Mobile Phone Expansion, Informal Risk Sharing, and Consumption Smoothing: Evidence from Rural Uganda

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Abstract

We study how the recent expansion of mobile phone coverage affects the degree of consumption smoothing using data collected in rural Uganda in 2003 and 2005. We found that mobile phone coverage helps consumption smoothing against covariate shocks but not idiosyncratic shocks. Unlike in studies on informal risk sharing, but in line with the permanent income hypothesis, we also found that household-level consumption changes are insenitive to transitory household income shocks, but sensitive to permanent household income shocks. Full intertemporal self-insurance is, however, impossible under imperfect credit and insurance markets. Our results show that households effectively combine self-insurance, local risk sharing, and long-distance risk sharing via mobile phone, where idiosyncratic shocks are partially mitigated by self-insurance as well as mutual insurance within local communities, while covariate shocks are partially mitigated by self-insurance and across distant communities via mobile phones.

Keywords: risk sharing, mobile phone network, consumption smoothing, Uganda
JEL Classification: D81, D85, O17

I Introduction

The livelihoods of rural households in developing countries are exposed and vulnerable to various exogenous income risks such as natural disasters, conflicts, disease epidemics, and price fluctuations. Protecting the poor from such risks has been one of the most important political and research agendas for achieving sustainable poverty reduction. It is theoretically possible for poor households to self-insure for those risks and smooth consumption by purchasing insurance or saving in good times and dissaving/borrowing in bad times, as the permanent income hypothesis (PIH) suggests. It has long been believed, however, that such autarkic intertemporal risk management does not work properly under imperfect credit and insurance markets, which have been pervasive in most developing countries.

The poor in developing countries have undertaken costly self-insurance strategies due to the limited risk management options available through financial markets. For example, they smooth income by diversifying their economic activities into pieces of low-return but stable income sources instead of pursuing risky but potentially higher income-generating activities (Morduch, 1995). They also sell productive assets such as livestock or withdraw children from school against income shocks, which jeopardizes their long-term income growth, thereby placing them into poverty traps (Fafchamps et al., 1998; Jacoby and Skoufias, 1997).

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The literature argues that informal interstate risk-sharing arrangements have developed as an alternative intertemporal insurance mechanism within small local communities, where household-specific idiosyncratic income fluctuations are pooled and shared among local community members. As a result of this informal mechanism, idiosyncratic income shocks are at least partly mitigated to help consumption smoothing, although the full income sharing hypothesis tends to be rejected (Townsend, 1994: Udry, 1994). On the other hand, since neighboring community members all suffer similar downside shocks, covariate income shocks impose serious challenges for welfare dynamics among the poor who rely on mutual assistance because such shocks cannot be insured through local risk-sharing arrangements (Takahashi et al., 2016). Rosenzweig and Stark (1989) point out that families in rural India spread risk over wide geographical areas by marrying their daughters to distant households and requesting remittances in times of need.

While a few case studies on long-distance risk sharing have been conducted, as transaction and communication costs are generally high, long-distance risk sharing has not been common until recently. Rapidly growing mobile phone networks in developing countries, including in sub-Saharan Africa, have dramatically changed the situation. Aker and Mbiti (2010) find that the expansion of mobile phone networks in Africa has remarkably reduced search and transaction costs, facilitating coordination among agents across geographical regions and thus decreasing price dispersion across them.

Along this line, several studies show that the reduced communication costs associated with expanding mobile telephone facilitate informal risk management over long distance. Bulmenstock et al. (2016) demonstrate that mobile money transactions over long distance were intensified immediately after local covariate shocks, exemplified by earthquakes, occurred in Rwanda. Jack and Suri (2014) show that mobile phone possession in Kenya reduces the sensitivity of consumption to negative income shocks because of the increased mobile money remittances among relatives after the shocks occur. Munyegera and Matsumoto (2016) also show that adopting mobile money services increases household per capita consumption by 72%, due mainly to the increased remittances.

In this paper, we investigate the differential impact of mobile phone coverage on the sensitivity of consumption to idiosyncratic and covariant income shocks. Long-distance risk sharing through mobile phone communication would be an emerging option for households, especially in the face of covariate risks that are difficult to cope with at the local community level. It could also be used for idiosyncratic shocks. Relative dependency on local risk sharing and long-distance risk sharing against idiosyncratic shocks is ambiguous and depends on the strength of the social ties within each network and the level of the transaction costs for each option. By interacting mobile phone networks with idiosyncratic and covariant income shocks, we explicitly investigate how mobile phones help household consumption smoothing against not only covariant income shocks but also idiosyncratic income shocks.

The data used in this study are drawn from two-year panel data collected in rural Uganda in 2003 and 2005. During this period, local communities covered by mobile phone networks sharply increased from 15.3% to 46.2%. Since mobile money had not been introduced during the survey periods, people used informal channels (e.g., servants, friends, relatives, bus drivers) to send remittances upon request. Although such means may still be risky and costly compared to mobile money transactions, it is hypothesized that expanding mobile phone networks would increase information flows, thereby promoting mutual assistance with friends and relatives over long distances.

