https://doi.org/10.13140/RG.2.2.28237.72168

Household-level welfare effects of land expropriation: Evidence from China

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March 3, 2023

Abstract

A number of developing countries use land expropriation policies to expand cities and develop peri-urban areas. In China alone, an average of 1,600 square kilometers were expropriated annually between 2004 and 2018. The impact of this urban development strategy on expropriated households is not well-understood. I estimate the causal effect of expropriation on Chinese households' livelihood choice and earned income, relying on panel data and comparison to non-expropriated households to observe how household-level outcomes change in response to expropriation. Controlling for baseline outcomes, I find that for at least the first two years, expropriation reduces household agricultural participation and production but does not increase other types of income-generating activities. The result is reduced food security and ability to earn income. Compensation paid to households does not fully offset these effects in cases where households lose all their land or are uncompensated. These findings suggest concrete policies governments can implement to lessen the negative welfare impacts of urban development on expropriated households: higher compensation rates, development of rural non-agricultural labor markets, and direct food assistance to expropriated households.

Keywords: Land rights, Land expropriation, Household Welfare, China

JEL codes: Q15, O15, H13

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https://doi.org/10.13140/RG.2.2.28237.72168

1 Introduction

Several developing countries have used land expropriation as a means of speeding urbanization, including China, Vietnam, Ethiopia, and Cambodia. While this process has public benefits, it also negatively impacts on expropriated households.

Between 2004 and 2018, the Chinese government expropriated over 24,000 square kilometers of rural land to reach urban development goals (National Bureau of Statistics of China, 2020b). This process redistributed rural households' land to management by urban developers, leaving them with a reduced capacity for agricultural production and limited other options. High rates of expropriation are driven by a dual-track land rights system in which rural land must be expropriated and recategorized as urban-track land before it can be leased to developers. This process has caused millions of households to lose their land (Tan et al., 2011). Compensation given to households is based on the value of agricultural production on the land in the years preceding expropriation. These rates are much lower than the hypothetical value of the land in a competitive land market (Du et al., 2017).

Sociologists have documented widespread dissatisfaction with the process of expropriation (Lora-Wainwright, 2012; Bao et al., 2019). The strength of this opposition is directly related to low levels of compensation relative to land market values (Cai et al., 2020). Over 1,500 protests against land seizure and low rates of compensation took place from 2000 to 2018, representing 52% of all rural protests in China (Jay Chen, 2020). The predominant perception among rural Chinese is that current levels of compensation are not enough to cover the costs of expropriation for affected households. These costs may include loss of agricultural income and the cost of transitioning to other livelihood strategies.

How and to what extent does land expropriation affect household income and livelihood strategies? Do current levels of compensation effectively offset the costs of expropriation for households? The majority of rural Chinese households rely on farm income, but a significant proportion also have wage or self-employment income (Chen et al., 2019). In an agricultural household model incorporating expropriation,[1] expropriation causes a decrease in agricultural activity on the intensive and extensive margins. If the household previously relied on self-produced food, demand for

[1] See Ju et al. 2016, based on the agricultural household model presented in Benjamin 1992.

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purchased food then increases. Reduced agricultural income increases the need for other earned income and shifts household labor to off-farm (non-agricultural) work. The effects of compensation for expropriation depend on the time period in question, the household's preferences, and the state of markets for land and labor. If taken as a one-time income shock, compensation may increase consumption; the household could alternately use compensation to invest in self-owned business, further agricultural assets, or to rent land to offset land lost to expropriation. In broad terms, the welfare effects of compensation should at least partially offset those of expropriation.

However, the assumptions underpinning these predictions are demonstrably not met in rural China. In their simplest form, agricultural household models assume perfectly competitive markets for land and labor.[2] Since rural Chinese households have use rights but limited transfer rights, there is effectively no market for the sale of land and only a limited market for rental (Brandt et al., 2002; Adamopoulos et al., 2022). Welfare effects are also complicated by underdeveloped local labor markets (Benjamin and Brandt, 2002; Taylor and Adelman, 2003). Since there is limited land for rent, agricultural activity is likely to decrease following expropriation and vary minimally with monetary compensation. Low availability of off-farm work further constrains the household's ability to shift to off-farm work after expropriation. In the case of total expropriation in particular, the household may be severely limited by an underdeveloped land rental market and limited opportunities for off-farm work.[3]

A small body of empirical research using non-causal methods finds an association between expropriation and lower agricultural participation (Wang et al., 019a; Li et al., 2018; Ju et al., 2016; Hui et al., 2013) and between expropriation and greater off-farm labor employment (Wang et al., 019a; Li et al., 2018). Other associations are less consistent; some find that household income and/or welfare is higher after expropriation (Wang et al., 019a; Li et al., 2015), but others find negligible or negative correlations (Wang et al., 019b; Ding et al., 2018; Li et al., 2018). Studies on the topic generally attribute changes in income to a shift from agricultural to non-agricultural work, sometimes from sending a temporary migrant to an urban area.

This literature typically either compares expropriated and non-expropriated households *ex post*.

[2] These assumptions result in separable decisions about farm and off-farm labor (see e.g. (Singh et al., 1986)).
[3] Modeling incomplete markets in an agricultural household framework introduces non-linearities into the analysis of comparative statics and leads to complicated predicted effects, often with inconclusive predictions of the direction of the change (de Janvry et al., 1991; Key et al., 2000).

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However, because expropriation is focused in peri-urban areas, the households with the highest risk of expropriation are also those most likely to have lower agricultural engagement, higher off-farm employment, and higher income to begin with. A few studies document livelihood and income before and after expropriation (e.g. Li 2018), but have no defined control group. Without comparison to a similar, unaffected cohort of Chinese households, it is difficult to tell if any differences are a general trend in rural China or the result of expropriation.

In this paper, I estimate the effects of expropriation on welfare proxies related to household agricultural production, off-farm employment, and earned income. I improve on previous evidence by applying causal methods to panel data on over 10,000 households from the 2013 and 2015 waves of a nationally-representative household survey. The structure of the data allows me to observe both expropriated and non-expropriated households over time, identifying the causal effects of expropriation on a variety of outcomes. To construct a sample of households facing a similar risk of expropriation, the analysis sample includes all households with rural *hukou* status that owned land in 2013. The treatment group is then any household that was expropriated between 2013 and 2015. I control for the household's baseline outcome prior to expropriation, addressing the issue of pre-existing differences between expropriated and non-expropriated households. Causal effects are identified under the assumption that, contingent on community-level fixed effects and controlling for *ex ante* household characteristics, expropriated households would have had the same expected change in outcomes between 2013 and 2015 as other households had they not been expropriated. I use inverse probability weights to correct for attrition bias, and base the interpretation of results on sharpened q-values to adjust for large number of hypothesis tests.

I find that land expropriation in China causes households to reduce agricultural activities, including production of food for own-consumption, but does not cause a shift towards non-agricultural income-generating activities or an increase in food spending. I show that expropriation reduces household agricultural participation, time spent on agriculture, agricultural assets (excluding land), and production of food for household consumption. Effects vary by the proportion of land expropriated and the amount of compensation received by the household. Decreases in agricultural activity are completely offset by the median level of monetary compensation in cases of partial expropriation, but they persist regardless of compensation when the household loses all their land. After total expropriation, the value of food produced for household consumption decreases by 36-76%

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per adult equivalent member, with no evidence that food spending increases. This finding suggests that, in addition to reduced agricultural participation, expropriation causes greater food insecurity for at least 1-2 years following expropriation in households that lose all their land. I find no evidence that expropriation increases off-farm employment, self-employment, or earned income. I also contribute evidence to the literature on migration and shocks with heterogeneity analysis showing that migrant-sending households are more resilient to an expropriation shock. These results are robust to alternative constructions of key variables, the use of alternate weights to address attrition and sampling methodology, and the use of alternative scales to calculate per adult equivalent measures.

These results echo evidence on the association between expropriation and reduced agricultural work in Ethiopia (Ghatak et al., 2013), Cambodia (Jiao et al., 2015), and Vietnam (Tuan, 2021; Tuyen et al., 2014). My findings are most similar to those of (Le and Nguyen, 2020) for Vietnam, which finds that expropriation decreases agricultural production and food expenditures, but that households were unable to shift toward off-farm work. It is therefore possible that similar land institutions and constraints on household behavior may be at play in both China and Vietnam.

My findings imply a number of policies that would reduce household welfare losses from expropriation. Greater compensation and food assistance would increase food security and offset agricultural losses in the short run. These types of assistance would benefit all expropriated households, but would be most effective if targeted at households that have lost all their land or have received lower than average monetary compensation. Improved land transfer rights and development of local labor markets might improve the ability of households to either continue agricultural production by renting more land or earn non-agricultural income by shifting to off-farm work, thus improving long-term income security. These policy recommendations may also be relevant to other developing countries with similar systems of land rights and expropriation to China, including Vietnam, Cambodia, and Ethiopia.

