Give a Man a Fish? Passive Income versus Livelihood Support for Persistent Poverty Alleviation

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Abstract

This paper examines whether poverty alleviation programs that strengthen households' livelihood capacity generate more persistent poverty reduction than programs that primarily provide income support. We study China's Industrial Poverty Alleviation Programs (IPAP) using household-level administrative panel data from 2014 to 2020 and exploit variation in the timing of program participation in a difference-in-differences framework. We measure persistent poverty risk using household vulnerability to expected poverty. On average, participation in IPAP significantly reduces household vulnerability while increasing income and productive engagement. However, these effects differ substantially across program types. Production-oriented programs increase production income and productive investment, while employment-oriented programs shift household labor toward wage employment; both reduce vulnerability to poverty. In contrast, photovoltaic programs substantially increase household income through asset-based dividends but generate little change in productive or employment activities and are associated with higher vulnerability. The benefits of livelihood-oriented programs are also larger among households with stronger labor and human-capital endowments. These findings suggest that raising current income alone may be insufficient for persistent poverty reduction; interventions that strengthen households' own income-generating capacity can provide more durable protection against future poverty.

Keywords:

JEL Codes:

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1 Introduction

A long-standing question in development economics is how poverty alleviation programs can generate sustained improvements in poor households' livelihoods. Existing studies show that both direct transfers of cash or capital and livelihood-oriented interventions can improve household economic outcomes, although they operate through different channels. Direct transfers primarily increase household resources and have been shown to affect consumption, asset accumulation, and economic well-being (Haushofer and Shapiro, 2016; Egger et al., 2022; Banerjee et al., 2024). By contrast, livelihood-oriented interventions seek to strengthen households' income-generating capacity by expanding productive assets, skills, employment, and other economic opportunities, and can generate substantial and persistent gains (Blattman et al., 2014; Banerjee et al., 2015; Bandiera et al., 2017). Yet it remains less clear whether these different approaches are equally effective in generating lasting reductions in households' risk of returning to poverty.

In this study, we exploit the institutional structure of China's Industrial Poverty Alleviation Programs (IPAP) to compare these two channels within a common policy framework. Some programs promote production or employment through productive inputs, technical assistance, market access, or job opportunities, directly linking support to income-generating activities. Others, such as photovoltaic programs, provide income through returns from collectively managed assets with limited household engagement in production or employment. This variation allows us to examine whether livelihood-oriented support and direct income provision differ in their effects on productive activities and persistent poverty risk. Complementing a literature largely based on large-scale randomized evaluations (Banerjee et al., 2015; Bandiera et al., 2017; Blattman et al., 2014; Banerjee et al., 2021), we provide evidence from a natural experiment. By comparing the two approaches within the same policy framework and institutional environment, we also reduce concerns that cross-study or cross-setting differences drive their estimated contrast.

We study the implementation of IPAP in a county in Shaanxi Province, China, where different forms of support were introduced to registered poor households over the course of the program. We use household-level administrative panel data covering 2014–2020, which record program participation, household income, productive activities, and demographic and employment characteristics. Using these data, we follow Chaudhuri et al. (2023) to construct a household-level measure of

vulnerability to poverty that captures the probability that a household will fall into or remain in poverty in the future, allowing us to evaluate the persistence of poverty reduction. Exploiting variation in the timing of household entry into IPAP, we employ a difference-in-differences (DID) design to estimate the effects of program participation on household vulnerability to poverty and related economic outcomes. We distinguish across program types to examine how support delivered through production, employment, and asset-based income channels affects household labor allocation, income composition, and longer-term poverty risk.

We first estimate the average effect of IPAP participation on household vulnerability to poverty. Across specifications, participation in IPAP significantly reduces household vulnerability, indicating that the program lowers households' exposure to future poverty risk. This reduction is accompanied by higher household income and greater engagement in productive activities.

More importantly, we document substantial heterogeneity across program types. Production-oriented programs, including planting, breeding, and manufacturing, increase production-and-business income and expenditures while reducing non-farm wage income and work time, indicating a shift toward self-operated production. Employment-oriented forestry programs generate the opposite reallocation, increasing wage income and work time while reducing production income and expenditures. Despite these contrasting patterns, both forms of livelihood support reduce household vulnerability, particularly breeding and forestry programs. These findings are consistent with experimental evidence that livelihood interventions reallocate labor toward supported activities and can generate sustained improvements in household welfare (Blattman et al., 2014; A. et al., 2018; Banerjee et al., 2021).

By contrast, photovoltaic programs raise household income primarily through property income and collective dividends, without significant changes in production income, expenditures, or work time. This pattern is consistent with evidence that cash transfers generally have limited adverse effects on adult labor supply or productive engagement (Banerjee et al., 2017; Baird et al., 2018; Bhorat and Köhler, 2025). However, because these income gains depend largely on continued policy-related transfers, they may provide limited protection against future poverty. Consistent with this interpretation, household vulnerability increases under photovoltaic programs, suggesting that higher income alone does not necessarily translate into persistent poverty reduction.

Finally, we show that the effects of livelihood-oriented support are stronger among households

with more favorable endowments, particularly those with better health, greater labor availability, and younger age structures. This heterogeneity suggests that households' ability to translate policy support into sustained poverty reduction depends importantly on their underlying capacity to engage in productive and employment activities.

Our study contributes to three strands of the literature. First, we contribute to the literature on cash transfers and labor supply. A longstanding concern is that income transfers may weaken incentives to work by increasing non-labor income. However, a growing body of evidence provides limited support for this concern. Studies across a range of conditional and unconditional transfer programs generally find small or negligible reductions in adult labor supply (De Brauw et al., 2015; Banerjee et al., 2017; Baird et al., 2018; Jones and Marinescu, 2022). Beyond avoiding work disincentives, cash transfers may relax liquidity, risk, and other constraints, thereby facilitating productive investment and labor-market participation (Haushofer and Shapiro, 2016; Vera-Cossio, 2022; Egger et al., 2022; Daidone et al., 2019). Yet improvements in current income or labor-market outcomes do not necessarily translate into longer-term economic transformation (Cahyadi et al., 2020; Bhorat and Köhler, 2025). We extend this literature by showing that income support can raise household income without reducing productive engagement, yet still fail to generate persistent reductions in poverty risk.

Second, we contribute to the literature on livelihood-oriented interventions. A growing body of experimental evidence shows that interventions providing productive assets, business training, and related support can alter occupational choices, expand self-employment, and reallocate household labor toward higher-return activities (Blattman et al., 2014; A. et al., 2018; Bandiera et al., 2017; Edmonds and Theoharides, 2020). Related studies comparing entrepreneurial and wage-employment interventions further show that different forms of livelihood support can generate distinct patterns of labor allocation and earnings (Blattman and Dercon, 2018; Blattman et al., 2022; Carranza and McKenzie, 2024). Evidence on persistence is more mixed. For example, some multifaceted and asset-based interventions generate sustained improvements in income, assets, poverty, and household resilience (Banerjee et al., 2015, 2021; Phadera et al., 2019), while gains from other interventions attenuate over longer horizons (Misha et al., 2019). We complement this literature by showing that different forms of livelihood support within a large-scale government poverty alleviation program reduce poverty vulnerability through distinct reallocations of household labor.

Third, we contribute to the literature comparing alternative forms of poverty assistance. A growing experimental literature shows that cash and in-kind transfers can generate different effects on consumption, nutrition, local prices, and cost-effectiveness (Cunha, 2014; Hidrobo et al., 2014; Cunha et al., 2019). Related studies benchmark more structured interventions against direct cash support and show that training, multidimensional programs, and productive-asset transfers do not necessarily outperform cost-equivalent cash across economic outcomes (McIntosh and Zeitlin, 2022, 2024; Leight et al., 2026). We extend this literature by comparing income support with production- and employment-oriented livelihood support within the same large-scale poverty alleviation program and examining their relative effectiveness in generating persistent reductions in poverty risk.

2 Background

2.1 Poverty Alleviation and IPAP

China has implemented a wide range of poverty alleviation programs over the past several decades. Earlier policies focused primarily on providing direct assistance to poor households, including transfers and support for basic living needs, to address subsistence needs. Over time, the policy emphasis shifted toward interventions designed to strengthen households' income-generating capacity. The Targeted Poverty Alleviation (TPA) strategy, introduced in 2013, established a framework for identifying poor households and assigning interventions according to household-specific constraints and local conditions. IPAP became one of the most widely adopted components of TPA. According to the Ministry of Agriculture and Rural Affairs, by the end of 2019, 92% of registered impoverished households had participated in IPAP, and 67% of households that exited poverty reported these programs as a primary source of income growth.

