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Mobile phone network expansion and agricultural income: A panel study

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Abstract

This study examines how the expansion of mobile phone networks affects rural development in Mongolia. The database is a detailed household panel survey with four waves implemented in western Mongolia, spanning the 2012–2021 period, which we combine with data on mobile phone towers. Our identification strategy exploits the uneven roll-out of mobile phone networks across rural areas over time. Using a two-way fixed effects approach, we show that network expansion strongly and significantly increases total household income of pastoralist households. The effect is driven by increased income from agriculture, particularly by higher producer prices for animal byproducts, improved access to transfer income, and increased household mobility. The expansion of mobile phone networks decreases income diversification among pastoralists. Instead, households specialize in agriculture. While findings suggest that investments in telecommunication infrastructure can help rural households to sustain a livelihood in the agricultural sector, the specialization in agriculture may increase households' vulnerability to climate change.

KEYWORDS
ICT, income diversity, mobile phone networks, Mongolia, rural development

JEL CLASSIFICATION
O12, O13, O33

1 | INTRODUCTION

The infrastructure gap between wealthier and poorer regions as well as between urban and rural areas is a major cause of increasing economic disparities within low- and middle-income countries (LMICs) (e.g., Andrés et al., 2015; Pearsall et al., 2021; World Bank, 2018). Poor infrastructure and a lack of opportunities in rural areas have contributed to rapid urbanization since the mid-20th century, especially in LMICs (United Nations, 2019). With the expansion of information and communication technology (ICT) since the 1990s, it is hoped that wireless technology can stimulate economic development in remote areas (Niebel, 2018; World Bank, 2020). Mobile devices enable households that are not connected by landlines to communicate over distance and access information. Affordable smartphones led to massive growth in the number of internet users. Despite the potential those technological advancesw may offer for rural development, there is a gap in research that empirically quantifies the effects of ICT on socio-economic outcomes.

This study provides novel evidence on the effects of mobile phone network expansion on income and income diversity of rural households in western Mongolia. The identification strategy exploits spatial and temporal variation in the roll-out of mobile phone networks across districts. Our analysis builds on a household panel survey with four waves that we implemented in three western Mongolian provinces between 2012 and 2021, which featured very low panel attrition. We complement the detailed socio-economic data with data on the location of mobile phone towers between 2012 and 2021 obtained from all Mongolian network providers. Exploiting the longitudinal dimension of the data, we apply a two-way fixed effects approach that controls for district and time-specific characteristics as well as district-specific linear time trends.

Results show that the expansion of mobile phone networks significantly increases the income of households in the survey area. The effect is driven by increased income from agriculture, particularly by higher producer prices for animal byproducts, improved access to transfer income, and increased household mobility. The expansion of networks decreases income diversification among rural pastoralists. Instead, households specialize in agriculture.

Our study expands the state of knowledge in various ways. First, the existing literature studies the impacts of ICT on a narrow set of socio-economic outcomes. Several studies document that the adoption of ICT and the expansion of mobile phone coverage increases labor supply (Bahia et al., 2020; Muto & Yamano, 2009), improves market efficiency (Aker, 2010; Jensen, 2007), and raises agricultural output (Kaila & Tarp, 2019) in LMICs. Yet, little is known about how ICT development affects the income strategies of rural households. Our study is the first to use household panel survey data to explore the impact of ICT on both income diversity and various income sources. To the best of our knowledge, there is only one existing study, by Leng et al. (2020), that investigates the impact of ICT on the income diversification of rural households. Analyzing cross-sectional data of the China Labour-force Dynamics Survey, Leng et al. find that ICT adoption, defined as whether a household possesses a smartphone or a personal computer, increases households' income diversity.

Second, most existing studies face data limitations that narrow the time window of analysis to a few years. For instance, existing studies investigating the effects of mobile phone networks on rural development consider a time period of 3 years (Muto & Yamano, 2009), 4 years (Labonne & Chase, 2009), and 6 years (Beuermann et al., 2012). In contrast, we examine the effects of ICT on rural development over a 9-year time span, which allows us to exploit plenty of variation in network expansion over time and space.

Third, methodological challenges make estimating effect sizes difficult in some existing studies. For instance, existing studies investigating the effects of mobile phone coverage focus on empirical contexts in which the mobile phone ownership rate among the survey population is as low as 4%–12% (Muto & Yamano, 2009), 2%–36% (Beuermann et al., 2012), and 16%–50% (Labonne & Chase, 2009). In these studies, results are driven by the group of early adopters, which makes it difficult to generalize results. In addition, the small group of treated households reduces statistical power in intent-to-treat settings. In contrast, mobile phone ownership is almost universal among the Mongolian survey population studied here.

Fourth, while existing studies analyzing the effect of ICT on household income focus on crop farming (Aker & Fafchamps, 2015; Aker & Ksoll, 2016; Kaila & Tarp, 2019; Labonne & Chase, 2009; Leng et al., 2020; Muto & Yamano, 2009) and the fishery sector (Jensen, 2007), our study is the first to provide evidence on the impact of ICT on households involved in animal husbandry.

The remainder of this study is organized as follows. Section 2 introduces the conceptual framework. Section 3 introduces the Mongolian context, followed by a description of the data in Section 4. Section 5 outlines the empirical approach. Results and robustness checks are reported in Section 6. Section 7 concludes.

2 | CONCEPTUAL FRAMEWORK

2.1 | The link between access to ICT and agricultural productivity

Examining the effects of improved infrastructure on economic development in rural areas is a long standing focus of development economics (see Timilsina et al., 2020 for a review). It is often assumed that ICT affects agricultural production primarily through the provision of information (Aker et al., 2016). Three channels have been identified. First, ICT may foster technology adoption (e.g., Foster & Rosenzweig, 2010; Genius et al., 2014). Focusing on villages in rural Vietnam, Kaila and Tarp (2019) show that internet access increases total agricultural production by 7%. This effect is driven by more efficient use of fertilizer as a result of improved access to information.

Second, mobile phone coverage may lower uncertainties about distant markets and make transportation to markets more efficient for farmers (e.g., Deichmann et al., 2016). For instance, Overå (2006) finds that the roll-out of mobile phone coverage in Ghana changes farmers'

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trading practices over long distances, reducing both transportation and transaction costs. Based on household panel survey data from Uganda, Muto and Yamano (2009) show that mobile phone coverage facilitates information exchange between farmers and traders, which improves the efficiency of transportation.

Third, improved access to information may increase producer prices by strengthening farmers' bargaining power and improving access to markets at larger distances. Beuermann et al. (2012) find a positive impact of mobile phone coverage on the mobility of farm households, suggesting that farmers travel to the market that offers the best price for their products. Proxying the bargaining power of farm households with self-reported trust in traders, Labonne and Chase (2009) show that access to information can enhance the bargaining power of farmers, which then results in higher producer prices.

2.2 | The link between access to ICT and income composition

The link between ICT expansion and income diversification receives little attention in the existing development economics literature and is mostly addressed in conceptual studies, with few empirical studies. The prevailing view in this literature posits that access to ICT encourages the income diversification of rural households. For instance, drawing on household panel survey data from Nigeria, Bahia et al. (2020) document that improved mobile phone coverage leads to greater labor force participation and more employment in wage jobs outside the agricultural sector, particularly among women. Leng et al. (2020) show that, in China, the ownership of a smartphone or a personal computer is associated with an increase in income diversification among rural households.

Several channels have been suggested to explain the positive effect of ICT expansion on income diversification. First, the investment in ICT infrastructure may stimulate rural non-farm business development and attract enterprises to rural regions, thereby creating new job opportunities (Haggblade et al., 2010). Second, households' access to ICT may encourage job mobility by improving access to information about job vacancies and reduced job searching costs (Aker & Mbiti, 2010; Ngan & Ma, 2008) as well as by facilitating remote communication with both employers and families left behind (Ureta, 2008). Third, ICT expansion may facilitate the receipt of remittances through mobile money. A positive relation between access to mobile money technology and remittances is, for instance, documented for Ghana (Apiors & Suzuki, 2018), Kenya (Kirui et al., 2013), and Uganda (Munyegera & Matsumoto, 2016). Munyegera and Matsumoto (2016) suggest that this positive effect works through a reduction in transaction, transport, and time costs associated with mobile phone-based financial transactions.

Yet, this view of a positive effect of ICT on income diversification is not uncontested. In their conceptual framework, Leng et al. (2020) outline that, in rural areas, where non-agricultural income opportunities are often rare, improved mobile phone infrastructure may lead to a specialization in farming activities. Accordingly, mobile phone coverage may allow households to take advantage of improved access to credits, improved access to risk-reducing market information, increased bargaining power towards traders to negotiate better prices for their produce, and decreased transportation costs (Leng et al., 2020). Among the few studies that provide evidence for an income diversification-reducing effect of ICT expansion is the study by Min et al. (2020). Using panel data from rural China, Min et al. document that the use of smartphones by farmers leads to crop specialization.

3 | EMPIRICAL CONTEXT

In 2012, when the collection of data used in our analysis began, 33% of the Mongolian population resided in rural areas (NSO, 2021). About 75% of the rural population engaged in agriculture, which, in the extreme continental climate of Mongolia, is predominantly animal husbandry, and 40% of the rural population derived their livelihood solely from pastoralism (NSO, 2021). Animal husbandry relies on extensive production techniques, with animals grazing on open rangelands year-round. Most pastoralist households are either semi or fully nomadic, moving their herds between two and 25 times per year, typically using the same campsites (Fernández-Giménez, 1999; Teickner et al., 2020). In some years, some households conduct additional movements, beyond the regular annual cycle of nomadic movements, in order to avoid overgrazed pasture land or unfavorable weather conditions (Fernández-Giménez et al., 2015; Murphy, 2011). Since the 1990s, the number of kilometers moved per year declined among nomadic pastoralists, with more households tending their herds in the vicinity of district and provincial centers that feature better infrastructure, thus exacerbating the problem of pastureland degradation (Jargalsaikhan et al., 2015; Lise et al., 2006).

Mongolian pastoralists typically own a mix of five species: sheep, goats, horses, cattle, and camel. Goats, sheep, and cattle cover subsistence needs and also generate income through the sale of meat, dairy products, wool, and other byproducts, such as skins and hides, while camels and horses are mainly used for transportation and storing wealth (Xu et al., 2019). A lack of market information and long distances to provincial centers are major challenges for boosting income from herding. Many pastoralists sell both their livestock and livestock byproducts to traders at the farm gate, often on a barter basis. When selling at local markets, pastoralists bear high transportation costs, have little ability to influence market outcomes, and no certainty whether they may be able to sell their products at all (Arulpragasam et al., 2004).

