Technologies follow technologies and occasionally social groups

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Abstract

An innovative model describing the convergence of technology use at the micro level is introduced. ICT (information and communication technology) ownership, measured as the number of smartphones within a household, depends upon socioeconomic characteristics, such as income, education, technologies and occupation. ICT ownership and the socioeconomic characteristics are specified in relative terms between household pairs. Indicators for jointly belonging to a social group define a new explanatory variable type. Applying this model to survey and geographic data on rural households in Thailand and Vietnam, Heckman-type regressions show that better education and existing technologies unequivocally enhance convergence of ICT ownership among households, whereas the effect of social groups depends on the specific group. Self-employment or employment outside agriculture enhance convergence, whereas farming or employment in agriculture lead to divergence. The results advice policymakers to support the spread of ICT that provides access to valuable information and creates income-generating opportunities.

JEL classifications: F63; O33; Q12; Q17; Q54

Keywords: ICT; smartphones; technology diffusion; rural development; social networks

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1 Introduction

The spread of mobile phones and later smartphones in developing countries has been a success story (see, e.g., Aker and Mbiti (2010) regarding Africa). Smartphones provide access to information, communication and services. Consequently, they open up new socioeconomic opportunities for millions of disadvantaged people living in rural areas of developing countries. The adoption of smartphones, and in general, ICT (information and communication technology), is assumed to be related to socioeconomic characteristics of users, existing technologies, occupational factors, and social network effects.

Considering how development policy can support the continuation of this success story, we address the following questions: Can policymakers expect the spread of ICT to proceed autonomously together with socioeconomic improvements in income, education, and so forth, towards an equal distribution of ICT? Do the joint social and technological characteristics of low-income households, i.e., owning the same technology, belonging to the same ethnic, religious, political or other social group[1], enhance the process of technology diffusion?

The increasing occurrence of climate change-related disasters and the COVID-19 pandemic have hit poor households the hardest. In light of these challenges it is key to have access to online information on *health and medical care* (Sadish et al. (2021)), *education and learning* (Balasubramanian et al. (2010)) as well as *finance and financial transactions* (Suri et al. (2021); Aker et al. (2020)). For smallholders it is also vital to obtain online information on *labor markets and agricultural inputs* (Hartje and Hübler (2017); Balasuriya and de Silva (2011)), *market prices for agricultural inputs and products* (Fafchamps and Minten (2012); Jensen (2007)) as well as *climate and weather* (Arslan et al. (2017); Fafchamps and Minten (2012)). Such information is easily accessible via mobile phones, smartphones or other mobile information and communication technologies (ICT) among smallholders.[2]

[1]We assume that social groups create social networks that support information exchange and the spread of technologies. However, we do not explicitly deal with any particular social network platforms, such as Facebook. Allcott (2020), for example, find negative welfare effects from using Facebook.

[2]Cf. the literature reviews by Baumüller (2018) and Aker (2011).

To address the relevance of ICT for rural households to get access to such information sources, this article studies the socioeconomic, occupational and technological factors related to the spread of ICT, measured as the per capita number of smartphones owned by a household. To this end, we introduce a conceptual and econometric model describing socioeconomic and technological similarities and joint membership in predefined social groups based on household dyads, which is novel in the literature. We apply the model to cross-sectional survey data on households residing in rural Thailand and Vietnam. The data are taken from the Thailand Vietnam Socio Economic Panel (TVSEP)[3], introduced by Hardeweg at al. (2013). The data were collected in 2017 and contain new information on smartphone ownership and (types of) usage. They have been combined with new corresponding geographic information system (GIS) data describing the distance between households.

In contrast with previous research using the TVSEP data (Bierkamp et al. (2021); Grabucker and Grimm (2021); Wagener and Zenker (2021); Bühler et al. (2020); Bühler et al. (2018); Zenker et al. (2018); Gröger and Zylberberg (2016); Hübler and Hartje (2016); Hübler (2016)), this article makes use of the new smartphone and GIS data and introduces a new research topic. While the previous literature on mobile phones in developing countries has focused on Africa and India (e.g., Muto and Yamano (2009); Jensen (2007)), this article studies Southeast Asia. To date, only a few smartphone studies have examined rural East or Southeast Asia (e.g., Nie et al. (2020); Hartje and Hübler (2017); Hübler and Hartje (2016)).

The literature on mobile phones and smartphones in Southeast Asia has identified the influence of the socioeconomic characteristics of rural households on the number of mobile phones (per capita) owned by a household (e.g., Hübler (2016); Hübler and Hartje (2016)). In this literature, higher income (per capita) and better education clearly increase the number of phones (per capita). While having a younger household head increases the number of phones (per capita), the maximum number is reached among householders who are approximately 40 years of age. A larger household size decreases the number of phones (per capita), which indicates that phones are shared. Ownership of existing technologies basically increases the

[3]`https://www.ifgb.uni-hannover.de/en/research/tvsep/`.

likelihood of owning phones.

Similar results have been found regarding Africa. For example, younger age, better education, high-skilled work, self-employment, English language, membership in associations, Internet use by friends and existing hard and software are identified as positive determinants of ICT use (see Penard et al. (2012) using data on mobile phone and Internet use in Gabon). In the same vein, better educated, younger and wealthier individuals are more likely to have Internet access in Western Europe, and the regional rate of highly educated employees and students is positively correlated with the regional proportion of Internet users (see Schleife (2010) using data sets from Germany).

These outcomes are in accordance with the broader literature on technology adoption with a focus on agriculture in developing countries as reviewed by Foster and Rosenzweig (2010) and Ruzzante et al. (2021). Accordingly, technology adoption is enhanced by better education and higher income or access to credit (among other determinants). The results of our research are in line with those of the literature on Southeast Asia and Africa as well as the broader literature on technology adoption in agriculture.

In contrast with this literature, our novel conceptual model measures *socioeconomic similarity* and *technological similarity*: Instead of studying individual household characteristics, it looks at the relationships between households and the geographic distance between them, i.e., their common characteristics and their specific attributes in relative terms. In particular, to explore socioeconomic and technological similarity, it compares households in terms of their socioeconomic characteristics, considers whether they jointly belong to a social group and measures the resulting effect on smartphone ownership. Due to the use of observation pairs that are connected across geographic distances, our model is similar to gravity models describing international trade (see, e.g., Yotov et al. (2023)).

Our research focus is particularly related to the literature on the role of social networks in technology diffusion summarized by Cheng (2021). According to this literature, social networks can entail a positive effect on technology adoption in two ways. First, a positive *network externality* emerges when the value of a technology increases in the number of users. Second, a positive *social learning* effect occurs when technology users influence each other via imitation, communication or peer group pressure (see Cheng (2021), p. 148).

From a broader perspective, the extensive literature studying the *digital divide* summarized by Srinuan and Bohlin (2011) identifies the following determinants of the digital divide: availability of infrastructure including existing technologies, such as landline phones or mobile phones; (per capita) income; skills, experience, education and literacy; age; occupation; gender and marital status; language, culture and ethnicity; psychological factors, such as trust; direct network effects enhanced by more ICT users in the corresponding region. (see Srinuan and Bohlin (2011), p. 8ff.). Our choice of determinants of ICT use described in Section 2 basically follows this literature. Our research differs from the literature on social networks and the literature on the digital divide by using a new approach to capturing network effects and by studying smartphones as the most relevant latest technology in the area of ICT and economic development.

Methodologically, we draw on a Heckman-type estimator to evaluate the model using data on household pairs from Thailand and Vietnam. We compare the outcome with Ordinary Least Squares (OLS) results as a reference point. In addition, we run country-wise regressions as a robustness check. Overall, the results indicate that technological convergence toward a geographically uniform spread of ICT, i.e., smartphones, across rural households is positively related to economic development, measured in terms of more equal income, education, assets, wage employment, self-employment or existing technologies. Hence, economic development together with increased equality can be expected to enhance the spread of ICT autonomously. The downside, however, is that insufficient socioeconomic or technological development hinders the spread of ICT, eventually widening the digital divide. Additionally, the role of social groups in enhancing or hindering technology diffusion appears to be ambiguous.

The article proceeds as follows. Section 2 establishes the new conceptual and econometric model and derives testable hypotheses. Section 3 describes the data, the method and the results. Section 4 concludes.

2 Model

In this section, first, a new conceptual model of technological convergence as related to the fostering of socioeconomic coherence is introduced. Second, a mathematical specification that is estimated econometrically in Section 3 is formulated. Third, the key testable hypotheses are stated.

2.1 Concept

Figure 1 illustrates the new conceptual framework that we introduce in this article.

The dependent variable under scrutiny is the technology level t of household i relative to the technology level of another household j as depicted by the level difference in the scales in the figure. We consider especially ICT (information and communication technology). In the following econometric application, we measure the technology level as the number of smartphones owned by a household. Technological convergence implies that t_i catches up to t_j, i.e., the scales in the figure become more horizontal and balanced.

All microeconomic agents, here households, are subject to the same macroeconomic foundations, depicted here with the gray area at the bottom of Figure 1. The macroeconomic foundations comprise the economy's GDP (gross domestic product), overall technology level, infrastructure, education system, legal framework, and so forth. One can assume that the quality of the macroeconomic foundations grows at a rate of ω; therefore, for example, an economy's GDP grows at the rate ω. Because all households face the same macroeconomic foundations and we study the characteristics of each household relative to any other household, these macroeconomic effects cancel out and are not taken into account in the analysis.