The preliminary policy framework underlying IPAP was first introduced in 2010 and was substantially expanded during the TPA period. In contrast to conventional relief programs centered on direct transfers, IPAP sought to increase households' productive and earning capacity by facilitating their participation in locally viable economic activities. In IPAP, industry broadly refers to locally based productive and commercial activities, ranging from agriculture and processing to rural services and renewable energy. Although implemented nationwide, IPAP varied across regions in both timing and design, reflecting differences in local resource endowments, economic conditions,

and development priorities.

IPAP combined local economic development with targeted participation by poor households. Local governments supported activities viewed as consistent with regional comparative advantage, while poor households participated through enterprises, farmer cooperatives, and other local organizations. Participation took several forms, including wage employment, household production, contractual production, market access, and benefit-sharing arrangements. Most of these arrangements were designed to expand households' engagement in production and labor markets instead of income solely through direct transfers.

In practice, IPAP can be grouped into four main implementation models (Pan et al., 2023). The first supports household production through subsidies, productive inputs, and technical assistance, particularly in agriculture. The second facilitates wage employment in enterprises, cooperatives, and other local organizations. The third uses asset-based arrangements, including photovoltaic projects, under which participating households receive dividends or other returns from collectively managed assets. The fourth connects households to local value chains through enterprises and cooperatives, including contractual production, market access, and benefit-sharing arrangements. These models operate through distinct channels and may therefore have different effects on household income, labor allocation, productive activity, and vulnerability to future poverty.

2.2 Implementation of Local IPAP

Our study focuses on a county in northern Shaanxi Province, China. The county is located on the Loess Plateau and has historically relied heavily on agriculture and rural labor for household livelihoods. Crop cultivation, livestock breeding, and economic forestry constitute important local economic activities, while opportunities for non-agricultural employment remain relatively limited. These characteristics make the county broadly representative of economically disadvantaged rural areas in which poverty alleviation policies seek not only to raise household income but also to expand local livelihood opportunities.

Following the introduction of the Targeted Poverty Alleviation strategy, the county placed increasing emphasis on industrial development as an instrument for poverty reduction. Large-scale implementation of IPAP began in 2017, and new participating households entered the program continuously in the following years, as shown in Figure xxxxxx. The program covered several

locally relevant activities, including crop cultivation, livestock breeding, agricultural processing, forestry, and photovoltaic power generation. Poor households were connected to these activities through a combination of subsidies, credit support, technical assistance, employment opportunities, and collective asset arrangements.

The details of each program is shown in Table 1. For households engaged in crop cultivation, livestock breeding, and agricultural processing, IPAP mainly supported household-operated production. Eligible households could choose an industry according to their production conditions and preferences and apply for subsidies after undertaking the corresponding productive activities. In addition to direct subsidies for production inputs and facilities, some households could obtain interest-free loans and technical or market-linkage support. Households were generally eligible to receive support for one industry in a given year, and continued support for the same activity could depend on further expansion of production.

Table 1: Overview of IPAP in the study county

Program	Program requirements and activities	Main subsidy/support
Production livelihood support		
Crop production	Support for crop cultivation and orchard development, including jujube, walnut, apple, goji berry, greenhouse vegetables, edible fungi, and other crops. Eligibility generally requires undertaking or expanding the specified production activity.	Area- or facility-based subsidies, ranging from 200–5,000 CNY per mu or 4,000–10,000 CNY per greenhouse, subject to household-level caps.
Livestock production	Support for raising sheep, pigs, cattle, donkeys, chickens, and other livestock, including construction or renovation of breeding facilities and livestock purchases.	Subsidies for facilities and livestock purchases, generally capped at RMB 5,000 per household.
Agricultural processing	Support for small-scale agricultural and sideline-product processing, including food, agricultural products, and wood/stone processing. Eligible facilities must have the required equipment and be in operation.	Up to 10,000 CNY per processing facility.
Employment livelihood support		
Ecological forest ranger employment	Eligible poor households are employed as ecological forest rangers.	600 CNY per person per month.
Passive income support		
Photovoltaic income distribution	Government-funded village-level photovoltaic facilities generate electricity revenues, with net proceeds distributed to eligible low-income households through collective dividends.	Each village typically generates approximately 150,000 CNY in annual revenue, which is distributed mainly among eligible low-income households.

Note:

Other programs operated through different implementation arrangements. Forestry-based poverty

alleviation provided employment opportunities by hiring eligible poor households as ecological forest rangers and paying regular wages. Photovoltaic poverty alleviation, by contrast, relied on village-level collectively managed photovoltaic facilities. Revenue generated from electricity sales was distributed to eligible poor households through collective economic dividends, requiring relatively limited direct household investment or participation in production. These differences in implementation provide useful variation for examining how different forms of poverty alleviation support affect household income sources, productive activities, labor allocation, and vulnerability to poverty.

2.3 Program Comparison

Although the programs implemented under IPAP share the common objective of improving the livelihoods of poor households, they differ substantially in how policy support is translated into household income. In the study county, these interventions can be grouped into three broad categories according to the main channel through which they affect household economic activities: production-oriented support, employment-oriented support, and asset-based income support.

Production-oriented programs include crop cultivation, livestock breeding, and agricultural processing. These interventions provide subsidies, productive inputs, credit support, technical assistance, and market-linkage services to households that directly engage in production. The resulting income gains therefore depend on households' own productive activities and are expected to be reflected primarily in production-and-business income, production expenditures, and the allocation of household labor toward self-operated activities.

Employment-oriented support operates through a different channel. Forestry programs employ eligible poor households as ecological forest rangers and provide wage income in exchange for labor participation. Unlike production-oriented programs, these interventions do not require households to operate their own productive activities. Instead, they expand access to wage employment and are therefore expected to affect household livelihoods mainly through wage income and work time.

Photovoltaic poverty alleviation represents a third model. Under these programs, photovoltaic facilities are established and managed at the village or collective level, and part of the revenue generated from electricity sales is distributed to eligible poor households through collective dividends. Household income can therefore increase without comparable engagement in production or

employment. In this sense, photovoltaic programs operate primarily through asset-based income provision rather than through direct expansion of household productive or employment activities.

These distinctions are central to our empirical analysis. Production- and employment-oriented programs both link policy support to household participation in income-generating activities, although they do so through different forms of labor allocation. We therefore view them as livelihood-oriented interventions. By contrast, photovoltaic programs primarily raise household resources through returns from collectively managed assets and require relatively limited direct household engagement. Comparing these program types allows us to examine whether poverty alleviation interventions that strengthen households' own income-generating activities produce different effects on income composition and vulnerability to poverty from interventions that primarily increase policy-related income.

Hypothesis 1 *Production- and employment-oriented IPAP affect household livelihoods through greater engagement in productive activities and wage employment, respectively, whereas photovoltaic programs primarily increase asset-based income without comparable changes in productive engagement.*

Hypothesis 2 *Livelihood-oriented IPAP generate larger reductions in household vulnerability to poverty than asset-based income support.*

3 Data and Empirical Strategy

In this section, we first present the data used in this study. Second, we show the construction of vulnerability to poverty . Third, we show the DID specification.

3.1 Data and Descriptive Statistics

Our study uses household-level administrative panel data from the registered poor household database in the treatment county, covering 2014–2020. The data were collected annually by local governments and compiled in a national administrative database managed by the National Rural Revitalization Administration. The database records information on both households and

each household member, including household income, productive activities, participation in poverty alleviation programs, and individual demographic and employment characteristics.

Table 2 reports the number of households covered by the database in each year. Most households had entered the database by 2014, with relatively few additions in subsequent years. We construct a balanced panel by restricting the sample to households observed continuously from 2014 through 2020 for the purpose of vulnerability construction. The resulting sample contains 14,660 households observed annually over the seven-year period.

