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GROWING UNDER THE GREEN GREAT WALL: AGRICULTURAL IMPACTS OF CHINA'S THREE-NORTH SHELTERBELT PROGRAM

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Abstract

This paper evaluates the economic and environmental impacts of China's Three-North Shelterbelt Program (Sanbei Program), one of the world's largest nature-based sand control initiatives, over the past two decades. We find that the villages initially most exposed to sandstorms experienced the sharpest declines in both their severity and frequency, demonstrating the program's effectiveness in combating desertification. Beyond its environmental success, the program has delivered substantial economic gains by revitalizing agricultural production. Improved land conditions have increased rural labor's willingness to remain in farming, spurred investments in productive fixed assets, and driven significant improvements in agricultural total factor productivity (TFP). These findings highlight the Sanbei Program's dual role in ecological restoration and rural economic development, offering critical insights for the design of large-scale conservation policies that balance environmental sustainability with economic resilience.

Keywords: Forestation; Sanbei Forest; Sandstorms and Dust; Agriculture; China
JEL Code: N5, Q23, O18

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1. Introduction

Forests play a pivotal role in shaping agricultural economies, offering ecosystem services that directly enhance productivity and long-term sustainability (Costanza et al., 1998; Yamamoto et al., 2019; Fatima et al., 2024). By mitigating soil erosion, regulating water availability and improving soil fertility, forests reduce input costs and increase yields (Sauer et al., 2012; Wang et al., 2019; Veldkamp et al., 2020; Castle et al., 2021; Teo et al., 2022), creating significant economic benefits for farmers. Moreover, forests contribute to climate stability, buffering agriculture from extreme weather events that can disrupt production and markets (Van Dijk et al., 2009; Bhattacharjee and Behera, 2017; United Nations, 2019; Zhang, 2021; Heino et al., 2023). Despite these critical functions, the economic impacts of forests on agriculture, particularly in regions experiencing rapid environmental and land-use changes, remain insufficiently understood. This paper investigates these dynamics, emphasizing the importance of forests as green infrastructure for agriculture and their role in the development of resilient and productive agricultural systems.

The China Three-North Shelterbelt Program (Sanbei) offers an unparalleled case for studying the relationship between large-scale afforestation and agricultural outcomes. Spanning 73 years (1978–2050) and covering vast stretches of China's arid and semi-arid northern regions, Sanbei is designed to combat desertification, improve ecological resilience and enhance economic sustainability. Over the past four decades, the program has completed three of its planned phases, with cumulative investments reaching USD13.52 billion by 2018, according to the National Forestry and Grassland Administration (NFGA, 2019). Its functions extend beyond soil erosion control and water conservation to fostering more stable agricultural systems and improving rural livelihoods. Among its most significant contributions is the substantial reduction in sandstorms, a severe and recurring form of extreme weather that has long plagued northern China. By creating extensive shelterbelts and increasing vegetation cover, Sanbei has significantly curbed the frequency and intensity of these storms, protecting farmland, urban centers and critical infrastructure. This reduction in extreme weather not only safeguards agricultural productivity but also reinforces the program's broader role in creating a more resilient and sustainable agricultural environment.

Existing research on the Sanbei Program has largely focused on its environmental achievements, such as reducing sandstorm frequency (Huang et al., 2018; AIIB, 2023), effectively highlighting its role in combating desertification and improving local ecosystems. However, much of this work is geographically narrow, concentrating on specific regions and overlooking the broader variability of its impacts across different areas.[1] Moreover, the program's wider economic implications, particularly in agriculture, remain underexplored. Filling these gaps is essential to develop a more comprehensive understanding of Sanbei Program's multifaceted effects and its potential lessons for other large-scale environmental and economic initiatives. This paper makes three key

[1] For instance, studies such as (AIIB, 2023) have analyzed the impact of the Sanbei Program primarily within its boundaries and neighboring areas, employing a difference-in-differences approach to conclude that the program has significantly increased the Leaf Area Index. However, there remains a notable gap in understanding the broader spillover effects of the program's impact on more distant regions.

contributions to the literature by examining the impact of the Sanbei Program on rural economic activities through its sandstorm inhibitory effect, leveraging a uniquely detailed and comprehensive dataset. The analysis integrates high-resolution sandstorm monitoring data, spatially explicit forest coverage data (capturing changes attributable to the Sanbei Program), and village-level agricultural performance records, combined with rural household panel datasets.

This paper presents robust evidence demonstrating the program's effectiveness in significantly reducing sandstorm frequency. Our identification strategy relies on substantial variations in initial exposure to sandstorms across Chinese villages at the early stages of the Sanbei Program, as well as the changes in the national trend of forest growth associated with the program's implementation, which creates a quasi-experimental setting that enables us to isolate the causal effects of the program. Villages with higher initial sandstorm frequency provide a natural contrast, as they were more directly affected by the program's environmental interventions. Meanwhile, changes in national Sanbei forest growth, which unfolded over time, allow us to capture the dynamic impacts of afforestation on sandstorm mitigation and economic outcomes. Importantly, the exogeneity of this identification strategy is supported by the plausibly predetermined nature of initial sandstorm conditions, which are unrelated to subsequent economic changes. By interacting these spatial and temporal variations, our empirical framework disentangles the causal relationship between the Sanbei Program's environmental interventions and their broader socioeconomic impacts.

The results indicate that the expansion of Sanbei forest coverage significantly reduces the frequency of extreme sandstorm events. Villages with higher initial exposure to sandstorms experienced greater reductions in sandstorm occurrences as the Sanbei Program progressed, demonstrating the program's targeted effectiveness. Further supporting this conclusion, placebo tests reveal that the observed impact is specific to extreme sandstorms. The Sanbei Program does not show statistically significant effects on milder dust storms or general air pollution, which are primarily influenced by local forest coverage rather than national afforestation efforts. The wider scope of our analysis provides a more comprehensive perspective on the program's environmental effectiveness across diverse geographical contexts, offering valuable insights into its role in mitigating severe environmental challenges on a national scale.

Our findings further reveal the significant and interconnected impacts of the Sanbei Program on rural agriculture, demonstrating how its influence extends beyond environmental improvements. Drawing on detailed microdata from the National Fixed-Point Survey (NFS)—an annual village- and household-level economic survey conducted by the Ministry of Agriculture—we uncover a clear progression of impacts. The program began by reducing rural labor outflow, as villagers increasingly devoted their time to crop cultivation. This shift stabilized rural labor markets, fostering greater agricultural engagement and ensuring that more hands were available for productive farming activities. This renewed focus on agriculture translated into substantial productivity gains. Total factor productivity (TFP) for both food and cash crops improved significantly, driven by the combined effects of better labor allocation and increased efficiency in farming practices. These gains were further strengthened by rising investments in productive fixed assets, such as modern agricultural equipment and infrastructure, which amplified the program's impact on agricultural output. The Sanbei Program's ripple effects created a virtuous cycle, strengthening rural agricultural economies and enhancing their resilience. Together, these findings paint a vivid picture of how a large-scale environmental initiative can also act as a powerful driver of rural economic transformation.

Related Literature. Our paper first contributes to the literature on sand dust control, which primarily examines the climatic and human factors driving its trends and their associated impacts. Sandstorms play a critical role in shaping agricultural productivity and broader economic outcomes. For instance, Ahmadzai et al. found that sand dust in Mongolia resulted in a 3% decline in crop and livestock production, while Al-Hemoud et al. quantified substantial economic losses caused by sand dust damage to fossil fuel production facilities in Kuwait (Al-Hemoud and v. A.-D.-S.-D., 2019; Ahmadzai and M., 2023). While these studies emphasize the disruptive economic consequences of sand dust, few have explored how large-scale environmental initiatives mitigate such effects. More recently, consensus has emerged that sand dust activity in East Asia has weakened since 2001, driven by reduced surface wind intensity and increased vegetation coverage (Wu and L., 2022; Fan and G., 2014). Vegetation mitigates sand dust through multiple mechanisms, including acting as a physical barrier to wind, stabilizing sand particles with root systems, and improving soil humidity (Kaufman and Gallaher, 2011; Wang et al., 2020). Among the prominent efforts to combat sand dust, the Sanbei Program has played a transformative role in northern China, employing extensive afforestation over the past four decades to address desertification and reduce sandstorm activity. Although prior research has extensively documented the environmental mechanisms and achievements of such vegetation efforts, it has largely overlooked the socioeconomic implications of these programs. Our paper addresses this critical gap by linking the Sanbei Program's environmental achievements to its economic impacts.