In the estimation, we extend the standard empirical model of full income sharing, which generally assumes that (1) permanent income components are, by definition, time invariant and that (2) both permanent and transitory incomes are fully pooled and shared within members of a social network. However, assets (and household demographic characteristics) that determine the time path of permanent future income may not necessarily be time invariant due to asset accumulation/loss and changes in expected returns to assets over time. In particular, when we rely only on short-term panel data, observed income changes will consist of transitions of the permanent income to the steady state, regardless of whether it is single or multiple equilibria, as well as stochastic changes due to transitory shocks (Naschold and Barrett, 2011). Furthermore, the permanent and transitory income changes will not be perfectly observable to community members, leading to a limited commitment to and violation of the second assumption above (Coate and Ravallion, 1993; Ligon, 1998). These demonstrate the importance of incorporating a permanent household income shock into an explanatory variable, allowing us to examine the extent of the sensitivity of consumption changes with respect to permanent and transitory income shocks as well as covariate shocks.

The rest of the paper is structured as follows. Section 2 explains the data source and presents the descriptive statistics of the sample households. Section 3 explains the estimation strategies. Section 4 discusses the estimation results, while Section 5 extends the analysis. Finally, Section 6 concludes the paper.

Ⅱ Data Description and Sample Villages

2.1. Data Source

This study uses data from 871 households in rural Uganda surveyed both in 2003 and 2005 as part of the Research on Poverty, Environment, and Agricultural Technology (RePEAT) project. The RePEAT project was initiated by the National Graduate Institute for Policy Studies and the Foundation of Advanced Studies on International Development in Japan, in close collaboration with Makerere University.

The sampling in the RePEAT project in Uganda was based largely on that of an earlier IFPRI survey. Out of the original 107 Local Councils (LC1: the lowest administrative unit in Uganda), 94 were selected. Because of security concerns in the northern and northeastern parts of the country, we excluded those LC1s from our samples. From each selected LC1, 10 households were randomly chosen, and 940 households were interviewed in 2003. Among the 940 households interviewed in the first round in 2003, the interview teams for the second survey in 2005 found that five households had been dissolved, 16 households had moved out, 15 households could not be contacted by the teams, three households refused to be interviewed, and seven households were not interviewed for unknown reasons. As a result, 895 households were interviewed again in 2005.

Out of those 895 households, we dropped 24 households with missing values, yielding 871 balanced-panel households for analysis.

2.2. Descriptive Statistics

Table 1 displays the sample distribution by region and by mobile phone coverage over time. We consider that LC1 is covered by mobile phone networks if at least one sample household in the LC1 possesses a mobile phone at the time of the survey. Because sharing mobile phones among local community members is common in rural Uganda, we believe that LC1-level mobile phone networks capture the household accessibility of mobile phones better than individual possession does. The numbers in each cell represent the percentage of households out of

Table 1. % Distribution of Mobile Phone Coverage by Region

Region	Both 2003 and 2005	Only 2005	No Access	Total
Central	8.61 (28.2)	8.61 (28.2)	13.32 (43.61)	30.54 (100)
East	3.21 (7.29)	13.66 (30.99)	27.21 (61.72)	44.09 (100)
West	3.44 (13.57)	8.61 (33.94)	13.32 (52.49)	25.37 (100)
Total	15.27	30.88	53.85	100

the total sample households, while the numbers in parentheses represent the percentage of households in each region.

As can be seen, about 15% of households were covered in both 2003 and 2005, 31% of households were newly covered in 2005, and the remaining 54% were never covered by mobile phone networks during the observation periods. There are variations across and within regions. In 2003, households in the central region, which is wealthier than the other regions, had better access to mobile phones: 28% of households within the central region were connected to mobile phone networks, and those in the east and west regions lagged behind. However, coverage improved more rapidly for the east and west regions, with 34% and 31% of households gaining access in 2005, respectively, compared with 28% in the central region in the same year. Although the central region still had the best access in 2005, nearly 40% and 50% of households in the east and west were covered by mobile phone networks by 2005.

Table 2 shows changes in household welfare over time via mobile phone coverage. We classify poverty status by consumption expenditure per adult equivalent. Following Appleton (2003) and Yamano et al. (2004), equivalence scales are computed by the age and gender of each household member. Total expenditure is constructed by summing up cash expenditure and the value of self-consumption of home-produced food items.

Table 2. Changes in Household Welfare by Mobile Phone Coverage

	Both 2003 and 2005		Only 2005		No Access		Total	
	2003	2005	2003	2005	2003	2005	2003	2005
Adult equivalent per capita consumption（US$）	233.9 (226.8)	214.5 (163.3)	206.5 (159.4)	221.5 (213.4)	177.1 (151.1)	183.8 (179.5)	199.5 (186.3)	195.5 (171.4)
Adult equivalent per capita income（US$）	214.8 (326.9)	187.5 (230.8)	227.0 (279.1)	193.2 (264.6)	145.4 (197.7)	161.4 (195.9)	170.8 (244.1)	185.7 (231.5)
Poverty head count ratio	0.481 (0.502)	0.481 (0.502)	0.480 (0.501)	0.498 (0.501)	0.591 (0.492)	0.603 (0.490)	0.545 (0.498)	0.546 (0.498)
Household Size	8.105 (4.193)	7.820 (4.264)	7.454 (3.732)	7.621 (3.812)	7.576 (4.394)	7.462 (3.690)	7.619 (4.170)	7.566 (3.818)
N	133		269		469		871	

Standard deviations in parentheses

Total income is the sum of self-employed and wage incomes, ranging over crop, livestock, nonfarm and non-labor sources, including remittances and rental earnings. We compute self-employed incomes by subtracting the paid-out costs from the total value production, while wage incomes are the sum of salaries from regular jobs as well as wage earnings from seasonal jobs. Total expenditure and income in 2003 are adjusted to 2005 price levels, and the poverty line is set at 161 USD per adult equivalent at the 2005 price levels. Households are identified as "poor" when the expenditure per adult equivalent is less than the poverty line.

