitude of the treatment effects escalates over the subsequent years, aligning with the increase in the annual volume of diverted water, as depicted in Figure A3. This progressive intensification of the effects post-initiation underscores the growing influence of the SNWDP over time.

Addressing Treatment Effect Heterogeneity. In our study, the initiation of water diversion in the Central Route counties lagged one year behind the Eastern Route. Recent advances in econometric literature have highlighted potential biases in staggered difference-in-differences designs, particularly arising from heterogeneous treatment effects across time and groups. To address this, we employ the methodology proposed by Sun and Abraham (2021) and re-estimate the effects. As shown in Appendix Table A9, the revised coefficients remain consistently positive, with stable magnitudes throughout. Additionally, to circumvent the staggered rollout issue, we harmonize the treatment initiation year for all water-receiving counties to 2014, uniformly treating the post-2014 period as the treatment phase. We do so because there was a relatively small volume of water diverted during 2013-2014, as shown in Appendix Figure A3. Results of this robustness check are presented in Appendix Table A10. Again, we find that this adjustment has minimal impact on our results.



(a) Grain Output



(b) TFP

Figure 5: Event-study Estimates for Grain Output and TFP

Notes: This figure plots coefficient estimates and their corresponding 95% confidence intervals from Equation 2. The markers at the left and right ends of the timeline represent the average effects observed 5 years before and 4 years after the initiation of water diversion, respectively. All effects are benchmarked against the year immediately preceding the start of water diversion ($k = -1$). Robust standard errors are clustered at the county level.

4.2 Mechanism Analysis

In this section, we conduct several analyses to shed light on potential mechanisms underlying our main findings. Given the critical role of water in agricultural production and the pre-existing water shortages in water-receiving counties, it is likely that our results stem from improved access to water resources and the alleviation of scarcity in these regions. More specifically, water provided by the SNWDP could have been utilized for irrigation, directly raising agricultural productivity and yields. Additionally, the diversion of water to non-agricultural sectors may have reduced the over-extraction of ecological water, leading to elevated groundwater levels and more accessible surface water. This, in turn, could lower the costs associated with water extraction in agriculture. Furthermore, the infusion of additional water into a region might have positively impacted soil quality and ecological conditions, indirectly contributing to increased agricultural productivity. While pinpointing each specific channel remains challenging, our analysis provides evidence suggesting that the increased water availability is the primary driver behind the observed effects.

Impacts on Groundwater Levels. Using groundwater levels as a measure of water resource availability, which is described in Section 3.1, we first examine whether the SNWDP has facilitated greater water accessibility in receiving regions, again by estimating Equation 1. We calculate annual groundwater levels relative to sea level, considering both ground elevation and groundwater depth. A higher value thus indicates greater water accessibility.

We present the results in Table 4. The findings in both columns indicate a statistically significant and positive impact of the SNWDP on groundwater levels in receiving counties. In terms of magnitude, the estimated coefficient in our preferred specification points to a 4.4-meter increase in groundwater level. This elevation is economically meaningful, amounting to approximately 3.3 percent of the mean level in our sample. As shown in Appendix Table A12, the estimates remain stable in size and significance when we use the Sun and Abraham (2021) method to adjust for treatment effect heterogeneity. Moreover, these estimates closely match data reported by local water authorities. For instance, as depicted in Appendix Figure A5, the Beijing Water Resources Bulletin noted a yearly decline of about 1 meter in groundwater levels from 2000 until the early 2010s. However, coinciding with the initiation of water diversion to Beijing around 2014, this declining trend ceased, and levels began to rise. The magnitude of these reported changes is also similar to our estimates, lending further credibility to our results. Overall, these findings indicate that the SNWDP has effectively improved water accessibility in the water-receiving areas.

Table 4: The Impact of SNWDP on Groundwater Levels

VARIABLES	Groundwater Levels	
	(1)	(2)
Treatment	5.927***	4.432**
	(1.929)	(1.898)
County & Year FE	Y	Y
Linear Trends	Y	Y
Weather Controls	N	Y
Mean of dep.	131.2	131.2
Observations	4,817	4,817

Notes: The dependent variables are groundwater levels. All models include county and year-fixed effects, and linear trends interacted with 2008 GDP, total population, longitude, latitude, altitude, and slope. Column 2 additionally adjusts for time-varying weather conditions, including annual mean precipitation, temperature, and total sunshine hours. Robust standard errors, clustered at the county level, are reported in parentheses (***p<0.01, **p<0.05, *p<0.1).

Heterogeneous Effects by Aridity. To explore whether the SNWDP's positive impact on agricultural productivity is directly due to improved water accessibility, we examine the heterogeneous effects of the project across regions with varying levels of aridity. If increased water availability is the primary driver of our results, more pronounced treatment effects should be observed in areas suffering from severe water scarcity. To investigate this, we follow existing literature and construct an aridity index based on the ratio of annual maximum potential evaporation to rainfall in each county. In line with meteorological research in China, counties with a ratio exceeding 1.5 are classified as experiencing drought conditions (Chinese Academy of Science, 1959; Meng et al., 2004). We define a 'drought' indicator, which takes the value of 1 when a county's aridity index exceeds this threshold in a given year, and 0 otherwise. We then estimate the following equation:

$$Y_{ct} = \beta_1 \times \text{Treatment}_{ct} \times D_{ct} + \beta_2 \times \text{Treatment}_{ct} + \beta_3 \times D_{ct} + \gamma \text{X}_{ct} + \lambda_c + \mu_t + \epsilon_{ct}, \qquad (3)$$

In this specification, the key explanatory variable is the interaction term between the treatment dummy and the drought indicator, D_{ct}, with their main effects included. To avoid collinearity, climatic variables are not included as covariates, given that the drought dummy is derived from evaporation and rainfall data. Other variables are defined consistently as in Equation 1. The estimates, as presented in Table 5, are in line with our previous findings: the treatment indicator shows consistently positive and significant coefficients across all columns, reinforcing the notion that the SNWDP has improved productivity in receiving regions. The positive coefficient on the interaction term indicates that the treatment effects are more substantial in counties facing higher levels of aridity, further corroborating our hypothesis that increased water availability is the primary pathway through which the SNWDP affects agricultural production.

Table 5: Heterogeneous Treatment Effects by Aridity

VARIABLES	Grain Output	Per Worker Output	TFP
	(1)	(2)	(3)
Treatment	.050***	.069*	.032***
	(.018)	(.042)	(.012)
Drought	-.024**	-.061***	-.017**
	(.010)	(.015)	(.007)
Treatment × Drought	.061***	.080**	.039**
	(.022)	(.039)	(.016)
County & Year FE	Y	Y	Y
Linear Trends	Y	Y	Y
Weather Controls	N	N	N
Mean of dep.	12.51	10.08	-.003
Observations	4,438	4,438	4,438

Notes: The dependent variables are as follows: the logarithm of total grain output in Columns 1, the logarithm of per worker output in Columns 2, and the logarithm of agricultural TFP in Columns 3, respectively. All models include county and year-fixed effects, and linear trends interacted with 2008 GDP, total population, longitude, latitude, altitude, and slope. Robust standard errors, clustered at the county level, are reported in parentheses (***p<0.01, **p<0.05, *p<0.1).

It is noteworthy that in Table 5, the estimated coefficients associated with the drought indicator are consistently negative, underscoring the significant adverse impacts of drought on agricultural productivity. The positive coefficients on the interaction term suggest that the SNWDP has played an effective role in mitigating these detrimental effects, making agricultural production less susceptible to extreme drought conditions. These findings echo recent studies that highlight the critical role of hydrological infrastructures and technological advancements in enhancing resilience to extreme weather events (Duflo and Pande, 2007; Hornbeck and Keskin, 2014).