The paper further contributes to the literature on the benefits of the Sanbei Program, which has predominantly focused on its direct environmental impacts, such as improved soil stability, reductions in air pollution and control of sand dust (Wang and Z., 2010; Li and Z., 2022; Zhang and Z., 2024). For instance, studies including NASA's satellite observations attribute much of China's greener landscape to sustained afforestation and grassland restoration efforts driven by initiatives like the Sanbei Program (Chen and P., 2019). Parallel research highlights the adverse effects of sand dust on public health, linking it to respiratory issues and broader health challenges (Fussell and J., 2021; Zhang and Y., 2023). While these studies provide extensive evidence of the environmental and health implications of sand dust and related mitigation efforts, they leave significant gaps in understanding the economic consequences of such programs, particularly at the microeconomic level. Our paper addresses this critical gap by investigating how the Sanbei Program's afforestation efforts have reshaped rural economic dynamics through their impact on sand dust mitigation. We provide empirical evidence on changes in labor allocation, highlighting reduced rural labor outflow and increased agricultural engagement, as well as improvements in agricultural productivity.

2. Background and Data Description

2.1 Background: Three-North Shelterbelt Program

Historically, there are few examples of large-scale nature restoration programs serving as critical infrastructure. China's Three-North Shelterbelt Program (Sanbei Program) is one of the most ambitious ecological restoration and conservation initiatives globally. Officially launched in 1978, the program aims to restore vegetation coverage across vast areas of northern China, particularly the arid and semi-arid regions in the northwest. Its primary goals are to combat severe soil erosion and mitigate frequent sand and dust storms that have long disrupted local agricultural activities and livelihoods.

As of 2020, the Sanbei Program had completed the first three phases of its 1978–2050 Plan, and it is now in its fourth phase. The program has evolved from early large-scale planting of single tree species to more scientifically informed and comprehensive approaches. These now include the restoration of diverse plant species tailored to local ecological conditions. Between 1978 and 2017, the forest coverage rate in the Sanbei region increased from 5.1% to 13.6%, while grass and forest coverage collectively rose from 31.7% to 42.4% (AIIB, 2023). Concurrently, the frequency of sand and dust storms declined, and the area affected by soil erosion was reduced by 66.6%, amounting to a recovery of 44.7 million hectares.

Moreover, deserts in northern China have shown signs of stabilization since 2000, with some areas transitioning to less severe desert conditions (CAS Earth, 2020). These results are supported by global satellite data from NASA's Leaf Area Index (LAI), which shows significant greening in China's northern regions between 2000 and 2017. Forest plantations alone accounted for 42% of this greening (Chen and P., 2019). This enhanced vegetation has significantly improved carbon sequestration capacity, with an estimated 900 teragrams of carbon (TgC) sequestered by plant growth in northern China from 2000 to 2018 (Hu et al., 2022). The Sanbei Program thus not only addresses environmental challenges but also contributes to global carbon reduction efforts, reinforcing its role as a model for large-scale ecological restoration initiatives.

Despite the environmental benefits, there are doubts about the Sanbei Program's economic viability over time. The program has been financed primarily by government fiscal support in various forms, including direct grant and subsidies, to pay for seeds and workers used for afforestation. But few of these local efforts under Sanbei generate direct cash revenue that can sustainably cover their maintenance costs. When government fiscal situation is worsened by economic downturn, local Sanbei afforestation projects can be difficult to maintain. Another key challenge facing the program is the lack of sufficient supporting infrastructure such as road and water systems. These are needed for irrigating and transporting other physical resources to keep the restored forests alive. In short, the Sanbei Program is faced with imminent financial sustainability challenges and has additional investment needs.[2] Moving forward, the program will

[2] Based on observations from an AIIB field trip to Sanbei Project sites in Gansu and Inner Mongolia in 2023.

need to be justified by clearer evidence of economic benefits, particularly to the rural economy in Sanbei area.

2.2 Data Sources Description

Sand Dust Data. Our sand dust data provides detailed records of sand dust weather events, capturing the total number of sand dust days per meteorological station. This dataset classifies sand dust into three categories—sandstorm, dust and mild dust—based on wind intensity, with sandstorms representing the most severe type. To integrate this data at the village level, we spatially matched each village to the nearest meteorological station. Remarkably, all 355 villages in our sample were successfully matched, with 83% located within 78.3 kilometers of the village's geometric centroid to the closest station. This granular matching ensures precise and localized measurements of sand dust exposure, enabling an accurate assessment of its impact on rural communities.

Forest Area Data. Forest area is measured using high-resolution data from the European Space Agency's Land Cover dataset, which classifies landscapes by vegetation type. Using this data, we compute the total forest area of counties participating in the Sanbei Program. For each village, we compute the total forest area within a 50-kilometer radius of its geometric centroid. This spatially detailed metric captures local vegetation dynamics, providing a robust proxy for changes in forest coverage driven by the Sanbei Program. The dataset's precision and consistent global methodology ensure comparability and reliability, making it invaluable in analyzing the relationship between forest expansion and sand dust mitigation.

Village Economic Indicators. Economic indicators at the village level are derived from the National Fixed-Point Survey, one of the most detailed and comprehensive rural economic surveys in China. This survey includes over 200 variables covering household income, demographics, labor force allocation and agricultural practices. Aggregating this micro-level data allows us to construct a rich portrait of rural economic dynamics, capturing both short-term and structural changes attributable to environmental interventions like the Sanbei Program.

Sanbei Program Participation. To identify villages affected by the Sanbei Program, we map counties participating in Phase 2 of the program using official government documents and academic studies on the Sanbei initiative (NFGA, 2019).[3] Villages are then classified as part of Phase 2 or not by matching village coordinates to the identified counties. This precise classification ensures that our analysis accurately reflects the program's targeted impact, distinguishing between participating and non-participating areas.

By integrating these diverse and high-quality datasets, our analysis benefits from exceptional granularity and spatial precision, enabling us to evaluate the environmental and economic effects of the Sanbei Program with unparalleled rigor and detail.

[3] (NFGA, 2018) lists all participating counties historically in Phase 1 and 2. Phase 2 includes all the participating counties in Phase 1, with additional ones. To our best efforts, we identify and match all counties listed, with a few county names manually corrected for data consistency over time.

3. Empirical Analysis

To evaluate the natural and economic impacts of the Sanbei Program, particularly on rural economies, we employ a comprehensive empirical strategy. We first introduce the key measures used in the regression analysis, followed by the identification framework that underpins our study. Our primary identification strategy involves regressing post-2000 sandstorm frequency at the city level on an interaction term combining initial sandstorm conditions in 2000 with the over-time change in total Sanbei forest area. The year 2000 serves as a natural pre-intervention baseline, as it precedes significant afforestation efforts under Phase 2 of the Sanbei Program. This timing ensures a clear demarcation for identifying program-induced changes in sandstorm frequency. In robustness check, we test 2003 as base year, the main conclusion remains unchanged. Building on this foundation, we extend our analysis to examine the program's indirect effects on a range of rural economic variables. These include changes in rural labor dynamics, such as reductions in outbound migration and increases in working hours devoted to agricultural activities, as well as improvements in agricultural productivity and growth in investments in productive fixed assets.

3.1 Key Variables Description

Exposure to Sanbei Forest Expansion. We construct an interaction term between the initial severity of sandstorms in 2000 for each village and the total forest area in the Sanbei region over time to capture the causal impact of the Sanbei Program. The initial severity of sand dust, measured by the number of sand dust days, reflects pre-existing local climatic and geographic conditions that influence future sandstorm patterns. Villages with higher baseline sandstorm severity are more likely to benefit significantly from the program, as greater initial exposure amplifies the potential for mitigation effects as forest coverage expands. The total Sanbei forest area included in the interaction term captures the cumulative effect of the program's large-scale reforestation efforts. Evidence suggests that effective sandstorm mitigation requires coordinated, large-scale afforestation rather than isolated local efforts. Sandstorms originate from broader regional and cross-border sources; thus, localized forest restoration, while valuable, cannot achieve significant reductions without being part of a collective and expansive afforestation program like Sanbei.

This interaction term also addresses potential endogeneity concerns. While local economic factors may influence outcomes ex-post, they are unlikely to correlate with initial sandstorm severity or the aggregate expansion of Sanbei forest area after the baseline year of 2000. This ensures that the interaction term primarily captures the causal impact of the Sanbei Program on sandstorm mitigation, free from confounding influences, and provides a robust framework for analyzing its environmental and economic effects.[4]

Measures for Rural Agricultural Activities. We leverage a rich set of rural economic variables as dependent variables, drawn from detailed rural household data. These variables are

[4] The use of interaction terms for identification is a widely established practice in empirical research, particularly in environmental and development studies (Lu et al., 2017). By leveraging this framework, our analysis robustly isolates the program's impact on both environmental and economic outcomes.

categorized into two key groups: rural labor force dynamics and agricultural economic activities. The central hypothesis underpinning our analysis is that the Sanbei Program's forest expansion mitigates sandstorm frequency, generating positive environmental externalities that benefit the rural economy.

Our analysis examines several key variables for the rural labor force, including the share of outbound migrant workers and labor participation in agricultural activities. The share of outbound migrant workers is measured as the proportion of workers who leave the village relative to the total labor force. And labor participation in agriculture is measured by the number of days spent on crop production over a year. The positive environmental externalities generated by the Sanbei Program's afforestation efforts are expected to influence these labor dynamics. Specifically, we hypothesize that reduced sandstorm frequency and improved environmental conditions will retain more workers locally and increase their engagement in agricultural activities, thereby strengthening rural labor markets.