It is clear that households covered by mobile phone networks are better off than are those that were never covered. The average expenditure per adult equivalent was greater than 200 USD in the first group (covered in both 2003 and 2005) and second group (newly covered in 2005), while it was only about 180 USD in the third group (never covered) both in 2003 and 2005. Similarly, the poverty head count ratios were around 48% in the first two groups, lower by about 12% than the third group in 2003 and 2005. The *t*-test on the mean differences reveals that the average per capita adult equivalent expenditure and poverty head count ratios were significantly different at the 1% level between the first two groups and the third group in both years. On the other hand, no statistical difference is observed in those figures between the first and second groups in both years. Obviously, these observations alone cannot establish a causal impact of mobile phone coverage on household welfare, as a reverse causality can exist (i.e., whereby better-off communities are more likely to be covered by mobile phones).

To obtain more insight into the welfare dynamics of mobile phone coverage, **Figure 1** shows a locally weighted scatterplot smoothing (LOWESS) on the log initial per adult equivalent expenditure (horizontal axis) and its change between 2003 and 2005 (vertical axis). It shows that all three groups exhibit almost linear downward slopes, suggesting that the rate of consumption growth is higher for the initially poorer households. It is also important to note that the slope is slightly flatter for households newly covered by mobile phone networks, implying that consumption volatility is smaller for households if they gained access to mobile phone networks in 2005.

Whether or not the demonstrated small consumption volatility is associated with the ability to mitigate idiosyncratic and covariate income shocks is an important question; this is addressed in the following sections.

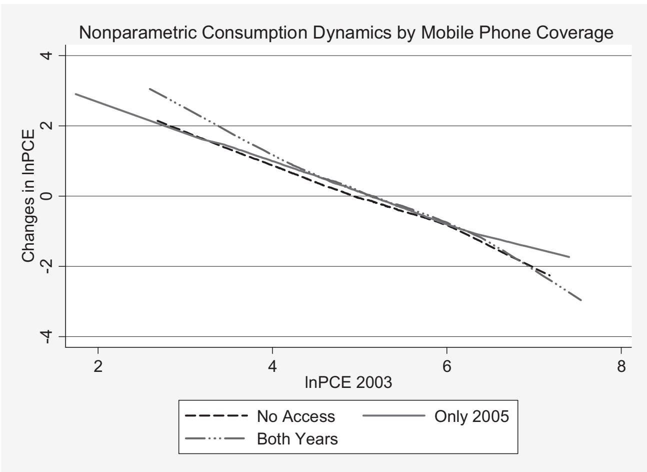

Figure 1. Nonparametric (Lowess) Consumption Dynamics

Ⅲ Estimation Strategies

3.1. Impact of Mobile Phone on Consumption Smoothing

Following Townsend (1994), the benchmark equation for examining consumption sensitivity against shocks can be expressed as

$$c_{ij,t} = a_1 + a_2 y_{ij,t} + a_3 \bar{c}_{j,t} + \theta_i + \mu_t + \varepsilon_{ij,t},$$

where $c_{ij,t}$, $y_{ij,t}$, and $\bar{c}_{j,t}$ are the per adult equivalent consumption of household i in community j at time t, per adult equivalent income of household i in community j at time t, and average per adult equivalent consumption of commodity j at time t, respectively; a_1, a_2, and a_3 are parameters to be estimated; θ_i and μ_t repserent household time-invariant fixed effects and a time dummy, respectively; and $\varepsilon_{ij,t}$ is an error term.

Taking the first difference, the above equation can be rewritten as

$$\Delta c_{ij,t} = \Delta\mu_t + a_2 \Delta y_{ij,t} + a_3 \Delta\bar{c}_{j,t} + \Delta\varepsilon_{ij,t}, \tag{1}$$

where Δ denotes changes in each variable over time, such that $\Delta c_{ij,t} = c_{i,t} - c_{i,t-1}$, $\Delta y_{ij,t} = y_{i,t} - y_{i,t-1}$, $\Delta\bar{c}_{j,t} = \bar{c}_{i,t} - \bar{c}_{i,t-1}$, $\Delta\mu_t = \mu_t - \mu_{t-1}$, and $\Delta\varepsilon_{ij,t} = \varepsilon_{i,t} - \varepsilon_{i,t-1}$.

The standard empirical model assumes that the permanent income component is time-invariant and is eliminated by taking the first difference. Therefore, $\Delta y_{ij,t}$ shows only transitory idiosyncratic income shocks, whereas $\Delta\bar{c}_{j,t}$ is the covariate shocks that affect all households within a community. Although we relax this assumption later, the coefficients of interests here are definitely a_2 and a_3. The full income-sharing hypothesis implies that the coefficient of a_2 is zero and that of a_3 is unity.

