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Long-distance water infrastructure, rural development and urban growth: Evidence from China☆

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ABSTRACT

Water is unevenly distributed across regions, yet the effectiveness of long-distance water transfer in addressing this issue remains understudied. This paper employs a difference-in-difference design to examine the impact of the world's largest water transfer project on water resources, rural development, and urban growth. We find that the project enhances water supply and agricultural production in water-receiving areas, while it leads to agricultural declines in water-sourcing areas. Such diverging patterns contribute to various consequences on labor market and rural welfare, thereby generating further differential impacts on nearby urban growth. The water-receiving areas witness urban expansion and economic activities thrive in the rural-urban fringe, but in the water-sourcing areas, economic activities decline outside the core urban areas. Further analysis reveals significant heterogeneity between the two water-transfer routes, distinguished by their engineering designs.

1. Introduction

Water is essential for life and civilization. Access to water has been a key defining factor in the location and prosperity of cities. Rivers like the Nile, Euphrates, Tigris and Yangtze enabled agricultural activities and thrived the development of the most recognized civilizations. And today, modern cities like London, New York and Shanghai continue this tradition, flourishing along waterways. However, the distribution of water resources exhibits significant disparities both across and within countries, and this uneven distribution is likely to become exacerbated as the changing climate is redistributing water resources (Mekonnen and Hoekstra, 2016; Scanlon et al., 2023). It remains unclear how changes of water resources reshape local economy and urban growth.

Throughout human history, endless efforts have been made to discipline and relocate water resources through drilling wells, digging channels, and building dams, etc. However, projects enabling water transfer over long distances are still rare given the technical challenges and resource constraints typically involved. Long-distance water transfer initiatives have been proposed and implemented by several countries, such as the California State Water Project in the United States, the National River Linking Project in India, and the South-to-North Water Transfer Project (SNWT) in China. However, these projects have sparked considerable controversy. While proponents highlight the potential benefits of redirecting water from surplus to deficit regions, rigorous empirical evaluations are still needed to quantify the economic returns and welfare distributions.

This study examines the effects of the long-distance water transfer project on water resources, rural development, and urban growth using the SNWT project in China as an example. As the world's largest water-transfer project, the SNWT project was initiated by the Chinese government to balance the huge disparity in water resources between its southern and northern regions. The first phase of the project involved building two separate cross-provincial water-transfer routes: the middle line and the east line. The two lines were designed under distinct engineering approaches, with their trunk line lengths totaling nearly 3,000 kilometers. The middle line and the east line started to function in 2015 and 2014 respectively, providing us a unique chance

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to study the effect of long-distance water transfer.

Our data combine remote sensing images and a wide range of economic outcomes in several nationally representative panel datasets at the levels of counties, villages, and households. Geographical information related to the SNWT project, after digitization, is spatially projected to these data layers. An empirical challenge arises from potential correlations between project locations and various economic conditions. Leveraging the least-cost considerations in designing the project routes and the inconsequential unit approach, our baseline model adopts a difference-in-difference (DID) design that compares the geographically determined affected regions with their nearby regions before and after the project's completion. We validate the parallel trend assumption in an event study framework and further provide a battery of tests such as using alternative DID estimators, a richer set of fixed effects, and various tailored control groups.

Our results reveal that the project brings a wide range of economic impacts. In the water demand areas, the project increases water coverage by 6.5% and boosts local GDP per capita by 6.0%. The economic impact is primarily driven by agriculture, instead of other sectors. Rural households directly benefit from the project as their agricultural income and consumption increase. The project water intensifies local agriculture and holds back extra incentives for rural labor to leave agriculture. Consistently, we find no evidence that the project increases rural non-agricultural returns, nor do we find the project induces labor relocation from farm to non-farm sectors.

The project-led growth in agriculture has profound implications on nearby cities. Using land-cover data, we find urban boundaries expand and city sizes grow by 6.9% in the water demand areas. We also track changes in night lights and population densities in the always-urban, always-rural, and rural–urban fringe areas, respectively. In the always-urban areas, the project leads to a 4.2% increase in night lights and a 3.1% increase in population densities. The rural–urban fringe has experienced even larger growth as these effects amount to 6.1% and 3.9%, respectively. In contrast, we do not find significant changes in the always-rural areas. Taken together the results on rural consumption and labor, the project-induced urban growth is most likely driven by the demand effects of rural residents.

A different picture emerges in the water supply areas. The project leads to a 5.6% decrease in agricultural GDP per capita, but this recession is offset by a 5.4% increase in non-agricultural GDP per capita. This structural transformation is also reflected in rural household income and labor allocation. Specifically, the project decreases rural farm income by 7.8% but increases non-farm income by 9.3%. Household consumption exhibits no discernible change. We also observe increases in non-farm employment and migration. These changes in rural villages reverberate in nearby cities. While urban areas become more vibrant, their physical boundaries remain largely unchanged. In the always-urban regions, the project increases night lights and population densities by 2.8% and 2.2%, respectively, while other regions experience economic declines. The findings are consistent with decreased agricultural returns, increased out-migration and stagnant rural consumption. They also align with the fact that water supply areas, which are rich in water bodies, face restrictive geography that limits urban expansion despite population growth (Saiz, 2010).

Finally, we explore potential heterogeneities across the two lines, motivated by their substantially different engineering designs. In the water demand areas, the project's effects are largely homogeneous, since the essential benefits of receiving more water do not differ in nature. However, in the water supply areas, the project effects are mostly driven by the middle line. This discrepancy stems from the fact that the sourcing region of the middle line involves heightening a dam and expanding its reservoir, imposing a much greater burden on its local agriculture compared to the east line. Our findings shed light on the fundamental disparities between dam-based and transfer network-based water relocation schemes. Both mechanisms provide similar benefits to the water-receiving areas, yet they differ in the costs they impose on the supply areas.

Existing studies have searched for what infrastructures deliver the largest benefits (Glaeser and Henderson, 2017). While numerous studies concentrate on transportation infrastructure (Banerjee et al., 2020; Baum-Snow, 2007; Baum-Snow et al., 2020; Behrens, 2007; Donaldson and Hornbeck, 2016; Dong et al., 2020; Lin, 2017), we underscore water infrastructure in light of anticipated climate change-induced shifts in water resource distribution across regions. Previous studies on water infrastructures have examined dams and canals that divert surface water, pumping facilities that exploit groundwater, and hydroelectric infrastructures that provide electrification (Duflo and Pande, 2007; Strobl and Strobl, 2011; Blakeslee et al., 2023; Rafey, 2023; Hornbeck and Keskin, 2014; Blakeslee et al., 2020; Dyer and Shapiro, 2022; Lipscomb et al., 2013; Severnini, 2023). Our paper differs by analyzing a distinctive long-distance water transfer project in China, in which the transferred water greatly surpasses the capacity of regular water infrastructures. Moreover, we are able to contrast the dam-based versus transfer network-based water relocation schemes, which sheds light on designing long-distance water transfer projects in other countries with similar hydrological environments.

This paper adds to the economics of environmental adaptation (Kelly et al., 2005; Hornbeck, 2012; Burke and Emerick, 2016, etc.). Our analyses reveal that the adaptation strategies involve two fundamental and complementary processes. First, variable inputs are simultaneously adjusted upon receiving the project water, consistent with previous studies documenting farmers' flexibility in making productive adjustments toward environmental change (Cui, 2020; Jagnani et al., 2021; Aragón et al., 2021; Cui and Zhong, 2024; Cui and Tang, 2024). Second, rural labor shifts from farm to non-farm sectors, constituting an important adjustment to attenuate agricultural loss associated with environmental shocks (Blakeslee et al., 2020; Colmer, 2021; Liu et al., 2023). The second process is also observed in the push-pull literature, featuring climate shock in agriculture as a push factor (Barrios et al., 2006; Henderson et al., 2017; Jedwab et al., 2017).

This paper also contributes to the broader literature on structural transformation. Developing countries have a large share of labor in agriculture, but agriculture's contribution in total value added is low (Restuccia et al., 2008). Yet, there is limited evidence on how changes in agriculture affect non-agricultural development and the findings are mixed (Foster and Rosenzweig, 2004; Adhvaryu et al., 2013; Blakeslee et al., 2023; Bustos et al., 2016; Hornbeck and Keskin, 2015; Emerick, 2018). We further enrich the literature by showing different pictures in water demand and supply areas. The project enhances water supply and agricultural production in water-receiving areas, while it induces agricultural declines in water-sourcing areas. Such diverging patterns are associated with various labor outcomes, rural welfare and urban growth. The mechanisms at play are consistent with existing studies about the demand effect on local non-tradables and the migration channel (Emerick, 2018; Bustos et al., 2016; Hornbeck and Keskin, 2015).

This paper is organized as follows. Section 2 introduces the background of the SNWT project. Sections 3 and 4 describe the data and empirical strategies. Sections 5 and 6 present the empirical findings on water coverage, economic growth, rural development, labor relocation, and urban growth in the water demand and supply areas, respectively. Sections Section 7 discusses the heterogeneity between the middle and east lines. Section 8 concludes.