Increased labor input in agriculture, driven by positive environmental externalities of the Sanbei Program, is expected to coincide with broader changes in the agricultural economy, particularly in productivity and capital investment. To investigate these effects, we employ the same reduced-form regression framework to assess the program's impact on agricultural productivity, focusing on metrics such as TFP and labor productivity across different crop types. Additionally, we extend the analysis to examine the impact on capital inputs in agriculture, using the value of fixed assets associated with agricultural production as a proxy. This comprehensive approach enables us to capture both labor and capital dynamics influenced by the program, providing a deeper understanding of its role in shaping agricultural economic outcomes.[5]

Other Control Variables. Our analysis incorporates a comprehensive set of control variables to account for economic, climate and environmental factors that may influence the outcomes of interest. These variables are essential in isolating the effects of the Sanbei Program by controlling for confounding influences.

Economic controls include per capita income, population size, forestry revenue, livestock revenue and the total number of households. These variables capture baseline economic conditions at the village level, ensuring that observed impacts are not driven by pre-existing disparities in economic activity or resource availability. Climate factors, such as temperature, wind speed and precipitation, are critical determinants of agricultural productivity and sandstorm activity. These variables are derived from GIS raster data provided by the European Space Agency's Land Cover database, which offers high-resolution data dating back to the 1990s. To match the temporal scope of our study, we aggregate these data to annual averages for each village starting from 2000, providing a precise measure of local climatic conditions over time. Environmental factors include predominant wind direction, the direction of maximum wind speed and the distance from sandstorm sources. These variables are constructed using data from the China Meteorological Administration, which records detailed information on sandstorm incidents in Mongolia and Inner

[5] Comprehensive details on the construction of these agricultural activity measures across Chinese villages are provided in Appendix A.

Mongolia, China. The dataset enables the calculation of distances between villages and sandstorm events and provides insights into wind direction patterns. These environmental controls are crucial in understanding the geographic and directional dynamics of sandstorm exposure and their potential impact on villages.

Together, these control variables ensure the robustness of our empirical analysis by accounting for a wide range of factors that could influence both environmental and economic outcomes. This comprehensive approach enhances the validity of our findings and strengthens the causal interpretation of the Sanbei Program's impacts.

3.2 Regression Specification

The regression specification outlined below estimates the impact of the expansion in forest coverage under the Sanbei Program on key outcome variables. Specifically, it examines how changes in forest cover influence the frequency of sandstorm days, controlling for other relevant factors. The model incorporates both temporal and regional variations, allowing for a robust analysis of the program's effects:

$$y_{it} = \beta_0 + \beta_1 SandDays_{it_0} * Sanbei_t + \beta_2 LocalForest_{it} + \beta_3 X_{it} + \lambda_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where the dependent variable, denoted as y_{it}, is first specified as $SandDays_{it}$, which represents the number of sandstorm days in village i during year t. This variable serves as the primary metric for assessing sandstorm frequency, a critical environmental outcome closely tied to the objectives of the Sanbei Program. The key interaction term, $SandDays_{it0} \cdot Sanbei_t$, reflects the interaction between the nationwide expansion of the Sanbei Program by year t and the baseline sandstorm frequency in region i in 2000. Local forest coverage, $LocalForest_{it}$, is defined as the forest area within a 50-kilometer radius of village i, capturing localized afforestation effects. Control variables, X_{it}, include economic factors such as per capita income, population size, forestry revenue, livestock revenue and household count; climatic factors such as temperature; and environmental factors such as wind speed, precipitation, predominant wind direction, direction of maximum wind speed and distance from sandstorm sources. Village fixed effects, λ_i, and year fixed effects, λ_t, account for unobserved heterogeneity at the spatial and temporal levels, ensuring robust estimation. Robust standard errors are clustered at the village level.

To ensure the robustness of our findings, we conduct placebo tests by estimating the impact of the Sanbei Program on dust days and mild dust days. Unlike sandstorm days, which are primarily driven by large-scale soil erosion and desertification—the central issues targeted by the Sanbei Program—dust days arise from a broader range of factors, such as agricultural activities, urban emissions and distant sources of particulate matter. This distinction makes dust days an appropriate placebo outcome, as they are less likely to be directly influenced by the program's afforestation efforts. Specifically, we replace $SandDays_{it}$ and $SandDays_{it0} \cdot Sanbei_t$ are replaced with $DustDays_{it}$, $DustDays_{it0} \cdot Sanbei_t$, $MilddustDays_{it}$, and $MilddustDays_{it0} \cdot Sanbei_t$, which represent the number of dust or mild dust days and their corresponding interactions with baseline conditions. By showing that the program significantly reduces sandstorm days while having no measurable effect on dust or mild dust days, the placebo tests reinforce the causal interpretation of our results and demonstrate that the Sanbei Program's impact is specific to its targeted outcomes.

We expect β_1 to be negative, indicating that the expansion of the total Sanbei forest area is associated with a reduction in the frequency of sandstorms. Furthermore, this negative coefficient would imply that the program's impact is more pronounced in villages that experienced more severe sandstorm conditions in 2000, as the interaction term captures the differential effects relative to the initial baseline conditions.

By modifying the dependent variable in the same model, we explore the indirect impact of the Sanbei Program on the rural economy using a range of indicators. These include the proportion of rural labor migrating for work, time allocated to crop farming, agricultural productivity, investment in productive fixed assets, and other related factors. We hypothesize that the Sanbei Program reduces the proportion of the rural labor force seeking employment outside their villages. This effect is likely driven by an increase in agricultural labor input, which can be indirectly attributed to the program's positive environmental externalities, such as improved farming conditions. Additionally, we expect the Sanbei Program to enhance TFP across agricultural activities and stimulate greater investment in productive fixed assets in rural areas. Importantly, these impacts on productivity may vary across different types of crops, reflecting heterogeneity in the program's influence on agricultural performance.

4. Empirical Results

4.1 Impact on Sandstorm Events

To examine the direct impact of the Sanbei Program, we test the hypothesis that the expansion of forested areas under the program mitigates the frequency of sandstorms. The results, presented in Table 1, provide robust evidence supporting this hypothesis. Column (1) reports the baseline estimates using the logged total days of sandstorms reported annually in a village as the dependent variable. Column (2) presents similar analyses, replacing the dependent variable with the logged sum of days of dust and mild dust, respectively, as robustness checks.

The interaction term's coefficient is negative and statistically significant, suggesting that expanding the Sanbei forest area correlates with a reduction in sandstorm days, with a more pronounced effect in villages that had higher sandstorm frequencies in the year 2000. On average, each one-unit increase in forest coverage interaction term leads to approximately a 1.43% decrease in sandstorm occurrences. To clarify this, consider two villages: Village A, which recorded 11 sandstorm days in 2000, and Village B, which had 20. Based on the interaction term, a 1,000 km^2 increase in Sanbei forest area would decrease sandstorm days in Village A by 14.5%, while in Village B, the reduction would be greater, at nearly 24.9%.[6] Despite the limitations of an unbalanced panel dataset, our results remain robust within specific temporal segments.

The smaller observed impact on dust weather can be attributed to its association with non-sandstorm sources, such as urban construction dust and industrial air pollution. These sources are less influenced by forest coverage in the Sanbei region, which primarily targets desertification and large-scale soil erosion. Meanwhile, local forest coverage also exhibits a statistically significant inhibitory effect on sandstorm frequency, though its impact is considerably smaller than that of the total forest expansion under the Sanbei Program. This finding highlights an important distinction: the mitigation of sandstorms becomes substantially more effective when forests are expanded at a large scale and interconnected as part of the "Green Great Wall". In contrast, local afforestation efforts, while beneficial, have a more limited capacity to control sandstorms.

[6] Using the Column 1 in Table 1 as an example. The estimated β1 is −0.0143. $SandDays_{At0}$ = 11, $SandDays_{Bt0}$ = 20. Assume Sanbei forest area increases by 1,000 km2, equivalent to $\Delta Sanbei_t$=1. Given these assumptions, the $\Delta lnY_A = \beta 1 \cdot SandDays_{At0} \cdot \Delta Sanbei_t = -0.0143 \cdot 11 \cdot 1 = -0.1573$, which is corresponding to $\Delta Y_A\% = (e-0.1573-1) \cdot 100\% = -14.5\%$. Similarly, $\Delta Y_B\% = -24.9\%$. Moving forward, the coefficient of this interactive term is interpreted in similar manner by comparing two concrete village examples, to demonstrate the marginal effect of Sanbei forest expansion at two different levels of initial sandstorm conditions.