To allow for the differential sensitivity of the consumption to idiosyncratic and covariate shocks via mobile phone accessibility, we introduce interaction terms with each variable in Eq (1) as

$$\begin{aligned} \Delta c_{ij,t} = {} & \Delta\mu_t + b_1 \Delta mob_{j,t} + a_2 \Delta y_{ij,t} + b_2(\Delta y_{ij,t} * \Delta mob_{j,t}) \\ & + a_3 \Delta\bar{c}_{j,t} + b_3(\Delta\bar{c}_{j,t} * \Delta mob_{j,t}) + \Delta\varepsilon_{ij,t}. \end{aligned} \tag{2}$$

$\Delta mob_{j,t}$ denotes a dummy variable equal to 1 if the community gained new access to mobile phones between 2003 and 2005 and zero otherwise. As explained, we do not use changes in individual possession of mobile phones during the same periods because the community-level coverage would be more likely to reflect individual mobile phone accessibility. Moreover, individual possession is more likely to be endogenous, depending on individual characteristics. Thus, we consider $\Delta mob_{j,t}$ as an exogenous shock to individuals.

In Eq. (2), if long-distance risk sharing is effective when covariate shoc occur, the coefficient of b_3 would be negative, implying a reduction in the degree of comovement in consumption with neighboring households. On the other hand, if long-distance risk sharing is effective in managing idiosyncratic shocks, the coefficient of b_2 would be negative.

One of the potential critiques of Eq. (2) is that changes in access to mobile phone network are not random, implying placement bias. In fact, Muto and Yamano (2009) argue that the population density of a community and other regional characteristics are associated with mobile phone network coverage in rural Uganda. We control for such non-random placement by fixed effects.

Besides, Ravallion and Chaudhuri (1997) criticize this type of estimation and recommend using community dummy variables instead of the average per capita consumption of the community to obtain consistent estimates of the coefficients on idiosyncratic income components. Thus, as a robustness check, we estimate the following equation:

$$\Delta c_{ij,t} = \Delta\mu_t + b_1 D_j + a_2 \Delta y_{ij,t} + b_2(\Delta y_{ij,t} * \Delta mob_{j,t}) + \Delta\varepsilon_{ij,t}. \tag{3}$$

where D_j is a set of community dummy variables.

3.2. Impacts of Permanent and Transitory Income Shocks and Covariate Shocks

An important assumption underlying Eq. (1) is that $\Delta y_{ij,t}$ captures only a transitory income shock. However, this assumption might be implausible for several reasons. First, assets that determine the time path of permanent future income may not necessarily be time invariant due to asset accumulation and changes in expected returns for those assets overtime. While asset dynamics could have a linear trend, several studies emphasize the possibility of non-linear asset dynamics that may yield multiple wealth equilibria (Carter and Barrett, 2006; Santos and Barrett, 2006). Thus, when we have to rely on short-term panel data, as in our case, observed income changes would be brought about by the transition process to multiple stable equilibria governed by initial asset holdings and their dynamics as well as by stochastic changes brought about by transitory shocks (Nashold and Barrett, 2011). While it is difficult to distinguish between these two, simply treating $\Delta y_{ij,t}$ as a transitory idiosyncratic shock would be misleading.

Second, in line with Paxson (2002) and Kazianga and Udry (2006), the test of the relative importance of permanent and transitory income on consumption smoothing is important in evaluating the validity of PIH along with the full income-sharing hypothesis. If autarkic self-insurance is possible and PIH is valid, permanent household income growth is perfectly correlated with consumption growth, while that of transitory income shocks and covariate shocks do not affect individual consumption changes at all. Moreover, if the full income sharing hypothesis is rejected because part of permanent income changes is hidden due to asymmetric information among members of a social network, permanent household income shocks would be partially correlated with individual consumption changes. In this circumstance, covariate shocks would also be partially correlated with individual consumption changes as long as local risk sharing at the community is active.

To test these alternative hypotheses, we assume that the realized income change can be decomposable into the permanent, transitory, and unexplained income changes, expressed by

$$\begin{aligned} \Delta\hat{y}^P_{ij,t} &= r_1 + \gamma_2 \Delta x^P_{ij,t}, \\ \Delta\hat{y}^T_{ij,t} &= \gamma_3 \Delta x^T_{ij,t}, \\ \Delta\omega_{ij,t} &= \Delta y_{ij,t} - \Delta\hat{y}^P_{ij,t} - \Delta\hat{y}^T_{ij,t}, \end{aligned} \tag{4}$$

where $\Delta\hat{y}^P_{ij,t}$ represents a permanent income change due to changes in household assets and demographic characteristics, denoted as $\Delta x^P_{ij,t}$, and due to their returns, r_1 and γ_2; $\Delta\hat{y}^T_{ij,t}$ represents a transitory income change due to individual shocks such as crop damage and illness of household members, denoted as $\Delta x^T_{ij,t}$, and their returns, γ_3; and $\Delta\omega_{ij,t}$ is the residual, representing the unexplained income change. Then, following Paxson (1992) and Kazianga and Udry (2006), the estimable income growth function is

$$\Delta y_{ij,t} = r_1 + \gamma_2 \Delta x^P_{ij,t} + \gamma_3 \Delta x^T_{ij,t} + \Delta\omega_{ij,t} \tag{5}$$

Substituting Eq. (4) and (5) into Eq. (1), we can derive the following specification:

$$\Delta c_{ij,t} = \Delta\mu_t + a_{21}\Delta\hat{y}^P_{ij,t} + a_{22}\Delta\hat{y}^T_{ij,t} + a_{23}\Delta\omega_{ij,t} + a_3\Delta\bar{c}_{j,t} + \Delta\varepsilon_{ij,t}. \tag{6}$$

As discussed, intertemporal PIH implies $a_{21} = 1$, $a_{22} = 0$, and $a_3 = 0$, while interstate full income sharing implies $a_{21} = 0$, $a_{22} = 0$, and $a_3 = 1$. As a combination, partial risk commitment at the local community implies $0 < a_{21} < 1$ and $0 < a_3 < 1$. By interacting each variable with mobile phone accessibility in a community, we also explore how the sensitivity of consumption with respect to each income shock differs according to mobile phone accessibility.