2. Background

Water resources per capita in China amount to approximately one-fourth of the global average, with a significantly imbalanced distribution nationwide. The northern region, home to half of the domestic population and roughly 60% of the arable land, receives less than

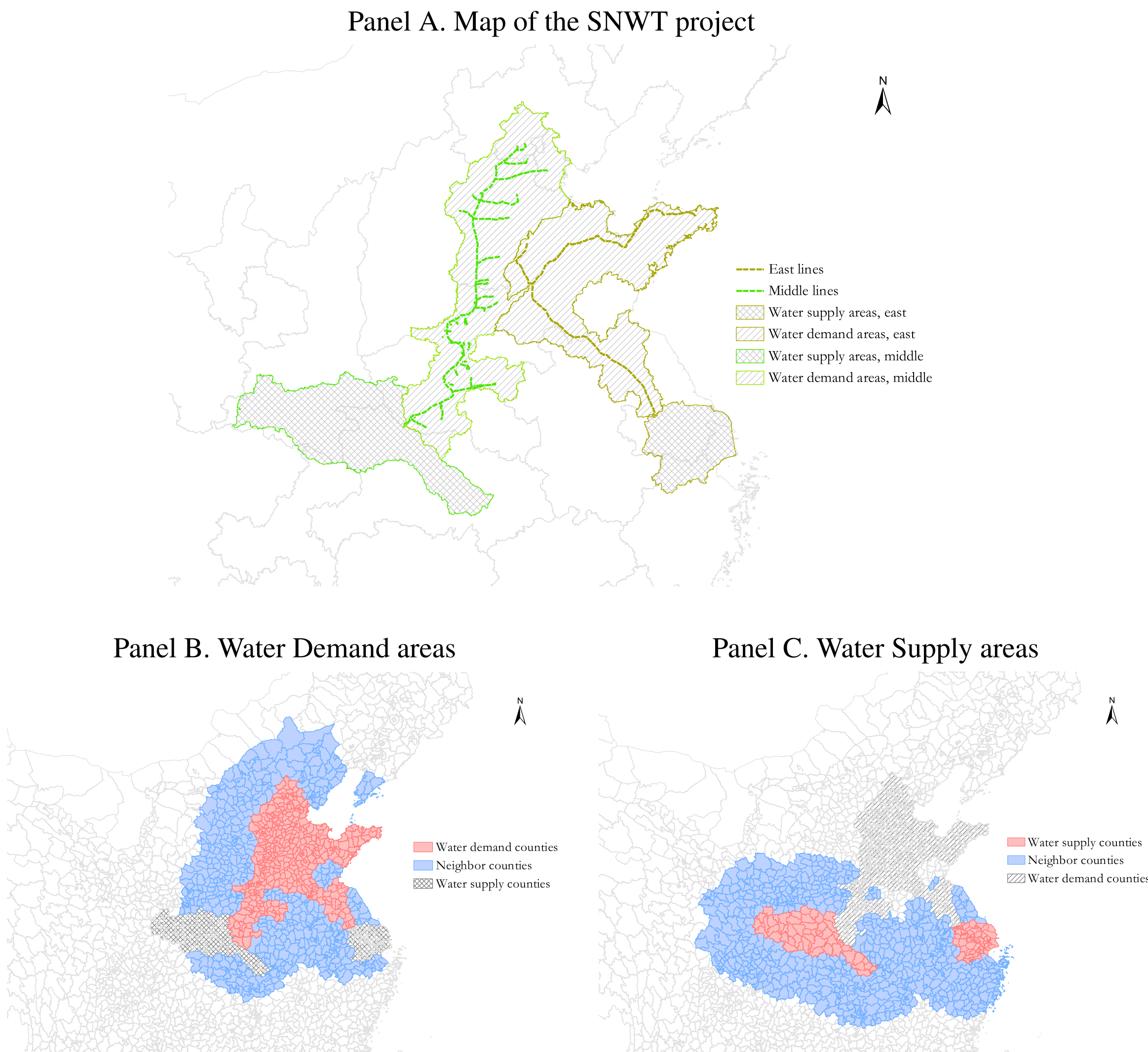

Fig. 1. Water Demand and Supply Areas of the SNWT Project
Notes: This figure shows the spatial map of the SNWT project. Panel A shows the project maps, in which the middle line is in red and the east line is in brown. The diagonal shades represent water demand areas and the gridded shades represent water supply areas. Panels B and C focus on the water demand and supply areas, respectively. The treated counties are in red, and the control counties are in blue. All panels in the figure are adapted from the official document of the project.

20% of the domestic water resources on average.[1] In the early 1950s, Chairman Mao first brought up the idea of transferring water from the south to the north, after he personally witnessed the residential water shortage in Beijing. However, due to technical, financial, and resource constraints, a feasible plan for the project was not proposed until the turn of the century.

The Chinese government officially approved the construction plan for the SNWT project in December 2002. The project's first phase involved establishing two separate water transfer routes, namely the middle line and the east line (the left and right lines in panel A of Fig. 1). The project was designed to reach the Beijing–Tianjin–Hebei (BTH) region where the urban population is large but the water is scarce. Both of the trunk lines stretch almost 1,500 kilometers and crossing multiple provinces.

This unprecedented project was planned, implemented, and financed almost entirely by the central government. Its primary objective, as stated in official documents, was to address water scarcity in the BTH region and other water-deficit regions along the routes. The routes were designed after decades of evaluations and the final decision was mostly based on least-cost considerations with the objective of transferring sufficient water to the north, especially to the BTH region.

All the places along the transferring routes benefit from receiving extra water. The official documents of the project clearly delineate the administrative units that are slated to receive transferred water from each of the two lines. This information is summarized and presented in Table A1. Despite certain areas being geographically proximate to both lines, the documents specify that they solely receive water from one of the two lines.

The project's middle and east lines have distinct engineering designs. The middle line sources water from an existing reservoir, *Danjiangkou*, located on the Han River, a major tributary of the Yangtze River. The construction involves heightening the dam and expanding the reservoir, and most of the route comprises newly established open channels. The route is designed to gradually decrease in elevation from south to north, facilitating gravity-driven water transfers over the long distance. Regions along this route benefit from receiving the water through newly established channels and pipe culverts.

The east line sources water from the downstream of the Yangtze River. Unlike the middle line, which transfers water through open

[1] More background about water shortage in China is documented in *China Water Resources Bulletin, 2019*, published by the Ministry of Water Resources in China.

channels and pipe culverts, the east line transfers water by connecting existing rivers and lakes along its way. This approach utilizes the water capacities of available water bodies, but the natural terrain precludes the design of gravity-driven water transfers. As a result, more than 20 pump stations have been established along the route to elevate water at certain locations.

The construction cost of the middle line is significantly higher than that of the east line. On the one hand, reforming the *Danjiangkou* reservoir and its dam is very costly, incurring significant expenses regarding both the construction and related compensation payments to nearby residents.[2] On the other hand, the middle line necessitates the creation of entirely new infrastructure, including open channels and pipe culverts spanning the 1500-kilometer route. Unlike the east line, which leverages existing water bodies, the middle line requires substantial investment to build these channels and culverts from scratch.

3. Data

We compile data from various sources, including digitized maps of the SNWT project, administrative statistics, rural household surveys, remote sensing measures, and climatological datasets.[3]

Official maps of the SNWT project. We obtain digitized maps of the SNWT project from the National Geospatial Information Center. Panel A in Fig. 1 shows the two water transfer lines, including trunk lines and major branches. Water receiving areas are indicated in diagonal shades and water supply areas are in gridded shades. The middle line is in green color and the east line is in brown. We collect detailed information on the engineering design, construction plans, and operation timing from the official publication of the *South-to-North Water Transfer Project Construction Yearbook*. The middle line started its operation in 2015, and the east line started one year earlier.

Water coverage. Surface water coverage serves as a proxy for water resources owing to a lack of detailed administrative data on actual water delivery and redistribution. Data on surface water coverage are from the Joint Research Centre in the European Commission. The data aim to support applications including water resource management, climate modeling, biodiversity conservation and food security. The dataset is derived from Landsat imagery, which provides information on whether water is detected in each 30m×30 m grid cell at a monthly frequency since 1984. We use the data waves from 2010 to 2018 to study the SNWT project's impacts. Specifically, we construct the annual water coverage at the county level by dividing the number of water-occupied grid cells by the total number of grid cells in each county and averaging across the months in a year.

County-level statistics. We obtain a set of administrative records at the county level from the *China Statistical Yearbook (County Level)*. The yearbook is published annually by the National Bureau of Statistics, containing a set of complete records including GDP per capita and its breakdown into agricultural and non-agricultural sectors. We supplement additional county-level data by digitizing county-level indices reported in various provincial statistical yearbooks. The compiled county-level data allow us to further examine year-to-year variation in cultivated cropland, irrigation, specific inputs such as fertilizer and machinery use.

Rural household survey. We supplement the county-level analysis with a large-scale rural household survey, administered by the Research Center of Rural Economy at the Chinese Ministry of Agriculture. The survey begins in 1986 and covers more than 20,000 households in 399 villages from 32 provinces. The villages are selected for representativeness based on region, income, cropping pattern, and population; additionally, within each village, a random sample of households was drawn. The data have been widely used in economic research (e.g., Benjamin et al., 2005; Chari et al., 2021).

We use annual data during 2010–2017, which report household-level information on production, consumption, and assets as well as village-level information on labor and migration. Specifically, the village-level records track labor composition, distinguishing between local and non-local employments in non-farm sectors. Information on migration distances is also recorded, ranging from within the local township to destinations outside the province.[4] The village and household samples in our analysis are minimally affected by the project-led displacement in the water supply areas, as we maintain continuous observations on these villages and households throughout the sample period.