Table 1: Impact of the Sanbei Program on Sandstorm Events

Dep Var:	(1) Annual Sandstorm Days	(2) Annual Total Dust Days
$Sandstorm_{2000}$ × Sanbei	-0.0143***	
	(-17.12)	
$Dust_{2000}$ × Sanbei		-0.0065***
		(-33.49)
Village Forest Areas within 50 km	-0.0715***	0.0170
	(-12.33)	(-0.37)
Village Per Capita Income	-0.0004***	-0.0026***
	(-4.45)	(-4.46)
Village Population	0.0042*	0.1011***
	(1.79)	(9.40)
Village Forestry Revenue	0.0136***	0.0125***
	(11.66)	(8.57)
Village Livestock Revenue	-0.0174***	-0.0013***
	(-17.41)	(-5.36)
Village Total Households	0.0092***	-0.3247***
	(2.37)	(-9.74)
Temperature	0.0073***	0.0758***
	(2.70)	(15.32)
Wind Speed	-0.0325***	0.0206***
	(-15.71)	(2.96)
Precipitation	-0.1392***	-1.3752***
	(-15.89)	(-18.91)
Mode Wind Direction Angle	-0.1543***	1.6736***
	(-11.63)	(18.55)
Max Wind Speed Direction Angle	-0.1000**	-0.7038***
	(-12.10)	(-8.55)
Distance from Sandstorm	-0.0000***	-0.0002***
	(-10.09)	(-17.05)
Observations	81,593	80,156
R-squared	0.731	0.745
Village FE	YES	YES
Year FE	YES	YES

Notes: The dependent variables include the logarithm of the annual number of sandstorms and the total number of mild dust and dust days (plus one). All models incorporate village and year fixed effects to account for unobserved heterogeneity. The analysis controls for a range of economic, climatic and environmental factors. Economic controls include per capita income, population size, forestry revenue, livestock revenue and the total number of households. Climatic variables capture temperature, wind speed and precipitation, while environmental factors account for predominant wind direction, direction of maximum wind speed and proximity to sandstorm sources. Robust standard errors clustered at the village level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The analysis also highlights the significant role of economic, climatic and environmental factors in shaping the frequency of sand and dust weather events. Economically, villages with higher per capita revenue, forestry revenue and livestock revenue tend to experience fewer sand and dust events, suggesting a strong link between economic development and improved environmental conditions. In contrast, larger village populations and a higher number of households are associated with an increase in such events, indicating the potential strain of population density on environmental outcomes. Climatic variables also emerge as critical determinants. Higher temperatures are correlated with an increase in sand and dust weather, while stronger wind speeds and greater precipitation are associated with notable reductions in their frequency, with respective impacts of 0.3%, 3.25% and 13.92%. Environmental factors further contribute to the observed variation. Villages located in downwind areas experience a significantly higher frequency of sand and dust events, reflecting the impact of windborne transport from source regions. Conversely, a greater distance from the center of sand and dust sources is linked to fewer events, highlighting the spatial dependency of these phenomena.

In summary, these results provide evidence of the Sanbei Program's effectiveness in reducing sandstorm frequency, particularly through large-scale, interconnected forest expansion.

4.2 Impact on Agricultural Activities

Outbound Migration Labor and Labor Input. In analyzing the indirect impacts of the Sanbei Program, we further investigate its effects on rural economic variables. The regression results are presented in Table 2. Column (1) uses the share of outbound migrant workers in total village population as the dependent variable, while Column (2) examines the impact on labor input in agriculture, measured by the share of working days spent on crop production in a village.

As expected, the coefficient of the interaction term in Column (1) is negative and statistically significant, indicating that the expansion of Sanbei forest expansion is associated with a reduction in the share of rural labor migrating out of villages for work. Specifically, a one-unit increase in the interaction term is linked to a 0.0005-point decrease in the share of migrant labor in the village. Intuitively, we use the same Village A and Village B for interpreting this coefficient. It reveals that a 1,000 km^2 expansion of Sanbei Forest would reduce the share of migrant labor in Village A by 0.55 percentage points.[7] For Village B, the reduction is slightly more pronounced, amounting to nearly 1 percentage point. In other words, the marginal impact of the Sanbei forest expansion on the share of migrant labor appears to be more significant in villages with worse initial sandstorm weather.

[7] Using the Column 1 in Table 2 as an example. The estimated β1 is −0.0005. $SandDays_{At0}$ = 11, $SandDays_{Bt0}$ = 20. Assume Sanbei forest area increases by 1000 km2, equivalent to ΔSanbeit=1. Given these assumptions, $\Delta lnY_A = \beta1 \cdot SandDays_{At0} \cdot \Delta Sanbei_t = -0.0005 \cdot 11 \cdot 1 = -0.0055$, which is corresponding to $\Delta Y_A\% = (e-0.0055-1) \cdot 100\% = -0.548\%$. Similarly, $\Delta Y_B\% = -0.995\%$.

Table 2: Impact of the Sanbei Program on Outbound Labor Migration and Agricultural Participation

	(1)	(2)
Dep Var:	**People Working Outside**	**Agri Labor input**
$Sandstorm_{2000}$ x *Sanbei*	-0.0005***	0.3136***
	(-9.66)	(59.23)
Village & Year FE	Y	Y
Economic Controls	Y	Y
Climate Controls	Y	Y
Environmental Controls	Y	Y
Observations	81,593	4,550

Notes: The dependent variables are as follows: Column (1) represents the proportion of the village's total population that works outside the village, and Column (2) represents the number of days spent on crop production in a village over the course of a year All models include village and year fixed effects. Control variables include economic factors such as per capita income, population size, forestry revenue, livestock revenue and the total number of households. Climatic factors include temperature, wind speed and precipitation, while environmental factors encompass predominant wind direction, direction of maximum wind speed and distance from sandstorm sources. Heteroskedasticity-robust standard errors clustered at the village level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

This finding is also well aligned with the result in Column (2). A one-unit increase in the interaction term corresponds to a 0.3136-point increase in the proportion of days spent on crop production in a village. The interaction term in the analysis shows that for every one-unit increase, the share of days devoted to crop production in a village rises by 0.3136 points. To illustrate, a 1,000 km^2 expansion of the Sanbei forest would lead to a 34.5 percentage point increase in the share of crop production days in Village A. In contrast, Village B would experience a larger increase of 62.72 percentage points.[8] Consistent with observations in the previous sections, the findings indicate that the environmental improvements of the Sanbei Program, especially the reduction of sandstorms, could increase the inclination to participate in agricultural activities.

Taken together, these findings provide compelling evidence that the Sanbei Program has increased the share of labor devoted to crop production while reducing rural labor migration. This shift reflects the larger economic impact of the program on rural communities by creating a more favorable environment for agricultural productivity and local economic stability. There are three possible channels to explain such a shift by reducing the necessity of finding jobs outside the home villages. First, fewer sandstorms may result in the retaining of traditional agricultural activities such as crop and livestock as the farming environment improves. Sanbei's sand-control effect may have reversed the rural exodus in the villages that had worse sandstorm weather in early 2000s. Secondly, forest expansion itself may have created new jobs in forestry and other related sectors locally. Finally, fewer health risks associated with sandstorms can also help retain local workers.

[8] 0.1*0.3136*11=0.34496·100%=34.496% and 0.1*0.3136*20=0.6272·100%=62.72%.

Impact on Agricultural Total Factor Productivity. In this section, we look at the impact of the Sanbei Program on villages' average agricultural TFP. We compute the TFP of two major groups of agricultural goods: grain and economic crops. Grain crops refer to goods mainly for food purposes, such as wheat, rice and corn. Economic crops include goods for industrial production like cotton, tobacco and sugar. In general, grain crops tend to be more adaptable to different environment and have with shorter farming cycle (usually under one year). Economic crops, in contrast, are more difficult to grow at scale, because they are more sensitive to changes in the surrounding environment although they have higher economic value than grain crops. Given these properties, economic crops are expected to benefit more from the Sanbei Program's sand mitigation effects than grain crops as they are simply more sensitive to subtle environmental changes.

The regression results are presented in Table 3. Columns (1) and (3) use the logarithm of average TFP for food crops as the dependent variable, while Columns (2) and (4) use the logarithm of average TFP for economic crops.[9] The independent variables vary across specifications: Columns (1) and (2) use the number of sandstorm days per year, Columns (3) and (4) use the number of dust days (including dust and mild dust).

The baseline results in Columns (1) and (2) are consistent with our expectation. Again, more severe initial sandstorm conditions amplify the positive impact of the Sanbei Program on TFP improvements, aligned with earlier discussions on other rural indicators. Moreover, when initial conditions are kept constant, the effect of the Sanbei Program on TFP is greater for economic crops than for grain crops, consistent with our expectation. On average, each one-unit increase in the interaction term for the program corresponds to a 1.33% rise in TFP for grain crops and a 3.4% rise for economic crops. To illustrate this, consider Villages A and B as examples again. A 1,000 km² expansion of the Sanbei forest would boost the TFP of grain crops in Village A by 15.76% and the TFP of economic crops by 45.35%.[10] In contrast, Village B, which faces more severe initial sandstorm conditions, experiences even larger increases, with TFP rising by nearly 30.47% for grain crops and nearly 97.39% for economic crops.[11] The effect of the Sanbei forest expansion on TFP varies across two types of crops, as well as villages, depending on their initial environmental conditions.

