ESSAYS ON NONSAMPLING ERRORS IN HOUSEHOLD PANEL SURVEYS

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The undertaking of writing a dissertation can be described with a quote by J. R. R. Tolkien: “It’s a dangerous business, […], going out your door. You step onto the road, and if you don’t keep your feet, there’s no knowing where you might be swept off to.”. Indeed, the journey was quite the adventure and looking back to the day on which I was offered the position as a PhD candidate, I never could have imagined where my feet would take me.

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ZUSAMMENFASSUNG

Haushaltsbefragungen stellen die vorherrschende Form der Datenerhebung in Ländern mit niedrigem und mittlerem Einkommen dar. Zudem fungieren sie als wichtige Substitute für eingeschränkte Verwaltungsdaten. Infolge einer steigenden Nachfrage nach Daten, haben Forscher und politische Entscheidungsträger gleichermaßen auf die Problematik von unzureichender Qualität von Daten verwiesen. Obwohl große Fortschritte erzielt werden konnten, wurden viele Datenquellen, einschließlich Haushaltserhebungen, als unzureichend in Bezug auf Genauigkeit und Zuverlässigkeit identifiziert. Dies schränkt eine fundierte Entscheidungsfindung seitens politischer Entscheidungsträger ein. Die Bedeutung qualitativ hochwertiger Daten wurde in den Zielen für die nachhaltige Entwicklung anerkannt. Daten seien der Schlüssel zur Überwachung von Fortschritten und zur Sicherstellung der Erreichung von Nachhaltigkeitszielen.

Die vorliegende Dissertation hat das Ziel, ein besseres Verständnis der erhebungsmethodischen Problemstellungen in Ländern mit niedrigem und mittlerem Einkommen zu entwickeln, sowie einen Ausblick über die Zukunft der Datenerhebung in Panelstudien darzubieten. Dabei befassen sich die ersten beiden Artiekl mit der Identifizierung von nicht-stichprobenbedingten Fehlern in Haushaltsbefragungen, sowie dessen Einflussfaktoren und die Auswirkungen solcher Fehler auf Entscheidungsfindungen. Der dritte Aufsatz befasst sich mit der fortdauernden Rolle der Landwirtschaft in der ländlichen Entwicklung.

Der erste Aufsatz untersucht das Vorkommen von nicht-stichprobenbedingten Fehlern in der siebten Erhebungswelle einer langfristen Haushaltspanelerhebung in Thailand und Vietnam, die 3.812 Haushalte umfasst. Eine Untersuchung der Verteilung solcher Fehler wird durchgeführt, um festzustellen, welche Fehlerart am häufigsten in computergestützen Erhebungsanwendungen vorkommt. Dieses Ergebnis wird dann mit einer früheren Studie verglichen, welche in einem papierbasierten Erhebungsinstrument das Vorkommen von nicht-stichprobebedingten Fehlern untersucht. Anschließend wird eine negative Binomialregression zur Analyse von Einflussfaktoren von nicht-stichprobenbedingten Fehlern angewandt. Dabei werden gleichzeitig der Einfluss des Befragers, des Befragten und Rahmenbedingungen des Befragungsumfelds berücksichtigt. Der zweite Aufsatz verwendet Daten aus derselben Haushaltspanelerhebung, nutzt jedoch den kompletten Erhebungszeitraum der Panelerhebung aus. Anhand von sieben Wellen von Paneldaten aus Thailand, die zwischen 2007 und 2019 erhoben worden sind, bilden 1.542 identische Haushalte die Grundlage der Analyse von inkonsistent gemeldeten Erwerbstätigkeiten. Dabei wird ein dreistufiger Ansatz entwickelt, um

inkonsistente Antworten zwischen zwei aufeinanderfolgende Erhebungswellen zu identifizieren. Zusätzlich wird ein zweistufiges Logistisches Mehrebenenmodell angewandt, um den Einfluss von Befrager- und Beschäftigungsmerkmalen auf inkonsistente Antworten zu untersuchen. Außerdem werden die Auswirkungen inkonsistenter Antworten auf politische Entscheidungen untersucht, die sich mit dem Wohlergehen von Haushalten befassen. Der dritte Aufsatz verwendet drei Wellen derselben Haushaltsbefragung aus Thailand, die in 2007, 2013 und 2019 durchgeführt wurden. Dabei werden 1.160 identische Haushalte in der Analyse berücksichtigt. Zunächst erfolgt eine deskriptive Analyse der Veränderung der Lebensgrundlagen ländlicher Haushalte in Nordostthailand. Zudem wird ein Logistisches Regressionsmodell angewandt, um Faktoren zu untersuchen, die die Armutshäufigkeit beeinflussen. Dabei wird nach Typologie des Haushalts basierend auf dessen landwirtschaftlicher Prägung unterschieden.

Der erste Artikel zeigt auf, dass eine wesentlich geringere Anzahl an Daten in computergestützen Umfragen fehlen, während Messfehler ein ernstzunehmendes Problem darstellen. Die Ergebnisse der negativen Binomialregression unterstreichen die Bedeutung des Befragertrainings und zeigen, dass aufgeschlossene und sympathische Befrager Befragungen von höherer Qualität durchführen. Darüber hinaus spielen die Rahmenbedingungen der Befragung sowie das Befragungsumfeld eine wichtige Rolle. Insbesondere deuten die Ergebnisse darauf hin, dass Messfehler am wahrscheinlichsten in der ersten Erhebungswoche vorkommen, wohingegen Verweigerungen bei der Beantwortung von Fragen im Laufe des Erhebungszeitraums zunehmen. In Vietnam deutete die Inkongruenz der ethnischen Zugehörigkeit zwischen Befragern und Befragten auf eine erhebliche Zunahme von nicht-stichprobenbedingten Fehlern hin. Darüber hinaus muss bei der Durchführung von Umfragen darauf geachtet werden, dass Unterschiede in der Umfragedurchführung eine Auswirkung auf die Datenqualität haben können. Der zweite Artikel deckt durch den Vergleich zweier aufeinanderfolgenden Erhebungswellen erhebliche Fälle von nicht gemeldeten Beschäftigungen auf. Insbesondere informelle Beschäftigungen werden mit geringerer Wahrscheinlichkeit zuverlässig mitgeteilt. Zudem korrelieren komplexere Haushaltsstrukturen positiv mit inkonsistent gemeldeten Beschäftigungen. Die Auswirkungen nicht gemeldeter Beschäftigungen auf Wohlfahrtsindikatoren sind erheblich und Armutszahlen auf der Provinzebene werden um 6,7 Prozentpunkte überschätzt. Der dritte Artikel hebt hervor, dass das Einkommen ländlicher Haushalte in einem Zeitraum von 12 Jahren stark zunahm, welches mit einer Abnahme der Armutsinzidenz bei landwirtschaftlich geprägten Haushalten einherging. Jedoch hat sich die Lebensgrundlage der Haushalte wenig geändert. Trotz erheblicher Abwanderung von Haushaltsmitgliedern im erwerbsfähigen Alter, bleiben die meisten Haushalte in der Landwirtschaft tätig und können als Teilzeit-Kleinbauern eingeordnet werden. Darüber hinaus sind Haushalte, die primär in der Landwirtschaft tätig sind aufgrund der Dürreanfälligkeit der Region zunehmend abhängig von staatlichen Eingriffen.

Zusammenfassend bieten die Artikel, die sich mit der Untersuchung von Datenqualität von Haushaltsbefragungen in Thailand und Vietnam befassen, neue Perspektiven hinsichtlich der Faktoren, die Umfrageanbieter bei der Durchführung von Erhebungen berücksichtigen müssen. Zudem wird auf Mängel in Modulen hingewiesen, die typischerweise in Erhebungen in Ländern mit niedrigem- und mittlerem Einkommen angewandt werden und die sich mit der Erwerbstätigkeit befassen. Dies bietet einen Einstiegspunkt für die Debatte über mögliche Ansätze zur Präzisierung der Erhebung von Beschäftigungsdaten. Der dritte Artikel zeigt auf, dass die ländliche Bevölkerung nach wie vor stark von der Landwirtschaft abhängig ist und dass die Rolle der Landwirtschaft für die Entwicklung nicht unterschätzt werden darf.

Stichworte: Datenqualität, nicht-stichprobenbedingte Fehler, Haushaltspanelstudien, computergestützte persönliche Interviews, Thailand, Vietnam, ländlicher Lebensgrundlagen

ABSTRACT

Household surveys represent the predominant form of data collection in low- and middle-income countries and function as crucial substitutes to constrained administrative data. In recent years, following an increasing demand for data, researchers and policymakers alike have addressed the continued issue of low-quality data. While much progress has been made, many sources of data, including household surveys, have been identified as being insufficiently accurate and reliable, thus constraining informed decision-making on behalf of policymakers. Indeed, the importance of obtaining high-quality outputs has been recognised in the Sustainable Development Goals, which emphasise that to date, data is key to informing policy, monitoring progress, and ultimately achieving formulated goals.

This thesis aims to provide a better understanding of survey methodological issues in low- and middle-income countries and provide an outlook on the future of panel survey applications. Thereby, the first two essays deal with identification of nonsampling errors in household survey datasets, factors influencing their prevalence, and their impact. Conversely, the third essay examines the continued role of agriculture in rural development. The first essay investigates the prevalence of nonsampling errors in the seventh survey wave of a long-term household panel survey conducted in Thailand and Vietnam, which encompasses 3,812 households. An analysis of the distribution of nonsampling errors is undertaken in order to ascertain which type of error is most prevalent in the underlying computerised survey instrument. These findings are then compared with those of an earlier study, which examined the prevalence of nonsampling errors in a paper-based survey instrument. Thereafter, a negative binomial model is applied to analyse factors influencing nonsampling errors, which simultaneously assesses the influence of the interviewer, respondent, and interview and survey environment. The second essay utilises data from the same panel, albeit making use of the longitudinal nature of data. Using seven waves of panel survey data from Thailand, which were collected between 2007 and 2019, interviews of 1,542 identical households were examined with a focus on the consistency of reported employments. A three-stage approach is developed to identify inconsistent reporting thereof between pairs of consecutive survey waves. Additionally, a two-stage multilevel logistic model is applied in order to analyse interviewer and employment characteristics that influence inconsistent reporting. Further, the impact of inconsistent reporting on policy pertaining to household welfare is examined. The third essay utilises three waves of household survey data from Thailand, which were conducted in 2007, 2013, and 2019, and considers 1,160 identical households. A descriptive analysis is undertaken in which changes in livelihoods of rural households in Northeast Thailand are examined. Further, a logit regression is

applied to identify factors influencing poverty incidence, which differentiates by the typology of household based on the importance of agriculture.

The first essay finds that computerised survey instruments have a substantially lower count of missing data, whereas measurement errors remain a pressing issue. The findings of the negative binomial regression model highlight the importance of interviewer training and indicate that more outgoing and sympathetic interviewers produce interviews of higher quality. Additionally, conditions of the interview and survey are shown to influence the prevalence of nonsampling errors. Notably, the results suggest that measurement errors are most likely to occur in initial survey weeks, whereas the likelihood of refusal increases as the survey progresses. In Vietnam, incongruence of ethnicity between interviewers and respondents indicated a substantial increase in nonsampling errors. Further, survey providers in endeavours to collect high-quality data must account for differences in survey implementation. The second essay identifies substantial cases of underreporting of employments throughout pairs of consecutive survey waves. Notably, informal employments are less likely to be consistently reported and more complex household compositions are positively correlated with inconsistency. The impact of omitted employments on welfare indicators is demonstrated to be substantial with poverty headcounts being overestimated by, on average 6.7 percentage points at the provincial level. The third essay highlights that while income has been observed to increase over a 12-year period, which has coincided with an increasing proportion of agriculture-based households being classified as non-poor, little has changed in rural livelihoods in rural Northeast Thailand. Despite substantial out-migration of working-aged household members, most households remain engaged in agriculture and can be described as part-time, small-scale farmers. Further, those households mainly engaged in agriculture are observed to become increasingly dependent on government interventions due to the region's propensity to droughts.

In conclusion, the essays examining data quality of household surveys in Thailand and Vietnam provide new perspectives regarding factors that survey providers must consider in conducting surveys. Further, shortcomings of labour modules that are typically used in household surveys in developing countries are identified and provide an entry point to a debate on possible approaches to more accurately collecting employment data. The third essay highlights that rural populations remain highly reliant on agriculture and that the role of agriculture in development cannot be understated.

Keywords: Data quality, nonsampling error, household panel surveys, computer-assisted personal interviewing, Thailand, Vietnam, TVSEP, rural livelihood

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LIST OF ABBREVIATIONS

AB	Agriculture-based
AIC	Akaike Information Criterion
BHPS	British Household Panel Survey
CAPI	Computer Assisted Personal Interviews
CDF	Cumulative Distribution Function
DFG	German Research Foundation
e.g.	exemplia gratia
FGT	Foster-Greer-Thorbecke
FGT0	Foster-Greer-Thorbecke Poverty Headcount Ratio
ha	Hectare
HAN	Hannover
HDX	Humanitarian Data Exchange
IARIW	International Association for Research in Income and Wealth
ICAE	International Conference of Agricultural Economists
i.e.	id est
ILO	International Labour Organisation
IPL	International Poverty Line
LFS	Labour Force Survey
LRX2	Likelihood Ratio Chi-square
LSMS	Living Standards Measurement Study
LSMS-ISA	Living Standards Measurement Study – Integrated Surveys on Agriculture
m^2	Square meter
MGGs	Millennium Development Goals
N	Number of observations

NAB	Non-agriculture-based
No.	Number
n.s.	Not significant
NBRM	Negative Binomial Regression Model
OECD	Organisation for Economic Co-operation and Development
OR	Odds Ratio
PAPI	Paper and Pencil Interviews
PPP	Purchasing Power Parity
PRM	Poisson Regression Model
ref	Reference category
SDGs	Sustainable Development Goals
SE	Standard Error
Std.dev	Standard Deviation
THB	Thai Baht
TSE	Total Survey Error
TVSEP	Thailand Vietnam Socio Economic Panel
UN	United Nations
UNGA	United Nations General Assembly
UMIC	Upper Middle-income Country
VND	Vietnamese Dong
ZINB	Zero-inflated Negative Binomial Regression
ZIP	Zero-inflated Poisson Regression

CHAPTER 1: INTRODUCTION

1.1 Background and motivation

The inception of data-driven decision-making can be traced back thousands of years to censuses that were implemented in ancient Babylon, Egypt, Rome, and China. Thereby, data collection included registration of citizens or formulation of statistical reports on agricultural, industrial, and commercial activities, which were used to inform administrative policy (Baffour et al., 2013). However, it was not until the early twentieth century that the collection of data from populations of interest, be it in the form of censuses, polls, or surveys, rose to prominence (Weisberg, 2005). The discipline of survey research has continuously evolved as a consequence of increasing demand for data, professionalisation, and rapidly evolving survey technologies. The importance of high-quality data has recently been recognised by policy-makers, in particular in the context of low- and middle- income countries (Dang & Serajuddin, 2020; Naudé & Vinuesa, 2021), as they strive to formulate and implement policies as well as assess their impact.

Frequently, administrative data, which encompass taxation, employment, and education records as well as census data, are used to inform policy. These are supplemented with household survey datasets, which provide valuable insights on households, their behaviour and well-being, which cannot be captured in administrative datasets. However, in low- and middle-income countries, where administrative data is often weak and under-resourced, household surveys have become the dominant form of data collection and instead function as viable alternative sources of data (Reid et al., 2017; Vaessen et al., 2005). Indeed, the Sustainable Development Goals (SDGs) recognise the importance of high-quality data and emphasise that increasing the quality, timeliness and reliability of data is key to decision-making, monitoring progress, and ensuring that SDGs are ultimately achieved (UNGA, 2015). However, despite substantial achievements in procuring high-quality data in low- and middle-income countries, many such datasets remain insufficiently accurate and reliable for monitoring and informing policy (e.g., Booth, 2019; Dang & Carletto, 2018; Dang & Serajuddin, 2020; Gibson, 2016; Meyer et al., 2015; Sanna & McDonnell, 2017). A gap has been identified, in particular related to poverty data, whereby Serajuddin et al. (2015) coined the issue of data deprivation. Constrained data represents a severe impediment to making and assessing progress towards achieving SDG goal 1, namely "*to end poverty in all its forms everywhere*" (UNGA, 2015).

The Total Survey Error (TSE) framework (Groves, 1989) is the most frequently applied framework in analysing data quality. Thereby, a comprehensive categorisation of multitudinous types of survey error that occurs throughout all stages of the survey is undertaken (Figure 1.1): from the conception of the survey (i.e., survey design) to post-survey data processing. Historically, sampling errors, which deal with the representativeness of survey samples in relation to the target population, were the focus of survey research. Sampling error, however, is considered to merely be the tip of the iceberg with nonsampling error constituting the largest detriment pertaining to the quality of survey outputs (Weisberg, 2005). Therefore, in this thesis, data quality of household surveys conducted in low- and middle-income countries is analysed with a focus on the extent and impact of nonsampling errors. Within these, item-level nonresponse and measurement errors have been observed to be most impactful (Biemer, 2010; Weisberg, 2005). Item nonresponse takes place when individual survey items are skipped and thus remain empty or when respondents do not provide an answer, e.g., if they are unable or refuse to provide a response. Measurement errors encompass deviations of responses from the true value of response.

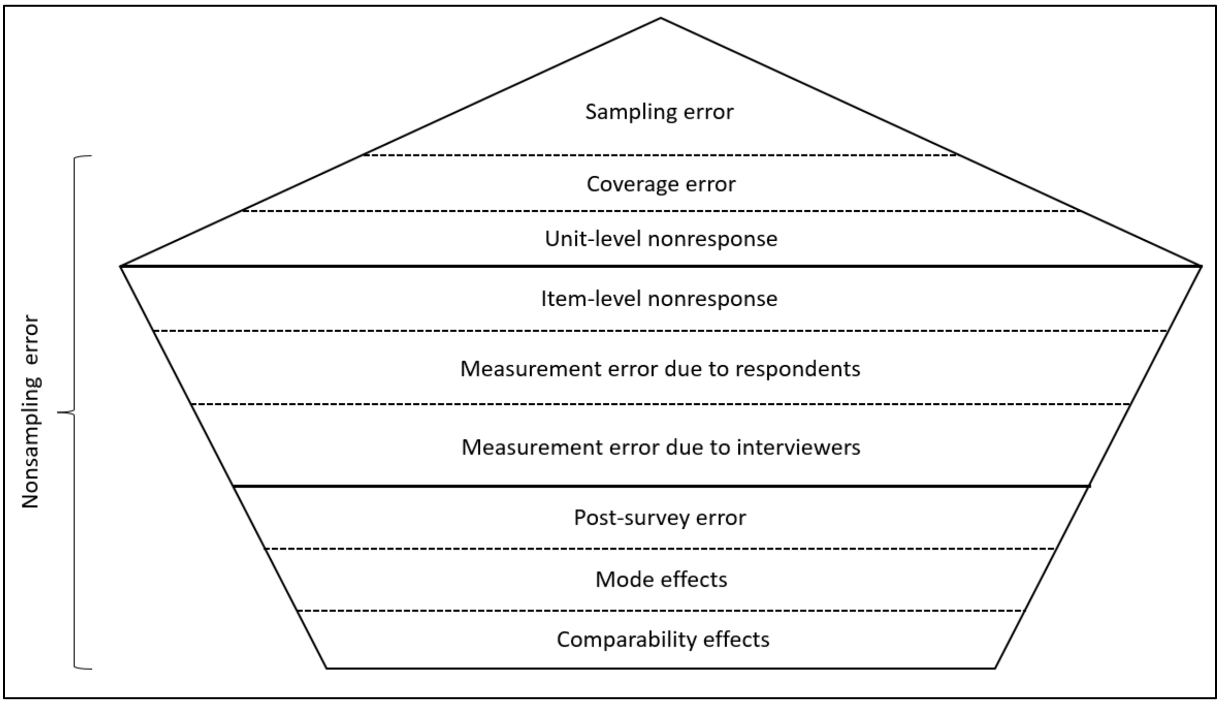

Figure 1.1 Types of survey error based on TSE
Source: Weisberg (2005), modified.

The overall objective of this thesis is to derive novel insights on factors influencing nonsampling errors and on modules of survey instruments that are particularly affected by low-quality outputs, namely those containing information on main sources of income. Thereby, income from off-farm wage employment, non-farm self-employment and agricultural activities is of great import for household livelihoods in low- and middle-income countries. The thesis consists of three essays. The first two essays address nonsampling errors in household survey data, while the third addresses the role of agriculture in rural livelihoods. The first essay is titled "***PAPI is gone, but errors remain: nonsampling errors in household surveys in developing countries***". In this essay, the focus lies in examining the prevalence of nonsampling error in a computerised survey instrument and analysing factors thereof. The second essay is "**Inconsistent responses over time in household panel surveys: the case of non-farm employment**", which investigates the extent of inconsistently reported employments and their effect on policy indicators pertaining to poverty using seven waves, which span twelve years of panel data. The third essay constitutes an analysis, which examines the continued role of agriculture in rural households in Northeast Thailand, and is titled "**Exiting the farm: an advisable strategy for poverty alleviation in rural Northeast Thailand?**". Thereby, changes in rural livelihood strategies that take place between 2007 and 2019 are illustrated and the impact of livelihood choices on poverty incidence is examined.

The following section introduces the specific objectives of each essay; subsequently a description of applied methodologies is presented in section 1.3. Section 1.4 describes the dataset used in the context of this thesis and section 1.5 summarises the results. Thereafter, conclusions, policy recommendations, and opportunities for future research are deduced with the final section presenting the thesis outline.

1.2 Objectives

The main objective of the **first essay** is the analysis of nonsampling errors that persist in household survey datasets despite being conducted using computerised survey instruments. Nonsampling errors have been found to reduce the representativeness and validity of survey data and constitute a large proportion of survey error (Groves et al., 2011 Weisberg, 2005). This issue is further exacerbated by the reliance of low- and middle-income countries on household survey outputs and has been observed to result in misguided policy implications (Booth, 2019; Dang & Carletto, 2018; Gibson, 2016; Serajuddin et al., 2015). Many household surveys are gradually transitioning from Paper and Pencil Interviews (PAPI), which are found to have a high count of missing data (e.g., Phung et al., 2015), to Computer Assisted Personal Interviews (CAPI). Thereby, the literature substantiates that CAPI has several notable advantages over PAPI (e.g., Baker et al., 1995; Caeyers et al., 2012; Couper, 2011; de Leeuw et al., 1995; Schraepler et al., 2010). Among these, CAPI allows for the generation of additional paradata, which can be further supplemented with detailed data on interviewers, such as personality traits of interviewers and respondents following the Big Five model (McCrae & John, 1992; Costa & McCrae, 1997). These are seldom collected in the context of low- and middle-income countries and yet are expected to influence data quality. However, utilising CAPI survey instruments does not automatically produce high-quality data and household surveys in low- and middle-income countries face unique challenges that remain irrespective of survey mode (Lupu & Michelitch, 2018; Meyer et al., 2015). The specific objectives of the first essay are to:

i) compare distributions of nonsampling errors between PAPI and CAPI in order to identify which error type poses the greatest constraint to obtaining high-quality data;
ii) examine how interviewer and respondent characteristics as well as interview/survey conditions are correlated with nonsampling errors and establish their relative importance; and
iii) assess whether the findings are applicable to a broad scope of survey backgrounds, or whether survey providers must take into consideration differences in the underlying target populations, survey implementation and characteristics of the survey area.

The **second essay** extends the analysis of nonsampling errors to account for the longitudinal nature of household panel surveys. Following decades of economic growth, a diversification of the economy of the previously agricultural oriented lower- and middle-income countries has taken place (Haraguchi et al., 2019; Stiglitz, 1996; World Bank, 2018). This phenomenon has extended to rural areas and rural households are observed to diversify their sources of income by pursuing off-farm employments and non-farm self-employments (Schultz, 1964; Hayami & Ruttan, 1971; Devereux et al., 2012). A growing literature underlines issues in the accuracy of such data, which is argued to be exacerbated by the high prevalence of informal labour (Ambler et al., 2021; Desiere & Costa, 2019; Huber & Schmucker, 2009; Jeong et al., 2023; Maré, 2006). The specific objectives of the third essay are to:

i) assess the extent of inconsistently reported employments throughout the span of a long-term household panel survey;
ii) analyse factors influencing inconsistent reporting stemming from characteristics of the respondent, their household, and the inconsistently reported employment; and
iii) assess the potential impact of inconsistent reporting on policy and provide practical recommendations for household survey providers based thereon.

The **third essay** shifts its focus towards the changing role of agriculture in rural households in Northeast Thailand. The region, despite experiencing substantial development (Barnaud et al., 2006), has historically lagged behind the other three regions of Thailand with unfavourable environmental conditions accelerating the early adoption of diversified livelihoods (Grandstaff et al, 2008; Rambo, 2017; Viriya, 2001). Despite being presented with novel opportunities, rural households have been observed to continue to base their livelihoods in agriculture, thus being coined as part-time, small-scale farmers in the literature (Grandstaff et al, 2008; Rigg et al., 2018; Shirai & Rambo, 2017). The role of agriculture in development and poverty reduction has historically been and remains subject to debate with policy mostly being oriented to facilitating an exit from agriculture in favour of a shift of labour to sectors that are considered more productive, e.g., industry and service (e.g., Kuznets 1957; Lewis 1954). However, opposing schools of thought argue that agriculture is not intrinsically less productive than other sectors and that the role of agriculture is being underestimated (e.g., Fuglie et al., 2019; Otsuka et al., 2016). Utilising three equidistant waves of household survey data collected between 2007 and 2019, the objectives of the third essay are threefold:

i) to investigate whether rural households are observed to give up agriculture over the course of more than a decade or exceedingly diversify sources of income;
ii) to conduct a descriptive analysis of the changing contribution of small-scale agriculture in Northeast Thailand; and
iii) to investigate whether household-level decisions related to intensity of agricultural activities influence household wellbeing – thereby linking rural livelihood strategies to poverty incidence.

1.3 Methodology

In the following section, the theoretical and empirical methodologies applied in the underlying thesis are introduced briefly.

In the **first essay**, the quality of household survey data is analysed based on the Total Survey Error framework (Groves, 1989). The essay focuses on nonsampling errors that occur during data collection and before survey data are subjected to processing. Thus, all errors that occur during the initial stage of the survey and factors thereof can be identified. Count models are considered and have been applied in the investigation of data quality (e.g., Barth & Schmitz, 2021; Yu, 2012). Thereby, a negative binomial regression approach is more suitable than other count models (i.e., Poisson, zero-inflated Poisson, and zero-inflated negative binomial regression models) due to the underlying distribution of nonsampling errors. Further, this approach is able to consider that the likelihood of an error occurring may differ between interviews due to differences in the number of survey items answered. We simultaneously assess the influence of characteristics of the interviewer and respondent as well as the interview and survey environment. Additionally, the model is estimated for the combined sample of Thailand and Vietnam and disaggregated at the country-level in order to generate additional insights. The corresponding negative binomial regression analysis was written in Stata 15.

The **second essay** focuses on the dimension of response accuracy (Weisberg, 2005). Response errors entail both item nonresponse and measurement error, whereby the latter is observed to be most detrimental to the collection of high-quality data (Biemer, 2010). Expanding on the approach of Maré (2006) in matching employments throughout a long-term household panel, a three-stage approach to identify inconsistently reported employment is developed. Thereby, employments reported in each individual survey wave are compared iteratively with those observed in the preceding wave of collected data. An automated matching procedure of employments is developed based on five identifying criteria, namely: the sector of the employment, the year in which the respondent begun pursuing the employment, whether the respondent has a leading position (i.e., for off-farm employment), the legal status of the organisation (i.e., for self-employment) and the reported location of the employment. Based on the underlying hierarchical structure of the dataset, a multilevel modelling approach is selected (Hox et al., 2017), which has been shown to be suitable in analysing factors of data quality (Barth & Schmitz, 2021; Borgers et al., 2004; Hox et al., 1991; Hox & de Leeuw, 1994; Hox et al., 2003; Pickery et al., 2001; Sun et al., 2021). A two-stage multilevel logistic model is specified, whereby level 1 represents the characteristics of the individual response and level 2 the socio-economic characteristics of the respondent. The outcome variable is a dichotomous measure of inconsistently reported employments, which is equal to one if the employment is inconsistently reported (i.e., omitted). Further, a scenario analysis was undertaken in order to determine the severity of inconsistent reporting on outcomes pertaining to household welfare and its implications for policy using the upper-middle income country (UMIC) poverty line as proposed by (Jolliffe & Prydz, 2016). The automatic matching procedure was written in R and the multilevel regression analysis in Stata 15.

The **third essay** aims to examine the continued role of agriculture in rural Northeast Thailand and its importance in rural livelihoods. As households in the region have previously been established as part-time farmers with diversified sources of income (e.g., Grandstaff et al, 2008; Rigg et al., 2018; Shirai & Rambo, 2017), it would be expected that most households would be characterised as agriculture-based. In a first step, we seek to distinguish between non-agriculture based (NAB) and agriculture-based (AB) households. Based on the prevalence of part-time farmers, the typical definition of AB households based on at least one household member being engaged in agriculture, be it part-time or full-time (Handbook of Household Surveys, 1984; Hill & Cook, 2002; Hill & Karlsson, 2005), is deemed infeasible in the context of Northeast Thailand. We apply a modified definition of AB households, which necessitates that at least one household member is primarily engaged in agriculture. A descriptive analysis of changing livelihood patterns and the continuing role of agriculture is conducted for each of the two typologies of households. Thereafter, we apply a logit regression in order to determine factors influencing poverty incidence (Foster et al., 1984) in both AB and NAB households. Thereby, a poverty line of 5.47 PPP$ is considered based on Jolliffe & Prydz (2016). Explanatory variables included based on the literature are characteristics of the household head (e.g., De Silva, 2008; Imai et al., 2015; Klasen et al., 2015; Malik, 1996; Sekhampu, 2013), the household dependency ratio and mechanised productive assets used in farming as well as the incidence of environmental shocks (e.g., Gloede et al., 2015; Hallegatte et al., 2020; Hill & Porter, 2017). The outcome variable is a dichotomous measure of poverty headcount, which is equal to one if the household is classified as poor. The logit regression analysis was conducted in Stata 15.

1.4 Data

The data used across all three essays stem from the research project “Impact of Shocks on the Vulnerability to Poverty: Consequences for Development of Emerging Southeast Asian Economies”, which spanned from 2007-2013 and its continuation “Poverty dynamics and sustainable development: A long-term panel project in Thailand and Vietnam, 2015-2024”. The research project in its entirety is titled the “Thailand Vietnam Socio Economic Panel” (TVSEP) and is funded by the German Research Foundation (DFG). The sampled population consists of 4,400 households and 440 villages from three provinces in Thailand, namely Buriram, Ubon Ratchathani and Nakhon Phanom and the provinces of Ha Tinh, Thua Thien Hue, and Dak Lak in Vietnam (Figure 1.2).

Figure 1.2 Study area in Southeast Asia
Source: Hardeweg et al. (2013), modified. Created with MapChart (2023).

The six provinces were selected and the households were sampled following a three-stage cluster sampling design (Hardeweg et al., 2013). Thereby, the sample is representative of Northeast Thailand as well as the Central Highlands and North Central Coast regions in Vietnam[1].

The survey instrument comprises standard components of Living Standard Measurement Studies (LSMS) as conducted by the World Bank (Grosh & Glewwe, 2000). Typical modules on household members, employment, agriculture, natural resource extraction, and finances are contained in the survey instrument. In addition, modules on shocks and risks as well as behavioural aspects of development complement the research goal of the project. Interviews are structured as in-person interviews with one member of the household, whereby the household head is preferentially interviewed. While the first five survey waves of TVSEP were conducted in PAPI, the sixth wave, which was conducted in 2016, saw the survey adopt CAPI in all subsequent survey waves. Thereby, the computerised survey instrument was developed using the World Bank's "Survey Solutions" framework[2].