Alternative Explanations. The above findings also address and refute several alternative hypotheses. One such hypothesis posits that it is the investment associated with the SNWDP, rather than the diverted water itself, that has driven the observed productivity increases. The logic here is that significant investment spending could stimulate local demand for products, labor, and raw materials, thereby increasing local output through fiscal multiplier effects (Acconcia et al., 2014; Nakamura and Steinsson, 2014; Serrato and Wingender, 2016). However, this hypothesis is inconsistent with the spending patterns associated with the SNWDP, as depicted in Figure 2. Most of the investment occurred before the commencement of water diversion, and spending decreased significantly post-diversion, mainly covering minor extensions and maintenance. Considering that annual investment in 2019 and 2020 was less than 4 million CNY per county, it seems implausible that such modest amounts could fully account for the substantial productivity increases we observe. Furthermore, this hypothesis fails to reconcile the increasing impact over time, as shown in our event-study analysis, where the effects intensify with the growing volume of diverted water.

Another potential explanation concerns the adverse effects of pollution from SNWDP construction. The argument is that construction activities might have disrupted agricultural production or introduced pollutants, thereby lowering productivity. Thus, the post-diversion increase in productivity might reflect a recovery to normal levels following construction completion. However, this hypothesis is unlikely for several reasons. First, the completion of construction did not uniformly coincide with the start of water diversion, as construction activities varied in phases across counties. While precise completion dates are unavailable, we do notice that major construction was largely finished at least a year before the commencement of water diversion, so as to facilitate trial operations. If the effects were primarily driven by the end of construction, we would expect to see significant productivity changes at least a year before treatment initiation. This contrasts the event-study findings in Figure 5, which demonstrate a discrete increase in output and productivity concurrent with the start of water diversion. Second, our heterogeneity analysis shows stronger treatment effects in more arid regions, suggesting a mechanism related to the alleviation of water scarcity, rather than a pollution reduction. If reduced pollution post-construction were the primary cause, it would be unclear why the effects are stronger in arid regions. Collectively, our results most convincingly align with the interpretation that the SNWDP has improved water resource availability, and consequently increased agricultural productivity in receiving areas.

4.3 Additional Outcomes

This section further explores the broader socioeconomic impacts of the SNWDP for water-receiving regions. We first aim to understand whether and how the increased agricultural productivity due to the project has translated into income gains for rural populations. In theory, an influx of agricultural products into local or national markets could potentially depress prices, while increased demand for inputs such as land and machinery could inflate their costs. Therefore, the overall effect of the SNWDP on farmers' income remains ambiguous. To investigate this, we apply our regression model to estimate the treatment effect on per capita rural income. The results presented in Column 1 of Table 6 show a modest yet statistically significant increase in rural income. The estimated coefficient is 0.02, with a p-value below 0.01, indicating a 2 percent increase. Furthermore, these estimates are stable in terms of size and significance when we use different control groups and remain robust to alternative estimation methods.[14] These findings suggest the presence of general equilibrium effects, where the income gains are somewhat muted compared to the productivity improvements.

Column 2 investigates the project's impact on urban income. This inquiry is critical for several reasons. First, as discussed earlier, the majority of the diverted water is supplied to urban areas for industrial and residential purposes. This largely substitutes for over-extracted groundwater and other ecological sources, potentially increasing the net water supply and overall water availability in urban areas. This improvement could benefit the industrial and service sectors, especially the water-intensive ones. Additionally, the improvements in agricultural productivity that we have documented might spill over to urban economic sectors. Since agricultural output constitutes key industrial inputs, the increased productivity and output in agriculture might reduce material costs for industrial production. Furthermore, increased rural incomes might raise the opportunity costs of migration, potentially leading to higher urban wages in equilibrium. Consistent with these hypotheses, the findings in Column 2 indicate a modest positive impact on per capita urban income, suggesting a 1.5 percent increase. Again, the estimate is statistically significant at conventional levels, implying that the SNWDP has contributed to overall income gains among urban populations as well.

We then examine whether industrial and service activities indeed have been affected by the SNWDP. For this purpose, we analyze the GDP of the secondary and tertiary sectors as the dependent variables in Columns 3 and 4, respectively. Consistent with our previous findings, both sectors exhibit positive growth effects as a result of the SNWDP. These effects are somewhat greater

[14] See Appendix Figure A6 and Tables A14 and A16 for details.

Table 6: The Impact of SNWDP on Additional Economic Outcomes

VARIABLES	Rural Income	Urban Income	Secondary GDP	Tertiary GDP	GDP	Population
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	.020***	.015**	.035	.014	.028	.008
	(.006)	(.006)	(.027)	(.019)	(.017)	(.006)
County & Year FE	Y	Y	Y	Y	Y	Y
Linear Trends	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
Mean of dep.	9.15	10.03	13.51	13.21	14.34	3.97
Observations	6,194	4,653	6,406	5,949	7,699	6,748

Notes: The dependent variables across Columns 1–6 are the logarithm of rural residents' income, urban residents' income, secondary gross domestic product, tertiary gross domestic product, gross domestic product and population, respectively. All models include county and year-fixed effects, annual mean precipitation, temperature, total sunshine hours, and linear trends interacted with 2008 GDP, total population, longitude, latitude, altitude, and slope. Robust standard errors, clustered at the county level, are reported in parentheses (***p<0.01, **p<0.05, *p<0.1).

in size than the previously estimated income effects, albeit with less precision. Due to the lack of detailed firm-level input-output data, we cannot fully disentangle specific mechanisms driving growth in these sectors or explore heterogeneous treatment effects on productivity across different firm types. Nonetheless, these results suggest an overall modest but positive impact on the growth of industrial sectors.

Column 5 of our analysis focuses on the overall GDP in water-receiving counties, indicating a 2.8 percent increase attributed to the SNWDP. This effect is statistically significant at the 5% level when using Conley (1999)'s method to adjust for spatial correlation across counties (see Appendix Table A15). While the precision of the estimate varies under different sample restrictions and specifications (as shown in Appendix Tables A14 and A16), the direction of the impact remains consistent, pointing to a modest yet positive impact on the overall economic performance of these areas. In terms of population dynamics, the impact of the project appears negligible. The estimated effects on population size are small and statistically indistinguishable from zero, implying that short-term migration patterns have remained largely unaffected by the initiation of the water diversion project. This finding is consistent with existing economic literature, which indicates that the observed income changes in our context, though positive, are relatively modest when compared to typical returns from internal migration in both developing and developed contexts (Bryan et al., 2014; Bryan and Morten, 2019; Nakamura et al., 2022). However, even these modest percentage increases in income, when considered across the large population base of the water-receiving areas, could represent substantial aggregate economic benefits. We quantify these income gains and compare them against the SNWDP's investment costs in subsequent sections of the paper.

4.4 Distributional Consequences

Our findings thus far indicate that the SNWDP has improved agricultural productivity, output, and income in water-receiving regions. This raises a natural and important question: do these benefits come at a significant cost to other areas? Specifically, since the project diverts water from the middle and lower reaches of the Yangtze River, there is a concern that these source areas might face substantial costs due to reduced water availability. However, if the water loss is relatively minimal in these areas, which are typically abundant in water resources, the distributional impacts could be marginal. To assess the net economic benefits of the SNWDP, this section examines its impact on the water source counties—those in the areas that may have experienced water losses due to the project.

As illustrated in Figure 1, the SNWDP diverts water through two primary routes: the Eastern and Central Routes. The Eastern Route sources its water from *Jiangdu* Water Conservancy, situated in the lower reach of the Yangtze River, close to its sea entrance. Consequently, areas downstream of *Jiangdu* along the Yangtze River may have experienced a reduction in water resources following the start of water diversion in 2013. Accordingly, counties along the lower reach of the Yangtze River are considered source areas. The Central Route, on the other hand, draws water from the *Danjiangkou* Reservoir, which intercepts and stores water from the Han River, a major tributary that meets the Yangtze at its middle reach. This implies that some of the water that would otherwise flow downstream of *Danjiangkou*, along both the Han River downstream of the reservoir and the Yangtze River downstream of the Han-Yangtze intersection, is redirected northwards. Therefore, counties located in these downstream areas are also classified as source counties and may have suffered water reductions after the Central Route became operational in 2014. These water source counties are highlighted in a darker shade in Figure 6, contrasted against the counties within a 200-kilometer radius shown in a lighter color.