Ⅳ Results

4.1. Impact of Mobile Phone on Consumption Smoothing

Table 3 presents the estimation results. $\Delta c_{ij,t}$ (changes in real per adult equivalent consumption expenditure), $\Delta y_{ij,t}$ (changes in real per adult equivalent income), $\Delta \bar{c}_{j,t}$ (changes in real per adult equivalent average consumption at LC1) are all expressed in the log form, such that the coefficients indicate elasticity.

Column (1) is the benchmark model based on Eq. (1). It is clear that both household income and average consumption at LC1 affect household consumption positively and statistically significantly. A 1% increase in household income leads to about a 0.11% increase in household consumption, while a 1% increase in average LC1-level consumption is associated with a 0.54% increase in household consumption. The two further statistical tests show that the following null hypotheses are rejected at the 1% level: (1) H_0: $a_3 = 1$ (the coefficient on covariate shock is equal to unity); and (2) H_0: $a_3 = a_2$ (the coefficient on covariate shock is equal to that on idiosyncratic income shocks). Consistent with a large body of literature (Townsend, 1994; Udry, 1994;

Table 3. Consumption Sensitivity by Mobile Phone Coverage

VARIABLES	(1) $\Delta c_{ij,t}$	(2) $\Delta c_{ij,t}$	(3) $\Delta c_{ij,t}$	(4) $\Delta c_{ij,t}$
$\Delta\mu_t$	0.323*** (0.0316)	0.255*** (0.0382)	0.425*** (0.0291)	0.240*** (0.0420)
$\Delta y_{ij,t}$	0.106*** (0.0243)	0.114*** (0.0280)	0.120*** (0.0290)	0.113*** (0.0293)
$\Delta\bar{c}_{j,t}$	0.541*** (0.0482)	0.690*** (0.0557)		0.723*** (0.0595)
$\Delta mob_{j,t}$		0.152** (0.0669)		
$\Delta mob_{j,05}$				0.118* (0.0632)
Interaction Terms				
$(\Delta y_{ij,t} * \Delta mob_{j,t})$		−0.0406 (0.0545)	−0.0273 (0.0587)	
$(\Delta y_{ij,t} * \Delta mob_{j,05})$				−0.0287 (0.0492)
$(\Delta\bar{c}_{j,t} * \Delta mob_{j,t})$		−0.332*** (0.0870)		
$(\Delta\bar{c}_{j,t} * \Delta mob_{j,05})$				−0.359*** (0.0873)
Observations	871	871	871	871
Community Fixed Effect	No	No	Yes	No
R-squared	0.180	0.198	0.266	0.198

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Dercon and Krishnan; 2000), the results imply that the full income-sharing hypothesis is rejected and that household consumption tends to be more vulnerable to covariate shocks than to idiosyncratic shocks.

Column (2) includes the changes in access to mobile phone networks and its interaction terms based on Eq. (2). Interestingly, the coefficient on changes in access to mobile phone networks is positive and significant, indicating that consumption grows more rapidly for households newly covered by mobile phone networks. Also, its interaction with idiosyncratic income shocks is negative but insignificant, while its interaction with covariate shocks is negative and significant. Indeed, the degree of consumption comovement with neighboring households decreases by 33% for households with improvements in mobile phone coverage relative to those without any improvement. This seems to suggest that households gaining access to mobile phones can better mitigate covariate shocks by mutual assistance over long distances.

Column (3) includes LC1 fixed effects based on Eq. (3). This specification drops two variables—changes in access to mobile phone networks and its interaction with covariate shocks—because neither variable has variations within LC1. Again, the full income-sharing hypothesis is rejected, with the coefficient on idiosyncratic income shocks being positive and statistically significant. Also, its interaction with changes in mobile phone access is not statistically significant, indicating that the introduction of the mobile phone has no significant impact on idiosyncratic risk management.

Finally, Column (4) uses a different dummy variable reflecting the access to mobile phones in 2005 instead of its change over time. The dummy variable takes the value of 1 if LC1 is covered by mobile phone networks in 2005 and zero otherwise. The difference from the previous definition is that, in this new dummy variable, households covered by mobile phone networks in both 2003 and 2005 now take the value of 1 (zero previously). One may argue that this is more plausible for examining the impact of mobile phone coverage on long-distance risk sharing. Nonetheless, we see a result consistent with the previous estimation in that access to mobile phones is positively associated with household consumption, that its interaction with idiosyncratic income shocks is negative but insignificant, and that its interaction with covariate shocks is negative and highly significant.

Overall, our findings suggest that covariate shocks tend to affect household consumption more, which cannot be effectively managed through the informal local risk sharing mechanism. In such a situation, households covered by mobile phone networks may rely on distant friends and relatives to maintain their consumption level.[1)] By contrast, once idiosyncratic income shocks occur, households do not rely as much on long-distance risk sharing mechanisms. Rather, it seems that idiosyncratic income shocks are not fully but partially managed through traditional informal local risk-sharing mechanisms, which would presumably be less risky and less costly via face-to-face transactions.