Pastoralism has a long tradition in Mongolia. At the same time, it is a risky business, with pastoralists increasingly facing extreme weather conditions and price fluctuations for livestock and cashmere wool. In 2018, 31% of the rural population lived below the national poverty line (NSO & World Bank, 2020, p. 18). In rural areas, job opportunities outside the agricultural sector are rare. Remote and scarcely inhabited rural areas still lack basic infrastructure, including access to safe drinking water, paved roads, and access to markets (NSO & World Bank, 2020).[1] Out-migration from rural areas intensified drastically, with the share of Mongolians living in urban areas increasing from 53% in 1995 to 68% in 2020 (NSO, 2021). The occurrence of several extreme weather events since 1993 threatened pastoralist livelihoods and was a major cause of distress migration by impoverished pastoralists to urban centers (Roeckert & Kraehnert, 2022).

Efforts in rural development, including an expansion of ICT, led to a decrease in the disparities between rural and urban areas (NSO & World Bank, 2020). Since 1999, the Mongolian Government has implemented various ICT development plans. An important pillar of the infrastructure expansion is the Universal Service Obligation Fund, established by the Mongolian Government in 2006, which provides funding for setting up telecommunication infrastructure in remote areas, where building mobile phone networks is not economically viable for private sector service providers (ESCAP, 2016). Expanding information technology and telecommunication coverage alongside the establishment of high-speed networks in rural areas are among the objectives of the Mongolian Sustainable Development Vision to reach the UN Sustainable Development Goals by 2030. The first phase of the three-stage process, from 2016 to 2020, focused on the provision of high-speed internet connections and the enforcement of the same price for internet access in all regions (ESCAP, 2020).

The share of individuals in Mongolia using mobile phones increased from 92% in 2010 to almost universal usage in 2019 (Figure 1).[2] Among the population in rural areas, about 94% owned at least one mobile phone in 2019, while 17% used the internet. The percentage of individuals living in areas covered by at least 3G networks, which allow access to mobile internet, rose from 50% in 2016 to almost 100% in 2020 (ITU, 2021).

Data from the household panel survey in western Mongolia, which we analyze below, suggest that, as of 2020, pastoralists used mobile phones primarily to communicate over long distances (Figure 2). Less than one-third of the sample population used their mobile phone to access the internet, mostly to transfer money and to obtain information relevant to animal husbandry.

4 | DATA

The database for the empirical analysis is the *Coping with Shocks in Mongolia Household Panel Survey*, implemented by the authors in collaboration with the National Statistical Office of Mongolia (NSO) (Kraehnert et al., 2022). The survey collects detailed data on agricultural livelihoods in the three neighboring provinces of Uvs, Zavkhan, and Govi-Altai in western Mongolia (Figure A1 in the Appendix). It was specifically designed to investigate the effects of climate change on communities dependent on agriculture in a region that is prone to extreme weather events. In this study, we draw on panel waves 1–4. Each panel wave was collected over a 12-month period, with wave 1 implemented June 2012–May 2013, wave 2 implemented June 2013–May 2014, wave 3 implemented June 2014–May 2015, and wave 4 implemented May 2020–April 2021. Each household was interviewed in exactly the same month in each panel wave.

A stratified three-stage design was applied to draw the sample, with the population and housing census of 2010 serving as the sampling frame (Otter & German Institute for Economic Research, 2012). In the first sampling step, each of the three survey provinces was subdivided into province centers, district centers, and rural areas, resulting in a total of nine mutually exclusive strata. In the second step, primary sampling units (PSU) were randomly selected from each stratum, resulting in a total of 221 PSU. In the third step, eight households were randomly selected from each PSU. All results presented in the following account for survey design effects. Sample households are located in 49 out of the 61 districts in the survey provinces. The sample is representative of the urban and the rural population in each of the three survey provinces as of 2010. The *Coping with Shocks* survey comprises 1768 households in the first panel wave, of which 1650 could be interviewed in wave 4. Overall, survey attrition is relatively low, about 6.7% between waves 1 and 4.

In this study, our focus is on the sub-sample of livestock-owning households. There are 1035

[1] Despite the large disparities in infrastructure across rural and urban areas, less than 1% of households were without access to electricity as of 2012, with households being either connected to the central power grid or obtaining electricity from self-owned solar panels (NSO, 2021).

[2] Among the sample of pastoralists studied here, mobile phone ownership was universal in 2012 (see Section 5).

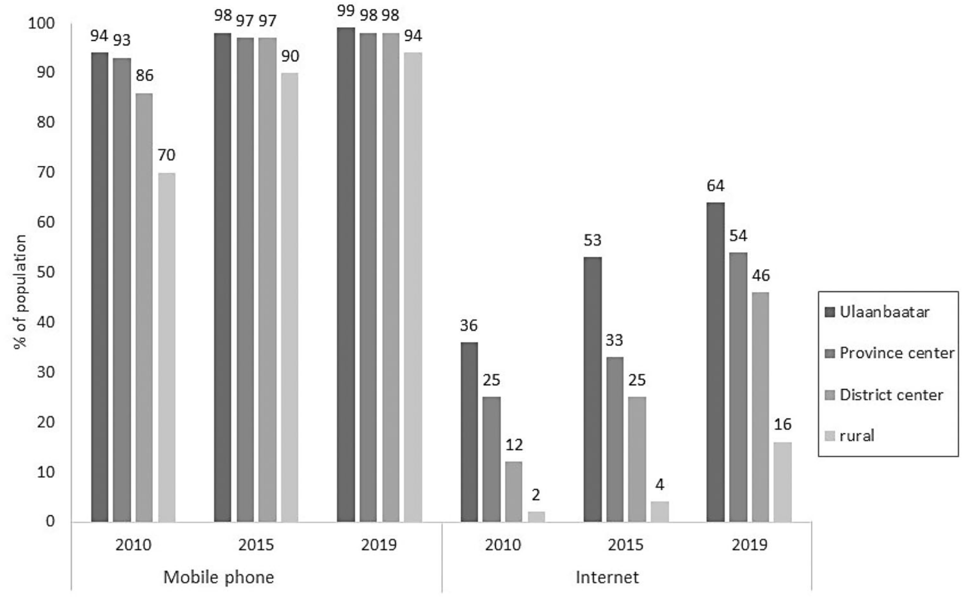

FIGURE 1 Share of the population using mobile phones and the internet, by location over time.

Source: Mongolia Household Socio-Economic Survey, cross-sectional rounds of 2010, 2015, and 2019.

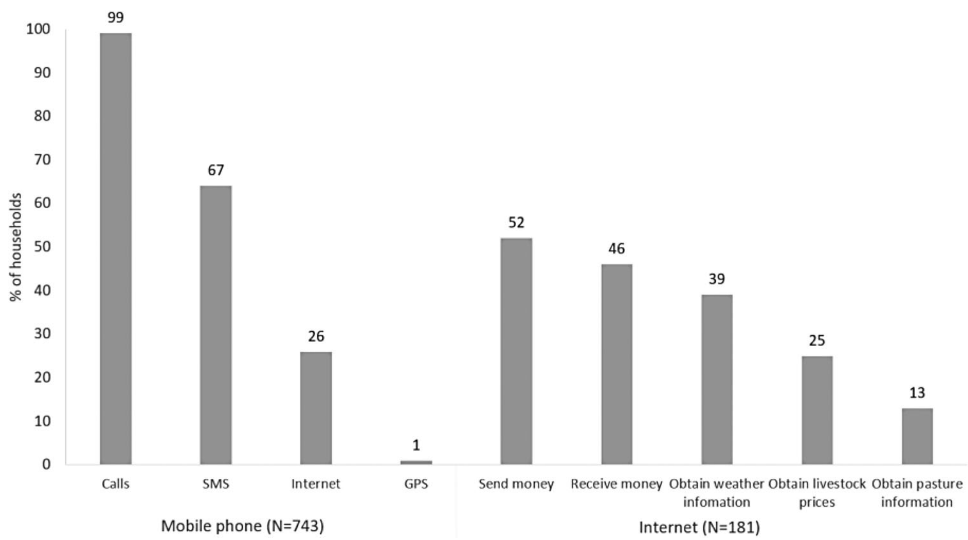

FIGURE 2 Purpose of mobile phone and internet use by pastoralist households in the survey area in 2020/21.

Note: Multiple answers were allowed for each survey item.
Source: Coping with Shocks in Mongolia Household Panel Survey, wave 4.

livestock-owning households in the first panel wave. From this sub-sample, 80 pastoralist households attritted from the survey between waves 1 and 4 as households had dissolved or could not be located. A further 172 households gave up animal husbandry between waves 1 and 4 (while they were still interviewed in waves 2–4). Moreover, we exclude 40 households that left their district of residence; for most of those households, we cannot precisely match households' location with data on mobile phone towers. Our analyses build on an unbalanced sample of 1035, 975, 934, and 743 pastoralist households in the first, second, third, and fourth panel waves. Attrition tests (discussed in Section 6) indicate that there is no evidence for a strong correlation between the expansion of mobile phone networks and survey attrition or households giving up pastoralism.[3]

[3] In experimental settings with random treatment assignment, Lee bounds are commonly used to address sample attrition. Yet, as they do not permit the inclusion of covariates and fixed effects, which are essential components of our analysis of non-experimental data, we do not implement Lee bounds.

The first outcome of interest is annual household income, measured in Mongolian Tugrik (MNT), which consists of three major categories. *Agricultural income* comprises, by order of importance, income from the sale of living and slaughtered livestock, the value of animal byproducts produced by the household (wool, skins and hides, milk), and the value of farming produce. *Non-agricultural income* includes income from wage work and non-agricultural businesses. *Transfer income* comprises state benefits, remittances, and other income, including inheritance and property rent. In the regression analyses presented below, both total annual household income[4] and agricultural income, non-agricultural income, and transfer income (both in absolute terms and expressed as share of total household income) are used as dependent variables. We corrected for outliers by replacing prices received for byproducts and livestock below the 1st or above the 95th percentile of the distribution with the price at the threshold. Wage incomes above the 99th percentile were replaced by values at the 99^{th} percentile. Table 1 displays mean values by wave for all variables used, while Table A1 in the Appendix shows further summary statistics for each variable.