Consistent with our previous analysis, we adopt an estimation strategy that compares the source

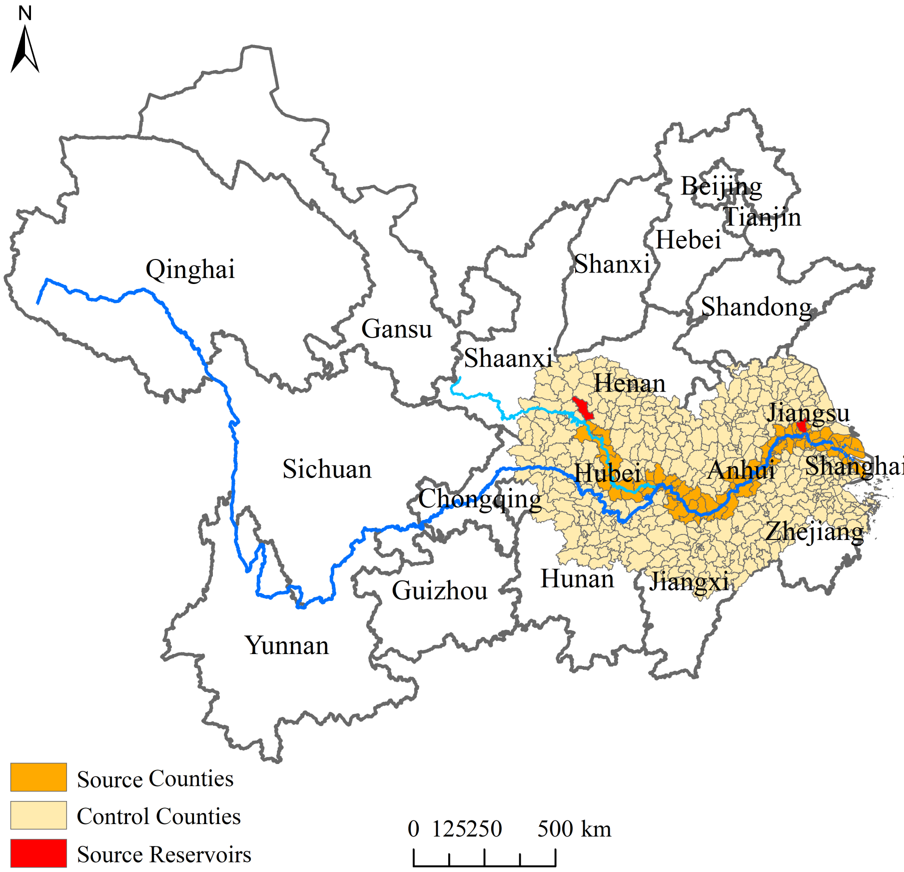


Figure 6: Illustration of Water Source Counties and Counties within a 200-km Radius

Notes: This figure illustrates the geographical layout of the counties potentially affected by water reductions due to the SNWDP, highlighted in a darker shade, and those within a 200-kilometer radius, indicated in a lighter color. The two source reservoirs, Danjiangkou and Jiangdu, are marked in red. The blue and green lines trace the paths of the Yangtze and Han Rivers, respectively.

counties to those located within a 200-kilometer radius, before and after the initiation of water diversion by the respective routes. Our model specification is analogous to Equation 1:

$$Y_{ct} = \beta \times \text{Source}_c \times \text{Post}_{t(c)} + \gamma \text{X}_{ct} + \lambda_c + \mu_t + \epsilon_{ct}, \tag{4}$$

where $Source_c$ is an indicator for counties situated along the Yangtze and Han Rivers downstream of the *Danjiangkou* Reservoir. The variable $Post_{t(c)}$ represents a dummy for the years following the initiation of water diversion. Given that the Eastern and Central Routes started operations at the end of 2013 and 2014, respectively, this dummy is set to 1 for counties downstream of *Jiangdu* after 2013 and for those downstream of *Danjiangkou* and upstream of *Jiangdu* after 2014. We exclude a small set of counties that are also categorized as water receiving counties from this analysis. County fixed effects, province-by-year fixed effects, climatic variables, and linear trends interacted with baseline characteristics are all included in the model.

Table 7 presents our main findings. Notably, the results do not show any statistically significant effects of the SNWDP on key outcomes in the source areas. Furthermore, the estimated effects for these regions are much smaller than those observed in water-receiving counties. Specifically, there is an estimated 0.7% decrease in per capita rural income, and a 0.6% increase in urban income, but these figures lack statistical significance at conventional levels. Furthermore, we do not observe statistically distinguishable impacts on agricultural productivity, total GDP, population size, or per capita GDP. These findings suggest that the SNWDP may not have imposed significant costs on the source areas.

Table 7: The Impact of SNWDP on Source Areas

VARIABLES	TFP	Rural Income	Urban Income	GDP	Population	GDP per capita
	(1)	(2)	(3)	(4)	(5)	(6)
Source × Post	-.014	-.007	.006	-.007	-.017	.002
	(.016)	(.007)	(.009)	(.020)	(.010)	(.021)
County & Year FE	Y	Y	Y	Y	Y	Y
Linear Trends	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
Mean of dep.	-.005	9.25	10.00	14.29	4.08	10.17
Observations	2,027	2,324	2,025	2,965	2,767	2,767

Notes: The dependent variables across Columns 1–6 are, respectively, the logarithm of agricultural TFP, rural residents' income, urban residents' income, gross domestic product, population, and per capita GDP. All models include county fixed effects, province-year fixed effects, annual mean precipitation, temperature, total sunshine hours, and linear trends interacted with 2008 GDP, total population, longitude, latitude, altitude, and slope. Robust standard errors, clustered at the county level, are reported in parentheses (***p<0.01, **p<0.05, *p<0.1).

The absence of substantial negative impacts on the source areas could be attributed to the relatively minimal volume of water diverted, set against the backdrop of the abundant water resources in these regions. In 2020, the SNWDP diverted approximately 9.5 billion cubic meters of water annually. While this quantity represents a significant share (about 15 percent) of the annual runoff of the Yellow River, China's largest river in the north, it constitutes only 1.1 percent of the Yangtze River's annual runoff. Given the Yangtze River Basin's substantial water resources, the modest reductions from the SNWDP are unlikely to cause significant adverse effects in these areas. This observation highlights the feasibility of large-scale inter-basin water diversion projects in benefiting receiving regions without detrimentally impacting the source areas.

However, it is important to acknowledge that our findings do not suggest an absence of adverse effects in all source areas. For example, the construction of dams for the project necessitated the relocation of thousands of farmers near the *Danjiangkou* Reservoir (Ministry of Water Resources of China, 2013). Additionally, there have been reports of closures of polluting firms in the area as part of efforts to maintain water quality. While these local losses are notable, our analysis suggests they appear relatively small in the broader context of the large populations benefiting from the SNWDP. It's also worth noting that the costs associated with displacement compensation are factored into the overall investment costs of the project, and thus are accounted for in our cost-benefit analysis.

In particular, the Chinese government set a relatively high compensation standard for those displaced in the water source areas. For instance, land compensation was elevated from 10 to 16 times the annual revenue from the three years prior to the relocation (The State Council of China, 2006, 2010), which generally exceeds market values (Sun, 2018). Additionally, each migrant is entitled to resettlement housing of at least 24 square meters and an annual subsidy of 600 Chinese yuan for 20 years (The State Council of China, 2010). Therefore, it is reasonable to consider the government's compensation as appropriately valued and to take it as the cost of displacement for the affected populations in the source areas.