The paper is organized as follows: Section 2 gives further background on land expropriation in China. In Section 3, I describe the household panel survey data used in the analysis and present descriptive statistics for key variables. The estimation strategy and method of inference are presented in Section 4, followed by results, robustness, and heterogeneity analysis in Section 5. Section 6 summarizes the main findings and discusses policy recommendations to improve household

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welfare after expropriation.

2 Land expropriation in China

2.1 Legal basis and the distribution of gains from expropriation

Land expropriation is more widespread in China than in most other countries due to China's dual-track land rights system. By law, rural land in China is owned by village collectives and granted only to households with rural *hukou*.[4] Urban land is owned by the national government and can be leased to anyone, including land developers. Rural land must be expropriated and changed to urban-track land before it can be developed.

The extent of expropriation grew rapidly after 2000. In 1998, the Land Administration Law was amended to allow for land expropriation in the public interest (1998, Article 2).[5] The amendment has since been used to justify extensive land expropriation to further urban development. Between 2004 and 2018, approximately 24.5 thousand square kilometers of land were expropriated (Figure 1) (National Bureau of Statistics of China, 2020b), about 0.26% of China's total land area (Food and Agriculture Organization of the United Nations, 2021).[6] An estimated 40-50 million people were expropriated in the few years prior to 2011 (Tan et al., 2011). Household experiences with expropriation vary widely, from partial land loss over a period of years to total expropriation within a few weeks (Sargeson, 2013; Guo, 2001).

The dual-track land system benefits developers and local governmental bodies, but distributes few gains to expropriated households. In China, local governments hold a monopoly on the market for land (He et al., 2022). The process of converting land from rural-track to urban-track offers opportunities for rent-seeking and arbitrage due to differences in expropriation fees and conveyance and allocation prices (Lin and Ho, 2005). By one estimate, only 5-10% of the profits from rural land development went to rural households, while another 20-30% went to local governments and

[4] *Hukou* is the national Chinese household registration system. It defines citizens as having either rural or urban status, and is tied specifically to a given village or city. Rural *hukou* holders are entitled to land and social services (education, healthcare, etc.) only in their registered village. See Chan (2019) for an overview.

[5] "Public interest" is not legally well-defined, leading to debate over the legality of expropriation in some cases (Mao and Qiao, 2021; Hui et al., 2013).

[6] The area of land expropriated between 2008 and 2018 corresponds to about 83% of the increase in urban land area during the same period (National Bureau of Statistics of China, 2020a), consistent with the idea that the primary purpose of expropriation is urban expansion and development.

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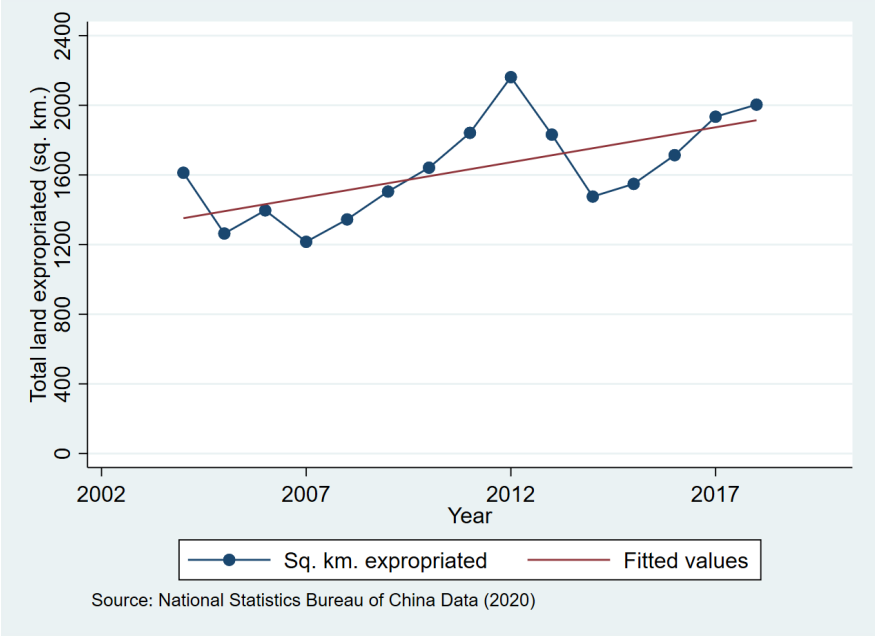

Figure 1: Area of land expropriated in China, 2004-2018

Source: National Statistics Bureau of China (2020b)
Notes: Line of best fit provided to show trend over time.

the rest to developers (Paik and Lee, 2012). Profits from rural land development form a large proportion of income for village-level governments (Tang et al., 2012; Lin and Ho, 2005) that has risen over time (Du et al., 2017). These adverse incentives have led to widespread over-conversion of rural land, as high as 33.5% in some contexts (Tan et al., 2011).

2.2 Compensation for expropriation

The unequal distribution of gains from expropriation is enabled by relatively low rates of compensation. Compensation for expropriated land is set by law at 6-10 times the value of its agricultural output over the preceding three years, with additional adjustments for other investments and surface fixtures (People's Republic of China, 1998).[7] Since compensation is based on the land's agricultural productivity and not on its value after development, compensation is much lower than the theoretical market value in a competitive land market (Du et al., 2017). Furthermore, compensation standards are often unevenly applied and seen as "ad hoc and arbitrary" by expropriated households (Hui et al., 2013). In some cases, households may receive non-monetary compensation such

[7] The level of monetary compensation within this range and the extent of any non-monetary compensation are decided by local governments, sometimes with more specific legal guidelines set at the province or local level.

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as food or relocation assistance. The latter in particular is rare outside of large-scale development projects like the Three Gorges Dam (Yang, 2012). Furthermore, compensation claims generally require a formal land title. Since rural land titling in China is still incomplete (Deininger and Jin, 2007; Wang et al., 2018), some households do not receive any compensation at all (Sargeson, 2013).

3 Data

3.1 CHFS 2013-2015

I test the household-level effects of expropriation using the China Household Finance Survey (CHFS). CHFS is a nationally representative[8] household panel survey that was piloted in 2011 and then collected every two years thereafter by the Southwestern University of Finance and Economics in Chengdu, Sichuan (Gan et al., 2014). Households were selected by a three-stage sampling methodology with randomization at the county, city or village, and household level. Household-level sampling weights provided in the data are used throughout the analysis.

To construct a sample that provides a comparable control group for expropriated households, I restrict the sample to only those households in the 2013 CHFS wave that (1) owned or managed land and (2) had at least one member with agricultural *hukou* (Figure 2). This selection criteria is the best available method of capturing households with rural land rights, and thus those that are most likely to be expropriated.[9]

To ensure that included households are observed both before and after the treatment group is expropriated, I restrict the sample only to households that appear in both the 2013 and 2015 CHFS waves.[10] 1,880 (6.7%) households attrite from the survey between 2013 and 2015; the inverse probability weighting used to correct for attrition is discussed in more detail in Section 4.

The full subsample used to estimate the effects of expropriation on household welfare is comprised of 10,237 unique households (highlighted by the last row in Figure 2). The sample includes

[8] All provinces and regions are represented except Hong Kong, Macau, Shanghai, Taiwan, and Tibet.

[9] Note that rural status as defined in the CHFS data does not necessarily match the *hukou* status of household individuals. Therefore, selection on the rural binary provided in the survey data is not the best method of identifying households with comparable risk of expropriation to those that were actually expropriated. The majority of households that were expropriated between 2013 and 2015 report at least one member with agricultural *hukou* (about 89%), but only 47% of those households are considered rural in 2013 by the CHFS definition.

[10] The 2011 pilot wave is used to supplement information on the household's history (e.g. past expropriation or the year they moved into the current residence), but is otherwise excluded from the main analysis to ensure that all collected outcomes and controls are comparable.