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[9] Comprehensive details on the process of calculating TFP and its distribution are provided in Appendix B.
[10] $e^{1*0.0133*11}-1=(e^{0.1463}-1)\cdot 100\%=15.76\%$ and $e^{1*0.0340*11}-1=(e^{0.374}-1)\cdot 100\%=45.35\%$.
[11] $e^{1*0.0133*20}-1=(e^{0.266}-1)\cdot 100\%=30.47\%$ and $e^{1*0.0340*20}-1=(e^{0.68}-1)\cdot 100\%=97.39\%$.

Table 3: Agricultural Total Factor Productivity: Impact of the Sanbei Program

	Agricultural Total Factor Productivity			
	(1)	(2)	(3)	(4)
Dep Var:	Grain Crops	Economic Crops	Grain Crops	Economic Crops
$Sandstorm_{2000}$ x *Sanbei*	0.0133***	0.0340***		
	(8.61)	(5.75)		
$Dust_{2000}$ x *Sanbei*			0.0004***	0.0021***
			(4.40)	(15.13)
Village & Year FE	Y	Y	Y	Y
Economic Controls	Y	Y	Y	Y
Climate Controls	Y	Y	Y	Y
Environmental Controls	Y	Y	Y	Y
Observations	75,812	13,839	74,503	13,741

Notes: The dependent variables are the logarithm of total factor productivity (TFP) for grain crops and the logarithm of TFP for economic crops. The independent variables in Columns (1)-(2) are interaction terms based on sandstorm weather conditions in the base year. Columns (3)-(4) use interaction terms derived from the number of days with mild dust events within a year. The regressions control for economic, climatic and environmental variables and include fixed effects at the village and year levels. Robust regressions are employed, with standard errors clustered at the village level. *** p<0.01, ** p<0.05, * p<0.1.

In Columns (3)-(4), we perform robustness checks by modifying our regression models, substituting sandstorms with dust (including both mild and regular dust) as the initial condition. The results continue to show an increase in TFP for both grain and economic crops due to the Sanbei forest expansion, but this increase is noticeably weaker compared to the models using sandstorms. This difference arises because sandstorms and dust are driven by distinct mechanisms, affecting how effectively the Sanbei forest mitigates each.

The Sanbei forest expansion is designed primarily to combat sandstorms. It achieves this by using tree cover to stabilize loose sand particles in deserts and semi-deserts, preventing strong winds from lifting and transporting them to other areas. Since sandstorms are predominantly caused by wind mobilizing these sand particles, the forest's approach is highly effective against them. In contrast, dust—including mild dust—consists of a broader mix of particles, such as sand and non-sand materials from sources like local construction sites or industrial emissions. Because dust originates from diverse locations beyond just deserts, the tree cover is less successful at controlling it. As a result, the Sanbei forest expansion has a stronger marginal positive effect on crop TFP when it mitigates sandstorms rather than dust. The forest's ability to stabilize sand makes it a powerful tool against sandstorms, but its impact is reduced when addressing dust due to the latter's varied sources.

These findings shed important light on the impact of the Sanbei Program, while simultaneously highlighting the intricate nature of its outcomes. The diverse impacts on TFP observed under varying sandstorm and dust weather conditions pose significant questions that warrant further exploration. To gain a clearer picture of the program's long-term effects, future efforts should prioritize improving TFP measurement approaches and delving into the distinct ways sandstorms and dust affect agricultural productivity.

Evidence on Agricultural Labor and Land Efficiency. We also examine the impact of the Sanbei Program on agricultural production efficiency from another angle—labor needed for producing one unit area (Chinese mu or 0.067 hectare) or amount (kilogram) of crops. The results, presented in Table 4, reveal significant heterogeneity in the program's effects across different crop types. The findings indicate that the Sanbei Program significantly reduces labor input per unit area for wheat and maize, while increasing it for rice and soybeans. As a robustness check, we also examined the logarithm of labor input per unit of output, with results reported in panel B, showing similar trends.

On average, a one-unit increase in the interaction term—combining the number of sandstorm days in 2000 with the total forest area of the Sanbei Program—reduces labor input per unit area by 3.67% for wheat and 3.06% for maize. When measured as labor input per unit of output, the reductions are slightly larger: 4.15% for wheat and 2.89% for maize. Consider the same Village A and B example again. The coefficient suggests that a 1,000 km^2 expansion of the Sanbei forest would reduce the labor input per unit area of wheat production in Village A by 33.2%. For Village B, which has more severe initial sandstorm conditions, the same expansion would lead to a greater reduction by nearly 52%.[12]

In contrast, the expansion of the Sanbei Program seems to be associated with more labor needed for producing one unit of rice and soybeans, with results robust when measured either by area or amount. These findings suggest the Sanbei Program has generated heterogeneous impacts on the production efficiency of major agricultural crops, with significant implications for labor allocation, resource management and rural economic outcomes. The program appears to enhance the efficiency of wheat and maize cultivation, as reflected by reduced labor input per unit area and output. The program appears to enhance the efficiency of wheat and maize cultivation, reducing the labor required per unit of land and per unit of output. In contrast, it diminishes the efficiency of water-intensive crops such as rice and soybeans, necessitating greater labor inputs to sustain production levels. These divergent effects highlight the complex interplay between ecological interventions and agricultural productivity, raising critical questions about the economic trade-offs embedded in afforestation policies.

[12] $e^{1*-0.0367*11}$-1=($e^{-0.4037}$-1)·100%=−33.2% and $e^{1*-0.0367*20}$-1=($e^{-0.734}$-1)·100%=−52%.

Table 4: Impact of the Sanbei Program on Agricultural Labor Input

(1) Dep Var:	Wheat	(2) Rice	(3) Corn	(4) Soybeans	(5) Potatoes	(6) Total
Panel A: Labor Input per Unit Area						
$Sandstorm_{2000}$ x Sanbei	-0.0367***	0.0623***	-0.0306***	0.8373***	0.0255	-0.4001***
	(-3.35)	(3.03)	(-3.46)	(4.92)	(1.62)	(-3.80)
Village & Year FE	Y	Y	Y	Y	Y	Y
Economic Controls	Y	Y	Y	Y	Y	Y
Climate Controls	Y	Y	Y	Y	Y	Y
Environmental Controls	Y	Y	Y	Y	Y	Y
Observations	15,867	30,781	31,302	10,589	14,981	1,580
Panel B: Labor Input per Unit Product						
$Sandstorm_{2000} * $ Sanbei	-0.0415***	0.1643***	-0.0289***	0.7864***	-0.0317*	-0.2170*
	(-3.36)	(7.07)	(-3.10)	(4.37)	(-1.93)	(-1.79)
Village & Year FE	Y	Y	Y	Y	Y	Y
Economic Controls	Y	Y	Y	Y	Y	Y
Climate Controls	Y	Y	Y	Y	Y	Y
Environmental Controls	Y	Y	Y	Y	Y	Y
Observations	15,820	30,774	31,206	10,732	15,061	1,611

Notes: Panel A reports the impact of the Sanbei Program on labor input per unit area, while Panel B reports the impact on labor input per unit product. The dependent variables are the logarithmic values of labor input for wheat, rice, corn, soybeans, tubers, and their aggregate. In Panel A, the dependent variables represent labor input per unit area, while in Panel B, they represent labor input per unit product. The regressions control for economic, climatic and environmental variables and include fixed effects at the village and year levels. Robust regressions are employed, with standard errors clustered at the village level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The observed heterogeneity in crop responses can be traced to the Sanbei Program's influence on the terrestrial water cycle, particularly in arid and semi-arid regions of China. Afforestation increases tree cover, elevating evapotranspiration rates and consequently reducing soil moisture and surface runoff (Y et al., 2018). This alteration in water dynamics intensifies competition for scarce water resources, disproportionately affecting water-intensive crops. Moreover, regional disparities in the precipitation-minus-evapotranspiration (P-E) balance are exacerbated, with wetter areas experiencing heightened evapotranspiration and drier areas facing further reductions in available water (Zan et al., 2024). These hydrological shifts impose additional production constraints on rice and soybeans, which are often grown in complementary systems, amplifying the labor burden as farmers adapt to declining efficiency.

The differential impacts of the Sanbei Program on crop production efficiency carry broader economic ramifications. For wheat and maize producers, efficiency gains may translate into cost savings and improved market competitiveness, potentially supporting rural income growth in regions suited to these crops. However, the increased labor demand for rice and soybeans could erode profitability, particularly in water-stressed areas, exacerbating income inequality among farmers and regions. These outcomes underscore the need for a nuanced cost-benefit analysis of afforestation programs, accounting not only for ecological gains but also for their distributional effects on agricultural livelihoods.