Table 2

Year	Database	Balanced panel	Analysis sample	Estimation sample			
				Never-treated	2017 cohort	2018 cohort	Total
2014	17,703	14,761	14,660	224	544	13,890	14,658
2015	17,427	14,761	14,660	224	544	13,889	14,657
2016	19,107	14,761	14,660	223	540	13,797	14,560
2017	18,711	14,761	14,660	205	538	13,675	14,418
2018	18,376	14,761	14,660	224	544	13,892	14,660
2019	18,069	14,761	14,660	224	544	13,892	14,660
2020	17,831	14,761	14,660	224	544	13,892	14,660
Household-years	127,224	103,327	102,620	1,548	3,798	96,927	102,273

Note:

This dataset offers several advantages for evaluating IPAP. First, administrative records provide direct information on household poverty status and program participation, reducing measurement error associated with self-reported survey data. Second, the database focuses on households that met the same national poverty identification criteria, resulting in a relatively homogeneous sample and improving comparability between participating and non-participating households for the purpose of IPAP impact identification. Third, the database contains detailed information on household demographics, labor capacity, income sources, productive activities, and assets, allowing us to account for observable household characteristics and examine heterogeneity in program effects.

Table 3 reports baseline descriptive statistics for households that entered IPAP in 2017 or 2018 and for non-participating households. IPAP participants generally had more favorable demographic characteristics, including larger household size, more working-age, literate, and healthy members, and longer working durations. Differences in productive resources were relatively small, although households entering IPAP in 2018 had somewhat larger landholdings. Despite these differences, both groups faced substantial human capital constraints, particularly in education and health.

In terms of income characteristics, households that subsequently participated in IPAP had lower per capita total income in 2016 than non-participating households, but higher wage, production, and property income. In contrast, non-participating households relied more heavily on transfer income. They were also more likely to receive dibao, whereas future IPAP participants had higher participation rates in relocation and vocational training programs.

Table 3

	Full sample (1)	Never treated (2)	Treatment 2017 (3)	Treatment 2018 (4)
Household characteristics				
Age of household head	56.60	53.04	53.12	56.79
	(14.25)	(14.72)	(11.35)	(14.32)
Family size	2.57	2.32	3.03	2.56
	(1.32)	(1.34)	(1.34)	(1.32)
No. of members aged >65	0.44	0.28	0.28	0.45
	(0.69)	(0.55)	(0.56)	(0.69)
No. of members aged <16	0.33	0.35	0.45	0.33
	(0.68)	(0.69)	(0.78)	(0.68)
No. of laborers	1.51	1.32	1.94	1.50
	(1.38)	(1.29)	(1.33)	(1.38)
No. of literate members	1.69	1.39	1.92	1.69
	(1.10)	(1.01)	(1.16)	(1.09)
No. of healthy members	1.77	1.41	2.09	1.76
	(1.53)	(1.54)	(1.50)	(1.53)
Working duration (month)	1.75	1.17	2.96	1.71
	(3.35)	(2.54)	(3.38)	(3.35)
Land endowment				
Per capita arable land (mu)	3.68	3.73	2.40	3.73
	(3.84)	(5.15)	(1.79)	(3.86)
Per capita forest land (mu)	1.91	1.55	1.30	1.94
	(2.76)	(2.07)	(2.00)	(2.79)
Per capita grain-to-green land (mu)	1.16	0.95	1.04	1.17
	(2.25)	(1.64)	(1.59)	(2.28)
Per capita orchard land (mu)	0.45	0.34	0.08	0.47
	(1.51)	(1.25)	(0.38)	(1.54)
Income				
Per capita wage income (yuan)	763.51	607.10	846.21	762.81
	(1499.25)	(1262.22)	(930.61)	(1520.51)
Per capita production income (yuan)	1116.69	743.78	1215.58	1118.84
	(1377.70)	(1104.60)	(1213.59)	(1386.81)
Per capita property income (yuan)	84.72	20.12	30.51	87.89
	(378.46)	(165.62)	(140.31)	(386.98)
Per capita transfer income (yuan)	2193.57	3405.88	1321.66	2208.11
	(1873.96)	(2747.64)	(1440.74)	(1857.32)
Observations	14,560	223	540	13,797

Note:

3.2 Vulnerability to Poverty

The main outcome variable is household vulnerability to poverty, which captures the likelihood that a household will enter or remain in poverty in the future (Gallardo, 2020). Unlike conventional poverty measures that describe current welfare status, vulnerability provides a forward-looking measure of households' exposure to future poverty risk.

Three approaches are commonly used to measure vulnerability to poverty: vulnerability as expected poverty (VEP) (Chaudhuri, 2003), vulnerability as low expected utility (VEU) (Ligon and Schechter, 2003), and vulnerability as uninsured exposure to risk (VER) (Dercon and Krishnan, 2000). We use VEP as our primary measure because it captures the probability that a household will fall below the poverty line in the future and thus provides an intuitive measure of future poverty risk. From a policy perspective, this measure can help identify households at risk of future poverty and inform the design of sustained poverty alleviation efforts. VEP has also been widely applied in empirical studies because of its straightforward interpretation and relatively modest data requirements (Yang et al., 2023; Maharana and Shaw, 2026).

Following xxxxxx, we use household income as a measure of welfare and calculate vulnerability. Let Y_{it} denote household income and Z the poverty line. Household i's vulnerability can be expressed as:

$$\Pr(Y_{it} < Z \mid X_{it}) = \Pr(\ln Y_{it} < \ln Z \mid X_{it}) \tag{1}$$

where X_{it} is a vector of observable household characteristics and fixed effects. To estimate this probability, we assume that household income is determined by observable household characteristics according to:

$$\ln Y_{it} = X_{it}\beta + \varepsilon_{it} \tag{2}$$

where β is a vector of parameters and ε_{it} is an idiosyncratic disturbance term.

The conditional expected value and conditional variance of log household income are given by:

$$\mathbb{E}(\ln Y_{it} \mid X_{it}) = X_{it}\beta \tag{3}$$

Assuming that the disturbance term is conditionally normally distributed, household vulnera-

bility can be written as:

$$\text{VEP}_{it} = \Pr\left(\ln Y_{it} < \ln Z \mid X_{it}\right) = \Phi\left(\frac{\ln Z - \mathbb{E}(\ln Y_{it} \mid X_i)}{\sqrt{\text{Var}(\ln Y_{it} \mid X_i)}}\right) \tag{4}$$

Empirically, we first estimate the following specification:

$$\ln Y_{it} = X_{it}\beta + \gamma_i + \eta_t + \varepsilon_{it} \tag{5}$$

where $\ln Y_{it}$ is the log of household i's per capita income (excluding transfer income) in year t. X_{it} is a vector of household characteristics. γ_i and η_i are household and year fixed effects, respectively. ε_{it} is the error term.

Second, using the estimated coefficients from the income specification, we obtain predicted household income and construct its expected value and variance. Household vulnerability is calculated as:

$$\widehat{\text{VEP}}_{it} = \Phi\left(\frac{\ln Z - \widehat{\mathbb{E}}(\ln Y_{it} \mid X_{it})}{\sqrt{\widehat{\text{Var}}(\ln Y_{it} \mid X_{it})}}\right) \tag{6}$$

The resulting index lies between zero and one and can be interpreted as the estimated probability that a household will fall below the poverty line in the future. A higher value indicates greater vulnerability to poverty.[1]

Figure 1 presents household vulnerability to poverty across the two treatment groups in 2014 and 2020. Before IPAP implementation, households that subsequently participated in the program had vulnerability levels similar to or slightly higher than those of non-participating households. Their vulnerability, however, declined more rapidly after 2018, and by 2020 both participating groups had lower average vulnerability than non-participating households. These patterns indicate differential changes in vulnerability across groups, which we examine formally in the empirical analysis.

[1] xxxxxx also model income uncertainty through the conditional variance of Y_{it}. Specifically, the uncertainty is defined as: $\text{Var}(\ln Y_{it} \mid X_{it}) = \text{Var}(\varepsilon_{it} \mid X_{it}) = X_{it}\theta$, which allows the heteroskedasticity across household i and year t. In this study, we do not separately model this component as a function of household characteristics since household vulnerability itself is the policy-relevant outcome of interest and directly captures households' exposure to future poverty risk.