4.2. Impacts of Permanent and Transitory Income Shocks and Covariate Shocks

Having discussed the consumption sensitivity against idiosyncratic and covariate shocks, and differential impacts depending on mobile phone coverage, we turn to decompose idiosyncratic income shocks into permanent and transitory components. The changes in the log per adult equivalent income is regressed on the changes in household assets and demographic characteristics, which yield permanent component changes, as well as the number of sick household members and the dummy for crop damages in 2005, which yield transitory component changes. Specifically, household assets and demographic characteristics include a) the number of household members by age group, b) household head characteristics, such as age, gender, and education attainment, c) the number of cultivated plots and area owned, d) tropical units of livestock, and e) value of durable assets. The first-stage income determination function and summary statistics of explanatory variables are presented in **Appendix 1** and **2**, respectively, and the residual is treated as "unexplained change."

Table 4 shows the results of the second-stage estimation based on Eq. (6). $\Delta\hat{y}^{P}_{ij,t}$ represents a predicted permanent income change, $\Delta\hat{y}^{T}_{ij,t}$ represents a predicted transitory income change, and $\Delta\omega_{ij,t}$ represents the residual.

Table 4. Consumption Sensitivity by Income Component and Mobile Phone

VARIABLES	(1) $\Delta c_{ij,t}$	(2) $\Delta c_{ij,t}$	(3) $\Delta c_{ij,t}$
$\Delta\mu_t$	0.322***	0.265***	0.430***
	(0.0342)	(0.0404)	(0.0331)
$\Delta\hat{y}^{P}_{ij,t}$	0.368***	0.356***	0.367***
	(0.0921)	(0.114)	(0.134)
$\Delta\hat{y}^{T}_{ij,t}$	−0.0325	0.237	0.328
	(0.441)	(0.524)	(0.569)
$\Delta\omega_{ij,t}$	0.0773***	0.0884***	0.0937***
	(0.0255)	(0.0297)	(0.0312)
$\Delta\bar{c}_{j,t}$	0.528***	0.677***	
	(0.0478)	(0.0553)	
$\Delta mob_{j,t}$		0.125*	
		(0.0755)	
Interaction Terms			
$(\Delta\hat{y}^{P}_{ij,t} * \Delta mob_{j,t})$		0.0160	0.0385
		(0.190)	(0.219)
$(\Delta\hat{y}^{T}_{ij,t} * \Delta mob_{j,t})$		−0.509	−0.215
		(0.954)	(1.072)
$(\Delta\omega_{ij,t} * \Delta mob_{j,t})$		−0.0528	−0.0368
		(0.0570)	(0.0611)
$(\Delta\bar{c}_{j,t} * \Delta mob_{j,t})$		−0.328***	
		(0.0865)	
Observations	871	871	871
Community Fixed Effect	No	No	Yes
R-squared	0.193	0.210	0.278

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Column (1) includes only each income component along with the covariate consumption level at LC1. Three important findings emerge. First, the coefficient on permanent incomes is positive and significant. The magnitude of this coefficient becomes larger than in the previous results, which assumes the capture of only a transient income shock. Second, the coefficient on transitory incomes is not statistically significant. Third, the coefficient on covariate shocks remains positive and significant. The null hypotheses that the coefficients on permanent income shocks and covariate shocks are unity are rejected at the 1% significance level. These findings partially support PIH, as transitory income does not affect consumption, yet full autarky insurance over the life cycle is also rejected because the coefficient on permanent income is not equal to unity. These results thus support the notion of limited commitment at the local community level, where idiosyncratic income shock is partially mitigated thorough local informal sharing, but they are far from perfect, presumably because not all idiosyncratic income changes are fully pooled and there is room to hide part of a household income from neighbors for self-insurance.

Column (2) includes each shock interacted with changes in mobile phone coverage. Consistent with the previous findings, access to mobile phones does not affect consumption sensitivity with respect to idiosyncratic income changes, regardless of whether they are permanent or transitory, as there are no statistical results on the interaction terms between mobile phone coverage and each idiosyncratic income component. The degree of consumption comovement with neighboring households again decreases by 33% for households with improvements in mobile phone coverage relative to those without any improvement, providing robust evidence that mobile phone coverage helps mitigate covariate shocks. Finally, we include LC1 fixed effects in Column (3). The qualitative inference is largely the same, in that the consumption is sensitive to permanent income changes but not transitory income changes, and mobile phone coverage does not help idiosyncratic income risk management.

V Extension of Analysis

One may argue that permanent, transitory, and unexplained income changes should be computed by the level, not in the log, because the sum of log income component changes does not match with the log total income change. To address this valid concern, we attempt to regress per adult equivalent income (USD) changes on the same explanatory variables (shown in **Appendix 1**) in the first stage, and the predicted values of permanent, transitory, and unexplained income changes are inserted in the second-stage estimation. The result in **Table 5** indicates that this does not alter our main findings: (1) household consumption is positively associated

Table 5. Consumption Sensitivity with the Level of Income

VARIABLES	(1) $\Delta c_{ij,t}$
$\Delta\mu_t$	0.264*** (0.0439)
$\Delta\hat{y}^P_{ij,t}$	0.000977** (0.000466)
$\Delta\hat{y}^T_{ij,t}$	0.000583 (0.00308)
$\Delta\omega_{ij,t}$	0.000506*** (0.000121)
$\Delta\bar{c}_{j,t}$	0.683*** (0.0558)
$\Delta mob_{j,t}$	0.178** (0.0753)
Interaction Terms	
$(\Delta\hat{y}^P_{ij,t} * \Delta mob_{j,t})$	−0.000435 (0.000661)
$(\Delta\hat{y}^T_{ij,t} * \Delta mob_{j,t})$	−0.00550 (0.00581)
$(\Delta\omega_{ij,t} * \Delta mob_{j,t})$	−0.000361* (0.000210)
$(\Delta\bar{c}_{j,t} * \Delta mob_{j,t})$	−0.336*** (0.0873)
Observations	871
Community Fixed Effect	No
R-squared	0.203

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

with permanent income change but not transitory income change; (2) the interaction terms of each idiosyncratic income change with mobile phone coverage are largely insignificant (except for unexplained income change); and (3) the interaction term of covariate shocks with mobile phone coverage is negative and highly significant.