The second outcome of interest is income diversification, which we approximate with the Simpson index of diversity, which takes the number of income sources and the relation between them into account (Minot et al., 2006):

$$SID = 1 - \sum_{m}^{n} p_{i,m} \tag{1}$$

where n is the number of income sources and $p_{i,m}$ is the share of income from source m for household i. The Simpson index of diversity varies between 0 (one single income source) and 1 (maximal diversity). We calculate three variants of the income diversity index. The first diversity index is constructed from three major income categories—agriculture income, non-agriculture income, and transfer income—and is meant to depict broad trends in livelihood strategies. The second, more nuanced, index considers eight categories: (1) income from the sale of livestock; (2) the value of animal byproducts; (3) the value of farming produce; (4) wage work; (5) non-agricultural businesses; (6) state benefits; (7) remittances; and (8) other income. The third index only considers seven sources of agricultural income, namely, (1) income from the sale of livestock; (2) the value of cashmere wool; (3) the value of sheep wool; (4) the value of animal skins; (5) the value of milk from sheep and goat; (6) the value of cow milk; and (7) the value of farming produce.

To shed light on factors that influence income generation, we explore several additional outcomes. These include, first, a household's herd size, transformed into sheep forage units (SFUs), the livestock conversion rate commonly used in Mongolia.[5] Second, we utilize the producer price per kilogram of cashmere wool, the most common byproduct of Mongolian pastoralists, as self-reported by households. The producer price for cashmere varies substantially across households, reflecting differences in quality, quantity sold, whether the product was sold to traders at the farm gate or sold by households in urban centers, and whether households are engaged in long-term relations with traders. Third, we employ the distance (in kilometers) between the campsite where the survey interview took place and the provincial center. With a population between 16,000 and 30,000 in 2020 (NSO, 2021), provincial centers are the main markets in the survey area. Fourth, we employ access to credit, measured through a binary variable that takes the value one if a household currently pays back a loan.

The key explanatory variable of interest is the expansion of mobile phone networks in a given district and year. It is constructed from secondary data on the location of mobile phone towers between 2012 and 2021 that we obtained from all four mobile phone companies operating in Mongolia, namely, Unitel, Skytel, Mobicom, and G-Mobile. Using a point-to-polygon approach, we generated, first, an indicator variable that takes the value one if at least one additional tower was installed in a given district and year (Figure A2 in the Appendix). Second, we employ a continuous variable accounting for the number of new towers installed in a given district and year.[6]

5 | EMPIRICAL STRATEGY

Our analysis exploits the uneven expansion of mobile phone networks across time and space. We estimate the effects of an improvement in mobile phone networks in the district on household income using a two-way fixed effects approach, as follows:

$$\begin{aligned} Y_{idt} = {} & \beta_1 NetworkExpansion_{dt} + \beta_2 X_{it} + \beta_3 X_{dt} + \alpha_d \\ & + \gamma_t + \alpha_d * t + \varepsilon_{idt} \end{aligned} \tag{2}$$

[4] Inflation was relatively moderate, varying between 4% and 14% per year over the time period of interest. We opted against adjusting income for inflation, as different income components are earned in different seasons of the year (with data on the exact timing lacking).

[5] One horse, cow, camel, and goat are equivalent to 7, 6, 6, and 0.9 SFU, respectively.

[6] Unfortunately, the data available to us do not contain the exact GPS coordinates of towers.

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TABLE 1 Mean values of all variables used, by wave.

	Wave 1	Wave 2	Wave 3	Wave 4
Dependent variables				
Total household income (in '000 MNT)	10,340.13	11,911.93	18,242.63	17,949.13
	(7466.01)	(8139.69)	(14,447.23)	(13,459.52)
Agriculture income (in '000 MNT)	5396.54	7778.84	13,873.78	12,386.15
	(5279.22)	(7371.98)	(13,891.96)	(13,105.98)
Non-agriculture income (in '000 MNT)	1906.63	2043.78	2121.72	2075.85
	(3846.85)	(4224.15)	(4744.13)	(5058.29)
Transfer income (in '000 MNT)	3036.82	2089.31	2247.13	3487.15
	(4825.23)	(3145.56)	(4687.28)	(3344.63)
Share of agricultural income	.54	.65	.71	.65
	(.27)	(.28)	(.28)	(.29)
Share of non-agricultural income	.15	.14	.12	.10
	(.24)	(.24)	(.23)	(.21)
Share of transfer income	.31	.20	.17	.26
	(.22)	(.20)	(.19)	(.25)
Income diversity (3 categories)	.41	.34	.29	.32
	(.16)	(.19)	(.20)	(.20)
Income diversity (8 categories)	.58	.57	.52	.54
	(.11)	(.11)	(.14)	(.14)
Income diversity in agriculture (7 categories)	.67	.67	.67	.61
	(.20)	(.21)	(.25)	(.23)
Income from livestock sales (in '000 MNT)	3026.56	4263.73	7915.73	6746.00
	(3813.47)	(5703.91)	(11,419.27)	(8847.78)
Income from livestock byproducts (in '000 MNT)	1758.71	2662.97	3421.39	4150.24
	(1766.81)	(2663.88)	(3369.29)	(4975.94)
Income from farming (in '000 MNT)	38.67	34.05	52.81	151.09
	(473.11)	(603.68)	(725.64)	(1909.61)
Herd size (in SFU)	279.89	334.64	391.40	508.91
	(267.45)	(315.40)	(363.11)	(426.58)
Price per kg cashmere wool (in '000 MNT)	44.01	58.23	69.57	62.49
	(4.89)	(5.27)	(8.39)	(13.12)
Distance to province center (in km)	127.33	135.94	137.59	153.01
	(100.89)	(101.00)	(101.94)	(103.25)
Repaying loan	.42	.45	.48	.58
	(.49)	(.50)	(.50)	(.49)
Mobile phone network expansion (district)				
At least one additional tower	.22	.52	.61	.89
	(.41)	(.50)	(.49)	(.31)
Number of additional towers	.34	.85	.82	2.88
	(.69)	(1.06)	(.76)	(2.74)
Time-varying household controls				
Female head	.09	.10	.11	.14
	(.29)	(.30)	(.31)	(.34)
Age of head	43.74	44.74	45.49	49.34
	(12.95)	(13.00)	(12.87)	(11.80)

(Continues)

TABLE 1 (Continued)

	Wave 1	Wave 2	Wave 3	Wave 4
Head has no education	.13	.13	.14	.13
	(.34)	(.34)	(.35)	(.34)
Head has primary education	.56	.57	.58	.61
	(.50)	(.49)	(.49)	(.49)
Head has secondary or higher education	.31	.29	.28	.26
	(.46)	(.46)	(.45)	(.44)
Head is married	.85	.85	.84	.83
	(.36)	(.36)	(.37)	(.38)
Household size	4.16	4.16	4.13	4.05
	(1.54)	(1.56)	(1.54)	(1.77)
Time-varying district controls				
Population size	6953.73	6306.20	6183.92	5837.75
	(7646.94)	(7324.40)	(7485.59)	(7611.45)
Spending on infrastructure (in mio MNT)	1809.16	10008.70	3698.72	5131.48
	(3146.98)	(22,277.14)	(6370.71)	(8531.36)
Permanent market available	.25	.22	.23	.16
	(.43)	(.41)	(.42)	(.37)
Meat market available	.27	.26	.26	.19
	(.44)	(.44)	(.44)	(.39)
Number of households	1035	975	934	743

Note: All income variables refer to annual household income. Standard deviations are reported in parentheses. For price per kg cashmere wool, the sample size decreases to 981 and 676 households in waves 1 and 4, respectively. For agricultural income diversity, the sample size decreases to 1028 and 931 households in waves 1 and 3, respectively. For distance to province center, the sample size decreases to 736 households in wave 4, respectively.

Source: Coping with Shocks in Mongolia Household Panel Survey (waves 1–4) and network expansion data.

where the dependent variable Y captures annual income or income diversity (described in Section 4 above) of household i living in district d at time t. $NetworkExpansion_{dt}$ stands for the expansion of mobile phone networks in a given district and year. We measure network expansion with either a binary variable that indicates whether at least one additional tower was installed in a given district and year or a continuous variable that captures the number of additional towers installed. X_{it} is a vector of time-varying household-level controls and X_{dt} is a vector of time-varying district-level controls. The equation contains district fixed effects α_d, wave fixed effects γ_t, district-specific linear time trends $\alpha_d * t$, and a stochastic error term. District fixed effects account for unobserved time-invariant heterogeneity across districts. Wave fixed effects control for unobserved heterogeneity across time periods. District-specific linear time trends, an interaction term between district indicators and a time trend, control for alternative variables associated with the dependent variable that vary within districts over time. In all analyses presented below, we account for survey design effects by clustering standard errors at the PSU level. Among the sample of pastoralists studied here, mobile phone ownership was universal in the first wave. Between waves 2 and 4, the ownership rate varied between 97.1% and 99.6%.[7] Our estimation approach is therefore based on an intention-to-treat framework.

We estimate the same model with alternative outcomes, thus providing insights into household income composition, including the contribution of specific income components to total annual household income, the value of animal byproducts produced by the household, the number of animals owned, producer prices obtained for cashmere wool, the distance to the province center, and whether the household currently repays a loan.

Considering the expansion of mobile phone coverage at the district level (rather than on a finer geographical

[7] Of the sample households, 97.1%, 97.8%, and 99.6% reported they owned a mobile phone at wave 2, 3, and 4, respectively. We consulted another survey, the Household Socio-Economic Survey (HSES), a cross-sectional survey implemented annually by the National Statistics Office of Mongolia, with a fresh sample drawn every year, for comparison. According to descriptive statistics calculated from HSES data (Table A2 in the Appendix), in the 2012-2021 period, mobile phone access was never universal among pastoralists in western Mongolia. In each year, there was a small share of households (in the range of 0.7% to 6.5%) that reported not having a mobile phone or land line phone in the household. This roughly corresponds to the figures obtained in the *Coping with Shocks* survey. However, given that the HSES is not representative at the provincial level, the figures should only be considered as rough indication.

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level) avoids potentially endogenous settlement decisions of (semi-) nomadic households that may set up their campsite in areas within a given district that feature better mobile phone networks. Mobility across district borders, both permanent and nomadic, is discouraged in Mongolia and, therefore, the district population remains relatively stable over time. This makes the district a suitable level for measuring the effects of improvements in ICT infrastructure.

The choice of control variables is informed by the literature on ICT and income diversity (e.g., Aker & Ksoll, 2016; Escobal, 2001; Kaila & Tarp, 2019; Leng et al., 2020; Viollaz & Winkler, 2021). As time-varying household-level controls, we include characteristics of the head of household (age, age squared, gender, education, marital status)[8] and household size. As time-varying district-level controls, we employ population size, the monetary value of public and private spending on transport and civil infrastructure,[9] as well as the availability of a permanent market and a meat market in the district center.