Nonetheless, there can be geographic differences that are captured by country-specific effects in the econometric model specified in Section 2.2.

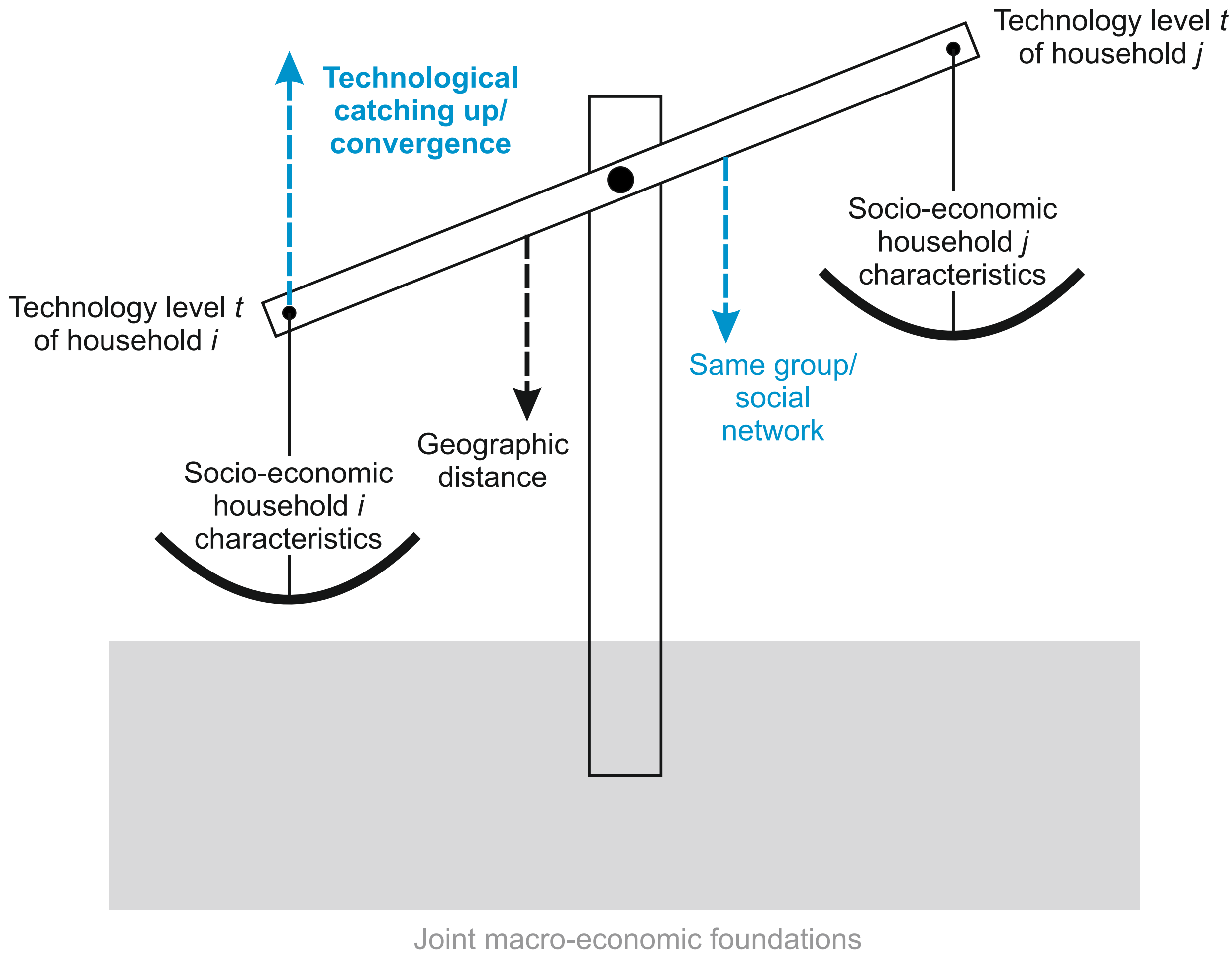
Based on these macroeconomic foundations, differences in technology levels between households occur at the microeconomic level because the households have different individual *socioeconomic characteristics* that may influence technological affinity, technological knowledge, the affordability of technology and technology usage. Specifically, in the analysis in Section 3, we use the number of smartphones per capita that each household owns as an indicator for the household technology level. In general, we are not interested in the absolute technology level but in the relative technology level. Therefore, we are not interested in measuring the explanatory household indicators in absolute terms either. Instead, we measure these indicators in relative terms, comparing their values between two households i and j; e.g., we use the ratio of the per capita number of smartphones between the two households. If two households are identical with respect to the relevant explanatory indicators, they will have the same technology level, $t_i = t_j$, such that the scales are horizontal in Figure 1. We define two types of indicators, (I) household indicators and (II) group indicators.

(I) We consider the following socioeconomic household indicators. As explained above, they are measured in terms of relative values, i.e., as ratios, between two households i and j and are expected to affect the relative technology level between i and j. The choice of indicators follows the literature summarized in Section 1.

In what follows, p.c. means per capita, (+) indicates a positive relation to the relative technology level, i.e., the relative household indicator and the relative technology level move in the same direction; (–) indicates a negative relation, i.e., they move in opposite directions; and (+/–) indicates an ambiguous relation. Whether these relations and directions hold empirically is tested in Section 3.

- **Financial:** (gross) income p.c. (+), total value of assets p.c. (+), number of shocks experienced (per year) (–).

Figure 1: Conceptual framework of technological convergence across households.



- **Social:** number of people in the household (+/–), share of children at school (among all children) (+), average household age (+/–), average number of years of education attained in the household (+), number of temple (or pagoda) visits (per year) (+/–), trust (+).
- **Technological:** technology owner share within the village (+) (see Section 3.2), value of technological assets p.c. (+).
- **Geographic:** travel (or street) distance (–).

In the *financial* indicator domain, we assume that higher income, (in the long-term) also reflected by a higher value of available assets, allows a household to purchase more smartphones. We pay special attention to *climate change-related weather shocks* that negatively affect income or assets, e.g., by destroying harvests or damaging buildings.

In the *social* indicator domain, we follow the literature (regarding Southeast Asia, specifically Hübler (2016); Hübler and Hartje (2016)) by considering household size-, education- and age-related indicators. Additionally, we include two *new* indicators: The average number of temple visits (per year) measures the intensity of practising a *religion*. *Trust* indicates whether the household (head) relies on other people, new technologies or new circumstances and hence, how far the household (head) is able to deal with new situations or technologies.[4]

In the *technological* indicator domain, the value of existing technologies is expected to enhance the adoption of new (ICT) technology by reflecting technology affinity and complementarity (see below).

In the *geographic* indicator domain, we expect a larger travel (or street) distance to hinder technology diffusion, i.e., to increase the discrepancy between the technology levels of the households, because proximity facilitates the exchange of information, devices or money.

(II) A key aspect of this analysis is its consideration of the role of *social networks* of any kind in technology diffusion. Social networks are expected to increase technology exchanges, information exchanges and financial exchanges, which may positively influence participant decisions to purchase technologies (cf. Section 2.3). In particular, we consider household participation in *social groups*, for example, belonging to the same ethnic group, religion or political party. Here, the assumption is that a social network exists within each group.[5]

We also consider social groups defined in a broader sense, comprising households with the same characteristics, for example, those households owning *similar technological devices*, such as a television set, or those households sharing the *same occupation*, particularly agricul-

[4]Trust is measured as a binary variable based on the following question: "generally speaking, would you say that most people can be trusted or that you need to be very careful when dealing with people?" The variable is zero if the respondent's answer is "no" and one if the answer is "yes".

[5]We do not explicitly study social network platforms, such as Facebook.

tural work. Here, besides social networks and enhanced exchange, the idea is that belonging to the same group implies a similar technological or socioeconomic level. Consequently, the participation in such groups contributes positively to technological convergence.

Against this backdrop, we expect the following household indicators that define social groups in a broader sense to have a *positive* effect on technological convergence (cf. Section 2.3). Technological convergence means that the extend of technology use in each household is becoming more similar. Particular groups, however, may have a negative attitude towards technologies. In this case, belonging to this group may hinder technological convergence or foster technological divergence reflected by a *negative* effect on convergence.

- **Social:** both household heads belong to the same ethnic group (+/–), both household heads practice the same religion (+/–), both household heads are literate (+), both households have a member who is a member of a (socio)political organization or party (+/–), both households have a member who migrated (within the country, e.g., to a city, or to another country abroad)[6] (+/–).

- **Technological:** both households have access to electricity (+), both households own the same complementary technology (at least one device): a radio device (+), a television set (+), a landline telephone (+/–), a personal computer (including laptop computers) (+) or a tablet (computer) (+/–).

- **Occupational:** both households have a member engaged in farming (including both, subsistence farming and farming for cash) (+/–), both households have a member engaged in fishing (+/–), both households have a member employed off the farm in the agricultural sector (+/–), both households have a member employed off the farm in the nonagricultural sector (+/–), both household have a member who is self-employed (+).

- **Geographic:** both households reside in a particular country (country-specific effect) (+/–).

[6] Immigration plays a minor role in the data.