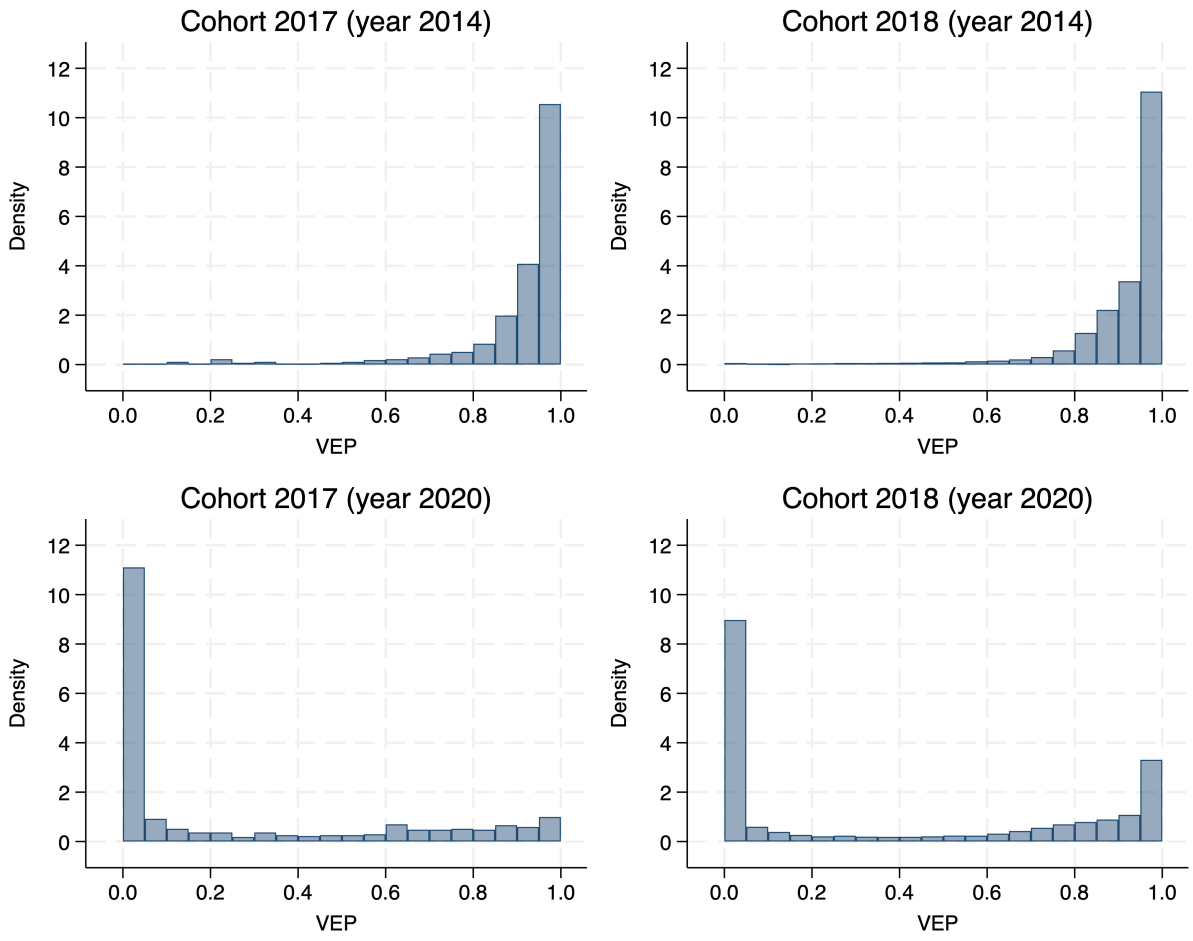


Figure 1: VEP distribution

Note:

3.3 DID Specification

We evaluate the average impact of IPAP policy on the VEP using a staggered DID specification, as shown in the following equation:

$$Y_{it} = \beta \cdot IPAP_{it} + X_{it}\beta + \gamma_i + \eta_t + \varepsilon_{it} \tag{7}$$

where Y_{it} is the outcome variable for household i in year t. It denotes VEP along with other variables related to income, such as wage, production and property income, and labor activities. $IPAP_{it}$ is a binary variable indicating whether IPAP is implemented in household i's village. X_{it} represents control variables. γ_i and η_i are household and year fixed effects. ε_{it} is the error term.

We also estimate the program effects separately for different types of IPAP, including production-oriented, employment-oriented, and photovoltaic programs. To this end, we estimate the following specification:

$$Y_{it} = \sum_{k=1}^{5} \beta_k \cdot \left(IPAP_{it} \times D_i^k\right) + X_{it}'\boldsymbol{\delta} + \gamma_i + \eta_t + \varepsilon_{it} \tag{8}$$

where Y_{it} denotes the outcome variable for household i in year t. $IPAP_{it}$ is a binary indicator of IPAP participation, and D_i^k is an indicator equal to one if household i participates in program type k, and zero otherwise. We distinguish five program types: crop production, livestock production, agricultural processing, forest ranger employment, and photovoltaic income distribution. The coefficient β_k captures the treatment effect of each program type relative to non-participation. X_{it} is a vector of household-level control variables, while γ_i and η_t denote household and year fixed effects, respectively. ε_{it} is the error term.

The identification of treatment effects depends on the assumption that the treated and control groups share the common trends of outcome variables without IPAP. We provide suggestive evidence on the parallel-trend assumption using the event-study approach as follows:

$$Y_{it} = \sum_{\tau \geq 2} \sigma_{-\tau} \cdot IPAP_{i,t-\tau} + \sum_{\tau \geq 0} \sigma_{\tau} \cdot IPAP_{i,t+\tau} + X_{it}\beta + \gamma_i + \eta_t + \varepsilon_{it} \tag{9}$$

where $IPAP_{i,t\pm\tau}$ indicates whether IPAP was implemented in household i's village in year $t \pm \tau$. $\sigma_{-\tau}$ captures the effect prior to IPAP implementation, and σ_{τ} represents the effect after the im-

plementation of the IPAP. the period immediately preceding IPAP is set as the reference. σ_{-1} is omitted. If assumption holds, $\sigma_{-\tau}$ should not differ significantly from zero, suggesting no pre-trend differences between the treated and control groups. A related concern is the heterogeneous treatment effects across different groups of household with different implementation timing, which might bias the staggered DID estimates. In Section 5, we provide alternative estimates for robustness.

4 Empirical Results

In this section, we present the estimates of IPAP impacts. First, we show that effects on household vulnerability to poverty, which is followed by the analysis of the change of productive activities and employment to better understand the mechanism. Second, we present how the effects differ from alternative programs. Third, we show the heterogeneous effects across household characteristics. Finally, we conclude this section by presenting several robustness checks.

4.1 Average Effects of IPAP

Table 4 reports the estimated effects of IPAP participation on household VEP. Since some household characteristics are used both to construct the VEP measure and as controls in the DID specification, Column (1) presents estimates without additional household controls, while Column (2) includes time-varying household characteristics. The estimated coefficients are similar in magnitude and statistically significant across both specifications, suggesting that our findings are not sensitive to the inclusion of these controls. In particular, Column (2) shows that IPAP participation reduces VEP by approximately 3.8 percentage points. Relative to the average VEP of approximately 0.846 in 2016, this represents a 4.5% reduction in household vulnerability.

The magnitude of the estimated effect is broadly comparable to previous evidence on poverty alleviation interventions. xxxxxx, for example, document substantial poverty-reduction effects of targeted assistance programs among poor households. Although direct evidence on the effects of IPAP on household vulnerability remains limited, related studies provide useful benchmarks. For example, Phan et al. (2023) find that microcredit borrowing reduces household vulnerability to poverty by approximately 0.7% in rural Vietnam, while Maharana and Shaw (2026) report a reduction of about 0.5% among microcredit borrowers relative to non-borrowers in India. In China,

Table 4

Dependent variable:	VEP	
	(1)	(2)
IPAP	-0.034**	-0.038**
	(0.016)	(0.019)
Controls	N	Y
Household FE	Y	Y
Year FE	Y	Y
Village-specific trend	Y	Y
R-squared	0.761	0.800
Observation	102,273	102,273

Note:

Yang et al. (2023) show that an increase by one standard deviation in digital financial inclusion is associated with a 5.29% decline in farmers' vulnerability to poverty.

We assess the parallel-trends assumption using the event-study specification (9). As shown in the first panel of Figure 2, the estimated coefficients are close to zero and statistically insignificant during the four years preceding IPAP implementation, suggesting no systematic differences in pre-treatment trends between participating and non-participating households. Following implementation, the coefficients become negative and statistically significant, indicating a reduction in household vulnerability to poverty.