One potential threat to our identification strategy is that the roll-out of mobile phone networks is unlikely to be random. Our estimations of the effects of mobile phone networks on income would be biased if the expansion of mobile phone networks was correlated with district characteristics that also affect the growth in household income. In order to address this concern, we control for annual spending on transport and infrastructure at the district level and include district-specific linear time trends in addition to district fixed effects in all models. Furthermore, we implement a placebo test in which we estimate a model without district-specific linear time trends and use the expansion of mobile phone networks in the following year as a proxy to test for parallel trends (discussed in the robustness test section).

To account for multiple hypothesis testing, we follow the step-down approach by Romano and Wolf (2005) and control for the familywise error rate, that is, the probability of rejecting at least one true null hypothesis. In addition to showing unadjusted p-values, we display Romano–Wolf adjusted p-values for all estimated coefficients of the treatment.

[8] Most variation in head of household characteristics stems from households in which the head changed over time, for instance because of marriage, illness, or death. As robustness test, we estimate the model on a slightly smaller sample of households in which the head stayed the same across waves (and leaving out the head of household characteristics). Results are qualitatively similar to the baseline results.

[9] More specifically, this comprises the monetary value of the sum of economic activities directed to the creation, renovation, repair, or extension of fixed assets in the form of buildings, land improvements of an engineering nature, and other such engineering constructions, such as roads, bridges, dams.

6 | RESULTS

Results from two-way fixed effects estimations on the effects of an expansion of mobile phone networks in the district on annual household income are displayed in Table 2. Network expansion is approximated with secondary data on network towers. Panel A shows results obtained when measuring treatment with a dummy variable indicating whether at least one additional tower was installed in a given district and year, while panel B displays results when measuring treatment with a continuous variable capturing the number of newly built network towers. The estimated coefficients of the full set of control variables are displayed in Table A3 in the Appendix.

The expansion of mobile phone networks strongly and significantly increases total annual income of pastoralist households when proxying network expansion with the installation of at least one additional tower, holding all else constant (Table 2, column 1, panel A). This finding is confirmed when measuring network expansion with the number of additional towers installed (column 1, panel B). The effect is particularly large for agricultural income (column 2), with each additional tower installed in a given district raising annual household income from agriculture on average by exp(.071) = 7.4%. In contrast, the expansion of mobile phone networks does not have a significant effect on households' non-agricultural income, regardless of what measure is used to approximate network expansion (column 3). We find that network expansion also significantly increases transfer income, a finding obtained from both the binary and the continuous measure of the treatment (column 4). Yet, the absolute effect of this increase is rather small, with transfer income contributing about 25% to total annual household income. When considering the effect of an expansion of mobile phone networks on specific income components, each additional tower installed in a given district and year has a significant and positive effect on the share of agricultural income (column 5, panel B), while there is some evidence that each additional tower installed in a given district and year has a significant and negative impact on the share of non-agricultural income (column 6, panel B). Most results discussed so far are robust to multiple hypothesis testing, with Romano–Wolf adjusted p-values being only slightly larger than the unadjusted p-values.

Turning to income diversity (Table 3), measured by the Simpson index of diversity, we find that each additional network tower significantly decreases households' income diversity when considering three broad income categories (agriculture income, non-agriculture income, and transfer income) (column 1, panel B). A decrease in income diversity is also found when breaking income into eight finer categories, including income from livestock sales,

TABLE 2 Impact of the expansion of mobile phone networks on household income (OLS).

Dependent variable	Total household income (log) (1)	Agricultural income (log) (2)	Non-agricultural income (log) (3)	Transfer income (log) (4)	Share of agricultural income (5)	Share of non-agricultural income (6)	Share of transfer income (7)
Panel A: Treatment is dummy							
At least one additional tower	.133***	.177***	.012	.175***	.012	−.005	−.008
	(.000)	(.000)	(.929)	(.006)	(.108)	(.516)	(.253)
	(.010)	(.010)	(1.000)	(.020)	(.366)	(.802)	(.644)
Panel B: Treatment is continuous							
Number of additional towers	.036***	.071***	−.049	.046*	.011***	−.006*	−.005
	(.000)	(.001)	(.363)	(.083)	(.001)	(.099)	(.109)
	(.010)	(.010)	(.466)	(.178)	(.010)	(.178)	(.178)
R-squared, panel A	.31	.35	.28	.23	.41	.29	.40
R-squared, panel B	.31	.35	.28	.23	.41	.29	.40
Time-varying household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying district controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trend by district	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of households, w1	1035	1035	1035	1035	1035	1035	1035
Number of households, w2	975	975	975	975	975	975	975
Number of households, w3	934	934	934	934	934	934	934
Number of households, w4	743	743	743	743	743	743	743
Observations	3687	3687	3687	3687	3687	3687	3687

Note: Further control variables are included, but not displayed here (see Table A3 in the Appendix for the estimated coefficients of the full set of controls). Household-level controls include household size as well as the gender, age, education, and marital status of the household head. District-level controls include population size, the amount of infrastructure spending, whether a permanent market exists in the district center, and whether a meat market exists in the district center. Standard errors clustered at the PSU level. Two types of p-values are reported in parentheses. Unadjusted p-values are displayed first with $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$. Romano–Wolf adjusted p-values, calculated using a bootstrap with 100 replications, are displayed second.

Source: Coping with Shocks in Mongolia Household Panel Survey (waves 1–4) and network expansion data.

TABLE 3 Impact of the expansion of mobile phone networks on income composition (OLS).

Dependent variable	Income diversity (3 categories) (1)	Income diversity (8 categories) (2)	Income diversity in agriculture (7 categories) (3)
Panel A: Treatment is dummy			
At least one additional tower	−.006	−.012**	−.007
	(.339)	(.036)	(.448)
	(.753)	(.109)	(.802)
Panel B: Treatment is continuous			
Number of additional towers	−.006**	−.004*	−.005
	(.012)	(.065)	(.165)
	(.050)	(.129)	(.277)
R-squared, panel A	.31	.14	.28
R-squared, panel B	.31	.14	.28
Time-varying household controls	Yes	Yes	Yes
Time-varying district controls	Yes	Yes	Yes
Linear time trend by district	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes
Wave fixed effects	Yes	Yes	Yes
Number of households, w1	1035	1035	1028
Number of households, w2	975	975	975
Number of households, w3	934	934	931
Number of households, w4	743	743	742
Observations	3,687	3,687	3,676

Note: Income diversity is measured by the Simpson index of diversity. Household-level controls include household size as well as the gender, age, education, and marital status of the household head. District-level controls include population size, the amount of infrastructure spending, whether a permanent market exists in the district center, and whether a meat market exists in the district center. Two types of *p*-values are reported in parentheses. Unadjusted *p*-values are displayed first with $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$. Romano–Wolf adjusted *p*-values, calculated using a bootstrap with 100 replications, are displayed second.

Source: Coping with Shocks in Mongolia Household Panel Survey (waves 1–4) and network expansion data.

the production of animal byproducts, farming, wage work, non-agricultural business, social benefits, remittances, and other sources, such as inheritance (column 2, panel A and B). However, the effects turn insignificant at conventional levels when correcting for multiple hypothesis testing. When considering only the diversity of income sources within the agricultural sector, none of the proxies of network expansion yields point estimates that are significant at conventional levels (column 3).

Next, we differentiate the effects of mobile phone network expansion on selected components of agricultural income (Table 4). Network expansion significantly increases households' income from livestock byproducts (column 1). Each additional mobile phone tower in the district increases household income from livestock byproducts on average by exp(.047) = 4.8%, holding all else constant (column 1, panel B). In addition, both proxies of network expansion show a significant positive effect on income from the sale of livestock (column 2). We also find a positive effect of network expansion on farming income (column 3, panel A and B). We further investigate whether mobile phone network expansion affects households' herd size (column 4). On average each additional tower leads to an increase in herd size by exp(.023) = 2.3%, holding all else constant (column 4, panel B). Yet, results for herd size are not confirmed when employing the binary treatment (column 4, panel A). Pastoralists living in districts where at least one additional network tower was installed report significantly higher prices per kilogram of cashmere wool sold compared to pastoralists living in districts without network expansion, holding all else constant (column 5, panel A). Surprisingly, this effect is significant and negative when employing the continuous treatment variable (column 5, panel B). We propose that this negative effect is driven by an outlier district in which 13 additional towers were installed in 2020. Table A4 in the Appendix displays sensitivity tests for the price of cashmere wool employed as outcome in which we restrict the sample to waves 1–3 (column 1), exclude the outlier district in wave 4 (column 2), and exclude the outlier district in all waves (column 3). In

TABLE 4 Impact of the expansion of mobile phone networks on income components (OLS).

Dependent variable	Income from livestock byproducts (log) (1)	Income from sale of livestock (log) (2)	Income from farming (log) (3)	Herd size (log) (4)	Price per kg cashmere wool (5)	Distance to province center (log) (6)	Repaying loan (7)
Panel A: Treatment is dummy							
At least one additional tower	.119***	.117***	.078**	.004	1.191***	.067***	.031
	(.003)	(.009)	(.027)	(.865)	(.000)	(.001)	(.140)
	(.010)	(.040)	(.089)	(1.000)	(.010)	(.010)	(.455)
Panel B: Treatment is continuous							
Number of additional towers	.047**	.051**	.032*	.023**	−.471***	.036***	.008
	(.014)	(.050)	(.074)	(.015)	(.003)	(.002)	(.371)
	(.050)	(.129)	(.168)	(.050)	(.010)	(.010)	(.466)
R-squared, panel A	.36	.29	.12	.35	.68	.90	.15
R-squared, panel B	.36	.29	.12	.35	.68	.90	.15
Time-varying household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying district controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trend by district	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of households, w1	1035	1035	1035	1035	958	1035	1035
Number of households, w2	975	975	975	975	975	975	975
Number of households, w3	934	934	934	934	934	934	934
Number of households, w4	743	743	743	743	675	736	743
Observations	3687	3687	3687	3687	3542	3680	3687

Note: Household-level controls include household size as well as the gender, age, education, and marital status of the household head. District-level controls include population size, the amount of infrastructure spending, whether a permanent market exists in the district center, and whether a meat market exists in the district center. Two types of p-values are reported in parentheses. Unadjusted p-values are displayed first with $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$. Romano–Wolf adjusted p-values, calculated using a bootstrap with 100 replications, are displayed second.