In the *social* indicator domain, social networks basically enhance information exchanges and hence technology diffusion within a social group. Personal meetings within a social group support information exchange but are not strictly necessary, because ICT allows for virtual information exchanges, provides information on technologies (such as smartphones), and enables financial transactions (e.g., buying a smartphone). For example, individuals belonging to the same group can receive the same newsletter or read the same Internet news sites or blogs, although they are remote from each other. In contrast, people belonging to different peer groups may read or receive the same information but interpret them in different ways in accordance with the opinion prevailing in their peer group. Notwithstanding, a negative attitude towards technology use, a lack of affordability or other obstacles to technology adoption within a social group can also create a negative effect of group participation on ICT use.

In the *technological* indicator domain, existing technologies are basically expected to enhance ICT adoption. First, they indicate people's affinity to (modern) technologies or to information exchanges, e.g., a landline telephone is upgraded or substituted by a smartphone or information obtained from radios or television is upgraded by Internet access via a smartphone. However, landline telephones and smartphones or tablet computers and smartphones can also act as substitutes such that a negative relationship emerges. Second, complementary older technologies are required to use more advanced new technologies, e.g., electricity is required to charge smartphones. If both households under consideration have access to the same type of existing technology, their number of smartphones can be expected to converge and become similar to each other.

In the *occupational* indicator domain, being engaged in the same activity, such as farming or running a business, is expected to create comparable advantages of ICT use and to create social networks that benefit from ICT for information exchange. ICT is expected to be particularly useful for self-employed work that includes management and communication activities. If, however, a negative attitude towards technology use prevails in a profession, if ICT is less advantageous or not affordable, then a joint profession, such as farming or fishing, can also have a negative effect on ICT adoption and hinder technological convergence.

In the *geographic* indicator domain, we consider country-specific effects capturing further unobserved country-specific factors.

In summary, if a given social group has a positive attitude toward technology, technological convergence toward a higher absolute technology level is expected. This is referred to as the normal case (see Section 2.3). If a social group has a negative attitude toward technology, convergence toward a lower absolute technology level or technological divergence are also possible.

2.2 Specification

Based on the conceptual framework introduced in the previous subsection, in this subsection, the corresponding econometric model is formulated mathematically. This *microeconometric* model is specified in relative terms, i.e., for household pairs ij, similar to the *macroeconometric* setup introduced by Hübler and Glas (2014):

$$T_{ij} = \bar{\rho}\bar{R}_{ij} + \bar{\gamma}\bar{G}_{ij} + \delta D_{ij} + \zeta C_{ij} + \kappa + \varepsilon_{ij} \tag{1}$$

T_{ij} denotes the *technology ratio*, in the following, particularly, the *smartphones per capita ratio*, between households i and j and is defined as:

$$T_{ij} = \begin{cases} \frac{t_i}{t_j} & \text{if } t_j > 0 \\ \text{undefined} & \text{if } t_j = 0 \end{cases} \tag{2}$$

where $t_i \geq 0$ and a larger t implies a higher technology level of i or j (for the econometric approach, see Section 3.2). Additionally, we impose the condition $t_i \leq t_j$ such that:

$$0 \leq T_{ij} \leq 1 \tag{3}$$

This means, the data are ordered such that the technology level of household i is at least as high as that of household j. We further impose the condition that households i and j must reside within the same province and hence country. This rules out the possibility of the households being completely separated due to remoteness, different languages or border obstacles, although they are not required to know each other or to be in personal contact.

D_{ij} measures the street-level distance between the two households, i.e., the travel distance using the available streets/roads. C_{ij} is a binary variable that captures country-specific effects related to the place of residence of the two households.[7]

$\bar{R}_{ij}$ represents a column vector of continuous socioeconomic indicators $R_{1,ij}$, $R_{2,ij}$, ..., $R_{m,ij}$ that measure the relative socioeconomic characteristics of households i and j, i.e., $R_{1,ij} = \frac{r_{1,i}}{r_{1,j}}$, $R_{2,ij} = \frac{r_{2,i}}{r_{2,j}}$, ..., $R_{m,ij} = \frac{r_{m,i}}{r_{m,j}}$. $\bar{R}_{ij}$ includes income, assets, shocks, age, household size, education, school kids, temple visits and trust (see Sections 2.1 and 3.1).

$\bar{G}_{ij}$ symbolizes a column vector of binary group membership indicators $G_{1,ij}$, $G_{2,ij}$, ..., $G_{k,ij}$. An indicator equals one if households i and j belong to the same social group. $\bar{G}_{ij}$ includes (in the base case) literacy, ethnicity, political party, migrant, religion and electricity access (see Sections 2.1 and 3.1).

$\bar{\gamma}$ and $\bar{\rho}$ are row vectors of coefficients to be estimated. Furthermore, the distance coefficient δ, the country-specific effect ζ and the overall constant κ are to be estimated. ε_{ij} captures the remaining error terms.

2.3 Hypotheses

A larger value of T_{ij} implies that the two households are more similar in terms of their technology levels.

Thus, if any indicator has a positive effect on T_{ij}, that indicator can be interpreted as increasing technology diffusion. Because we assume that $t_i \leq t_j$, technology diffusion can be

[7] In the data set introduced below, C_{ij} equals one if the household pair ij resides in Thailand and zero if it resides in Vietnam. Province-specific effects could be used alternatively.

assumed to occur from household j to household i, particularly via technology exchanges, related information exchanges or financial transfers that allow household i to purchase technologies. Alternatively, household i can obtain technologies, related knowledge or financial means that allow the purchase of technologies from any other external source. In any case, the result, ceteris paribus, is a higher T_{ij} defined in relative terms, a higher t_i in absolute terms, and convergence toward the higher technology level t_j.

In theory, t_j can also decline, which results, ceteris paribus, in a higher T_{ij} in relative terms and convergence toward the lower technology level t_i in absolute terms.

These considerations allow us to formulate the following testable hypothesis:

H1: When households i and j belong to the same social group (creating a social network), technological convergence will occur, which implies that:

$$\frac{dT_{ij}}{dG_{1..k,ij}} = \alpha_{1..k} > 0 \tag{4}$$

In contrast with the expected positive effect of the group indicator G, the socioeconomic indicators $R_{1,ij}$ can have positive or negative effects. When the indicator $r_{1,i}$ has a positive effect on t_i, then $R_{1,ij}$ has a positive effect on T_{ij}.[8] Therefore, a relatively higher $R_{1,ij}$ fosters technological convergence by increasing T_{ij}. The opposite mechanisms operate when the effect of indicator $r_{1,i}$ on t_i is negative; in this case, the effect of $R_{1,ij}$ on T_{ij} is also negative.

Technology and information exchange processes are expected to be stronger when the exchange partners are closer to each other and to decay over larger distances. Hence, we can formulate the following testable hypothesis:

H2: A greater distance between households i and j causes technological divergence, which

[8] This becomes obvious when considering the special case in which $r_{1,j}$ and hence t_j are constant, but it also holds for the variables $r_{1,j}$ and t_j. Similarly, when the indicator $r_{1,j}$ has a positive effect on t_j, then both $R_{1,ij}$ and T_{ij} are also reduced. Thus, $r_{1,j}$ having a positive effect on t_j is equivalent to $R_{1,ij}$ having a positive effect on T_{ij}.

implies that:

$$\frac{dT_{ij}}{dD_{ij}} = \delta < 0 \tag{5}$$

For the country-specific effects C_{ij}, there is no unambiguous hypothesis.

3 Analysis

This section first introduces and describes the data set used. Second, it explains the econometric approach. Third, it presents and interprets the estimation results.

3.1 Data

Data sources

This study uses microeconomic data to analyze the level of technological equality among households in rural Southeast Asia. The main data set contains household-level survey data from the Thailand and Vietnam Socio Economic Panel (TVSEP). The data contain smartphone ownership and usage as novel indicators. Geographic information on the locations of households collected during the TVSEP survey is combined with open source information on streets/roads and their conditions to obtain an additional new indicator.

- **TVSEP data:** To analyze the level of technological equality among households, we examine data from the 2017 TVSEP survey carried out in Thailand and Vietnam. Questions on smartphone ownership and usage were first introduced in this wave.[9] The data were collected in three rural provinces in each country. In Thailand, these provinces are Buri Ram, Nakhon Panom and Ubon Ratchathani, and in Vietnam, Thua Thien

[9]The TVSEP is a panel survey that has been carried out since 2007. Surveys are regularly administered among rural households in Thailand and Vietnam. To date, eight waves have been completed. The survey covers approximately 4,400 households in 440 villages. The household sample in each province was randomly drawn based on a stratification process that accounted for the heterogeneity in the agro-ecological conditions within regions. Please refer to Hardeweg at al. (2013) for a detailed review of the sampling strategy. For more information on the project, please visit the project website: https://www.tvsep.de/overview-tvsep.html.

Hue, Ha Tinh and Dak Lak. Appendix Figure A1 provides an overview of the survey region, where these provinces are marked red. In the Heckman (OLS) regressions, we utilize data from 209,552 (210,700) household pairs in Thailand and 508,862 (513,550) household pairs in Vietnam.[10] In addition to the household questionnaire, a short questionnaire on key village characteristics was administered to each village chief of the 440 villages in the sample. These data contain information on key statistics of the village, such as the number of residents, the number of workers or access to electricity in the village.