The 2017 survey wave introduced an additional module on respondent personality traits based on the "Big Five" model developed by Costa and McCrae (1997). Furthermore, the add-on project "Data quality in long-term panel surveys in emerging market economies" was implemented in order to facilitate the study of household survey data quality. Thereby, complementary data on the interviewer, sub-team leaders and respondents were collected throughout all stages of the survey (Appendix 1.A). First, during the interviewer training, an examination of the interviewers took place in order to assess their level of understanding pertaining to the survey instrument and survey guidelines. Complementary, in-depth interviewer information, including socio-economic and demographic characteristics were collected, which were supplemented by self-assessed interviewer personality traits. Second, evaluations of the 2017 interview process were administered to the respondent in which they were asked to evaluate their interactions with the interviewer and give their opinion on how the interview was conducted. Overall, the response rate was high with over 96% of households completing the post-interview supplementary questionnaire. Furthermore, interviewers evaluated their interaction with the respondent and provided additional information on, for example, modules they perceived to be exceedingly demanding for the respondent and whether others were present during the interview. Third, after data collection concluded, sub-team

[1] Further information on the sampling procedure is presented in Hardeweg et al. (2013).
[2] For further information refer to the Survey Solutions website: https://mysurvey.solutions/en/

leaders, who were on average present as observers in 30% of interviews, were tasked with evaluating interviewer performance and provided an additional assessment of each interviewer's personality from an outside perspective. A final element of the add-on project was the modification of the data collection and processing procedure to allow for storage of interview data in a separate database. On a daily basis, the researcher extracted interviews that were completed before they were subjected to initial steps of data monitoring. Thereby, the interviews represent closely the exact responses that were obtained during the interview prior to application of initial cleaning steps in the form of evening group discussions and manual reviews of the interviewers conjointly with their respective sub-team leader. This approach facilitated the analysis of the full extent of nonsampling errors that occurred during the interview process.

The **first essay** utilises one full wave of the household panel survey, namely the sixth, which was conducted in 2017. Thereby, 1,816 households in Thailand and 1,830 household in Vietnam form the basis of analysis. Due to attrition and missing data, the number of households analysed is lower than the initially sampled 4,400 households. Data from the add-on project "Data quality in long-term panel surveys in emerging market economies" supplemented the analysis.

The **second essay** incorporates the longitudinal nature of TVSEP and analyses seven waves of household survey data from Thailand, which span from 2007 to 2019. Of the 2,200 Thai households that were interviewed in 2007, 1,542 are identified as having consistently been interviewed throughout the entirety of the panel and are thus considered in the analysis.

In the **third essay**, three waves of the household survey from Thailand are utilised, namely the 2007, 2013, and 2019 waves. Thereby, 1,160 identical households are considered in the essay, which were interviewed in all seven consecutive waves and for which full income data were available.

1.5 Results

In comparing the prevalence of nonsampling errors in CAPI with results of a previous study by Phung et al. (2015), the **first essay** provides evidence that CAPI, indeed, substantially reduces missing data. Conversely, measurement error remains a significant problem. The results of the negative binomial regression model indicate that nonsampling error is influenced not only by characteristics of the interviewer and respondent but also by the conditions under which the interview took place as well as the survey environment. Generally, interviewer experience specific to TVSEP and higher attentiveness and performance during interviewer training predicted higher quality-outputs. Further, personality traits of interviewers were significantly correlated with the expected count of non-sampling errors. Interviewers that were more socially outgoing (i.e., extraverted) and sympathetic (i.e., agreeable) were less likely to produce interviews with a high count of nonsampling errors, whereas those characterised as being less attentive and focused (i.e., less open) conducted interviews of lower quality. Further, faster entry time is positively correlated with an increasing expected count of non-sampling error as is the presence of others during interviews. The progress of the survey is shown to influence the prevalence of error, with measurement errors decreasing with each additional survey week signalling interviewer learning effects (e.g., Baird et al., 2008; Townsend et al., 2013) and cases of refusal increasing, which may be explained by the onset of interviewer fatigue in later survey weeks.

Country-level models evidence the importance of considering differences in survey populations and implementation, despite utilisation of an identical survey instrument and homogeneous implementation of interviewer training. Notably, incongruence of interviewer and respondent ethnicity is significantly positively correlated with the expected count of nonsampling errors in Vietnam, which in contrast to Thailand is characterised by high ethnic diversity (Dang, 2012). For example, measurement errors are indicated to increase by 88% in interviews in which an ethnic majority Kinh respondent is interviewed by a minority interviewer. Further, differences in survey implementation, for example, related to the hiring process of interviewers substantiate that approaches to minimising nonsampling error must be adjusted to consider particularities of each survey. In Thailand, interviewers were students and those with a field of study in agriculture or economics matching the subject of the survey produced higher-quality interviews. In Vietnam, interviewers were full-time professionals with more experience in survey work. Thereby, additional experience was observed to have a negative impact on data quality, which may be explained by non-confirming to survey procedures and guidelines in favour of following those of other surveys as argued by Fowler and Mangione (1990).

The **second essay** demonstrates that fluctuations in employment data stem from substantial underreporting of both off-farm employment and non-farm self-employment. In comparing pairs of consecutive waves of household survey data, one third of employments are identified as being inconsistently reported throughout twelve years of panel data. The average household is shown to fail to report between one and two cases of employment per survey wave. Factors influencing inconsistent reporting are examined using a two-level multilevel logistic regression model, which suggests that inconsistent reporting is three-times as likely to occur in cases of off-farm employment when compared with self-employment. Notably, informal employments that are located outside of the boundaries of the village district are less likely to be reported. Additionally, the likelihood of inconsistent reporting is positively correlated with household size, which coincides with a 7.6% average increase in the likelihood of an employment being omitted for each additional household member over the sample mean. A possible explanation for this phenomenon is likely respondent fatigue experienced during the interview due to the increased volume of questions required to be answered for each additional household member. Further, initial insights generated by one pair of survey waves indicates that the degree of trust, i.e., which may be derived from personality traits of the respondent (Costa & McCrae, 1997), influences the consistency of reporting. Lack of trust towards strangers was significantly positively correlated with increasing likelihoods of inconsistent reporting.

A scenario analysis adjusted household income, as measured, by supplementing omitted income and suggests that annual per capita income is substantially underestimated by over 800 PPP$ in the case of off-farm employment and almost 300 PPP$ for self-employment. These substantial shifts in total household income indicate that poverty headcounts are overestimated by 6.7 percentage points at the provincial level. At the district-level, this observation is exacerbated with extreme cases of over 20 percentage point differences in poverty incidence being identified.

The **third essay** confirms that structural transformation in Thailand has resulted in substantial out-migration of middle-aged adults from rural Northeast Thailand. Despite the increasingly ageing population in rural villages, most households remain primarily engaged in agriculture and on average, 40% of their income is derived from agriculture. Our results indicate that NAB and AB households in Northeast Thailand remain small-scale, part-time farmers in 2019 with 98% of households cultivating less than 10 hectares of land, which is in line with the literature (e.g., Hayami & Ruttan, 1971; Johnston & Mellor, 1961; Ranis & Fei, 1961; Schultz, 1964). While the share of NAB households has more than doubled to over 20% since 2007, their share of income derived from agriculture remains substantial and ranges between 5-10% in the sample.

Throughout the 12-year period, poverty incidence, using the upper-middle-income country poverty threshold of 5.47 PPP$ (Joliffe & Prydz, 2016), has declined slightly from 43.9-41.1% in NAB households. Conversely, poverty headcounts of AB households have declined substantially. While over 50% of households could be characterised as poor based in 2007, this share has dropped to 43.1%, which brings poverty incidence to a comparable level between the two typologies of households. However, a higher share of NAB households (26.7%) earn a per capita daily income of over 15.00 PPP$ when compared with their counterparts (18.1%), which indicates substantial income inequality. Examining correlations between poverty incidence and household characteristics suggests that AB households are increasingly likely to be poor when the head is elderly, less educated, and mainly engaged in agriculture. Further, demographic change resulted in increased dependency ratios of rural households. Notably, climate-based shocks are indicated to be the driving force behind poverty in households that rely on agriculture despite increasing intensity of government interventions, which quadrupled during the 12-year observation period and made up, on average, 20% of AB income in 2019.

1.6 Conclusion, policy recommendations, and future research

The main finding from the **first essay** is that while CAPI can substantially reduce the overall presence of nonsampling error, substantial measurement errors remain. Thereby, the implementation of plausibility rules cannot guarantee that high-quality data are obtained. Rather, many dimensions factor into data quality, which stem from the interactions between the interviewer and the respondent, their characteristics and the conditions in the field. The results indicate that on the interviewer side, survey outcomes seem to generally be improved by hiring interviewers with experience in the specific survey, which nonetheless require intensive training. In contrast, when prior experience stems from other survey contexts, data quality may decline. Targeting specific characteristics in the hiring of interviewers, such as personality traits, could facilitate rapport and trust building with the respondent. Further, respondent-interviewer allocations based on congruent characteristics may be beneficial. For survey implementation, paradata such as entry time and interview duration is indicated to be significantly correlated with nonsampling error. We recommend that survey providers make use of the extensive set of paradata and paradata analyses, which can be generated by many CAPI frameworks in real-time in data monitoring. By monitoring individual survey items and interviewers, paradata are expected to facilitate identification of errors in advance, facilitating prompt action to ensure that high-quality outputs are produced.

The analysis of nonsampling errors is based on one wave of CAPI data, which utilised a survey framework in its early development stages. Since 2017, the framework has improved substantially and novel features allow for generation of additional paradata such as item-level response time, timestamps and logged interviewer actions. Further, lessons learned in the first two waves of survey data collected in CAPI by the panel were implemented and an improved CAPI instrument was developed in 2019. Extending on the methodology of the first essay in the context of the subsequent survey waves, may generate valuable insights on further improving data quality.

In the **second essay**, shortcomings of labour modules of household surveys are demonstrated to have severe policy implications using seven waves of survey data. Given the similarity between modules on labour throughout most household survey instruments and the extent of inconsistently reported employments, survey providers must take action to ensure that underlying datasets are sufficiently reliable and accurate. Among others (e.g., Ambler et al., 2021; Desiere & Costa, 2019; Jeong et al., 2023), our research implies that informal activities are not properly represented in household survey data. Promising approaches to improving the reliability of response are the implementation of independent interviewing, which is purported to minimise respondent bias in reporting while increasing reliability of data (Lugtig & Jäckle, 2014; Lynn et al., 2006; Lynn et al., 2012; Perales, 2014), utilisation of external validation sets (e.g., Epland & Kirkeberg, 2012; Mathiowetz et al., 2002; Meyer et al., 2019), or, in case of panel surveys, retrospectively validating internal consistency of survey datasets (e.g., Halpin, 1998; Maré, 2006).

However, these conclusions are based on the analysis of household survey data stemming from one source. Expanding the analysis to encompass further sources of survey data from, for example, LSMS studies would allow for the testing of the robustness of results. Applying the approach to other modules important for policy, such as those on agricultural activity seems promising. For example, verifying estimated agricultural data on yields based on GPS-based plot measurement, satellite data and field-based yield measurement is expected to yield major contributions to the assessment of household survey data quality in low- and middle-income countries.

The main finding of the **third essay** is that most rural households in Northeast Thailand remain primarily engaged in agriculture, despite the unfavourable environmental conditions and availability of alternative sources of income. Thereby, the large gap in poverty rates between NAB households with more diversified sources of income and AB households is shown to decrease rapidly from 2007-2019. Indeed, the overall poverty rate has converged. However, AB households are implied to be more vulnerable to climate-based shocks with policy interventions not being sufficient to ensure that households do not drop below the poverty line following long periods of droughts. For both typologies of households, agriculture continues to play an important role in the region, which cannot be understated or neglected, and indicates that the particularities of Northeast Thailand, and indeed throughout Asia (Hazell & Rahman, 2014; Yamauchi et al., 2021). Continued support of small-scale farmers is necessitated, especially in their function as safety nets in times of crisis (Waibel et al., 2020).

1.7 Thesis Outline

The three essays are outlined in Table 1.1 and are organised in the following three chapters:

Chapter 2 contains the **first essay**, "PAPI is gone, but errors remain: Nonsampling errors in household surveys in developing countries“, of which an earlier version titled "Comprehensive data quality studies as a component of poverty assessments" was published in the TVSEP Working Paper Series in 2020. Further, the first essay was presented at the IARIW World Bank Conference, Washington, United States, in 2019, as well as the GDE Conference (Online) and ICAE Conference (Online) in 2021. In the first essay, Mark Brooks collected and processed the supplemental data, developed, and estimated the negative binomial regression models, and wrote the essay. Rattiya S. Lippe provided suggestions on different aspects of the manuscript alongside Hermann Waibel, who also took on a supervisory role.

Chapter 3 contains the **second essay** "Inconsistent responses in household panel surveys: the case of non-farm employment" and was presented at the ASAE conference (Online) in 2021. In the third essay, Mark Brooks and Niels Wendt developed the code in Stata and R used to identify inconsistently reported employments and estimated the multilevel logit regression model jointly. The essay was written jointly aside from the literature review, of which the author wrote major parts. Hermann Waibel took a supervisory role and provided suggestions on various aspects of the manuscript.

The **third essay** "Exiting the farm: An advisable strategy for poverty alleviation in rural Northeast Thailand?" is organised in Chapter 4. Mark Brooks developed the model and wrote the essay. Hermann Waibel performed a supervisory role and commented on content of the manuscript.

In all three chapters, data from the Thailand Vietnam Socio Economic Panel was used. From 2016 to 2018, the author developed and implemented the computerised, tablet-based survey instrument using the World Bank's "Survey Solutions" framework. Additionally, the author supported the further design of the TVSEP household survey and Migrant Tracking Survey questionnaires, participated in the implementation of interviewer training, and supervision of data collection in Thailand and Vietnam in 2017. In addition to tasks performed in 2017, the author partially managed data collection during the migrant survey in Thailand in 2018.

Table 1.1 Overview of essays

Chapter 2	**Title**	**PAPI is gone, but errors remain: Nonsampling errors in household surveys in developing countries**
	Authors	*Mark Brooks, Rattiya S. Lippe, and Hermann Waibel*
	Comments	Earlier version published as a working paper in: TVSEP Working Paper Series (June 2020) Presented at: IARIW World Bank Conference "New Approaches to Defining and Measuring Poverty in a Growing World", 7-8th November 2019 in Washington D.C., United States of America German Development Economics Conference 2021, 17-18th June 2021 (Online) 31st ICAE 2021: International Conference of Agricultural Economists, 17-31st August 2021, New Delhi, India (Online)
Chapter 3	**Title**	**Inconsistent responses in household panel surveys: The case of non-farm employment**
	Authors	*Mark Brooks, Niels Wendt, and Hermann Waibel*
	Comments	Presented at: Asian Society of Agricultural Economists 10th International Conference, 6-8th December 2021, Beijing, China (Online)
Chapter 4	**Title**	**Exiting the farm: An advisable strategy for poverty alleviation in rural Northeast Thailand?**
	Authors	*Mark Brooks and Hermann Waibel*

Source: Own illustration.

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Appendix 1.A Add-on project questionnaires

I. Interviewer examination

Leibniz University Hannover
Institute of Development and Agriculture Economics

Interviewer Exam - 2017

Leibniz Universität Hannover

Introductory remarks:

All of the questions in each individual section must be answered. Kindly fill in the sections chronologically beginning with section 1. Please answer truthfully.

The results of this exam will not influence your contract of work in any way and information gathered will not be made available to your peers. I hereby ensure you that all information given is kept strictly confidential and will only be used for scientific purposes and not handed to any outside person. Thank you very much in advance for your kind cooperation.

Hints:

1) Please note that no technical aids are allowed for the purpose of this exam (e.g. mobile phone, laptop, and tablet). The only exception to this is that you may make use of a standard calculator during the exam alongside the printed out version of your questionnaire.

2) For your answers please avoid telling long stories (e.g., be as precise as possible) and make use of the space that is allocated to each question.

3) The overseers cannot answer any questions about the content of the exam, so please work on the exercises by yourself.

Code A

1	Male
2	Female

Code C

1	Urban
2	Rural

Code AA

1	Yes
2	No
98	No answer

Code D

0	None
1	VHLSS
2	Thailand Socio-Economic Household Survey
3	DFG waves (Our survey)
4	TVSEP
90	Other, specify
98	No answer

Code E

1	1-2 times
2	3-4 times
3	5+ times

Code B

1	Kinh
2	Tay
3	Thai
4	Chinese origin (Han)
5	Khmer
6	Muong
7	Nung
8	Hmong
9	Dao
10	Gia rai
11	Ngai
12	Ede
14	Sedang
15	San chay (Cao lan -S)
16	Coho
17	Cham (Cham)
20	Mnong
21	Ra glai
23	Bru - Van kieu/blu
24	Tho
26	Co tu
31	Ta oi
37	Lao
56	Phu thai
57	Suai
58	Foreigner
59	Moo sir
60	Thai yor
61	Thai so
62	Kalerng
63	Paco
90	Other, specify
98	No answer

Code J

0 ☐☐☐☐☐☐☐☐☐☐☐ 10

0 = Extremely impatient — Extremely patient = 10

Code K

0 ☐☐☐☐☐☐☐☐☐☐☐ 10

0 = Unwilling to take risks — Fully prepared to take risks = 10

Code G

1	Kasetsart University
2	Buriram Rajabhat University
3	Suan Dusit Rajabhat University
4	Mahidol University
5	Sakonnakhon University
6	Nakomphanom University
7	Khon Kaen University
8	Ubon Ratchathani University
10	Hue University
11	Tay Nguyen University
12	Ha Noi Univeristy of Agriculture
90	Other, specify
98	No answer

Code H (Thailand)

1	P. 1
2	P. 2
3	P. 3
4	P. 4
5	P. 5
6	P. 6
7	P. 7
8	M or MS 1
9	M or MS 2
10	M or MS 3
11	M or MS 4
12	M or MS 5
13	M or MS 6
14	MS 7
15	MS 8
16	PWC 1
17	PWC 2
18	PWC 3
19	PWS 1
20	PWS 2
21	PWT 1
22	PWT 2
23	Univ. 1
24	Univ. 2
25	Univ. 3
26	Univ. 4
27	Univ. 5
28	Univ. 6 or Master degree
29	PhD
98	No answer

Code H (Vietnam)

51	Grade 1
52	Grade 2
53	Grade 3
54	Grade 4
55	Grade 5
56	Grade 6
57	Grade 7
58	Grade 8
59	Grade 9
60	Grade 10
61	Grade 11
62	Grade 12
65	Univ. 1
66	Univ. 2
67	Univ. 3
68	Univ. 4
69	Univ. 5
70	Univ. 6
71	PhD
72	Professional school 1
73	Professional school 2
74	College 1
75	College 2
76	College 3
77	Master degree
98	No answer

Code I

1	Basic communication skills
2	Good working knowledge
3	Very good command
4	Highly proficient (spoken & written)
5	Fluent
6	Native speaker

Code F

1	Not at all familiar
2	Slightly familiar
3	Moderately familiar
4	Very familiar
5	Extremely familiar

Code O

1	Thailand
2	Vietnam

Section 1: Interviewer Information

0 Country | | Code O

1	2	3	4	5a	5b	5c	6a	6b	6c	7
Name	Gender	Age	Ethnic Group	Place of birth			Where do you currently live?			Have you ever worked as an interviewer before?
				Province	District	Urban or rural area?	Province	District	Urban or rural area?	*If no, skip to Q12*
	Code A		Code B			Code C			Code C	Code AA

8	8a	9	10	11	12	13a	13b	13c	14	15
Have you ever worked in a household survey as an interviewer?	Specify the most recent household survey that you participated in as an enumerator?	How many times have you worked as an interviewer?	In which year did you last participate in a survey as an interviewer?	Have you ever worked with a tablet based survey tool?	How familiar are you with technology such as tablets and computers?	Where did you go to elementary school?			Are you currently enrolled?	At which university are you enrolled?
If no, skip to Q9						Province	District	Urban or rural area?	*If no, skip to Q18*	
Code AA	Code D	Code E	year	Code AA	Code F			Code C	Code AA	Code G

16	17	18	18a	19	20	21	22	23
What is your field of study?	What is your highest educational attainment?	Do you speak English?	How would you assess your English skills?	Do you speak any other foreign languages?	Are any of your family members (e.g., parents or siblings) engaged in agriculture?	Were you ever engaged in agriculture for at least 1 year at a time during your life?	Are you generally a person who is very patient or do you tend to become impatient quickly?	Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?
		If no, skip to Q19						
	Code H	Code AA	Code I	Code AA	Code AA	Code AA	Code J	Code K

Section 2: Character Traits

(Info: The following questions are about how you see yourself as a person. Do not ask other people for help when answering. Just decide on your own. Please answer each statement using the scale provided using the answer that describes you best. In this case 1 means "does not apply to me at all" and 7 means "applies to me perfectly")

Please answer the following questions about yourself:

Do you see yourself as someone who....

1	... works thoroughly?	Code A
2	... is talkative?	Code A
3	... worries a lot?	Code A
4	... is original, comes up with new ideas?	Code A
5	... has a forgiving nature?	Code A
6	... tends to be lazy?	Code A
7	... is outgoing, sociable?	Code A
8	... gets nervous easily?	Code A
9	... values artistic, aesthetic experiences?	Code A
10	... is considerate and kind to almost everyone?	Code A
11	... does tasks efficiently?	Code A
12	... is reserved?	Code A
13	... is relaxed, handles stress well?	Code A
14	... has an active imagination?	Code A
15	... is interested in learning new things?	Code A
16	... is sometimes a bit rude to others?	Code A

Code A

1	2	3	4	5	6	7

1 = does not apply to me at all **7 = applies to me perfectly**

Section 3: Knowledge and understanding

In the following section of the exam you will be presented with prefilled sections of the questionnaire for this years' survey. It will be your task to check the data presented for potential errors or questionable values. It is possible that there are no errors within a column or row, but it is also possible that there are multiple errors. Errors may also include values, which should be deemed as being unlikely or particularly alarming. After you have determined whether or not there are errors in the presented example please briefly explain why you believe each appropriate case is an error. In addition, there will be questions that you have to answer briefly alongside a number of multiple choice questions.

1) **Section 2.2: Education (4pts)**

In this section we would like to know the educational attainment of all household members

Fill in only for household members whose educational status has changed during 5/16 and 4/17 and for new members.

1	2	3	4	5a	5	6	14	7	8	9	10	11	12	13
I.D. Code	**Name / Nickname**	Can [NAME] read and write? AA	Is [NAME] currently enrolled in school? *if no, go to Q6* AA	Educational level *skip to Q11* BB	What grade is [NAME] currently enrolled in? B	Has [NAME] ever been to school? *If no, go to next row* AA	How many years did [NAME] go to school? (years)	What was [NAME]'s highest educational attainment? B	How old was [NAME] when he/she left school?	Why did [NAME] leave school? C	Where did [NAME] obtain his/her highest educational attainment? CC	How old was [NAME] when he/she started school?	Was [NAME] ever absent for a whole school year or more? *If no , go to next row* AA	Why was [NAME] absent? C
01	Name 1	1	2			1	18	26	22	5	5	4	2	
02	Name 2	1	2			2								
03	Name 3	2	1	2(TH) / 9(VN)	9(TH) / 57(VN)							7	1	7

2) General question (1pts):

A household with 4 persons (father and mother with two children at the age of 12 and 16) has a small home-based shop in operation in order to sell food and drinks to people in the village. When you get to the home, the mother and the oldest daughter are sitting behind the desk in said shop. The father tells you the business is run by the mother, is not registered, and that there are also no employees (no family and no non-family members). Do you accept this information? Please briefly explain how you come to your conclusion.

3) Section 3.1.3: Shocks (3pts)

Intervie

When considering the time period between 5/16 - 4/17, has there been any event causing a big problem (shock) affecting the household?

Please think of any problems related to your family, farm, house or job.

a. What were the three major shocks that affected your household between 5/16 - 4/17?

1	2	2a	3	3a	4	5a	5b	6a	7	8	9	10	11	12a	27
Event ID	Type of event	HH-Member-ID of person being affected */	When did the event occur?		Estimated severity of the event on your household?	Estimated total loss of income due to the event	Estimated total extra expenditure due to the event	Estimated loss of assets due to the event	Aside from your HH who else was affected by the event?	Coping activity to deal with the event			Did your household still have to reduce household consumption because of the event?	How many months did it take to recover from the event?	Did you report this event to...
										major activity	2nd activity	3rd activity			
	A		month	year	*Interv.: Read code B 1-4*	THB/1000 VND	THB/1000 VND	THB/1000 VND	C	D	D	D	AA	*(number of months; If not yet recovered fill in "90")*	E
1	74	1	8	2016	1	0	0	600/600.000	1	1	60	61	2	90	0
2	11	1	4	2017	2	150/150.000	500/500.000	0	1	15	43	28	2	1	0
3	74	1	6	2016	3	0	0	30000/30.000.00	1	52	54	61	1	3	0

4) General questions (3pts):

Hypothetically, if you find that a monetary value in this section is very high how would you cross-check with other sections or within the section to determine if the value is plausible?

a) Loss of income:

b) Extra expenditure:

c) Loss of assets:

5) Crosscheck (1pts):

The household of [Name] was affected by a serious shock two years ago. You know that the shock took place in form of an illness of the household head due to your information sheet. This year the household answered that it is better off than last year. In which section would you be least likely to find any information to crosscheck whether this could be correct or not?

Section 2.3 ☐
Section 3.2 ☐
Section 4.4 ☐

6) Section 1 (1pts):

The interview per plan was supposed to start at 8.30 a.m., but because the respondent was not there the interview actually started at 2 p.m. What would you enter for 10008 in section 1?

7) Section 2.4 (3pts):

The household received money from a friend. The friend TH: Sommai / VN: Tung, is 28, was born in the same village and currently lives in Bangkok / Hanoi. The gifts sent had a monetary value of approximately 98 THB / 980.000 VND. In addition, the household received some gifts for a wedding, but are not sure from whom they received the money. In total the sum of payments for the wedding are equal to 2000 THB / 2.000.000 VND. These are the only cases of household dynamics. Fill in the table below!

1	2a	2	3	4	5	6	11	12	13
I.D. Code	Is [Name] an event or a person *If = 1 skip to Q12* D	Name or Nickname	Gender 1=male, 2=female	Age	Relation to household head A	Place of birth *read out answer categories* CC	Location CC	Amount of money/value of gifts the household received from [NAME] between 5/16 - 4/17 THB/1000 VND	Amount of money/value of gifts the household sent to [NAME] between 5/16 - 4/17 THB/1000 VND

8) Section 4.1/4.2 (1pts):

The respondent has 10 rai / 16.000 m2 of rice field on which he/she plants traditional varieties. He/she reports the use of 20.000 Baht/ 200.000 VND of pesticides for this area of land. Would you accept this information? Please give an explanation why or why not.

9) Section 6.2 (3pts):

The HH bought the rice field of their neighbour in 05/2013 for 60.000 THB / 60 million VND. In 07/2016 they had to buy seeds for the rice plantation for 7.000 THB / 7 million VND. Buying a water pump was necessary in 09/2016. Normally a water pump has a price of 5.500 THB / 5.5 million VND, but because the household head knew the shop owner they were able to buy a pump for 4.000 THB / 1.4 million VND. In addition, the harvest was good, so the household built a new storage room for hired labour and materials which cost 7.000 THB / 7 million VND. In 01/2017 the son decided to participate in additional education in the provincial capital, so they bought a motorcycle for him for 7.000 THB / 7 million VND. The family also lives near a lake. Since one of their boats had a leak and the father decided that is was too dangerous to use, they needed a new one. Since they found a really good offer (each 4.800 THB/ 1.1 million VND), they even bought a second one at the same time for the uncle, who also lives in the household. Which of these cases are relevant for the investment section? Please briefly explain how you came to your conclusion.

II. Interviewer evaluation of the interview

Code LL		
01	Section 1	
02	Section 2.1	
03	Section 2.2	
04	Section 2.3	
05	Section 2.4	
06	Section 2.5	
07	Section 3.1	
08	Section 3.2	
09	Section 4.1	
10	Section 4.2	
11	Section 4.3	
12	Section 4.4	
13	Section 5	
14	Section 6	
15	Section 6.2	
16	Section 7.1	
17	Section 7.2	
18	Section 7.3	
19	Section 8	
20	Section 9.1	
21	Section 9.2	
22	Section 10	
23	No second section	Only 6b
24	No third section	Only 6c

Code AA	
01	Yes
02	No
98	No answer

Code JJ	
01	No assistance
02	Somewhat assisted
03	Greatly assisted

Code KK	
01	Very good
02	Good
03	Adequate
04	Poor
05	Very poor

Code NN	
01	Highly interested
02	Somewhat interested
03	Neutral
04	Somewhat disinterested
05	Highly disinterested

Code MM	
01	Very negatively
02	Somewhat negatively
03	No effect

Section 11: Interview Evaluation - Enumerator

Enumerator: Throughout the following section you, as the enumerator, are required to give an assessment of the interview. Please answer the questions truthfully and note that these questions capture your perceptions of the interview as a whole.

1 Time finished (hh:mm) [ ][ ]

2 Comprehension level of respondent [ ] Code KK

3 Cooperation level of respondent [ ] Code KK

4 Was anyone else present during the interview? [ ] Code AA

4a How many others were present? [ ]

Enumerator: Answer the questions in this table if Q4 == 1. (Only account for individuals who sat through at least 25% of the total interview duration)

8 I.D. Code	9 Name of person who was present during the interview	10 Is %name% a member of the household? Code AA	11 Did %name% assist the respondent with answers? *If no, skip to next row.* Code JJ	12 In which section did %name% assist the respondent the most? Code LL
01				
02				
03				
04				
05				
06				
07				
08				
09				
10				

Enumerator: Please answer the following questions if Q4 == 1

5 Did the main respondent answer most of the questions in each section? [ ] Code AA

Enumerator: Please answer Q6 if Q5 == 2

6 In which sections were you unable to interview the main respondent?
a. [ ] Code LL
b. [ ] Code LL
c. [ ] Code LL

13 Did the tablet have a technical malfunction during the interview? [ ] Code AA

Enumerator: Please answer Q14 if Q13 == 1

14 How did this influence the conduct of the interview? [ ] Code MM

15 How would you describe the degree of interest/participation of the respondent? [ ] Code NN

16 Did the respondent have difficulties understanding questions? [ ] Code AA

Enumerator: Please answer Q17 if Q16 == 1

17 In which section did the respondent have the most difficulties? [ ] Code LL

Comment field: specifics about these questions or other data quality issues

18 [ ]

III. Respondent evaluation of the interview

Section 12: Interview Evaluation - Respondent

Throughout the following module you, as the respondent are requested to give an assessment of the interview. Please answer the questions truthfully and note that these questions capture your perceptions of the interview as a whole.

0e **Please state your name:** [ ]

0f **Time started (hh:mm)** [ ] [ ]

In the following sections you may be asked to give your opinion about elements of the survey. Please select the option that best captures what you think.

Part 1: The Interview

1 **At what time of the day would the interview be best for you?**

Morning	Afternoon	Evening

2 **How would you rate the overall duration of the interview?**

Not at all acceptable	Slightly acceptable	Moderately acceptable	Very acceptable	Completely acceptable

Part 2: Tablet vs paper-based survey

3 **Have you previously participated in tablet-based interviews aside from our 2016 survey?**

Yes	No	No answer

4 **How familiar are you with tablets?**

Not at all familiar	Slightly familiar	Moderately familiar	Very familiar	Extremely familiar

5 **Do you prefer the tablet-based interview or the paper-based interview?**

Tablet-based interview	Paper-based interview	Indifferent

6 **Would you say that the interview this year was better than last year?**

Completely disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Completely agree

[ ] Did not participate in last years survey

Part 3: Interviewer continuity

7 **Would you prefer to be interviewed by someone who has interviewed you previously?**

Yes	No	Indifferent	The interviewer from this year would be prefered

Section 12: Interview Evaluation - Respondent

Throughout the following module you, as the respondent are requested to give an assessment of the interview. Please answer the questions truthfully and note that these questions capture your perceptions of the interview as a whole.