Satellite data on spatial economic activities. We put together three sets of geo-spatial data for understanding urban expansion and growth. The Global Urban Boundary (GUB) dataset is adopted to identify changes in city boundaries over time. The GUB data are derived from the global artificial impervious area (GAIA) data and provide built-up areas and city boundaries in 2010, 2015, 2018 within our study period (Li et al., 2020). The original resolution of GUB data is 30-meter and we sum up the build-up areas in each county, by which we measure changes in city size and urban expansion.

We also collect high-resolution data on night lights and population densities. The former is from the National Tibetan Plateau Data Center, refined based on the Defense Meteorological Satellite Program (Zhang et al., 2021). The latter is a gridded dataset from the WorldPop Spatial Demographic Data and Research. We pair urban boundaries with annual data on light and population, enabling us to separately examine economic activities in always-urban areas, always-rural areas, and rural–urban fringes. The always-urban areas are within the 2010 city boundaries; the rural–urban fringes are the spatial differences between 2018 and 2010 city boundaries; and the always-rural areas are outside the 2018 city boundaries. Figure A1 provides an illustrative example. Within each space in each county, we calculate the annual average nightlights and population densities. In addition, for constructing control variables, we use land ruggedness from the NASA's Shuttle Radar Topography Mission.

Weather data. Station-based daily weather records are from the China Meteorological Data Service Centre, hosted by the China Meteorological Administration. Weather information includes temperature, precipitation, sunshine hours, relative humidity and wind speed from 2010 to 2018. There were 699 monitoring stations in operation during the time period of our study. We employ an inverse-distance weighting (IDW) strategy to interpolate weather information to each cross-sectional unit, using station measurements within 100 miles. We construct flexible weather variables at the annual level, including 10 °C temperature bins, 5 mm precipitation bins, cumulative sunshine duration, average wind speed and relative humidity.

Data merging. The data structure differs across datasets. For county-level data, the county centroid is spatially linked with the SNWT project map. For village-level and household-level data, we use the locations of the villages. In the final samples for analyses, the county-level data span 2010–2018, and the household-level and village-level data span 2010–2017. All nominal variables are deflated using a price index based on 2010. Summary statistics of the main outcome variables are presented in Table 1, separately for water demand and supply areas.

[2] The expansion of the *Danjiangkou* reservoir resulted in the flooding of certain areas that were previously inhabited. To address this displacement, the government initiated the construction of new housing complexes in alternative locations. Additionally, the affected residents received compensation to facilitate their relocation.

[3] See the replication files from Cui et al. (2025) for more details.

[4] The hierarchy of administrative units from top to down in China is nation-province-prefecture-county-township-village.

Table 1
Summary statistics.

	Water Demand Sample			Water Supply Sample		
	Obs	Mean	SD	Obs	Mean	SD
Panel A. Water and GDP (county)						
Water coverage (%)	4,500	2.44	5.12	4,776	3.06	6.10
GDP per capita, overall (yuan)	4,500	144 934.15	108 420.30	4,776	120 241.81	81 406.99
GDP per capita, agriculture (yuan)	4,500	117 271.45	212 245.17	4,776	117 569.27	251 880.65
GDP per capita, non-agriculture (yuan)	4,500	166 758.23	151 475.64	4,776	131 920.73	109 959.29
Panel B. Rural development (household)						
Income, overall (yuan)	35,226	38 376.05	35 338.52	38,407	46 767.74	44 997.62
Income, agriculture (yuan)	35,226	7322.50	11 012.72	38,407	6741.98	11 103.15
Income, non-agriculture (yuan)	35,226	30 863.54	34 540.94	38,407	39 725.59	44 617.14
Income, local wage work (yuan)	19,391	14 510.19	13 879.63	20,778	15 842.68	15 997.40
Income, non-local wage work (yuan)	20,179	22 761.35	17 453.72	24,523	24 757.86	19 355.01
Consumption (yuan)	35,226	17 828.02	20 640.56	38,407	21 960.29	24 399.54
Bank deposits (yuan)	22,208	36 266.68	44 437.57	24,240	40 390.06	53 688.49
Cash savings (yuan)	26,215	5019.31	9236.19	28,435	5544.96	10 160.24
Draft animals (count)	3,742	0.89	2.75	5,424	1.18	2.97
Powered machines (count)	11,386	1.29	0.95	12,530	1.41	1.13
Family labor (count)	35,226	2.46	1.23	38,407	2.60	1.22
Cultivated land area (mu)	35,226	5.27	5.51	38,407	5.39	5.99
Panel C. Rural development (village)						
Total number of labor forces	679	1059.10	852.45	805	1082.32	740.87
Labor share, farm	679	0.45	0.25	805	0.43	0.24
Labor share, non-farm	679	0.55	0.25	805	0.58	0.24
Labor share, migrants (all)	679	0.35	0.19	805	0.42	0.19
Labor share, migrants (out of town)	679	0.35	0.19	805	0.42	0.19
Labor share, migrants (out of county)	679	0.21	0.16	805	0.27	0.18
Labor share, migrants (out of province)	679	0.11	0.13	805	0.16	0.17
Panel D. Urban growth (county)						
City size (km^2)	2,337	63.53	67.50	2,357	51.97	82.74
Night light, always-urban (brightness)	7,011	3440.92	1410.76	7,073	3223.28	1584.24
Population, always-urban(person/km^2)	7,011	2863.77	2542.25	7,073	3661.99	3249.60
Night light, fringe (brightness)	7,011	2455.19	1204.66	7,073	2341.44	1310.60
Population, fringe(person/km^2)	7,011	1083.62	1719.55	7,073	1308.95	1457.52
Night light, always-rural (brightness)	7,011	932.66	999.82	7,073	789.09	1093.64
Population, always-rural(person/km^2)	7,011	370.01	884.54	7,073	316.65	736.57
Panel E. Additional controls (county)						
Ruggedness index	7,011	26.30	29.50	7,073	47.49	47.09
Land area (km^2)	7,011	1366.54	1287.52	7,073	1518.51	1180.38
Population density in 2010 (person/km^2)	7,011	862.36	2085.12	7,073	1057.74	2901.11
Sunshine duration (hour)	7,011	2083.65	349.75	7,073	1747.05	318.70
Relative humidity (%)	7,011	65.84	8.07	7,073	72.33	6.42
Wind speed (m/s)	7,011	2.25	0.50	7,073	2.03	0.52
Temperature (degree)	7,011	13.83	3.00	7,073	15.74	2.63
Precipitation (mm)	7,011	836.39	395.44	7,073	1176.63	475.56

4. Empirical design

4.1. DID and event study

We employ a difference-in-difference (DID) approach to study the effects of the SNWT project. Several features of this project make the DID a suitable empirical strategy in this context. The project's design and construction are commanded and coordinated by the central government under a least-cost consideration. Most of the water-receiving areas are thus determined by the least-cost routes with their boundaries largely shaped by geographical and hydrological factors. In addition, both lines start to operate at clear time points, offering sharp treatments to the affected regions.

The regression equation is specified as follows,

$$y_{it} = \beta Treat_i \times Post_t + \theta(X_i \times t) + \gamma W_{it} + \alpha_i + \lambda_t + \epsilon_{it}, \tag{1}$$

where y_{it} represents outcomes of interest in unit i in year t. The cross-sectional unit varies across different data structure. In our main regressions on water coverage and local economic growth, i represents a county. For additional analyses on household behaviors and village outcomes, i represents a household and a village, respectively. $Treat_i$ is a dummy variable that equals one if unit i is located in the treated group and zero if in the control group. $Post_t$ equals one in years that the project starts its operation. The middle line and the east line started to function in 2015 and 2014, respectively. The coefficient β measures the SNWT project's treatment effect.

Our design also follows the *inconsequential unit* approach, pioneered in Chandra and Thompson (2000), by excluding the Beijing–Tianjin–Hebei (BTH) region from the sample. While the routes and engineering design are under a least-cost consideration, the BTH region is the key target of the SNWT project, which could pose identification challenges, as economic outcomes in that region may change for reasons other than receiving the project water. By excluding the BTH region, the remaining areas receive the project water "by chance", strengthening the causal interpretation of our DID estimates.

Previous studies have shown that large water infrastructures may incur differential impacts on agriculture between water demand and supply areas (e.g. Duflo and Pande, 2007; Strobl and Strobl, 2011). Therefore, we examine treatment effects in water demand and supply regions separately. From the official project release, we obtain exact locations of areas receiving and supplying water, as shown in Fig. 1. Panel A first depicts the four key regions: the demand and supply areas of the east and middle lines, respectively. These four regions have clearly defined boundaries, i.e., the regions do not overlap with each other spatially, and thus alleviate the concern of multiple treatments. In the baseline estimation, we pool the two lines together, and we further explore heterogeneities between the lines in later sections.

Panels B and C illustrate the treated and the control groups in the analysis of water demand and supply areas, respectively. In the baseline regression, the control group comprises the areas surrounding the treated ones, with a distance buffer of 300 km. For water demand areas, our group definition designates 287 treated counties and 595 control counties. Notably, the control group for water demand areas excludes counties within water supply areas. For water supply areas, the corresponding numbers are 139 treated counties and 755 control counties, respectively. The control group for water supply areas excludes counties in water demand areas.