Another possible extension is dealing with heterogeneity. So far, we have implicitly assumed that idiosyncratic and covariate shocks are linearly related to consumption changes and that the impacts are the same for poor and non-poor households. We relax this assumption and allow the coefficients to differ across distributions using a quantile regression method. We present the estimation results for the 10, 25, 50, 75, and 90 percentiles in **Table 6** and graphically show the differential coefficients in **Figure 2**. Again, the statistical inference is largely consistent with the previous estimation. Also, while Table 6 reports somewhat nonlinear relationships between the explanatory variables and consumption changes, Figure 2 shows no particular patterns of the differential coefficient across distributions (such as U-shaped or inversed-U shaped). Rather, Figure 2 suggests that the coefficients differ little and are almost flat across the distributions.

Table 6. Consumption Sensitivity by Quantile Regression

	(1) q10	(2) q25	(3) q50	(4) q75	(5) q90
$\Delta\mu_t$	−0.740*** (0.0822)	−0.295*** (0.0521)	0.281*** (0.0512)	0.801*** (0.0460)	1.240*** (0.0805)
$\Delta\hat{y}^P_{ij,t}$	0.513*** (0.170)	0.406*** (0.130)	0.378*** (0.0941)	0.430*** (0.157)	0.365* (0.203)
$\Delta\hat{y}^T_{ij,t}$	1.034 (0.802)	−0.457 (0.632)	−0.407 (0.634)	0.773 (0.683)	−0.489 (1.138)
$\Delta\omega_{ij,t}$	0.0334 (0.0406)	0.0943** (0.0400)	0.117*** (0.0300)	0.121*** (0.0431)	0.116* (0.0648)
$\Delta\bar{c}_{j,t}$	0.773*** (0.153)	0.758*** (0.0718)	0.614*** (0.0661)	0.591*** (0.0589)	0.622*** (0.0742)
$\Delta mob_{j,t}$	−0.0153 (0.125)	0.0318 (0.119)	0.174* (0.0903)	0.0412 (0.0839)	0.395* (0.213)
Interaction Terms					
$(\Delta\hat{y}^P_{ij,t} * \Delta mob_{j,t})$	−0.0450 (0.264)	−0.0805 (0.270)	−0.116 (0.272)	0.0579 (0.276)	0.159 (0.382)
$(\Delta\hat{y}^T_{ij,t} * \Delta mob_{j,t})$	−2.356* (1.336)	−0.172 (1.296)	0.212 (1.200)	−1.440 (0.925)	1.911 (2.794)
$(\Delta\omega_{ij,t} * \Delta mob_{j,t})$	0.0397 (0.0835)	−0.0490 (0.0837)	−0.0710 (0.0650)	−0.131* (0.0748)	−0.126 (0.139)
$(\Delta\bar{c}_{j,t} * \Delta mob_{j,t})$	−0.392* (0.204)	−0.263* (0.142)	−0.326** (0.136)	−0.234** (0.107)	−0.369*** (0.127)
	871	871	871	871	871

Bootstrapped standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

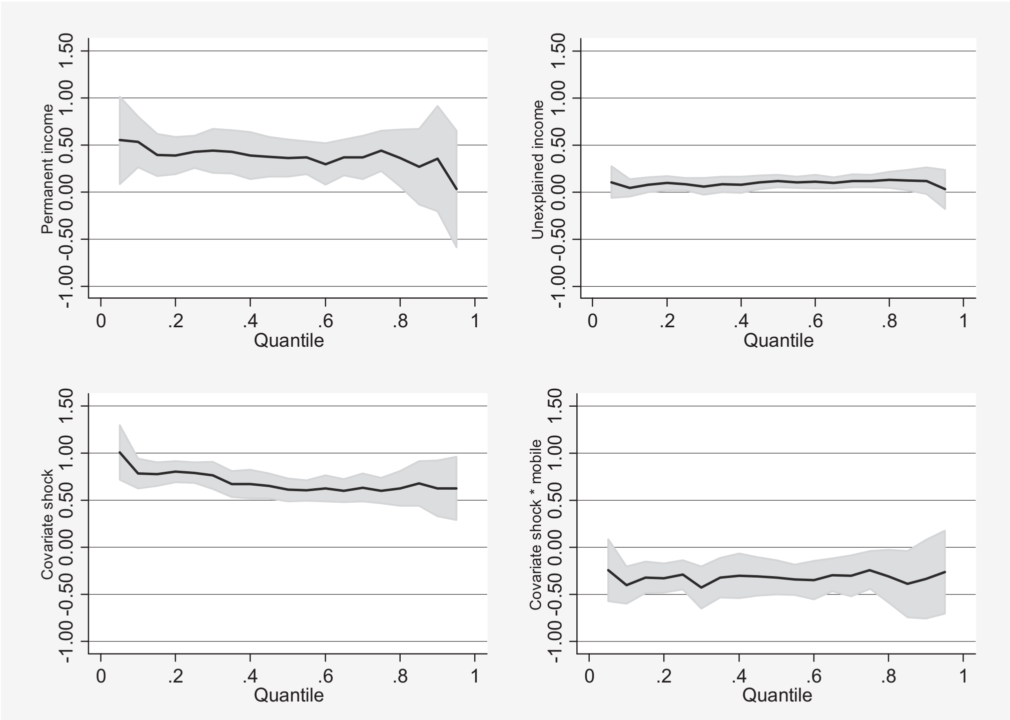

Figure 2. Estimated Coefficients with 95% Confidence Intervals by Quantile Regression