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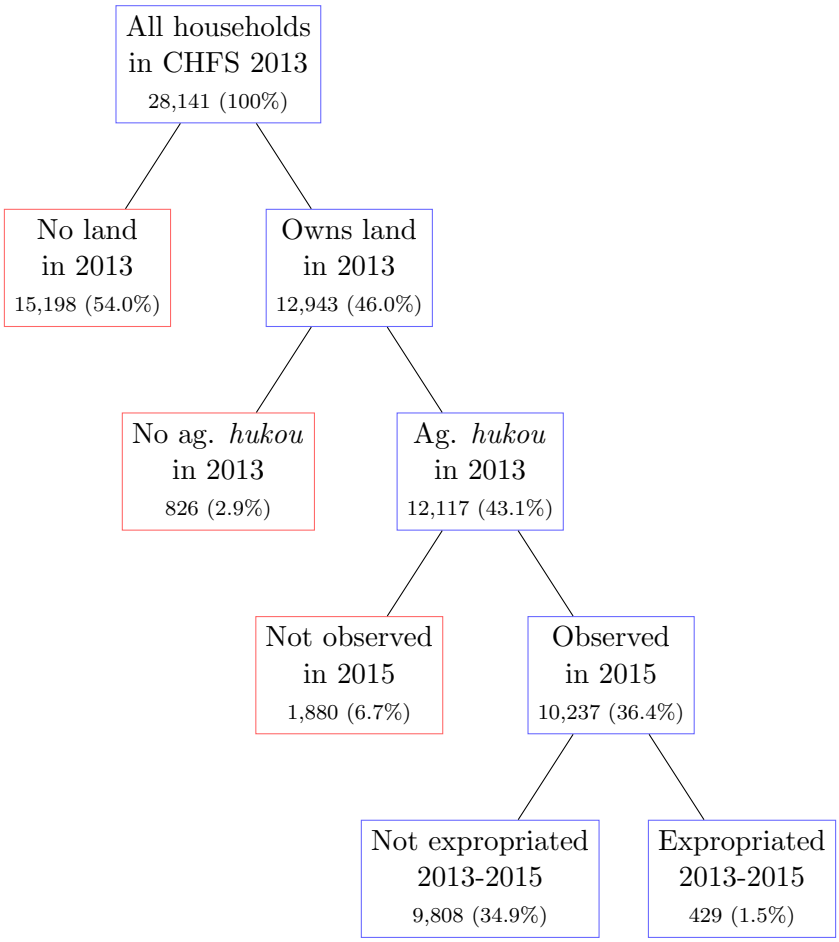

Notes: Excluded households are indicated by red boxes to the left and included households by blue boxes to the right. The final sample is comprised of 10,237 households. All percentages are out of all households that appear in the 2013 wave of the CHFS data ($N = 28,141$).

Figure 2: Sample selection within CHFS data

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429 households that were expropriated between 2013 and 2015 and a control group of 9,808 households.

3.2 Expropriation in CHFS data

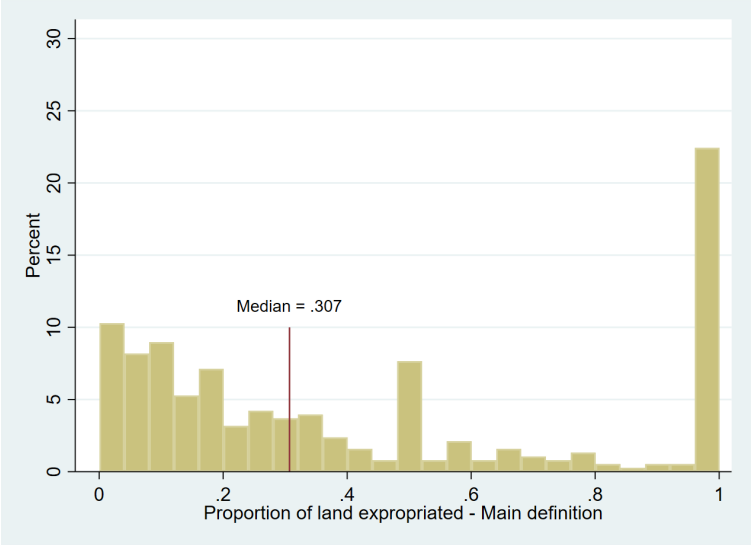

Figure 3: Proportion of land expropriated

Source: Author calculations from CHFS data, 2015
Notes: Proportion of land expropriated calculated using 2015 data according to Eq. 1. An alternative calculation and the effects of its use in estimations is discussed in Section 5.

CHFS contains more extensive information on expropriation than other household surveys, including whether the household has ever been expropriated, the year of their last expropriation episode, how much land was expropriated, and what type of compensation and how much monetary compensation was received. The main explanatory variable used in the analysis is the proportion of land expropriated. Figure 3 shows the distribution of this proportion, calculated by taking:

$$P = \frac{L'_{2015}}{L_{2015} + L'_{2015}} \tag{1}$$

where L'_{2015} is the area of land expropriated between 2013 and 2015 and L_{2015} is the land area reported by the household in 2015.[11] The median proportion of land expropriated is 31%, with

[11] An alternate construction would be to take $P = \frac{L'_{2015}}{L_{2013}}$, but the construction using only data from 2015 is preferred to reduce measurement error (typically high when households report land areas; see e.g. Carletto et al., 2015). When the alternative method is applied, one-fourth of households appear to have had more land expropriated than they actually owned in 2013, in some cases by factors over 100. The alternative method also gives a significantly higher rate

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about 22% of expropriated households facing complete land loss.

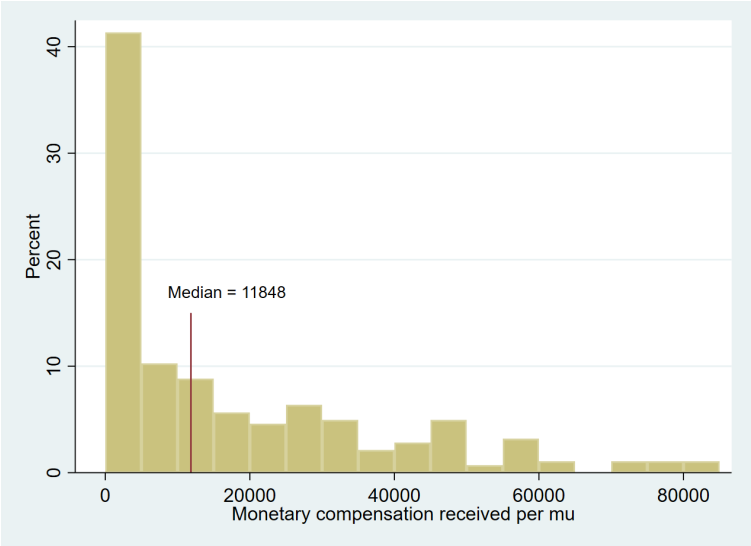

Figure 4: Monetary compensation rate per *mu* among expropriated households

Source: Author calculations from CHFS data, 2015
Notes: Distribution represents the amount received by all expropriated households in the analysis subsample with any monetary compensation where land area is observed. The distribution is shown up to the 95^{th} percentile.

Other explanatory variables include a binary for receipt of any compensation for expropriation and a continuous measure of monetary compensation per *mu* of land expropriated. The majority of households, about 76%, receive some monetary compensation. Only 6.5% of households receive any non-monetary compensation (Table 1).[12] 17% receive no compensation, possibly because these households lack formal land titles. The median monetary compensation received is about 12,000 *yuan* per *mu* (Figure 4), equivalent to roughly 13% of total household assets per adult equivalent (see Table 3).

of households with total expropriation, 29% as compared to 22% using Eq. 1 (see Figure A1). Eq. 1 is bounded at one by design. Furthermore, using data only from 2015 increases the likelihood that the same amount of measurement error applies to both total land area and area expropriated, reducing bias in the resulting proportion. However, 13 households report receiving land as compensation; this measure may not be accurate for those households if the land they received is not the same area as the land expropriated. Neither method fully accounts for any changes in land area that happened between survey waves for reasons other than expropriation. The robustness of the results to the construction of this variable is discussed in Section 5.

[12] Non-monetary compensation may include food or relocation assistance, housing grants, a pension, a change in *hukou* status, or other benefits. As is reflected here, these types of compensation are rare compared to the incidence of monetary compensation.

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Table 1: Distribution of compensation types

Type of compensation	# of households	% of total
Monetary only	318	74.3%
Non-monetary only	22	5.1%
Both monetary and non-monetary	6	1.4%
No compensation	72	16.8%
Other	8	1.8%
Missing	3	0.7%
Total	429	100%
Any monetary compensation	324	75.5%
Any non-monetary compensation	28	6.5%

Source: CHFS data 2013-2015
Notes: Information given is for households reporting expropriation between 2013-2015 in the analysis subsample. See Figure 2 for the selection criteria applied to obtain the analysis subsample.

3.3 Dependent variables and descriptive statistics

I focus on a number of household-level livelihood strategies and income categories as proxies for household welfare. These outcomes are roughly divided into agricultural and non-agricultural outcomes. In 2013, about 67% of households in the analysis sample participate in agriculture, and 40% of household adults report agriculture as their main occupation (Table 2). Consistent with an extremely limited rental market, only 11% of households rent any land. Besides agriculture, about 13% of households report owning a non-agricultural business, and 34% of household adults do some form of non-agricultural work.

Most monetary variables are aggregated from more specific categories of income, assets, or expenditures (see the descriptions in Tables 2-3 for the components of each aggregated variable). Before aggregation, the top and bottom 1% of each input are Winsorized to reduce the impact of outliers on the estimation results.[13] All monetary variables are measured in annual terms at the household level and expressed in contemporary Chinese *yuan*. For households where continuous measures are available only as interval data, values imputed by the survey administrators using interpolation are used.