Source: Coping with Shocks in Mongolia Household Panel Survey (waves 1–4) and network expansion data.

all three regressions, the estimated coefficient of the continuous treatment variable is again positive, although not in all cases statistically significant at conventional levels.

Moreover, the expansion of mobile phone networks significantly increases the distance between households' campsites and the province center (Table 4, column 6); this finding is obtained with both the binary and the continuous proxy of treatment. One additional tower installed in a given district increases the average distance of a household's campsite and the next provincial center by about 5 km, a sizeable effect. Lastly, there is no evidence that mobile phone network expansion increases the likelihood that households repay a loan (column 7).[10]

6.1 | Robustness tests

As a robustness test, we explore whether the positive effect of network expansion on income is specific to the agricultural sector by restricting the sample to households that are not engaged in animal husbandry (Table A5, column 1 in the Appendix). The expansion of mobile phone networks does not have a statistically significant effect on the total annual income of households not engaged in animal husbandry; this is regardless of whether the binary or continuous treatment measure is used. We interpret this as supporting evidence that the positive effects of an expansion of mobile phone networks for rural incomes only hold for the agricultural sector.

Recall that while all sample households reported owning a mobile phone in wave 1, ownership rates were slightly lower in the other panel waves, with 97.1%, 97.8%, and 99.6% of households reporting they owned a mobile phone in wave 2, 3, and 4, respectively. Our model intentionally omits households' mobile phone ownership to avoid potential endogeneity that may stem from household decision making. The effect of mobile phone ownership gets absorbed into the error term. If mobile phone ownership is correlated with network coverage, the omission of mobile phone ownership may introduce another sort of endogeneity that may bias the estimated effects of network coverage on the outcomes of interest. If existent, such correlation may likely be positive, with good network coverage possibly encouraging households to obtain a mobile phone, while network providers may install new towers particularly in areas with large numbers of mobile phone users. To address this concern, we estimate the baseline model with household fixed effects, which account for time-invariant heterogeneity across households, such as openness towards technological change. Results, displayed in Table A6 in the Appendix, roughly point into the same direction as the baseline model that contains district fixed effects.

A related bias may stem from the omission of mobile phone technology—smartphones versus non-smart mobile phones—used by households.[11] Unfortunately, the *Coping with Shocks* survey questionnaire only differentiated between smartphones and non-smart mobile phones in wave 4, implemented in 2020/21, when 53% of sample households reported using a smartphone.[12] Yet, data from the Household Socio-Economic Survey, another cross-sectional household survey conducted annually in Mongolia, indicate that the share of pastoralist households in western Mongolia with internet access at home, through whatever technical devices, was below 4% until 2015 (see footnote 6 and Table A2 in the Appendix). Our conclusion from these descriptive figures is that it seems that smartphones were not common among pastoralist households in the survey area during waves 1–3 (2012–2015), except for a minor share of probably less than 5% of sample households. Smartphones and internet access in general had become much more prevalent by wave 4 (2020/21). When estimating the model with data from waves 1 to 3 only (Table A8 in the Appendix), we obtain similar effects of network expansion on total income and on agricultural income, while effects are no longer statistically significant at conventional levels for transfer income as well as for the shares of agricultural income and non-agricultural income.

Next, we explore whether results obtained with the binary treatment are robust to heterogeneous treatment effects in a setting of staggered treatment adoption, applying the imputation estimator approach by Borusyak et al. (2022). This approach allows estimating a two-way fixed effects model under staggered treatment adoption, which yields robust estimates even in the presence of effect heterogeneity. The imputation approach comprises three steps. First, fixed effects and coefficients for other control variables are estimated solely for the untreated observations. Second, these computed effects are used to impute potential untreated outcomes for the treated group. Treatment-effect estimates are then derived as the difference between the actual outcomes and the potential untreated outcomes. Third, we compute a weighted aver-

[10] We follow Angrist and Pischke (2008) and use a linear probability model to estimate the effect on this binary outcome.

[11] We are grateful to an anonymous reviewer for pointing this out.

[12] Table A7 in the Appendix displays information on the type of mobile phone owned as well as mobile phone usage, extracted from the *Coping with Shocks* survey. Data on mobile phone usage were collected from wave 3 (2014/15) onward. When asked for what purposes households use their mobile phones, less than 3% of households in wave 3 indicated accessing the internet, compared to 26% in wave 4. Note, however, that this survey item has missing values for more than half of the sample because of a wrong skipping pattern in the questionnaire module.

age of the treatment effect estimates. We estimate the Average Treatment Effect on the Treated (ATT) across all treated observations while controlling for district and wave fixed effects, as well as the control variables used in our baseline model. Twenty households treated in each wave are excluded from the sample. Results, displayed in Table A9 in the Appendix, indicate that the sign of the coefficients align with our baseline findings and that most are statistically significant at conventional levels. We consider this exercise as demonstrating the robustness of our results when using improved approaches from recent econometric research.

Due to the inclusion of district-specific linear time trends, our identification strategy does not rest on a strict parallel trends assumption but, instead, requires that, in the absence of the network expansion, the change in trends in agriculture income in districts with network expansion is equal to the change in the trends in districts without network expansion (Mora & Reggio, 2019). While we cannot conclusively test for this parallel trends-in-trends assumption, we provide some suggestive evidence from a placebo test that is commonly used to test for the parallel trend assumption. We estimate the model without district-specific linear trends and test, in a second step, whether agriculture income is predicted by the expansion of mobile phone networks in the following year (t + 1). While the effect of mobile phone networks on agricultural income remains significant and positive in the model without district-specific linear trends (Table A5, column 2 in the Appendix), the estimated coefficients of the proxies measuring the expansion of mobile phone networks in the following year are statistically indistinguishable from zero in the placebo regression (column 3), which we interpret as an indication for parallel trends. Moreover, an event study plot showing pre-treatment trends for agricultural income (displayed in Figure A3 in the Appendix) also demonstrates the absence of pre-treatment effects in the 3 years prior to the network expansion.

Lastly, given that the dataset employed here spans a window of 9 years, we conduct various attrition tests to explore whether results are biased by survey attrition. First, we estimate the baseline model for agricultural income on a balanced sample consisting only of households that were surveyed and owned livestock in all four waves (Table A5, column 4 in the Appendix). Results are qualitatively similar to the baseline results derived from the unbalanced sample, suggesting that the effect of network expansion on agricultural income is not driven by households that dropped out of pastoralism or attritted from the survey. A Hausman test between the balanced and the unbalanced sample, as suggested by Verbeek and Nijman (1992), fails to reject the null hypothesis that the difference in the estimated coefficients of the two models is not systematic, indicating that results are not biased due to attrition (*p*-value of .32). Second, we examine whether the probability that households quit pastoralism over time, attritted from the survey, or moved away from their district is correlated with the expansion of mobile phone networks (Table A10 in the Appendix). Results from a probit model suggest that network expansion does not significantly influence attrition between waves 1 and 2 (column 1) and waves 2 and 3 (column 2). Network expansion only significantly influences attrition between wave 3 and 4 (column 3), with the estimated effect being negative. Third, when estimating the baseline model for agricultural income with data from panel waves 1 to 3 only, results for total income and agricultural income are qualitatively similar to the baseline model (Table A8 in the Appendix). While we cannot dispel concerns about attrition bias entirely, we conclude from those tests that attrition is not a major cause of concern.

7 | CONCLUSION

This study provides new insights into the role of ICT infrastructure for rural development in an LMIC, examining the case of rural households in western Mongolia. Our identification strategy exploits the uneven roll-out of mobile phone networks across rural areas over time, examining a 9-year window. We apply a two-way fixed effects approach with district-specific time trends, making use of a household panel survey collected in three western Mongolian provinces with four waves that contains detailed information on agricultural activities. The socioeconomic data are complemented with secondary data on the location of mobile phone towers. Building on these rich data, our analysis quantifies how the expansion of mobile phone networks affects household income and income diversification.

Our analysis has three main findings. First, mobile phone network expansion increases the total annual income of survey households involved in animal husbandry, the dominant livelihood in rural areas. The increase in total household income is driven by higher income from agriculture and, to a smaller extent, by higher transfer income. Agricultural income appears to rise because of both higher profits per animal and increased herd size. Households living in areas with better mobile phone network infrastructure report they received higher producer prices for cashmere wool, the most important livestock byproduct. This result is in line with findings by Labonne and Chase (2009) for the Philippines and Beuermann et al. (2012) for Peru, who document that access to mobile phone networks enhances households' access to information, which in turn results in higher producer prices. While Beuermann et al. (2012) suggest that mobile phone coverage allows farmers to obtain price information for their products and, consequently, travel to the market that offers the best price, Labonne and Chase (2009) argue that easier access to information increases farmers' bargaining power to conclude better price deals with their existing trading partners. Unfortunately, our dataset does not provide more detailed information about pastoralists' selling practices at markets or the way contracts with wholesale traders are concluded. A closer examination of this mechanism is left for future analysis.

Second, the expansion of mobile phone networks counteracts the tendency among pastoralist households in western Mongolia to camp in the vicinity of urban centers. Nomadic movements are an important strategy to access high quality pastures and maximize the fodder intake of livestock, which both enhance livestock productivity and strengthen households' capacity to cope with extreme weather events.

Third, mobile phone network expansion leads to a decrease in income diversification of rural households in western Mongolia. Instead, with better mobile phone networks, households specialize in agriculture. This result contrasts with the findings by Leng et al. (2020), who document that the ownership of a communication device is associated with an increase in households' income diversification in rural China. Our result also contrasts with Bahia et al. (2020), who show that the roll-out of mobile broadband internet in Nigeria increases households' labor force participation and wage employment. We propose that the income diversity-decreasing effect of ICT infrastructure for Mongolian households may be due to structural differences in the rural economy in Mongolia compared to China and Nigeria. In Mongolia, provincial centers offer few non-agricultural job opportunities for individuals with rather little formal education, as is often the case for men engaged in pastoralism. Hence, improved access to the provincial labor market has few benefits for pastoralists.