- **Georeferenced data:** In addition to the information from the household survey, information on the geographic locations of households and on streets and street conditions are used to calculate the travel distances between households. The information on the geographic locations of households has been added to the TVSEP survey in the 2016 and 2017 waves, with tablets used to identify the household locations. This information has been mapped with GIS software and merged with open source information from street maps.[11]

Descriptive statistics

This section describes households' usage of smartphones and differences between smartphone users and non-users.

Appendix Figures A2 and A3 depict households' *primary* smartphone usage type in Thailand and Vietnam.[12] According to the survey data, most households use smartphones mainly for entertainment (84.1% of all households of the survey in Thailand, 75.4% in Viet-

[10]The sample is slightly smaller than the original TVSEP sample due to attrition as well as nonresponse. No other restrictions were applied to the sample. Some observations drop out in the Heckman regressions compared with the OLS regressions because the data required for the identifying variables are missing for some households.

[11]The travel distances have been retrieved by combining information on the geographic locations of households and information from open source street maps, including information on street/road conditions. With this information, the approximate travel distance between household pairs residing within the same province has been calculated.

[12]"If your household has a smartphone, what is the Internet on the smartphone mainly used for?"

nam). Education is the second most frequent usage in Thailand (12.5%), whereas contacting family members is the second most frequent usage in Vietnam (24.2%). Checking news is the third most frequent usage in Thailand (1.4%), followed by contacting family members (1.0%) and contacting friends (1.0%). In Vietnam, contacting friends is less often reported to be the most important usage and exhibits minor importance (0.3%).

Table 1 provides descriptive statistics of two household groups within all survey areas (referring to the base case, see Section 3.2) that are defined as follows: In the first non-user group, at least one household lives without a smartphone.[13] This is indicated by a zero value. In the second user group, both households own at least one smartphone. The ratio describes the number of smartphones per capita in the household with less smartphones to the corresponding number in the household with more smartphones. The distinction between indicators defined as ratios and indicators for belonging to the same group follows the concept introduced in Section 2.

According to the data, the number of smartphone users (547,004 or 75.5%) is more than three times as large as the number of non-users (177,246 or 24.5%). According to a *t*-test, significant differences between the two groups exist in all indicators except the travel distance between the household pairs. Thus, there appears to be no region, in which smartphones are generally absent.

Per definition, the smartphones ratio is zero in the non-user group. In the user group, the mean value of 0.52 indicates that on average a household with more smartphones (in the denominator) has twice as many phones than a household with less phones (in the numerator). Appendix Figure A4 plots the distribution of the smartphones ratio between the household pairs in the survey areas in Thailand and Vietnam.

Per capita income is a straightforward household indicator. It entails negative values when households' (farming) costs exceed their revenues. The average income ratio in the user group is smaller and closer to one than in the non-user group; this implies that the

[13]Given that, in our sample, households reside in poor rural areas, not all households own a smartphone.

Table 1: Descriptive statistics

	Non-user group: at least one household without smartphone				User group: both households with smartphone(s)				Difference (*t*-test)
	Mean	Std. dev.	Min.	Max.	Mean	Std. dev.	Min.	Max.	Signif.
Smartphones (ratio)	0.00	0.00	0.00	0.00	0.52	0.25	0.03	1.00	***
Income p.c. (ratio)	1.67	4.44	-267.84	368.50	1.33	10.34	-733.73	2440.04	***
Assets p.c. (ratio)	2.50	3.64	0.00	15.00	1.41	2.62	0.00	15.00	***
Shocks (ratio)	0.60	0.93	0.00	7.00	0.55	0.88	0.00	7.00	***
Age (ratio)	0.78	0.38	0.07	4.76	1.01	0.59	0.07	8.49	***
Household size (ratio)	1.96	1.09	1.00	11.00	1.47	1.08	0.13	11.00	***
Trust (ratio)	0.24	0.43	0.00	1.00	0.20	0.40	0.00	1.00	***
Temple visits (ratio)	2.39	14.75	0.00	400.00	2.61	14.13	0.00	416.00	***
Education (ratio)	1.07	0.52	0.00	2.00	0.89	0.44	0.00	2.00	***
School kids (ratio)	0.18	0.46	0.00	6.00	0.31	0.64	0.00	18.00	***
Literacy (group)	0.81	0.39	0.00	1.00	0.83	0.38	0.00	1.00	***
Ethnicity (group)	0.79	0.41	0.00	1.00	0.76	0.43	0.00	1.00	***
Religion (group)	0.35	0.48	0.00	1.00	0.36	0.48	0.00	1.00	***
Political party (group)	0.55	0.50	0.00	1.00	0.53	0.50	0.00	1.00	***
Migrant (group)	0.17	0.38	0.00	1.00	0.27	0.44	0.00	1.00	***
Electricity access (group)	0.98	0.14	0.00	1.00	0.98	0.14	0.00	1.00	*
Distance (in km)	58.80	37.48	0.00	266.80	58.78	36.83	0.00	266.64	
Number of obs.	177,246 (24.5%)				547,004 (75.5%)				

Significance levels from a two-sided *t*-test: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. P.c. means per capita.

income values of smartphone users are on average more similar than those of non-users. The standard deviation of income, however, is much smaller in the non-user than in the user group due to outliers (very high or low values) in the latter group. Such outliers, particularly high values, lift the average ratio above the theoretically and statistically ideal mean of one. The dispersion of the total asset value per capita is clearly higher among non-users than among users indicated by the higher mean (above one) and the larger standard deviation. Like the smartphones ratio, the ratio of the number of perceived shocks is smaller than one among phone users, which suggests that within this group, households with less smartphones statistically experience also less shocks.

The age ratio in the user group of approximately one points to an equal age distribution across household pairs independent of the number of phones. The household size ratio exceeds one in the user group indicating that larger households on average tend to have less smartphones per capita which indicates smartphone sharing. On, average, however, households with less smartphones also exhibit a lower trust level but more temple (or pagoda) visits. The education ratio and the school kids ratio are smaller than one in the user group. This indicates, in accordance with the literature (cf. Section 1), that households with more smartphones on average have a higher education level and a larger share of kids at school.

The mean values of the group indicators represent the share of household pairs in which both households *jointly* belong to the corresponding social group. In the user group, more household pairs are jointly literate (83%), have the same religion (36%) or both have a household member who migrated (27%) than in the non-user group. In the non-user group, more household pairs belong to the same ethnicity (79%) or the same political party (55%) than in the user group. In both groups, almost all household pairs jointly have access to electricity. Finally, the travel distance (in km) between household pairs is on average almost equal between the two groups.

Appendix Table A1 reports the pairwise correlations between the base case regression indicators. Most of the correlations are low, i.e., not larger than 0.11. The dependent variable, the smartphones ratio, exhibits correlations of approximately 0.27 and 0.30 with the household size ratio and age ratio. Among the explanatory variables, the household size ratio and kids at school ratio feature a correlation of –0.17, the literacy and ethnicity group indicators a correlation of 0.27, the household size ratio and age ratio of –0.51 and the religion and political party group indicators of –0.64. Therefore, we carry out a robustness check addressing these correlations (see Sections 3.2 and 3.3).

3.2 Method

Our main approach is the estimation of a two-stage Heckman-type model based on Equation (1). We apply the Heckman approach because there are pairwise households that do not simultaneously own smartphones such that the data are truncated at zero. This truncation occurs due to the households' choice not to buy a smartphone, i.e., there is self-selection (sample-selection). As a result, in one part of the household data, the smartphone indicator is not defined such that the number of smartphones cannot be measured as a (positive) ratio. Heckman (1974) solves the resulting selection bias problem via a two-stage approach. Accordingly, first, we estimate the probability of at least one household owning at least one smart phone (Equations (1) and (6)). Second, we determine the smartphone ratio among those households pairs that fulfill this condition (Equations (1) and (2)). This means precisely:

In the first stage, a selection equation is required, in which the probability of a household pair owning at least one smartphone is predicted depending on a vector of household pair characteristics. The selection equation follows Equation (1), where the dependent variable now takes the form:

$$T'_{ij} = \begin{cases} 1 & \text{if } t_i \geq 0 \text{ and } t_j > 0 \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

The dependent variable of the second stage (T_{ij}) defined by Equation (2) will be considered if the dependent variable of the first stage (T'_{ij}) is one in Equation 6. According to the level equation (2), in the second stage, the ratio of the per capita number of smartphones between households i and j is regressed on a vector of household pair characteristics following Equation (1) for those household pairs that own at least one smartphone.

In addition to the indicators described by Equation (1), the first-stage regression includes a vector of the identifying variables I_{ij} that does not appear in the second-stage equation. The vector includes two instruments (see, e.g., Hübler and Hartje (2016), Hartje and Hübler (2017)): (i) a Bartik-type (Bartik (1992)) instrument capturing the share of smartphone owners compared to all villagers within the village of household i relative to the same share within the village of household j. (ii) A binary variable that equals one if both households have access to electricity and equals zero otherwise. The average smartphone ratio in the village is supposed to be independent of the individual household's smartphone ownership as long as the number of villagers is sufficiently large. Similarly, access to the electricity grid in the village where the household resides is supposed to be independent of the individual smartphone ownership. Access to electricity, however, is essential for charging a smartphone. The remaining explanatory variables are the same in the first- and second-stage equations (regressions) (see Section 2 and Equation (1)).