While the control counties are spatially close to the treated counties, they may still have slightly different characteristics. In Tables A2 and A3, we show a balance test between the treated and control groups based on a set of economic, geographic, and environmental indices in 2010. The comparison suggests that the two groups may differ in land geography and demography. Concerning that these differences could lead to differential growth paths, we include additional control variables.

The vector X_i includes a set of time-invariant characteristics. For county-level regression, we consider ruggedness, county size and population density (in 2010); for household-level regressions, we further add total labor force and total area of land in operation (in 2010). Considering potentially differential trends across places with different geographic and demographic features, these time-invariant variables are interacted with linear time trends. Besides, in the vector W_{it} we include a host of weather conditions in flexible function forms because they are likely to directly affect local outcomes, particularly those associated with agriculture. These weather variables include 10 °C temperature bins, 5 mm precipitation bins, cumulative sunshine duration, average wind speed and relative humidity.

A causal interpretation rests on the identifying assumption that, conditional on controls and fixed effects, the outcomes of interest in different locations would change similarly were they not affected by the project. To bolster the validity of this parallel trend assumption, we implement an event study in the following form,

$$y_{it} = \sum_j \beta_j \times D_{i,t-j} + \theta(X_i \times t) + \gamma W_{it} + \alpha_i + \lambda_t + \epsilon_{it}, \tag{2}$$

where $D_{i,t-j}$ is an indicator of cross-sectional unit i being treated in year $t-j$. We consider all available years before and after the treatment in this event study and regard the year immediately preceding the operation year as the reference. This setup not only allows us to evaluate the pre-trend, but also facilitates estimating the project's dynamic effects. All other variables are defined as in Eq. (1).

We employ the standard two-way fixed effects, where α_i captures time-invariant characteristics of the cross-sectional units and λ_t absorbs the common arbitrary time shocks. Standard errors are clustered at the county level. We also report additional two-way standard errors clustered at both the county and province-by-year levels as well as the Conley standard errors with linear decaying weights for observations within a 100 km radius.

4.2. Robustness checks

We assess the robustness of our baseline results through a battery of checks. Specifically, we explore alternative DID estimators, augment our analysis with a richer set of fixed effects and additional controls, and examine various tailored control groups.

Staggered treatments. Recent advances in applied econometrics have pointed out potential biases of conventional DID estimates under a two-way fixed-effect specification (Roth et al., 2023). This issue is most worrisome when the treatments are staggered. Our case features a sharp timing in the operation of each line, and the operation of middle line followed immediately after the east line. While the staggered issue is unlikely to bias our baseline estimates, we nonetheless assess the robustness of our baseline DID estimates by implementing an alternative estimator proposed in Callaway and Sant'Anna (2021). To further bolster the robustness of our findings, we conduct additional regressions where we set the treatment year as 2014 for both lines.

Controlling province-by-year fixed effects. In the baseline specification, we use the year fixed effects to address time-varying common shocks. However, one concern arises regarding the variation of certain time-specific shocks across different regions. For instance, agricultural and resource conservation policies are effective in some provinces but not others. We address this concern by employing a richer set of province-by-year fixed effects. This conservative specification absorbs any arbitrary time shocks that are specific to each province, and the identifying variation comes from within-province comparisons across counties.

Controlling for water quality. We posit that improved water supply is the primary reason contributing to agricultural growth in the demand areas. However, in addition to raising quantity of the water, the transferred water is also regulated to meet higher quality standard. To assess the sensitivity of our estimates to water quality, we include water quality as an additional control variable at the county-by-year level. We derive this quality measure by implementing an inverse-distance weighting strategy over readings collected by the monitors surrounding the county centroid. If our baseline estimates remain unchanged after controlling for water quality, it implies that changes in water quality are unlikely to drive the project effects.

Using alternative buffer zones. Our baseline estimation uses a buffer of 300 km to define the control group. This choice ensures that the control units are both spatially close to the treated areas and comparable while also maintaining a sufficient number of observations in the control group. However, it is essential that our estimation results remain robust across different distance cutoffs. To verify the robustness of our results, we examine various cutoff distances and report additional results using a 200 km buffer for the control group.

Removing areas adjacent to the transfer lines. Another concern with the sample selection relates to the areas adjacent to the transfer lines. These adjacent areas may have experienced changes in their landscape and encountered additional regulation due to the construction of the routes. This concern is particularly relevant for the middle line because the majority of this line is connected by newly established open channels and pipe culverts. To address this concern, we conduct a regression using the baseline specification but exclude the samples within 10 km from the lines.

Restricting to places near water bodies. Different from the middle line, the east line adopts an engineering approach that connects existing water bodies from south to the north. This feature may potentially weaken the identification if areas near water bodies are inherently different from those farther away. We address this concern by limiting our control units to areas close to rivers. Specifically, we only consider the cross-sectional units within 10 km from the level-4 rivers as the control units in this analysis.

Using a matching method. In addition to using the tailored control groups above, we apply a propensity score matching (PSM) to improve the comparability between the treated and control units. Specifically, we calculate propensity scores by considering covariates including ruggedness, county size, population density, temperature, precipitation, relative humidity, and sunshine hours in 2010. We adopt a 1:3 matching ratio to ensure balanced comparison without sacrificing the number of observations. The PSM procedure is conducted separately for the water demand and supply areas. We illustrate the common support, bias reduction, and balancing achieved through the PSM process in Figure A2.

Table 2
Effects of the SNWT project on water and GDP in water demand areas.

	Water	Local GDP per capita		
	Coverage	Overall	Agriculture	Non-agri
	(1)	(2)	(3)	(4)
Treat × Post	0.065***	0.060***	0.073***	−0.018
	(0.010)	(0.013)	(0.014)	(0.014)
All controls	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	4,500	4,500	4,500	4,500

Notes: This table shows the effects of the SNWT project on surface water coverage and GDP measures in water demand areas from estimating equation (1). The unit of analysis is county by year. Dependent variables are in logarithms. All regressions contain county fixed effects and year fixed effects, as well as a full set of control variables including flexible weather variables and trend-interacted geographic and demographic variables. Standard errors in parentheses are clustered at county level. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

5. Economic impacts on water demand areas

5.1. Water relocation and local economies

We first examine how the SNWT project affects local water abundance in water demand areas from estimating Eq. (1). Column (1) in Table 2 reveals that the project significantly expands water bodies in the water-receiving regions. With the full set of climatic, geographic, and demographic controls, the SNWT project increases water coverage by 6.5% in water demand areas, relative to their neighboring counties unaffected by the project. Although this estimate cannot be directly translated into the exact amounts of water, it is sizable enough to illustrate a substantial improvement in local water supply, consistent with official reports on the actual water relocation efforts.[5]

Panel A of Fig. 2 plots the event-study results on water coverage estimated from Eq. (2). The pre-period coefficients are close to and not statistically different from zero. This pattern lends support to the parallel-trends assumption and indicates that, conditional on other controls, water coverage within and outside of the water demand areas changes in a parallel way if unaffected by the SNWT project. The post-period coefficients corroborate our baseline DID result both in terms of their estimated magnitude and statistical significance. These estimates also suggest that water resource gradually increases in the water-receiving areas following the completion of the project.

Next, we explore how this resource windfall affects the local economy. Column (2) in Table 2 reports the effect of the SNWT project on county-wide GDP per capita. This estimate indicates that the SNWT project significantly boosts local economy in the demand areas, leading to a 6.0% increase in GDP per capita. A breakdown by sector in columns (3) and (4) reveals that the project's impact on economic growth is primarily driven by agriculture. Specifically, the marginal impact on agricultural GDP per capita is significant, amounting to 7.3%, while its impact on non-agricultural GDP is close to zero and not significant. This suggests that non-agricultural sectors have not harvested the water benefit during the period of our study.

Panels B-D of Fig. 2 show the event-study plots of the project's impacts on the overall and sectoral GDP per capita. Across all panels, we observe no significantly diverging pre-trends, and the post-period coefficients are consistent with our baseline DID estimates. The project's impacts on local agriculture increase gradually, as the magnitude of the post-period coefficients grows over time. This observation can be attributed to several reasons. First, as our earlier results suggest, it takes time for the local hydrological system to adjust to the increased water availability. Additionally, farmers may have been continuously making adjustments and investments to fully reap the benefits of the transferred water, thereby leading to a progressive growth in agriculture over time.

Fig. 3 summarizes a battery of robustness checks. First, the statistical significance is not compromised when using more conservative clustering strategies such as two-way clustering and Conley clustering. Second, the estimates are consistent when using the Callaway and Sant'anna estimator or setting 2014 as the single treatment year. Third, the estimates are robust to adding more demanding province-by-year fixed effects, and controlling for water quality. Lastly, the results are also insensitive to using alternative control groups, when we define the control units as (i) those within a 200 km buffer, (ii) those netting out the areas adjacent to the water lines, (iii) those close to rivers, and (iv) those chosen by the propensity-score matching method. These tests underscore the reliability of our results.