Our results suggest that the expansion of mobile phone infrastructure is essential for improving the livelihood of the rural population in remote areas of western Mongolia. The expansion of mobile phone networks supports agricultural households in the survey area in improving their position on the market and increasing the profit per animal. In more general terms, results suggest that, in western Mongolia, ICT can play an important role in the eradication of rural poverty, thus counteracting migration flows to urban centers. Therefore, policies may be directed toward the expansion of mobile phone networks outside of urban centers and in less-developed regions. While specializing in agricultural activities, particularly the production of cashmere wool, has welfare-enhancing effects for rural households in the survey area, it increases their vulnerability to both extreme weather events and gradual environmental changes that are further exacerbated by overgrazing. Extreme winter events remain a major economic threat to Mongolian pastoralists and are a strong predictor of out-migration from rural areas (Roeckert & Kraehnert, 2022). Hence, a specialization in agriculture should be accompanied by measures that assist households in adapting to climate change. As suggested by the World Bank (2020), encouraging intensive pastoralist practices, promoting smaller herd sizes, and diminishing overgrazing may be needed to increase the resilience of pastoralists in the long term.

However, we caution that results and policy implications presented here are obtained from detailed survey data collected in western Mongolia. Although we do not have reason to expect rural livelihoods and ICT infrastructure in other Mongolian regions to systematically differ from those in western Mongolia, results and policy implications should not be interpreted as being nationally representative and, hence, they may not be generalizable to rural areas of other Mongolian regions. Supporting Information.

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CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest to declare that are relevant to the content of this article.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX

FIGURE A1 Map of Mongolia, survey provinces are dark shaded.

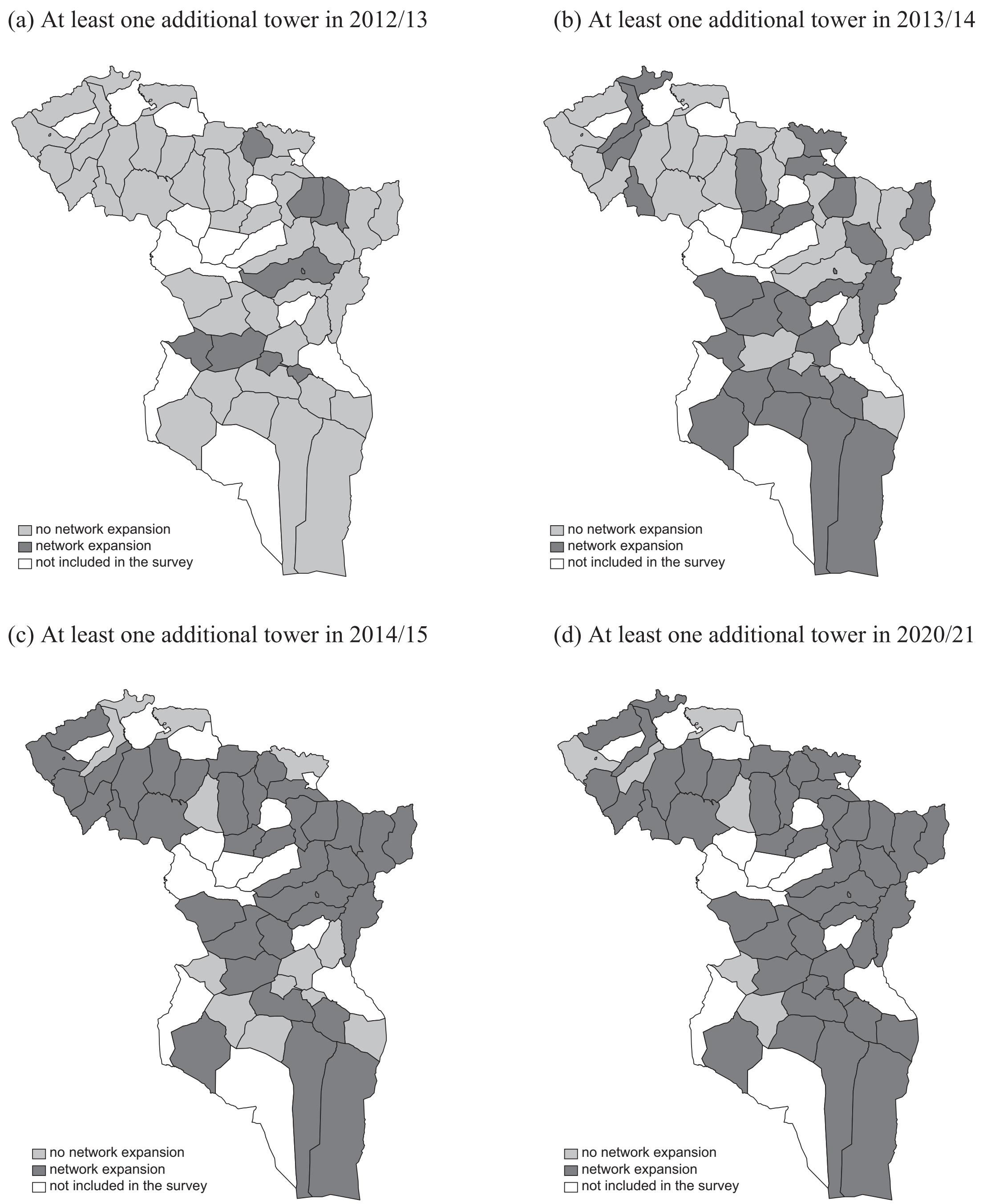

FIGURE A2 Expansion of mobile phone networks, across districts over time.

Source: Network expansion data.

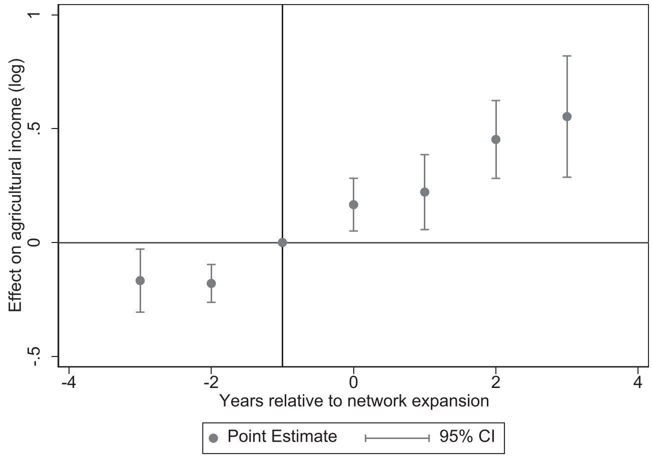

FIGURE A3 Event study plot: Impact of the expansion of mobile phone networks on agricultural income.

Note: Displayed are point estimates of the event-time path of agricultural income (log) on the y-axis and event time on the x-axis, with x = 0 denoting the first year of network expansion. The depicted intervals correspond to pointwise 95 percent confidence intervals for the point estimates. The event study accounts for wave fixed effects and district fixed effects. Household-level controls include household size as well as the gender, age, education, and marital status of the household head. District-level controls include population size, the amount of infrastructure spending, whether a permanent market exists in the district center, and whether a meat market exists in the district center.
Source: Coping with Shocks in Mongolia Household Panel Survey (waves 1–4) and network expansion data.

TABLE A1 Further summary statistics, by wave.

	Mean	Std. dev.	Min	Max	Number of households
Dependent variables					
Total household income (in ‘000 MNT), w1	10,340.13	7466.01	876	97,306	1035
Total household income (in ‘000 MNT), w2	11,911.93	8139.69	797	114,321	975
Total household income (in ‘000 MNT), w3	18,242.63	14,447.23	1500	115,382	934
Total household income (in ‘000 MNT), w4	17,949.13	13,459.52	310	130,008	743
Agriculture income (in ‘000 MNT), w1	5396.68	5279.28	0	54,719	1035
Agriculture income (in ‘000 MNT), w2	7778.84	7371.98	174	113,841	975
Agriculture income (in ‘000 MNT), w3	13,873.78	13,891.96	0	114,422	934
Agriculture income (in ‘000 MNT), w4	12,386.15	13,105.98	0	121,256	743
Non-agriculture income (in ‘000 MNT), w1	1906.63	3846.85	0	37,760	1035
Non-agriculture income (in ‘000 MNT), w2	2043.78	4224.15	0	50,450	975
Non-agriculture income (in ‘000 MNT), w3	2121.72	4744.13	0	78,000	934
Non-agriculture income (in ‘000 MNT), w4	2075.85	5058.29	0	54,000	743
Transfer income (in ‘000 MNT), w1	3036.82	4825.23	20	91,057	1035
Transfer income (in ‘000 MNT), w2	2089.31	3145.56	0	71,805	975
Transfer income (in ‘000 MNT), w3	2247.13	4687.28	0	96,488	934
Transfer income (in ‘000 MNT), w4	3487.15	3344.63	0	14,500	743
Share of agricultural income, w1	.54	.27	0	.99	1035
Share of agricultural income, w2	.65	.28	0	1	975
Share of agricultural income, w3	.71	.28	0	1	934
Share of agricultural income, w4	.65	.29	0	1	743
Share of non-agricultural income, w1	.15	.24	0	.96	1035
Share of non-agricultural income, w2	.14	.24	0	.96	975
Share of non-agricultural income, w3	.12	.23	0	.95	934

(Continues)

TABLE A1 (Continued)

	Mean	Std. dev.	Min	Max	Number of households
Share of non-agricultural income, w4	.10	.21	0	.95	743
Share of transfer income, w1	.31	.22	0	1	1035
Share of transfer income, w2	.20	.20	0	1	975
Share of transfer income, w3	.17	.19	0	1	934
Share of transfer income, w4	.26	.25	0	1	743
Income diversity (3 categories), w1	.41	.16	0	.67	1035
Income diversity (3 categories), w2	.34	.19	0	1	975
Income diversity (3 categories), w3	.29	.20	0	1	934
Income diversity (3 categories), w4	.32	.20	0	1	743
Income diversity (8 categories), w1	.58	.11	.05	.79	1035
Income diversity (8 categories), w2	.57	.11	0	1	975
Income diversity (8 categories), w3	.52	.14	0	1	934
Income diversity (8 categories), w4	.54	.14	0	1	743
Income diversity in agriculture (7 categories), w1	.67	.20	0	1	1028
Income diversity in agriculture (7 categories), w2	.67	.21	0	1	975
Income diversity in agriculture (7 categories), w3	.67	.25	0	1	931
Income diversity in agriculture (7 categories), w4	.61	.23	0	1	742
Income from livestock sales, w1	3026.70	3813.55	0	44,435	1035
Income from livestock sales, w2	4264.63	5703.34	0	112,000	975
Income from livestock sales, w3v	7916.47	11,418.86	0	113,475	934
Income from livestock sales, w4	6736.16	8849.05	0	72,856	743
Income from livestock byproducts, w1	1758.71	1766.81	0	13,256	1035
Income from livestock byproducts, w2	2662.97	2663.88	0	25,930	975
Income from livestock byproducts, w3	3421.39	3369.29	0	31,121	934
Income from livestock byproducts, w4	4150.24	4975.94	0	40,420	743
Income from farming, w1	38.67	473.11	0	8960	1035
Income from farming, w2	34.05	603.68	0	13,400	975
Income from farming, w3	52.81	725.64	0	16,060	934
Income from farming, w4	151.09	1909.61	0	42,000	743
Herd size (in SFU), w1	279.89	267.45	7	2484	1035
Herd size (in SFU), w2	334.64	315.40	5	3067	975
Herd size (in SFU), w3	391.40	363.11	7	2815	934
Herd size (in SFU), w4	508.91	426.58	10	2620	743
Price per kg cashmere wool (in '0v00 MNT), w1	44.01	4.89	35	57	981
Price per kg cashmere wool (in '000 MNT), w2	58.23	5.27	40	71	975
Price per kg cashmere wool (in '000 MNT), w3	69.57	8.39	45	80	934
Price per kg cashmere wool (in '000 MNT), w4	62.49	13.12	20	80	676
Distance to province center (in km), w1	127.33	100.89	0	380	1035
Distance to province center (in km), w2	135.94	101.00	0	365	975
Distance to province center (in km), w3	137.59	101.94	0	380	934
Distance to province center (in km), w4	153.01	103.25	0	750	736