For all computations, we use the statistical software *Stata* (version 14 SE). We compute the Heckman model results with a two-step estimator. In the base case regressions, we include the two technological identifiers as well as financial, social and geographic indicators. In the extended regression, we add technological and occupational indicators. The regressions make use of the entire dataset encompassing Thailand and Vietnam. As a reference point, we begin with a corresponding Ordinary Least Squares (OLS) regression based on Equation (1).

In a detailed robustness check, we run separate country-wise regressions. In another robustness check, we consider possible colinearity between the household size and the age ratio as well as religion and political party membership (see the descriptive statistics in Section 3.1 and Appendix Table A1). To check the robustness of the regression results with respect to these two pairs of correlated variables, we run the regressions by omitting one of the regressors household size, age, religion or political party membership each time.

Finally, we consider possible endogeneity. The prevalence of entertainment and the importance of private communication (see Appendix Figures A2 and A3), however, mitigate possible reverse causality and hence endogeneity: If the primary use was business-related communication or information gathering, one could expect an influence of smartphone ownership on income and income-related indicators. Moreover, smartphone use is unlikely to have an influence on belonging to social groups. Nonetheless, in Thailand, 12.5% of the households report education as their primary smartphone use which might influence household members' education level. Therefore, to evaluate the robustness of our estimations with regard to possible endogeneity-related biases, in a first step, we check the possible influence of income and assets, and in a second step, of education, literacy and kids at school on the significance and magnitude of the remaining indicators by omitting them in the regressions.

3.3 Results

Base case regressions

Table 2 shows the base case regression results with 724,250 (OLS) or 718,414 (Heckman) observations of household pairs living in rural areas in Thailand in Vietnam. The OLS results are reported in the first column, the Heckman results of the second stage are reported in the second column and the Heckman results of the first stage appear in the third column. In the first stage, a positive effect increases the likelihood that a household pair owns at least one smartphone, i.e., the dependent variable takes a value of one. In the second stage, a positive effect increases the number of smartphones (per capita) in the household with less phones relative to the number of smartphones (per capita) in the household with more smartphones. This implies technological convergence. Conversely, a negative effect implies technological divergence. In the following, we jointly interpret the OLS and Heckman results focusing on qualitative insights.

The R^2 value obtained from the OLS regression reaches approximately 0.12.[14] The F-statistic of testing the null hypothesis that all coefficients estimated with OLS are jointly zero rejects the null hypothesis with a highly significant value. The corresponding χ^2 value of a Wald test that all coefficients (except the constant) are jointly zero reaches a highly significant value and rejects null hypothesis as well. Due to the very large number of observations, we consider high significance levels (of 0.1%). Against this backdrop, most estimates are statistically highly significant.

Likewise, highly significant (transformed atanh) ρ and (ln) σ values support the validity of the two-stage Heckman selection model. Accordingly, the likelihood-ratio test of independent equations ($\rho = 0$) yields a highly significant χ^2 value that justifies the Heckman selection model.

The omission of one of the correlated regressors, i.e., household size, age, religion and

[14] Relatively low R^2 values are typically found in models defined in relative terms (cf. Hübler and Glas (2014); Hübler et al. (2022)).

Table 2: Base case regression results

Dep. var.: / *Reg. type:* / *Explan. var.:*	Smartphones (ratio) OLS	Smartphones (ratio) Heckman 2^{nd} stage	Smartphones (1|0) Heckman 1^{st} stage
Technological (identifiers):			
Smartphones village (ratio)			-0.133*****
			(0.00127)
Electricity access (group)			0.0580*****
			(0.00656)
Financial:			
Income (ratio)	0.000126*****	0.000186*****	5.38e-05
	(3.18e-05)	(3.81e-05)	(0.000141)
Assets (ratio)	0.00241*****	0.00848*****	-0.0162*****
	(0.000149)	(0.000141)	(0.000513)
Shocks (ratio)	-0.00604*****	-0.00574*****	-0.0264*****
	(0.000383)	(0.000414)	(0.00159)
Social:			
Age (ratio)	0.126*****	0.125*****	0.322*****
	(0.000669)	(0.000761)	(0.00334)
Household size (ratio)	-0.0424*****	-0.0561*****	-0.0885*****
	(0.000373)	(0.000406)	(0.000406)
Education (ratio)	0.0137*****	0.0419*****	-0.182*****
	(0.000824)	(0.000858)	(0.00332)
School kids (ratio)	0.0195*****	0.0148*****	0.127*****
	(0.000544)	(0.000609)	(0.00273)
Literacy (group)	0.0212***	0.0217*****	0.0771*****
	(0.000937)	(0.00101)	(0.00395)
Ethnicity (group)	0.0202*****	0.0229*****	0.0187*****
	(0.000932)	(0.00101)	(0.00401)
Political party (group)	-0.00559***	-0.00273***	-0.0454*****
	(0.000963)	(0.00104)	(0.00413)
Migrant (group)	0.0342*****	0.0260***	0.238***
	(0.000800)	(0.000858)	(0.00350)
Religion (group)	-0.00128	-0.00543*****	0.0478*****
	(0.00137)	(0.00150)	(0.00590)
Temple visits (ratio)	-0.000305*****	-0.000323*****	-0.000878*****
	(2.25e-05)	(2.59e-05)	(0.000103)
Trust (ratio)	-0.0198*****	-0.0178*****	-0.0991*****
	(0.000852)	(0.000910)	(0.00351)
Geographic:			
Distance (in km)	-1.64e-05*	2.51e-05***	-0.000153*****
	(9.73e-06)	(1.04e-05)	(4.10e-05)
Thailand (group)	-0.0192*****	-0.0195*****	-0.100*****
	(0.00162)	(0.00174)	(0.00688)
Constant	0.291*****	0.282*****	0.762*****
	(0.00173)	(0.00192)	(0.0101)
Number of obs.	724,250	718,414	718,414

Using household data on farmers in Thailand and Vietnam. Significance levels:
**** p<0.001 **** p<0.005, *** p<0.01, ** p<0.05, * p<0.1.
Standard errors in parentheses.

political party in the OLS or Heckman regressions does not alter the results qualitatively (sign or statistical significance) and has small quantitative effects (magnitudes of the coefficients). Similarly, the omission of income and assets or of education, literacy and kids as school does not alter the the significance of the remaining coefficients and affects their magnitudes to a minor extent. Accordingly, there does not seem to be a relevant endogeneity bias.

In Table 2, joint access to electricity has the expected positive effect on ICT (smartphone) use in the first stage. This result is reported in the third column of Table 2. In contrast, the ratio of the smartphone shares in the two villages of residence of the considered household pairs entails a negative effect.

The *financial* indicators, income and assets, have the expected positive effect on technological convergence of ICT (with OLS and in the second stage of Heckman), while the shocks ratio has the expected negative effect, i.e., shocks hinder technological convergence.

Among the *social* indicators, a higher relative age increases the smartphones ratio and hence fosters technological convergence of ICT.[15] In accordance with the literature (e.g., Hübler (2016); Hübler and Hartje (2016)), in our results, a larger relative household size decreases the number of (shared) smartphones. Likewise, in accordance with this literature, education enhances technology use. The education ratio, the ratio of the shares of kids at school and joint literacy all have a positive effect on the smartphones ratio.[16]

Furthermore, when both households belong to the same ethnicity or both have a household member who migrated, technological convergence will be enhanced as expected (cf. Hübler (2016) regarding the effect of migration on technology diffusion in terms of the spread of mobile phones). Jointly belonging to a political party, however, clearly has a negative effect. A possible explanation is that members of the political parties under scrutiny tend to have negative or diverse attitudes towards modern technologies resulting in larger differences in smartphone ownership. Similarly, relatively more temple visits decrease the relative num-

[15]In the literature (e.g., Hübler (2016); Hübler and Hartje (2016)), the maximum of mobile phone ownership is reached at an age of approximately 40 years.

[16]The estimated coefficient on education is significant and negative in the first stage.

ber of smartphones. This outcome indicates a lower affinity to technology adoption or to technology ownership of people practising religion more actively. The estimates for jointly belonging to the same religion are ambiguous, though. Surprisingly, a relatively higher trust level reduces the relative number of smartphone as well.

A larger *geographic* distance between the households mostly reduces technological convergence (except in the second stage of Heckman) as expected. According to the negative country-specific effect, technological convergence in Thailand is weaker than in Vietnam.

In summary, the effect of jointly belonging to the same social group on ICT use is inconclusive. The direction of the effect may depend on the attitude to modern technologies and the heterogeneity of technology use and technology adoption within a group. The effect of the travel distance between household pairs is inconclusive as well. Accordingly, hypotheses H1 and H2 are neither generally confirmed nor rejected. The financial and social determinants of household pairs, on the contrary, mostly exhibit the expected effects on ICT use following the literature and intuition. Particularly, our results confirm the positive effect of education on technology, i.e., ICT or smartphone, use. The results appear to be robust with respect to possible colinearity or endogeneity.

Extended regressions

The extended Heckman-type regression results displayed in Table 3 implicitly include the regressors reported in Table 2. Additionally, they include *technological* indicators: the ratio of the values of technological assets (each per capita) between the two households and several group indicators defining that both households own at least one of the following technological devices: radio, television, landline telephone, personal computer or tablet computer. Appendix Table A2 displays the corresponding OLS regression results.