[13] An x% Winsorization replaces any value below the $\frac{100-x}{2}$ percentile with the $\frac{100-x}{2}$ percentile value, and values above the $100-\frac{100-x}{2}$ percentile with the $100-\frac{100-x}{2}$ percentile value. This process reduces the impact of outliers on estimates without dropping outlying observations entirely, a method that may bias results (Chen and Dixon, 1972; Broderick et al., 2021). Here, $x = 98$. Winsorization is done before aggregation to reduce the overall impact of measurement error and outliers on the resulting aggregated variables.

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Table 2: Descriptions and summary statistics for key variables

Variable	Mean (s.d.)	Definition
Explanatory variables		
% land expropriated	0.42 (0.36)	Area of land expropriated divided by total land owned prior to expropriation (unit: *mu*)
Compensation binary	0.79 (0.41)	Binary for receipt of any compensation for expropriation
Compensation rate per *mu*	18,858.0 (31,197.1)	Total monetary compensation divided by area of land expropriated (unit: *yuan/mu*)
Agricultural livelihood		
Participation in ag.	0.67 (0.47)	Binary for participation in agricultural production
Ag. income per AE	1,891.5 (5,146.4)	Per adult equivalent net income from agriculture last year, including gross income from selling products and cost of inputs
Ag. assets per AE	1,177.1 (2,875.9)	Per adult equivalent agricultural assets, including agricultural machinery and tools but excluding the value of land
Value of food produced per AE	1,551.5 (2,659.6)	Per adult equivalent value of food produced for own-consumption last year, based on estimated market prices
Food spending per AE	5,532.0 (5,235.7)	Per adult equivalent spending on food last year
% adults in ag. labor force	0.39 (0.36)	Proportion of household adults (16+) that list household agriculture as their main occupation, regardless of employment status
Months on household ag.	4.49 (4.39)	Number of months spent by household members on household agricultural production (max: 12)
Production value per *mu*	622.1 (4,837.6)	Value of agricultural production per unit of land (unit: *yuan/mu*)
Cash crop production	0.23	Binary for whether or not the household reports producing cash crops; observed only for households with agricultural production
Staple crop production	0.58	Binary for whether or not the household reports producing staple crops; observed only for households with agricultural production

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Table 2: Descriptions and summary statistics of key variables (continued)

Continued from previous page		
Land rental	0.11	Binary for whether or not the household rents land
Area land rented per AE	2.95	Area of land rented by the household (unit: *mu*)
	(215.0)	
Ag. subsidies per AE	149.3	Amount of agricultural subsidies received per AE,
	(265.7)	including cash and value of in-kind subsidies
Non-agricultural livelihood		
Non-ag. business	0.13	Binary for ownership of non-agricultural business
Bus. income per AE	2,621.2	Income from non-agricultural businesses run or partially
	(11,472.2)	owned by the household
% adults in non-ag.	0.34	Proportion of household adults (16+) that list a
labor force	(0.32)	non-agricultural occupation, regardless of current
		employment status
Wage income per AE	6,771.8	After-tax wages and cash and in-kind bonuses
	(10,831.5)	
% adults unemployed	0.006	Proportion of adults (16+) unemployed out of all
	(0.06)	household adults
Members 16-22 in school	0.49	Proportion of household members 16-22 not working
	(0.48)	because they are in school
N	10,237	

Source: Author's calculations based on CHFS data, 2013.
Notes: Summary statistics are for 10,237 households, measured in 2013. All income, assets, spending, and value of food produced for own-consumption are denominated in *yuan* per AE. The value of land owned or managed is excluded from assets, and the value of compensation for expropriation is excluded from income. Means and standard deviations for all expropriation variables are measured in 2015 and reference expropriation episodes that occurred between 2013 and 2015. All means are calculated using full survey weights, including sampling weights and weights to correct for attrition bias.

To account for differences in household composition and economies of scale in consumption, I calculate per adult equivalent (per AE) income, expenditures, and assets using the modified OECD scale (Hagenaars et al., 1994). Since not all household members have the same demand for goods and income, simple per-capita measures of household income, assets, and consumption may misrepresent comparisons between households with different compositions (Deaton, 2019, pp. 241-44). In the modified OECD scale, weights are assigned to each household member depending on age.[14] Each variable is then divided by the sum of the weights for a given household, resulting in a weighted average representing per adult equivalent income, assets, and so on. The robustness of the main results to the use of different equivalence scales is discussed in Section 5.

[14] A large number of rural Chinese households have temporary migrants. Migrants are included in weights applied to income and assets, but not in weights applied to expenditures. This approach takes into account that migrants contribute to household income and that households often support migrants monetarily, but that migrants are not present in the household to benefit from consumption.

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Table 3: Descriptions and baseline means for control variables

Variable	Mean (s.d.)	Definition
Rural	0.70	Household is in a rural area (binary)
Assets per AE	90,111.0 (151,200.3)	Total household assets per adult equivalent at baseline; includes value of financial products owned by household and value of non-financial assets such as business assets, vehicles, houses, etc.; does not include agricultural or land assets (unit: *yuan* per AE)
Head age	51.6 (12.9)	Age of household head
Head education	*Mode:* Junior high (39%)	Highest education level of household head (categories: Never attended, Primary school, Junior high, High school, Secondary school, College/vocational, Undergraduate degree, Master's degree)
Head gender	0.13	Household head is female (binary)
CCP affiliation	0.009	Household head or head's spouse is a local cadre or Party leader
Child share	0.14 (0.17)	Share of children (0-15) out of all household members
Elderly share	0.14 (0.27)	Share of elderly (65+) out of all household members
Male share	0.52 (0.17)	Share of males out of all household adults (16+)
Main occupation	*Mode:* Household ag. (53%)	The industry of the household's main earner; identified by individually-reported income, where the household head or oldest working adult is substituted as main earner when industry information is not available for the member reporting the highest wage income

Source: Summary statistics are the author's calculations based on CHFS data, 2013
Notes: Summary statistics are for 10,237 households, measured in 2013. All means are calculated using full survey weights, including sampling weights and weights to correct for attrition bias.

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Agricultural income is about 1,900 *yuan* per AE, and the value of food produced for own-consumption is another 1,550 *yuan* per AE (Table 2). Business income per AE is over 2,600 *yuan*, and is heavily right-skewed by a few high-earning households. Wage income is the largest on average, over 6,700 *yuan* per AE, but is also right-skewed. A large number of households report zero wage and/or business income.

4 Methodology

This section presents the estimation and identification strategies used to identify the effects of expropriation. I discuss the choice of estimation, as well as a correction procedure for testing a large number of hypotheses.

4.1 Estimation strategy

I estimate the effect of expropriation on household outcomes using the following ANCOVA (analysis of covariance) specification:

$$Y_{jv,15} = \alpha + \beta_1 P_{jv,15} + \beta_2 C_{jv,15} + \beta_3 ln(MC_{jv,15}) + \eta Y_{jv,13} + \boldsymbol{\gamma} \mathbf{X}_{jv,13} + v_j + \epsilon_{jv,15} \quad (2)$$

where $Y_{jv,15}$ is the outcome for household j in city/village v_j in 2015. $P_{jv,15}$ represents the proportion of land expropriated between time 2013 and 2015. $C_{jv,15}$ is a binary for the receipt of any compensation for expropriation between 2013 and 2015, and $MC_{jv,15}$ is the monetary compensation rate per *mu* of land. The use of ANCOVA estimation entails inclusion of the lagged value of the dependent variable ($Y_{jv,13}$).[15] All equations are estimated using OLS.[16]

Each estimation controls for a variety of household-level characteristics and includes a community-level fixed effect to control for differential *ex ante* expropriation risk. These controls are summarized in Table 3. $\boldsymbol{X_{jv,13}}$ is a vector of controls measured in 2013 (prior to expropriation for the treatment group), including: rural status; logged assets agricultural assets per AE; household head character-

[15] ANCOVA estimation is an alternative to methods such as a difference-in-differences and fixed-effects models. It effectively estimates the effects of the other covariates on the change in the dependent variable over time.

[16] This includes binary outcomes, where estimations are of a linear probability model of a latent variable. OLS is used in these cases to facilitate calculation of approximate linear combinations and meaningful marginal effects. I also estimate probit models for binary dependent variables as a robustness check; use of linear probability models rather than binary choice models for these outcomes does not significantly change the main conclusions of my analysis.

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istics (age, age-squared, gender, marital status, and highest education level completed); household composition variables (share of children (0-15), share of elderly (65+), and share of men among adults 16+); a binary for household CCP affiliation; whether or not the household had at least one migrant; and the occupation of the household's main income earner. Finally, v_j is a city- or village-level fixed effect. The standard errors are clustered at the city/village level.