Ⅵ Conclusion

The literature argues that a mutual informal insurance mechanism within a small local community has worked effectively to help smooth the consumption of households in the face of idiosyncratic, household-specific income shocks. However, covariate shocks whereby neighboring households suffer similar income shocks generally inactivate such informal arrangements. Using panel data collected in rural Uganda in 2003 and 2005, we examined whether covariate risk exposure could be mitigated by the introduction or expansion of mobile phone technology, which may make it easier and less costly for a household to communicate with and request assistance from long-distance friends and relatives who do not suffer the same downside risks.

The results indicated that both idiosyncratic and covariate shocks affect household-level consumption changes over time, at a magnitude greater for covariate shocks than for idiosyncratic shocks. Households in communities covered by mobile phone networks can, however, effectively reduce the degree of household consumption comovement with neighboring households by about 33%. This result implies that part of the covariate shocks is mitigated by long-distance risk sharing via mobile phone. On the other hand, there is no difference in the impact of idiosyncratic income shocks on household intertemporal consumption change across communities with different mobile phone coverage levels, even though partial risk sharing within local communities is identified.

This paper also attempted to decompose household income shock into permanent and transitory components and examined the role of each income component on intertemporal household-level consumption changes. We found that consumption changes are insensitive to transitory income shocks but sensitive to permanent income shocks. This finding seems to demonstrate that the positive relationship between the first-differenced income and consumption, observed in the literature and in this study, is largely driven by permanent income component changes rather than transitory income changes, as is usually assumed in the literature. This finding partially supports PIH in that transitory income does not affect consumption, yet our results also demonstrate that full autarky insurance over the life cycle is rejected.

Overall, these results imply that households combine self-insurance, local risk sharing, and long-distance risk sharing via mobile phone to manage risks, where idiosyncratic shocks are partially mitigated by self-insurance as well as mutual insurance within local communities, whereas covariate shocks are partially mitigated by self-insurance and across distant communities via mobile phones. This result clearly suggests that the extension of mobile phones effectively enhances households' risk management strategies, especially for covariate shocks, by easily connecting them with households outside of their local communities, who do not suffer the same shocks.

Note

1) To understand the mechanism, we attempt to regress remittances income on mobile phone coverage using the pooled observations in 2003 and 2005. The results (not presented here) show that remittances significantly increase with mobile phone coverage, consistent with Munyegera and Matsumoto (2016).

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Appendix 1. First-Stage Income Determination Function

VARIABLES	Changes in log adult equivalent income	Changes in Adult equivalent income (US$)
Changes in # Children (age<6)	−0.0380 (0.0430)	−10.18 (11.69)
Changes in # Young (6<age<15)	−0.110*** (0.0305)	−26.41*** (6.560)
Changes in # Adult (16<age<60)	−0.116*** (0.0293)	−22.10*** (6.562)
Changes in Elderly (61<age)	−0.117* (0.0592)	−9.020 (14.34)
Changes in Head Education	0.00976 (0.0193)	0.746 (3.186)
Changes in Head Gender	0.138 (0.185)	20.94 (21.68)
Changes in Head Age	−0.00490 (0.00317)	−0.178 (0.669)
Changes in # of Cultivate Plots	0.0774** (0.0342)	13.42 (8.875)
Changes in Landholdings (ha)	0.00130 (0.00141)	−1.704** (0.835)
Changes in TLU	0.0394*** (0.00797)	13.90*** (4.326)
Changes in value of durables	0.000105 (7.19e−05)	0.0249 (0.0224)
# Sick members in 2005	0.0941 (0.0635)	18.14 (12.61)
Crop Damage Dummy (=1)	−0.0953 (0.0964)	0.546 (19.20)
Constant	0.128 (0.0811)	0.763 (18.66)
Observations	871	871
R-squared	0.109	0.165

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix 2. Summary Statistics

	Mean	S.D.
Changes in Adult equivalent consumption (US$)	−3.889	218.468
Changes in Adult equivalent income (US$)	14.672	288.123
Changes in Access to Mobile Phone Network	0.309	0.462
Changes in # Children (age<6)	0.015	1.195
Changes in # Young (6<age<15)	0.117	1.430
Changes in # Adult (16<age<60)	0.202	1.750
Changes in Elderly (61<age)	0.047	0.524
Changes in Head Education	0.037	2.316
Changes in Head Gender	0.007	0.179
Changes in Head Age	1.197	11.670
Changes in # of Cultivate Plots	0.721	1.103
Changes in Landholdings (ha)	1.206	24.267
Changes in Toropical Livestock Unit	0.413	5.536
Changes in the value of durables	80.423	768.473
# Sick members in 2005	0.350	0.585
Crop Damage Dummy (=1)	0.662	0.473