(Continues)

TABLE A1 (Continued)

	Mean	Std. dev.	Min	Max	Number of households
Repaying loan, w1	.42	.50	0	1	1035
Repaying loan, w2	.45	.50	0	1	975
Repaying loan, w3	.48	.50	0	1	934
Repaying loan, w4	.58	.49	0	1	743
Mobile phone network expansion (district)					
At least one additional tower, w1	.22	.41	0	1	1035
At least one additional tower, w2	.52	.50	0	1	975
At least one additional tower, w3	.61	.49	0	1	934
At least one additional tower, w4	.89	.31	0	1	743
Number of additional towers, w1	.34	.69	0	2	1035
Number of additional towers, w2v	.85	1.06	0	4	975
Number of additional towers, w3	.82	.76	0	2	934
Number of additional towers, w4	2.88	2.74	0	13	743
Time-varying household controls					
Female head, w1	.09	.29	0	1	1035
Female head, w2	.10	.30	0	1	975
Female head, w3	.11	.31	0	1	934
Female head, w4	.14	.34	0	1	743
Age of head, w1	43.74	12.95	19	87	1035
Age of head, w2	44.74	13.00	20	88	975
Age of head, w3	45.49	12.87	21	89	934
Age of head, w4	49.34	11.80	16	89	743
Head has no education, w1	.13	.34	0	1	1035
Head has no education, w2	.13	.34	0	1	975
Head has no education, w3	.14	.35	0	1	934
Head has no education, w4	.13	.34	0	1	743
Head has primary education, w1	.56	.50	0	1	1035
Head has primary education, w2	.57	.49	0	1	975
Head has primary education, w3	.58	.49	0	1	934
Head has primary education, w4	.61	.49	0	1	743
Head has secondary or higher education, w1	.31	.46	0	1	1035
Head has secondary or higher education, w2	.29	.46	0	1	975
Head has secondary or higher education, w3	.28	.45	0	1	934
Head has secondary or higher education, w4	.26	.44	0	1	743
Head is married, w1	.85	.36	0	1	1035
Head is married, w2	.85	.36	0	1	975
Head is married, w3	.84	.37	0	1	934
Head is married, w4	.83	.38	0	1	743
Household size, w1	4.16	1.54	1	10	1035

(Continues)

TABLE A1 (Continued)

	Mean	Std. dev.	Min	Max	Number of households
Hould size, w2	4.16	1.56	1	10	975
Household size, w3	4.13	1.54	1	9	934
Household size, w4	4.05	1.77	1	10	743
Time-varying district controls					
Population size, w1	6953.73	7646.94	1356	25,015	1035
Population size, w2	6306.20	7324.40	1268	25,098	975
Population size, w3	6183.92	7485.59	842	26,594	934
Population size, w4	5837.75	7611.45	728	31,154	743
Spending on infrastructure, w1	1809.16	3146.98	0	9814	1035
Spending on infrastructure, w2	10,008.70	22,277.14	0	85,698	975
Spending on infrastructure, w3	3698.72	6370.71	0	21,113	934
Spending on infrastructure, w4	5131.48	8531.36	0	25,726	743
Permanent market available, w1	.25	.43	0	1	1035
Permanent market available, w2	.22	.41	0	1	975
Permanent market available, w3	.23	.42	0	1	934
Permanent market available, w4	.16	.37	0	1	743
Meat market available, w1	.27	.44	0	1	1035
Meat market available, w2	.26	.44	0	1	975
Meat market available, w3	.26	.44	0	1	934
Meat market available, w4	.19	.39	0	1	743

Note: All income variables refer to annual household income.

Source: Coping with Shocks in Mongolia Household Panel Survey (waves 1–4) and network expansion data.

TABLE A2 Descriptive statistics on access to and use of mobile phones over time, from Mongolia Household Socio-Economic Survey.

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Does the household have a telephone?										
Yes, land line phone	2.1%	.4%	.6%	1.9%	.3%	.3%	2.6%	2%	1.3%	2.5%
Yes, mobile phone	90.1%	93.8%	94.3%	93.4%	95.5%	93.8%	89.3%	88.6%	91.7%	88.4%
Yes, both land line and mobile	1.2%	2.8%	1.7%	1.5%	2.3%	4%	7%	7.3%	4.3%	8.4%
No	6.5%	3%	3.5%	3.2%	1.9%	1.9%	1.1%	2%	2.6%	.7%
Does the household have internet access at home?[a]										
Yes	2.8%	2.3%	2.2%	4%	7.9%	8.9%	31.4%	25.8%	14.5%	12.1%
No	97.2%	97.7%	97.8%	96%	92.1%	91.1%	68.6%	74.2%	85.5%	87.9%
Do household members use internet through smartphone? [b]										
Yes	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	58.4%	62.9%
No	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	41.6%	37.1%
Does the household own a mobile phone? [c]										
Smart mobile phone	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	2.2%	.4%
Non-smart mobile phone	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	73.7%	76%
Sample size	891	705	1065	619	953	632	920	640	1040	692

Notes: The sample shown in this table only comprises livestock-owning households in the provinces of Govi-Altai, Uvs, and Zavkhan.
[a]In 2020, this survey item slightly changed, with a filter question being introduced; hence, responses before and after 2019 are not strictly comparable.
[b]This does not imply that the household also owns a smartphone; a "yes" answer could indicate that a household member uses the smartphone of a friend to access the internet.
[c]For each category, a yes/no answer was recorded. Source: Mongolia Household Socio-Economic Survey, annual cross-sectional rounds 2012–2021.

TABLE A3 Baseline results with full set of controls displayed (OLS).

	Total household income (log)		Agricultural income (log)		Non-agricultural income (log)		Transfer income (log)	
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Treatment is dummy								
At least one additional tower	.133***		.177***		.012		.175***	
	(.000)		(.000)		(.929)		(.006)	
Panel B: Treatment is continuous								
Number of additional towers		.036***		.071***		−.049		.046*
		(.000)		(.001)		(.363)		(.083)
Time-varying household controls								
Female head	−.252***	−.253***	−.201*	−.202*	−1.199***	−1.201***	.332	.330
	(.000)	(.000)	(.093)	(.092)	(.005)	(.005)	(.104)	(.106)
Age of head	.019**	.019**	.035***	.035***	.246***	.245***	−.144***	−.144***
	(.012)	(.013)	(.004)	(.004)	(.000)	(.000)	(.000)	(.000)
Age of head (sq)	−.000	−.000	−.000***	−.000***	−.002***	−.002***	.002***	.002***
	(.182)	(.185)	(.001)	(.001)	(.000)	(.000)	(.000)	(.000)
Head has primary education	.205***	.205***	.217***	.218***	−.135	−.136	.121	.122
	(.000)	(.000)	(.001)	(.001)	(.585)	(.584)	(.221)	(.221)
Head has secondary education	.329***	.329***	.122	.122	1.397***	1.397***	.159	.159
	(0.000)	(0.000)	(0.119)	(.118)	(.000)	(.000)	(.160)	(.160)
Head is married	.015	.013	.132	.131	−.376	−.377	−.127	−.129
	(.796)	(.819)	(.166)	(.173)	(.363)	(.361)	(.478)	(.471)
Household size	.074***	.074***	.086***	.085***	.114*	.114*	.280***	.280***
	(.000)	(.000)	(.000)	(.000)	(.098)	(.098)	(.000)	(.000)
Time−varying district controls								
Population size (log)	.010	−.020	−.228*	−.269**	−.220	−.219	.005	−.034
	(.884)	(.773)	(.076)	(.039)	(.456)	(.460)	(.988)	(.919)
Spending infrastructure (log)	.010	.010	.005	.007	−.013	−.015	.031	.031*
	(.168)	(.162)	(.533)	(.447)	(.735)	(.694)	(.102)	(.098)
Permanent market	−.366**	−.275*	−.332*	−.240	−.176	−.099	−.865	−.744
	(.012)	(.053)	(.090)	(.207)	(.869)	(.924)	(.149)	(.203)
Meat market	.284***	.232**	.403***	.359***	.196	.133	.484	.413
	(.003)	(.012)	(.001)	(.003)	(.809)	(.869)	(.248)	(.316)

(Continues)

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TABLE A3 (Continued)

Dependent variable	Total household income (log)		Agricultural income (log)		Non-agricultural income (log)		Transfer income (log)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Linear time trend by district	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.31	.31	.35	.35	.28	.28	.23	.23
Number of households, w1	1035	1035	1035	1035	1035	1035	1035	1035
Number of households, w2	975	975	975	975	975	975	975	975
Number of households, w3	934	934	934	934	934	934	934	934
Number of households, w4	743	743	743	743	743	743	743	743
Observations	3687	3687	3687	3687	3687	3687	3687	3687

Note: Standard errors clustered at the PSU level. Unadjusted p-values in parentheses with $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$. In education of the head of household, the excluded category is 'no education'.

Source: Coping with Shocks in Mongolia Household Panel Survey (waves 1–4) and network expansion data.

TABLE A4 Sensitivity tests on the impact of the expansion of mobile phone networks on the price of cashmere wool (OLS).