4.5 Cost-Benefit Analysis

Finally, we perform a cost-benefit analysis of the South-North Water Diversion Project, using detailed annual investment data and our estimated effects on incomes in both the water-receiving and source regions.[15] The net economic benefits of the project are calculated as follows:

$$\text{Net Benefit} = \sum_{t=2013}^{T} Y_t (\frac{1}{1+\delta})^{t-2012} - \sum_{t=2002}^{T} I_t (\frac{1}{1+\delta})^{t-2012} \tag{5}$$

Here, Y_t represents the total economic benefits derived from the SNWDP in year t, which includes income gains for both rural and urban populations across water-receiving counties. Since water diversion began in 2013, we start our calculation of benefits from that year. More specifically,

[15]Our analysis focuses on income increases rather than GDP since the latter is less precisely estimated and varies across samples and specifications.

$Y_t = \sum_c \sum_i \beta^i y^i_{ct} p^i_{ct}$, where y^i_{ct} and p^i_{ct} represent the per capita income and population in rural or urban areas ($i \in \{r, u\}$) of county c in year t. We use 2012 as the base year and assume future per capita income and population levels to be the same as those of the base year. Per capita income is then multiplied by population size and the estimated effects on incomes (β^i) from Table 6, with the sum calculated across all areas and counties to determine the annual total economic benefits. The benefits for each year are discounted back to their 2012 present value, and these discounted values are then aggregated to calculate the total economic benefits over time. It is worth noting that our method may underestimate the economic benefits, considering that the annual volume of diverted water has been increasing over time.

Since the adverse effects on source regions are insignificant and the costs to the displaced populations have already been factored into the project's investment, our calculation of costs, denoted as I_t in the equation, only includes the annual investments made in the SNWDP from 2002 onwards. These investments, detailed in Appendix Table A13 and spanning from 2002 to 2020, encompass construction expenditure, maintenance, and relocation compensations. With the major construction and relocation efforts completed by 2020, we project future annual investments, primarily for maintenance, to remain consistent with the levels observed in 2020. As with the benefits, these costs are discounted to their 2012 present value. The net benefits of the SNWDP are then derived by subtracting the total discounted costs from the total discounted benefits.[16]

We conduct two analyses to evaluate the economic viability of the South-North Water Diversion Project. The first involved calculating the project's Internal Rate of Return (IRR). Specifically, the IRR is determined as the discount rate, denoted as δ^*, that equates the net present value (NPV) of all project-related benefits and costs to zero. This calculation effectively measures the annualized rate of return that can be earned from the project investment. Our calculations find $\delta^* = 0.064$, suggesting an annual Internal Rate of Return of 6.4 percent. This rate is favorable, surpassing the typical returns on Chinese highways and other large infrastructure projects, which averaged between 4 and 6 percent in the 1990s and 2000s (Shirley and Winston, 2004; Wu et al., 2021). This indicates that the economic benefits of the SNWDP may well outweigh its opportunity costs.

In addition to the internal rate of return, we also calculate the break-even timing of the SNWDP. This is defined as the year in which the cumulative economic benefits equal the total investment costs.

[16]It is important to note that this analysis focuses solely on the economic dimensions and does not include potential environmental impacts of the SNWDP. If the project achieves its goal of restoring ecological conditions in the target areas, our calculations may undervalue its full benefits. Conversely, should the project lead to adverse outcomes such as climatic shifts or the spread of pollutants and invasive species, the net benefits could be overstated. To date, however, there have been no significant reports indicating such negative environmental consequences.

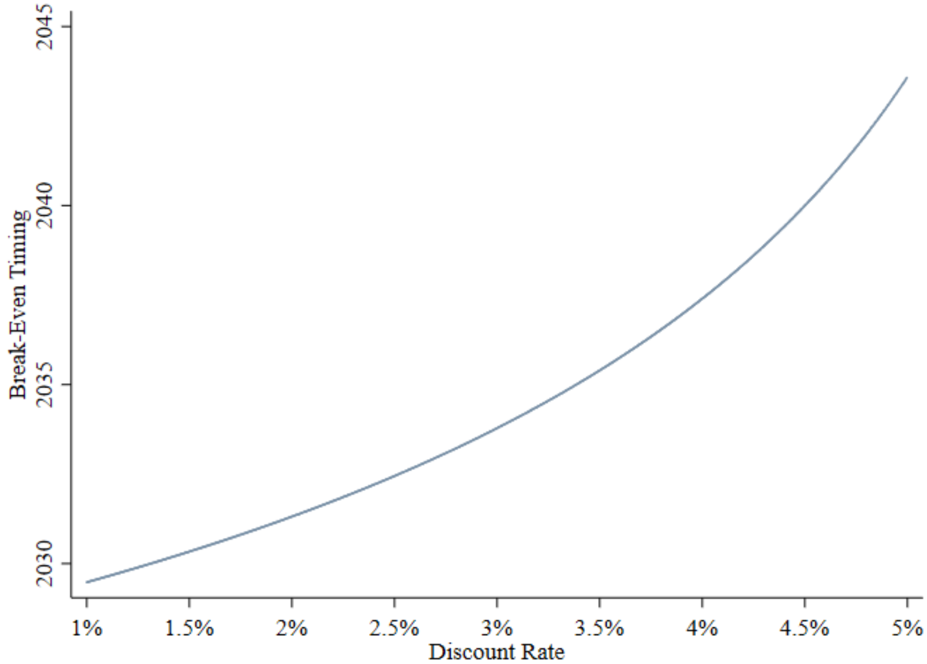


Figure 7: Break-Even Timing of the SNWDP under Different Discount Rates

To account for varying perspectives on the time value of money, we perform this calculation under different discount rate assumptions, with the results illustrated in Figure 7. Our analysis indicates that, with a 1 percent discount rate, the SNWDP is projected to reach its break-even point by 2030. At a higher discount rate of 5 percent, the break-even year extends to 2044. Utilizing a median discount rate of 2.5 percent, similar to the rates commonly used in macroeconomic studies, the project is expected to break even around 2034, approximately two decades after the commencement of water diversion. Collectively, these findings suggest that the benefits derived from the SNWDP are sufficient to justify its significant investment, underscoring the project's economic feasibility and potential for long-term profitability.

5 Conclusion

As the global population grows and climate change intensifies, water scarcity has emerged as a paramount global challenge. In this context, large-scale inter-basin water diversion projects have been proposed as promising solutions to improve water allocative efficiency and alleviate water scarcity. However, these projects are often controversial due to their significant financial requirements and lengthy construction timelines. A crucial debate centers around whether the considerable financial investments required for such initiatives can be justified by the benefits they yield. This uncertainty has significantly impeded progress, causing many proposed projects to stall or advance slowly.

This paper examines the South-North Water Diversion Project (SNWDP) in China, the world's largest project of its kind. Despite the Chinese government's positive view of the project, international perspectives are more divided. Our study pioneers a comprehensive evaluation of the impacts of the SNWDP. Employing detailed project implementation data and county-level statistics, we uncover significant improvements in agricultural output and productivity in the water-receiving areas, alongside modest yet positive impacts on local incomes and other economic activities. Importantly, our analysis indicates that the source regions have not experienced significant adverse effects. This finding suggests that with strategic design and execution, large-scale water diversion projects like the SNWDP can deliver substantial benefits to receiving regions without causing considerable harm to source areas. Our benefit-cost analysis further underscores the economic viability of the SNWDP, demonstrating its potential to offset the extensive investments through the economic benefits it generates.

Our paper contributes to the discourse on water management strategies in the face of pressing global challenges. It highlights the potential of large-scale water diversion projects to address critical water scarcity issues, particularly in arid regions. The insights provided are instrumental for policymakers globally, who may be considering similar water management initiatives. However, our study is not without its limitations. The lack of detailed household and firm-level data limits our ability to unpack the micro-level mechanisms driving the observed changes in rural and urban incomes. Additionally, our analysis predominantly focuses on the short-term impacts of the SNWDP, leaving its long-term effects an open area for future exploration. While we assess the economic benefits and potential costs, the study does not account for the environmental consequences of the project. Considering the SNWDP's goal to improve long-term ecological conditions in water-receiving regions, this omission likely leads to an underestimation of the project's overall benefits. Future research could address these gaps, particularly with improved data accessibility, offering a more comprehensive understanding of the multifaceted impacts of large-scale water diversion projects.