The Heckman and OLS results show unequivocally that existing technologies, particularly, ownership of similar technologies, enhance the adoption of new technologies, here particularly ICT, measured as the number of smartphones. In this way, they enhance technological

Table 3: Extended regression results

Dep. var.: / *Reg. type:* / *Explan. var.:*	Smartphones (ratio) Heckman 2^{nd} stage	Smartphones (1|0) Heckman 1^{st} stage	Smartphones (ratio) Heckman 2^{nd} stage	Smartphones (1|0) $I(SP_{ij} = 1$ Heckman 1^{st} stage
Technological:				
Technolog. assets (ratio)	0.000505*****	0.00141*****	0.000494*****	0.00132*****
	(1.84e-05)	(7.49e-05)	(1.83e-05)	(7.45e-05)
Radio (group)	0.00842*****	0.0236*****	0.00865*****	0.0233*****
	(0.00168)	(0.00676)	(0.00167)	(0.00683)
Television (group)	0.0833*****	0.450*****	0.0792*****	0.437*****
	(0.00127)	(0.00468)	(0.00126)	(0.00471)
Landline phone (group)	0.0870*****	0.222****	0.0735*	0.150*****
	(0.0162)	(0.0753)	(0.0161)	(0.0770)
Personal computer (group)	0.141*****	0.785*****	0.133*****	0.764*****
	(0.00190)	(0.0134)	(0.00190)	(0.0137)
Tablet computer (group)	0.0518*****	0.579*****	0.0472*****	0.579*****
	(0.00706)	(0.0446)	(0.00701)	(0.0453)
Occupational:				
Farming (group)			-0.00871*****	-0.0521*****
			(0.000774)	(0.00315)
Agri. wage labor (group)			-0.0756*****	-0.288*****
			(0.00526)	(0.0199)
Fishing (group)			-0.00909	0.0107
			(0.0188)	(0.0762)
Non-agri. wage labor (group)			0.0305*****	0.254*****
			(0.000891)	(0.00377)
Self-employment (group)			0.0392*****	0.255*****
			(0.00179)	(0.00832)
Constant	0.209*****	0.425*****	0.215*****	0.470*****
	(0.00217)	(0.0108)	(0.00223)	(0.0112)
Number of obs.	718,414	718,414	718,414	718,414

Using household data on farmers in Thailand and Vietnam. Significance levels:***** p<0.001, ****p<0.005, *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. The explanatory variables listed in Table 2 are also included in the regressions reported here, although the results are not displayed for convenience.

convergence (towards the same number of smartphones across households). Accordingly, in this case, hypothesis H1 is confirmed.

When considering *occupational* indicators, the picture looks different but again clear-cut. Occupational indicators are added in the right two columns of Table 3 and in the right column of Appendix Table A2. As before, the OLS results are in line with the Heckman results and entail R^2 values of approximately 0.14. If (members of) both households under consideration are active in the agricultural sector in terms of farming or wage employment, the smartphones ratio will be lower, which indicates divergence of ICT use across households in the agricultural sector. If (members of) both households are active in fishery, however, a significant effect is not detected. In contrast to these findings, wage employment outside the agricultural sector or being self-employed, i.e., running a business, increase the smartphones ratio and hence support convergence of ICT use. Apparently, hypothesis H1 is confirmed contingent on the work environment. Technological convergence seems to require a work environment that supports the equal spread of modern technologies, which is found outside agriculture.

As in the base case regressions, the results of the regressions with technological indicators and those with occupational indicators are robust to the omission of income and assets or of education, literacy and kids at school. In the first stage, however, access to electricity loses its significance. The significance of the remaining coefficients remains unaffected and their magnitudes change only to a minor extent.

Country-wise regressions

The previous regressions used the full sample with combined data from households in Thailand and Vietnam. As a robustness check, we repeat the regressions separately for each country. Appendix Table A3 details the *base case* Heckman results.

The results for Vietnam are predominantly in accordance with the previous results presented in Table 2 encompassing both countries. One exception is the significant and counterintuitively negative first stage coefficient on income. The results for Thailand, however, are subject to some changes in the signs of the estimated effects. While the positive effects of shocks and the travel distance as well as the negative second-stage effect of a migrant on technological convergence are unexpected, other changes in the signs of *social* determinants are plausible: different to the results for Vietnam, belonging to the same ethnic group entails a significant and negative effect and belonging to the same political party a significant and positive effect in Thailand. Unlike in Vietnam, more temple visits increase technological convergence in the first stage in Thailand.

In summary, these results indicate that due to the larger number of observations from Vietnam (more than 500,000 compared with more than 200,000 from Thailand), the previous full sample results are dominated by the observations from Vietnam. They confirm that the classical indicators, such as income, assets, age or education, exhibit relatively stable effects, while the effects of the novel social (group) indicators on technological convergence are country- and group-dependent. Consequently, the evaluation of hypothesis H1 is inconclusive.

Appendix Table A4 reports the country-wise *extended* Heckman regression results focusing on *technological* indicators. The new results confirm the positive effect of existing technologies on new ICT presented in Table 3. Two minor changes are detected in the country-wise results: while the coefficient on landline phones becomes weakly significant and negative in the first stage of the Thailand regression, the coefficient on radio devices becomes weakly significant and negative in the first stage of the Vietnam regression. The corresponding coefficients in the second stage are, however, insignificant.

Appendix Table A5 details the corresponding results including *technological* and *occupational* indicators. The new results confirm the full sample results presented in Table 3. Again, the results for Vietnam are qualitatively very close to the full sample results. Merely the coefficient on radio devices becomes insignificant in both stages. The effects of farming and self-employment become insignificant in the second stage of the Thailand regression. While the coefficient on farming in Thailand becomes weakly significant and positive in the first stage, the coefficient on fishing becomes weakly significant and positive in the second stage.

Overall, the robustness check confirms our previous findings. The observed changes in significance levels occur because the number of observations becomes substantially smaller in each country sample when the full sample is split into two parts.

4 Conclusion

We have introduced a novel concept of microeconomic technological convergence among household pairs. A central new feature of this concept is the definition of social groups and pairwise (relative) characteristics. This allows us to study weather households that belong to the same group or share the same characteristics converge in terms of their technology level. We have applied the concept to household data from Thailand and Vietnam.

Descriptive evidence suggests that the use of smartphones in rural communities centers on entertainment. Accordingly, the social benefits of ICT (smartphones) in terms of education, health, market information and so forth, seem to be insufficiently realized. Such a situation justifies public support of ICT. Public support may include information about the advantages of ICT and training regarding its effective use as well as improvements of the ICT infrastructure, access to finance and subsidies for ICT devices and usages.

The regression results provide the following insights for development policy with the aim to foster rural technological development. One can expect that successful economic development with increasing household incomes towards a more equal income distribution will go along with more equal spread of ICT. When existing technologies, such as radio or television, are widespread, new ICT, such as smartphones, can be expected to follow. The importance of education for (technological) development is confirmed. The spread of technologies, however, works better outside the agricultural sector than inside. As a consequence, there is a significant risk that in rural regions with low income and lack of technologies, the spread of ICT will fail. Therefore, development assistance should support technologically underdeveloped regions and poor households that solely live on subsistence farming or insufficient farm income. Relying on social networks within ethnic or religious groups, political parties or the like, is *not* sufficient to foster the spread of new technologies successfully. Whether such groups have a positive or negative effect on the equal spread of technologies depends on their characteristics and location. The identification of relevant groups that foster the spread of ICT can ease technological assistance by targeting these groups.

We hope that our article provides a useful new approach and fruitful inspiration for further studies. Future research may try to detect the role of specific social groups or networks in technology diffusion.

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Appendix

Figure A1: The underlying survey areas in Southeast Asia (within red borders)