Test Dependent variable	Data from waves 1 to 3 only Price per kg cashmere wool (log) (1)	Excluding outlier district in wave 4 Price per kg cashmere wool (log) (2)	Excluding outlier district in all waves Price per kg cashmere wool (log) (3)
Panel A: Treatment is dummy			
At least one additional tower	.058	1.555***	1.748***
	(.847)	(.000)	(.00)
Panel B: Treatment is continuous			
Number of additional towers	.327**	.181	.225
	(.029)	(.273)	(.200)
R-squared, panel A	.85	.69	.68
R-squared, panel B	.85	.69	.68
Time-varying household controls	Yes	Yes	Yes
Time-varying district controls	Yes	Yes	Yes
Linear time trend by district	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes
Wave fixed effects	Yes	Yes	Yes
Number of households, w1	981	981	922
Number of households, w2	975	975	903
Number of households, w3	934	934	876
Number of households, w4	–	648	648
Observations	2890	3538	3349

Note: Household-level controls include household size as well as the gender, age, education, and marital status of the household head. District-level controls include population size, the amount of infrastructure spending, whether a permanent market exists in the district center, and whether a meat market exists in the district center. Standard errors are clustered at the PSU level. Unadjusted p-values in parentheses with $^*p < .1$, $^{**}p < .05$, $^{***}p < .01$.

Source: Coping with Shocks in Mongolia Household Panel Survey (waves 1–4) and network expansion data.

TABLE A5 Robustness tests (OLS).

Test Dependent variable	Effects for non-herding households Total household income (log) (1)	Excluding linear time trend by district Agricultural income (log) (2)	Parallel trends assumption Agricultural income (log) (3)	Attrition bias: Balanced sample of households owning livestock in each wave Agricultural income (log) (4)
Panel A: Treatment is dummy				
At least one additional tower	−.003	.126***	−.032	.165***
	(.965)	(.000)	(.405)	(.000)
Panel B: Treatment is continuous				
Number of additional towers	.007	.042***	−.027	.071**
	(.672)	(.001)	(.154)	(.004)
R-squared, panel A	.18	.34	.31	.35
R-squared, panel B	.18	.34	.32	.35
Time-varying household controls	Yes	Yes	Yes	Yes
Time-varying district controls	Yes	Yes	Yes	Yes
Linear time trend by district	Yes	No	No	Yes
District fixed effects	Yes	Yes	Yes	Yes
Wave fixed effects	Yes	Yes	Yes	Yes
Number of households, w1	634	1035	1001	724
Number of households, w2	601	975	964	724
Number of households, w3	590	934	875	724
Number of households, w4	503	743	–	724
Observations	2328	3687	2863	2896

Note: Household-level controls include household size as well as the gender, age, education, and marital status of the household head. District-level controls include population size, the amount of infrastructure spending, whether a permanent market exists in the district center, and whether a meat market exists in the district center. Standard errors are clustered at the PSU level. Unadjusted p-values in parentheses with $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.

Source: Coping with Shocks in Mongolia Household Panel Survey (waves 1–4) and network expansion data.

TABLE A6 Baseline results with household fixed effects (OLS).

Dependent variable	Total household income (log) (1)	Agricultural income (log) (2)	Non-agricultural income (log) (3)	Transfer income (log) (4)	Share of agricultural income (5)	Share of non-agricultural income (6)	Share of transfer income (7)
Panel A: Treatment is dummy							
At least one additional tower	.061*	.084*	−.022	.066	.014***	−.006	−.007*
	(.068)	(.090)	(.692)	(.112)	(.002)	(.171)	(.058)
Panel B: Treatment is continuous							
Number of additional	.008	.021	−.025	.011	.006*	−.003***	−.003
	(.563)	(.184)	(.290)	(.630)	(.056)	(.009)	(.285)
R-squared, panel A	.28	.26	.03	.12	.19	.02	.24
R-squared, panel B	.28	.26	.03	.12	.19	.02	.24
Time-varying household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying district controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trend by district	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of households, w1	1035	1035	1035	1035	1035	1035	1035
Number of households, w2	975	975	975	975	975	975	975
Number of households, w3	934	934	934	934	934	934	934
Number of households, w4	743	743	743	743	743	743	743
Observations	3687	3687	3687	3687	3687	3687	3687

Note: Household-level controls include household size as well as the gender, age, education, and marital status of the household head. District-level controls include population size, the amount of infrastructure spending, whether a permanent market exists in the district center, and whether a meat market exists in the district center. Standard errors are clustered at the PSU level. Unadjusted p-values in parentheses with $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.

Source: Coping with Shocks in Mongolia Household Panel Survey (waves 1–4) and network expansion data.

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TABLE A7 Descriptive statistics on access to and use of mobile phones over time, from Coping with Shocks survey.

	Wave 1 2012/13	Wave 2 2013/14	Wave 3 2014/15	Wave 4 2020/21
Do you use the following phones in your household?[a]				
Non-smart mobile phone	n.a.	n.a.	n.a.	84.5%
G-mobile desktop phone	n.a.	n.a.	n.a.	28%
Smartphone	n.a.	n.a.	n.a.	53.2%
Do you use your mobile phone for the following purposes?[a,b]				
Calls	n.a.	n.a.	99.4%	99.2%
SMS	n.a.	n.a.	59%	64.2%
Internet	n.a.	n.a.	2.4%	26.4%
GPS	n.a.	n.a.	.4%	1.4%
Does the household have access to the internet?				
Yes, via own smartphone	n.a.	n.a.	n.a.	21.3%
Yes, via mobile router	n.a.	n.a.	n.a.	2.8%
Yes, via neighbors' device	n.a.	n.a.	n.a.	0%
Yes, in an internet cafe	n.a.	n.a.	n.a.	.3%
No	n.a.	n.a.	n.a.	75.5%
Sample size			466	743

Note:
[a]For each category, a yes/no answer was recorded.
[b]This survey item has missing values for more than half of the sample because of a wrong skip. Source: Coping with Shocks in Mongolia Household Panel Survey (waves 1–4).

TABLE A8 Impact of the expansion of mobile phone networks on household income with wave 1–3 data only (OLS).

Dependent variable	Total household income (log) (1)	Agricultural income (log) (2)	Non-agricultural income (log) (3)	Transfer income (log) (4)	Share of agricultural income (5)	Share of non-agricultural income (6)	Share of transfer income (7)
Panel A: Treatment is dummy							
At least one additional tower	.111***	.156***	.174	.070	.006	−.000	−.006
	(.000)	(.000)	(.238)	(.242)	(.403)	(.957)	(.376)
Panel B: Treatment is continuous							
Number of additional towers	.055***	.092***	.066	.036	.004	−.001	−.003
	(.000)	(.000)	(.321)	(.202)	(.280)	(.773)	(.381)
R-squared, panel A	.33	.37	.29	.29	.44	.30	.41
R-squared, panel B	.33	.37	.29	.29	.44	.30	.41
Time-varying household controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying district controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear time trend by district	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of households, w1	1035	1035	1035	1035	1035	1035	1035
Number of households, w2	975	975	975	975	975	975	975
Number of households, w3	934	934	934	934	934	934	934
Observations	2944	2944	2944	2944	2944	2944	2944

Note: Further control variables are included, but not displayed here. Household-level controls include household size as well as the gender, age, education, and marital status of the household head. District-level controls include population size, the amount of infrastructure spending, whether a permanent market exists in the district center, and whether a meat market exists in the district center. Standard errors are clustered at the PSU level. Unadjusted p-values in parentheses with $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.

Source: Coping with Shocks in Mongolia Household Panel Survey (waves 1–3) and network expansion data.

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TABLE A9 Robustness test for heterogeneous treatment effects (imputation estimator approach).

Dependent variable	Total household income (log) (1)	Agricultural income (log) (2)	Non-agricultural income (log) (3)	Transfer income (log) (4)	Income diversity (3 categories) (5)	Income diversity (8 categories) (6)
Treatment is dummy						
At least one additional tower	.120***	.118**	−.040	.121	−.018*	−.024***
	(.001)	(.022)	(.836)	(.221)	(.077)	(.001)
Time-varying household controls	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying district controls	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Wave fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3667	3667	3667	3667	3667	3667

Note: Results from an imputation estimator approach developed by Borusyak et al. (2022). Further control variables are included, but not displayed here. Household-level controls include household size as well as the gender, age, education, and marital status of the household head. District-level controls include population size, the amount of infrastructure spending, whether a permanent market exists in the district center, and whether a meat market exists in the district center. Standard errors are clustered at the PSU level. Unadjusted p-values in parentheses are displayed first with $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$. Source: Coping with Shocks in Mongolia Household Panel Survey (waves 1–4) and network expansion data.

TABLE A10 Attrition analysis (Probit).

	Households quit pastoralism, attrited from survey or left district...		
	between wave 1 and 2	between wave 2 and 3	between wave 3 and 4
Dependent variable	**(1)**	**(2)**	**(3)**
At least one additional tower	.051	.026	−.586***
	(.717)	(.769)	(.000)
Female head	−.029	.506*	.042
	(.949)	(.054)	(.872)
Age of head	.028	−.080**	−.043
	(.381)	(.010)	(.100)
Age of head (sq)	−.000	.001**	.001**
	(.374)	(.012)	(.028)
Head has primary education	.398*	.250	−.170
	(.070)	(.272)	(.245)
Head has secondary education	.703***	.912***	.232
	(.005)	(.000)	(.176)
Head is married	.013	−.309	−.057
	(.968)	(.249)	(.761)
Household size	−.038	−.040	−.072*
	(.475)	(.429)	(.058)
Population size (log) (district)	−.820***	.097	.014
	(.006)	(.634)	(.928)
Spending infrastructure (log)	.120*	−.007	.011
	(.067)	(.855)	(.745)
Permanent market (district)	5.465***	.689	.628***
	(.000)	(.185)	(.001)
Meat market (district)	−3.244***	−.111	−.383*
	(.000)	(.807)	(.051)
R-squared	.20	.17	.12
Observations	1035	1031	995

Note: The outcome variable is a dummy variable indicating whether a household has quit pastoralism, attrited from survey or left district (1) or not (0) in the following wave. The independent variables are the main control variables from the baseline model and variables of interest; they are constructed based on wave 1 data (column 1), wave 2 data (column 2), and wave 3 data (column 3). In education of the head of household, the excluded category is 'no education'. Standard errors are clustered at the PSU level. Unadjusted *p*-values in parentheses with $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$.

Source: Coping with Shocks in Mongolia Household Panel Survey (waves 1–4) and network expansion data.