Part 4: Interviewer evaluation

8 **How would you rate your personal interaction with your interviewer?**

Not at all acceptable	Slightly acceptable	Moderately acceptable	Very acceptable	Completely acceptable

9 **Which adjectives would you use to describe your interviewer. State 3 that you think are most fitting.**

Polite/curteous	Knowledgeable	Talkative	Understanding	Professional	Well-prepared
Talked slow and clearly	Nervous	Impolite	Unprepared	Hasty	Relaxed

10 **Would you say that the interviewer was very knowledgeable about the subject of the questionnaire?**

Completely disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Completely agree

11 **What characteristics do you prefer in an interviewer. Choose the three characteristics that are most important for you.**

Same gender	Same age	Local	Same ethnicity	Agricultural background	Good-looking
Moderate level of education	High level of education	Is very familiar with tablets	Alot of experience in surveys	Good communication skills	Well mannered

Part 5: Respondent comprehension

12 **Would you say that you were able to understand most of the questionnaire?**

Completely disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Completely agree

13 **In your opinion which section was the most difficult?**

Introduction + Household information	Shocks and risks	Land, agriculture, livestock and natural resources	Employment	Finance and expenditure	Assets + Housing information	Expenditure

14 **Which section was the most tedious in your opinion?**

Introduction + Household information	Shocks and risks	Land, agriculture, livestock and natural resources	Employment	Finance and expenditure	Assets + Housing information	Expenditure

Part 6: Future surveys

15 **Would you like to know about what the survey is used for and the results of the survey?**

Yes	No	Indifferent

16 **Please write any other comments you have here:**

17 **Time finished (hh:mm)**

IV. Sub-team leader assessment of the interviewer

Interviewer Evaluation - By Sub-team Leader

0a Name of interviewer: [ ]

0b How many interviews that were held by the interviewer in question did you participate in? [ ]

Please give your opinion to the statements provided below with regard to the performance of the interviewer in question

Part 1: Training performance

1a	The interviewer was punctual in attending training		Code B
1b	The interviewer actively participated during training and provided constructive comments		Code B
1c	The interviewer had extensive knowledge of the meaning of survey questions by the end of the training		Code B

Part 2: Data collection

2a	The interviewer probed the respondent without leading the respondent during interviews		Code B
2b	The interviewer used CAPI effectively		Code B
2c	The interviewer followed survey procedures		Code B
2d	The interviewer was able to explain difficult concepts presented in the questionnaire to the respondent		

Part 3: Dependability

3a	The interviewer was consistently able to submit completed interviews		Code B
3b	The interviewer was able to follow the set survey schedule without issues		Code B
3c	The interviewer had no issues with accepting additional work		Code B
3d	The interviewer consistently handed the interview to the STL immediately after each interview for checking		Code B

Interviewer Evaluation - By Sub-team Leader

Part 4: Efficiency

4a	The interviewer used his/her daily work time efficiently (including any overtime when necessary)		Code B
4b	The interviewer made use of the training manual provided effectively		Code B

Part 5: Public relations

5a	The interviewer commonly left the respondent with a positive attitude		Code B
5b	The interviewer was able to convert reluctant respondents and generally had few cases of refusal		Code B
5c	The interviewer was able to motivate the respondent to actively participate in the interview(s)		Code B
5d	The interviewer was motivated during the interview(s)		Code B
5e	The interviewer was able to draw the respondent into constructive conversations during the interview(s)		Code B
5f	The interviewer was able to create personal interactions with the respondent during the interview(s)		Code B

Part 6: Other qualities

6a	The interviewer recommended feasible improvements to survey procedures		Code B
6b	The interviewer was able to implement constructive criticism to improve on his/her own skills		Code B
6c	The interviewer was willing to step outside of his/her own boundaries in order to acquire new skills		Code B

Code B

0	1	2	3	4	5	6	7

1 = Fully disagree 7= Fully agree

Interviewer Evaluation - By Sub-team Leader

Part 7: Characteristic traits

(Info: The following questions are about how you see the interviewer stated in variable 0 as a person. Do not ask other people for help when answering. Just decide on your own based on what you have seen during training and in the field. Please answer each statement using the scale provided using the answer that you believe describes the interviewer best. In this case 1 means "does not apply to the interviewer in question at all" and 7 means "applies to the interviewer in question

Please answer the following questions about the interviewer in question:

1	... is interested in learning new things?		Code A
2	... works thoroughly?		Code A
3	... is talkative?		Code A
4	... worries a lot?		Code A
5	... is original, comes up with new ideas?		Code A
6	... has a forgiving nature?		Code A
7	... tends to be lazy?		Code A
8	... is outgoing, sociable?		Code A
9	... gets nervous easily?		Code A
10	... values artistic, aesthetic experiences?		Code A
11	... is considerate and kind to almost everyone?		Code A
12	... does tasks efficiently?		Code A
13	... is reserved?		Code A
14	... is relaxed, handles stress well?		Code A
15	... has an active imagination?		Code A
16	... is sometimes a bit rude to others?		Code A

Code A

1	2	3	4	5	6	7

1 = does not apply to the interviewer in question at all

7 = applies to the interviewer in question perfectly

CHAPTER 2: PAPI IS GONE, BUT ERRORS REMAIN: NONSAMPLING ERRORS IN HOUSEHOLD SURVEYS IN DEVELOPING COUNTRIES

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3) 31st ICAE 2021: International Conference of Agricultural Economists, 17-31st August 2021 in New Delhi, India (Online).

Abstract

Despite considerable advances in survey technology, the quality of data collected in household surveys remains an issue, especially in developing countries. Computerised questionnaires have become the norm and have helped to reduce errors in data collection. However, they do not automatically resolve the issue of low-quality survey data. Using data from a household panel survey in Thailand and Vietnam, we conduct a comprehensive analysis that considers respondent and interviewer characteristics, including personality traits, congruency of traits, and indicators of interview and survey conditions. We develop a negative binomial regression model variant for each of the three identified types of nonsampling errors, namely, (a) item nonresponse in the form of missing data; (b) item nonresponse in the form of refusal; and (c) measurement error. In addition to model variants using the combined sample of Thailand and Vietnam, we apply disaggregated, country-level model variants to control for country-specific differences. Our results show that item-level missing data are substantially reduced when computerised questionnaires are implemented, whereas refusal and measurement errors remain. Most importantly, nonsampling errors are observed to stem not only from respondent and interviewer characteristics, but also be influenced by interview and survey conditions. In addition, differences in factors influencing nonsampling error are observed between the two samples. For example, incongruence of respondent and interviewer ethnicity is found to increase measurement errors by 88% in Vietnam. Finally, personality traits of interviewers, such as agreeableness are found to be significantly negatively correlated with nonsampling errors.

Keywords: Nonsampling errors, data quality, paradata, household survey, Thailand, Vietnam

JEL: C81, C83, O10

2.1 Introduction

High-quality data are essential for research, policy formulation and decision-making in private and public organisations in developed and developing countries alike. Especially in developing countries, where national statistical services are often weak, household surveys are used to generate and enhance the quality of micro data employed for research and policy design. However, high-quality longitudinal household data remain sparse (Dang & Carletto, 2018). A prominent example of a widely used dataset is the World Bank's Living Standard Measurement Study (LSMS), which was implemented in the 1980s and has continuously contributed to advances in data collection in developing countries (Grosh & Glewwe, 2000). Despite substantial achievements in establishing databases in developing countries, there is room for improvement. For example, recent studies (e.g., Booth, 2019; Gibson, 2016; Sanna & McDonnell, 2017) observe that household survey data in developing countries are not sufficiently accurate and reliable for undertaking valid poverty assessments.

Data quality is a complex concept that encompasses several dimensions such as accuracy, credibility, comparability, usability, relevance, accessibility, timeliness, completeness, and coherence (Biemer, 2010). In this paper, we focus on three of these criteria, namely, completeness, accuracy, and consistency of data. Following Groves & Lyberg (2010), nonsampling errors consist of coverage error (e.g., completeness, relevance), nonresponse (e.g., completeness) and measurement error (e.g., accuracy, consistency). Minimizing these errors remains a challenge regardless of the mode of data collection, i.e., self-administered or interviewer-administered, telephone, postal, web-based, face-to-face, or mixed-mode types of surveys (Couper, 2011; Groves et al., 2011). More recently, surveys in developing countries have transitioned from *"Paper and Pencil Interviews*" (PAPI) to "*Computer Assisted Personal Interviews*" (CAPI), which has increased the overall effectiveness of surveys and can, in principle, substantially reduce the prevalence of nonsampling errors. For example, automated routing can mitigate the extent of missing data by guiding interviewers through the survey instrument and inhibiting them from erroneously skipping questions or modules. Furthermore, the implementation of validation checks further improves the quality of data collection and several studies substantiate the advantages of CAPI over PAPI (Baker et al., 1995; Caeyers et al., 2012; Couper, 2011; de Leeuw et al., 1995; Schraepler et al., 2010; Vandenplas et al., 2019). Nonetheless, CAPI does not automatically solve the problem of low-quality data. Foremost, the underlying complexity of developing and implementing CAPI survey instruments necessitates that survey providers pay close attention to the specification of, for example, enabling conditions and validation rules lest erroneous coding adversely affect the quality of obtained data. Furthermore, other errors arising from misinterpretation of questions or difficult interview and survey conditions remain a challenge irrespective of whether PAPI or CAPI are implemented (Lupu & Michelitch, 2018; Meyer et al., 2015).

In this paper, we aim to contribute to a better understanding of the causes of nonsampling errors in household surveys that make use of CAPI and that are conducted in rural areas of developing countries. We base our analysis on a dataset that comprises of some 4,000 households located in Northeast Thailand, i.e., the provinces of Buriram Ubon Ratchathani, and Nakhon Phanom, and Vietnam, i.e., the provinces of Ha Tinh, Thua Thien Hue, and Dak Lak. The underlying dataset is drawn from the 7th full survey household survey wave of the Thailand Vietnam Socio Economic Panel (TVSEP), which was conducted in 2017. Our study addresses at least four research gaps. First, we complement existing studies that focus on the role of the interviewer and respondent, by additionally considering the role of personality traits (Costa & McCrae, 1997), on which research is scarce. Second, in addition to individual characteristics, we account for conditions under which the interview and survey took place, e.g., the time of day during which an interview took place and whether other individuals were present during the interview. Further, we control for provincial effects and examine differences in interview quality between provincial interviewer teams. Third, we make use of interview paradata[3] such as interviewer entry speed and the extent of technical malfunctions, which are increasingly sought after in the literature (Choumert-Nkolo et al., 2019). Fourth, we model quantitative and qualitative explanatory variables simultaneously and thereby identify the relative importance of respondent and interviewer characteristics, behavioural parameters and interview and survey conditions. Using a negative binomial regression model, we identify main factors of: (a) item nonresponse due to missing data; (b) item nonresponse due to refusal; and (c) measurement error. Our study has four major results. First, we show that missing data are substantially lower in CAPI than in PAPI, although they are not eliminated in their entirety. Rather, it is demonstrated that survey providers must concentrate on measurement error, which is shown to be pervasive in household survey data. Second, interview and survey conditions are shown to play a more important role for data quality than previously assumed. Third, interactions between respondent and interviewer characteristics are significant and congruence of characteristics tends to yield higher-quality interviews. Finally, personality traits of interviewers are found to be a crucial factor influencing data quality.

The remainder of the paper is structured as follows: Section 2.2 provides a definition of nonsampling errors and an overview of the determinants thereof as identified in the literature. Based on the hypotheses derived from the literature review, we introduce our empirical model in section 2.3 and variants thereof for each of the three types of nonsampling error analysed. Section 2.4 describes the study area, survey implementation and data utilised in this paper. Section 2.5 summarises and discusses the main results. In the final section, conclusions derived from the empirical model results are drawn and recommendations for survey providers in developing countries are submitted.

[3] Paradata refers to data collected that describe the process of survey production that are not part of the interview itself (Kreuter et al., 2010; Sinibaldi et al., 2013).

2.2 Literature review

In the literature on data quality (e.g., Groves, 1989; Weisberg, 2005), nonsampling errors are defined as consisting of coverage error, nonresponse, and measurement error.

A coverage error occurs when the sampled population inadequately covers the target population, for example, when important sampling units are excluded, e.g., due to the sampling frame not accurately representing the target population (Groves et al., 2011). In this paper, we omit coverage error and focus on nonresponse and measurement error.

Nonresponse errors transpire when information on either a sampling unit, i.e., unit non-response, or an individual item of the survey instrument, i.e., item non-response, cannot be obtained. Unit nonresponse refers to sampling units that are entirely missing from the survey database, e.g., when the respondent refuses to participate in the interview or is unavailable due to other commitments. Item nonresponse occurs when responses of a sampling unit are only available partially either due to survey items being erroneously skipped or respondents being unable or unwilling to provide an answer. Item nonresponse is often observed in sensitive subjects such as income (Lynn & Clarke, 2002) or details of shocks related to severe illness or death of household members (Phung et al., 2015).

Measurement errors occur when a value provided as a response by a sampling unit deviates from its true value. Generally, the literature differentiates between three types of measurement error based on their source: response, interviewer, and post-survey error (Weisberg, 2005). Deviation from the true value on behalf of the respondent may occur, for example, due to misinterpretation of question meaning, poor cognitive ability, proxy responses (Bardasi et al., 2011), or recall bias (Beegle et al., 2012; Wollburg et al., 2021). For example, the respondent may be unable to recall the yield of their rice plot if the period of recall is too long. An interviewer error may occur when a question or response is modified in such a way that its meaning changes (Tourangeau et al., 2000). For example, an interviewer rephrasing the question *"How healthy are you?"* as *"Are you doing well?"* may change the elicited response. Additionally, in CAPI-based surveys, validation rules based on incorrect assumptions may result in post-survey errors. For example, the implementation of upper and lower limits to the price range of a commodity based on preliminary data may no longer be reflective of the market situation during subsequent survey period. Hence, an interviewer may attempt to cope by adjusting the entered response in order to adhere to the validation rules and erroneously reject the true response. Notably, even the best survey instruments that are subjected to rigorous pretesting may contain flaws. In addition, interviewer motivation and their willingness to adhere to survey rules may decline towards the end of the survey.

In order to develop a suitable model that can identify sources of nonsampling errors, we undertake a systematic review of the literature to establish our hypotheses. Accordingly, we organise findings of the literature regarding determinants of nonsampling errors in Table 2.1. The direction of influence for variables identified as influencing nonsampling errors are presented in four categories: respondent, household, and interviewer characteristics as well as interview and survey conditions.

Regarding respondent characteristics, the literature has shown that interviewing older and less educated respondents results in more counts of nonsampling errors (Knäuper et al. 1997; Krosnick, 1991). Although preferable in theory, interviewing all household members in household surveys is infeasible due to resource constraints (Bardasi et al., 2011). Therefore, interviews are conducted with proxy respondents, which in most cases constitute the household head or their representative (Grosh & Glewwe, 2000). The literature is ambiguous about the effect of interviewing household heads on the prevalence of nonsampling errors. Phung et al. (2015) found that interviews with household heads result in fewer cases of item nonresponse. Conversely, Fisher et al. (2010) observed that household heads significantly underestimated the income of other household members, particularly that of their spouses. Beegle et al. (2012) and Wollburg et al. (2021) found some evidence that interviews with households with more agricultural land tend to be prone to recall bias resulting in missing data or measurement errors. Additionally, wealthier households tend to misreport or refuse to disclose sources of income (e.g., Meyer et al., 2022; Moore et al., 2000).

Studies that examine the implications of interviewer gender effects on the quality of data are inconclusive. For example, while Campanelli & O'Muircheartaigh (1999) and Fowler & Mangione (1990) observed more cases of item nonresponse in interviews conducted by male interviewers, Phung et al. (2015) observed the opposite. Deviations from designated survey procedures by the interviewer can influence the respondent in their response formulation. Prominent examples are: (1) neglecting to follow interview instructions and (2) skipping questions to reduce workload or due to perceived sensitivity of a question. Furthermore, directly assisting the respondent in framing their response, either by rephrasing difficult questions or explaining questions and utilising probing techniques to elicit responses, can lead to measurement errors. For example, Biemer (2010) found that interviewers' emphasis on or intonation of questions can directly influence the respondents' replies. Campanelli & Muircheartaigh (1999) and Singer et al. (1983) demonstrated that such faulty methods of enumeration are caused by insufficient training or lack of interviewer experience. Accordingly, prior experience of interviewers in survey activities and thorough training may prompt better cooperation (Couper & Groves, 1992; Olson & Bilgen, 2011). However, other studies (e.g., Fowler & Mangione, 1990) found that inexperienced interviewers may outperform more experienced interviewers as they are more likely to strictly follow survey guidelines. While in the past, interviewer education has been found to significantly reduce the risk of technical errors such as skipping questions or modules (Axinn, 1989), studies that are more recent have argued that survey experience is a more appropriate in analysing data quality (Olson & Bilgen, 2011). In terms of qualitative characteristics, personality traits were observed to be significantly correlated with data quality (Jäckle et al., 2013; Olson et al., 2016). For example, interviewers exerting friendly or motivating behaviours were found to procure higher rates of cooperation, whereas individuals who are more open-minded were less likely to elicit respondent cooperation.

Congruency of interviewer and respondent characteristics is an important component of survey design (Kahn & Cannell, 1957). Age and gender have been found to positively influence data quality in several studies (e.g., Baird et al., 2008; Feskens et al., 2006; Phung et al., 2015). In countries with pronounced social norms and high ethnic diversity and in surveys dealing with sensitive topics, congruency was found to be crucial (Adida et al., 2016; Catania et al., 1996; Feskens et al., 2006; Pennell et al., 2017).

More recently, interview and survey conditions have been recognised as an important factor of data quality in the literature on nonsampling errors. First, lengthy interviews have been shown to lead to interviewer and respondent fatigue and loss of motivation resulting in a higher prevalence of nonsampling errors (e.g., Galesic & Bosnjak, 2009; Phung et al., 2015). In addition, studies of interview paradata observed that response times that are outside of the "normal" response frame are more likely to be afflicted with measurement errors (Couper & Hansen, 2002; Couper & Kreuter, 2013; Kreuter et al., 2010; Olson & Peytchev, 2007). The presence of other household and non-household members has been found to provide an incentive for respondents to adjust their responses to adhere to perceived social norms (Krumpal, 2013; Smith, 1997). Regarding the characteristics of the survey, Baird et al. (2008) and Townsend et al. (2013) find that the prevalence of missing data and measurement errors decreases as the survey progresses due to interviewers becoming more accustomed to the survey instrument. Finally, Phung et al. (2015) identified that item nonresponse increases in interviews that take place in the afternoon as opposed to morning interviews.

Table 2.1 Overview of hypothesised influence on nonsampling errors

Variable/Category	Direction of influence	Source(s)
Respondent characteristics		
Age	+	Knäuper et al. (1997); Krosnick (1991)
Education	-	Knäuper et al. (1997); Krosnick (1991)
Ethnic majority	-	Adida et al. (2016); Feskens et al. (2006); Pennell et al. (2017)
Head of household	+	Fisher et al. (2010)
	-	Phung et al. (2015)
Openness	+	Jäckle et al. (2013); Olson et al. (2016)
Extraversion	-	Jäckle et al. (2013); Olson et al. (2016)
Neuroticism	+	Jäckle et al. (2013); Olson et al. (2016)
Household characteristics		
Agricultural land size	+	Beegle et al. (2012); Wollburg et al. (2021)
Yearly per capita income	+	Meyer et al. (2018); Moore et al. (2000)
Interviewer characteristics		
Gender (Male)	+	Campanelli & O'Muircheartaigh (1999); Fowler & Mangione (1990)
	-	Phung et al. (2015)
Education	-	Axinn (1989)
Ethnic majority	-	Adida et al. (2016); Feskens et al. (2006); Pennell et al. (2017)
Survey experience	+	Fowler & Mangione (1990)
	-	Campanelli & O'Muircheartaigh (1999); (1992); Singer et al. (1983); Olson & Bilgen (2011)
Openness	+	Jäckle et al. (2013); Olson et al. (2016)
Extraversion	-	Jäckle et al. (2013); Olson et al. (2016); West & Blom (2017)
Agreeableness	-	Jäckle et al. (2013); Olson et al. (2016)
Interview and survey conditions		
Interview duration	+	Galesic & Bosnjak (2009); Phung et al. (2015)
Response time	+	Couper & Hansen (2002); Couper & Kreuter (2013); Kreuter et al. (2010); Olson & Peytchev (2007)
Morning interview	-	Phung et al. (2015)
Presence of others	+	Krumpal (2013); Smith (1997)
Survey week	-	Baird et al. (2008); Townsend et al. (2013); Boehme & Stoehr (2014)

Source: Own illustration.

2.3 Methodology and hypotheses

In the context of our study, we distinguish between two types of item nonresponse, i.e., missing data and refusal. In computerised questionnaires, validity checks can be implemented that forbid the continuation or completion of an interview should a survey item be erroneously missing. Alternatively, softer validity checks can be implemented that provide warnings when survey items are implausibly skipped, but allow the interview to continue and be completed. Based on the latter approach, we define missing data to occur when survey items are unfeasibly skipped and consider cases that remain after completion of interviews. Thereby, missing data is most likely attributable to interviewer error. Conversely, refusals stem from the unwillingness of the respondent to provide an answer. In most surveys, respondents are presented, whether directly or indirectly, with the option to deny their response. Refusal to cooperate is denoted and identified by entry of the code "no answer" in the computerised questionnaire. While interviewers were trained to carefully probe for responses and to ask the respondent to provide an estimate in cases in which the respondent was unsure, the "no answer" code was instructed to be selected for cases in which the respondent refused to provide a response or an estimate. In this study, measurement errors are identified based on validity checks implemented in the survey instrument and supplementary information, such as interviewer comments. When a validity check was triggered and the interviewer comment was not feasibly able to confirm the validity of the entry, the response was considered erroneous. Additionally, data monitoring taking place in later stages of the survey was taken into consideration that identified further inconsistent or implausible information, such as data checking in the field by survey staff, remote data checking by data checking assistants and post-survey data processing. Notable for the approach of this study is the utilisation of "raw" survey data that were not yet subjected to the "quality assurance process" of the survey, thus representing the baseline data quality directly after completion of the interview[4]. Based on this approach, we differentiate between types of nonsampling error and hypothesise that missing data, refusals, and measurement errors, are influenced by different factors.

Regarding models that can capture factors influencing nonsampling errors, variations of count models, such as negative binomial regression models have previously been applied to investigate similar issues of data quality (Barth & Schmitz, 2021; Yu, 2012). To ascertain the suitability of a negative binomial model we compared goodness-of-fit of Poisson and zero-inflated count models. The results show that the negative binomial model outperforms other

[4] An overview of the survey data collection procedure is illustrated in Figure 2.A1

count models (Table 2.A1 & Figures 2.A2-2.A4). Furthermore, the criteria of the negative binomial are satisfied, namely overdispersion of the outcome variables and variance exceeding the mean. A further advantage of the negative binomial model is its ability to consider that the exposure of an observation to an event (e.g., a count of the outcome variable) differs between observations. More precisely, the distinct likelihood of a nonsampling error occurring in an interview are dependent on the number of questions answered, which differs between individual interviews. This is accounted for by including the number of questions answered in each individual interview as an exposure variable.

In a first step, an aggregate analysis of the combined samples obtained from Thailand and Vietnam is conducted. First, in order to examine aggregate-level factors of data quality and second, to establish whether modelling at the individual country-level is warranted. The negative binomial regression model considers three model variants – one for each type of nonsampling error and the combined model is specified as follows:

$$Y_{ji} = \exp(\alpha_{j0} + \beta_{kj}X_{ki} + \vartheta_{pj}S_{pi} + \delta_{mj}Z_{mi} + \rho_{nj}F_{ni} + \eta_{oj}I_{oi} + \varepsilon_{ji}) \quad (1)$$

where Y_{ji} are the count of the j types of nonsampling errors, namely, (a) missing data; (b) refusals; and (c) measurement errors, which are observed in survey items of the interview of household i (i=1, 2, …, n), respectively. X_{ki} are respondent characteristics; S_{pi} are household characteristics; Z_{mi} are interviewer characteristics; F_{ni} are congruent characteristics between the interviewer and respondent; and I_{oi} characterise interview and survey conditions.

Table 2.A2 provides an overview and description of explanatory variables that are included based on the literature review and novel variables that are hypothesised to be correlated with the count of nonsampling errors. Accordingly, we adopt the findings of the literature for the formation of our hypotheses (Section 2.2, Table 2.1). In case of ambiguity, we follow the reference that best reflects the conditions observed in our study in specifying our hypotheses. For novel variables, we formulate the following hypotheses:

First, regarding the missing data model variant, soft validity checks are likely to result in missing data being mostly attributable to the interviewer (e.g., typographical errors). Hence, we hypothesise that interviewers who are more experienced and more educated will be significantly less likely to produce missing data. Further, interviewer personality traits that are linked to attentive and focused behaviour such as openness are hypothesised to result in lower counts of missing data. Interviewer fatigue, which is likely to be higher in interviews conducted during the afternoon or evening, is hypothesised to be strongly correlated with increased counts of missing data. Data entry errors are expected to decrease with each additional survey week as interviewers become more accustomed to the survey instrument and computerised questionnaire. Technical malfunctions of tablet devices and their low performance due to difficult field conditions (e.g., high temperature and humidity) in the field may influence performance and result in missing data.

Second, in the refusal model variant, we hypothesise that interviewer and respondent characteristics are the most important influencing factors. Foremost, incongruence of characteristics is hypothesised to result in reduced levels of cooperation and hence an increase in the count of refusals. In addition, based on the findings of Phung et al. (2015), who studied nonsampling errors in earlier waves of the TVSEP, we hypothesise that household heads will be more likely to cooperate. We consider long-standing respondents, who have frequently participated in interviews, to be more likely to be cooperative and trusting. Interviewers exerting amicable personality traits and respondents who are characterised as being more open and trusting are hypothesised to be important for cooperation and thus result in a lower count of refusal. Thereby, we expect that interviewers who rank higher on the agreeableness scale will be more capable of eliciting responses. In addition, more experienced interviewers and those who performed well during interviewer training are expected to be more competent.

Thirdly, measurement errors are hypothesised to stem mainly from response and interviewer error. Regarding the household head, we hypothesise that overall household heads will provide more reliable data as this study does not focus solely on income. We postulate that personality traits significantly influence the prevalence of measurement errors. For example, ranking high in terms of openness is expected to result in higher counts of measurement errors. Hence, we hypothesise that interviews with open respondents and/or interviewers will be more prone to measurement errors. The opposite influence is assumed for extraverted interviewers and those who are more experienced.

Finally, the model controls for the country-level, whereby the prevalence of nonsampling error is hypothesised to differ significantly between the two countries despite identical survey instruments and overall homogeneity of interviewer training, and overall supervision.

In a second step, the model variants are modified to analyse country-level factors that influence the prevalence of nonsampling errors separately for Thailand and Vietnam. The objective is to determine whether variables are robust and results consistent with the combined model variants. Furthermore, analysing their applicability for both contexts may generate valuable initial insights whether results are applicable to a broad scope of survey backgrounds or limited to specific contexts. The country-level specifications of the model variant are formalised as follows:

$$Y_{cji} = \exp(\alpha_{cj0} + \beta_{jk} X_{kci} + \vartheta_{jp} S_{pci} + \delta_{jm} Z_{mci} + \rho_{jn} F_{nci} + \eta_{jo} I_{oci} + \varepsilon_{cji}) \tag{2}$$

where c is indicative of the country with 0 = Thailand, whereas 1 = Vietnam.

While the categories and explanatory variables in the country-level regression model variants are generally identical to those of the combined model variants, we hypothesise that differences in terms of survey implementation, e.g., typologies of interviewers hired as well as potential country-specific factors necessitate further analysis at the country-level. Hereby three major aspects must be considered. First, the sample in Vietnam is characterised by high ethnic diversity with some 20% of households belonging to so-called ethnic minorities such as the "Thai" or "Mường" in the province of Ha Tinh or the "Ede" in Dak Lak. These groups are shown to differ significantly in several cultural aspects from the "Kinh", who represent the majority group in Vietnam (Dang, 2012). In Thailand, 97% of the sample consists of the "Thai" ethnic group. Accordingly, respondent and interviewer ethnicity and interactions thereof are included only in the Vietnamese model variants and congruency thereof is hypothesised to result in fewer counts of nonsampling error in all model variants. Second, interviewers hired in Thailand were mostly students; whereas Vietnamese interviewers were often freelancers, working in Vietnam's growing survey industry. We expect that education will play a more influential role for university students due to recency of enrolment, whereas its impact will be less accentuated in the Vietnamese sample. Third, disaggregating the data at the country-level allows us to better investigate potential provincial effects that could stem from differences in topography, infrastructure, and accessibility as well as survey organisation.

In summary, we hypothesise that nonsampling errors are influenced by five broad variable categories: (i) respondent characteristics, (ii) household characteristics; (iii) interviewer characteristics, (iv) congruency of respondent and interviewer characteristics, and (v) interview and survey conditions.

2.4. Data

In this section, the study area and survey instrument utilised in this study are introduced. Furthermore, detailed paradata, which were collected to supplement data quality studies are described.

2.4.1 Study area and data collection

The survey area of TVSEP covers six provinces. In Thailand, these are the provinces of Buriram, Ubon Ratchathani and Nakhon Phanom, which are located in Northeast Thailand. In Vietnam, the three provinces belong to the Central Highlands and include Ha Tinh, Thua Thien Hue and Dak Lak. The sample has been drawn in such a way that the households are representative of the rural population in these regions (Hardeweg et al., 2013). The first survey wave was conducted in 2007 and encompassed 4,400 households in 440 villages and 110 sub-districts (Thailand) and 110 communes (Vietnam). The data used in this study originate from the 6th full panel wave[5], which encompasses 3,812 households due to panel attrition. The computerised questionnaire included all components of LSMS surveys (Grosh & Glewwe, 2000) extended by modules on shocks, risks and behavioural aspects pertaining to development. The survey took place from mid-June to the beginning of August 2017. Regarding the organisational structure, there were commonalities and dissimilarities between the two countries. In both countries, the national team leader organised provincial teams consisting of a provincial team leader, sub-team leaders and interviewers, which were grouped into sub-teams. In Thailand, interviewers were allocated to four teams consisting of five interviewers, which were supervised by an experienced sub-team leader in the two larger provinces of Buriram and Ubon Ratchathani, whereas two teams were formed in the province of Nakhon Phanom due to its smaller sample size. In Vietnam, the sample size of the individual provinces was near equal and three sub-teams of five interviewers and one sub-team leader were formed in each province. Prior to the onset of the survey an intensive, eight-day, interviewer training program[6] was conducted. Figure 2.A1 illustrates the data collection and processing procedure of the survey. Interviews were uploaded to a separate database on a daily basis after being subjected to initial supervision instruments in the form of evening group discussions and

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[5] Further information and survey documents can be found on the TVSEP website: https://www.tvsep.de/en/data-/survey-documents/.

[6] The training was conducted under the supervision of TVSEP headquarters staff, who maintained overall supervision during the survey. Further information on training and guidelines can be found on the TVSEP website: https://www.tvsep.de/en/data/survey-documents/.

manual reviews by interviewers. They were then reintroduced to the survey's data quality control process (e.g., in-depth reviews by data checking assistants) on the following day. This study utilises the data that were uploaded each evening to a separate database from that of the main survey, and hence, we coin these interviews as raw data. These data still contain most nonsampling errors that occurred throughout each individual interview.

The computerised questionnaire was programmed using the World Bank's Survey Solutions framework. Over 450 plausibility rules were implemented in the program, which prompted warning messages in cases in which validation checks were violated or data were missing. While interviews could still be uploaded in cases in which such issues remained, interviewers were instructed to resolve any issues directly and to provide commentary to confirm implausible entries. The "no answer" code was implemented to record unwillingness to respond and was taught to be used deliberately, albeit cautiously, in situations in which careful probing to elicit a response was unsuccessful.

Detailed paradata were generated throughout several stages of the survey and across different actors (Figure 2.1). First, during the interviewer training, data consisting of examinations of interviewers, in-depth interviewer information and self-assessed interviewer personality traits were compiled. Second, during data collection, the interviewer and respondent individually evaluated the interview and the interaction with their counterpart. Third, after the conclusion of data collection, sub-team leaders evaluated interviewers based on their performance during training and in the field. The evaluation is based on their daily interactions with interviewers and their presence as an observer in some 30% of interviews. Fourth, sub-team leaders assessed the personality traits of each interviewer in their team, which can then be compared with the assessment on behalf of each interviewer. Finally, a module on personality traits of the respondent was appended to the survey instrument. Interviewer and respondent personality trait items were based on the "Big Five" model developed by Costa and McCrae (1997). Each trait is obtained using weighted averages of three survey items used to capture each trait and the module has been determined to be internally and externally valid (Bühler et al., 2020).