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Appendix: Not for publication.

Figure A1: The Water Source for the Central Route: *Danjiangkou* Reservoir

Figure A2: The *Taocha* Canal along the SNWDP's Central Route

Source: China South-to-North Water Diversion Corporation Limited.

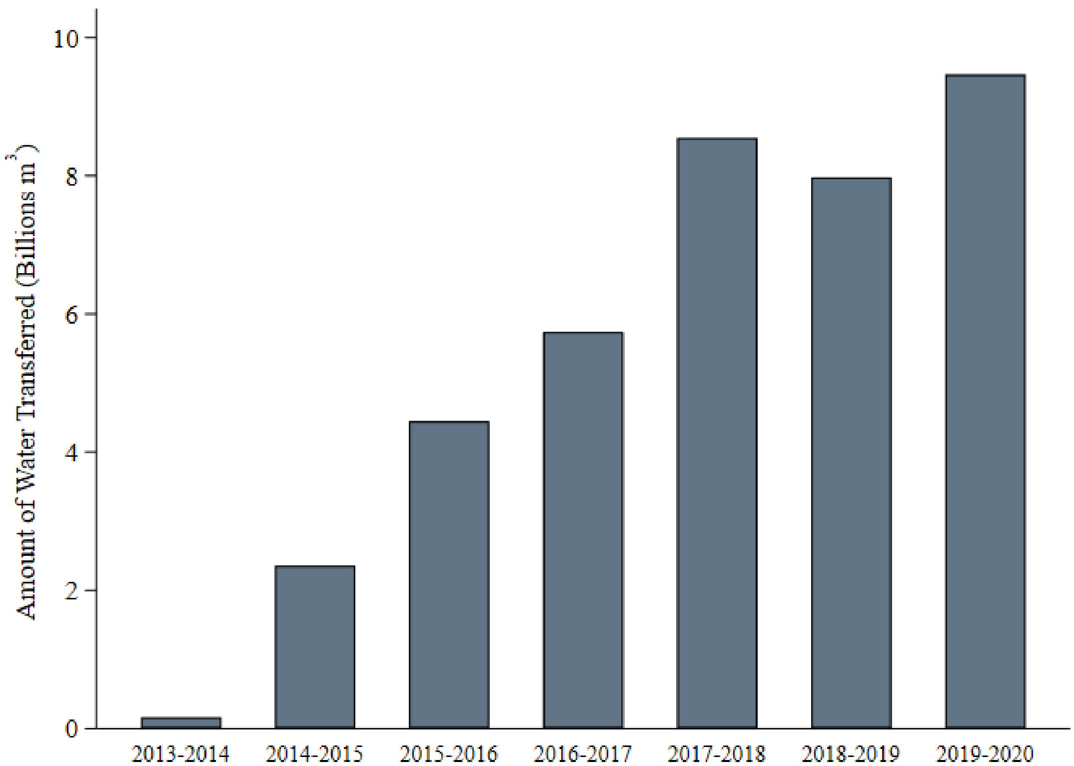
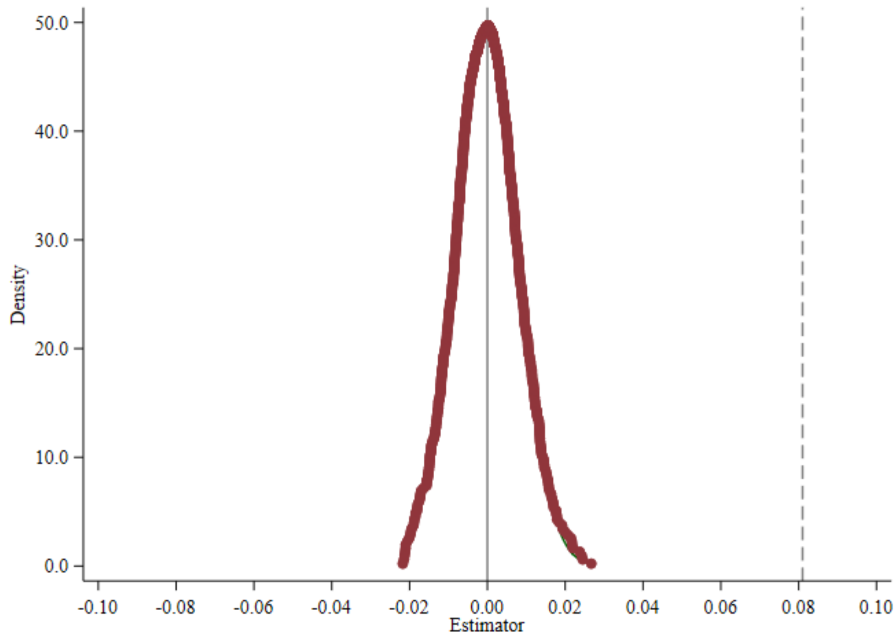
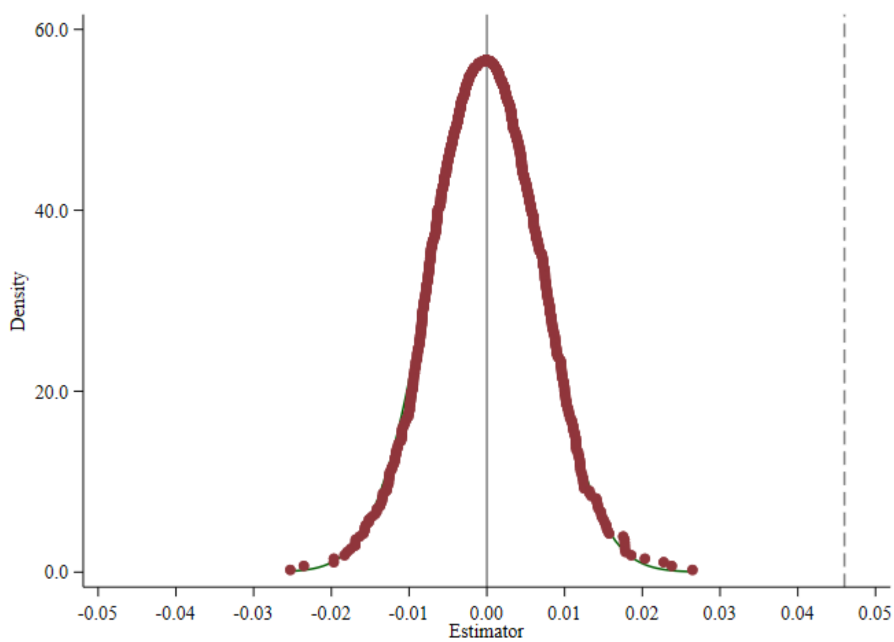


Figure A3: Annual Volume of Transferred Water from 2013 to 2020

Notes: This figure plots the yearly volume of water transferred through the Central and Eastern Routes, measured in billion cubic meters. The Eastern Route's data is recorded from October 1 of the given year to September 30 of the subsequent year. For the Central Route, the data collection period spans from November 1 to October 31 of the following year. *Source*: China South-to-North Water Diversion Project Construction Yearbook.