Figure A2: Smartphone uses in Thailand

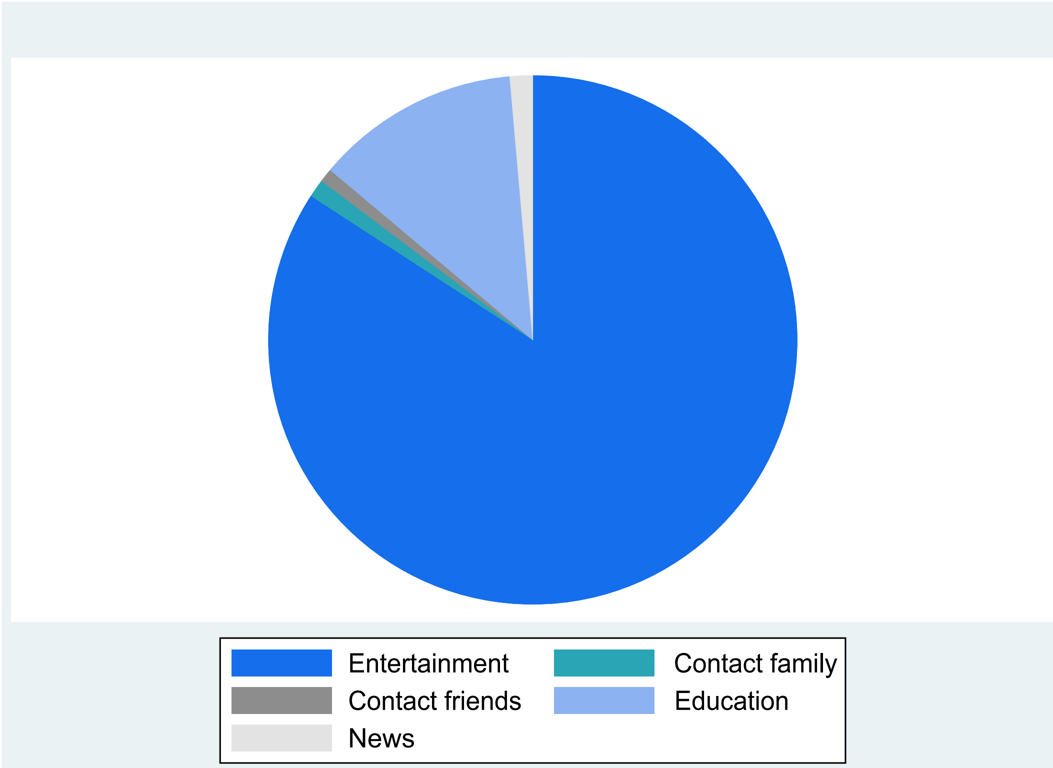

Figure A3: Smartphone uses in Vietnam

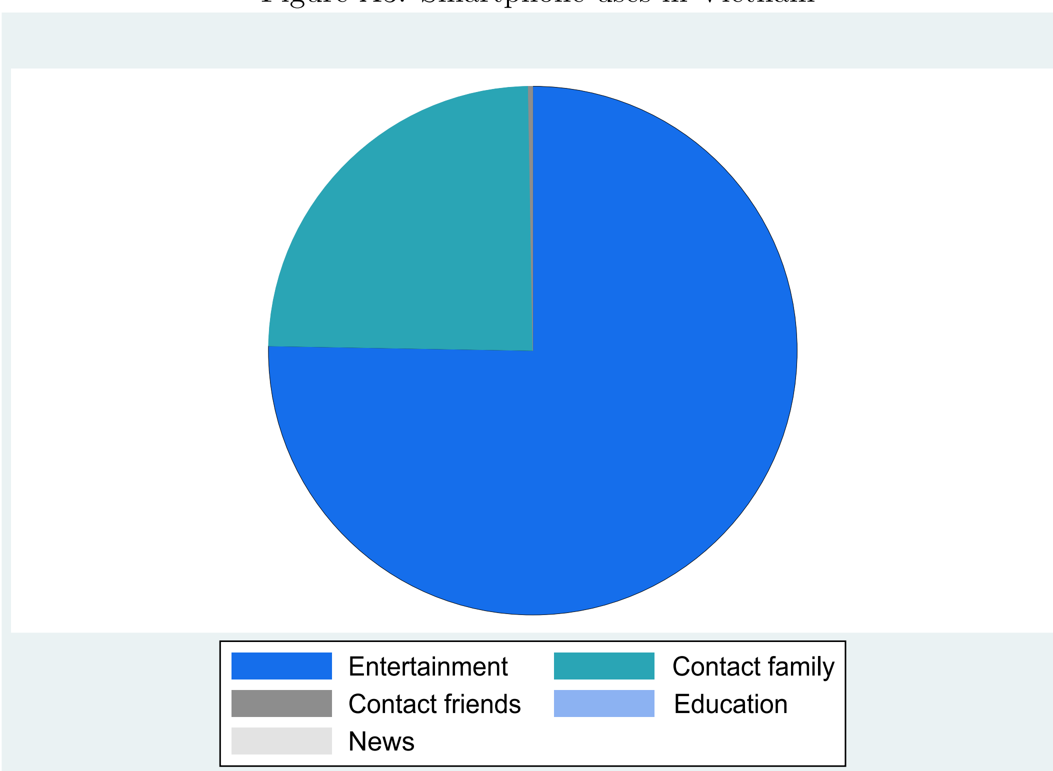

Figure A4: Distribution of the smartphones ratio of household pairs in the survey areas

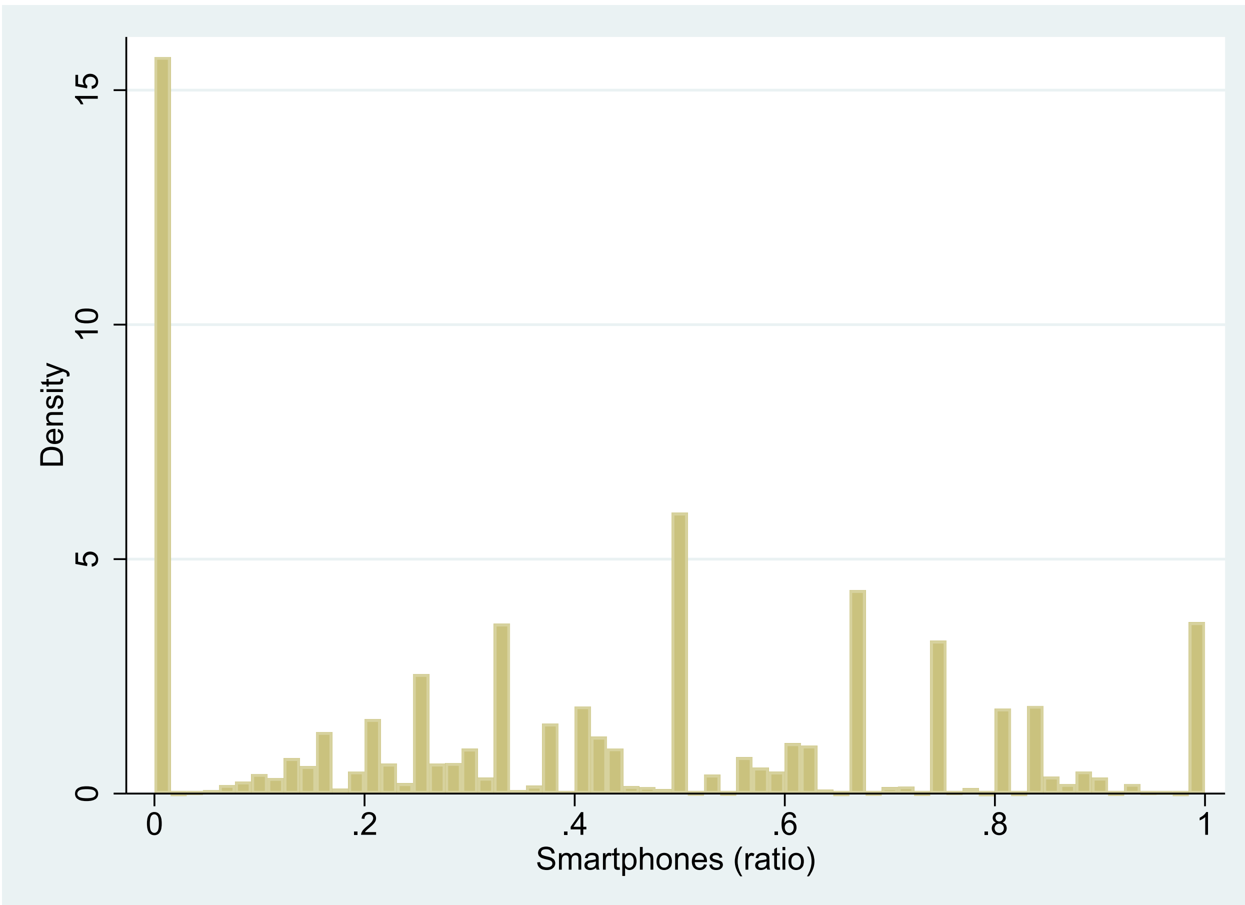

Table A1: Correlation matrix of the indicators used in the regressions

Variables	Phones	Income	Assets	Literat	Educa	Size	Age	Shocks	Distan	Ethnic	Relig	Temple	School	Party	Migrant	Trust
S. Phones	1															
Income	0.0126	1														
Assets	0.0038	0.0852	1													
Literacy	0.0416	0.0050	-0.0005	1												
Education	0.0206	0.0558	0.2726	0.0577	1											
Hsh. size	-0.2679	-0.0041	0.1152	-0.0123	0.1033	1										
Age	0.3037	0.0221	-0.0215	0.0217	0.0256	-0.5054	1									
Shocks	-0.0254	0.0020	0.0016	0.0072	0.0016	0.0183	-0.0293	1								
Distance	-0.0070	-0.0069	-0.0073	-0.0346	-0.0193	-0.0131	0.0003	-0.0107	1							
Ethnicity	0.0483	0.0235	0.0784	0.2734	0.0955	-0.0031	0.0668	-0.0130	-0.2294	1						
Religion	0.0167	0.0281	0.0924	0.0245	0.0549	-0.0161	0.0683	-0.0865	0.0320	0.2678	1					
Temple vis.	-0.0101	0.0007	-0.0089	0.0002	-0.0197	-0.0055	0.0133	0.0103	-0.0214	-0.0051	0.0502	1				
School kids	0.0671	0.0089	-0.0234	-0.0043	0.0032	-0.1742	0.0194	-0.0036	0.0338	-0.0525	0.0112	0.0025	1			
Pol. party	-0.0092	-0.0190	-0.0689	0.0338	-0.0253	0.0121	-0.0441	0.0943	-0.0542	-0.0605	-0.6427	-0.0409	-0.0218	1		
Migrant	0.0572	-0.0061	-0.0306	0.0718	0.0155	-0.0360	0.0138	0.0172	-0.0143	0.1107	0.0781	0.0225	0.0069	-0.0253	1	
Trust	-0.0260	-0.0052	-0.0016	0.0015	0.0086	0.0073	-0.0010	0.0326	-0.0356	0.0169	-0.1085	-0.0078	-0.0277	0.1084	-0.0117	1

Household data on farmers in Thailand and Vietnam referring to the base case.