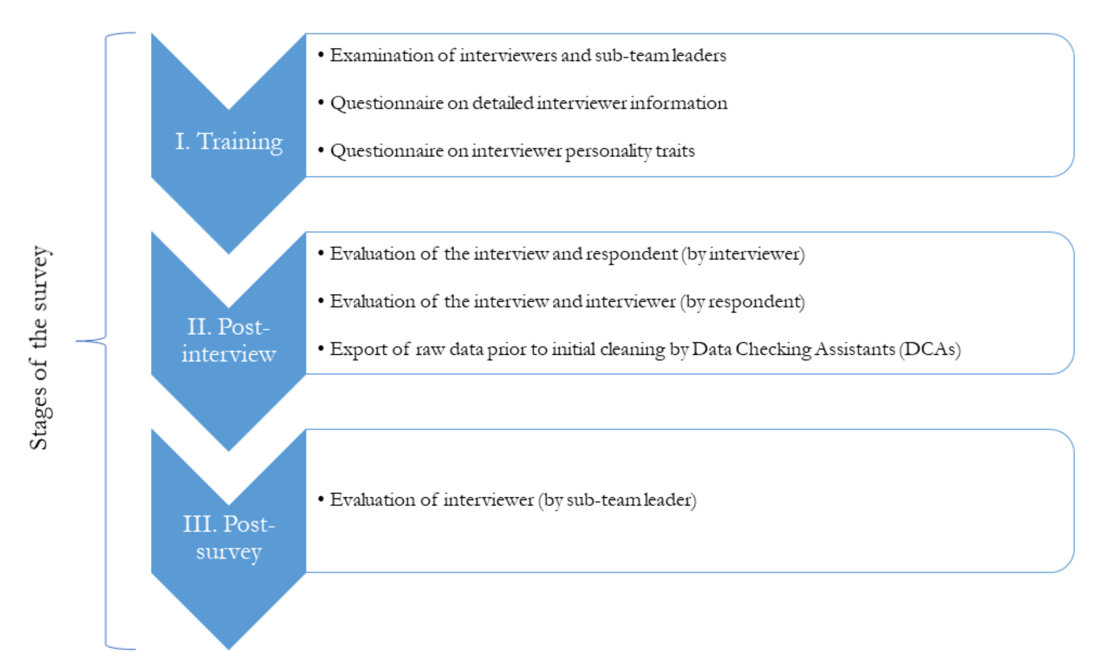

Figure 2.1 Supplemental household survey paradata[7]
Source: Own illustration.

2.4.2 Data description

Tables 2.2-2.4 present the mean and standard deviation of explanatory and outcome variables utilised in the model and undertake a country comparison using the Wilcoxon rank-sum test and Pearson's chi squared test.

Figure 2.2, illustrates the cumulative distribution function (CDF) of the three types of nonsampling error examined in this paper. Thereby, substantial country-level differences are observed between Thailand and Vietnam. Notably, interviews are rarely afflicted with refusals with no cases of uncooperative behaviour taking place in ~50% of interviews in Thailand, whereas substantially fewer interviews are free of item-level nonresponse in Vietnam (~30%). Conversely, all interviews are observed to have at least one case of measurement error irrespective of country. Thereby, interviews in Thailand exhibit higher counts of measurement errors than those in Vietnam. The CDF of missing data suggests that they are more prevalent in the Thai sample, especially towards the upper bound of the distribution. Further, no cases of missing data were observed in 140 interviews (8%) in Thailand and 38 interviews (2%) in Vietnam.

[7] The questionnaires and materials used to collect the supplemental paradata are available on request.

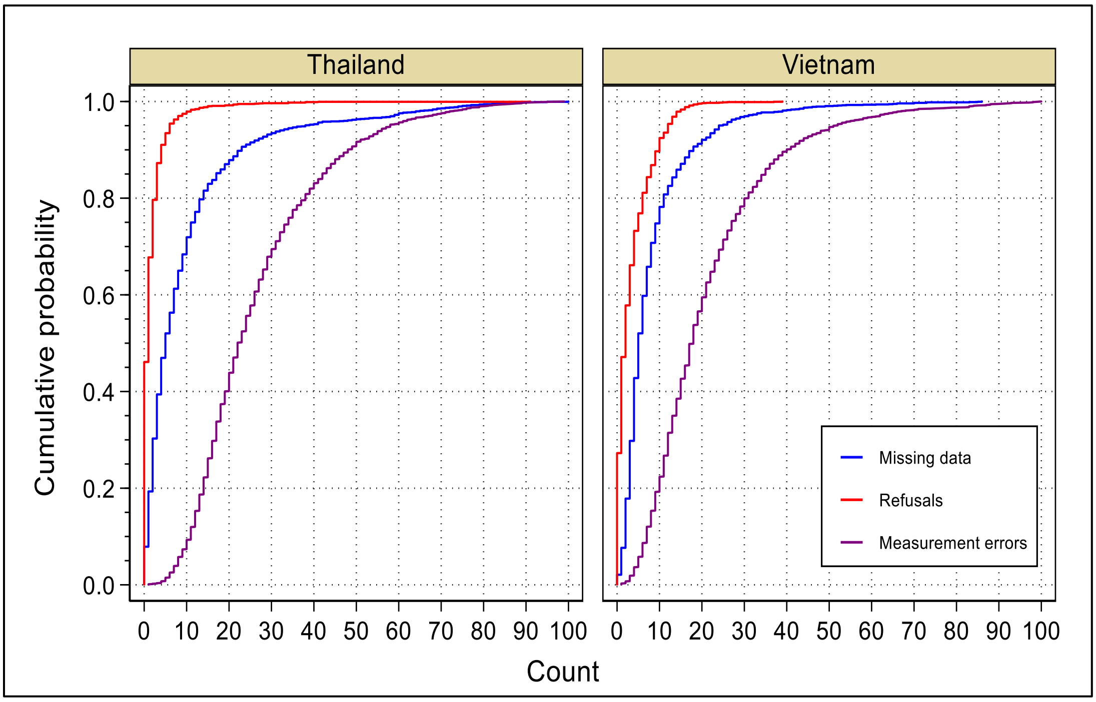

Figure 2.2 CDF of nonsampling errors, by country
Source: Own calculations based on TVSEP (2018).

In Table 2.2, summary statistics pertaining to each type of nonsampling error are presented. Thereby, the findings of Phung et al. (2015), who utilised TVSEP data collected using PAPI in 2007 and 2008, are compared with the 2017 TVSEP survey wave that was conducted using CAPI. First, as hypothesised, the overall count of missing data decreased substantially following the implementation of a computerised survey instrument containing automated routing and validation rules. In CAPI, we observe an average of 15 cases of missing data in Thailand and 9 in Vietnam. In contrast, Phung et al. (2015) determine that the average interview in the first two waves of TVSEP, which used PAPI, contains 60 missing items in Thailand and 111 in Vietnam. Second, refusal is found to be significantly higher in the Vietnamese sample in 2017; however a comparison with the previous PAPI waves is not possible. Last, measurement error counts in CAPI were lower in Vietnam with an average of 22 cases per interview compared to the 28 observed in Thai interviews. While the findings of Phung et al. (2015) suggest that the average number of measurement errors encountered in PAPI is substantially lower, the extent and sophistication of plausibility rules implemented in CAPI compared to PAPI, allows for the identification of more cases of implausible and inconsistent data.

Table 2.2 Summary statistics of nonsampling errors – Comparing CAPI with PAPI

Variables	**Thailand**		**Vietnam**		
	Mean	**Std. dev.**	**Mean**	**Std. dev.**	**Diff. of means**[a]
CAPI: TVSEP 2017					
Missing data (per interview)	14.76	44.50	9.14	24.26	n.s.
Refusals (per interview)	1.81	5.96	3.40	4.23	***
Measurement errors (per interview)	27.65	18.88	22.13	17.28	***
PAPI: TVSEP 2007 & 2008[8]					
Missing data (per interview)	57.12	40.80	111.33	54.23	-
Measurement errors (per interview)	3.07	3.45	3.27	2.59	-

Note: * Significant at 10%.; ** Significant at 5%.; *** Significant at 1%. [a] calculated using the Wilcoxon rank-sum test. 1,816 observations in Thailand/1,830 observations in Vietnam. Source: Phung et al. (2015) and own calculations based on TVSEP (2018).

In Figure 2.3, we report the frequency of the three types of nonsampling error over the progress of the survey, separately for the two countries. As expected, errors decline during the first three to four weeks of the survey before becoming stable in later weeks. Clearly, measurement errors can be identified as the main issue, although, in Thailand, the share of missing data is high during the initial survey week. While refusals are seldom encountered in early survey weeks, they increase at later stages. In comparison, the prevalence of refusal in Vietnam is relatively consistent (Figure 2.3). Note that the survey period was longer and data collection activities were delayed by a week in Vietnam due to unexpected administrative problems related to obtaining government permission for the survey. Therefore, lessons learned from conducting the survey in Thailand could be applied to Vietnam before data collection began.

[8] The following values are based on the findings of Phung et al. (2015) – Tables 2a. & 2b.

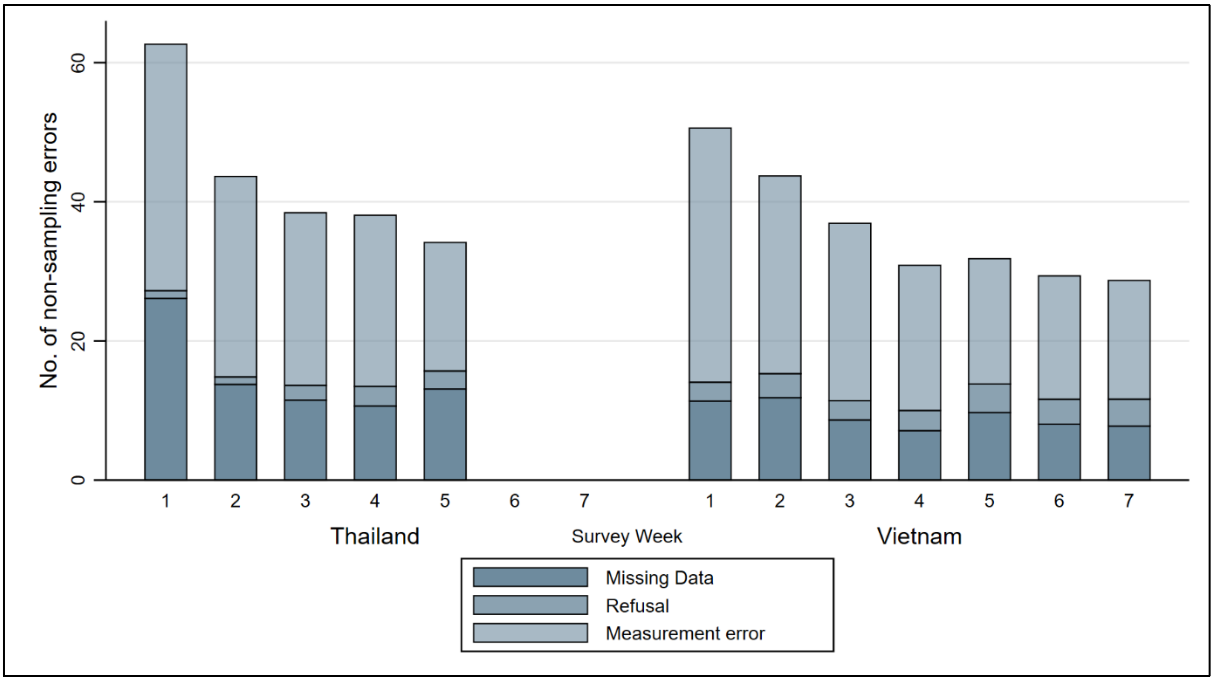

Figure 2.3 Mean nonsampling errors per interview and survey week, by country
Source: Own calculations based on TVSEP (2018).

Table 2.3 presents the descriptive statistics of respondent and household characteristics. It is interesting to note that although household heads were the primary target; this goal was met in 60% of interviews. Respondents are typically above the age of 50, with respondents being significantly older in Thailand. On average, respondents have five years of schooling in Thailand with Vietnamese respondents visiting school an average of two additional years. As mentioned in section 2.2, ethnic diversity is highly relevant to the Vietnamese sample. On average, respondents were interviewed between two and three times in prior waves of the survey, and of those interviewed in 2016, 70% were reinterviewed in 2017 in Thailand and 50% in Vietnam. Self-reported personality traits differ significantly between the two countries with Thai respondents assessing themselves as being more open while ranking lower on scales of extraverted and neurotic behaviour. The average household in both countries consists of four to five members. Furthermore, the average aggregate size of agricultural land in Vietnam is significantly smaller (9,000 m^2) than that in Thailand (23,000 m^2). Conversely, the number of individual plots is higher in Vietnam with households owning up to 18 plots of land.

Table 2.3 Respondent and household characteristics

Variables	Thailand		Vietnam		
	Mean	**Std. dev.**	**Mean**	**Std. dev.**	**Diff. in means**
Respondent characteristics					
Age (years)	57.86	12.76	52.99	13.87	***[a]
Gender (1=male, 0=female)	0.34	0.48	0.43	0.50	***[b]
Years of education	5.42	2.96	6.75	3.75	***[a]
Ethnicity (1=Kinh, 0=other)	-	-	0.79	0.41	-
Head of Household (1=yes, 0=no)	0.57	0.49	0.57	0.49	n.s.[b]
Number of times interviewed	2.51	0.79	2.41	0.74	***[a]
Openness (scale 1-7)	4.61	1.27	4.05	1.38	***[a]
Extraversion (scale 1-7)	4.49	1.05	4.56	1.10	**[a]
Neuroticism (scale 1-7)	3.32	1.12	4.42	1.07	***[a]
Household characteristics					
Household size (no. of members)	4.57	1.91	4.49	1.79	n.s.[a]
Agricultural land size (1,000 m^2)	22.83	26.45	9.23	29.95	***[a]
Land plots (no.)	2.69	1.45	4.19	2.62	***[a]
Yearly per capita income (PPP$)	3,214.76	6,045.62	2,936.44	4,316.58	n.s.[a]
<u>Household location - province (Thailand|Vietnam):</u>					
Buriram|Ha Tinh (1=yes, 0=no)	0.47	0.50	0.34	0.48	-
Ubon Ratchathani|Thua Thien Hue (1=yes, 0=no)	0.37	0.48	0.31	0.46	-
Nakhon Phanom|Dak Lak (1=yes, 0=no)	0.17	0.37	0.35	0.48	-

Note: * Significant at 10%.; ** Significant at 5%.; *** Significant at 1%. [a] calculated using the Wilcoxon rank-sum test. [b] calculated using Pearson’s chi-squared test. 1,816 observations in Thailand/1,830 observations in Vietnam. A description of explanatory variables can be found in Table 2.A2. Source: Own calculations based on TVSEP (2018).

Table 2.4 presents the descriptive statistics of interviewers as well as interview and survey characteristics. In both countries, interviewers can be characterised as young, with most interviewers being below the age of 25. In Thailand, most interviewers were female, whereas the share of male interviewers was significantly higher (40%) in Vietnam. Interviewers almost exclusively belong to the ethnic majority group in Vietnam. Furthermore, almost 50% of interviewers were native to their allocated survey province, whereas the share was significantly lower in Thailand (20%). Interviewers in Vietnam tend to be more experienced both in terms of their education and in terms of previous experience as interviewers with on average three years of experience in other surveys. In Thailand, interviewers have at most three years of experience in the field with only 10% of Thai interviewers being employed in previous waves of TVSEP. In Vietnam, interviewer continuity was significantly lower. In terms of personality traits, interviewers in both countries are socially outgoing, cooperative, polite, curious, and kind. There are, however, significant differences between the two countries concerning the personality traits of openness and agreeableness, which are significantly higher for Vietnamese interviewers. Technical constraints to the survey devices were observed due to high temperatures and humidity levels experienced in the field. These were characterised by prolonged periods of input conversion and lagged transitions between items and modules. Occurrence thereof was self-assessed on behalf of the interviewers and reported in 20% of interviews.

Table 2.4 Interviewer characteristics and interview/survey conditions

Variables	Thailand		Vietnam		
	Mean	Std. dev.	Mean	Std. dev.	Diff. in means
Interviewer characteristics					
Age (years)	22.31	1.99	24.88	2.33	***[a]
Gender (1=male, 0=female)	0.28	0.45	0.40	0.49	***[b]
Education (years)	15.31	1.19	16.12	1.26	***[a]
Ethnicity (1=Kinh, 0=other)	-	-	0.97	0.16	-
Survey experience – Other (1=yes, 0=no)	0.40	0.49	0.88	0.32	***[b]
Survey experience – TVSEP (1=yes, 0=no)	0.13	0.33	0.04	0.21	***[b]
Years of survey experience	0.79	0.93	2.91	2.43	***[a]
Local (1=yes, 0=no)	0.45	0.50	0.21	0.41	***[b]
Training (scale 1-7)	6.12	0.64	6.19	0.59	***[a]
Openness (scale 1-7)	4.42	0.67	4.47	0.58	**[a]
Extraversion (scale 1-7)	3.80	0.48	3.81	0.37	n.s.[a]
Agreeableness (scale 1-7)	5.15	0.64	5.83	0.59	***[a]
Field of study					
Agriculture|Economics (1=yes, 0=no)	0.22	0.41	0.52	0.50	***[b]
Sociology|Languages|Education(1=yes, 0=no)	0.39	0.49	0.43	0.50	***[b]
Administration|Politics|Law (1=yes, 0=no)	0.39	0.49	0.05	0.22	***[b]
Interview/Survey conditions					
Interview duration (minutes)	165.05	56.75	274.59	95.99	***[a]
Entry time	10.06	3.56	6.95	2.09	***[a]
Morning interview (1=yes, 0=no)	0.53	0.50	0.59	0.49	***[b]
Presence of others (1=yes, 0=no)	0.21	0.41	0.12	0.33	***[b]
Tablet malfunction (1=yes, 0=no)	0.23	0.42	0.18	0.39	***[b]
Survey week	2.65	1.14	4.06	1.51	***[a]

Note: * Significant at 10%.; ** Significant at 5%.; *** Significant at 1%. [a] calculated using the Wilcoxon rank-sum test. [b] calculated using Pearson's chi-squared test. 1,816 observations in Thailand/1,830 observations in Vietnam. A description of explanatory variables can be found in Table 2.A2. Source: Own calculations based on TVSEP (2018).

The average interview duration was slightly under three hours in Thailand and over four hours in Vietnam. This is not surprising, as the interview complexity of interviews in Vietnam is higher due to, for example, a higher number of land plots. As shown in the right panel of Figure 2.4, Thai interviewers are faster in terms of data entry than their Vietnamese counterparts are. These differences are at least partially driven by a higher share of interviews that were completed within 100 minutes in Thailand (Figure 2.4).

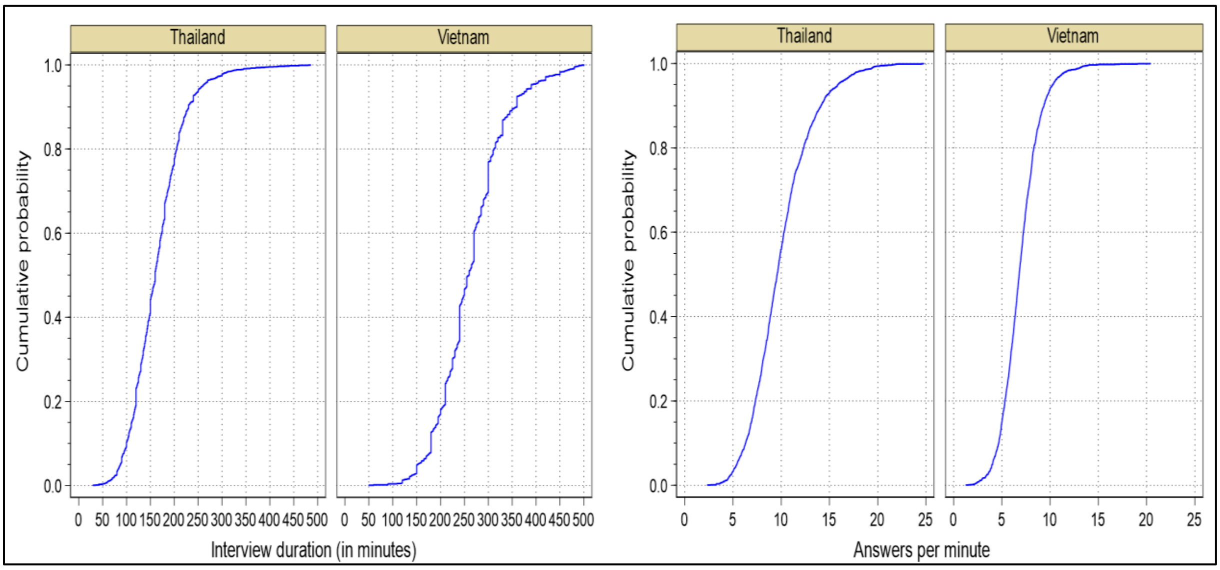

Figure 2.4 CDF of interview duration and entry speed, by country
Source: Own calculations based on TVSEP (2018).

In summary, the descriptive analysis provides some reasonable indications for our hypotheses and is a good point of departure for further econometric analysis.

2.5 Results

Table 2.5 reports on the results of the model variants of the combined sample of Thailand and Vietnam. Thereafter, the results of the country-level model variants are presented and discussed.

As hypothesised, interviewer characteristics are found to significantly influence the prevalence of missing data. As expected, most interviewer characteristic variables are significant, mostly with the hypothesised sign. While interviewer participation in earlier waves of TVSEP is found to significantly reduce the expected count of missing data (Phung et al., 2015), the coefficient of experience in other surveys was not significant. This suggests that survey providers must consider interviewer continuity, alongside general survey experience in the selection of interviewers. Further, higher levels of education and fields of study that match the subject of the survey are observed to result in fewer cases of missing data. Notably, interviewers who rank high on the openness scale, who are generally creative but also less focused (Costa & McCrae, 1992a), tend to have higher counts of missing data. Regarding household characteristics, we find that household size is significant and positively correlated with missing data. This is plausible when taking into consideration that a higher number of household members likely results in interviews that are more complex. Regarding interview and survey conditions, our results confirm the findings of Phung et al. (2015), who observed that interviews conducted at later stages of the day, tend to have more errors. Furthermore, we find that missing data decrease as the survey progresses, which matches the findings of Townsend et al. (2013).

In the refusal model variant, most of the respondent characteristics are significant and have the expected sign. The exception is the variable household head, which, against expectations, is positively correlated. While this finding, in principle, contradicts the literature, possible explanations could be that there may be some level of panel fatigue with household heads having repeatedly been interviewed since 2007 or that their ageing by some ten years may result in additional burden of response as found by Knäuper et al. (1997) and Krosnick (1991). Respondents ranking high on the scale of neuroticism, i.e., who are easily frustrated and impatient (Costa & McCrae, 1992b), are found to be less cooperative. Households that are better off in terms of per capita income are less likely to disclose full information throughout the interview, which is in line with Meyer et al. (2018). The personality traits of interviewers were also found to significantly influence refusal. Those ranking higher on the scale of agreeableness, i.e., who are characterised as sympathetic (Costa & McCrae, 1992b), are more likely to elicit respondent cooperation. While the literature (e.g., Baird et al., 2008; Feskens et al., 2006; Phung et al., 2015) suggests that congruency of characteristics, in particular gender, can help to reduce refusals, our model does not confirm this. The difference could be explained by the very low prevalence of sensitive questions in the 2017 survey instrument. i.e., when compared with studies that deal with subjects such as sexual violence (i.e., Baird et al., 2008). Regarding interview and survey conditions, as expected, interview duration is negatively correlated, i.e., dedicating more time to the interview helps to reduce errors. On the other hand, the count of refusals increases as the survey progresses.

In the model variant on measurement errors, only few respondent variables are significant. First, the coefficient of the household head matches our findings of the refusal model variant. Second, respondent continuity is shown to significantly decrease the expected count of measurement errors. Third, the coefficient of openness is significant and positively correlated, which is plausible as less focused individuals are more prone to making mistakes. Interviews with larger households have fewer cases of measurement errors. This could be related to the fact that households with more members (e.g., more children) tend to be poorer and therefore have simpler economic structures. To some extent, this is supported by the positive and significant coefficient for income, which is also reported by Meyer et al. (2018). Most interviewer characteristics are significant and to a large degree confirm our previous results, especially those of the missing data model variant. First, the training variable underlines that interviewer performance during training is an essential component of survey preparations. The model reaffirms that specific survey experience with the panel is advantageous. At first glance, the negative coefficient for interviewers who are native to the survey province is puzzling, as one would expect locals to be more knowledgeable of the general conditions in the survey area. A possible explanation is that local interviewers may be more preconceived. In addition, the majority of interview and survey condition variables are significant and generally are plausible. For example, the coefficient of the entry time is positively correlated, which is in line with the literature (e.g., Olson & Peytchev, 2007). As hypothesised, the presence of others during an interview leads to an increasing prevalence of erroneous data, which is likely due to distractions or the result of a lack of confidentiality during the interview (Krumpal, 2013).

Finally, across all model variants, we observe statistically significant differences in the country indicator variable, which warrants further examination at the country-level.

Table 2.5 Negative binomial regression results – combined model

	(1) Missing data		(2) Refusals		(3) Measurement errors	
	β	**SE**	**β**	**SE**	**β**	**SE**
Respondent characteristics						
Age (years)	-0.009	(0.009)	-0.066***	(0.011)	0.002	(0.004)
Age squared	0.000	(0.000)	0.001***	(0.000)	0.000	(0.000)
Gender (1=male, 0=female)	0.011	(0.049)	-0.221**	(0.070)	-0.026	(0.026)
Secondary education (1=yes, 0=no)	0.012	(0.048)	-0.292***	(0.059)	0.042	(0.023)
Head of household (1=yes, 0=no)			0.216**	(0.066)	0.062*	(0.024)
Number of times interviewed			-0.018	(0.015)	-0.021***	(0.006)
Openness (scale 1-7)					0.015*	(0.007)
Extraversion (scale 1-7)			-0.033	(0.022)		
Neuroticism (scale 1-7)			0.051*	(0.023)		
Household characteristics						
Household size (no. of members)	0.036**	(0.012)	-0.004	(0.015)	-0.014*	(0.006)
Agricultural land size (1,000 m²)	0.001	(0.001)	0.001	(0.001)	-0.000	(0.000)
Yearly per capita income (1,000 PPP$)	0.004	(0.002)	0.010*	(0.005)	0.007***	(0.002)
Interviewer characteristics						
Age (years)	0.064***	(0.009)	0.007	(0.013)	-0.025***	(0.004)
Gender (1=male, 0=female)	0.083	(0.053)	-0.250***	(0.068)	0.003	(0.025)
Education (years)	-0.042*	(0.017)	-0.021	(0.022)	0.001	(0.008)
Local (1=yes, 0=no)	0.103*	(0.045)	-0.076	(0.059)	0.171***	(0.022)
Training (scale 1-7)			-0.009	(0.043)	-0.083***	(0.016)
Agriculture/Economics (1=yes, 0=no)	-0.138**	(0.051)	0.304***	(0.061)	-0.084***	(0.024)
Politics/Administration/Law (1=yes, 0=no)	-0.217***	(0.053)	0.352***	(0.070)	-0.143***	(0.025)
Openness (scale 1-7)	0.171***	(0.032)			0.063***	(0.016)
Extraversion (scale 1-7)					-0.128***	(0.022)
Agreeableness (scale 1-7)			-0.295***	(0.041)	-0.001	(0.016)
Survey experience – Other (1=yes, 0=no)# Years of survey experience	-0.021	(0.011)	-0.007	(0.016)	0.006	(0.005)
Survey experience – TVSEP (1=yes, 0=no)# Years of survey experience	-0.190***	(0.032)	-0.022	(0.044)	-0.038*	(0.015)
Congruency						
Respondent gender #Interviewer gender (male/male)	0.077	(0.081)	0.195	(0.104)	-0.064	(0.038)
Interview/Survey conditions						
Interview duration (minutes)	0.000	(0.000)	-0.001**	(0.000)	0.001***	(0.000)
Entry time (questions per minute)	0.016	(0.008)	-0.013	(0.011)	0.021***	(0.004)
Morning interview (1=yes, 0=no)	-0.112**	(0.038)	0.081	(0.048)	0.029	(0.018)
Presence of others (1=yes, 0=no)	-0.036	(0.049)	-0.038	(0.067)	0.059*	(0.024)
Tablet malfunction (1=yes, 0=no)	0.104*	(0.049)	0.086	(0.062)	-0.003	(0.023)
Survey week	-0.151***	(0.014)	0.102***	(0.018)	-0.130***	(0.007)
Country (1=Vietnam, 0=Thailand)	-0.420***	(0.079)	0.840***	(0.103)	-0.211***	(0.040)
Constant	-5.792***	(0.415)	-3.140***	(0.604)	-2.600***	(0.245)
/lnalpha	0.132	(0.024)	0.436	(0.035)	-1.470	(0.027)
AIC	24,6662		14,813		27,831	

Note: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. 3,633 observations across Thailand and Vietnam. Source: Own calculations based on TVSEP (2018).

The results of the country-level analysis are presented for both countries by type of nonsampling error in Tables 2.6-2.8. In addition to presenting the output of the negative binomial regression model, a column is added in which a model transformation of coefficients to percent change coefficients is depicted following Long & Freese (2014). The results of the three model variants are summarised as follows:

First, for the missing data model variants (Table 2.6), coefficients are widely consistent with the results of the combined model. Second, congruence of ethnicity is shown to be preferable in the Vietnamese sample and interviews between majority Kinh results in a lower expected count of missing data. Third, aspects of survey management alongside interviewer team effects can likely explain the significance of the provincial indicators. For example, in Thailand, prior experience of provincial team leaders in conducting and managing surveys varied. In Vietnam, administrative constraints affecting the survey schedule and resulting in a delayed start in some provinces may explain the significance of provincial indicators. For example, items are more likely to be missing in Thua Thien Hue when compared with the first province in which interviews were conducted, namely Ha Tinh. An additional explanation for significance of the province was identified by examining the distribution of missing data at the team level. In doing so, we observe that interviews conducted by “Team 1” in Thua Thien Hue account for a disproportionally high share of missing data and likely drive significance of the provincial variable (Figure 2.A5).