5.2. Agriculture and rural development

The agricultural growth observed in water demand areas indicates that local agriculture has capitalized the water benefits. Left panel in Figure A3 provides additional results to illustrate the changes within local agriculture. Specifically, yields of major crops are enhanced by about 6%–9%, accompanied by significant improvements in irrigation. There is no evidence of land expansion such that the growth is likely realized through intensification. Consistent with this intensification, machinery usage also increases. One counter-intuitive finding is the decline in fertilizer usage, despite its conventional role as a complement to water in agricultural production. We attribute this result primarily to the government's explicit requirement to curtail fertilizer application along the transfer lines, mitigating potential pollution of the water along the lines.[6]

Given the significant boost in agriculture resulting from the project's water, how does this resource windfall affect rural households that heavily rely on agriculture? Column (1) in Table 3 shows that the project significantly increases rural household income by 5.5% in water demand areas. Columns (2) and (3) in Table 3 indicate that this income effect is predominantly driven by agricultural activities. Specifically, the project increases agricultural income by 9.4% but has no significant effect on non-agricultural income. Moreover, based on additional information on wage-work income for a subset of the sample, we find no evidence that the project increases economic returns from local or

[5] One example can be found from the governmental release https://www.gov.cn/xinwen/2022-12/12/content_5731608.htm.

[6] This requirement is documented in the *Construction Yearbook of the SNWT Project, 2018*. This publication includes a section on "securing water quality", which outlines various explicit arrangements aimed at enhancing water quality along the transfer lines.

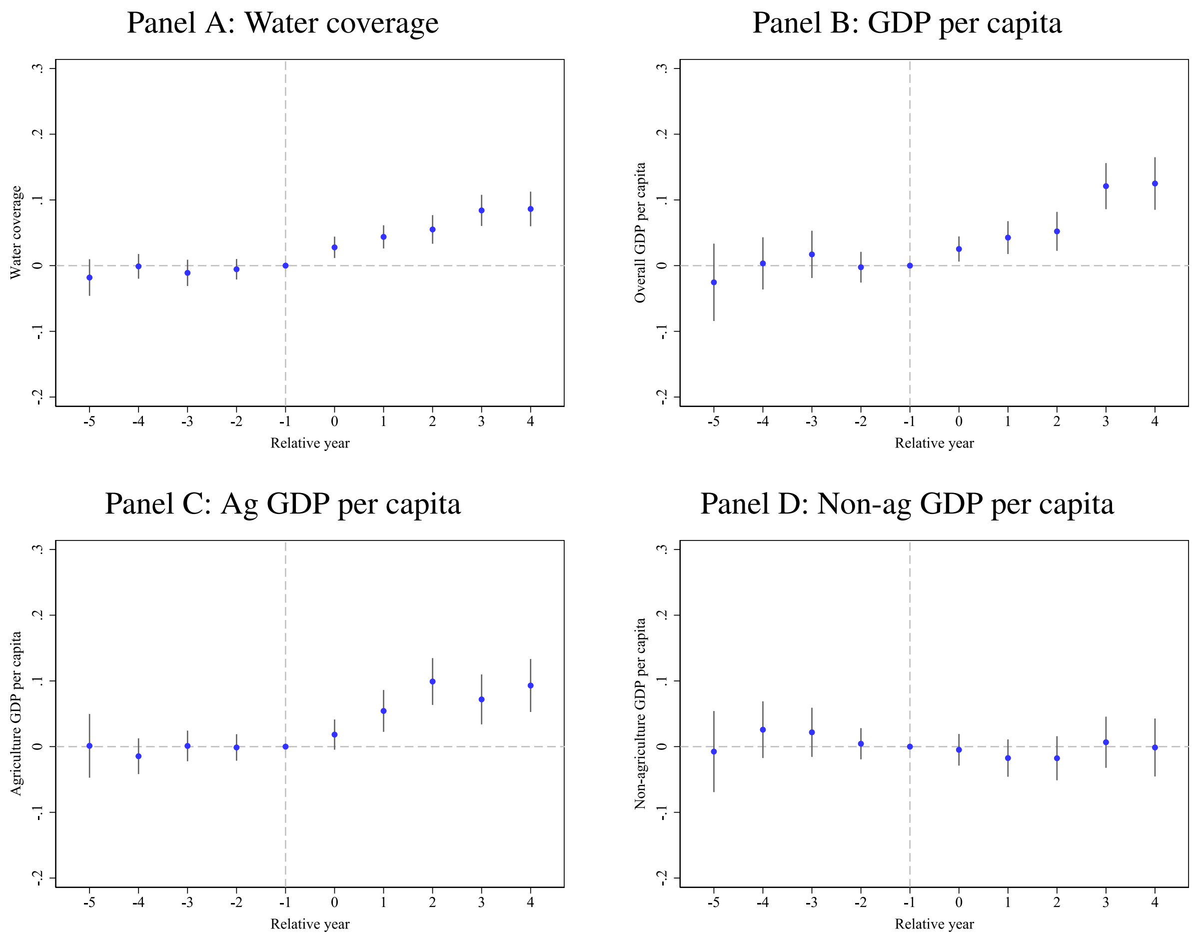

Fig. 2. Event Study of the SNWT Project Effects in Water Demand Areas
Notes: This figure presents the event-study plots of the SNWT project on water coverage and GDP measures in the demand areas from estimating Eq. (2). Data span over 2010–2018. The blue dots are the estimated coefficients and the black bars are 95% confidence intervals.

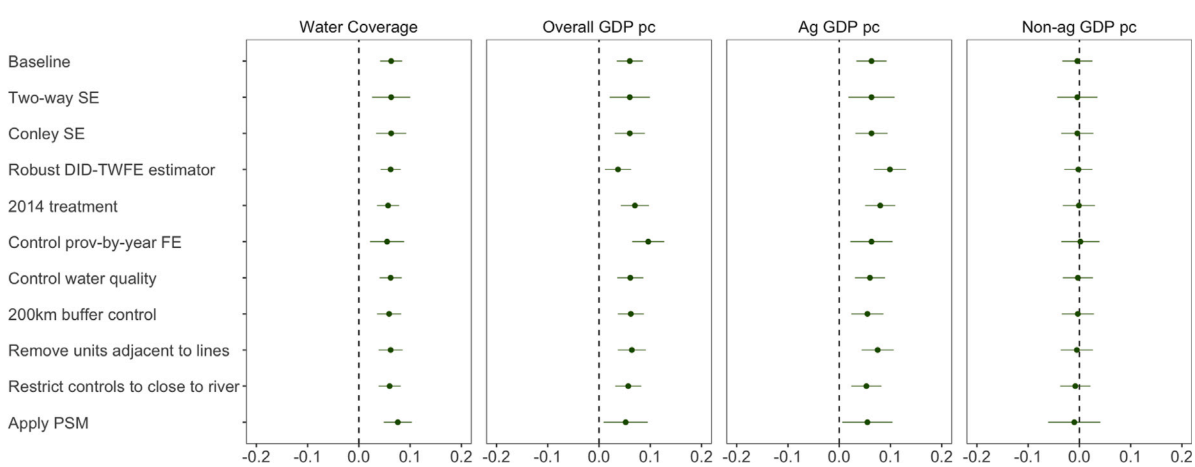

Fig. 3. Robustness Tests of the SNWT Project Effects in Water Demand Areas
Notes: The figure presents effects of the SNWT project on surface water coverage and GDP measures in water demand areas from various robustness checks. The points indicate point estimates and the associated bars indicate 95% confidence intervals.

non-local wage work. Taken together, these household-level estimates echo the county-level estimates on GDP per capita, indicating that the project's benefits in the demand areas primarily stem from the improvement in agriculture.

The accumulated wealth from agricultural growth has directly translated into a rise in living standards. Column (1) in Table 4 shows that aggregate household expenditures increase by 5.3%. We also examine induced changes in these rural households' financial and productive assets by separating the intensive and extensive margins, utilizing relevant information collected in the household survey. Columns (2)-(4) show that, although the project does not significantly affect the likelihood of rural households holding formal or informal assets, it leads to a 6.7% higher bank deposits and a 9.2% higher cash savings for the asset holders. Similarly, columns (5)-(7) indicate that, along

Table 3
Project effects on household income in water demand areas.

	Overall	Agri	Non-agri		
				Wage work	
				Local	Non-local
	(1)	(2)	(3)	(4)	(5)
Treat × Post	0.055***	0.094***	0.013	0.016	0.018
	(0.013)	(0.029)	(0.015)	(0.026)	(0.029)
All controls	Y	Y	Y	Y	Y
Household FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Observations	35,226	35,226	35,226	19,391	20,179

Notes: This table shows the effects of the SNWT project on rural household income in water demand areas from estimating equation (1). The unit of analysis is household by year. Dependent variables are in logarithms. All regressions contain household fixed effects and year fixed effects, as well as a full set of control variables including household-level labor force counts and cultivated land, flexible weather variables, and trend-interacted geographic and demographic variables. Standard errors in parentheses are clustered at the county level. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

the intensive margin, rural households expand their investments into productive assets, such as draft animals and powered machines, related to agricultural activities. These results suggest that the project likely reinforces the agricultural sector in water demand areas, which may inhibit additional incentives for rural-to-urban migration.

Based on a set of village-level labor measures, we show that the agricultural boom brought by the project water indeed refrains rural labor from leaving the farm sector. Columns (1)–(3) in Table 5 show that, the project does not affect total labor in the rural villages, nor does it induce movement of rural labor from the farm to non-farm sector. Columns (4)–(7) also indicate that the project does not induce significant out-migration. We support these results by providing additional estimates based on the county-level employment statistics. In Table A4, we show that the project does not significantly affect employments or employment shares in agriculture, manufacture, and service.