From a policy perspective, the findings emphasize the importance of integrating targeted water resource management into the design of afforestation initiatives. Strategies such as supplemental irrigation, water-efficient cropping systems, or compensatory support for affected farmers could mitigate the trade-offs between environmental restoration and agricultural productivity. Without such measures, the Sanbei Program risks undermining the economic sustainability of water-intensive crop production, particularly in regions already vulnerable to resource scarcity.

Impact on Agricultural Capital Investment. Finally, we probe the impact of the Sanbei Program on yet another dimension of agricultural production-capital investment in rural fixed assets. This dependent variable is defined as the original value of productive fixed assets in the villages. These assets largely consist of the following categories—productive livestock, traditional farming tools (e.g., tools made of iron and wood), agricultural machinery, industrial machinery, transport, farm buildings (e.g., livestock barns), and essential infrastructure (e.g., irrigation, utilities, wastewater). Columns (1) through (6) of Table 5 present the logarithms of the original values for these categories of productive fixed assets, while Column (8) reports the logarithm of the total original value of these fixed assets held by villages at the end of the year.

Table 5: Impact of Sanbei Program on Agricultural Capital Investment

Dep Var:	(1) Productive livestock	(2) Traditional farming tools	(3) Agri-cultural machinery	(4) Industrial machinery	(5) Transport	(6) Farming buildings	(7) Essential infrastructure	(8) Total of all rural fixed assets
$Sandstorm_{2000}$ x Sanbei	0.0088***	-0.0045*	0.0530***	-0.0002	0.0077***	0.0223	0.0195**	0.0062***
	(5.90)	(-1.77)	(3.11)	(-0.05)	(5.32)	(1.30)	(2.03)	(4.09)
Village & Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Economic Controls	Y	Y	Y	Y	Y	Y	Y	Y
Climate Controls	Y	Y	Y	Y	Y	Y	Y	Y
Environmental Controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	28,464	35,387	20,147	8,867	24,927	33,494	6,744	65,153

Notes: The dependent variables are the logarithmic values (in Chinese renminbi) of productive livestock, traditional farming tools (e.g., tools made of iron and wood), agricultural machinery, industrial machinery, transport, farm buildings (e.g., livestock barns), essential infrastructure (e.g., irrigation, utilities, wastewater). Note that the total of all rural fixed assets includes all of the above categories, and some unclassified assets labeled as "others" in the data. *** p<0.01, ** p<0.05, * p<0.1.

The expansion of the Sanbei forest is associated with a marginal increase in total rural fixed assets. Specifically, each unit increase in the interaction term corresponds to a 0.62% rise in total rural fixed assets. This effect varies across asset categories, as evidenced in Columns (1) through (7), with most categories exhibiting positive marginal effects of differing magnitudes. Agricultural machinery demonstrates the most pronounced growth, with a 5.3% increase per unit rise in the interaction term, particularly in villages experiencing more severe initial sandstorm conditions. Other categories, including essential infrastructure (1.95%), productive livestock (0.89%) and transport (0.77%), also exhibit positive coefficients, albeit of smaller magnitude. In contrast, traditional farming tools are adversely affected, registering a -0.45% change per unit increase in the interaction term. The effects on industrial machinery and farming buildings lack statistical significance.

These findings highlight the positive environmental externalities of the Sanbei forest expansion. As sandstorm frequency declines, agricultural productivity in rural areas may recover, spurring demand for efficient farming equipment, such as agricultural machinery. This increased demand appears to extend to complementary assets, including transport and essential infrastructure, while traditional iron-wood farming tools are progressively displaced, as reflected in their negative coefficient. These impacts are particularly notable in regions with initially severe sandstorm conditions, underscoring the Sanbei Program’s role in transforming agricultural production practices and enhancing resilience in areas historically constrained by environmental degradation.

5. Heterogeneity Analysis

To deepen our understanding of the Sanbei Program’s impact on sandstorm events, we conducted a heterogeneity analysis across various dimensions, including economic development levels, geographic exposure to sandstorm centers (upwind versus downwind areas), and initial forest coverage. This approach allowed us to explore how the program’s effects vary across different regional characteristics.

Economic Development: Low vs High Per Capita GDP Regions. We divided the Sanbei area into two groups based on the median per capita GDP in the baseline year 2000:. Table 6 presents the regression results. Columns (1)–(3) correspond to regions with lower per capita GDP, while Columns (4)–(6) represent more regions with higher per capital GDP.

The results reveal that the suppressive effect of the Sanbei Program on sandstorm events is more pronounced in economically developing areas. Specifically, in regions with lower per capita GDP, each unit increase of the interaction term reduces sandstorm occurrences by 7.52%, compared to just 0.89% in regions with higher per capita GDP. These findings highlight that the environmental benefits of the Sanbei Program are concentrated in less developed regions, suggesting that the program not only addresses environmental challenges but also contributes to narrowing regional disparities by delivering greater benefits to less affluent areas.

Geographic Exposure: Upwind vs Downwind Regions. Villages were classified into upwind and downwind regions based on the median angle between two vectors: the vector from sandstorm centers to villages and the wind direction vector in the baseline year 2000. Villages with angles smaller than the median were categorized as downwind regions, where wind transports sand and dust from sandstorm centers toward the villages. Conversely, villages with larger angles were categorized as upwind regions, where wind blows away from the villages.

The regression results, shown in Table 7, indicate that the Sanbei Program has a stronger suppressive effect on sandstorm events in downwind regions. For example, in downwind areas, each unit increase of the interaction term results in a 0.81% reduction in mild dust days, compared to a smaller reduction of 0.63% in upwind areas.

This pattern suggests the program effectively blocks the inflow of dust in downwind areas, while its impact in upwind areas is less pronounced or even counterproductive, as it may hinder the dispersion of locally generated dust. These findings underscore the importance of relative geographic locations in shaping the effectiveness of the Sanbei Program.

Local Forest Coverage: Low vs High Initial Levels. Villages were further classified into two groups based on the 25th percentile of forest coverage within a 50 km radius in the baseline year 2000, distinguishing between low and high initial forest coverage areas. The regression results, presented in Table 8, demonstrate that the Sanbei Program has a significantly stronger impact on regions with low initial forest coverage.

On average, in low-coverage regions, each unit increase of the interaction term reduces sandstorm occurrences by 1.24%, whereas the reduction is only 0.2% in high-coverage regions. This suggests the program's impact is most pronounced in areas with sparse initial forest coverage, where the environmental improvements from afforestation are more transformative. These results highlight the Sanbei Program's role in addressing regional disparities, as it not only improves overall climate conditions but also disproportionately benefits areas that were initially more vulnerable to sandstorm events.

The heterogeneity analysis demonstrates that the Sanbei Program's effectiveness varies significantly across regions, depending on economic development, geographic exposure to sandstorm centers, and initial forest coverage. The program delivers the greatest environmental benefits in economically underdeveloped areas, downwind regions and areas with low initial forest coverage. These findings underscore the Sanbei Program's dual role in improving environmental conditions and reducing regional disparities, offering valuable lessons for designing and implementing future large-scale ecological restoration programs.

6. Robust Analysis

We also replaced forest area with both grassland area and the sum of grassland and forest areas. Additionally, we conducted a robustness check using 2003 as the initial year. The results remained robust, confirming that the Sanbei Program significantly reduced the frequency of sandstorms, aligning with our expectations.

As shown in Tables 9, 10 and 11, when replacing forest area with grassland area, a one- unit increase in the interaction term led to a 1.58% reduction in sandstorm frequency. When using the sum of grassland and forest areas instead, the reduction was 1%. Furthermore, when changing the baseline year from 2000 to 2003, the results remained consistent, with a one-unit increase in the interaction term reducing sandstorm frequency by 2.31%. Additionally, we replaced the base year with 2013, 2014 and 2015. However, the results proved to be unstable, as shown in Tables 12 13 and 14, with coefficients fluctuating between positive and negative values. These erratic results suggest that our identification strategy effectively differentiates between initial and terminal conditions. If the observed effects were purely driven by spurious trends or other confounding factors, we would expect more consistent patterns across different placebo base years.

7. Conclusion

This paper investigates the economic impact of the Sanbei Program, focusing on its effects on rural economies through the mitigation of sandstorm events. We first evaluate the program's success in reducing sandstorm frequency and then extend the analysis to its broader implications for rural labor migration, time allocation to farming, agricultural productivity, and investment in productive fixed assets.

Our findings demonstrate that the expansion of the Sanbei Program significantly reduces the frequency of sandstorm days, with the most substantial benefits occurring in regions that experienced severe initial sandstorm conditions. This reduction generates meaningful economic benefits, including decreased rural labor migration, increased agricultural labor input, and enhanced TFP for both food and cash crops. Furthermore, the program spurs investments in productive fixed assets, signaling improved economic conditions in rural areas. However, the impacts are not uniform across crop types; while the program boosts the production efficiency of maize and wheat, it reduces efficiency for rice and soybeans. This divergence likely arises from a dual mechanism: improvements in climatic and soil conditions benefiting some crops, offset by increased competition for water resources, which constrains the productivity of water-intensive crops. Our heterogeneity analysis further reveals that the Sanbei Program has stronger effects in economically advanced regions, downwind areas and regions with initially low forest coverage. These findings underscore the nuanced and context-specific outcomes of large-scale afforestation efforts, offering valuable lessons for policy and development.