In the case of continuous measures of income, assets, and expenditures per AE, the left-hand side variable is tranformed using a log-modulus transformation. [17] A log-modulus transformation is different from a natural log transformation only in the case of negative values, where it preserves the sign and relative magnitude of the measure instead of returning a missing value. Like a natural log transformation, a log-modulus transformation preserves zeroes. These characteristics are most important for income measures, where some households have zero or negative agricultural or business income due to high costs.

4.2 Inference

The use of an ANCOVA specification with community-level fixed effects and other controls allows for a causal interpretation of Eq. 2. Given these controls and specification, the identifying assumption for estimation of the effects of expropriation on household outcomes is: within the same community and conditional on other controls, expropriated and non-expropriated households would have had the same change in the outcomes over the survey period if no expropriation had taken place. Causal interpretation depends on quasi-random assignment of expropriation at the household level. Previous research using CHFS data establishes that characteristics at the community level, not the household level, explain whether or not the household is likely to be expropriated (Ma and Mu, 2020). Thus, the inclusion of community-level fixed effects in all estimations controls for *ex ante* differences in expropriation risk. Consistent with the hypothesis that expropriated households are likely to live closer to urban areas, be wealthier, and participate less in agriculture compared to households that are never expropriated, t-tests show pre-expropriation differences in total and agricultural assets per AE and in rural status. I control for these variables in all estimations to fully account for these pre-existing differences between the control and treatment groups.

[17] The transformation takes the form $lm(Y^*) = sign(Y^*) \times ln(|Y^* + 1|)$, where Y^* is per adult equivalent income or assets, calculated as described in Section 3.

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I choose an ANCOVA specification over other panel methods for reasons of efficiency. When autocorrelation of the dependent variable is relatively low (as is usual for variables like rural household income in developing countries), ANCOVA is more efficient than difference-in-differences or fixed-effects methods. Instead of fully adjusting for the differences between groups at baseline, ANCOVA adjusts for this difference depending on the autocorrelation of the dependent variable, and thus has efficiency gains in cases of lower autocorrelation (McKenzie, 2012; Frison and Pocock, 1992). Assuming that autocorrelation is constant over time and that the treatment and control groups have the same autocorrelation, difference-in-differences is only preferred in cases where autocorrelation exceeds $\frac{1}{m+1}$, where m is the number of baseline observations. In this case, there are efficiency gains from using ANCOVA over differences-in-differences or fixed effects models if the autocorrelation of the outcomes is less than 0.5. The continuous outcomes used in this analysis have lag-one autocorrelations ranging from 0.11 to 0.50, making ANCOVA the appropriate choice. Some binary outcomes (non-agricultural business participation, proportion of adults in the non-agricultural labor force, and the proportion of members 16-22 in school) have autocorrelations between 0.50 and 0.55; efficiency losses from the use of ANCOVA in these cases are minimal.

There are two additional challenges to correct inference: attrition bias and a high probability of a Type I error. First, I address household attrition between waves by applying inverse probability weights. Of the 12,117 households that fit the criteria for inclusion in the analysis sample in 2013, 1,880 (15.5%) attrite by 2015 (Figure 2). In addition to sampling weights, I address attrition bias by applying weights to 2015 observations that represent the inverse probability of attrition between waves.[18] The effectiveness of this approach in addressing attrition bias may be limited if there is a strong association between attrition from the survey and expropriation (Wooldridge, 2007).

Second, the likelihood of at least one Type I error (a false rejection of the null hypothesis) increases with the number of hypotheses being tested (Anderson, 2008; List et al., 2019; Romano et al., 2010; Glennerster and Takavarasha, 2013, p. 366-67). I use Anderson's sharpened q-values to control for the false discovery rate (the proportion of false rejections) in each set of results

[18] I calculate inverse probability weights using a probit model to estimate the probability of being observed in 2015 on characteristics in 2013. Weighting observed households by the inverse probability of being observed upweights households that most resemble households that attrited from the survey. This method produces consistent estimates of the effects of expropriation under appropriate assumptions (Wooldridge, 2002, 2007). Covariates used in the estimation of the inverse probability weights to correct for attrition include baseline controls, lagged outcome variables, and a categorical measure of willingness to participate in a follow-up survey by phone as an indicator of survey quality. See Table A1 for probit model results used to calculate the inverse probability weights.

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(Anderson, 2008). This approach trades a small number of Type I errors for greater power compared to controlling for the familywise error rate (the probability of rejecting at least one true null) (List et al., 2019). All significance stars on table coefficients are based on sharpened q-values, rather than on the original p-values. Theoretically, sharpened q-values may adjust p-values downwards in a few special cases. However, there is no case in this analysis in which using sharpened q-values makes a coefficient appear statistically significant at a level not indicated by the original p-value.

5 Results

5.1 The household-level welfare effects of expropriation

Estimations of Eq. 2 show a sharp decrease in agricultural activity after expropriation, particularly in cases of complete or uncompensated expropriation. Specifically, land loss from expropriation causes decreases in the probability of participation in agricultural production, as well as reductions in agricultural assets per AE, the logged value of food produced for own-consumption per AE, and months spent on household agriculture (Table 4).

The linear combinations at the bottom of each table show how these effects vary with the amount of land expropriated and the level of compensation. Households with the median proportion of land expropriated (about 31% of land) with no monetary compensation reduce their agricultural participation by 7 percentage points, while households that lose all their land become 23 percentage points less likely to participate relative to a mean of 66%. Linear combinations for uncompensated households with total expropriation are similarly larger by a factor of about three for agricultural assets and value of food produced for own-consumption per AE. Notably, partially expropriated households that receive the median rate of compensation do not significantly reduce any measure of agricultural activity.

https://doi.org/10.13140/RG.2.2.28237.72168

Table 4: Effects of expropriation on household agriculture

	Participates in ag. production	Ln(Ag. income per AE)	Ln(Ag. assets per AE)	Ln(Food spending per AE)	Ln(Value of food produced)	% adults in ag. labor force	Months spent on household ag.
ANCOVA coefficients							
Prop. land expropriated	-0.232***	0.033	-1.884***	-0.214	-1.432**	-0.079	-2.088***
	(0.056)	(0.750)	(0.531)	(0.135)	(0.481)	(0.043)	(0.619)
Any comp. received	-0.07	-1.345	-0.125	0.119	0.142	0.013	-0.289
(0.078)	(0.986)	(0.639)	(0.218)	(0.626)	(0.075)	(0.753)	
ln(Comp. per *mu*)	0.015	0.139	0.088	0.007	0.029	0.001	0.086
	(0.008)	(0.111)	(0.073)	(0.019)	(0.062)	(0.007)	(0.078)
Linear combinations (median prop. of land)							
No comp.	-0.071***	0.01	-0.580***	-0.066	-0.441**	-0.024	-0.643***
	(0.017)	(0.231)	(0.164)	(0.041)	(0.148)	(0.013)	(0.190)
Median comp.	-0.002	-0.029	0.122	0.115	-0.026	0.002	-0.129
	(0.036)	(0.451)	(0.320)	(0.076)	(0.254)	(0.023)	(0.303)
Linear combinations (all land)							
No comp.	-0.232***	0.033	-1.884***	-0.214	-1.432**	-0.079	-2.088***
	(0.056)	(0.750)	(0.531)	(0.135)	(0.481)	(0.043)	(0.619)
Median comp.	-0.163***	-0.006	-1.182***	-0.033	-1.017***	-0.053	-1.575***
	(0.036)	(0.330)	(0.358)	(0.105)	(0.319)	(0.032)	(0.438)
Mean $Y_{jp,t}$	0.66	0.94	3.75	8.20	3.83	0.34	4.57
N 9952	7544	9894	9952	9953	9948	9872	
Adj. R^2	0.420	0.111	0.303	0.222	0.330	0.368	0.311

Source: Author's calculations from CHFS data 2013-2015.

Notes: All coefficients are ANCOVA (OLS) estimates of Eq. 2. All per AE measures are calculated using the modified OECD scale (see Section 3). Linear combinations are evaluated at the median proportion of land expropriated (0.31) and when all land is expropriated, for both uncompensated expropriation and at the median logged compensation rate per *mu* (9.38, representing an average compensation rate of 11,848 *yuan* per *mu* among households that received monetary compensation). Standard errors in parentheses.