5.3. Spillover and urban growth

The growth in local agriculture can have profound implications on nearby cities. On the one hand, the resource windfall in agriculture may increase the value of agricultural land and push up the opportunity costs of urban expansion. For rural individuals, the agricultural growth could also disincentivize rural-to-urban migration, potentially slowing down the development of nearby cities. On the other hand, wealth accumulation through rural development may create the demand effects, attracting migrants and boosting urban economy. It is essentially an empirical question to pin down the direction and extent of the spatial spillover from rural to urban areas in this context.

In column (1) in Table 6, we report the project's effect on city sizes governed by the boundaries of built-up areas. The estimate shows that the project is associated with a 6.9% expansion of city areas in water demand areas. For a round-shaped town of the average size in our sample, this increase would translate into an expansion of 4.26 square kilometers, equivalent to pushing out the city boundary by nearly 100 meters in the radius. Columns (2) and (3) in Table 6 show that, in the always-urban areas, the project leads to city growth by a 4.2% change in night lights and a 3.1% change in population densities. The rural–urban fringe has experienced even larger growth. Columns (4) and (5) show that the increases in night lights and population densities amount to 6.1% and 3.9%, respectively. In contrast, we find no significant changes in night lights and population in the always-rural areas, as shown in columns (6) and (7). Pairing these night-light estimates with the elasticities obtained from Henderson et al. (2012), these would imply a 1–1.5% increase in GDP in the urban and fringe areas.[7]

[7] Henderson et al. (2012) show that a best fit elasticity of measured GDP growth with respect to nightlight growth is roughly 0.3.

A seemingly counter-intuitive result is that the project induces population growth in the urban and fringe areas but our earlier estimates do not show a significant increase in rural out-migration in the demand areas. It is likely that this urban population growth mainly comes from places outside the project's demand areas. As shown in our earlier results, the project brings a significant increase in rural consumption in the demand areas, which constitutes a strong demand effect that invigorates urban sectors. The attraction of these urban sectors in the demand areas is stronger for rural migrant workers coming from villages outside the demand areas, where agricultural returns are not positively affected by the project. Alternatively, it could also be that the migrants drawn from these villages are relatively small in numbers such that our earlier estimates of non-farm and migrant shares are positive but not statistically significant.

6. Economic impacts on water supply areas

6.1. Water relocation and local economies

In the water-supply areas, we do not find evidence of shrinking water bodies. Column (1) in Table 7 shows that the effect of SNWT project on water coverage is positive while this estimate is not significant. In the middle line, there is a mechanical effect of water expansion owing to the intentional scale-up of the *Danjiangkou* reservoir. In the east line, although no dam construction is involved, the transferred water does not account for a large share of its local water resources since the east line sources from water-abundant regions. Despite no negative impacts on water coverage in the supply areas, the water-sourcing arrangements of the two lines have de facto moved water out of these regions and imposed further restrictions that eventually transform the local economy.

Columns (2)-(4) in Table 7 indicate that, although the project does not affect the overall GDP per capita, it significantly alters the relative contributions of the farm and non-farm sectors. Specifically, in water supply areas, the project leads to a 5.6% decrease in agricultural GDP per capita, but this recession is offset by a 5.4% increase in non-agricultural GDP per capita.

Fig. 4 plots the event-study results on water coverage and GDP measures, estimated from Eq. (2), confirming that there are no differential trends in the pre-treatment period. Panels A and B illustrate that the project brings no significant impacts on water coverage and overall GDP per capita. However, Panels C and D show clear diverging patterns in the post-treatment effects. After the project starts to transfer water out of the supply areas, agricultural GDP per capita continues to decline while non-agricultural GDP per capita steadily increases. These event-study results align with the DID estimates in both economic magnitude and statistical significance.

To ensure the robustness of our findings regarding the SNWT project's effects on water coverage and GDP measures in the supply areas, we provide additional robustness checks. Fig. 5 shows that our estimates are consistent when using different clustered standard errors, using alternative estimators, adding province-by-year fixed effects, controlling for water quality, and adopting alternative control groups based on various strategies.

6.2. Agriculture and rural development

The decline in agricultural GDP per capita in water supply areas is also reflected in significant reductions in both crop outputs and inputs, as illustrated in the right panel of Figure A3. Specifically, the project leads to 5%–6% lowered yields of the major crops, accompanied by reductions in irrigated areas, fertilizer application, and machinery use at a similar magnitude. The project also induces a roughly 8.7% contraction in the cultivated land, partly due to the flooding of arable land for scaling up the *Danjiangkou* reservoir.

Table 4
Project effects on household consumption and assets in water demand areas.

	Consumption	Financial Assets			Productive Assets		
		Holding (0/1)	Bank Deposits	Cash Savings	Holding (0/1)	Draft Animals	Powered Machines
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treat × Post	0.053***	0.005	0.067***	0.092***	0.017	0.075***	0.032***
	(0.013)	(0.006)	(0.025)	(0.023)	(0.011)	(0.022)	(0.006)
All controls	Y	Y	Y	Y	Y	Y	Y
Household FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	35,226	35,226	22,208	26,215	35,226	3,742	11,386

Notes: This table shows the effects of the SNWT project on rural household consumption and assets in water demand areas from estimating equation (1). The unit of analysis is household by year. Dependent variables are in logarithms in columns (1), (3), (4), (6), (7), and dummy variables in columns (2) and (5). All regressions contain household fixed effects and year fixed effects, as well as a full set of control variables including household-level labor force counts and cultivated land, flexible weather variables, and trend-interacted geographic and demographic variables. Standard errors in parentheses are clustered at the county level. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 5
Project effects on rural labor composition in water demand areas.

	Total	Labor shares					
	Num	Farm	Non-farm	Migrant worker			
				All	Out of Town	Out of County	Out of Province
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treat × Post	0.023	−0.016	0.016	0.016	0.008	0.008	−0.003
	(0.033)	(0.027)	(0.027)	(0.022)	(0.023)	(0.016)	(0.010)
All controls	Y	Y	Y	Y	Y	Y	Y
Village FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	679	679	679	679	679	679	679

Notes: This table shows the effects of the SNWT project on village-level rural labor outcomes in water demand areas from estimating equation (1). The unit of analysis is village by year. Dependent variables are in logarithms in column (1), and ratios between 0-1 in columns (2)-(7). All regressions contain village fixed effects and year fixed effects, as well as a full set of control variables including flexible weather variables and trend-interacted geographic and demographic variables. Standard errors in parentheses are clustered at the county level. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 6
Project effects on urban expansion and growth in water demand areas.

	City size	Always-urban		Rural–urban		Always-rural	
		Light	Pop	Light	Pop	Light	Pop
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treat × Post	0.069***	0.042***	0.031***	0.061***	0.039***	0.005	−0.001
	(0.014)	(0.008)	(0.004)	(0.009)	(0.004)	(0.008)	(0.003)
All controls	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	2,337	7,011	7,011	7,011	7,011	7,011	7,011

Notes: This table shows the effects of the SNWT project on urban-related outcomes in water demand areas from estimating equation (1). Column (1) examines the project's effect on urban built-up areas using data in 2010, 2015 and 2018. Columns (2)-(7) examine the project's effect on night lights and population densities using data from 2010 to 2018. The unit of analysis is county by year. Dependent variables are in logarithms. All regressions contain county fixed effects and year fixed effects, as well as a full set of control variables including flexible weather variables, and trend-interacted geographic and demographic variables. Standard errors in parentheses are clustered at the county level. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

How would this agricultural decline affect rural development? In Table 8, columns (1)-(2) show that the project has increased household income by 6.1%, despite a reduction in agricultural income by 7.8%. This is due to a substantial 9.3% increase in non-agricultural income, as indicated in column (3), which more than compensates the lost profits from agricultural activities. Based on the additional data on wage-work returns, columns (4)-(5) further suggest that both local and non-local wage work contribute to this growth in non-agricultural income.

Unlike rural households in water demand areas, households in the water supply areas do not increase consumption despite income growth. Column (1) in Table 9 shows that the project's effect on household consumption is not statistically significant and economically negligible. Although column (2) suggests that the project does not change the likelihood of holding financial assets, columns (3) and (4) show that, for asset holders, the increased income primarily goes into savings. Specifically, the project triggers a 8.3% increase in bank deposits and a 8.9% increase in cash savings. Along with these changes, columns (5)-(7) show that households tend to decrease agricultural productive assets.