While the preceding results show that IPAP significantly reduces household vulnerability to poverty, they provide limited insights into the underlying economic mechanisms. To better understand this reduction, we turn to household income and related economic activities, which are central to households' ability to maintain their livelihoods and avoid future poverty. Importantly, the implications for vulnerability depend not only on the level of income but also on how that income is generated. Higher income and asset accumulation can strengthen households' ability to withstand adverse shocks (Phadera et al., 2019), while the composition of income sources may also shape their exposure to future poverty risks (Lensink et al., 2017; Yang et al., 2023). In particular, interventions that promote productive investment and income-generating opportunities can generate persistent improvements in household welfare (Banerjee et al., 2021; Aggarwal et al., 2024). These considerations motivate us to examine whether IPAP improves household livelihoods primarily by increasing income levels or by strengthening households' income-generating activities. Therefore, we investigate its effects on total income, income composition, and related productive

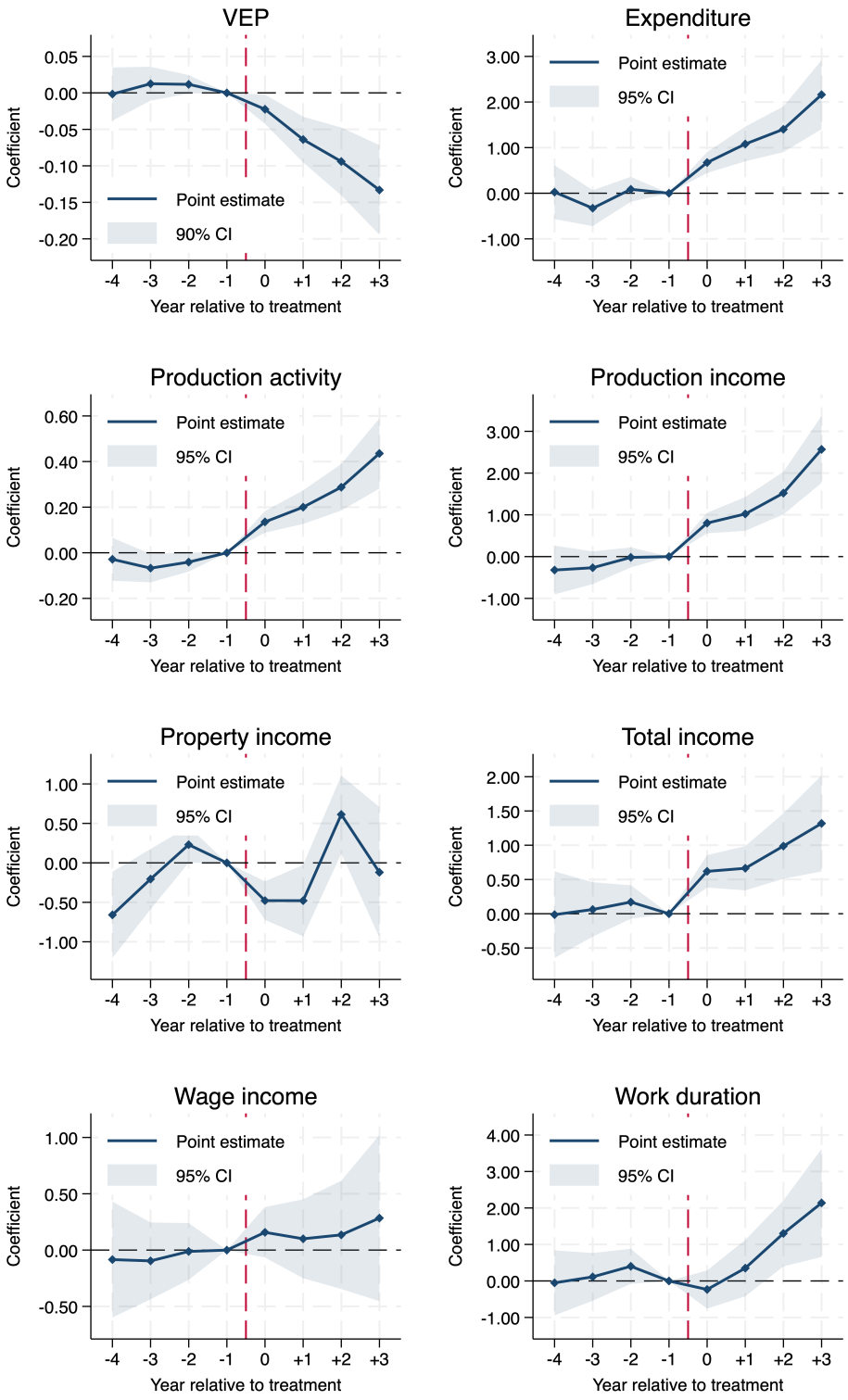


Figure 2: Coefficients and 95% confidence intervals of event study

Note:

and employment activities.

Table 5 reports the estimated effects of IPAP on household per capita income and related economic activities. Column (1) shows that IPAP significantly increases per capita total income, consistent with previous evidence that livelihood-oriented interventions improve household economic well-being by expanding access to productive resources and income-generating opportunities (Blattman et al., 2014; Banerjee et al., 2015). Higher per capita income may enable households to accumulate resources and better cope with adverse economic shocks, potentially contributing to the observed reduction in vulnerability to poverty.

Table 5

Dept. var. (per household member):	Total income (1)	Farm and family business income (2)	Farm and family business expenditure (3)	Nonfarm employment income (4)	Nonfarm employment duration (5)	Property income (6)
$IPAP_{it}$	0.725***	0.884***	0.765***	0.205	-0.239	-0.385***
	(0.147)	(0.149)	(0.126)	(0.129)	(0.310)	(0.126)
Controls	Y	Y	Y	Y	Y	Y
Household FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Village linear trend	Y	Y	Y	Y	Y	Y
R-squared	0.673	0.527	0.509	0.759	0.621	0.465
Observation	102,620	102,620	102,620	102,620	102,620	102,620

Note:

We next examine whether IPAP affects household income composition and income-generating activities. Column (2) shows that IPAP significantly increases per capita farm and family business income, consistent with the program's provision of production subsidies, credit support, technical assistance, and market access to support household farming and business activities. Column (3) further shows a significant increase in per capita farm and family business expenditure, suggesting that households expand their investment in productive activities following IPAP participation. These findings suggest that IPAP not only raises household income but also supports the expansion of household-operated economic activities, potentially strengthening households' income-generating capacity beyond direct policy support.

Columns (4) and (5) show no statistically significant effects on nonfarm employment income or duration, suggesting that the expansion of household farming and business activities does not systematically crowd out nonfarm employment. Finally, Column (6) shows that IPAP significantly

reduces per capita property income. One possible explanation is that households reallocate resources from passive asset holdings toward their own farming and business activities following program participation. However, property income accounts for only 2.04% of total household income on average in our sample, suggesting that this decline has a relatively limited contribution to overall household income. The substantial increase in farm and family business income may therefore more than offset the reduction in property income, consistent with the positive effect on per capita total income.

4.2 Passive Income versus Livelihood Support

The preceding analysis shows that IPAP increases household income and reduces vulnerability to poverty on average. However, these effects may differ across program types due to their distinct income-generating mechanisms. Production-oriented programs, including crop cultivation, livestock breeding, and agricultural processing, provide subsidies, productive inputs, and other support to encourage household engagement in self-operated production. Employment-oriented forestry programs instead provide wage income through direct employment opportunities. Both forms of livelihood support link income gains to households' participation in productive or employment activities. In contrast, photovoltaic programs primarily provide property income through collective dividends from electricity generation, requiring limited direct household participation in income-generating activities. These differences motivate us to examine whether livelihood-oriented support and passive income provision have distinct effects on household income, labor allocation, and vulnerability to future poverty.

To investigate these differences, we exploit detailed administrative records on households' participation in specific IPAP interventions. The data identify the program type in which each household participates, with households participating in only one type in a given year. We distinguish five program types, corresponding to the three broader categories summarized in Table 1. We then estimate their respective effects on household vulnerability, income, and economic activities. The results are reported in Table 6.