(a) Grain Output



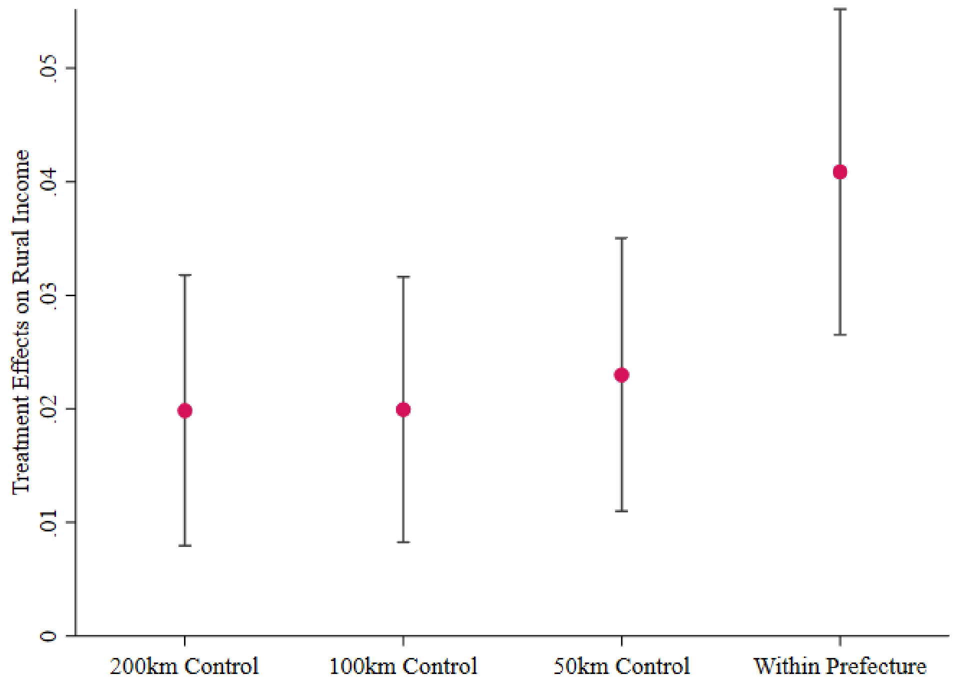
(b) TFP

Figure A4: Placebo Test on Grain Output and TFP

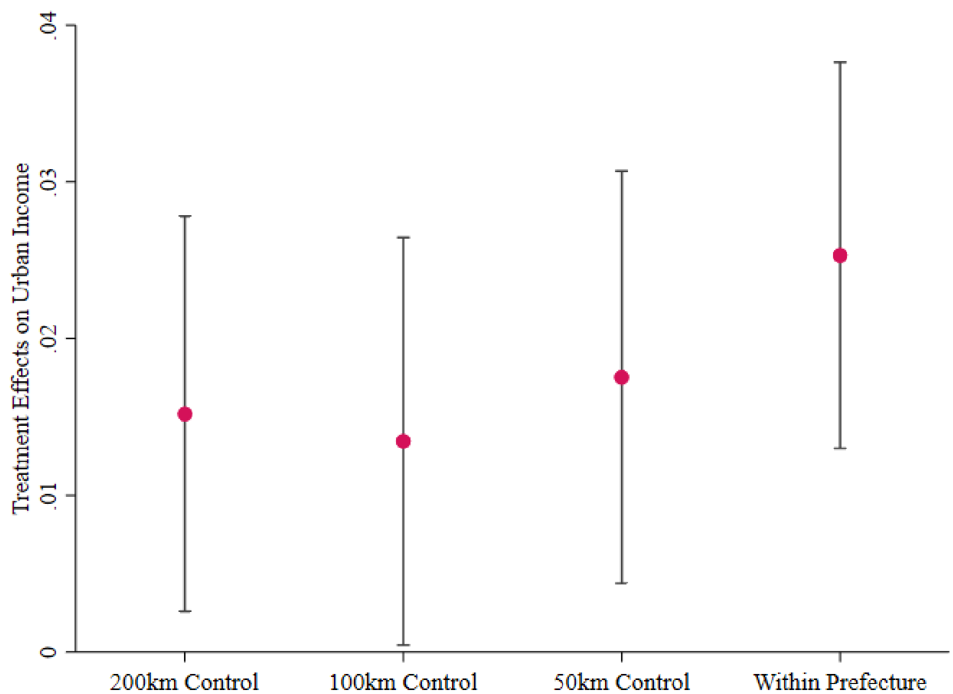
Notes: This figure plots the distribution of estimated effects on grain output and agricultural TFP in two separate panels. These estimates are derived from a placebo test where the water recipient status is randomly assigned across all sample counties. This process is repeated 1,000 times to generate the distribution. The estimated effects based on the actual treatment status are indicated by dash lines for comparison.

Figure A5: Groundwater Depth in Beijing

Notes: This figure depicts the annual average depth of groundwater (in meters) in Beijing from 2000 to 2018. On the y-axis, a higher value indicates a greater depth and a lower level of groundwater.
Source: Beijing Water Resources Bulletin.



(a) Rural Income



(b) Urban Income

Figure A6: Estimated Effects on Income Using Different Control Groups

Notes: This figure plots coefficient estimates and 95% confidence intervals for treatment effects of SNWDP from Equation 1, using counties within 200, 100, and 50 km, and the same prefecture of the treatment areas as the control groups, respectively. Robust standard errors are clustered by county.

Table A1: The Amount of Water Transferred and Supplied from 2013 to 2020

Periods	Amount of Water Transferred	Amount of Water Supplied
2013–2014	0.160	0.078
2014–2015	2.355	2.097
2015–2016	4.445	4.161
2016–2017	5.737	5.045
2017–2018	8.546	7.562
2018–2019	7.976	7.450
2019–2020	9.463	9.056

Notes: The amount of water in the table is in billions of cubic meters. The water scheduling year for the eastern route is from October 1 of each year to September 30 of the following year, while that for the central route is from November 1 of each year to October 31 of the following year.

Table A2: Robustness Check: Employing Alternative Radii to Define Control Group

VARIABLES	Within 100km			Within 50km		
	Grain Output	Per Worker Output	TFP	Grain Output	Per Worker Output	TFP
Treatment	.093***	.131***	.058***	.092***	.137***	.056***
	(.024)	(.034)	(.015)	(.026)	(.037)	(.017)
County & Year FE	Y	Y	Y	Y	Y	Y
Linear Trends	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
Mean of dep.	12.63	10.14	-.0005	12.71	10.17	.000
Observations	4,030	4,030	4,030	3,476	3,476	3,476

Notes: Columns 1–3 use counties within 100 kilometers of treatment areas as the control group, while Columns 4–6 use those within 50 kilometers. The dependent variables are as follows: the logarithm of total grain output in Columns 1 and 4, the logarithm of per worker output in Columns 2 and 5, and the logarithm of agricultural TFP in Columns 3 and 6, respectively. All models include county and year-fixed effects, annual mean precipitation, temperature, total sunshine hours, and linear trends interacted with 2008 GDP, total population, longitude, latitude, altitude, and slope. Robust standard errors, clustered at the county level, are reported in parentheses (***p<0.01, **p<0.05, *p<0.1).

Table A3: Robustness Check: Employing Counties within the Same Prefecture as the Control Group

VARIABLES	Grain Output		Per Worker Output		TFP	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	.097***	.103***	.130***	.134***	.066***	.070***
	(.031)	(.031)	(.045)	(.044)	(.019)	(.019)
County & Year FE	Y	Y	Y	Y	Y	Y
Linear Trends	Y	Y	Y	Y	Y	Y
Weather Controls	N	Y	N	Y	N	Y
Mean of dep.	12.73	12.73	10.25	10.25	.0002	.0002
Observations	2,622	2,622	2,622	2,622	2,622	2,622

Notes: This analysis employs counties within the same prefecture as the treatment areas for comparison. The dependent variables are as follows: the logarithm of total grain output in Columns 1–2, the logarithm of per worker output in Columns 3–4, and the logarithm of agricultural TFP in Columns 5–6, respectively. All models include county and year-fixed effects, and linear trends interacted with 2008 GDP, total population, longitude, latitude, altitude, and slope. Even-numbered columns additionally adjust for time-varying weather conditions, including annual mean precipitation, temperature, and total sunshine hours. Robust standard errors, clustered at the county level, are reported in parentheses (***p<0.01, **p<0.05, *p<0.1).