The rural labor composition in water supply areas have also experienced meaningful changes. Columns (1)-(3) in Table 10 show that, although the total number of rural labor remains largely unchanged,

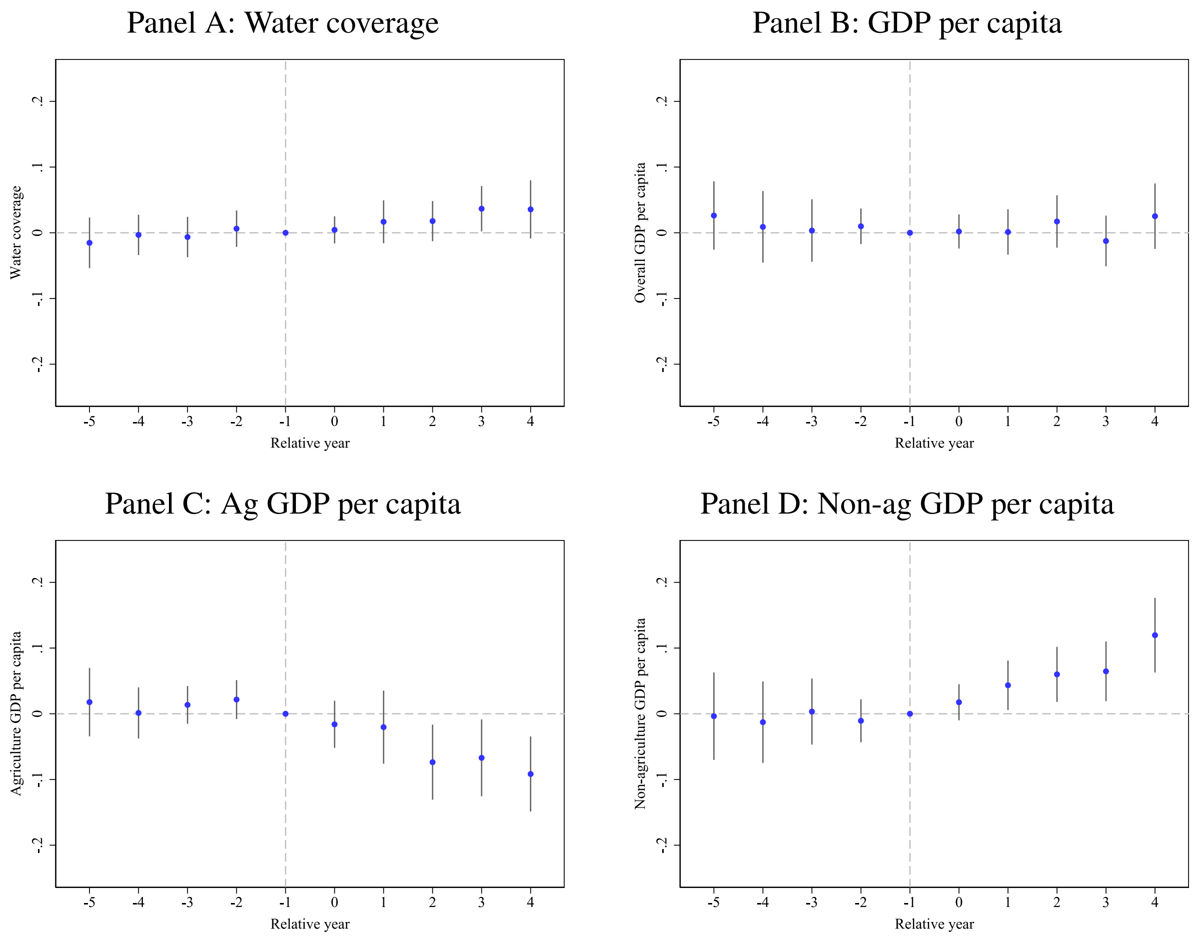

Fig. 4. Event Study of the SNWT Project Effects in Water Supply Areas
Notes: This figure presents the event-study plots of the SNWT project on water coverage and GDP measures in the supply areas from estimating Eq. (2). Data span over 2010–2018. The blue dots are the estimated coefficients and the black bars are 95% confidence intervals.

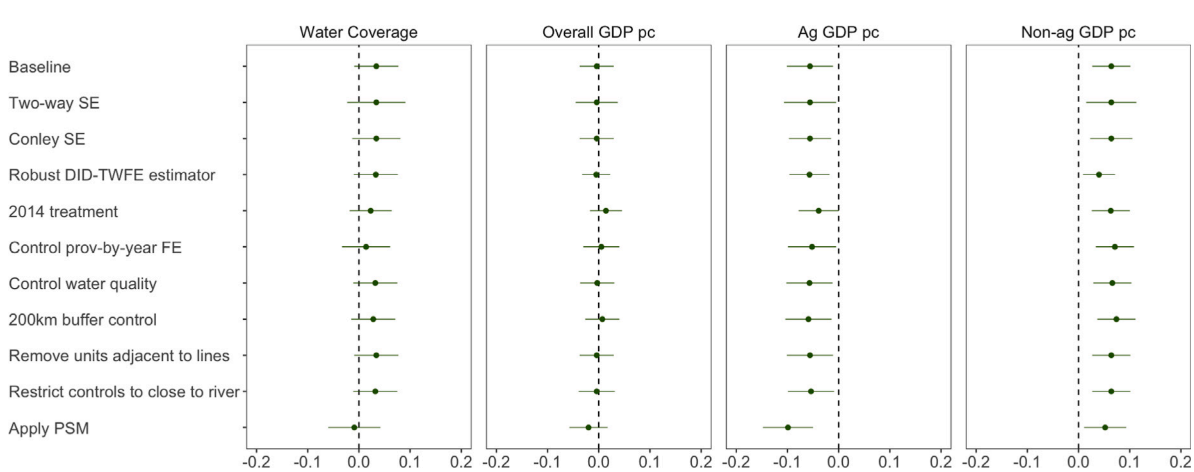

Fig. 5. Robustness Tests of the SNWT Project Effects in Water Supply Areas
Notes: The figure presents effects of the SNWT project on surface water coverage and GDP measures in water supply areas from various robustness checks. The points indicate point estimates and the associated bars indicate 95% confidence intervals.

there is a notable labor shift from farm to non-farm sectors. Specifically, propelled by the project, farm labor in rural villages declines by 7.6 percentage points, offset by an increase in non-farm labor. These village-level estimates of labor reallocation are also supported by additional results based on county-level statistics, as shown in Table A5.

The non-farm labor share includes both local and non-local employments in non-farm sectors. Non-farm workers that are not employed

Table 7
Effects of the SNWT project on water and GDP in water supply areas.

	Water	Local GDP per capita		
	Coverage	Overall	Agriculture	Non-agri
	(1)	(2)	(3)	(4)
Treat × Post	0.030	−0.004	−0.056***	0.054***
	(0.020)	(0.016)	(0.020)	(0.018)
All controls	Y	Y	Y	Y
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	4,776	4,776	4,776	4,776

Notes: This table shows the effects of the SNWT project on surface water coverage and GDP measures in supply areas from estimating equation (1). The unit of analysis is county by year. Dependent variables are in logarithms. All regressions contain county fixed effects and year fixed effects, as well as a full set of control variables including flexible weather variables and trend-interacted geographic and demographic variables. Standard errors in parentheses are clustered at county level. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 8
Project effects on household income in water supply areas.

	Overall	Agri	Non-agri		
				Wage work	
				Local	Non-local
	(1)	(2)	(3)	(4)	(5)
Treat × Post	0.061***	−0.078**	0.093***	0.070**	0.100***
	(0.017)	(0.031)	(0.022)	(0.028)	(0.027)
All controls	Y	Y	Y	Y	Y
Household FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Observations	38,407	38,407	38,407	20,778	24,523

Notes: This table shows the effects of the SNWT project on rural household income in water supply areas from estimating equation (1). The unit of analysis is household by year. Dependent variables are in logarithms. All regressions contain household fixed effects and year fixed effects, as well as a full set of control variables including household-level labor force counts and cultivated land, flexible weather variables, and trend-interacted geographic and demographic variables. Standard errors in parentheses are clustered at the county level. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

locally have migrated out of the local village, typically for seasonal or temporary jobs. The *Hukou* (household registration) system in China assigns each individual either an agricultural or a non-agricultural (urban) *Hukou* tied to a specific locality. Despite gradual reforms of the system over years, rural residents still face substantial challenges in permanently migrating to cities as *Hukou* conversion is restricted. Consequently, rural migrants normally have limited access to local public services and social protections in cities.

Columns (4)–(7) in Table 10 illustrate that a substantial portion of the non-farm labor growth can be attributed to an increasing number of migrant workers, some of whom traveling long distances for non-farm work. In particular, the share of migrant workers whose destinations are outside their home province increases by 4.1 percentage points. Given the institutional barriers in *Hukou* conversion, it is very likely that most of these migrant workers are still affiliated with their original *Hukou*, that they still have family members (especially the children and the elderly) living in their *Hukou*-affiliated locations, and that they send remittances back and regularly return to their home villages during vacations.

The source of income growth determines that the project's impact on rural consumption in the water supply areas can be very different from that in the water demand areas. In the demand areas, rural consumption increases with total income growth driven by agricultural income boost. In the supply areas, rural consumption remains stagnant even though non-farm income growth leads to a higher total income. This inconsistency is likely due to different expectations on future income, shaped by institutional barriers in permanent migration. Households in water demand areas tend to consume more because the project is expected to bring sustainable resources that would persistently enhance the agricultural revenue flows. In contrast, households in water supply areas tend to save more because a large share of their income is remittance, involving higher uncertainties in the long run given that rural migrants lack sufficient social protections in the cities (Chen, 2018). These precautionary behaviors may have further implications on how the SNWT project generates rural-to-urban spatial spillover in water supply areas.