The results show that production-oriented programs, including crop cultivation, livestock breeding, and agricultural processing, significantly reduce household vulnerability to poverty by 5.1, 9.3, and 8.8 percentage points, respectively. These programs also significantly increase per capita to-

Table 6

Dep. var. (per household member):	Household VEP	Total income (log)	Farm and family business income (log)	Farm and family business expenditure (log)	Nonfarm employment income (log)	Nonfarm employment duration (log)	Property income (log)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Production livelihood support							
Program: crop production							
$IPAP_{it} \times program_i$	-0.051**	0.764***	1.241***	1.206***	0.260*	-0.123	-0.203
	(0.020)	(0.178)	(0.195)	(0.168)	(0.140)	(0.336)	(0.157)
Program: livestock production							
$IPAP_{it} \times program_i$	-0.093***	0.689***	1.625***	1.512***	-0.042	-0.364	-0.275**
	(0.021)	(0.153)	(0.170)	(0.155)	(0.142)	(0.333)	(0.136)
Program: agricultural processing							
$IPAP_{it} \times program_i$	-0.088**	1.093***	1.538***	1.777***	0.314	-0.822	-0.457**
	(0.040)	(0.288)	(0.385)	(0.284)	(0.295)	(0.604)	(0.229)
Employment livelihood support							
Program: forest ranger employment							
$IPAP_{it} \times program_i$	-0.162***	0.065	0.131	0.085	0.677***	0.806**	-1.661***
	(0.028)	(0.191)	(0.222)	(0.218)	(0.212)	(0.372)	(0.230)
Passive income support							
Program: photovoltaic income distribution							
$IPAP_{it} \times program_i$	0.067*	2.339***	0.085	-0.026	0.313	-0.115	1.680***
	(0.035)	(0.673)	(0.758)	(0.682)	(0.529)	(1.005)	(0.336)
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
Village trend	Y	Y	Y	Y	Y	Y	Y
R-squared	0.806	0.674	0.534	0.517	0.759	0.622	0.470
Observation	102,273	102,273	102,273	102,273	102,273	102,273	102,273

Note:

tal income, production-and-business income, and related expenditures, suggesting an expansion of household-operated productive activities. In contrast, the effects on nonfarm employment income and work duration are generally statistically insignificant, indicating that greater productive engagement does not necessarily come at the expense of wage employment. These findings are consistent with experimental evidence that livelihood-oriented interventions can stimulate productive investment, expand self-employment, and generate sustained improvements in household welfare (Blattman et al., 2014; Banerjee et al., 2015; Bandiera et al., 2017; Banerjee et al., 2021). Our results extend this evidence to a large-scale government poverty alleviation program, showing that support for household production is associated not only with higher current income but also with lower vulnerability to future poverty. This pattern suggests that strengthening households' income-generating capacity may provide benefits beyond the immediate financial assistance received.

Employment-oriented forestry programs operate through a different channel but also significantly reduce household vulnerability, with an estimated reduction of 16.2 percentage points, the largest among the five program types. Unlike production-oriented programs, forestry interventions significantly increase wage income and employment duration, with estimated coefficients of 0.677 and 0.806, respectively, reflecting expanded employment opportunities as ecological forest rangers. Meanwhile, the estimated effects on production-and-business income and expenditures are statistically insignificant, suggesting that increased wage employment does not necessarily displace household production. These findings are consistent with experimental evidence that employment-oriented interventions can expand labor-market opportunities and reshape household livelihood choices (Blattman and Dercon, 2018; Blattman et al., 2022). Although forestry programs do not significantly increase total household income, they generate a substantial reduction in vulnerability to poverty. One possible explanation is that regular employment provides a more predictable income stream, helping households manage income uncertainty even without substantial increases in average earnings. Taken together, the results for production- and employment-oriented programs suggest that livelihood support can reduce poverty vulnerability through different forms of income-generating activities.

In contrast, photovoltaic programs significantly increase per capita total income, with an estimated coefficient of 2.339, primarily through property income derived from collective dividends. Despite these income gains, household vulnerability increases by approximately 6.7 percentage points.

Importantly, we find no statistically significant changes in production-and-business income, related expenditures, nonfarm employment income, or employment duration. This pattern is consistent with experimental evidence that income transfers generally do not substantially discourage adult labor supply or productive engagement (Banerjee et al., 2017; Baird et al., 2018). However, our findings highlight an important distinction between improving current income and reducing future poverty risk. Unlike production- and employment-oriented programs, photovoltaic interventions increase household resources without a corresponding expansion of household income-generating activities. Moreover, the additional income depends primarily on revenues from collectively managed assets and continued policy-related distribution arrangements, rather than households' own productive or employment capacity. This dependence may limit the extent to which income gains translate into greater economic resilience. The increase in vulnerability despite higher income therefore suggests that income support alone may be insufficient to generate persistent poverty reduction, even when it does not discourage productive engagement.

4.3 Heterogeneoity Analysis

To further understand the heterogeneous effects of IPAP, we examine whether its effectiveness varies with households' human capital and labor endowments. Given that livelihood-oriented interventions rely on households' participation in productive and employment activities, their ability to reduce vulnerability to poverty may depend on households' capacity to engage in these activities.

Households with more favorable endowments, including better health, higher educational attainment, greater labor availability, and younger age structures, may be better positioned to translate IPAP support into income-generating opportunities and sustained improvements in their livelihoods. In contrast, households facing substantial human capital and labor constraints may have more limited capacity to participate in productive activities or take advantage of employment opportunities. Consequently, even when receiving similar policy support, these households may experience smaller reductions in vulnerability to poverty. This distinction is particularly relevant for evaluating livelihood-oriented interventions, whose effectiveness depends not only on the resources provided but also on households' ability to utilize them.

To this end, we construct four indicators of household endowments using demographic information: health, education, labor availability, and age structure. Each indicator is defined using a 50%

threshold based on the share of household members with the relevant characteristics. Specifically, households are classified as having favorable endowments if the majority of their members are free from serious illness, chronic disease, or disability; are literate; or are of working age, respectively. For age structure, households are classified as having favorable endowments if less than half of their members are aged 65 or above. We interact each indicator with IPAP participation to examine whether its effects on household vulnerability differ across these dimensions. Table 7 presents the estimation results.

Table 7

	Dep. var.: VEP			
Interaction var.:	Health	Education	Labor	Age
	(1)	(2)	(3)	(4)
IPAP	-0.076***	-0.049**	-0.080***	-0.073***
	(0.019)	(0.019)	(0.019)	(0.020)
IPAP × interaction	0.096***	0.032***	0.200***	0.128***
	(0.007)	(0.005)	(0.008)	(0.008)
Controls	Y	Y	Y	Y
Household FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Village linear trend	Y	Y	Y	Y
R-squared	0.803	0.800	0.806	0.804
Observation	102,273	102,273	102,273	102,273

Note:

Columns (2)–(5) of Table 7 reveal significant heterogeneity in the effects of IPAP across household endowments. Households with more favorable characteristics, particularly better health, greater labor availability, and younger age structures, experience larger reductions in vulnerability to poverty. Among the four dimensions, health, labor availability, and age structure appear to play more prominent roles, whereas educational attainment has a relatively modest moderating effect. This pattern is consistent with the labor-intensive nature of rural production and employment activities, for which physical capacity and labor availability may be more important than formal education. More broadly, these findings suggest that the effectiveness of livelihood-oriented support depends partly on households' ability to engage in income-generating activities and translate policy assistance into sustained improvements in their livelihoods. For households facing substantial human capital and labor constraints, productive or employment opportunities alone may be insufficient to generate comparable reductions in poverty vulnerability, highlighting the importance

of tailoring interventions to household circumstances.

5 Robustness Checks

5.1 Staggered DID and Heterogeneous Treatment Effects

Given the staggered implementation of IPAP, conventional two-way fixed effects estimators may yield biased estimates in the presence of heterogeneous treatment effects across cohorts and over time. To address this concern, we employ the alternative DID estimators proposed by De Chaisemartin and D'Haultfœuille (2020) and Callaway and Sant'Anna (2021), which account for treatment effect heterogeneity under staggered adoption. As reported in Columns (2) and (3) of Appendix Table B1, the estimated effects remain similar in magnitude and statistical significance to those obtained from the baseline TWFE specification. These findings suggest that our main results are robust to alternative estimation methods that accommodate heterogeneous treatment effects.

5.2 Selection into IPAP

Table 3 reveals differences in baseline characteristics between households participating in IPAP and those not participating, raising concerns about potential selection bias in our estimated treatment effects. To address these concerns, we conduct two additional analyses.