* $0.10 > p \geq 0.05$, ** $0.05 > p \geq 0.01$, *** $0.01 > p$, where p is the adjusted p-value using sharpened q-values (Anderson, 2008).

https://doi.org/10.13140/RG.2.2.28237.72168

Table 5: Effects of expropriation on non-agricultural employment

	Household owns non-ag. business	Ln(Bus. income per AE)	% adults in non-ag. labor force	Ln(Wage income per AE)	% members 16-22 in school	% household adults unemployed
ANCOVA coefficients						
Prop. land expropriated	-0.061	-0.427	-0.003	0.995	-0.073	-0.01
	(0.058)	(0.573)	(0.044)	(0.631)	(0.177)	(0.013)
Any comp. received	0.033	0.543	0.079	-1.528	0.278	0.024
	(0.054)	(0.653)	(0.083)	(0.810)	(0.159)	(0.015)
ln(Comp. per *mu*)	0.002	0.006	-0.008	0.059	-0.026	-0.001
	(0.006)	(0.069)	(0.008)	(0.091)	(0.020)	(0.002)
Linear combinations (median prop. of land)						
No comp.	-0.019	-0.131	-0.001	0.306	-0.023	-0.003
	(0.018)	(0.176)	(0.014)	(0.194)	(0.055)	(0.004)
Median comp.	0.034	0.468	0.007	-0.664	0.015	0.01
	(0.024)	(0.275)	(0.024)	(0.438)	(0.086)	(0.009)
Linear combinations (all land)						
No comp.	-0.061	-0.427	-0.003	0.995	-0.073	-0.01
	(0.058)	(0.573)	(0.044)	(0.631)	(0.177)	(0.013)
Median comp.	-0.009	0.172	0.005	0.025	-0.035	0.003
	(0.045)	(0.470)	(0.032)	(0.481)	(0.173)	(0.008)
Mean $Y_{jp,t}$	0.16	1.19	0.35	4.49	0.59	0.02
N	9952	9785	9949	9132	1995	9952
Adj. R^2	0.363	0.347	0.430	0.232	0.351	0.036

Source: Author's calculations from CHFS data 2013-2015.

Notes: All coefficients are ANCOVA (OLS) estimates of Eq. 2. All per AE measures are calculated using the modified OECD scale (see Section 3). Linear combinations are evaluated at the median proportion of land expropriated (0.31) and when all land is expropriated, for both uncompensated expropriation and at the median logged compensation rate per *mu* (9.38, representing an average compensation rate of 11,848 *yuan* per *mu* among households that received monetary compensation). Standard errors in parentheses.

* $0.10 > p \geq 0.05$, ** $0.05 > p \geq 0.01$, *** $0.01 > p$, where p is the adjusted p-value using sharpened q-values (Anderson, 2008).

https://doi.org/10.13140/RG.2.2.28237.72168

The cumulative effects of expropriation on food spending and the value of food produced for own-consumption raise questions about short-term household food security after expropriation. Among households with agricultural production in 2013, an average of 30% of the value of food consumed by the household is produced by the household itself. While the proportion of land expropriated causes a reduction in the value of food produced for own-consumption by the household per AE, there is no corresponding increase in spending on purchased food (Table 4). When the median proportion of land is expropriated (31%), any positive level of compensation returns the household's value of food produced to its pre-expropriation levels. When all land is expropriated, the value of food produced by the household is reduced by 36-76% of the mean per AE, depending on the level of monetary compensation. Spending on purchased food does not increase at any proportion of land expropriated or level of monetary compensation, indicating a net decrease in the value of food consumed per AE.

Contrary to descriptive findings in the literature, there is no evidence that households increase their off-farm engagement after expropriation (Table 5). One possibility that cannot tested with these data is that households do not increase the proportion of members working in off-farm work, but those already working in such jobs simply increase their time spent on such employment. This hypothesis is consistent with the positive (but inconsistent) effect of expropriation on wage income, but would require more information to be conclusive. Nevertheless, there is no evidence of greater off-farm employment on the extensive margin; that is, no evidence that more adults work off-farm, although those already doing so many increase hours worked in off-farm labour. This finding may be driven by constraints imposed by under-developed local labor markets.

Despite decreases in agricultural activity, there is no significant decrease in agricultural income from expropriation. The data available are not sufficient to evaluate why that is.[19] Table A2 shows ANCOVA results for a set of outcomes that represent potential mechanisms by which the household maintains agricultural income post-expropriation. There is no evidence that households rent more land, become more likely to produce cash crops or a greater crop value per unit of land, or hire fewer workers to reduce costs. There is some indication that households that are expropriated are less likely to produce staple crops. These effects do more to explain why the value of food for own-

[19] The lack of significance is partially attributable to high standard errors and relatively low explanatory power of the estimation for logged agricultural income per AE, even with the inclusion of a lagged dependent variable.

https://doi.org/10.13140/RG.2.2.28237.72168

consumption decreases than they do to explain agricultural income. Agricultural subsidies decrease following expropriation, but subsidies are not included in agricultural income. One explanation that cannot be tested with these data is that expropriated land tends to be unproductive, low-quality land relative to land that is unlikely to be expropriated. Alternatively, households may purchase better-quality seed or buy fertilizer or other productive investments with compensation that are not observed in these data.

5.2 Does migration increase resilience to expropriation shocks?

Research on migration in China indicates that sending a migrant provides income diversification for households and helps to protect against shocks (Démurger et al., 2010; Zhao and Barry, 2014). Descriptive statistics on expropriated households before and after expropriation show that households with higher income post-expropriation are those that relied less on agriculture to begin with, including migrant-sending households (Hui et al., 2013). This finding is consistent with the literature on migration as a shock-coping mechanism, which typically finds that sending households are more resilient to shocks (Gröger and Zylberberg, 2016). Migrant-sending prior to expropriation may therefore help households to shift from agricultural to non-agricultural employment more quickly or effectively than other households.

Results in Tables A3-A4 support the assertion that migrant-sending households are better-positioned to respond to an expropriation shock. I re-estimate Eq. 2 for only those households that had at least one migrant member at first observation ($N = 1,928$). The median sending household has a less severe expropriation experience than other expropriated households, with only 23% of land expropriated and 13,500 *yuan* in compensation per *mu* at the median. Significance is limited by the smaller sample size, but negative coefficients relating to agricultural production are typically larger than for the full sample, indicating even greater decreases in agricultural activity for these households. Unlike other expropriated households, a significant proportion of sending households reduce the proportion of adults working in household agriculture in addition to reducing the time spent on agriculture. Also in contrast to the results for all households, linear combinations for food spending per AE after both partial and total expropriation for sending households are all positive (but insignificant). These positive coefficients may indicate that total value of food consumed does not fall for migrant-sending expropriated households as it does for other expropriated households.

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Although most remain insignificant, several coefficients on non-agricultural activities change sign to positive, or are larger positives than the results for all households (although none of the linear combinations are significant). For example, the coefficient on the proportion of land expropriated for logged wage income per AE in sending households is more than triple the coefficient for all households. These results indicate that households that send migrants *ex ante* are better able to fully shift away from agriculture toward wage work or self-employment, and therefore are more resilient to expropriation.

5.3 Robustness to key variable construction and alternate weights

I verify that the main results of this analysis are robust to changes in the construction of key variables and the use of alternate population weights. Tables are excluded for brevity, but are available from the author on request.[20]

The main robustness tests for variable construction decisions vary the scale used to calculate per adult equivalent measures. The simplest alternative to the modified OECD scale used for the main results is a per-capita measure, in which all the weights for each household member are reset to one. This scale essentially assumes that all household members have the same marginal demand for consumption and that there are no economies of scale in household income, assets, and expenditures. A second alternative is a square-root scale (OECD, 2008), which accounts for economies of scale but not differences in consumption demand by age. Changing the scale primarily affects the results for outcomes measured in per AE terms, but also causes small variations in results for other outcomes due to the use of per AE control variables. The modified OECD scale used in the main specification weights children less heavily than adults, whereas the change in the denominator of the square root scale from an additional household member is the same regardless of the additional member's age. The coefficients obtained from estimation using the square root scale are therefore larger in most cases, albeit by only a small amount. In contrast, the coefficients on results for simple average outcomes per person are slightly smaller than the results for the preferred estimations, since these measures take into account neither household economies of scale nor differences in marginal demand for consumption goods by age. Regardless of which scale is used, differences from the preferred results are minimal, usually within $\pm$ 0.1 compared to means for logged per AE variables that range

[20] Tables are excluded for brevity, but are available from the author on request.

https://doi.org/10.13140/RG.2.2.28237.72168

from 0.5 to 7.8.

The second set of robustness specifications changes the method of calculating the proportion of land expropriated. I construct the alternative proportion of land expropriated as $P = \frac{L'_{2015}}{L_{2013}}$ (see Figure A1 for a comparison of the distributions for these two measures). If the alternate measure over-estimates the proportion of land expropriated, then estimates of the effects of expropriation using this measure will tend to under-estimate the marginal effects. Using this measure, there are still significant negative effects of expropriation measured for household participation in agriculture, months spent working on agriculture, and production of staple crops. Coefficients on proportion of land expropriated for logged agricultural assets per AE and logged own-food production per AE remain relatively large and negative, but are no longer significant.