Table 2.6 Negative binomial regression results (missing data), by country

	Thailand			Vietnam		
	β	**SE**	**Percent Δ**	**β**	**SE**	**Percent Δ**
Respondent characteristics						
Age (years)	-0.008	(0.018)	-0.80	-0.008	(0.010)	-0.80
Age squared	0.000	(0.000)	0.00	0.000	(0.000)	0.00
Gender (1=male, 0=female)	-0.025	(0.078)	-2.50	0.014	(0.056)	1.50
Secondary education (1=yes, 0=no)	-0.068	(0.098)	-6.60	0.135**	(0.051)	14.40
Ethnicity (1=Kinh, 0=other)				0.459	(0.300)	58.20
Household characteristics						
Household size (no. of members)	0.044*	(0.019)	8.80	0.007	(0.015)	0.70
Agricultural land size (1,000m²)	-0.000	(0.001)	-0.20	0.001	(0.001)	0.10
Yearly per capita income (1,000 PPP$)	0.002	(0.003)	1.30	0.019***	(0.005)	2.00
Interviewer characteristics						
Age (years)	0.031	(0.022)	3.10	0.026**	(0.010)	2.60
Gender (1=male, 0=female)	0.250**	(0.096)	28.40	-0.019	(0.064)	-1.90
Education (years)	-0.047	(0.037)	-4.60	-0.052**	(0.018)	-5.10
Ethnicity (1=Kinh, 0=other)				-0.260	(0.271)	-22.90
Local (1=yes, 0=no)	0.093	(0.078)	9.80	0.294***	(0.065)	34.10
Agriculture/Economics (1=yes, 0=no)	-0.467***	(0.095)	-37.30	0.002	(0.058)	0.20
Politics/Administration/Law	-0.321***	(0.073)	-27.50	-0.121	(0.118)	-11.40
Openness (scale 1-7)	0.070	(0.063)	7.20	0.070	(0.045)	7.30
Survey experience – Other (1=yes, 0=no) # Years of survey experience	-0.010	(0.042)	-1.00	0.014	(0.011)	1.40
Survey experience – TVSEP (1=yes, 0=no) # Years of survey experience	-0.170***	(0.050)	-15.60	-0.160***	(0.046)	-14.80
Congruency						
Respondent gender # Interviewer gender (male/male)	0.161	(0.142)	17.40	0.148	(0.087)	16.00
Respondent ethnicity # Interviewer ethnicity (majority/majority)				-0.629*	(0.302)	-46.70
Interview/Survey conditions						
Interview duration (minutes)	0.001	(0.001)	0.10	0.000	(0.000)	0.00
Entry time (answers per minute)	0.017	(0.014)	1.70	-0.002	(0.016)	-0.20
Morning interview (1=yes, 0=no)	-0.109	(0.062)	-10.40	-0.131**	(0.043)	-12.30
Presence of others (1=yes, 0=no)	-0.047	(0.077)	-4.60	-0.073	(0.066)	-7.10
Tablet malfunction (1=yes, 0=no)	0.143	(0.079)	15.40	-0.127*	(0.059)	-11.90
Survey week	-0.246***	(0.028)	-21.80	-0.141***	(0.021)	-13.20
Provinces (Thailand|Vietnam):						
Ubon Ratchathani|Thua Thien Hue (ref: Buriram|Ha Tinh)	0.093	(0.091)	9.80	0.302***	(0.081)	35.30
Nakhon Phanom|Dak Lak (ref: Buriram|Ha Tinh)	0.330**	(0.112)	39.10	-0.311***	(0.072)	-26.70
Constant	-4.576***	(0.806)		-4.256***	(0.589)	
/lnalpha	0.412	(0.033)		-0.440	(0.037)	
AIC	12,708			11,474		

Note: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. 1,806 observations in Thailand/1,827 observations in Vietnam. Percent Δ = percent change in expected count for unit increase in X. The full output tables for the factor and percent change transformation following Long & Freese (2014) can be found in Tables 2.A3-2.A4. Source: Own calculations based on TVSEP (2018).

The refusal model variant (Table 2.7) shows that coefficients of the respondent in the combined model are driven by the Vietnamese sample. Interestingly, cooperation is found to be higher in incongruent respondent-interviewer dyads. For example, the expected count of refusal was 30% lower when male respondents were interviewed by female interviewers and 45% lower when the gender roles were reversed. In contrast to the combined model, household heads are no longer expected to be less likely to cooperate at the country-level. Hence, the significance in the combined model is driven by variation of the general response rate between the two countries. In terms of interviewer characteristics, we observe that a background in more social fields of study, such as education, as opposed to economics or agriculture, results in significantly higher levels of cooperation, which is unsurprising. Furthermore, we reaffirm that ranking high on the scale of agreeableness reduces the expected count of refusal in both countries. The effect of survey experience is mixed. While in Thailand, additional experience in other surveys is associated with a higher expected count of refusals, the opposite is observed in the Vietnamese model. It is likely that the overall low amount of survey experience (at most 3 years) in Thailand is responsible for this finding. In Vietnam, where cultural diversity has been shown to play a key role, local interviewers are more likely to gain the trust of the respondent and reduce the count of refusal by 20%. However, against expectations, we cannot confirm the frequently reported effect of ethnicity. Interviewer fatigue was an issue for the less experienced Thai interviewers with the expected count of refusal cases increasing by 30% with each additional survey week. In Vietnam, the more experienced, professional interviewers, however, did not experience an increased likelihood of refusal, which decreased by 5% per survey week. This is plausible as Vietnamese interviewers were more used to the conditions in the field during prolonged periods of data collection; hence, the onset of fatigue may have been delayed or its impact dampened. We observe significant provincial effects, albeit only for Vietnam. Interviews in the first province surveyed (Ha Tinh) are expected to have half as many cases of refusals as in the two remaining provinces: Thua Thien Hue and Dak Lak. In particular, 40% of interviews in Ha Tinh were free of refusal, whereas a significantly higher share of interviews had at least one count of refusal in the two remaining provinces (Figure 2.A6). Furthermore, in examining the distribution of refusal at the team level, we identify that one of the three provincial sub-teams that collected data in Ha Tinh ("Team 2") outperformed most other interviewer teams in terms of eliciting responses (Figure 2.A7). Accordingly, these observations may explain the importance of indicators at the provincial level in Vietnam.

Table 2.7 Negative binomial regression results (refusals), by country

	Thailand			Vietnam		
	β	SE	Percent Δ	β	SE	Percent Δ
Respondent characteristics						
Age (years)	-0.030	(0.020)	-2.90	-0.042***	(0.013)	-4.10
Age squared	0.000	(0.000)	0.00	0.000***	(0.000)	0.00
Gender (1=male, 0=female)	-0.068	(0.105)	-6.60	-0.358***	(0.087)	-30.10
Secondary education (1=yes, 0=no)	0.038	(0.122)	3.80	-0.235***	(0.066)	-20.90
Ethnicity (1=Kinh, 0=other)				0.142	(0.373)	15.30
Head of household (1=yes, 0=other)	0.075	(0.095)	7.80	0.082	(0.088)	8.50
Number of times interviewed	-0.023	(0.022)	-2.30	-0.015	(0.021)	-1.40
Extraversion (scale 1-7)	-0.076*	(0.035)	-7.30	-0.034	(0.025)	-3.30
Neuroticism (scale 1-7)	0.045	(0.035)	4.60	0.029	(0.028)	3.00
Household characteristics						
Household size (no. of members)	-0.027	(0.025)	-2.70	-0.010	(0.020)	-1.00
Agricultural land size (1,000m²)	-0.001	(0.001)	-0.10	0.001	(0.000)	0.10
Yearly per capita income (1,000 PPP$)	0.016*	(0.006)	1.60	-0.013	(0.007)	-1.30
Interviewer characteristics						
Age (years)	0.096***	(0.025)	10.10	-0.040**	(0.014)	-3.90
Gender (1=male, 0=female)	-0.048	(0.110)	-4.60	-0.589***	(0.090)	-44.50
Education (years)	-0.025	(0.044)	-2.50	0.036	(0.024)	3.60
Ethnicity (1=Kinh, 0=other)				-0.558	(0.335)	-42.70
Local (1=yes, 0=no)	0.160	(0.097)	17.40	-0.248**	(0.083)	-22.00
Agriculture/Economics (1=yes, 0=no)	0.343***	(0.113)	40.90	0.282***	(0.077)	32.50
Politics/Administration/Law (1=yes, 0=no)	0.126	(0.098)	13.40	-0.100	(0.162)	-9.50
Agreeableness (scale 1-7)	-0.239**	(0.084)	-21.20	-0.254***	(0.053)	-2.40
Survey experience – Other (1=yes, 0=no) # Years of survey experience	0.331***	(0.049)	39.20	-0.050**	(0.015)	-4.90
Survey experience – TVSEP (1=yes, 0=no) # Years of survey experience	0.085	(0.063)	8.90	-0.118	(0.063)	-11.10
Congruency						
Respondent gender # Interviewer gender (male/male)	-0.098	(0.175)	-9.30	0.418***	(0.117)	52.00
Respondent ethnicity # Interviewer ethnicity (majority/majority)				-0.598	(0.377)	-45.00
Interview/Survey conditions						
Interview duration (minutes)	-0.000	(0.001)	-0.00	-0.002***	(0.000)	-0.20
Entry time (answers per minute)	0.027	(0.019)	2.70	-0.085***	(0.020)	-8.10
Morning interview (1=yes, 0=no)	0.136	(0.075)	14.60	0.042	(0.057)	4.30
Presence of others (1=yes, 0=no)	-0.078	(0.097)	-7.50	0.029	(0.088)	3.00
Tablet malfunction (1=yes, 0=no)	0.118	(0.095)	12.50	-0.082	(0.079)	-7.90
Survey week	0.267***	(0.035)	30.60	-0.056*	(0.028)	-5.50
Provinces (Thailand|Vietnam):						
Ubon Ratchathani|Thua Thien Hue (ref: Buriram|Ha Tinh)	0.106	(0.102)	11.20	0.729***	(0.107)	107.30
Nakhon Phanom|Dak Lak (ref: Buriram|Ha Tinh)	-0.261	(0.148)	-23.00	0.795***	(0.094)	121.40
Constant	-7.350***	(1.025)		-0.743	(0.934)	
/lnalpha	0.518	(0.055)		-0.003	(0.050)	
AIC	6,098			8,297		

Note: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. 1,806 observations in Thailand/1,827 observations in Vietnam. Percent Δ = percent change in expected count for unit increase in X. The full output tables for the factor and percent change transformation following Long & Freese (2014) can be found in Tables 2.A5-2.A6. Source: Own calculations based on TVSEP (2018).

The measurement error model variant (Table 2.8) finds that measurement errors are driven significantly by the characteristics of the respondent and interviewer. In both countries, the continuity of respondents, as proxied by the number of times they were interviewed, is shown to reduce the expected count of measurement errors by 2%. We find mixed results regarding respondent-interviewer gender dyads. In particular, mismatched gender dyads with female respondents and male interviewers are shown to decrease the expected count of erroneous data by 8% in the Thai sample, whereas the opposite is observed in the Vietnamese sample, in which their expected count increases by 13%. In Vietnam, ethnicity is shown to play a key role, which matches our hypotheses. For example, interviews between Kinh respondents and minority interviewers are found to lead to an 88% increase in the expected count of measurement errors when compared with matching minority dyads. Conversely, when Kinh interviewers interviewed minority respondents, the count of measurement errors did not differ significantly from matching minority dyads. This suggests that while Kinh respondents may discriminate against minority interviewers, minority respondents are indifferent to the ethnicity of the allocated interviewer. Nonetheless, interviews with minority households are observed to be of overall lower quality when compared to those of Kinh households, which contain 50% fewer counts of measurement error. Regarding interviewer characteristics, prior experience in other surveys is found to have a negative effect on the quality of data in Vietnam. Following the study of Fowler and Mangione (1990), this can be explained by experienced interviewers conforming to survey procedures and guidelines of other surveys rather than to those in which they are currently employed. Nonetheless, specific experience in TVSEP is shown to result in a lower expected count of measurement errors, which matches our findings from the missing data model variant. The coefficient that represents interviewer performance during training is shown to be robust and highly significant in both countries. Notably, training is determined to be of great importance regardless of whether the pool of interviewers is less experienced or professional. The coefficient shows that 20% fewer counts of measurement errors are expected for those who rank higher on the scale of training performance. The significant decrease in measurement errors observed in the variable field of study in our combined model is shown to be limited to the younger Thai student interviewers. Extraverted, sympathetic, and cooperative personality traits are shown to be highly significantly correlated in the Thai model alongside more focused and analytical interviewers procuring data of higher quality. In the Vietnamese sample, the result that more sympathetic and cooperative interviewers provide interviews of lesser quality does not match our expectations. A potential explanation lies in the distribution of agreeableness, which is highly skewed towards the higher scores on the scale in Vietnam. The interview and survey conditions are shown to be significantly predict measurement errors at the country-level. Longer interviews and an increased entry speed are shown to result in a higher expected count of erroneous data. Unexpectedly, tablet malfunctions that interviewers assess as being very negative are found to reduce the expected count of measurement errors in the Vietnamese sample. Potentially, professional interviewers are more careful in completing interviews in which such malfunctions occurred or are more able to reliably replicate lost data. Provincial indicator variables are significant in the Vietnamese sample, which is argued to be driven by the survey schedule and topography of provinces. This assumption is further substantiated as the distribution of error by interviewer teams is found to be very similar with no clear outliers being ascertained (Figure 2.A8). Rather, differences in the complexity of agricultural activities are likely drivers of measurement errors in Vietnam. For example, while the mean number of unique crops planted per household is eleven in Ha Tinh, fewer varieties of crops are planted in Thua Thien Hue (nine) and Dak Lak (five). Furthermore, land parcels in Dak Lak are less fragmented with the average household having two plots that total 3,800 m^2, whereas the other provinces have on average three to four plots of 1,500 m^2, which further increases the complexity of the interview and likely explains the increased prevalence of measurement errors.

Table 2.8 Negative binomial regression results (measurement errors), by country

	Thailand			Vietnam		
	β	**SE**	**Percent Δ**	**β**	**SE**	**Percent Δ**
Respondent characteristics						
Age (years)	-0.008	(0.007)	-0.80	0.008	(0.006)	0.80
Age squared	0.000	(0.000)	0.00	-0.000	(0.000)	-0.00
Gender (1=male, 0=female)	0.008	(0.032)	0.80	-0.056	(0.039)	-5.50
Secondary education (1=yes, 0=no)	-0.017	(0.037)	-1.60	0.051	(0.029)	5.20
Ethnicity (1=Kinh, 0=other)				0.632***	(0.185)	88.10
Head of household (1=yes, 0=other)	0.055	(0.030)	5.70	0.082*	(0.039)	8.50
Number of times interviewed	-0.021**	(0.007)	-2.10	-0.020*	(0.009)	-2.00
Openness (scale 1-7)	0.002	(0.010)	0.20	0.013	(0.010)	1.40
Household characteristics						
Household size (no. of members)	-0.009	(0.008)	-0.90	-0.021*	(0.009)	-2.10
Agricultural land size (1,000m²)	-0.000	(0.000)	-0.00	-0.000	(0.000)	-0.00
Yearly per capita income (1,000 PPP$)	0.007***	(0.002)	0.70	0.005	(0.003)	0.50
Interviewer characteristics						
Age (years)	0.010	(0.008)	1.00	-0.047***	(0.006)	-4.60
Gender (1=male, 0=female)	-0.085*	(0.038)	-8.10	0.126***	(0.038)	13.40
Education (years)	-0.036*	(0.014)	-3.50	-0.009	(0.010)	-0.90
Ethnicity (1=Kinh, 0=other)				0.325	(0.170)	-51.00
Local (1=yes, 0=no)	0.195***	(0.030)	21.50	0.019	(0.037)	1.90
Training (scale 1-7)	-0.059**	(0.021)	-5.70	-0.188***	(0.024)	-17.20
Agriculture/Economics (1=yes, 0=no)	-0.270***	(0.037)	-23.70	0.070*	(0.033)	7.30
Politics/Administration/Law (1=yes, 0=no)	-0.199***	(0.030)	-18.00	0.204**	(0.073)	22.70
Openness (scale 1-7)	0.096***	(0.025)	10.10	0.040	(0.028)	4.10
Extraversion (scale 1-7)	-0.127***	(0.029)	-11.90	-0.030	(0.039)	-2.90
Agreeableness (scale 1-7)	-0.069**	(0.025)	-6.70	0.061*	(0.025)	6.30
Survey experience – Other (1=yes, 0=no) # Years of survey experience	-0.015	(0.017)	-1.50	0.021**	(0.007)	2.10
Survey experience – TVSEP (1=yes, 0=no) # Years of survey experience	0.005	(0.019)	0.50	-0.130***	(0.027)	-12.20
Congruency						
Respondent gender # Interviewer gender (male/male)	-0.040	(0.055)	-3.90	-0.062	(0.050)	-6.00
Respondent ethnicity # Interviewer ethnicity (majority/majority)				-0.714***	(0.186)	-51.00
Interview/Survey conditions						
Interview duration (minutes)	0.001	(0.000)	0.10	0.001***	(0.000)	0.10
Entry time (answers per minute)	0.011	(0.006)	1.10	0.034***	(0.010)	3.40
Morning interview (1=yes, 0=no)	0.022	(0.024)	2.20	0.012	(0.025)	1.20
Presence of others (1=yes, 0=no)	0.009	(0.030)	0.90	0.097*	(0.038)	10.20
Tablet malfunction (1=yes, 0=no)	0.044	(0.030)	4.50	-0.104**	(0.033)	-9.90
Survey week	-0.159***	(0.011)	-14.70	-0.096***	(0.012)	-9.20
Provinces (Thailand|Vietnam):						
Ubon Ratchathani|Thua Thien Hue (ref: Buriram|Ha Tinh)	-0.023	(0.035)	-2.30	-0.025	(0.047)	-2.50
Nakhon Phanom|Dak Lak (ref: Buriram|Ha Tinh)	-0.087	(0.048)	-8.40	-0.251***	(0.042)	-22.20
Constant	-2.075***	(0.037)		-2.773***	(0.466)	
/lnalpha	-1.584	(0.039)		-1.572	(0.041)	
AIC	14,133			13,427		

Note: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. 1,806 observations in Thailand/1,827 observations in Vietnam. Percent Δ = percent change in expected count for unit increase in X. The full output tables for the factor and percent change transformation following Long & Freese (2014) can be found in Tables 2.A7-2.A8. Source: Own calculations based on TVSEP (2018).

Overall, we observe that nonsampling errors are influenced by respondent and interviewer characteristics. Notably, their personality traits are found to be of relevance. In Vietnam, which boasts high cultural diversity, interviewers with similar ethnic backgrounds are found to collect data of significantly higher quality, and matching dyads based on this characteristic plays an important role. Finally, potential patterns of nonsampling errors are observed as the survey progresses as well as differences at the provincial level, which may be explained by interviewer team effects, the survey schedule, or topographical factors.

2.6 Conclusions and outlook

In applying a comprehensive approach, we show that it is important to consider not only interviewer and respondent characteristics, but also the underlying interview and survey conditions. While missing data were shown to be the most prevalent type of nonsampling error in PAPI (e.g., Phung et al., 2015), CAPI, in principle, is shown to substantially reduce missing data. Conversely, measurement errors remain a significant problem. Using an identical survey instrument applied in two different countries, we find that differences in survey populations and survey implementation result in distinct findings related to factors of nonsampling error in our models. Accordingly, we suggest that best-practice approaches must also take into consideration features of individual surveys, e.g., the typologies of interviewers targeted in the hiring process or important characteristics of the survey population such as ethnicity, in order to minimise nonsampling error. Notably, the findings highlight the importance of interviewer continuity, experience, and training in obtaining high-quality outputs. However, rehiring interviewers is often not feasible in the context of surveys based in developing countries; thus, we recommend that training should be a focal point of survey design.

Nonsampling errors identified and analysed in this study represent an exacerbated illustration of household survey data quality based on data that had not yet been subjected to post-interview data monitoring. However, we argue that identifying cases of erroneous data at their source yields important insights for survey providers. A key benefit of CAPI that should be considered is its ability to generate supplementary paradata in real-time (e.g., how long the interview took to be completed, response times for individual survey items, and input timestamps). Such data can easily be generated and utilised in data monitoring to identify survey items, interviews, or interviewers with underlying issues. Our results show that even basic indicators such as the entry time are significantly correlated with nonsampling errors. Further expanding existing plausibility rules and implementing a stricter framework that prohibits the further progress in and the submission of interviews with flagged data is expected to further reduce error. However, based on experience in the field we recommend a more cautious approach that makes use of warning messages, which allow interviewers progress conditional on provision of an explanation why a flagged value may be plausible.

Increasingly, novel research is committed to studying rapport, i.e., the relationship between the interviewer and respondent, and how interactions between traits influence the quality of data (e.g., Bell et al., 2016; Garbarski et al., 2016; Sun et al., 2021). By including personality traits in our model, we provide some initial insights that highlight the relevance of rapport in data quality studies. In particular, targeted respondent-interviewer allocations based upon personality traits may in some cases result in higher levels of cooperation.

Finally, the increasing importance of panel surveys in generating scientific outputs and policy necessitates further research on longitudinal data quality. A logical next step could be to retrospectively study data quality and factors thereof in existing longitudinal datasets. An analysis of the consistency of reported values, similar to studies that utilise validation data, albeit with prior waves of data is expected to provide further insights.

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Appendix 2.A Tables and figures

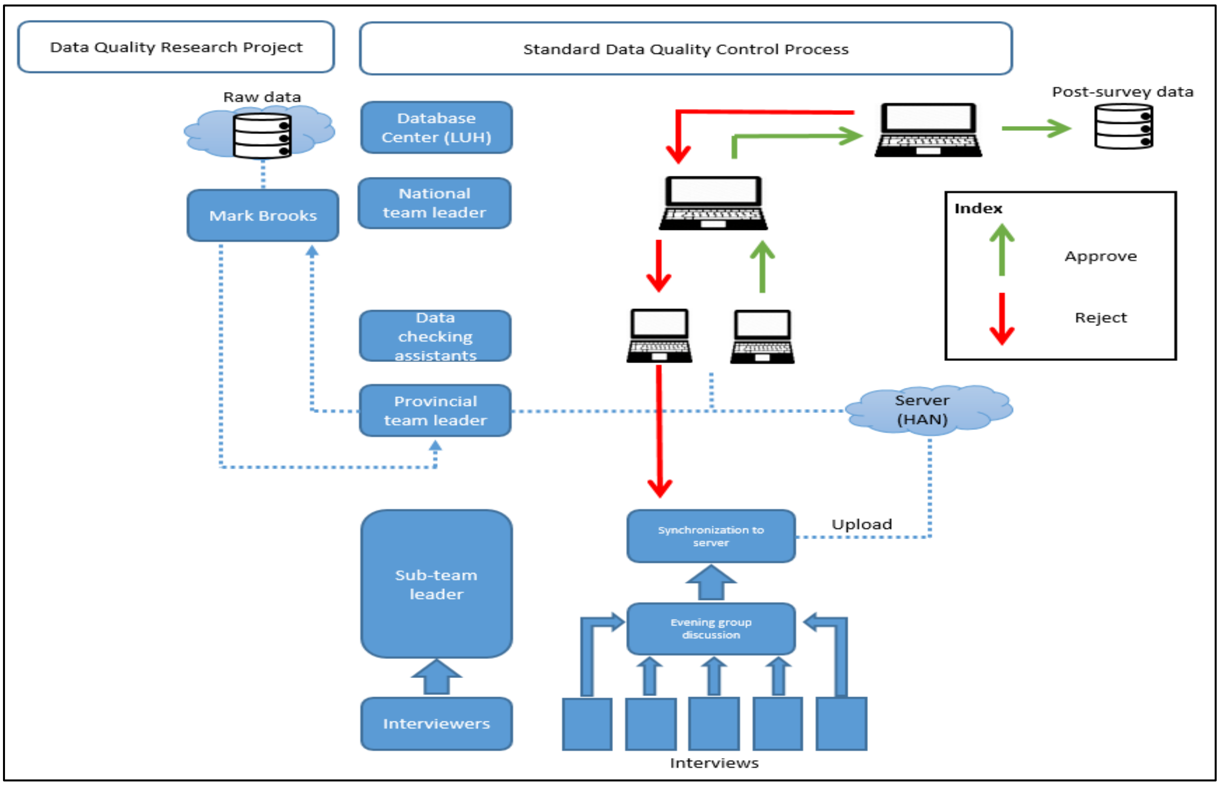

Figure 2.A1 Survey data collection procedure – Example with one survey team
Source: Own illustration.

Table 2.A1 Comparison of goodness-of-fit for combined and country-level count models

	Combined regression model			**Country-level regression model**					
					Thailand			**Vietnam**	
	Missing data	**Refusals**	**Measurement errors**	**Missing data**	**Refusals**	**Measurement errors**	**Missing data**	**Refusals**	**Measurement errors**
AIC	24633	14734	27890	12708	6098	14133	8297	14125	13427
Countfit preferred model	NBRM	NBRM	NBRM	NBRM	NBRM	NBRM	NBRM	NBRM	NBRM
Cragg-Uhlert/ Nahelkerke r^2	0.16	0.14	0.28	0.14	0.14	0.22	0.25	0.23	0.26
Lnalpha significance	6.10E+04***	7,074***	1.50E+04***	4.20E+04***	3,181***	7,666***	2,526***	7,587***	5,887***

Note: * Significant at 10%; ** Significant at 5%; *** Significant at 1%. The countfit command by Long & Freese (2014) compares the fit of Poisson, negative binomial, zero-inflated Poisson and zero-inflated negative binomial models and in doing so provides a table of estimates and results of tests/measures on goodness-of-fit. Thus, the output specifies which count model is preferred by comparing each individual count model with one another. Source: Own calculations based on TVSEP (2018).

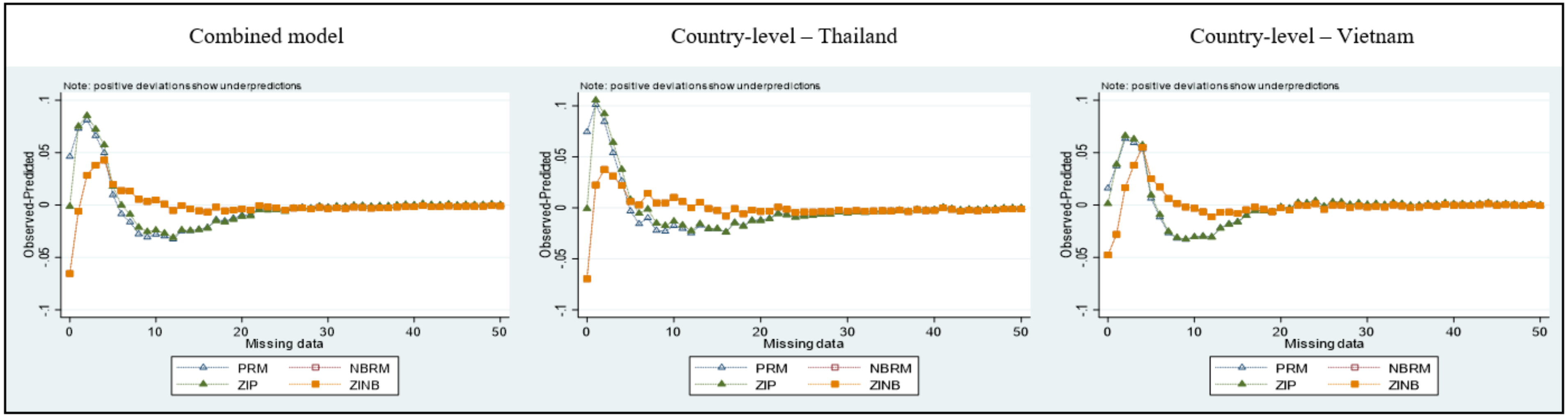

Figure 2.A2 Count model comparison – Missing data
Source: Own calculations using Long & Freese (2014) based on TVSEP (2018).

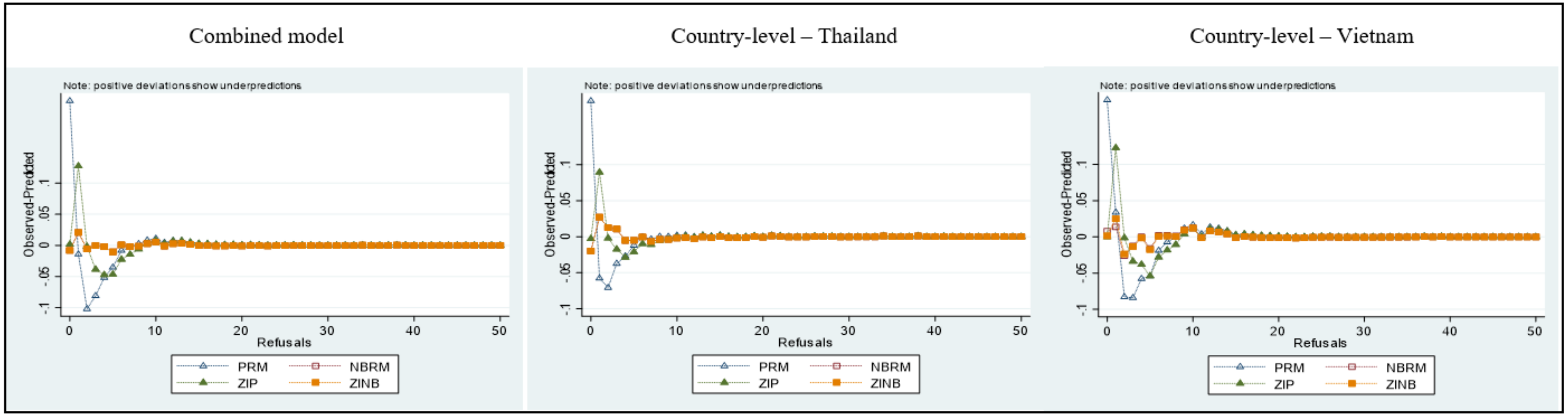

Figure 2.A3 Count model comparison – Refusals
Source: Own calculations using Long & Freese (2014) based on TVSEP (2017).

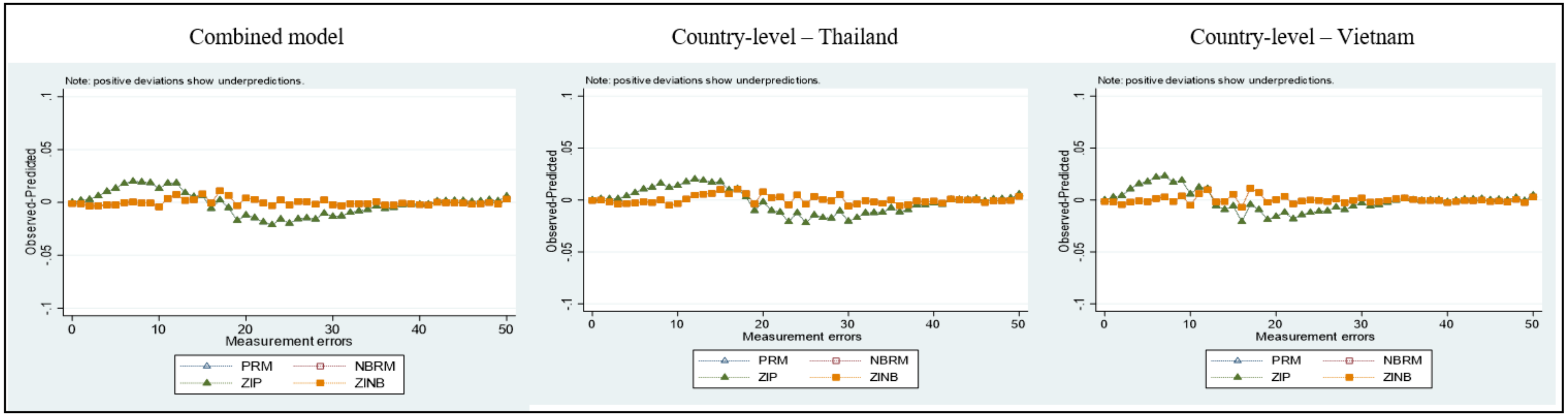

Figure 2.A4 Count model comparison – Measurement errors
Source: Own calculations using Long & Freese (2014) based on TVSEP (2018).

Table 2.A2 Description of explanatory variables

Explanatory variables	Type	Model	Description
Respondent characteristics			
Age	Continuous	All	Age of respondent (years).
Gender	Dummy	All	1 if respondent is male, 0 otherwise.
Secondary education	Dummy	All	1 if respondent has at least completed secondary education, 0 otherwise.
Ethnicity[1]	Dummy		1 if respondent is from the majority ethnic group at the country-level, 0 otherwise.
Head of household	Dummy	II, III	1 if respondent is the head of household, 0 otherwise.
Number of times interviewed	Continuous	II, III	Number of times that a respondent has previously been interviewed.
Openness	Continuous	III	Weighted average score of self-assessed openness (scale 1-7).
Extraversion	Continuous	II	Weighted average score of self-assessed extraversion (scale 1-7).
Neuroticism	Continuous	II	Weighted average score of self-assessed neuroticism (scale 1-7).
Household characteristics			
Household size	Continuous	All	Number of household members (open household definition).
Agricultural land size	Continuous	All	Size of household agricultural land plots (1,000m²).
Yearly per capita income	Continuous	All	Yearly household per capita income (1,000 PPP$).
Interviewer characteristics			
Age	Continuous	All	Age of interviewer (years).
Gender	Dummy	All	1 if interviewer is male, 0 otherwise.
Education	Continuous	All	Interviewer's level of education (years).
Ethnicity[1]	Dummy		1 if interviewer is from the majority ethnic group at the country-level, 0 otherwise.
Survey experience - Other	Dummy	All	1 if interviewer has prior experience in other surveys, 0 otherwise.
Survey experience - TVSEP	Dummy	All	1 if interviewer has prior experience in TVSEP, 0 otherwise.
Years of survey experience	Continuous	All	Interviewer's experience in survey work (years).