Table A4: Robustness Check: Addressing Spatial Correlations in Model Errors

VARIABLES	Grain Output		Per Worker Output		TFP	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	.081***	.082***	.096***	.101***	.046***	.047***
	(.016)	(.017)	(.024)	(.024)	(.012)	(.012)
County & Year FE	Y	Y	Y	Y	Y	Y
Linear Trends	Y	Y	Y	Y	Y	Y
Weather Controls	N	Y	N	Y	N	Y
Mean of dep.	12.47	12.47	10.06	10.06	-.0004	-.0004
Observations	5,244	5,244	5,244	5,244	5,244	5,244

Notes: This table presents the results from estimating Equation 1, using Conley (1999)'s method to adjust for spatial correlation across counties. The dependent variables are as follows: the logarithm of total grain output in Columns 1–2, the logarithm of per worker output in Columns 3–4, and the logarithm of agricultural TFP in Columns 5–6, respectively. All models include county and year-fixed effects, and linear trends interacted with 2008 GDP, total population, longitude, latitude, altitude, and slope. Even-numbered columns additionally adjust for time-varying weather conditions, including annual mean precipitation, temperature, and total sunshine hours. Robust standard errors, clustered at the county level, are reported in parentheses (***p<0.01, **p<0.05, *p<0.1).

Table A5: Testing for Geographic Spillover Effects

VARIABLES	Grain Output		Per Worker Output		TFP	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{I}$(Distance $\leq$ 50km) $\times$ Post	-.007	-.002	-.031	-.046	.013	.018
	(.025)	(.026)	(.038)	(.040)	(.021)	(.022)
County & Year FE	Y	Y	Y	Y	Y	Y
Linear Trends	Y	Y	Y	Y	Y	Y
Weather Controls	N	Y	N	Y	N	Y
Mean of dep.	12.55	12.55	9.98	9.98	-0.001	-0.001
Observations	2,305	2,305	2,305	2,305	2,305	2,305

Notes: The sample is restricted to control group counties located within 100 kilometers of the treatment areas. The key explanatory variable is the interaction term between a dummy that equals one for counties within 50 kilometers of any water-receiving counties, and an indicator that equals one when the nearest water-receiving county has begun receiving water from the SNWDP. The dependent variables are as follows: the logarithm of total grain output in Columns 1–2, the logarithm of per worker output in Columns 3–4, and the logarithm of agricultural TFP in Columns 5–6, respectively. All models include county and year-fixed effects, and linear trends interacted with 2008 GDP, total population, longitude, latitude, altitude, and slope. Even-numbered columns additionally adjust for time-varying weather conditions, including annual mean precipitation, temperature, and total sunshine hours. Robust standard errors, clustered at the county level, are reported in parentheses (***p<0.01, **p<0.05, *p<0.1).

Table A6: Robustness Check: Controlling for Province by Year Fixed Effects

VARIABLES	Grain Output		Per Worker Output		TFP	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	.088***	.091***	.083**	.090**	.044***	.046***
	(.024)	(.024)	(.035)	(.036)	(.015)	(.015)
County & Year FE	Y	Y	Y	Y	Y	Y
Linear Trends	Y	Y	Y	Y	Y	Y
Weather Controls	N	Y	N	Y	N	Y
Mean of dep.	12.47	12.47	10.06	10.06	-.0003	-.0003
Observations	5,223	5,223	5,223	5,223	5,223	5,223

Notes: The dependent variables are as follows: the logarithm of total grain output in Columns 1–2, the logarithm of per worker output in Columns 3–4, and the logarithm of agricultural TFP in Columns 5–6, respectively. All models include county-fixed effects, province-year fixed effects, and linear trends interacted with 2008 GDP, total population, longitude, latitude, altitude, and slope. Even-numbered columns additionally adjust for time-varying weather conditions, including annual mean precipitation, temperature, and total sunshine hours. Robust standard errors, clustered at the county level, are reported in parentheses (***p<0.01, **p<0.05, *p<0.1).

Table A7: Robustness Check: Transcendental Logarithmic TFP

VARIABLES	Within 200km		Within 100km		Within 50km	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	.049***	.050***	.060***	.060***	.055***	.057***
	(.015)	(.015)	(.016)	(.016)	(.017)	(.017)
County & Year FE	Y	Y	Y	Y	Y	Y
Linear Trends	Y	Y	Y	Y	Y	Y
Weather Controls	N	Y	N	Y	N	Y
Mean of dep.	-.0004	-.0004	-.0006	-.0006	.0000	.0000
Observations	5,224	5,224	4,030	4,030	3,476	3,476

Notes: The dependent variables are the logarithm of agricultural TFP estimated from a transcendental logarithmic production function. Columns 1–2 use counties within 200 kilometers of treatment areas as the control group, while Columns 3–4 and 5–6 use those within 100 and 50 kilometers, respectively. All models include county and year-fixed effects, and linear trends interacted with 2008 GDP, total population, longitude, latitude, altitude, and slope. Even-numbered columns additionally adjust for time-varying weather conditions, including annual mean precipitation, temperature, and total sunshine hours. Robust standard errors, clustered at the county level, are reported in parentheses (***p<0.01, **p<0.05, *p<0.1).

Table A8: Robustness Check: Excluding Outliers

VARIABLES	Excluding Shandong Province			Excluding Cangzhou & Hengshui		
	Grain Output	Per Worker Output	TFP	Grain Output	Per Worker Output	TFP
Treatment	.095***	.124***	.050***	.077***	.107***	.046***
	(.024)	(.027)	(.015)	(.023)	(.037)	(.015)
County & Year FE	Y	Y	Y	Y	Y	Y
Linear Trends	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
Mean of dep.	12.39	10.07	-.0003	12.46	10.02	-.0003
Observations	4,506	4,506	4,506	4,993	4,993	4,993

Notes: In this analysis, Columns 1–3 exclude counties in Shandong Province, while Columns 4–6 omit those in Cangzhou and Hengshui Prefectures, areas that started receiving water later compared to other regions along the Central Route. The dependent variables are as follows: the logarithm of total grain output in Columns 1 and 4, the logarithm of per worker output in Columns 2 and 5, and the logarithm of agricultural TFP in Columns 3 and 6, respectively. All models include county and year-fixed effects, annual mean precipitation, temperature, total sunshine hours, and linear trends interacted with 2008 GDP, total population, longitude, latitude, altitude, and slope. Robust standard errors, clustered at the county level, are reported in parentheses (***p<0.01, **p<0.05, *p<0.1).

Table A9: Robustness Check: Addressing Treatment Effect Heterogeneity

VARIABLES	Grain Output		Per Worker Output		TFP	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	.077***	.078***	.094***	.098***	.043***	.044***
	(.022)	(.022)	(.032)	(.032)	(.015)	(.015)
County & Year FE	Y	Y	Y	Y	Y	Y
Linear Trends	Y	Y	Y	Y	Y	Y
Weather Controls	N	Y	N	Y	N	Y
Mean of dep.	12.47	12.47	10.06	10.06	-.0004	-.0004
Observations	5,244	5,244	5,244	5,244	5,244	5,244

Notes: This table presents the results from estimating Equation 1, using Sun and Abraham (2021)'s method to adjust for treatment effect heterogeneity across time and units. The dependent variables are as follows: the logarithm of total grain output in Columns 1–2, the logarithm of per worker output in Columns 3–4, and the logarithm of agricultural TFP in Columns 5–6, respectively. All models include county and year-fixed effects, and linear trends interacted with 2008 GDP, total population, longitude, latitude, altitude, and slope. Even-numbered columns additionally adjust for time-varying weather conditions, including annual mean precipitation, temperature, and total sunshine hours. Robust standard errors, clustered at the county level, are reported in parentheses (***p<0.01, **p<0.05, *p<0.1).