The Sanbei Program demonstrates how large-scale ecological interventions can serve as a blueprint for multinational development bank-supported programs. By aligning environmental objectives with socioeconomic development goals, multilateral development banks can play a pivotal role in addressing global challenges like desertification and rural poverty while fostering inclusive and sustainable growth. These insights suggest that similar initiatives could be adapted to other regions facing environmental degradation, offering a powerful tool for promoting long-term resilience and development.

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Appendix A

Measures of Rural Economic Variables

Rural Labor Force. The share of the labor force engaged in migrant work is calculated as the ratio of the number of migrant workers in a village to its total labor force. On average, 33.2% of the labor force engages in out-migration for employment. To measure total time input in agriculture, we follow a two-step process: first, we calculate the proportion of a year total annual labor days devoted to food crop cultivation for each household; second, we compute the village-level average. For data spanning 2000 to 2002, the survey directly reports total labor days for crop cultivation. From 2003 onward, labor input data is disaggregated by crop type, requiring aggregation to estimate total labor input for crop cultivation. Crops are categorized into food crops—such as rice, maize, soybeans and tubers—and cash crops, including cotton, oil seeds, sugar crops, hemp, tobacco and tea. While labor input data for food crops is available for 2000–2015, cash crop data extends only until 2008, prompting us to focus on annual labor days dedicated to food crops. Across all years, the average proportion of annual labor input for food crops is 33.8%.

Agricultural Productivity. Total factor productivity for food and cash crops is calculated using data from the Ministry of Agriculture and Rural Affairs of China. These data include inputs such as crop output, intermediate goods, capital, land and labor. TFP is estimated using a Cobb-Douglas production function, following established methodologies in the literature (Kantor and Whalley, 2019; Chen and Gong, 2021). TFP data for food crops spans 2000–2015, with mean TFP values of 1.04 for grain crops and 1.16 for economic crops, indicating higher production efficiency for economic crops compared to grain crops.

Labor Productivity. Labor productivity metrics are computed by measuring labor input per unit of output and per unit of cultivated area for different crop types. For food crops such as wheat, rice, maize, soybeans and tubers, we calculate labor input per mu (a unit of land area) and per unit of crop output. These values are expressed in natural logarithms for consistency. On average, total labor input per mu for grain production is 29.6 days, while labor input per unit of output is 0.081 days. Labor productivity data spans the period 2000–2015.

Capital Input. Capital input in agriculture is derived from the year-end value of productive fixed assets reported in the rural household survey. These assets include draft animals, breeding livestock, medium and large iron-wood farming tools, machinery for agriculture, forestry, animal husbandry and fishery, as well as transportation equipment, production buildings and infrastructure for facility agriculture. For each category, we calculate capital input per unit of cultivated area, taking the natural logarithm of these values to facilitate analysis. Household-level data is matched with village data using village and provincial codes, with missing values cleaned to construct a comprehensive dataset covering 2000–2015. Additionally, capital input per unit area for crop cultivation is computed to assess the role of fixed assets in agricultural production.

Appendix B

Estimation of Agricultural TFP

We utilize household-level agricultural production data from the National Fixed-Point Survey. These data include total crop output, sown area, labor, intermediate inputs and machinery. Using this information, we calculate agricultural Total Factor Productivity (TFP) employing a Cobb-Douglas production function, consistent with methodologies adopted in recent studies (Kantor and Whalley, 2019; Chen and Gong, 2021).

As mentioned earlier, grain crops include wheat, rice, corn, soybeans and tubers, while economic crops consist of cotton, oilseed crops, sugar crops, hemp, tobacco, sericulture and vegetables. The database records the number of labor days invested in each crop, which are aggregated to calculate the total labor input for grain and economic crops.

Intermediate inputs are calculated based on total expenditures on seeds and seedlings, chemical fertilizers, agricultural diesel, plastic film and pesticides. Machinery input is measured using the original value of productive fixed assets at year-end, which includes draft animals, breeding stock and livestock for production; large and medium-sized iron and wooden farm tools; agricultural, forestry, animal husbandry and fishery machinery; industrial machinery; transport machinery; production buildings; and fixed assets for facility agriculture.

Due to data limitations, our TFP calculations are divided into two categories: food crops and cash crops. The time range for food crops spans 2000 to 2015, while for cash crops it is limited to 2000 to 2008. The specific calculation methodology is outlined as follows:

$$y = f\,(X;\,\beta) + \text{tfp} = X\beta + \text{tfp} \qquad (1)$$

where y represents yield in logarithmic form; $f\,(X;\,\beta)$ captures the input-output relationship in the agricultural production process; $X = c(l,\, I,\, m,\, L)$ is a vector of agricultural inputs, including labor (l), intermediate goods (I), machinery (m), and land (L), all expressed in logarithms; $\beta = c(\beta_1,\, \beta_2,\, \beta_3,\, \beta_4)$ is a vector of coefficients corresponding to these inputs; and *tfp* represents agricultural total factor productivity in logarithmic form. After cleaning the data, we calculated the TFP, and its distribution is illustrated in Figures 1 and 2 below.

Figure 1: The Distribution of TFP for Grain Crops (2000-2015)

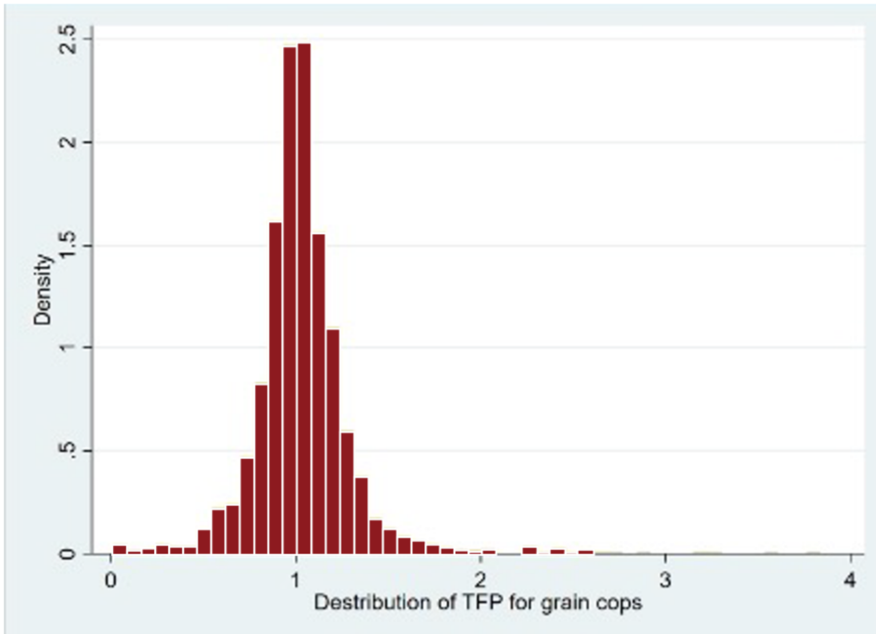
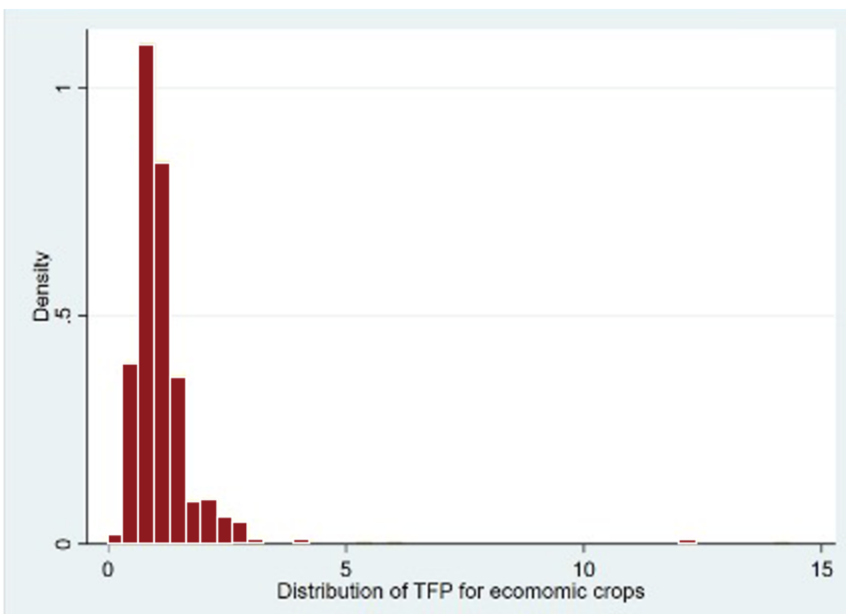


Figure 2: The Distribution of TFP for Economic Crops (2000-2008)