Local	Dummy	All	1 if interviewer is native to province of survey, 0 otherwise.
Training	Continuous	II, III	Overall performance during interviewer training (scale 1-7).
Field of study	Categorical	All	1 if field of study is economics or agriculture. 2 if field of study is sociology, languages, or education. 3 if field of study is administration, politics or law.
Openness	Continuous	I, III	Weighted average openness - self-assessed and by supervisor (scale 1-7).
Extraversion	Continuous	III	Weighted average of extraversion - self-assessed and by supervisor (scale 1-7).
Agreeableness	Continuous	II, III	Weighted average of agreeableness - self-assessed and by supervisor (scale 1-7).
Interview/Survey conditions			
Interview duration	Continuous	All	Duration of interview (minutes).
Entry time	Continuous	All	Number of answers entered to tablet per minute.
Morning interview	Dummy	All	1 if interview took place during the morning, 0 otherwise.
Presence of others	Dummy	All	1 if others aside from the interviewer and respondent were present during the interview, 0 otherwise.
Tablet malfunction	Dummy	All	1 if highly negative technical issues affected the interview (as assessed by the interviewers), 0 otherwise.
Survey week	Continuous	All	Progression of the survey (weeks).
Country	Dummy	All (combined)	1 if Thailand, 0 if Vietnam.
Province	Categorical	All (country)	TH / VN 1 Buriram / Ha Tinh 2 Ubon Ratchathani / Thua Thien Hue 3 Nakhon Phanom / Dak Lak

Note: I: model variant – missing data; II: model variant – refusal; III: model variant – measurement errors. [1]Applies only to Vietnamese model variants. Source: Own illustration.

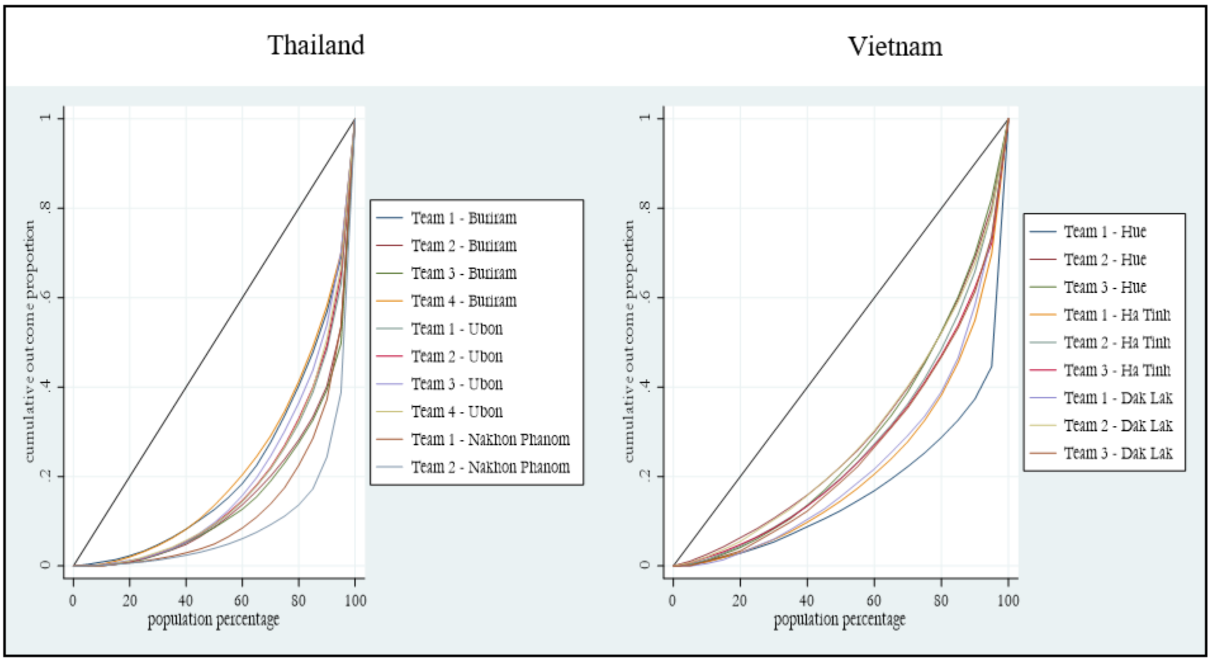

Figure 2.A5 Distribution of provincial team-level inequalities – Missing data
Source: Own calculations based on TVSEP (2018).

Table 2.A3 Factor and percent change transformation – Missing data (Thailand)

	b	z	P>|z|	%	%StdX	SDofX
Respondent characteristics						
Age (years)	-0.008	-0.437	0.662	-0.8	-9.3	12.745
Age squared	0.000	0.854	0.393	0.0	20.8	1,468.752
Gender (1=male, 0=female)	-0.025	-0.322	0.747	-2.5	-1.2	0.475
Secondary education (1=yes, 0=no)	-0.068	-0.697	0.486	-6.6	-2.4	0.363
Household characteristics						
Household size (no. of members)	0.044	2.261	0.024	4.5	8.8	1.915
Agricultural land size (1,000m²)	-0.000	-0.062	0.950	-0.0	-0.2	26.473
Yearly per capita income (1,000 PPP$)	0.002	0.815	0.415	0.2	1.3	6.049
Interviewer characteristics						
Age (years)	0.031	1.426	0.154	3.1	6.3	1.990
Gender (1=male, 0=female)	0.250	2.614	0.009	28.4	11.9	0.450
Education (years)	-0.047	-1.279	0.201	-4.6	-5.5	1.192
Local (1=yes, 0=no)	0.093	1.200	0.230	9.8	4.8	0.498
Agriculture/Economics	-0.467	-4.897	0.000	-37.3	-17.6	0.415
Politics/Administration/Law	-0.321	-4.426	0.000	-27.5	-14.5	0.489
Openness (scale 1-7)	0.070	1.103	0.270	7.2	4.7	0.666
Survey experience – Other (1=yes, 0=no) # Years of survey experience	-0.010	-0.238	0.812	-1.0	-0.8	0.798
Survey experience – TVSEP (1=yes, 0=no) # Years of survey experience	-0.170	-2.372	0.000	-15.6	-11.1	0.695
Congruency						
Respondent gender # Interviewer gender (male/male)	0.161	1.129	0.259	17.4	4.9	0.298
Interview/Survey conditions						
Interview duration (minutes)	0.001	1.161	0.246	0.1	6.4	56.647
Entry time	0.017	1.196	0.232	1.7	6.2	3.521
Morning interview (1=yes, 0=no)	-0.109	-1.776	0.076	-10.4	-5.3	0.499
Presence of others (1=yes, 0=no)	-0.047	-0.613	0.540	-4.6	-1.9	0.408
Tablet malfunction (1=yes, 0=no)	0.143	1.820	0.069	15.4	6.2	0.418
Survey week	-0.246	-8.945	0.000	-21.8	-24.4	1.139
Provinces (Thailand):						
Ubon Ratchathani (ref: Buriram)	0.093	1.022	0.307	9.8	4.8	0.499
Nakhon Phanom (ref: Buriram)	0.330	2.957	0.000	39.1	13.0	0.371
Constant	-4.576	-5.674	0.000	-	-	-
lnalpha	0.412					
alpha	1.510					
LR test of alpha	4.2e+04					
Prob.>= LRX2	0.000					
Observed SD	43.950					

b = raw coefficient
z = z-score for test of b = 0
P>|z| = p-value for z-test
% = percent change in expected count for unit increase in X
%StdX = percent change in expected count for SD increase in X
SDoFX = standard deviation of X

Note: Results are calculated using the listcoef command in Stata; 1,806 observations in Thailand. Source: Own calculations based on TVSEP (2018).

Table 2.9 Factor and percent change transformation – Missing data (Vietnam)

	b	z	P>|z|	%	%StdX	SDofX
Respondent characteristics						
Age (years)	-0.008	-0.816	0.414	-0.8	-10.3	13.8
Age squared	0.000	1.041	0.298	0.0	15.1	1,533.6
Gender (1=male, 0=female)	0.014	0.256	0.798	1.5	0.7	0.4
Secondary education (1=yes, 0=no)	0.135	2.665	0.008	14.4	6.7	0.4
Ethnicity (1=Kinh, 0=other)	0.460	1.528	0.126	58.2	20.7	0.4
Household characteristics						
Household size (no. of members)	0.007	0.467	0.640	0.7	1.3	1.7
Agricultural land size (1,000m²)	0.001	0.849	0.396	0.1	2.1	29.9
Yearly per capita income (1,000 PPP$)	0.019	3.864	0.000	2.0	8.7	4.3
Interviewer characteristics						
Age (years)	0.026	2.659	0.008	2.6	6.1	2.3
Gender (1=male, 0=female)	-0.019	-0.292	0.770	-1.9	-0.9	0.4
Education (years)	-0.052	-2.953	0.003	-5.1	-6.4	1.2
Ethnicity (1=Kinh, 0=other)	-0.260	-0.961	0.336	-22.9	-4.0	0.1
Local (1=yes, 0=no)	0.294	4.510	0.000	34.1	12.7	0.4
Agriculture/Economics	0.002	0.037	0.971	0.2	0.1	0.5
Politics/Administration/Law	-0.122	-1.030	0.303	-11.4	-2.6	0.2
Openness (scale 1-7)	0.070	1.554	0.120	7.3	4.2	0.5
Survey experience – Other (1=yes, 0=no) # Years of survey experience	0.014	1.301	0.193	1.4	3.5	2.5
Survey experience – TVSEP (1=yes, 0=no) # Years of survey experience	-0.160	-3.452	0.001	-14.8	-7.9	0.5
Congruency						
Respondent gender # Interviewer gender (male/male)	0.148	1.694	0.090	16.0	5.8	0.3
Respondent ethnicity # Interviewer ethnicity (majority/majority)	-0.629	-2.084	0.037	-46.7	-23.3	0.4
Interview/Survey conditions						
Interview duration (minutes)	0.000	0.079	0.937	0.0	0.2	96.0
Entry time	-0.002	-0.133	0.894	-0.2	-0.4	2.0
Morning interview (1=yes, 0=no)	-0.131	-3.026	0.002	-12.3	-6.2	0.4
Presence of others (1=yes, 0=no)	-0.073	-1.113	0.266	-7.1	-2.4	0.3
Tablet malfunction (1=yes, 0=no)	-0.127	-2.154	0.031	-11.9	-4.8	0.3
Survey week	-0.141	-6.724	0.000	-13.2	-19.2	1.5
Provinces (Vietnam):						
Thua Thien Hue (ref: Ha Tinh)	0.302	3.713	0.000	35.3	14.9	0.4
Dak Lak (ref: Ha Tinh)	-0.311	-4.332	0.000	-26.7	-13.8	0.4
Constant	-4.256	-7.228	0.000	-	-	-
lnalpha	-0.440					
alpha	0.644					
LR test of alpha	1.3e+04					
Prob.>= LRX2	0.000					
Observed SD	24.272					

b = raw coefficient
z = z-score for test of b = 0
P>|z| = p-value for z-test
% = percent change in expected count for unit increase in X
%StdX = percent change in expected count for SD increase in X
SDoFX = standard deviation of X

Note: Results are calculated using the listcoef command in Stata; 1,827 observations in Vietnam. Source: Own calculations based on TVSEP (2018).

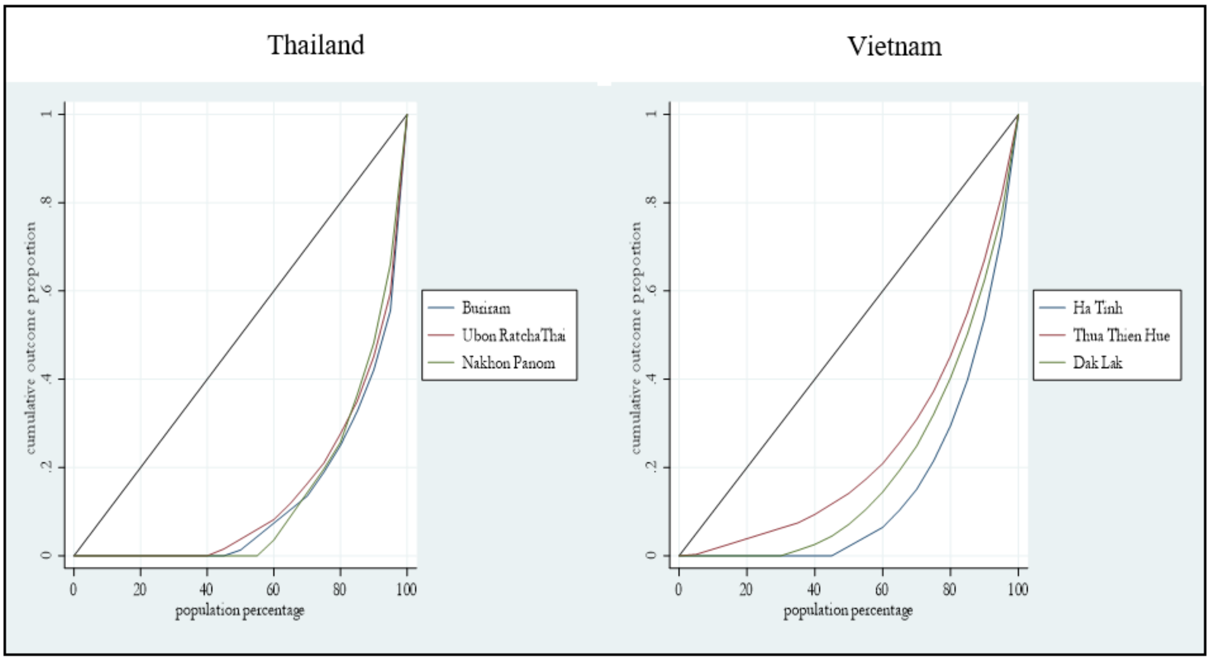

Figure 2.5 Distribution of provincial-level inequalities – Refusals
Source: Own calculations based on TVSEP (2018).

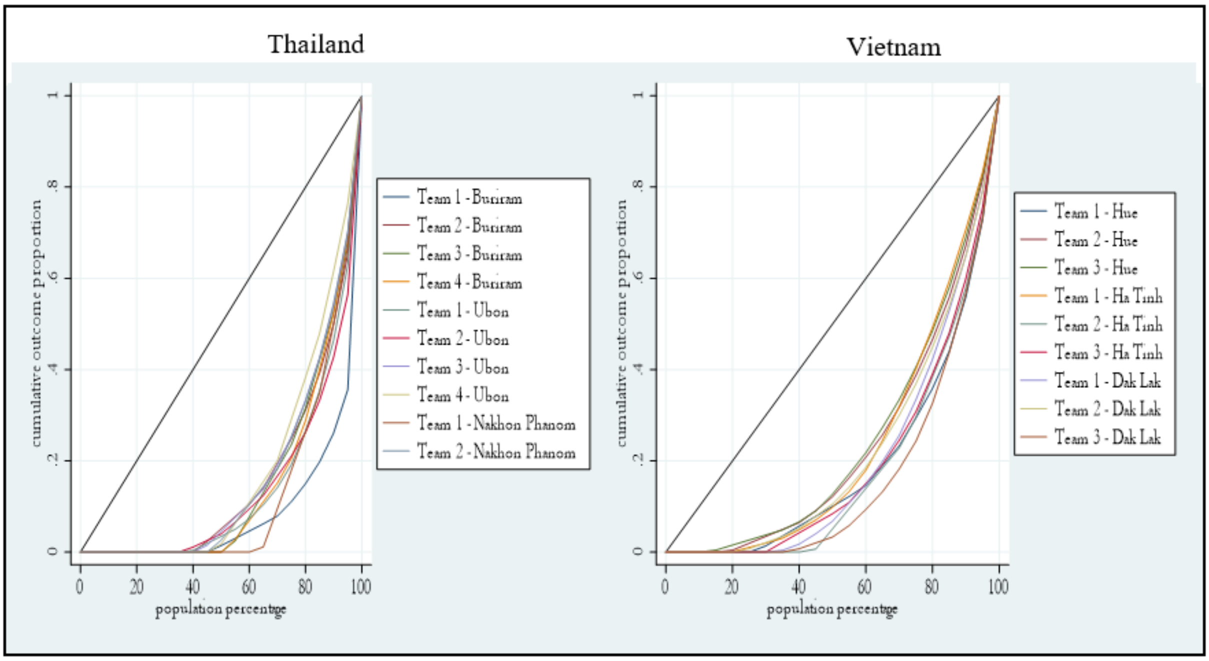

Figure 2.A7 Distribution of provincial team-level inequalities – Refusals
Source: Own calculations based on TVSEP (2018).

Table 2.A5 Factor and percent change transformation – Refusals (Thailand)

	b	z	P>|z|	%	%StdX	SDofX
Respondent characteristics						
Age (years)	-0.030	-1.472	0.141	-2.9	-31.6	12.745
Age squared	0.000	1.776	0.076	0.0	57.4	1,468.752
Gender (1=male, 0=female)	-0.068	-0.646	0.518	-6.6	-3.2	0.475
Secondary education (1=yes, 0=no)	0.038	0.307	0.759	3.8	1.4	0.363
Head of household (1=yes, 0=no)	0.075	0.788	0.431	7.8	3.8	0.495
Number of times interviewed	-0.023	-1.017	0.309	-2.3	-4.1	1.816
Extraversion (scale 1-7)	-0.076	-2.153	0.031	-7.3	-7.7	1.054
Neuroticism (scale 1-7)	0.045	1.295	0.195	4.6	5.2	1.124
Household characteristics						
Household size (no. of members)	-0.027	-1.091	0.275	-2.7	-5.1	1.915
Agricultural land size (1,000m²)	-0.001	-0.699	0.485	-0.1	-2.7	26.473
Yearly per capita income (1,000 PPP$)	0.016	2.538	0.011	1.6	10.0	6.049
Interviewer characteristics						
Age (years)	0.096	3.855	0.000	10.1	21.0	1.990
Gender (1=male, 0=female)	-0.048	-0.432	0.666	-4.6	-2.1	0.450
Education (years)	-0.025	-0.583	0.560	-2.5	-3.0	1.192
Local (1=yes, 0=no)	0.160	1.655	0.098	17.4	8.3	0.498
Training (scale 1-7)	-0.032	-0.479	0.632	-3.2	-2.0	0.644
Agriculture/Economics	0.343	3.028	0.002	40.9	15.3	0.415
Politics/Administration/Law	0.126	1.278	0.201	13.4	6.3	0.489
Agreeableness (scale 1-7)	-0.239	-2.851	0.004	-21.2	-14.2	0.644
Survey experience – Other (1=yes, 0=no) # Years of survey experience	0.331	6.749	0.000	39.2	30.2	0.798
Survey experience – TVSEP (1=yes, 0=no) # Years of survey experience	0.085	1.353	0.176	8.9	6.1	0.695
Congruency						
Respondent gender # Interviewer gender (male/male)	-0.098	-0.557	0.577	-9.3	-2.9	0.298
Interview/Survey conditions						
Interview duration (minutes)	-0.000	-0.160	0.872	-0.0	-1.0	56.647
Entry time	0.027	1.409	0.159	2.7	9.8	3.521
Morning interview (1=yes, 0=no)	0.136	1.828	0.067	14.6	7.0	0.499
Presence of others (1=yes, 0=no)	-0.078	-0.801	0.423	-7.5	-3.1	0.408
Tablet malfunction (1=yes, 0=no)	0.118	1.236	0.216	12.5	5.1	0.418
Survey week	0.267	7.639	0.000	30.6	35.5	1.139
Provinces (Thailand):						
Ubon Ratchathani (ref: Buriram)	0.107	1.047	0.295	11.2	5.5	0.499
Nakhon Phanom (ref: Buriram)	-0.261	-1.768	0.077	-23.0	-9.2	0.371
Constant	-7.351	-7.172	0.000	-	-	-
lnalpha	0.518					
alpha	1.678					
LR test of alpha = 0	3,812.39					
Prob.>= LRX2	0.000					
Observed SD	5.947					
b = raw coefficient	% = percent change in expected count for unit increase in X					
z = z-score for test of b = 0	%StdX = percent change in expected count for SD increase in X					
P>|z| = p-value for z-test	SDoFX = standard deviation of X					

Note: Results are calculated using the listcoef command in Stata; 1,806 observations in Thailand. Source: Own calculations based on TVSEP (2018).

Table 2.A6 Factor and percent change transformation – Refusals (Vietnam)

	b	z	P>|z|	%	%StdX	SDofX
Respondent characteristics						
Age (years)	-0.042	-3.317	0.001	-4.1	-44.3	13.858
Age squared	0.001	3.994	0.000	0.0	100.7	1,533.658
Gender (1=male, 0=female)	-0.358	-4.109	0.000	-30.1	-16.3	0.496
Secondary education (1=yes, 0=no)	-0.235	-3.561	0.000	-20.9	-10.6	0.479
Ethnicity (1=Kinh, 0=other)	0.142	0.381	0.703	15.3	6.0	0.410
Head of household (1=yes, 0=no)	0.082	0.926	0.355	8.5	4.1	0.495
Number of times interviewed	-0.015	-0.682	0.495	-1.4	-2.5	1.746
Extraversion (scale 1-7)	-0.034	-1.331	0.183	-3.3	-3.6	1.096
Neuroticism (scale 1-7)	0.029	1.048	0.295	3.0	3.2	1.074
Household characteristics						
Household size (no. of members)	-0.010	-0.532	0.594	-1.0	-1.8	1.791
Agricultural land size (1,000m²)	0.001	0.824	0.410	0.1	2.1	29.971
Yearly per capita income (1,000 PPP$)	-0.013	-1.726	0.084	-1.3	-5.3	4.318
Interviewer characteristics						
Age (years)	-0.040	-2.839	0.005	-3.9	-8.9	2.332
Gender (1=male, 0=female)	-0.589	-6.576	0.000	-44.5	-25.1	0.490
Education (years)	0.036	1.494	0.135	3.6	4.6	1.264
Ethnicity (1=Kinh, 0=other)	-0.558	-1.667	0.096	-42.7	-8.4	0.157
Local (1=yes, 0=no)	-0.248	-2.998	0.003	-22.0	-9.6	0.407
Training (scale 1-7)	-0.0445	-0.832	0.405	-4.4	-2.6	0.587
Agriculture/Economics	0.282	3.680	0.000	32.5	15.1	0.500
Politics/Administration/Law	-0.100	-0.616	0.538	-9.5	-2.2	0.220
Agreeableness (scale 1-7)	-0.254	-4.779	0.000	-22.4	-13.9	0.591
Survey experience – Other (1=yes, 0=no) # Years of survey experience	-0.050	-3.247	0.001	-4.9	-11.8	2.503
Survey experience – TVSEP (1=yes, 0=no) # Years of survey experience	-0.118	-1.877	0.060	-11.1	-5.9	0.516
Congruency						
Respondent gender # Int. gender (male/male)	0.419	3.570	0.000	52.0	17.3	0.381
Respondent ethnicity # Int. ethnicity (majority/majority)	-0.598	-1.587	0.112	-45.0	-22.3	0.423
Interview/Survey conditions						
Interview duration (minutes)	-0.002	-4.272	0.000	-0.2	-15.1	96.011
Entry time	-0.085	-4.302	0.000	-8.1	-16.2	2.089
Morning interview (1=yes, 0=no)	0.042	0.741	0.459	4.3	2.1	0.492
Presence of others (1=yes, 0=no)	0.029	0.334	0.738	3.0	1.0	0.327
Tablet malfunction (1=yes, 0=no)	-0.082	-1.048	0.295	-7.9	-3.1	0.385
Survey week	-0.056	-2.022	0.043	-5.5	-8.1	1.508
Provinces (Vietnam):						
Thua Thien Hue (ref: Ha Tinh)	0.729	6.809	0.000	107.3	39.9	0.461
Dak Lak (ref: Ha Tinh)	0.795	8.482	0.000	121.4	46.1	0.477
Constant	-0.743	-0.795	0.426	-	-	-
lnalpha	-0.003					
alpha	0.997					
LR test of alpha = 0; 4.2e+04	2,525.62					
Prob.>= LRX2 = 0.000	0.000					
Observed SD	4.228					

b = raw coefficient | % = percent change in expected count for unit increase in X
z = z-score for test of b = 0 | %StdX = percent change in expected count for SD increase in X
P>|z| = p-value for z-test | SDoFX = standard deviation of X

Note: Results are calculated using the listcoef command in Stata; 1,827 observations in Vietnam. Source: Own calculations based on TVSEP (2018).

Table 2.A7 Factor and percent change transformation – Measurement errors (Thailand)

	b	z	P>|z|	%	%StdX	SDofX
Respondent characteristics						
Age (years)	-0.008	-1.183	0.237	-0.8	-9.4	12.745
Age squared	0.000	1.160	0.246	0.0	10.0	1,468.752
Gender (1=male, 0=female)	0.008	0.254	0.800	0.8	0.4	0.475
Secondary education (1=yes, 0=no)	-0.017	-0.451	0.652	-1.6	-0.6	0.363
Head of household (1=yes, 0=no)	0.055	1.860	0.063	5.7	2.8	0.495
Number of times interviewed	-0.021	-2.913	0.004	-2.1	-3.7	1.816
Openness (scale 1-7)	0.002	0.219	0.827	0.2	0.3	1.270
Household characteristics						
Household size (no. of members)	-0.009	-1.175	0.240	-0.9	-1.8	1.915
Agricultural land size (1,000m²)	-0.000	-0.104	0.917	-0.0	-0.1	26.473
Yearly per capita income (1,000 PPP$)	0.007	4.051	0.000	0.7	4.6	6.049
Interviewer characteristics						
Age (years)	0.010	1.274	0.203	1.0	2.1	1.990
Gender (1=male, 0=female)	-0.085	-2.242	0.025	-8.1	-3.7	0.450
Education (years)	-0.036	-2.532	0.011	-3.5	-4.2	1.192
Local (1=yes, 0=no)	0.195	6.443	0.000	21.5	10.2	0.498
Training (scale 1-7)	-0.059	-2.821	0.005	-5.7	-3.7	0.644
Agriculture/Economics	-0.270	-7.734	0.000	-23.7	-10.6	0.415
Politics/Administration/Law	-0.199	-6.663	0.000	-18.0	-9.2	0.489
Openness (scale 1-7)	0.096	3.827	0.000	10.1	6.6	0.666
Extraversion (scale 1-7)	-0.127	-4.344	0.000	-11.9	-6.0	0.484
Agreeableness (scale 1-7)	-0.069	-2.755	0.006	-6.7	-4.4	0.644
Survey experience – Other (1=yes, 0=no) # Years of survey experience	-0.015	-0.899	0.369	-1.5	-1.2	0.798
Survey experience – TVSEP (1=yes, 0=no) # Years of survey experience	0.005	0.270	0.787	0.5	0.4	0.695
Congruency						
Respondent gender # Int. gender (male/male)	-0.040	-0.730	0.465	-3.9	-1.2	0.298
Interview/Survey conditions						
Interview duration (minutes)	0.001	1.867	0.062	0.1	4.0	56.647
Entry time	0.011	1.879	0.060	1.1	4.0	3.521
Morning interview (1=yes, 0=no)	0.022	0.937	0.349	2.2	1.1	0.499
Presence of others (1=yes, 0=no)	0.009	0.290	0.771	0.9	0.4	0.408
Tablet malfunction (1=yes, 0=no)	0.044	1.481	0.139	4.5	1.9	0.418
Survey week	-0.160	-14.917	0.000	-14.7	-16.6	1.139
Provinces (Thailand):						
Ubon Ratchathani (ref: Buriram)	-0.023	-0.669	0.503	-2.3	-1.2	0.499
Nakhon Phanom (ref: Buriram)	-0.087	-1.837	0.066	-8.4	-3.2	0.371
Constant	-2.075	-5.576	0.000	-	-	-
lnalpha	-1.584					
alpha	0.205					
LR test of alpha = 0	7,665.71					
Prob.>= LRX2	0.000					
Observed SD	18.917					

b = raw coefficient; % = percent change in expected count for unit increase in X
z = z-score for test of b = 0; %StdX = percent change in expected count for SD increase in X
P>|z| = p-value for z-test; SDoFX = standard deviation of X

Note: Results are calculated using the listcoef command in Stata; 1,806 observations in Thailand. Source: Own calculations based on TVSEP (2018).

Table 2.A8 Factor and percent change transformation – Measurement errors (Vietnam)

	b	z	P>|z|	%	%StdX	SDofX
Respondent characteristics						
Age (years)	0.008	1.452	0.147	0.8	12.0	13.858
Age squared	-0.000	-1.022	0.307	-0.0	-7.6	1,533.658
Gender (1=male, 0=female)	-0.056	-1.446	0.148	-5.5	-2.7	0.496
Secondary education (1=yes, 0=no)	0.051	1.732	0.083	5.2	2.4	0.479
Ethnicity (1=Kinh, 0=other)	0.632	3.420	0.001	88.1	29.5	0.410
Head of household (1=yes, 0=no)	0.082	2.092	0.036	8.5	4.1	0.495
Number of times interviewed	-0.020	-2.159	0.031	-2.0	-3.5	1.746
Openness (scale 1-7)	0.013	1.408	0.159	1.4	1.9	1.375
Household characteristics						
Household size (no. of members)	-0.021	-2.309	0.021	-2.1	-3.7	1.791
Agricultural land size (1,000m²)	-0.000	-0.509	0.611	-0.0	-0.6	29.971
Yearly per capita income (1,000 PPP$)	0.005	1.829	0.067	0.5	2.0	4.318
Interviewer characteristics						
Age (years)	-0.047	-8.177	0.000	-4.6	-10.3	2.332
Gender (1=male, 0=female)	0.126	3.348	0.001	13.4	6.4	0.490
Education (years)	-0.009	-0.916	0.360	-0.9	-1.2	1.264
Ethnicity (1=Kinh, 0=other)	-0.714	-3.840	0.000	-51.0	-26.0	0.423
Local (1=yes, 0=no)	0.019	0.501	0.616	1.9	0.8	0.407
Training (scale 1-7)	-0.188	-7.866	0.000	-17.2	-10.5	0.587
Agriculture/Economics	0.070	2.109	0.035	7.3	3.6	0.500
Politics/Administration/Law	0.205	2.788	0.005	22.7	4.6	0.220
Openness (scale 1-7)	0.040	1.424	0.155	4.1	2.3	0.578
Extraversion (scale 1-7)	-0.030	-0.757	0.449	-2.9	-1.1	0.374
Agreeableness (scale 1-7)	0.061	2.394	0.017	6.3	3.7	0.591
Survey experience – Other (1=yes, 0=no) # Years of survey experience	0.021	2.985	0.003	2.1	5.4	2.503
Survey experience – TVSEP (1=yes, 0=no) # Years of survey experience	-0.130	-4.806	0.000	-12.2	-6.5	0.516
Congruency						
Respondent gender # Int. gender (male/male)	-0.062	-1.240	0.215	-6.0	-2.3	0.381
Respondent ethnicity # Int. ethnicity (majority/majority)	-0.714	-3.840	0.000	-51.0	-26.0	0.423
Interview/Survey conditions						
Interview duration (minutes)	0.001	4.992	0.000	0.1	9.8	96.011
Entry time	0.034	3.548	0.000	3.4	7.3	2.089
Morning interview (1=yes, 0=no)	0.012	0.493	0.622	1.2	0.6	0.492
Presence of others (1=yes, 0=no)	0.097	2.539	0.011	10.2	3.2	0.327
Tablet malfunction (1=yes, 0=no)	-0.104	-3.112	0.002	-9.9	-3.9	0.385
Survey week	-0.096	-7.926	0.000	-9.2	-13.5	1.508
Provinces (Vietnam):						
Thua Thien Hue (ref: Ha Tinh)	-0.025	-0.532	0.594	-2.5	-1.2	0.461
Dak Lak (ref: Ha Tinh)	-0.251	-5.960	0.000	-22.2	-11.3	0.477
Constant	-0.743	-0.795	0.426	-	-	-
lnalpha	-1.572					
alpha	0.208					
LR test of alpha = 0	5,887.03					
Prob.>= LRX2	0.000					
Observed SD	17.280					

b = raw coefficient; % = percent change in expected count for unit increase in X
z = z-score for test of b = 0; %StdX = percent change in expected count for SD increase in X
P>|z| = p-value for z-test; SDoFX = standard deviation of X

Note: Results are calculated using the listcoef command in Stata; 1,827 observations in Vietnam. Source: Own calculations based on TVSEP (2018).