Table A10: Robustness Check: Harmonizing Treatment Initiation Year to 2014

VARIABLES	Grain Output		Per Worker Output		TFP	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	.063***	.069***	.113***	.123***	.034**	.039**
	(.022)	(.023)	(.036)	(.036)	(.015)	(.016)
County & Year FE	Y	Y	Y	Y	Y	Y
Linear Trends	Y	Y	Y	Y	Y	Y
Weather Controls	N	Y	N	Y	N	Y
Mean of dep.	12.47	12.47	10.06	10.06	-.0004	-.0004
Observations	5,244	5,244	5,244	5,244	5,244	5,244

Notes: In all model of this table, we harmonize the treatment initiation year to 2014 for all water-receiving counties. The key explanatory variable is thus the interaction term between a dummy for water-receiving counties and an indicator for the post-2014 period. The dependent variables are as follows: the logarithm of total grain output in Columns 1–2, the logarithm of per worker output in Columns 3–4, and the logarithm of agricultural TFP in Columns 5–6, respectively. All models include county and year-fixed effects, and linear trends interacted with 2008 GDP, total population, longitude, latitude, altitude, and slope. Even-numbered columns additionally adjust for time-varying weather conditions, including annual mean precipitation, temperature, and total sunshine hours. Robust standard errors, clustered at the county level, are reported in parentheses (***p<0.01, **p<0.05, *p<0.1).

Table A11: Separate Results for the Central and Eastern Routes

VARIABLES	Central Route			Eastern Route		
	Grain Output	Per Worker Output	TFP	Grain Output	Per Worker Output	TFP
Treatment	.083***	.079***	.051***	.089***	.125***	.058***
	(.026)	(.036)	(.017)	(.020)	(.037)	(.015)
County & Year FE	Y	Y	Y	Y	Y	Y
Linear Trends	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
Mean of dep.	12.38	10.14	-.0005	12.71	10.22	.0000
Observations	4,246	4,246	4,246	3,188	3,188	3,188

Notes: Columns 1–3 limit the sample to water-receiving counties along the Central Route and those within a 200-kilometer radius, while Columns 4–6 focus on the Eastern Route. Due to overlapping control groups for both routes, the combined sample size for these analyses differs from that in Table 2. The dependent variables are as follows: the logarithm of total grain output in Columns 1 and 4, the logarithm of per worker output in Columns 2 and 5, and the logarithm of agricultural TFP in Columns 3 and 6, respectively. All models include county and year-fixed effects, annual mean precipitation, temperature, total sunshine hours, and linear trends interacted with 2008 GDP, total population, longitude, latitude, altitude, and slope. Robust standard errors, clustered at the county level, are reported in parentheses (***p<0.01, **p<0.05, *p<0.1).

Table A12: Groundwater Levels: Addressing Treatment Effect Heterogeneity

VARIABLES	Groundwater Levels (1)	(2)
Treatment	5.824***	4.339**
	(1.904)	(1.884)
County & Year FE	Y	Y
Linear Trends	Y	Y
Weather Controls	N	Y
Mean of dep.	131.2	131.2
Observations	4,817	4,817

Notes: This table presents the results from estimating Equation 1, using Sun and Abraham (2021)'s method to adjust for treatment effect heterogeneity across time and units. The dependent variables are groundwater levels. All models include county and year-fixed effects, and linear trends interacted with 2008 GDP, total population, longitude, latitude, altitude, and slope. Column 2 additionally adjusts for time-varying weather conditions, including annual mean precipitation, temperature, and total sunshine hours. Robust standard errors, clustered at the county level, are reported in parentheses (***p<0.01, **p<0.05, *p<0.1).

Table A13: The Amount of Investment from 2001 to 2020

YEAR	Planned Investment		Actual Investment	
	Annual Investment	Cumulative Investment	Annual Investment	Cumulative Investment
2001	0.03	0.03	–	–
2002	0.45	0.48	–	0.06
2003	1.34	1.82	0.77	0.83
2004	4.82	6.64	1.26	2.09
2005	6.36	13.00	1.83	3.92
2006	8.74	21.74	8.05	11.97
2007	8.70	30.44	7.13	19.10
2008	15.91	46.35	5.11	24.21
2009	16.45	62.80	14.79	39.00
2010	53.46	116.26	40.83	79.83
2011	47.94	164.20	57.80	137.63
2012	51.62	215.82	65.29	202.92
2013	29.41	245.23	40.49	243.41
2014	10.93	256.16	10.92	254.33
2015	5.61	261.77	4.35	258.68
2016	0.18	261.95	0.47	259.15
2017	1.99	263.94	1.78	260.93
2018	3.93	267.87	3.92	264.85
2019	2.60	270.47	1.5	266.35
2020	–	–	0.52	266.87

Notes: The amount of investment in the table is billions of Yuan. The missing value is represented by " – ".

Table A14: Additional Outcomes: Robustness to Different Control Groups

VARIABLES	Rural Income	Urban Income	Secondary GDP	Tertiary GDP	GDP	Population
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Within 100km						
Treatment	.020***	.013**	.009	-.004	.011	-.003
	(.006)	(.007)	(.027)	(.020)	(.018)	(.005)
Panel B: Within 50km						
Treatment	.023***	.018**	.008	-.022	.008	-.001
	(.006)	(.007)	(.026)	(.020)	(.017)	(.004)
Panel C: Within Prefecture						
Treatment	.041***	.025***	.032	-.050**	.027	.002
	(.007)	(.006)	(.027)	(.023)	(.018)	(.005)
County & Year FE	Y	Y	Y	Y	Y	Y
Linear Trends	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y

Notes: The dependent variables in Columns 1–6 are the logarithm of rural residents' income, urban residents' income, secondary gross domestic product, tertiary gross domestic product, gross domestic product and population, respectively. All models include county and year-fixed effects, annual mean precipitation, temperature, total sunshine hours, and linear trends interacted with 2008 GDP, total population, longitude, latitude, altitude, and slope. Robust standard errors clustered by county are reported in parentheses (***p<0.01, **p<0.05, *p<0.1).

Table A15: Additional Outcomes: Addressing Spatial Correlations in Model Errors

VARIABLES	Rural Income	Urban Income	Secondary GDP	Tertiary GDP	GDP	Population
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	.020***	.015***	.035*	.014	.028**	.008*
	(.005)	(.005)	(.019)	(.015)	(.011)	(.005)
County & Year FE	Y	Y	Y	Y	Y	Y
Linear Trends	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
Mean of dep.	9.15	10.03	13.51	13.21	14.34	3.97
Observations	6,194	4,653	6,406	5,949	7,699	6,748

Notes: The dependent variables across Columns 1–6 are the logarithm of rural residents' income, urban residents' income, secondary gross domestic product, tertiary gross domestic product, gross domestic product and population, respectively. All models include county and year-fixed effects, annual mean precipitation, temperature, total sunshine hours, and linear trends interacted with 2008 GDP, total population, longitude, latitude, altitude, and slope. Robust standard errors, clustered at the county level, are reported in parentheses (***p<0.01, **p<0.05, *p<0.1).

Table A16: Additional Outcomes: Addressing Treatment Effect Heterogeneity

VARIABLES	Rural Income	Urban Income	Secondary GDP	Tertiary GDP	GDP	Population
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	.019***	.013*	.023	.008	.027	.009
	(.006)	(.007)	(.028)	(.020)	(.018)	(.007)
County & Year FE	Y	Y	Y	Y	Y	Y
Linear Trends	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
Mean of dep.	9.15	10.03	13.51	13.21	14.34	3.97
Observations	6,194	4,653	6,406	5,949	7,699	6,748

Notes: This table presents the results from estimating Equation 1, using Sun and Abraham (2021)'s method to adjust for treatment effect heterogeneity across time and units. The dependent variables across Columns 1–6 are the logarithm of rural residents' income, urban residents' income, secondary gross domestic product, tertiary gross domestic product, gross domestic product and population, respectively. All models include county and year-fixed effects, annual mean precipitation, temperature, total sunshine hours, and linear trends interacted with 2008 GDP, total population, longitude, latitude, altitude, and slope. Robust standard errors, clustered at the county level, are reported in parentheses (***p<0.01, **p<0.05, *p<0.1).