Appendix C

**Table 6: Heterogeneous Impacts of the Sanbei Program:
Low vs High Per Capita GDP Regions**

	Lower per capita GDP			Higher per capita GDP		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var:	**Annual Sandstorm Days**	**Annual Dust Days**	**Annual Mild-dust Days**	**Annual Sandstorm Days**	**Annual Dust Days**	**Annual Mild-dust Days**
$Sandstorm_{2000}$ x Sanbei	-0.0752***			-0.0089***		
	(-6.77)			(-13.91)		
$Dust_{2000}$ x Sanbei		-0.0254***			-0.0072***	
		(-14.67)			(-15.38)	
$Mild\text{-}dust_{2000}$ x Sanbei			-0.0050***			-0.0077***
			(-4.62)			(-23.41)
Village & Year FE	Y	Y	Y	Y	Y	Y
Economic Controls	Y	Y	Y	Y	Y	Y
Climate Controls	Y	Y	Y	Y	Y	Y
Environmental Controls	Y	Y	Y	Y	Y	Y
Observations	43,149	43,149	43,149	38,294	38,294	38,294

Notes: Columns (1)-(3) represent lower GDP areas, while Columns (4)-(6) represent higher GDP areas. The dependent variables are the logarithmic values of the number of days with sandstorms, mild dust and dust weather occurring within a year, respectively. Robust standard errors, clustered at the village level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

**Table 7: Heterogeneous Impacts of the Sanbei Program:
Upwind vs Downwind Regions**

	Downwind Area			Upwind Area		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var:	**Annual Sandstorm Days**	**Annual Dust Days**	**Annual Mild-dust Days**	**Annual Sandstorm Days**	**Annual Dust Days**	**Annual Mild-dust Days**
$Sandstorm_{2000}$ x *Sanbei*	-0.0089***			0.1940***		
	(-11.93)			(23.23)		
$Dust_{2000}$ x *Sanbei*		-0.0052***			-0.0331***	
		(-12.97)			(-26.04)	
$Mild\text{-}dust_{2000}$ x *Sanbei*			-0.0081***			-0.0063***
			(-13.65)			(-18.15)
Village & Year FE	Y	Y	Y	Y	Y	Y
Economic Controls	Y	Y	Y	Y	Y	Y
Climate Controls	Y	Y	Y	Y	Y	Y
Environmental Controls	Y	Y	Y	Y	Y	Y
Observations	40,153	40,153	40,153	41,440	41,440	41,440

Notes: Columns (1)-(3) represent lower downwind areas, while Columns (4)-(6) represent higher upwind areas. The dependent variables are the logarithmic values of the number of days with sandstorms, mild dust and dust weather occurring within a year, respectively. Robust standard errors, clustered at the village level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Heterogeneous Impacts of the Sanbei Program: Low vs High Local Forest Coverage

	Low Initial Forest Coverage			High Initial Forest Coverage		
Dep Var:	**(1) Annual Sandstorm Days**	**(2) Annual Dust Days**	**(3) Annual Mild-dust Days**	**(4) Annual Sandstorm Days**	**(5) Annual Dust Days**	**(6) Annual Mild-dust Days**
Sandstorm$_{2000}$ x *Sanbei*	-0.0124***			-0.0020***		
	(-16.95)			(-2.73)		
Dust$_{2000}$ x *Sanbei*		-0.0041***			-0.0129***	
		(-14.26)			(-36.41)	
Mild-dust$_{2000}$ x *Sanbei*			-0.0098***			-0.0072***
						(-23.00)
Village & Year FE	Y	Y	Y	Y	Y	Y
Economic Controls	Y	Y	Y	Y	Y	Y
Climate Controls	Y	Y	Y	Y	Y	Y
Environmental Controls	Y	Y	Y	Y	Y	Y
Observations	18,820	18,820	18,820	62,583	62,583	62,583

Notes: Columns (1)-(3) represent areas with lower initial forest coverage, while Columns (4)-(6) represent areas with higher initial forest coverage. The dependent variables are the logarithmic values of the number of days with sandstorms, mild dust and dust weather occurring within a year, respectively. Robust standard errors, clustered at the village level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Robustness Check: Replacing Forest Area with Grassland Area

Dep Var:	**(1) Annual Sandstorm Days**	**(2) Annual Dust Days**	**(3) Annual Mild-dust Days**
Sandstorm$_{2000}$ × Grass	-0.0158*** (-34.95)		
Dust$_{2000}$ × Grass		-0.0050***(-40.02)	
Mild-dust$_{2000}$ × Grass			-0.0077***(-50.21)
Village & Year FE	Y	Y	Y
Economic Controls	Y	Y	Y
Climate Controls	Y	Y	Y
Environmental Controls	Y	Y	Y
Observations	80,918	80,918	80,918

Notes: The dependent variables are the logarithmic values of the number of days with sandstorms, mild dust and dust weather occurring within a year, respectively. Robust standard errors, clustered at the village level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Robustness Check: Replacing Forest Area with the Sum of Grassland and Forest Areas

Dep Var:	(1) Annual Sandstorm Days	(2) Annual Dust Days	(3) Annual Mild-dust Days
Sandstorm$_{2000}$ × Grass and forest	-0.0100***		
	(-20.34)		
Dust$_{2000}$ × Grass and forest		-0.0039***	
		(-30.34)	
Mild-dust$_{2000}$ × Grass and fores			-0.0053***
			(-46.42)
Village & Year FE	Y	Y	Y
Economic Controls	Y	Y	Y
Climate Controls	Y	Y	Y
Environmental Controls	Y	Y	Y
Observations	80,918	80,918	80,918

Notes: The dependent variables are the logarithmic values of the number of days with sandstorms, mild dust and dust weather occurring within a year, respectively. Robust standard errors, clustered at the village level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Robustness Check: Using 2003 as the Base Year

Dep Var:	(1) Annual Sandstorm Days	(2) Annual Dust Days	(3) Annual Mild-dust Days
Sandstorm$_{2003}$ × *Sanbei*	-0.0231***		
	(-17.06)		
Dust$_{2003}$ × *Sanbei*		-0.0104***	
		(-28.94)	
Mild-dust$_{2003}$ × *Sanbei*			-0.0244***
			(-49.31)
Village & Year FE	Y	Y	Y
Economic Controls	Y	Y	Y
Climate Controls	Y	Y	Y
Environmental Controls	Y	Y	Y
Observations	81,593	81,593	81,593

Notes: The dependent variables are the logarithmic values of the number of days with sandstorms, mild dust and dust weather occurring within a year, respectively. Robust standard errors, clustered at the village level, are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 12: Results of the Placebo Test: Using 2015 as the Base Year

	(1) Annual Sandstorm Days	(2) Annual Dust Days	(3) Annual Mild-dust Days
Sandstorm$_{2015}$ × *Sanbei*	0.5262***		
	(22.98)		
Dust$_{2015}$ × *Sanbei*		0.0012	
		(1.06)	
Mild-dust$_{2015}$ × *Sanbei*			0.0135***
			(5.24)
Village & Year FE	Y	Y	
Economic Controls	Y	Y	Y
Climate Controls	Y	Y	Y
Environmental Controls	Y	Y	Y
Observations	72,735	72,735	72,735

Notes: The dependent variables are the logarithmic values of the number of days with sandstorms, mild dust and dust weather occurring within a year, respectively. Robust standard errors are reported in parentheses. **** p<0.01, ** p<0.05, * p<0.1.

Table 13: Results of the Placebo Test: Using 2014 as the Base Year

	(1) Annual Sandstorm Days	(2) Annual Dust Days	(3) Annual Mild-dust Days
Sandstorm$_{2014}$ × *Sanbei*	-0.0831***		
	(-17.03)		
Dust$_{2014}$ × *Sanbei*		0.0117***	
		(18.01)	
Mild-dust$_{2014}$ × *Sanbei*			-0.0098***
			(-5.06)
Village & Year FE	Y	Y	
Economic Controls	Y	Y	Y
Climate Controls	Y	Y	Y
Environmental Controls	Y	Y	Y
Observations	75,212	75,212	75,212

Notes: The dependent variables are the logarithmic values of the number of days with sandstorms, mild dust and dust weather occurring within a year, respectively. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 14: Results of the Placebo Test: Using 2013 as the Base Year

	(1) Annual Sandstorm Days	(2) Annual Dust Days	(3) Annual Mild-dust Days
$Sandstorm_{2013} \times Sanbei$	-0.2145***		
	(-23.20)		
$Dust_{2013} \times Sanbei$		0.0009	
		(0.93)	
$Mild\text{-}dust_{2013} \times Sanbei$			-0.0007
			(-1.10)
Village & Year FE	Y	Y	
Economic Controls	Y	Y	Y
Climate Controls	Y	Y	Y
Environmental Controls	Y	Y	Y
Observations	71,469	71,469	71,469

Notes: The dependent variables are the logarithmic values of the number of days with sandstorms, mild dust and dust weather occurring within a year, respectively. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.