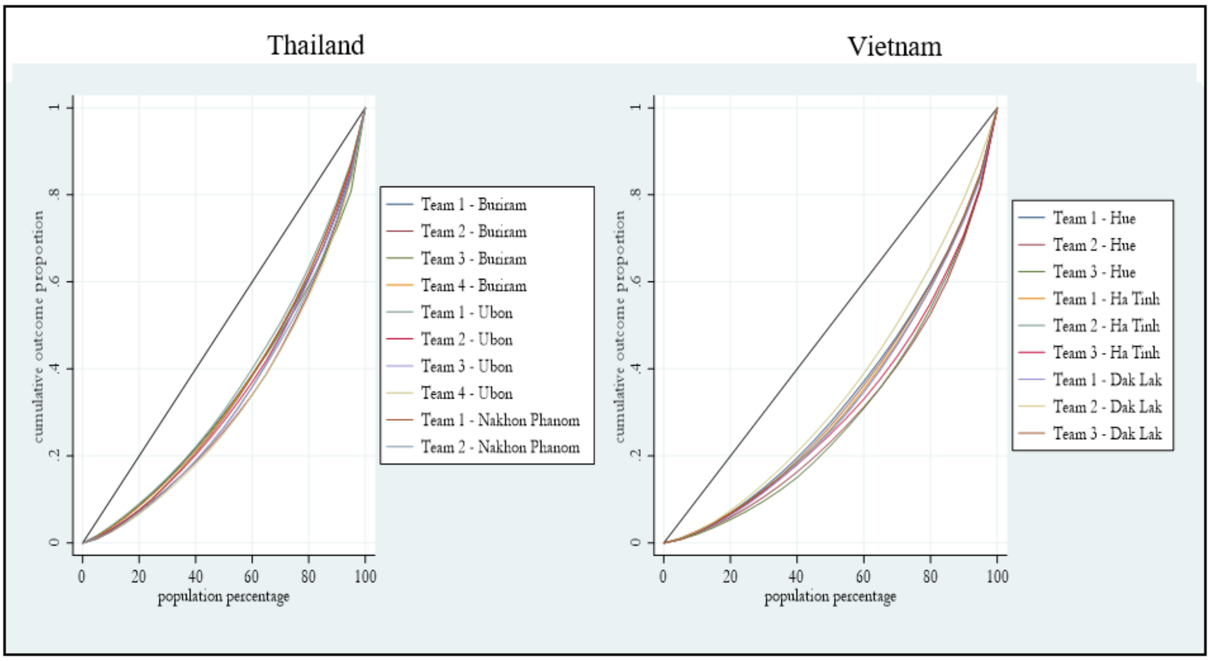

Figure 2.A8 Distribution of provincial team-level inequalities – Measurement errors
Source: Own calculations based on TVSEP (2018).

CHAPTER 3: INCONSISTENT RESPONSES IN HOUSEHOLD PANEL SURVEYS: THE CASE OF NON-FARM EMPLOYMENT

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Abstract

Using seven waves, spanning twelve years, of a household panel survey conducted in Thailand, we develop a methodology that allows to identify inconsistencies between pairs of consecutive panel waves. A multilevel logistic approach is applied with respondent and employment characteristics constituting major explanatory variables. Substantial inconsistencies are observed to be correlated with employment characteristics. In particular, informal employments exhibit a significantly higher likelihood of inconsistent reporting. Respondent behaviour, rather than socio-economic characteristics of the respondent, is suggested to drive the decision to misreport. Policy implications are derived by calculating poverty head counts at the district and provincial levels, whereby income from omitted employments has severe implications on poverty indicators. We demonstrate that the analysis of consistency of reported employments between pairs of consecutive survey waves yields important insights for survey providers allowing for validation and improved robustness of underlying datasets.

Keywords: Nonsampling errors, data quality, household panel surveys, rural livelihoods, employment, multilevel regression, Thailand

JEL: C8, J2, O1

3.1 Introduction

Household panel surveys are an important source of longitudinal data for research, policy formulation and decision-making. Household surveys often function as substitutes for constrained administrative data, particularly in low- and middle-income countries (Reid et al., 2017; Vaessen et al., 2005). The number of household panel surveys conducted has surged in recent years, which is facilitated by readily available, user-friendly survey tools, technological advances and increasing computational capacities.

Despite substantial achievements in household surveys conducted in low- and middle-income countries, high-quality outputs remain sparse (Dang & Carletto, 2018). Recent research indicates that data generated by household surveys may be unreliable and insufficiently accurate (Meyer et al., 2015; Sanna & McDonnell, 2017). Strikingly, it has been established that relatively few data sets collected are suitable for calculating valid poverty estimates (Booth, 2019; Dang & Serajuddin, 2020; Gibson, 2016; Serajuddin et al., 2015).

While the issue of data quality can be assessed from numerous perspectives (Biemer, 2010), the longitudinal nature of household panel surveys inevitably raises the issue of consistency. Inconsistencies in reporting constitute nonsampling errors and typically arise due to nonresponse or measurement errors (Groves & Lyberg, 2010). Especially survey modules on employment have been identified as being prone to inconsistent reporting across waves in household surveys in Europe (Huber & Schmucker, 2009; Maré, 2006). However, this issue has not yet been sufficiently explored in development economics, which is reliant on household panel surveys such as the World Bank's Living Standards Measurement Study (LSMS).

Following decades of rapid economic growth in Asian economies, a transition from predominantly agricultural production to diversified, emerging market economies is observed (Haraguchi et al., 2019; Stiglitz, 1996; World Bank, 2018). Thereby, changes in predominantly agricultural dominated livelihood strategies are induced driven by novel opportunities presented and challenges inherent to agricultural production (Hayami, 2007; Reardon et al., 2007). This phenomenon is not confined to major cities and urban areas with rural households being observed to diversify their income-generating activities by modernising agricultural activities and increasingly pursuing off-farm employments and non-farm self-employment, which increases their reliance on off-farm income (Devereux et al., 2012; Gödecke & Waibel, 2011; Hayami & Ruttan, 1971; Hohfeld & Waibel, 2013; Schultz, 1964). A substantial source of employment is observed to stem from informal activities (Charmes, 2012; ILO, 2018; Lee et al., 2020), which are characterised by high fluctuations in employment due to, for example, low barriers of entry and exit such as the absence of written contracts (Grimm et al., 2011; Henley et al., 2009).

This study strives to fill the gap in the literature by assessing the consistency of reported employments across panel waves in household surveys. We base our analysis on a data set from Thailand consisting of seven waves, collected from 2007-2019, which stems from the Thailand Vietnam Socio Economic Panel (TVSEP). Thereby, 1,542 identical households interviewed throughout all survey waves are considered in order to facilitate the identification of inconsistent responses between pairs of consecutive waves. We implement a multilevel logistic regression in order to examine the factors that influence inconsistent responses pertaining to household member employment. Further, we discuss the applicability of results for other household surveys and their potential impact on policy.

Three major results are identified in this study. First, both off-farm and non-farm self-employments are shown to be afflicted with substantial incidence of inconsistent reporting. Second, although the respondent level is shown to explain a significant proportion of variance in reporting employment, socio-economic characteristics are not found to be significant, rather traits intrinsic to the respondent are, i.e., their level of trust. Further, informal employments are found to be most likely to be inconsistently reported. Third, considering the growing importance of income obtained from off-farm wage employment and self-employment in rural Thailand, misreporting thereof results in an overestimation of rural poverty at the provincial level by on average 6.7 percentage points.

The remainder of the paper is structured as follows: Section 3.2 provides an overview of data quality identified in the literature in the context of employment upon which our hypotheses are derived. Section 3.3 describes our study area and introduces the dataset. Section 3.4 introduces the empirical strategy used to identify inconsistently reported employments and model factors thereof. Section 3.5 contains a descriptive and empirical analysis pertaining to inconsistencies of reported employments using a long-term household panel data set. Further, the impact of inconsistent reporting on poverty outcomes is visualised. The final section draws conclusions from the model results and provides practical recommendations to survey providers in low- and middle-income countries.

3.2 Data quality in employment modules

With the rising importance of survey data and measuring the quality thereof, frameworks were developed with which one can describe and categorise survey error. The most widely used framework, the Total Survey Error (TSE) approach (Groves, 1989), is based on the premise that survey error occurs during each stage of the survey. Thereby, a systematic description and categorisation of survey error spanning from the conception of the survey to post-survey data processing is facilitated (Weisberg, 2005). Typically, survey error is split into three overarching categories, namely: (a) issues of respondent selection; (b) issues of response accuracy; and (c) issues of post-survey processing. Respondent selection errors encompass the well-known sampling, coverage, and unit non-response errors. Response accuracy errors pertain to inaccurate responses collected during the interview procedure and encompass both interviewer and respondent effects on the quality of data as well as other outside effects. Post-survey errors are introduced to data sets after data collection has concluded, for example, during data processing or analyses.

This study focuses on measurement error and item nonresponse, which are considered as some of the most impactful detriments to collecting high-quality data (Biemer, 2010). Measurement error is defined as the discrepancy observed between an obtained measure and the true value of measurement, e.g., when a respondent reports some off-farm employments while omitting others. Conversely, item nonresponse describes the respondent's decision to decline to answer an individual survey item – either due to lack of cooperation or knowledge. For example, a respondent may elect to state that a household has no off-farm employment despite members being employed. This study focuses on the role of the respondent in reporting of employments of household members.

There is an abundance of literature that examines the impact of the respondent on aspects of data quality with most studies controlling for socio-economic characteristics such as, age, gender, or education. Cognitive ability of respondents is frequently controlled for using age and education. Typically, both elderly and young respondents are considered to have a negative impact on the quality of collected data. Further, respondents with lower levels of educational attainment are found to be more likely to provide lower-quality responses (Knäuper et al., 1997; Knäuper, 1999; Krosnick, 1991). Generally, studies on the effect of gender on data quality are inconclusive (Heerwegh & Loosveldt, 2008; Phung et al., 2015; Silber et al., 2019). Panel conditioning is a distinct feature of household panel surveys and indicates that increasing time spent within the survey results in downward bias of reported employments (Halpern-Manners & Warren, 2012). A common approach for household surveys in low- and middle-income countries is the use of proxy respondents, whereby the head of household is preferred due to be being considered as being most knowledgeable about household activities (Bardasi et al., 2011). Respondent fatigue, as proxied for by measurements of interview complexity, is shown to influence the quality of data. Lengthy interviews and the positioning of survey modules are found to fatigue the respondent and thereby increase the prevalence of nonsampling errors (Ambler et al., 2021; Galesic & Bosnjak, 2009; Jeong et al., 2023; Phung et al., 2015).

In the literature, the quality of data obtained from modules on labour activities has been observed to be prone to measurement error (Bound et al., 2001). In observing wage-earning trends, large inconsistencies have been identified in the reporting of employments (Gottschalk & Huynh, 2010; Uhrig & Watson, 2020). Further studies have compared employment data collected by surveys with administrative data and observed underreporting of employment status in household surveys (Huber & Schmucker, 2009; Meyer et al., 2015). Implementing a field experiment, Ambler et al. (2021) observe one in eleven employments are mistakenly not reported due to systematic biases introduced by the structure of the survey instrument. Attempts to construct consistent work-life histories using household survey employment data have proved challenging with low reliability (74%) of reported industry and employment categories hindering clear matches (Maré, 2006). Therefore, in the context of rapid industrialisation and diversifying livelihoods, we hypothesise that employment data collected in household surveys in low- and middle-income countries fluctuate highly.

A further parallel underlining the difficulty of obtaining true measurements of employment can be observed in the literature concerning accuracy of reported income. Studies find that income is often under-/overestimated and subject to nonresponse (Groves & Couper, 1998; Hurst et al., 2014; Lynn & Clarke, 2002) due to its sensitive nature, in particular when true values of income constitute outliers on the outer tails of a distribution (Meyer et al., 2022; Moore et al., 2000).

This issue is hypothesised to be exacerbated in low- and middle-income countries that are characterised with high-shares of informal employment with literature pointing out further weaknesses of household surveys in obtaining accurate measures thereof (Alkire, 2007; Desiere & Costa, 2019; Hussmanns, 2004). Based on the literature review, we hypothesise that factors influencing erroneously reported employments stem from characteristics from the respondent and employment. Additionally, the prevalence of erroneous employment data is hypothesised to have severe implications for outcome variables related to poverty.

3.3 Study area and survey instrument

This study focuses on Thailand as an example of a Southeast Asian country that achieved substantial growth. In the past decades, Thailand rapidly transitioned from a low-income country founded on an undiversified agricultural rice economy, to an upper-middle-income economy (Ahmad & Isvilanonda, 2005; Falkus, 1995). Economic growth was heavily concentrated in the Bangkok Metropolitan Region resulting in thriving rural-urban migration (Amare et al., 2012). In rural Thailand, non-farm employment yields higher incomes and is observed to be preferred over agriculture (Chawanote & Barrett, 2013), which further drives internal migration to urban centres (Harris & Todaro, 1970; Lall & Selod, 2006; Todaro, 1980). Thailand is home to a pronounced informal sector with 56% of labour being based therein. Notably, informality of employment is not limited to rural areas with the service sector being found to account for over one third of informal employment (Fleischer et al., 2018).

The Thailand Vietnam Socio Economic Panel[9] (TVSEP) is a long-term household panel survey that collects data on poverty dynamics of rural households in three provinces of Thailand and was designed to be representative of the rural population of Northeast Thailand (Hardeweg et al., 2013). The initial sample encompassed 2,200 households located in the provinces of Buriram, Ubon Ratchathani, and Nakhon Phanom (Figure 3.A1.1). Data was collected from 220 villages, of which two villages were drawn from each sampled sub-district using a three-stage sampling design (Hardeweg et al., 2013). In total, seven full household surveys were conducted and made available between 2007 and 2019 in Thailand. We limit the sample to those households that are observed consistently throughout the entirety of the survey. Thus, the final sample includes 1,542 households from the 2,200 households that were initially sampled in 2007.

The underlying survey instrument is based on the Living Standards Measurement Study (LSMS) of the World Bank, which is the standard for many surveys in low- and middle-income countries. Typical modules are supplemented with modules on shocks, risks, and behavioural

[9] Further information and survey documents can be found on the TVSEP website – see: https://www.tvsep.de/en/data/survey-documents/.

aspects of development. The modules on off-farm and self-employment follow closely the suggestions and guidelines of the LSMS, in particular the work of Grosh and Glewwe (2000). Thereby, the survey instrument entails a detailed labour module split into sections on off-farm employment and non-farm self-employment, which is extended and provides more in-depth information on individual employments (Figure 3.1). LSMS-style surveys typically collect detailed information for primary employments of household members but only provide aggregates on all additional employments (Durazo et al., 2021; UN, 2005). This is also observed to be typical in derivatives of LSMS, such as Integrated Surveys on Agriculture (LSMS(-ISA)), and national Labour Force Surveys (LFS) (Desiere & Costa, 2019). In TVSEP, however, each employment is captured individually. Further, the reference period utilised in LSMS often spans the last seven days prior to date of interview for detailed information only (e.g., Desiere & Costa, 2019; Durazo et al., 2021), whereas the reference period spans 365 days in TVSEP. The analysis of inconsistent reporting in this study is further facilitated by additional information provided, such as on geographic location of employment, work experience and disaggregated sources of income (Figure 3.1).

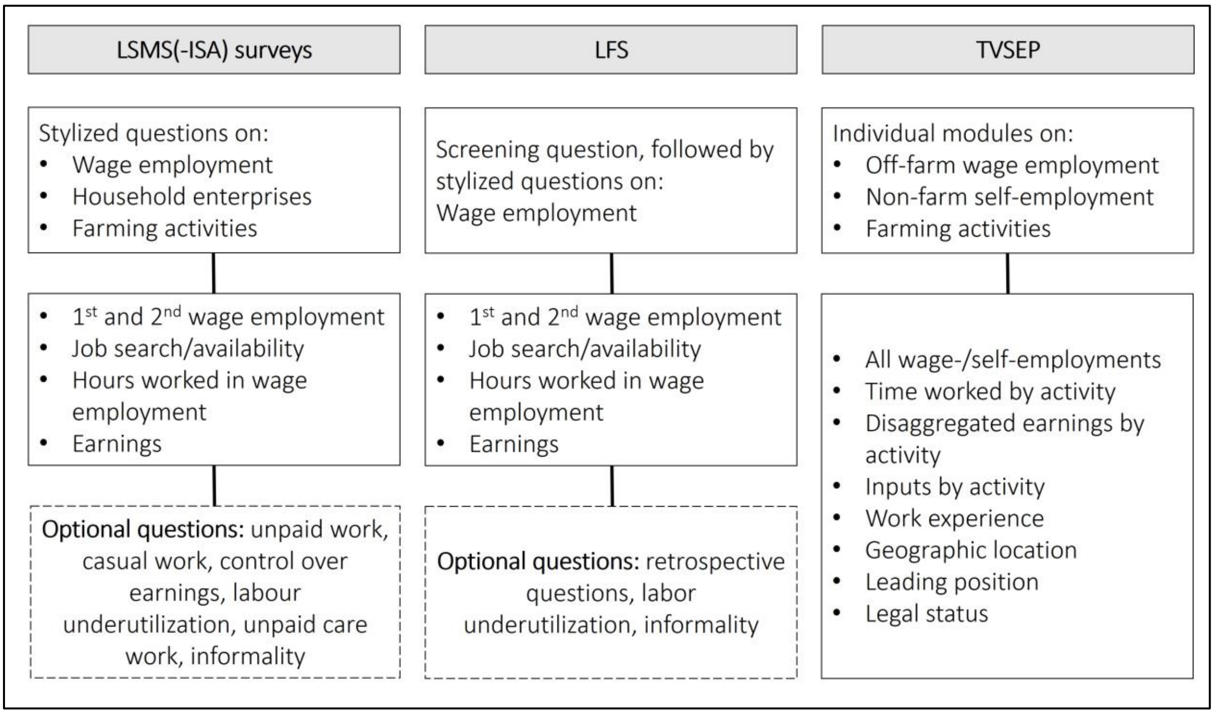

Figure 3.1 Comparison of labour module structures
Source: Desiere & Costa (2019), modified.

3.4 Methodology

3.4.1 Defining and identifying inconsistencies in reported employments

In this section, we develop an approach to identify the extent of and factors influencing inaccurate measures, i.e., consistency, which are present in employment data of a long-term household panel survey. Notably, while consistency need not necessarily infer accuracy, inconsistency clearly indicates that at least one of the two responses is inaccurate (Jaeger & Pennock, 1961). We define inconsistency to encompass the most obvious and severe form of inconsistent reporting, which takes place when an observation is not reported in its entirety. This can be interpreted as being comparable to unit nonresponse, albeit being attributable to only one member in one particular section, i.e., employment, rather than the failure of collecting data on a sample unit as a whole.

Individuals are often observed to fluctuate between different employments throughout their lives. While, fluctuations in reported employments in the context of household surveys often represent plausible transitions, these have been identified to be inflated by inconsistent responses (e.g., Ambler et al., 2021; Gottschalk & Huynh, 2010; Uhrig & Watson, 2020). Therefore, the first step is to verify the presence of fluctuations in reported employments in the underlying dataset and visualise their extent.

Thereafter, a three-stage approach is developed to identify cases of inconsistent reporting between pairs of consecutive survey waves, which is a modification of the approach implemented in the British Household Panel Survey (Maré, 2006). Maré (2006) base their analysis of internal consistency on three criteria, namely, the label of the employment, the industry, and the year in which the individual began pursuing the employment. Where labels were mismatched, congruent information on when the employment was first pursued was determined to be sufficient to allow for matching. This study modifies this approach to accommodate for the informal nature of employment in rural Thailand and availability of supplemental information provided in the questionnaire in order to allow for a more stringent matching approach, which is specified as follows:

Inconsistencies, as defined in this study, are identified by first determining all employments reported in wave w_n, which are expected to also occur in w_{n-1}. This expectation is driven by the response provided in w_n, which captures the year in which the individual began pursuing the reported employment. The underlying survey instrument utilises the following items:

- Off-farm wage employment: "Since when has [Name] been working in this job?"
- Self-employment: "Since when have you run this business?"

Thereby, employments are inconsistent if they are, in contradiction with responses in w_n, not observed in w_{n-1}.

As illustrated in Figure 3.2, the reported information in w_n indicates that the employment of member 3 is expected to also have been reported in w_{n-1}. The reported information would be deemed consistent if all identifying criteria of both employments match (e.g., type of employment and member I.D.). However, if no employment is reported or identifying criteria (e.g., employment label) are mismatched in w_{n-1}, this would potentially constitute inconsistent reporting[10].

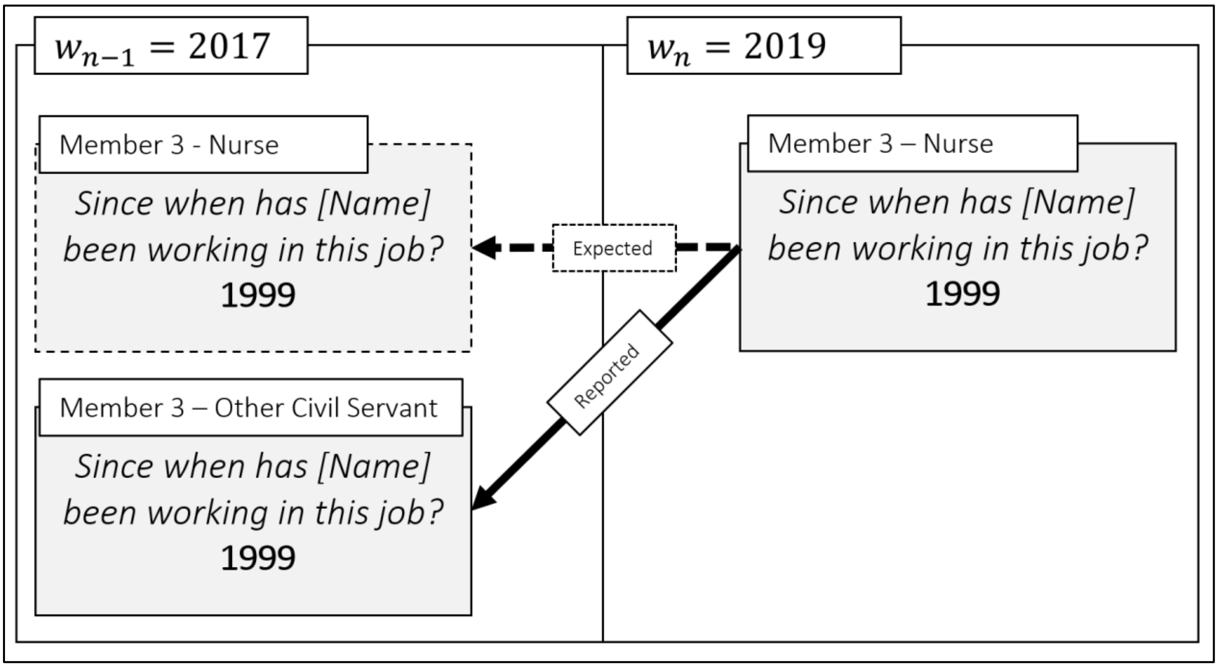

Figure 3.2 Identifying expected employments
Source: Own illustration.

[10] An example of inconsistent reporting is provided in Appendix 3.A2 – Case study 2; whereas an example of consistent reporting is provided in Appendix 3.A2 – Case study 1.

In the next stage, employments are iteratively compared with one another. Key variables are identified that are sufficient to retrospectively match employments. For off-farm employment, these consist of the household I.D, household member I.D., the type of employment (e.g., nurse), and the year in which the individual began pursuing the employment. Similarly, the household I.D, the type of employment (e.g., retail-shop), and the year in which the business was started were selected for self-employment. Based on these variables, a matching status is generated that can take on one of three values. First, the status "missing" is generated when no matching employment is observed in w_{n-1}. Second, the status "potentially mislabelled" is generated when the type of employment does not match as this may represent either two entirely different employments or inconsistent labelling of an identical employment. Third, the status "match" is generated when all four key variables match between waves w_n and w_{n-1}.

In the third stage, all "potentially mislabelled" observations are subjected to an additional automated matching procedure at the individual level based on five identifying criteria (Table 3.1). These criteria are then used to generate a score that captures the level of similarity of each employment at the individual level that was reported in w_n and all employments reported in w_{n-1}. Observations of off-farm employments are nested at the individual level (i.e., the household member), whereas self-employments are nested at the household level. A dichotomous variable is generated for each of the five criteria, which is equal to one if the specified identifying criteria (Table 3.1) are fulfilled in both w_n and w_{n-1}, and equal to zero if they are not.

The minimum required score in order to be able to uniquely match employments between pairs of consecutive waves was set at four out of five criteria[11]. Hereby, if the reported year in which the employment was first pursued does not match, it must at least have been reported in a similar timeframe. Gradually increasing plausible intervals are applied based on theoretical homogeneity of tenured employments (Miller, 1984; McCall, 1990) and to counteract potential recall bias in the reporting of the year. While the position of the individual is required to be congruent, exceptions are made for transitions from a regular position in w_{n-1} to a leading position in w_n (e.g., promotion), which is considered as matching. Demotions are assumed to be unlikely in the context of our study area. Employments are then matched based on the highest

[11] Due to the multitudinous, project-based activities in construction and agricultural wage labour, the constraints regarding location are loosened and a minimum score of three matching criteria is sufficient.

scoring employment in w_{n-1}. Should multiple employments that score below five have an identical score, these remain unmatched.

Table 3.1 Identifying criteria of matching procedure using pairs of consecutive survey waves

Variable label	**Matching procedure**		**Off-farm employment**	**Self-employment**
Sector of employment	Captures whether employment sectors derived from the type of employment (e.g., agricultural; industrial; service; public) match.	1 if match; else 0.	X	X
Year same	Captures whether the year in which the individual reports that they began pursuing the reported employment matches. Thereby a deviation of at most one year is deemed acceptable.	1 if match; else 0.	X	X
Year similar	Captures whether the year in which the individual reports that they began pursuing the reported employment matches. Thereby a deviation of: at most one (max. 5 years ago); two (6-10 years ago); three (> 10 years ago) is deemed acceptable to counteract recall bias.	1 if match; else 0.	X	X
Leading position	Captures whether an individual has a leading position and whether it matches between waves.	1 if match; else 0.	X	
Form of organisation	Captures whether the legal form under which the business operates matches.	1 if match; else 0.		X
Employment location	Captures whether location categories derived from the reported location (e.g., same province; other province; other country) match.	1 if match; else 0.	X	X

Source: Own illustration.

3.4.2 Modelling factors associated with inconsistent responses

In order to examine the factors associated with inconsistent responses in reporting of off-farm wage and non-farm self-employment, a model was developed that accommodates for their hierarchical structure. Thereby, repeat measurements (i.e., responses) are observed to be nested in each individual respondent that is interviewed in proxy for a household. The underlying structure of the data set necessitates a multilevel modelling approach (Hox et al., 2017).

In the field of survey methodology, hierarchical data structures are typically observed and multilevel models have frequently been applied to model various aspects pertaining to data quality such as nonresponse, interview duration or other measures of interview quality (e.g., Barth & Schmitz, 2021; Borgers et al., 2004; Hox et al., 1991; Hox & De Leeuw, 1994; Hox et al., 2003; Pickery et al., 2001; Sun et al., 2021).

A two-level multilevel logistic model is applied for each pair of consecutive survey waves. Level 1 represents the individual responses (i) in survey wave w_n and level 2 the respondent (j) in survey wave w_{n-1}. The model is specified as follows:

$$status_{ij} = \beta_{00} + \sum_{p}^{P} \beta_{p0} X_{pij} + \sum_{q}^{Q} \beta_{0q} Z_{qj} + \sum_{p}^{P} \sum_{q}^{Q} \beta_{pq} X_{pij} Z_{qj} + \sum_{p}^{P} u_{pj} X_{pij} + u_{0j} + e_{ij} \quad (1)$$

where $status_{ij}$ is a dichotomous measure of inconsistently reported employments, which is 1 if the employment reported in w_n is inconsistently not reported in w_{n-1} and 0 otherwise, X_{pij} are a set of response-level characteristics, Z_{qj} are a set of respondent-level characteristics and the response-respondent-characteristic interactions are displayed as $X_{pij} Z_{qj}$.

Figure 3.3 and Table 3.A1.1 illustrate the explanatory variables included in the model. Based on the literature, respondent socio-economic characteristics and income generated by the omitted employment are included and hypotheses regarding the direction of influence of explanatory variables are formulated based on these findings (Table 3.2). Where the literature is incongruent, our hypothesised influences follow the observations that are most closely related to our study area. We include household size and whether a household is engaged in agriculture as proxies for respondent fatigue. We argue that with increasing household size, the burden on the respondent in labour modules and other prior household member related modules increases. Further, the structure of the questionnaire, which includes a complex module on agriculture that precedes the module on labour, suggests higher levels of burden for households that are engaged in agriculture. Therefore, we hypothesise that these variables are positively correlated with the omission of employments. The prevalence of informal employments in Thailand and difficulties in measurement thereof warrant inclusion of variables that control for informality of employments, hence the inclusion of three related variables in the model. First, the location of the employment is included, whereby it is hypothesised that employments near the household are more likely to be informal and result in lower likelihoods of reporting. Second, we control for the type of employment in order ascertain whether inconsistent response behaviour is more likely to occur for off-farm wage employment or non-farm self-employment. Third, off-farm wage employment in the public sector and formally registered businesses are argued to reliably capture formal employments (Charmes, 2012; Fleischer et al., 2018). We hypothesise that omitting informal employments is more likely. Additionally, variables to control for the geographic location of the household are added, namely the province, which may also capture survey management and team effects.

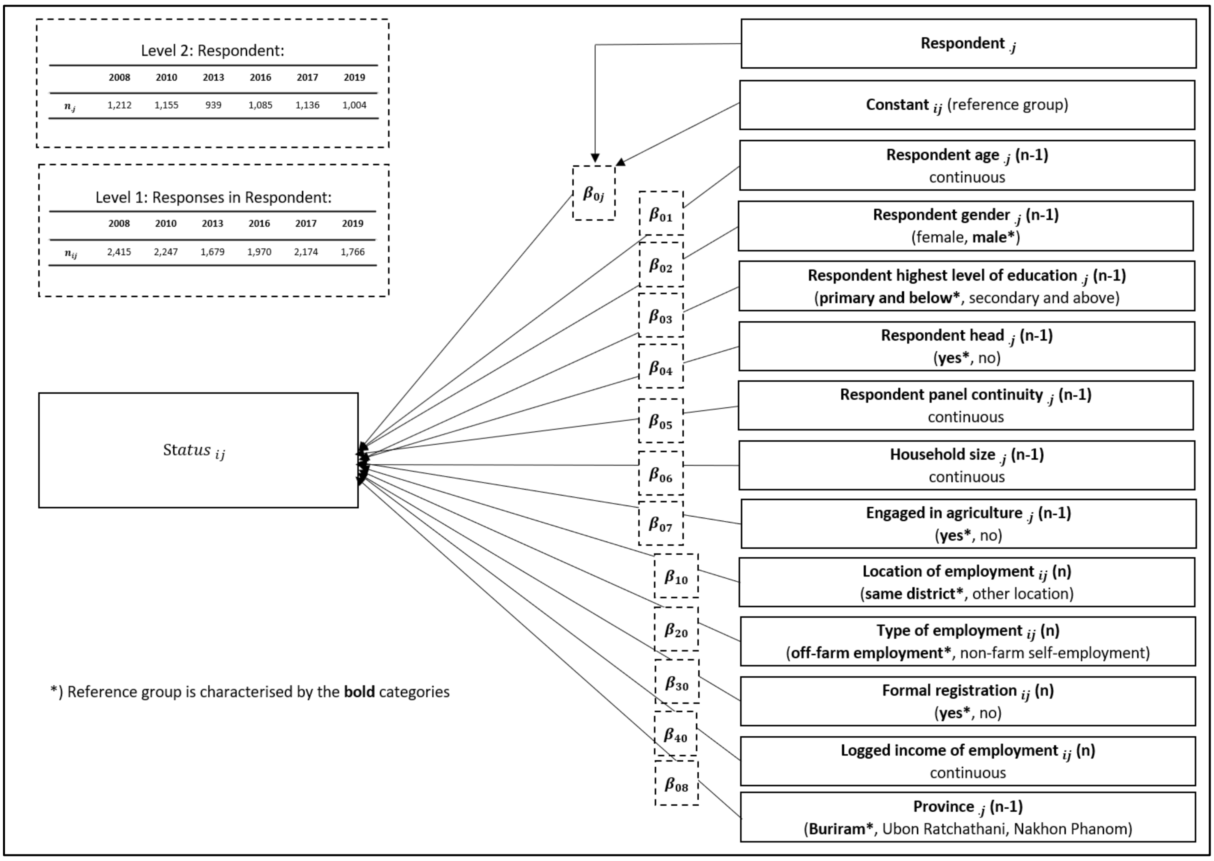

Figure 3.3 Overview of respondent- and response-level explanatory variables
Source: Own illustration.