First, we examine whether pre-treatment household vulnerability predicts subsequent IPAP participation. Specifically, we consider three measures of prior vulnerability: one-year lagged VEP, two-year lagged VEP, and average pre-treatment VEP. As reported in Columns (1)–(3) of Appendix Table B2, none of these measures is significantly associated with subsequent program participation, providing limited evidence of selection into IPAP based on prior vulnerability.

Second, we account for potential selection based on observable household characteristics by combining propensity score matching (PSM) with the DID framework. We estimate propensity scores using pre-treatment household characteristics and match participating households with comparable non-participating households. We also employ inverse probability weighting (IPW) to construct a reweighted comparison group with more similar observable characteristics. As shown in Columns (4) and (5) of Appendix Table B2, both approaches yield estimates that are consistent in magnitude and statistical significance with our baseline findings. These results suggest that our estimated

effects are not driven solely by observable differences between participating and non-participating households.

5.3 Anticipation Effect

5.4 Omitted Variables

Our empirical specification accounts for various household-level characteristics and fixed effects, but there may still be concerns about omitted variable bias. The challenge is that IPAP could interact with unobserved factors, such as changes in local economic development, market access, and households' productive capacity and adaptability, that evolve alongside policy implementation and household vulnerability.

To alleviate concerns, we follow Oster (2019) to examine whether our results are robust to concerns about unobserved confounding. Specifically, the Oster method assesses the extent to which selection on unobservables would have to increase, relative to observables, to explain away the estimated treatment effect.Column (1) of Appendix Table B3 presents the identified set of bias-adjusted coefficients under the proportional selection assumption, which ranges from -0.043 to -0.040 and remains negative. The limited change in the estimated coefficient suggests that the main results are unlikely to be driven by omitted variable bias. Moreover, we set , allowing unobserved factors to explain up to 30% more variation than observed covariates. The implied selection ratio required to eliminate the estimated effect is 14.16, indicating that unobserved factors would need to be more than 14 times stronger than observed factors in terms of selection strength to fully explain away the estimated effect. Thus, our results are robust.

5.5 Confounding Policies

Since IPAP was implemented within a broader poverty alleviation framework, its estimated effects may be confounded by other concurrent interventions. To address this concern, we examine four major poverty alleviation programs: ecological compensation, housing reconstruction, relocation, and vocational training. In Columns (1)–(4) of Appendix Table B4, we sequentially exclude households participating in each program and re-estimate the baseline specification. In Column (5), we instead control for all four interventions simultaneously. Across these specifications, the estimated

effects of IPAP on household vulnerability remain negative and statistically significant, consistent with our baseline findings. These results suggest that the observed reduction in vulnerability is not solely driven by other concurrent poverty alleviation programs.

5.6 Alternative Vulnerability Measures

Since vulnerability can be analyzed from various perspectives, we investigate whether our findings are influenced by specific measures. We employ three alternative measures based on previous studies. First, we create a risk-adjusted vulnerability measure following Ligon and Schechter (2003), which takes into account households' risk preferences. Second, we adopt a downside-risk vulnerability measure based on Calvo and Dercon (2003), which highlights vulnerability resulting from adverse shocks. Lastly, we use an asset-based vulnerability measure inspired by Hoddinott and Quisumbing (2008), which considers households' asset holdings as a buffer against future risks. In Columns (1)-(3) of Appendix Table B5, the estimated effects remain consistent across these alternative vulnerability measures.

5.7 COVID-19 Shock

The year 2020 was significantly impacted by the COVID-19 pandemic, which may influenced economic activities and household livelihoods. Additionally, global evidence suggests that the pandemic greatly obstructed poverty reduction efforts Aiken et al. (2023). To mitigate concerns that the shocks from the pandemic might affect our estimates, we have excluded data from 2020 and re-estimated our baseline model. In Column (4) of Appendix Table B5, the estimated effect of the IPAP remains consistent.

5.8 Leave-One-Out Analysis

To determine whether our findings are influenced by specific observations, we performed a leave-one-out analysis. Following the methodology outlined by Li and Xia (2026), we sequentially excluded one village at a time and re-estimated the baseline model. Appendix Figure B3 presents the distribution of the estimated coefficients of IPAP across these alternative samples, with the red line indicating the baseline estimate from the full sample. The coefficients remain closely centered

around the baseline estimate and consistently maintain the same sign across specifications. This evidence suggests that our results are not driven by any single village.

6 Conclusion

Existing studies have explored the impact of one-time transfers of productive assets or financial resources on poverty reduction. However, there is limited knowledge about how comprehensive and targeted IPAP affect household vulnerability. By using unique data from registered impoverished households in rural China, we can identify the causal effects of IPAP on vulnerability. We find IPAP significantly reduces vulnerability. We further demonstrate that this effect occurs through both income expansion and improvements in income structure. However, the benefits of IPAP are not uniformly distributed across households and industries. Households with stronger initial conditions tend to benefit more from IPAP. Programs that focus on production and employment reduce vulnerability by enhancing productive capacity and income stability, whereas income-based interventions alone may fail to reduce household vulnerability and could even weaken it.

Our findings have several policy implications. First, policymakers should continue to support and improve IPAP. On average, IPAP not only increases household income but also reduces vulnerability. This suggests that IPAP can generate both immediate economic gains and longer-term risk-reduction benefits. At the same time, policy design should consider both short-term returns and households' exposure to future risks, rather than focusing solely on current income growth. Second, IPAP should be tailored to households with different initial conditions. Our results show that households with stronger economic and human-capital endowments benefit more from IPAP. For these households, policy should focus on helping them fully utilize their existing capabilities and reduce the risk of falling back into poverty in the future. For households with weaker initial endowments, however, providing productive opportunities alone may not be sufficient. They may require more comprehensive and gradual support, such as complementary assistance in health, education, labor capacity, and other basic capabilities, before they can effectively benefit from production-oriented interventions. Third, IPAP should be better designed to promote stable and sustainable household incomes. Production-oriented programs, such as planting, breeding, and manufacturing, can stimulate productive activities and reduce vulnerability, but greater continuity

of policy support is needed to sustain these effects. Employment-based programs, such as forestry, can provide stable wage income but may also crowd out productive activities, requiring careful design of employment arrangements. Asset-based programs, such as photovoltaic poverty alleviation, can increase household income but may weaken productive activities and increase reliance on policy-related income. These programs should therefore be complemented by measures that encourage productive engagement and maintain diversified income sources, thereby strengthening households' long-term resilience.

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Appendix

A VEP Distribution

Table A1

Year	Never treated	2017 cohort	2018 cohort
2014	0.881	0.890	0.885
2015	0.879	0.862	0.870
2016	0.866	0.841	0.846
2017	0.823	0.780	0.808
2018	0.631	0.447	0.535
2019	0.659	0.485	0.564
2020	0.652	0.504	0.567

Note:

B Robustness Checks

B.1 Staggered DID and Heterogeneous Treatment Effects

Table B1

	VEP		
	TWFE	DCDH	CS
	(1)	(2)	(3)
IPAP	-0.029**	-0.058**	-0.046**
	(0.014)	(0.028)	(0.022)
Observations	102,273	57,100	101,602
R^2	0.754		
Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Village linear trend	Yes	No	No

Note:

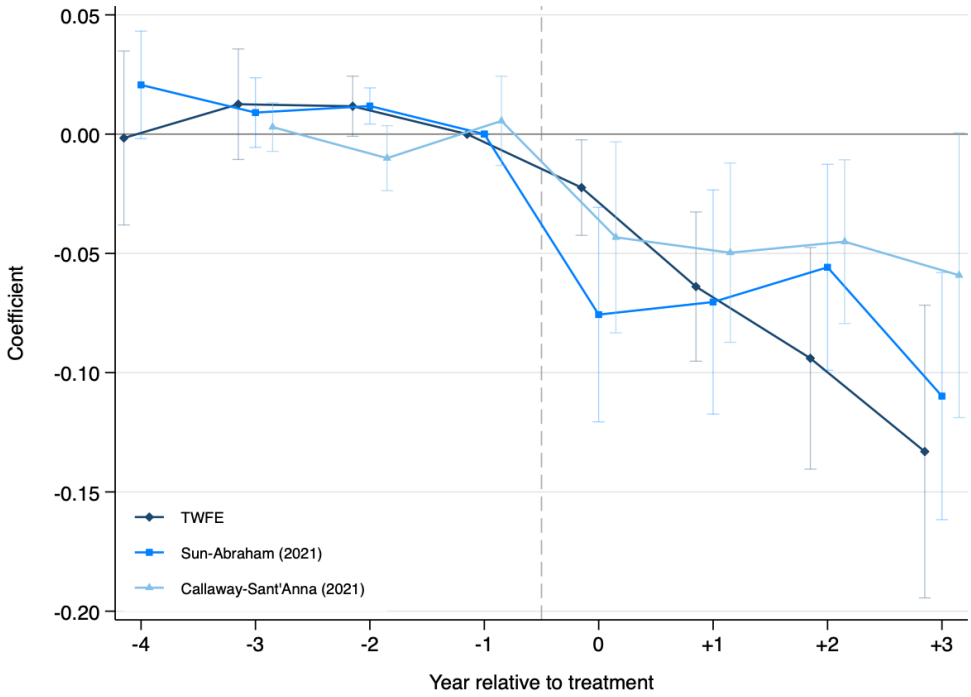


Figure B1: Caption

B.2 Selection into IPAP

Table B2

	IPAP entry (0/1)			VEP	
	(1)	(2)	(3)	(4) PSM-DID	(5) IPW
VEP, one-year lag (2016)	-0.003	-0.001			
	(0.012)	(0.012)			
VEP, two-year lag (2015)		-0.005			
		(0.008)			
Mean pre-treatment VEP (2014–2016)			-0.005		
			(0.017)		
IPAP				-0.030**	-0.026*
				(0.015)	(0.015)
Observations	14,557	14,557	14,557	100,434	101,602
R^2	0.004	0.004	0.004	0.752	
Controls	Yes	Yes	Yes	Yes	Yes
Household FE	No	No	No	Yes	Yes
Year FE	No	No	No	Yes	Yes
Village linear trend	No	No	No	Yes	No

Note:

B.3 Anticipation Effect

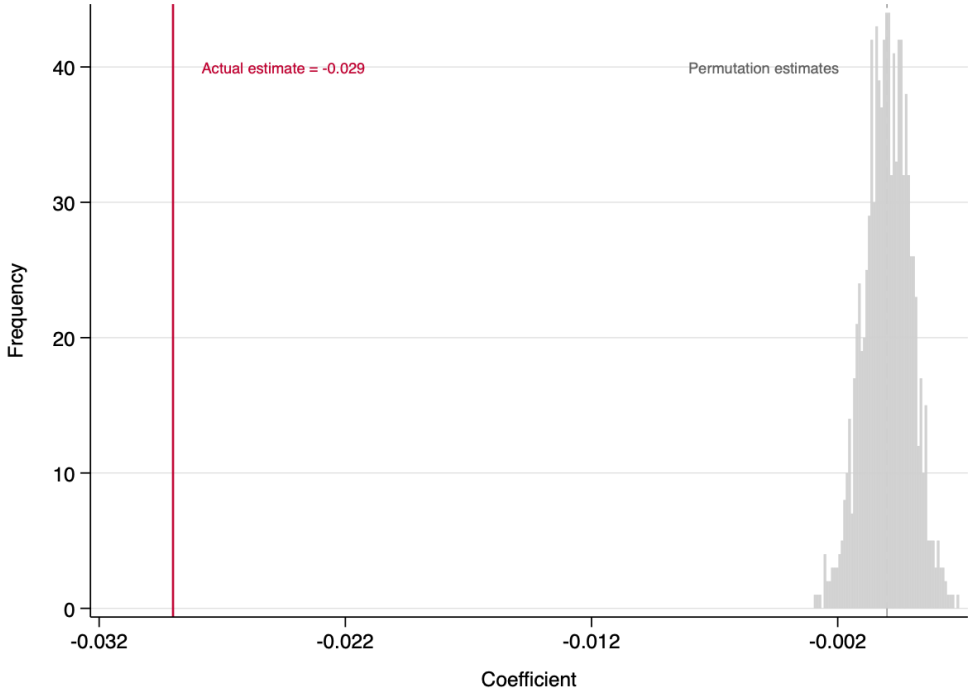


Figure B2: Caption

B.4 Omitted Variables

Table B3

Dependent variable	(1) Controlled effect ($\tilde{\beta}$)	(2) Oster bounds ($\tilde{\beta}$, β^*)	(3) *Rmax* value	(4) Delta ($\lvert\delta\rvert$)
Vulnerability Index (VEP)	-0.029** (0.014)	[-0.031, -0.029]	0.397	19.38 > 1
Controls	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Village linear trend	Yes	Yes	Yes	Yes
Excluded zero		Yes		

Note:

B.5 Confounding Policies

Table B4

	VEP				
	(1) Excl. ecological	(2) Excl. housing	(3) Excl. relocation	(4) Excl. training	(5) Control all
IPAP	-0.035*	-0.030**	-0.029*	-0.031**	-0.029**
	(0.019)	(0.015)	(0.015)	(0.015)	(0.014)
Ecological compensation					-0.028***
					(0.003)
House rebuilding					0.073***
					(0.004)
Relocation					0.061***
					(0.009)
Vocational training					-0.055***
					(0.003)
Observations	52,016	98,861	101,497	91,848	102,273
R^2	0.739	0.761	0.755	0.733	0.759
Controls	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Village linear trend	Yes	Yes	Yes	Yes	Yes

Note:

B.6 Alternative Vulnerability Definition and Covid-19 Shock

Table B5

	(1) Risk-adjusted VEP	(2) Downside-risk VEP	(3) Asset-based VEP	(4) VEP, excl. 2020
IPAP	-0.031*	-0.027**	-0.032**	-0.029**
	(0.013)	(0.012)	(0.015)	(0.015)
Observations	102,273	102,273	102,273	87,613
R^2	0.743	0.856	0.752	0.725
Controls	Yes	Yes	Yes	
Household FE	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	
Village linear trend	Yes	Yes	Yes	

Note:

B.7 Sensitivity to Specific Observations

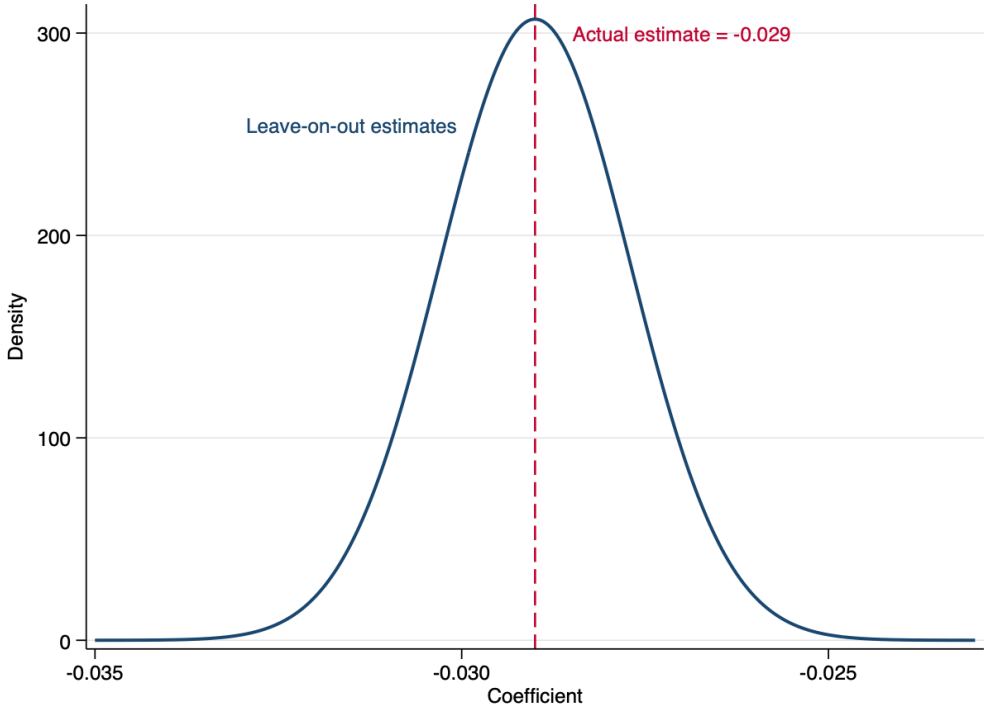


Figure B3: Caption