Table A2: Extended OLS regression results

Explan. var.: / *Dep. var.:* / *Reg. type:*	Smartphones (ratio) OLS	Smartphones (ratio) OLS
Technological:		
Technolog. assets (ratio)	0.000543***	0.000533***
	(5.75e-05)	(5.62e-05)
Radio (group)	0.00936***	0.00967***
	(0.00162)	(0.00162)
Television (group)	0.0929***	0.0895***
	(0.00115)	(0.00115)
Landline phone (group)	0.0879***	0.0730***
	(0.0144)	(0.0145)
Personal computer (group)	0.147***	0.139***
	(0.00158)	(0.00159)
Tablet computer (group)	0.0529***	0.0492***
	(0.00615)	(0.00618)
Occupational:		
Farming (group)		-0.00887***
		(0.000731)
Agri. wage labor (group)		-0.0706***
		(0.00463)
Fishing (group)		0.000286
		(0.0185)
Non-agri. wage labor (group)		0.0382***
		(0.000825)
Self-employment (group)		0.0460***
		(0.00163)
Constant	0.204***	0.208***
	(0.00291)	(0.00292)
Number of obs.	724,250	724,250

Using household data on farmers in Thailand and Vietnam. Significance levels:***** p<0.001, ****p<0.005, *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. The explanatory variables listed in Table 2 are also included in the regressions reported here, although the results are not displayed for convenience.

Table A3: Country-wise base case regression results

	Thailand		Vietnam	
Dep. var.:	Smartphones (ratio)	Smartphones (1|0)	Smartphones (ratio)	Smartphones (1|0)
Reg. type:	Heckman 2^{nd} stage	Heckman 1^{st} stage	Heckman 2^{nd} stage	Heckman 1^{st} stage
Explan. var.:				
Technological (identifiers):				
Smartphones village (ratio)		-0.164***		-0.113***
		(0.00253)		(0.00152)
Electricity access (group)		0.101***		0.0570***
		(0.0168)		(0.00729)
Financial:				
Income (ratio)	9.68e-05**	0.000646	0.000647***	-0.00155***
	(4.26e-05)	(0.000415)	(8.78e-05)	(0.000336)
Assets (ratio)	0.00618***	-0.00660***	0.0110***	-0.0277***
	(0.000206)	(0.000779)	(0.000193)	(0.000703)
Shocks (ratio)	0.00372***	0.0137***	-0.00855***	-0.0402***
	(0.000842)	(0.00340)	(0.000469)	(0.00183)
Social:				
Age (ratio)	0.102***	0.340***	0.133***	0.335***
	(0.00137)	(0.00668)	(0.000906)	(0.00400)
Household size (ratio)	-0.0536***	-0.0958***	-0.0564***	-0.0832***
	(0.000750)	(0.00293)	(0.000479)	(0.00193)
Education (ratio)	0.0437***	-0.381***	0.0415***	-0.127***
	(0.00174)	(0.00686)	(0.000980)	(0.00385)
School kids (ratio)	0.00864***	0.167***	0.0172***	0.119***
	(0.00112)	(0.00535)	(0.000717)	(0.00321)
Literacy (group)	0.00710***	0.0622***	0.0240***	0.0787***
	(0.00212)	(0.00829)	(0.00114)	(0.00453)
Ethnicity (group)	-0.0590***	-0.0769***	0.0226***	0.0105**
	(0.00495)	(0.0200)	(0.00103)	(0.00418)
Political party (group)	0.126***	0.539***	-0.00521***	-0.0574***
	(0.0108)	(0.0559)	(0.00103)	(0.00416)
Migrant (group)	-0.0118***	0.0797***	0.0427***	0.336***
	(0.00148)	(0.00600)	(0.00104)	(0.00442)
Religion (group)	omitted	omitted	-0.00507***	0.0504***
			(0.00147)	(0.00593)
Temple visits (ratio)	1.62e-05	0.00167***	-0.000393***	-0.00115***
	(6.49e-05)	(0.000292)	(2.78e-05)	(0.000112)
Trust (ratio)	-0.0222***	-0.109***	-0.0173***	-0.107***
	(0.00205)	(0.00797)	(0.00100)	(0.00395)
Geographic:				
Distance (in km)	0.000184***	0.000454***	-3.13e-06	-0.000253***
	(2.20e-05)	(8.86e-05)	(1.16e-05)	(4.67e-05)
Constant	0.376***	0.944***	0.272***	0.709***
	(0.00596)	(0.0294)	(0.00215)	(0.0113)
Number of obs.	209,552	209,552	508,862	508,862

Using separate household data on farmers in Thailand and Vietnam. Significance levels:***** p<0.001, ****p<0.005, *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. The explanatory variable religion is omitted in Thailand because all households identify themselves as Buddhists.

Table A4: Country-wise extended regression results

	Thailand		Vietnam	
Dep. var.:	Smartphones (ratio)	Smartphones (1|0)	Smartphones (ratio)	Smartphones (1|0)
Reg. type:	Heckman 2^{nd} stage	Heckman 1^{st} stage	Heckman 2^{nd} stage	Heckman 1^{st} stage
Explan. var.:				
Technological:				
Technolog. assets (ratio)	0.000448***	0.00103***	0.000461***	0.00190***
	(2.83e-05)	(0.000114)	(2.46e-05)	(0.000102)
Radio (group)	0.00874***	0.0409***	-0.0258	-0.123*
	(0.00172)	(0.00701)	(0.0163)	(0.0635)
Television (group)	0.0723***	0.483***	0.0837***	0.440***
	(0.00428)	(0.0154)	(0.00130)	(0.00494)
Landline phone (group)	-0.151	-0.912*	0.0902***	0.282***
	(0.122)	(0.477)	(0.0160)	(0.0772)
Personal computer (group)	0.146***	0.900***	0.136***	0.764***
	(0.00415)	(0.0304)	(0.00211)	(0.0151)
Tablet computer (group)	0.0419***	0.515***	0.0611***	0.545***
	(0.00876)	(0.0504)	(0.0121)	(0.0884)
Constant	0.305***	0.583***	0.199***	0.368***
	(0.00717)	(0.0323)	(0.00238)	(0.0120)
Number of obs.	209,552	209,552	508,862	508,862

Using separate household data on farmers in Thailand and Vietnam. Significance levels:***** p<0.001, ****p<0.005, *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. The explanatory variables listed in Table A3 are also included in the regressions reported here, although the results are not displayed for convenience.

Table A5: Country-wise extended regression results (2)

	Thailand		Vietnam	
Dep. var.:	Smartphones (ratio)	Smartphones (1|0)	Smartphones (ratio)	Smartphones (1|0)
Reg. type:	Heckman 2^{nd} stage	Heckman 1^{st} stage	Heckman 2^{nd} stage	Heckman 1^{st} stage
Explan. var.:				
Technological:				
Technolog. assets (ratio)	0.000441***	0.000989***	0.000454***	0.00178***
	(2.81e-05)	(0.000110)	(2.44e-05)	(0.000101)
Radio (group)	0.00873***	0.0423***	-0.0205	-0.105
	(0.00171)	(0.00705)	(0.0162)	(0.0640)
Television (group)	0.0732***	0.471***	0.0786***	0.423***
	(0.00428)	(0.0155)	(0.00130)	(0.00498)
Landline phone (group)	-0.142	-0.837*	0.0730***	0.188**
	(0.121)	(0.480)	(0.0159)	(0.0793)
Personal computer (group)	0.142***	0.900***	0.126***	0.729***
	(0.00414)	(0.0308)	(0.00210)	(0.0154)
Tablet computer (group)	0.0417***	0.529***	0.0489***	0.472***
	(0.00872)	(0.0510)	(0.0120)	(0.0911)
Occupational:				
Farming (group)	0.00227	0.0126**	-0.0133***	-0.0874***
	(0.00140)	(0.00567)	(0.000920)	(0.00386)
Agri. wage labor (group)	-0.0371***	-0.162***	-0.0852***	-0.327***
	(0.0110)	(0.0433)	(0.00591)	(0.0226)
Fishing (group)	0.106*	0.148	-0.0211	-0.0178
	(0.0632)	(0.244)	(0.0193)	(0.0804)
Non-agri. wage labor (group)	0.0243***	0.250***	0.0355***	0.282***
	(0.00164)	(0.00689)	(0.00105)	(0.00461)
Self-employment (group)	0.00600	0.167***	0.0466***	0.284***
	(0.00378)	(0.0164)	(0.00200)	(0.00986)
Constant	0.305***	0.583***	0.199***	0.368***
	(0.00717)	(0.0323)	(0.00238)	(0.0120)
Number of obs.	209,552	209,552	508,862	508,862

Using separate household data on farmers in Thailand and Vietnam. Significance levels:***** p<0.001, ****p<0.005, *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. The explanatory variables listed in Table A3 are also included in the regressions reported here, although the results are not displayed for convenience.