I also check for robustness by removing from the analysis the 13 expropriated households that received land as compensation. Including these households will tend to under-estimate the proportion of land expropriated on average, and thus over-estimate the marginal effects of a change in the proportion of land lost. When those households are omitted from the sample, estimates are nearly identical to those obtained with the full analysis sample. The exceptions are logged business and wage income per AE, where the coefficients are generally smaller but remain insignificant. The differences suggest that households that receive land as compensation increase their non-agricultural business income and wage income by more than other households after expropriation. However, more general conclusions about households receiving land compensation are not possible given the small size of the group and the lack of information about how much land was received as compensation.

The third and final set of robustness specifications ensures that applying both sampling and inverse probability weights does not drive the results. The main results are calculated with weights that adjust for both sampling methodology and attrition bias. I re-estimate Eq. 2 using only weights to correct for sampling; only weights to correct for attrition; and no weights at all. The main results are robust to the choice of weights used in the analysis; in most cases, the coefficients in the preferred specification are smaller than those estimated using alternate weights.

https://doi.org/10.13140/RG.2.2.28237.72168

6 Conclusion

I use nationally-representative data on over 10,000 Chinese households from 2013-2015 to investigate the welfare effects of land expropriation at the household level. Measures of agricultural participation and production, non-agricultural employment, and earned income serve as indicators for welfare. I use ANCOVA estimation, which controls for lagged outcomes, and quasi-random assignment of expropriation (independent of household decisions and controlling for community-level characteristics) to causally identify these effects.

I find that affected households reduce their agricultural activity following expropriation, and significantly reduce the value of food produced and consumed per AE. These reductions are offset by sufficiently high monetary compensation in the case of partial expropriation, but remain significant for households that lose all their land. Total expropriation reduces the value of food produced for own-consumption per AE by between 36-76% of the mean value, depending on how much compensation is given. The reduction is likely driven by decreased staple crop production, and is not followed by higher food spending in at least the first two years after expropriation. This decrease in the value of food consumed may have long-term implications for household food security, with particularly detrimental effects on households that relied more heavily on self-produced food prior to expropriation. Low food security can lead to poorer health and educational outcomes (Ling, 2001; Hannum et al., 2014), particularly for children (Yang et al., 2021); the costs of such long-term effects should be considered in cost-benefit analyses of specific expropriation projects.

Contrary to previous work on this topic for China, I find no evidence that expropriated households successfully shift to off-farm labor or non-agricultural business ownership within two years of experiencing expropriation. Due to constraints on household responses to expropriation imposed by incomplete labor markets, this may indicate that households lack local off-farm employment, or that constraints on sending migrants to urban areas for work after expropriation are too high for these households. Policies to improve local labor market conditions in areas with high rates of expropriation could potentially increase household off-farm engagement and earned income, thus increasing long-term welfare for expropriated households.

However, I do find that households that have sent migrants prior to expropriation are more able to shift to off-farm work and reliance on non-agricultural income, making them more resilient

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to shocks. This follows on a literature relating migration to shock resilience, and emphasises that while urban China has a wealth of employment opportunities, the labour market in rural China is still dominated by agriculture.

These findings suggest several ways that targeted policies could improve expropriated households' welfare. First, increasing monetary compensation to households would help to maintain agricultural production, particularly in cases of partial expropriation. Compensation should be awarded based on all expected costs of expropriation, not just lost agricultural production on the land. Second, increased food assistance as part of compensation would address reduced food security in expropriated households. Finally, in cases of total expropriation, continued agricultural production is contingent on the availability of land to rent; no increase in land rental is found, suggesting that continued development of rural land rental markets might also help. Further research in this area should evaluate the extent to which such targeted policies improve household welfare and outcomes following land expropriation.

https://doi.org/10.13140/RG.2.2.28237.72168

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Appendix A Additional figures and tables

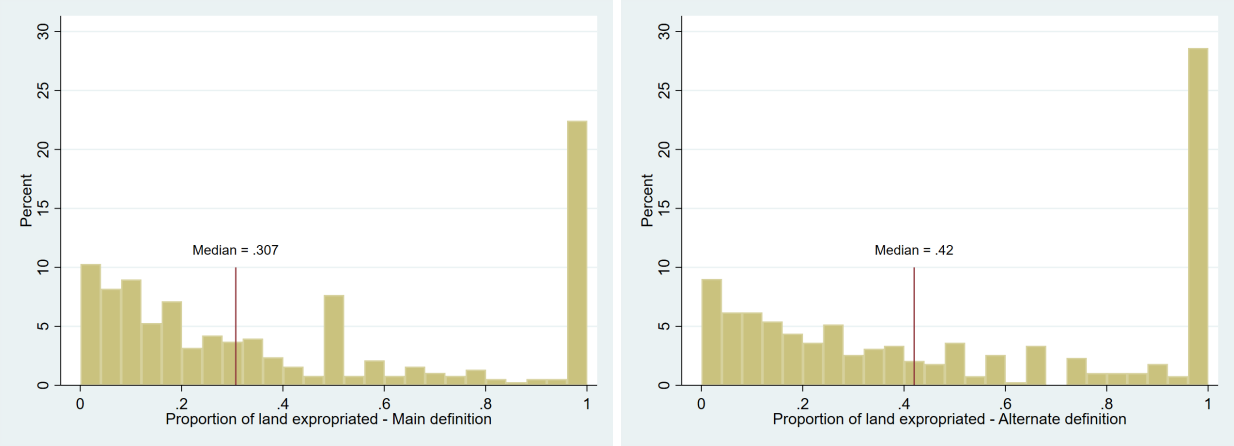

Figure A1: Distribution of proportion of land expropriated - Main and alternate definitions

Source: CHFS 2013-2015

Notes: Based on calculations of the proportion of land expropriated using Eq. 1 (left) and $P = \frac{L'_{2015}}{L_{2013}}$ (right). The main definition is preferred due to concerns that reporting error may be magnified by using land areas reported in two separate waves.

https://doi.org/10.13140/RG.2.2.28237.72168

Table A1: Predictors of attrition by 2015

Covariate	**Pr(Household attrited by 2015)**	**Pr(Household attrited by 2017)**
Household's willingness to participate in follow-up		
Comparison: Very willing		
Willing	0.107***	0.116***
	(0.037)	(0.032)
Generally willing	0.191***	0.231***
	(0.045)	(0.040)
Reluctant	0.262***	0.327***
	(0.096)	(0.089)
Very reluctant	0.592***	0.610***
	(0.119)	(0.119)
Household is affiliated with CCP	-0.413*	-0.364**
	(0.223)	(0.173)
Land per AE	0.014**	0.017***
	(0.005)	(0.005)
Household is rural	-0.364***	-0.364***
	(0.041)	(0.035)
Ln(Assets per AE)	-0.017	-0.023**
	(0.010)	(0.009)
Ln(Ag. assets per AE)	-0.004	-0.003
	(0.009)	(0.008)
Share of elderly	0.018	0.142**
	(0.079)	(0.066)
Head age	-0.008***	-0.012***
	(0.002)	(0.001)
Head is female	0.109**	0.144***
	(0.046)	(0.042)
Head is married	-0.227***	-0.192***
	(0.050)	(0.045)
Household has migrant	0.096**	0.135***
	(0.045)	(0.038)
Share of children	-0.149	-0.191**
	(0.102)	(0.088)
Share of males out of adults	0.192**	0.160*
	(0.094)	(0.083)
Household was expropriated prior to 2013	-0.305***	-0.254***
	(0.074)	(0.062)
Years since last expropriated (if ever)	0.003	-0.002
	(0.008)	(0.007)
Ln(Ag. income per AE)	-0.001	-0.005
	(0.004)	(0.003)
Ln(Value of food prod. per AE)	-0.041***	-0.035***
	(0.005)	(0.005)
Ln(Food spending per AE)	0.006	0.019
	(0.013)	(0.012)
% adults in ag. labor force	-0.161	-0.052
	(0.093)	(0.078)

Continued on next page

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Table A1: Predictors of attrition by 2015 and by 2017 (continued)

Continued from previous page			
Household participates in ag.		-0.117	-0.088
		(0.080)	(0.067)
Household owns non-ag. business		-0.098	-0.100
		(0.095)	(0.083)
% adults in non-ag. labor force		-0.021	-0.102
		(0.089)	(0.080)
% adults unemployed		-0.101	-0.300
		(0.290)	(0.265)
% members 16-22 in school		-0.021	0.001
		(0.049)	(0.043)
Ln(Business income per AE)		0.012	0.007
		(0.010)	(0.009)
Ln(Wage income per AE)		-0.007	-0.001
		(0.005)	(0.004)
Binary for land rental		-0.126**	-0.150***
		(0.063)	(0.051)
Area of land rented per AE		0.000	-0.000
		(0.000)	(0.000)
Ln(Ag. production value per *mu*)		0.004	0.005
		(0.010)	(0.008)
Cash crop production		-0.047	-0.077*
		(0.052)	(0.042)
Staple crop production		0.022	-0.030
		(0.069)	(0.057)
Constant		0.191	0.920***
		(0.246)	(0.213)
	N	12,004	12,043

Source: Author calculations from CHFS 2013-2017

Notes: Standard errors in parentheses. A categorical variable for the occupation of the household's main earner is also included as a covariate; F-test statistics and p-values for the joint significance of all occupation categories are at the bottom of the table.