6.3. Spillover and urban growth

We follow the same procedure in Section 5.3 and examine urban-related outcomes in water supply areas. Column (1) in Table 11 shows that the project does not induce a significant expansion of the city boundaries. However, economic activities and populations still grow within the cities. In the always-urban regions, night lights and population densities increase by 2.8% and 2.2%, respectively, as reported in columns (2) and (3). The results are consistent with our earlier findings of increased out-migration from rural villages, especially given that the project has lowered the agricultural returns in the supply areas. The findings are also consistent with existing studies showing that water supply areas are rich in wetlands, lakes, rivers, and other internal water bodies such that the restrictive geography limits the growth in urban boundaries (Saiz, 2010).

Regions outside the always-urban regions experience declines in both night lights and populations. Specifically, in the rural–urban fringe, the project reduces night lights and population by 2.9% and 2.3%, respectively. The associated reductions in the always-rural regions are even more pronounced, amounting to 4.7% and 2.9%, respectively. Our earlier finding of increased out-migration from rural villages contributes to the economic declines outside the always-urban regions. Additionally, unlike in the demand areas, the stagnant growth of rural consumption in the supply areas, stemming from income uncertainties, is insufficient to generate the demand effects that are strong enough to boost local economies.

7. Heterogeneity across two lines

The two lines of the SNWT project feature distinct construction approach. The middle line sources water from the *Danjiangkou* reservoir by raising the height of an existing dam and flooding originally planted cropland. It delivers water northward using a gravity-based approach. In contrast, the east line sources water from the downstream of the Yangtze River and connects various water bodies along the route. Although both transferring water over long distances, the former resembles a dam system while the latter functions like a water-transfer network. This difference in infrastructure construction may generate differential impacts between the two lines. To formally assess this potential heterogeneity, we adapt the baseline regression as follows.

$$y_{it} = \beta Treat_i \times Post_t + \delta Treat_i \times Post_t \times MidLine_i + \theta(X_i \times t) + \gamma W_{it} + \alpha_i + \lambda_t + \epsilon_{it}, \quad (3)$$

where $MidLine_i$ indicates the middle line of the project. By construction, β represents the project effect on the east line, and δ characterizes the differential effect on the middle line as opposed to that of the east line.

Water demand areas. As shown in Table A6, we find no evidence that the project leads to differential impacts on water coverage, economic growth, rural development and labor market outcomes between the two lines in water demand areas. In panels A–D in Table A6, all the estimated β coefficients align with the earlier baseline estimates, and the estimated δ coefficients are generally small and statistically insignificant. This homogeneity is expected because the essential benefits,

Table 9
Project effects on household consumption and assets in water supply areas.

	Consumption	Financial Assets			Productive Assets		
		Holding (0/1)	Bank Deposits	Cash Savings	Holding (0/1)	Draft Animals	Powered Machines
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treat × Post	0.007	0.005	0.083***	0.089**	−0.031	−0.017	−0.038***
	(0.014)	(0.006)	(0.025)	(0.037)	(0.036)	(0.018)	(0.012)
All controls	Y	Y	Y	Y	Y	Y	Y
Household FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	38,407	38,407	24,240	28,435	38,407	5,424	12,530

Notes: This table shows the effects of the SNWT project on rural household consumption and assets in water supply areas from estimating equation (1). The unit of analysis is household by year. Dependent variables are in logarithms in columns (1), (3), (4), (6), (7), and dummy variables in columns (2) and (5). All regressions contain household fixed effects and year fixed effects, as well as a full set of control variables including household-level labor force counts and cultivated land, flexible weather variables, and trend-interacted geographic and demographic variables. Standard errors in parentheses are clustered at the county level. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 10
Project effects on rural labor composition in water supply areas.

	Total	Labor shares					
	Num	Farm	Non-farm	Migrant worker			
				All	Out of Town	Out of County	Out of Province
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treat × Post	0.007	−0.076***	0.076***	0.072**	0.070**	0.057**	0.041***
	(0.038)	(0.025)	(0.025)	(0.029)	(0.030)	(0.027)	(0.012)
All controls	Y	Y	Y	Y	Y	Y	Y
Village FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	805	805	805	805	805	805	805

Notes: This table shows the effects of the SNWT project on village-level rural labor outcomes in water supply areas from estimating equation (1). The unit of analysis is village by year. Dependent variables are in logarithms in column (1), and ratios between 0-1 in columns (2)-(7). All regressions contain village fixed effects and year fixed effects, as well as a full set of control variables including flexible weather variables and trend-interacted geographic and demographic variables. Standard errors in parentheses are clustered at the county level. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 11
Project effects on urban expansion and growth in water supply areas.

	City size	Always-urban		Rural–urban		Always-rural	
		Light	Pop	Light	Pop	Light	Pop
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treat × Post	0.016	0.028***	0.022***	−0.029***	−0.023***	−0.047***	−0.029***
	(0.017)	(0.008)	(0.006)	(0.010)	(0.007)	(0.011)	(0.004)
All controls	Y	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Observations	2,357	7,073	7,073	7,073	7,073	7,073	7,073

Notes: This table shows the effects of the SNWT project on urban-related outcomes in water supply areas from estimating equation (1). Column (1) examines the project's effect on urban built-up areas using data in 2010, 2015 and 2018. Columns (2)-(7) examine the project's effect on night lights and population densities using data from 2010 to 2018. The unit of analysis is county by year. Dependent variables are in logarithms. All regressions contain county fixed effects and year fixed effects, as well as a full set of control variables including flexible weather variables, and trend-interacted geographic and demographic variables. Standard errors in parentheses are clustered at the county level. Significance: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

i.e., transferred water, in the demand areas do not differ in nature, even though the two lines are constructed differently.

The only discernible heterogeneity we find in the demand areas is the extent of growth in always-urban and rural–urban fringe areas. The estimates in panel E in Table A6 indicate that, although the project leads to urban growth in the demand areas of both lines, the positive effects on night light and population densities are stronger in the middle line. This effect may reflect the additional benefit of electricity provision powered by the dam system even though electricity generation is not a primary function of the project. Other factors may also contribute to a stronger agglomeration effect upon receiving the project water but we are unable to explicitly characterize. Future research is still needed to gain a deeper understanding on the driver of this heterogeneity.

Water supply areas. Heterogeneities clearly emerge when we examine the project effects in water supply areas. As summarized in Table A7, our baseline results on local economy, rural development, labor relocation, and urban dynamics are mostly driven by the middle line. The coefficients β estimated from Eq. (3) are generally modest in their economic and statistical significance, while the coefficients δ are highly significant and directly aligned with our baseline estimates.

This stark difference can be attributed to the different engineering approaches adopted by the two lines. In the middle line, raising the dam and expanding the reservoir lead to the flooding of preexisting crop fields in the supply areas. Moreover, strict restrictions on agricultural activities are imposed in this area to guarantee both the quantity and quality of the water transferred northward. These actions have substantially weaken agricultural activities in the supply areas of the middle line. At the county level, agricultural GDP per capita decreases; at the household level, agricultural income reduces; at the village level, rural labor shifts out of agriculture.

The agricultural decline in the supply areas of the middle line is accompanied by sectoral reallocation. The supply areas have experienced a nearly 10% increase in non-agricultural GDP per capita. This estimate aligns closely with our household-level findings on non-agricultural income and our village-level findings on the non-farm labor share. The urban booms and rural busts in night lights and population densities echo these dynamics.

It is worth noting that the middle line's implementation has involved active governmental actions. Anecdotal evidence shows that local governments ordered and financially incentivized rural households in certain areas to migrate.[8] Given the simultaneity in agricultural declines and governmental actions, we cannot fully disentangle the specific mechanisms in shaping the sectoral reallocation. But our results are still informative especially since these two mechanisms often occur jointly in such circumstances.

In contrast to the middle line, the results above do not apply to the east line's supply areas, since the east line relies on a distinct engineering design and its source area is blessed with richer water endowments. These features determine that local agriculture faces less disruption from the project. Since agricultural declines do not occur in the supply areas of the east line, no consequent labor and sectoral adjustments follow, and their further spillovers on urban growth become minimal.

8. Concluding remarks

Climate change is expected to worsen the disparities in water distribution across regions. Taking advantage of the South-to-North Water Transfer Project in China, we examine the effects of long-distance water transfers on water resources, rural development, and urban growth. This project allows us to examine the heterogeneous effects across water-receiving and water sourcing areas. It also offers us a unique opportunity to contrast the potentially differential effects of a dam-based system (the middle line) and a network-based system (the east line) for long-distance water transfers. We find similar effects of the project on the water-receiving areas across the two lines. The project significantly enhances water supply and boosts agriculture. It also induces urban growth and expansion, particularly in the rural–urban fringe.

In the water-sourcing areas, the dam-based approach leads to substantial agricultural loss and increases rural out-migration. Although economic activities in core urban areas still grow, non-urban areas and rural–urban fringes experience declines. The network-based approach, in contrast, results in minimal impacts on the water-sourcing areas. This heterogeneity underscores the differential outcomes resulting from adopting different engineering designs for long-distance water transfer. However, we note that, given the project's recent launch, our estimates likely only reflect short-run impacts. The long-term effects remain unclear, representing an important question for future research.

[8] See a report from http://news.cntv.cn/china/20120130/103027.shtml.

CRediT authorship contribution statement

Xiaomeng Cui: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Conceptualization. **Wangyang Lai:** Writing – review & editing, Writing – original draft, Visualization, Validation, Project administration, Formal analysis, Data curation, Conceptualization. **Tao Lin:** Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jue.2025.103736.

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