* $0.10 > p \geq 0.05$, ** $0.05 > p \geq 0.01$, *** $0.01 > p$, where p is the adjusted p-value using sharpened q-values (Anderson, 2008).

https://doi.org/10.13140/RG.2.2.28237.72168

Table A2: Effects of expropriation on other agricultural outcomes

	Household rents land	Area rented per AE	Ln(Ag. subsidies per AE)	Cash crop production	Staple crop production	Ln(Value ag. production per *mu*)	Number ag. workers hired
ANCOVA coefficients							
Prop. land expropriated	-0.055	-0.272	-1.305***	-0.055	-0.234***	-0.217	0.065
	(0.038)	(0.327)	(0.355)	(0.049)	(0.053)	(0.860)	(0.390)
Any comp. received	-0.056	0.657	-0.303	-0.009	-0.083	-0.445	-0.499
	(0.048)	(0.845)	(0.435)	(0.061)	(0.089)	(0.593)	(0.819)
ln(Comp. per *mu*)	0.008	-0.076	0.073	0.002	0.019	0.067	0.001
	(0.005)	(0.080)	(0.042)	(0.007)	(0.009)	(0.071)	(0.081)
Linear combinations (median prop. of land)							
No comp.	-0.017	-0.084	-0.402***	-0.017	-0.072***	-0.067	0.02
	(0.012)	(0.101)	(0.109)	(0.015)	(0.016)	(0.265)	(0.120)
Median comp.	0.005	-0.136	-0.022	-0.007	0.026	0.117	-0.469
	(0.021)	(0.177)	(0.173)	(0.032)	(0.035)	(0.312)	(0.268)
Linear combinations (all land)							
No comp.	-0.055	-0.272	-1.305***	-0.055	-0.234***	-0.217	0.065
	(0.038)	(0.327)	(0.355)	(0.049)	(0.053)	(0.860)	(0.390)
Median comp.	-0.033	-0.324	-0.925***	-0.045	-0.136***	-0.033	-0.424
	(0.020)	(0.218)	(0.252)	(0.027)	(0.039)	(0.617)	(0.265)
Mean $Y_{jp,t}$	0.12	0.86	2.37	0.18	0.49	2.71	0.86
N	9931	9939	9776	7570	7570	8116	9919
Adj. R^2	0.151	0.055	0.359	0.261	0.424	0.184	0.013

Source: Author's calculations from CHFS data 2013-2015.

Notes: All coefficients are ANCOVA (OLS) estimates of Eq. 2. All per AE measures are calculated using the modified OECD scale (see Section 3). Linear combinations are evaluated at the median proportion of land expropriated (0.31) and when all land is expropriated, for both uncompensated expropriation and at the median logged compensation rate per *mu* (9.38, representing an average compensation rate of 11,848 *yuan* per *mu* among households that received monetary compensation). Standard errors in parentheses.

* $0.10 > p \geq 0.05$, ** $0.05 > p \geq 0.01$, *** $0.01 > p$, where p is the adjusted p-value using sharpened q-values (Anderson, 2008).

https://doi.org/10.13140/RG.2.2.28237.72168

Table A3: Effects of expropriation on household agriculture (migrant-sending households only)

	Household participates in ag. production	Ln(Ag. income per AE)	Ln(Ag. assets per AE)	Ln(Food spending per AE)	Ln(Value of food produced)	% of adults in ag. labor force	Months spent on household ag.
ANCOVA coefficients							
Prop. land expropriated	-0.598***	-5.098	-3.605*	0.289	-3.874***	-0.348*	-4.617**
	(0.159)	(3.613)	(1.538)	(0.750)	(0.934)	(0.129)	(1.557)
Any comp. received	0.012	-3.333	-0.452	0.916	0.649	0.038	2.305
	(0.172)	(1.961)	(2.082)	(0.818)	(1.303)	(0.234)	(1.522)
ln(Comp. per *mu*)	0.01	0.717	0.117	-0.08	0.041	0.009	-0.22
	(0.018)	(0.324)	(0.238)	(0.077)	(0.136)	(0.024)	(0.156)
Linear combinations (median prop. of land)							
No comp.	-0.138***	-1.177	-0.832*	0.067	-0.894***	-0.080*	-1.066**
	(0.037)	(0.834)	(0.355)	(0.173)	(0.215)	(0.030)	(0.359)
Median comp.	-0.029	2.312	-0.174	0.217	0.141	0.039	-0.85
	(0.079)	(1.378)	(0.695)	(0.198)	(0.714)	(0.063)	(0.557)
Linear combinations (all land)							
No comp.	-0.598***	-5.098	-3.605*	0.289	-3.874***	-0.348*	-4.617**
	(0.159)	(3.613)	(1.538)	(0.750)	(0.934)	(0.129)	(1.557)
Median comp.	-0.489**	-1.609	-2.947	0.439	-2.838*	-0.228**	-4.402**
	(0.154)	(1.858)	(1.445)	(0.639)	(1.125)	(0.078)	(1.343)
Mean $Y_{jp,t}$	0.73	0.80	4.19	8.10	4.34	0.35	5.27
N	1928	1421	1915	1928	1928	1925	1914
Adj. R^2	0.374	0.148	0.288	0.188	0.315	0.310	0.291

Source: Author's calculations from CHFS data 2013-2015.

Notes: All coefficients are OLS estimates of Eq. 2. All per AE measures are calculated using the modified OECD scale (see Section 3). Linear combinations are evaluated at the median proportion of land expropriated (0.23) and when all land is expropriated, for both uncompensated expropriation and at the median logged compensation rate per *mu* (9.51, representing an average compensation rate of 13,500 *yuan* per *mu* among households that received monetary compensation). Standard errors in parentheses.

* $0.10 > p \geq 0.05$, ** $0.05 > p \geq 0.01$, *** $0.01 > p$, where p is the adjusted p-value using sharpened q-values (Anderson, 2008).

https://doi.org/10.13140/RG.2.2.28237.72168

Table A4: Effects of expropriation on household non-agricultural employment (migrant-sending households only)

	Household owns non-ag. business	Ln(Bus. income per AE)	% of adults in non-ag. labor force	Ln(Wage income per AE)	% members 16-22 in school	% of adults unemployed
ANCOVA coefficients						
Prop. land expropriated	0.148	1.13	0.177	3.557	-0.688	0.02
	(0.277)	(2.104)	(0.117)	(2.032)	(0.436)	(0.057)
Any comp. received	-0.019	-0.109	0.015	-1.583	-0.378*	0.118
	(0.067)	(0.640)	(0.157)	(1.725)	(0.159)	(0.082)
ln(Comp. per *mu*)	0.007	0.004	0	0.004	0.084*	-0.014
	(0.010)	(0.090)	(0.015)	(0.232)	(0.030)	(0.009)
Linear combinations (median prop. of land)						
No comp.	0.034	0.261	0.041	0.821	-0.159	0.005
	(0.064)	(0.486)	(0.027)	(0.469)	(0.101)	(0.013)
Median comp.	0.082	0.191	0.057	-0.721	0.261	-0.011
	(0.092)	(0.791)	(0.060)	(1.192)	(0.197)	(0.011)
Linear combinations (all land)						
No comp.	0.148	1.13	0.177	3.557	-0.688	0.02
	(0.277)	(2.104)	(0.117)	(2.032)	(0.436)	(0.057)
Median comp.	0.196	1.06	0.193	2.015	-0.268	0.005
	(0.250)	(1.994)	(0.093)	(2.149)	(0.465)	(0.051)
Mean $Y_{jp,t}$	0.13	0.96	0.40	5.67	0.39	0.02
N	1928	1905	1926	1651	430	1927
Adj. R^2	0.303	0.332	0.255	0.152	0.379	0.056

Source: Author's calculations from CHFS data 2013-2015.

Notes: All coefficients are OLS estimates of Eq. 2. All per AE measures are calculated using the modified OECD scale (see Section 3). Linear combinations are evaluated at the median proportion of land expropriated (0.23) and when all land is expropriated, for both uncompensated expropriation and at the median logged compensation rate per *mu* (9.51, representing an average compensation rate of 13,500 *yuan* per *mu* among households that received monetary compensation). Standard errors in parentheses.

* $0.10 > p \geq 0.05$, ** $0.05 > p \geq 0.01$, *** $0.01 > p$, where p is the adjusted p-value using sharpened q-values (Anderson, 2008).