Table 3.2 Overview of hypothesised influence on inconsistent reporting

Variable/Category	Direction of influence	Source(s)
Respondent		
Age	+	Knäuper et al., 1997; Knäuper, 1999; Krosnick, 1991
Gender	+	Heerwegh & Loosveldt, 2008; Phung et al., 2015; Silber et al., 2019
Secondary education	–	Knäuper et al., 1997; Knäuper, 1999; Krosnick, 1991
Head of household	–	Bardasi et al., 2011
Panel continuity	+	Halpern-Manners & Warren, 2012
Household		
Household Size	+	Ambler et al., 2021; Galesic & Bosnjak, 2009; Jeong et al., 2023; Phung et al., 2015
Engaged in agriculture	+	Ambler et al., 2021; Galesic & Bosnjak, 2009; Jeong et al., 2023; Phung et al., 2015
Employment		
Location	+	Alkire, 2007; Desiere & Costa, 2019; Hussmanns, 2004
Employment type	+	Alkire, 2007; Desiere & Costa, 2019; Hussmanns, 2004
Formal registration	–	Alkire, 2007; Desiere & Costa, 2019; Hussmanns, 2004
Log yearly income (in PPP$)	+	Groves & Couper, 1998; Hurst et al., 2014; Lynn & Clarke, 2002; Meyer et al., 2022; Moore et al., 2000

Source: Own illustration.

All continuous variables are centred using grand mean centering following Hox et al. (2017). The model selection process is based on a comparison of goodness-of-fit of suitable model types. The multilevel logistic regression with random intercepts including level 1 and 2 coefficients is selected based on the goodness-of-fit in comparison to (1) null random models, (2) logistic regression models including fixed effects and (3) random intercept regression models including fixed effects (Tables 3.A1.2-3.A1.7). Additionally, for all model variants, the chosen levels are shown to provide sufficient variation in the outcome variable[12].

[12] On average, 21.57% of total variance in inconsistent responses can be explained at the respondent level. Thereby, the minimum threshold for the intraclass correlation of 10% is exceeded, which justifies the use of multilevel modelling (Hox et al.,2017).

3.5 Results

In the following chapter, the results of the analyses based on the approaches described in the methodology are presented and discussed. First, fluctuations in employment in the underlying sample are described. Second, the results of the three-stage matching procedure are presented. Third, factors associated with inconsistent reporting are analysed using a multilevel logistic approach. Fourth, the applicability of results in a wider context and their impact on policy is discussed.

3.5.1 Employment fluctuation or measurement error?

Foremost, it must be established whether fluctuations in employment are present in the underlying dataset.

Most households in the TVSEP sample (~80%) had at least one active member in an off-farm wage employment in 2007 (Figure 3.4). This share is observed to decrease slightly with each ensuing wave, with the 2019 wave indicating that the share of households engaged in off-farm employment had fallen to ~70%. A similar trend is observed for self-employment.

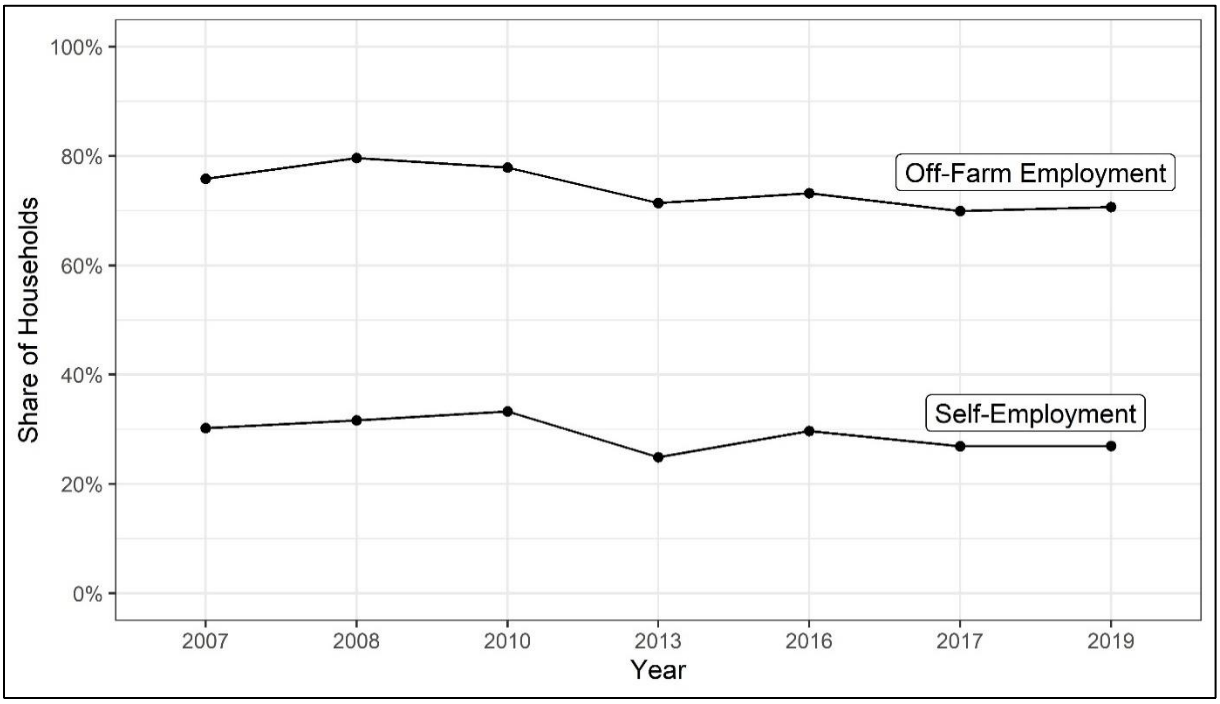

Figure 3.4 Overview – Share of households with at least one member in off-farm wage employment, 2007-2019
Source: Own calculations based on TVSEP (2019).

Although the total number of households engaged in off-farm activities are shown to have decreased, the number of employments in remaining households is observed to be somewhat stable throughout the panel (Figure 3.5). While large fluctuations in the maximum number of employments reported across waves can be observed, these represent outlier cases, which decrease throughout the span of the panel (Table 3.A1.8). In contrast, the remainder of the sample can, on average, be characterised as being overall consistent with households that are active in off-farm employment activities reporting two employments (Figure 3.5).

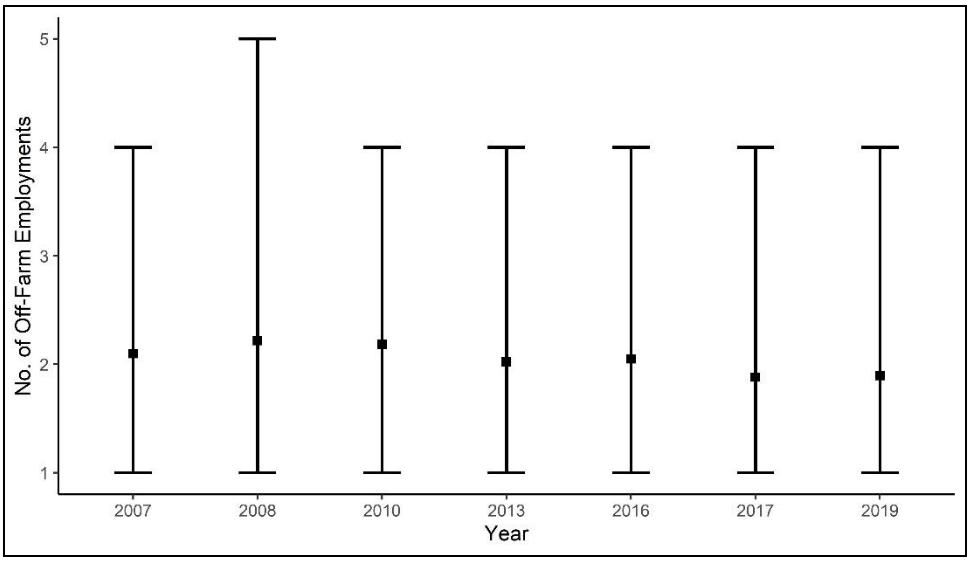

Figure 3.5 Overview of distribution of off-farm employment
Note: The upper and lower thresholds represent the 95th percentile and 25th quartile of the distribution. The mean is displayed as a square point. Source: Own calculation based on TVSEP (2019).

When taking into consideration reported income from off-farm activities in the form of equivalised per capita income[13], we observe, on average, an increase. Equivalised per capita income increases more than twofold from 2,245 PPP$ in 2007 to 4,681 PPP$ in 2019. Income stemming from off-farm employment initially constitutes under half of total household income (44.9%), but is shown to increase with slight fluctuations over time (Figure 3.6). In 2019, the share of off-farm employment and consequently its relevance increased to 56.3% of total household income.

[13] Equivalised refers to the adjustment of household size to better reflect differences in household's size and composition based on the number of equivalent adults in accordance to a modified OECD scale (Hagenaars, et al., 1994) equivalised household size approach.

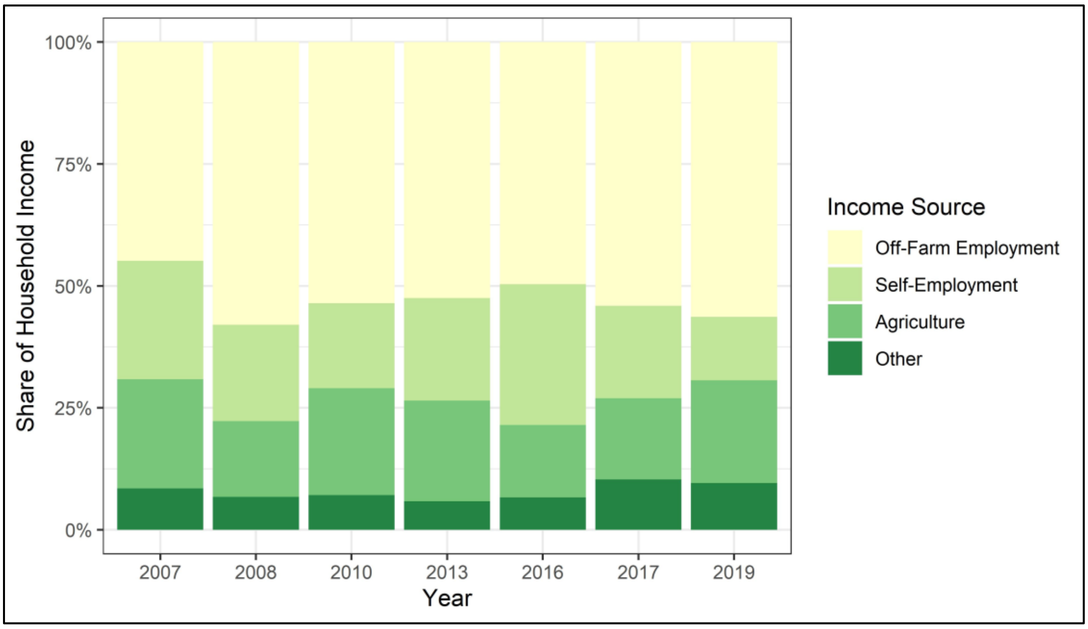

Figure 3.6 Overview – Income composition (total income).
Source: Own calculations based on TVSEP (2019).

In almost one third of households, members are engaged in self-employment (Figure 3.4). The overwhelming majority of such households indicate that they operate one business (Figure 3.7). However, some households report multiple businesses. Notably, households engaged in more than three cases of self-employment represent outliers in the panel (Table 3.A1.9). In excluding these outliers, the observation that the remainder of the sample is overall consistent is mirrored with that of the off-farm employment section.

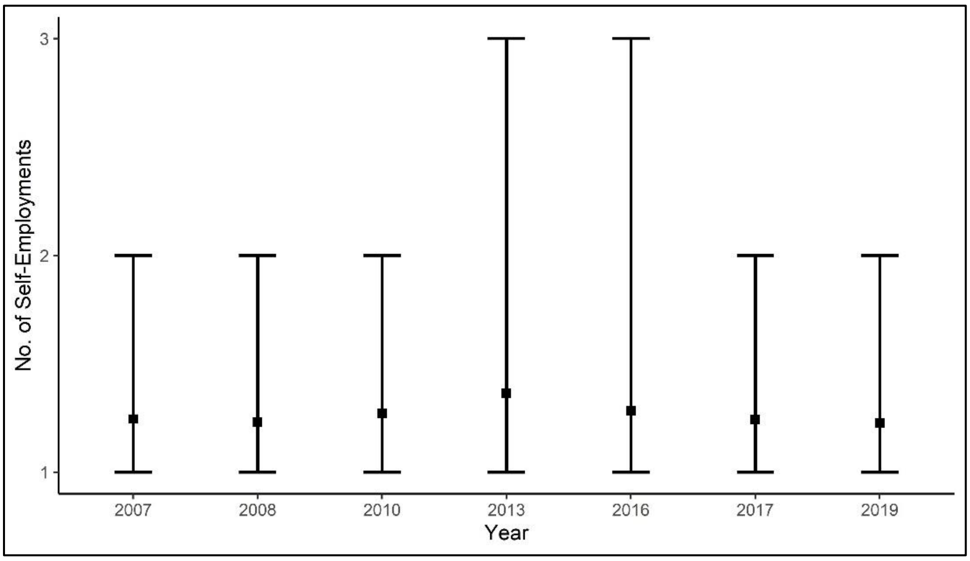

Figure 3.7 Overview of distribution of self-employment
Note: The upper and lower thresholds represent the 95th percentile and 25th quartile of the distribution. The mean is displayed as a square point. Source: Own calculation based on TVSEP (2019).

On average, equivalised per capita income from self-employment activities in households that own a business was 3,216 PPP$ in 2007, which is higher than the average initial level observed for off-farm employment households. Income from self-employment activities is observed to fluctuate strongly from wave-to-wave, but overall is shown to be trending towards increasing monetary values in the most recent survey waves (Table 3.3). Generally, equivalised per capita income from off-farm employment is higher than that derived from self-employment, in particular in the sixth and seventh waves of the survey. Figure 3.6 highlights that the average share of income from self-employment has declined over the years. Initially, 24.3% of household income stemmed from self-employment activities, which declined to 13.0% by 2019.

Table 3.3 Equivalised per capita income (PPP $) – Self-employment

	2007	**2008**	**2010**	**2013**	**2016**	**2017**	**2019**
Obs.	466	488	513	384	458	415	416
Mean	3,216.77	2,434.49	2,526.03	4,634.07	5,694.28	3,725.26	3,800.85
Std. Dev.	15,754.11	6,748.65	4,611.44	13,435.80	34,373.20	6,647.46	11,870.97

Note: Calculated for households engaged in non-farm self-employment activities. Source: Own calculations based on TVSEP (2019).

Consistency in terms of reported off-farm employments at the household level is illustrated in Figure 3.8. While initially almost 50% of households reported a consistent number of employments (incl. reports of zero employment), we observe that this share decreases in each pair of consecutive waves until 2016. Thereafter, fluctuations in off-farm employment decrease slightly. Notably, a large share of some 20% of households enter or exit the off-farm labour market in their entirety between pairs of consecutive survey waves. Despite being characterised as somewhat stable and consistent in the aggregate descriptive of the sample, the opposite is implied at the household level. Further, those households that are consistently reported as engaged in off-farm employment activities are shown to exhibit high shares of fluctuating counts of employment.

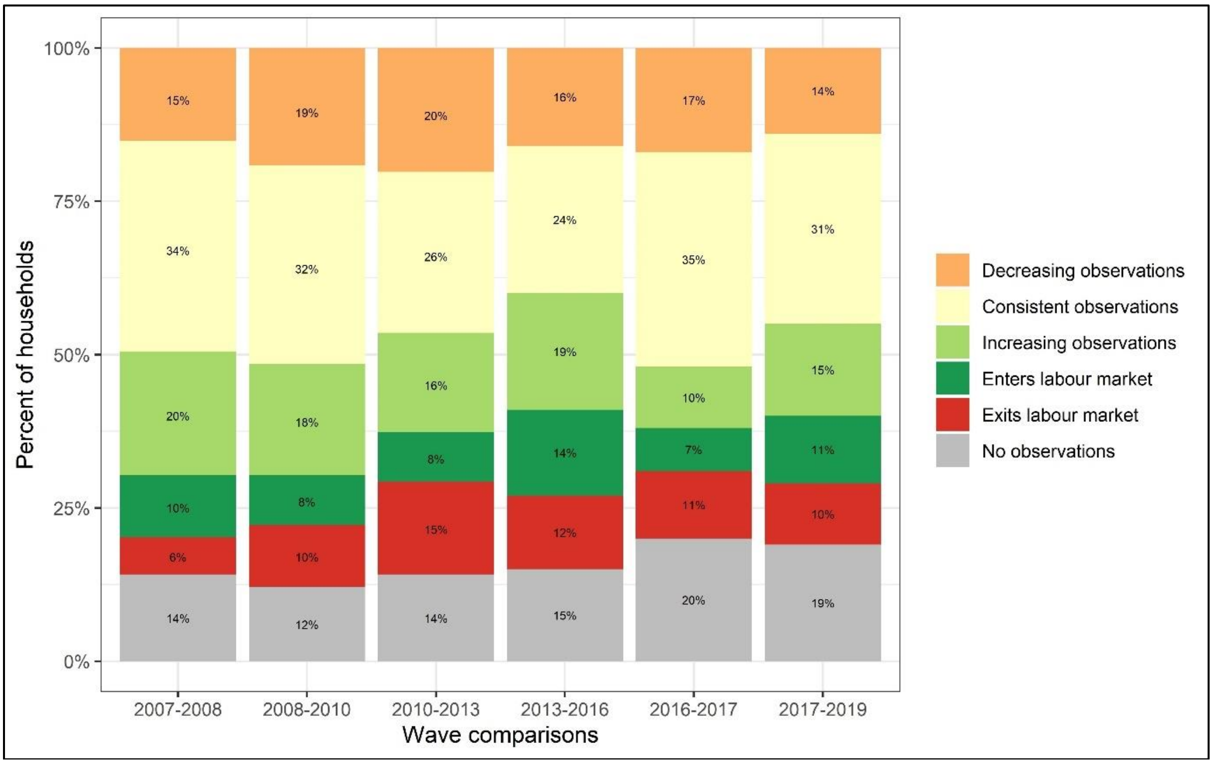

Figure 3.8 Consistency of no. of reported activities over time – Off-farm employment
Source: Own calculations based on TVSEP (2019).

Figure 3.9 depicts the consistency of the number of reported self-employments at the household level. Initially, over 70% of households reported a consistent number of self-employments (incl. reports of zero self-employment). Further, households permanently exiting self-employment throughout the remainder of the panel represents a case of consistent reporting. The figure demonstrates that an ever-increasing share of households branches out into self-employment over time. The share of households that at no previous point engaged in self-employment decreased from 59% in 2007 to 37% in 2019. However, withdrawal from self-employment as captured by the categories "Exits business", "Temporary gap in business" and "Permanently exits business" is observed to increase as the panel progresses.

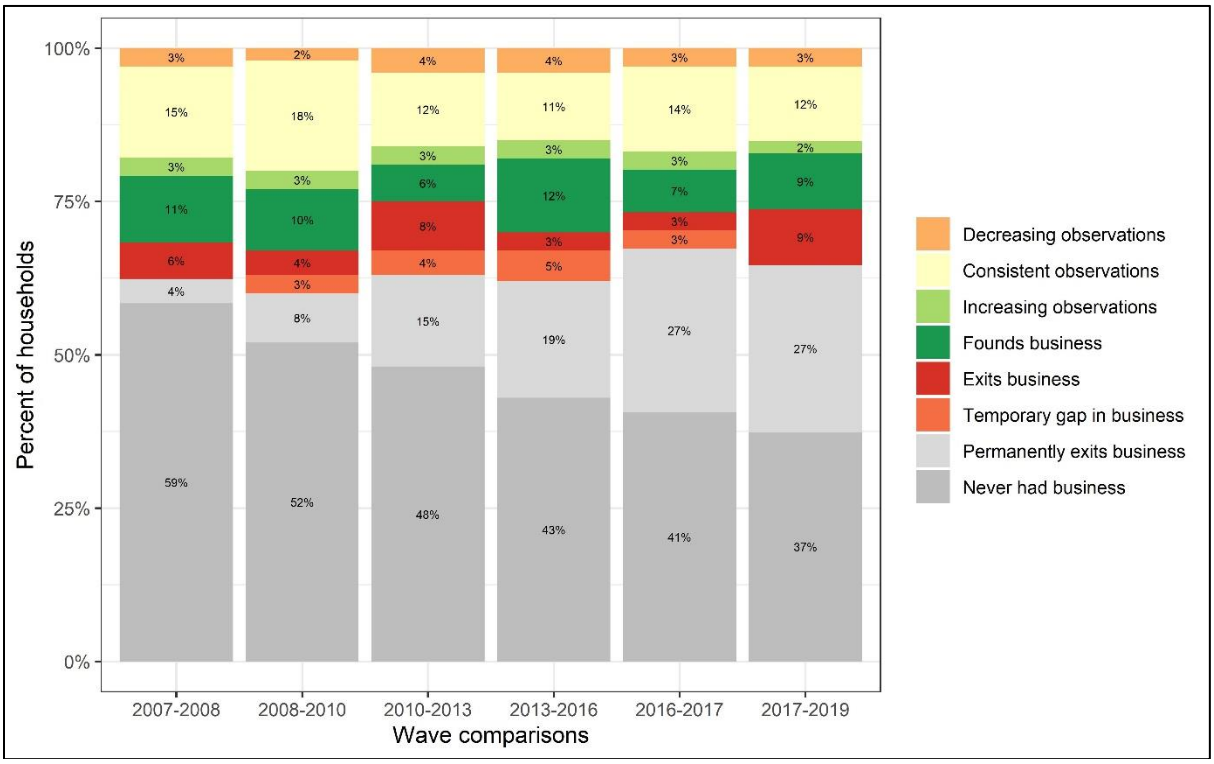

Figure 3.9 Consistency of no. of reported activities over time – Self-employment.
Source: Own calculations based on TVSEP (2019).

Overall, on an aggregate level, we observe a pattern of increasing equivalised per capita income being derived from off-farm employment, which is to be expected as structural transformation of rural areas and development occurs. However, reports of income from self-employment are observed to fluctuate strongly around the mean, which is perhaps reflective of the predominantly informal nature of small-scale businesses. At the household level, substantial fluctuations in reported off-farm employments are observed, which are mirrored in self-employments, albeit being less prominent. Based on the literature review, fluctuations are to be expected to some extent in the context of low- and middle-income countries due to the informality of the economy. However, the extent of fluctuations observed warrants further examination in order to ensure that deviations in employments are not driven by misreported data.

3.5.2 Inconsistencies in reporting

The results of the three-stage matching procedure are presented in Table 3.4. On average, 34.53% of off-farm employments reported in w_n are identified as inconsistently not being reported in w_{n-1}. In contrast, a slightly lower share of 31.90% of self-employments are inconsistently reported. Households that fail to report employments are mostly observed to inconsistently report between one and two employments, irrespective of whether off-farm wage or self-employment is considered.

Table 3.4 Overview of inconsistently reported employments

	Off-farm employment				**Self-employment**			
	Share of employments not reported (in %)	No. of employments inconsistently reported, by household			Share of employments not reported (in %)	No. of employments inconsistently reported, by household		
		1	2	3+		1	2	3+
2008	35.09	414	145	67	43.74	201	26	3
2010	30.44	400	127	41	23.69	122	14	1
2013	29.99	343	94	37	25.24	70	27	2
2016	37.12	430	128	53	32.31	154	15	2
2017	40.76	414	143	39	34.56	142	18	0
2019	33.77	367	91	48	31.83	114	21	2

Source: Own calculations based on TVSEP (2019).

Overall, the share and scale of misreporting in both forms of employment confirms our assumption that employments are being misreported. Therefore, it is necessary to further analyse factors associated with and severity of inconsistent reporting of employments.

3.5.3 Factors associated with inconsistent reporting

In order to obtain robust results for factors influencing inconsistently reported employments, six multilevel logistic regressions (Equation (1)) are run, one for each pair of consecutive survey waves. Key findings of the six model variants are reported in Table 3.5. The model titles denote the survey year w_n, which is compared to w_{n-1}. The general model fits the data quite well for the purposes of this study and is robust across all model variants. Using the user-generated syntax 'fit_meologit_2lev.ado' (Langer, 2017), a suitable measure of fit for multilevel regressions in the form of a McKelvely & Zavoina pseudo-R^2 can be calculated. On average, across model variants, 13.3% of the variance can be explained by modelling at the respondent level and 19.0% at the response level.

Notably, characteristics of the employment are identified as influencing inconsistent reporting throughout all model variants. As hypothesised, off-farm wage employment is highly prone to omission in comparison to self-employment throughout all pairs of consecutive waves. On average, inconsistent reporting thereof is over three times as likely[14], which represents the largest effect. Conversely, when off-farm employment takes place in close proximity to the village, it is more likely to be reported than self-employment.

The models provide evidence that the respondent level explains a substantial share of the variance not explained by fixed effects with intra-class correlation coefficients between 0.16 and 0.25, which exceeds the minimum threshold needed to justify a multilevel approach (Hox et al., 2017). However, in contrast to the literature, e.g., on panel conditioning (Halpern-Manners & Warren, 2012), we could not confirm that respondent characteristics influence inconsistent reporting in the model (Table 3.A1.10). Therefore, we cannot confirm our hypothesis that respondent characteristics drive inconsistent responses, which suggests that respondent behaviour differs irrespective of shared characteristics and that other unobserved factors may play a role. As hypothesised, household size and involvement in agriculture, as proxies for interview complexity and duration, are positively correlated with inconsistent reporting of employment in the majority of waves. Thus, each additional household member above the mean household size in each wave results in a 7.6% average increase of the likelihood of omitting an employment. This is likely explained by respondent fatigue experienced by the higher number of survey items required to be answered prior to and in the modules on off-farm and self-employment.

[14] Holding all categorical variables constant (i.e., 0) and all continuous variables at their mean.

Characteristics of the reported employments generally exhibit highly significant correlations with the likelihood of inconsistent reporting in prior waves. Thereby, off-farm employments are more likely to be omitted. In particular, when off-farm employments are located outside of the boundaries of the village district, the likelihood of reporting decreases. Conversely, self-employment is more likely to be reported irrespective of location. Employments that can be characterised as informal based on the type of contract or legal form of registration are observed to be less likely to be consistently reported. We find a highly significant, negatively correlated coefficient for the log of annual income (PPP$) of reported employments, which suggests that higher-income activities are more likely to be consistently reported. We argue that this may be driven by the importance of employment for household income, which may increase recall and thus the consistency of reporting.

A further observation that can be made based on the utilisation of all six pairs of consecutive survey waves pertains to the gaps between survey wave w_n and w_{n-1}. In the analysed dataset gaps between surveys range between one and three years. Longer gaps between interviews may result in increasing likelihoods of true fluctuations in employment, which may also increase recall bias due to additional response burden. However, the survey utilises the same 12-month long reference period in each survey year, which may explain why results are mostly robust across model variants.

Table 3.5 Multilevel regression results of status: Random intercepts level 1 & 2, by year

	2008 OR (SE)	**2010** OR (SE)	**2013** OR (SE)	**2016** OR (SE)	**2017** OR (SE)	**2019** OR (SE)
Household						
Household Size (continuous)	1.107***	1.057*	1.046	1.065**	1.029	0.995
	(0.031)	(0.030)	(0.034)	(0.031)	(0.025)	(0.033)
Engaged in agriculture	1.174	1.263	0.820	0.921	1.502***	1.388*
(1=yes, 0=no)	(0.186)	(0.250)	(0.170)	(0.165)	(0.230)	(0.235)
Employment						
Location	1.527	1.252	1.503	1.298	1.626	1.650
(1=same district, 0=other)	(0.403)	(0.412)	(0.504)	(0.381)	(0.530)	(0.578)
Employment type	2.436***	4.333***	4.865***	4.683***	2.014***	3.285***
(1=off-farm, 0=self)	(0.386)	(0.726)	(0.979)	(0.782)	(0.301)	(0.558)
Location #Employment type	0.308***	0.593	0.559	0.520**	0.666	0.373***
(Same district|Off-farm)	(0.088)	(0.205)	(0.208)	(0.165)	(0.227)	(0.139)
Formal registration	1.127	0.700**	0.458***	0.518***	0.618***	0.446***
(1=yes, 0=no)	(0.165)	(0.117)	(0.088)	(0.082)	(0.087)	(0.076)
Log annual income	0.769***	0.770***	0.845***	0.831***	0.766***	0.770***
(continuous; in PPP$)	(0.032)	(0.037)	(0.047)	(0.045)	(0.039)	(0.043)
Provinces						
Ubon Ratchathani	0.770**	0.836	1.096	1.231	1.281**	1.150
(ref. Buriram)	(0.093)	(0.113)	(0.165)	(0.169)	(0.156)	(0.159)
Nakhon Phanom	1.147	1.197	1.932***	1.344	1.243	0.959
(ref. Buriram)	(0.193)	(0.202)	(0.422)	(0.250)	(0.190)	(0.177)
Intercept	0.528**	0.198***	0.322***	0.529**	0.288***	0.373***
	(0.141)	(0.060)	(0.107)	(0.152)	(0.075)	(0.105)
Random effects	**Variance (SE)**	**Variance (SE)**	**Variance (SE)**	**Variance (SE)**	**Variance (SE)**	**Variance (SE)**
Respondent-level variance	0.878	1.038	1.107	0.992	0.629	0.811
	(0.205)	(0.242)	(0.297)	(0.260)	(0.196)	(0.259)
Goodness-of-fit						
AIC	3,158.50	2,848.62	2,142.60	2,531.65	2,903.76	2,304.80
R^2 (Respondent-level)	0.112	0.148	0.174	0.161	0.077	0.124
N Respondents	1,212	1,155	939	1,085	1,136	1,004
R^2 (Response-level)	0.177	0.213	0.243	0.221	0.113	0.170
N Employments	2,415	2,247	1,679	1,970	2,174	1,766

Note: * $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$. Odds ratios (OR) reported. Standard errors (SE) in parentheses. The full result table is displayed in Table 3.A1.10. Source: Own calculations based on TVSEP (2019).

Availability of data in the 2017-2019 pair of survey waves allows an additional model to be fitted, which includes proxies for the intrinsic motivation of the respondent. Thereby, we transform individual items related to respondent personality traits based on the “Big Five” personality traits (Costa and McCrae 1997) to weighted Likert scales (1-7) that represent respondent openness, conscientiousness, extraversion, agreeableness, and neuroticism. In order to ensure robustness, cases were excluded in which reported traits were observed to have deviated strongly for consistent respondents between 2017 and 2019 and resulted in a loss of 77 cases in the full model. In a first step, test models were run to determine whether each trait significantly affected the outcome (Table 3.6). These suggested that agreeableness should be considered in the full model.

Table 3.6 Test for personality traits – 2019

	Model 1: Respondent Openness OR (SE)	**Model 2: Respondent Conscientiousness** OR (SE)	**Model 3: Respondent Extraversion** OR (SE)	**Model 4: Respondent Agreeableness** OR (SE)	**Model 5: Respondent Neuroticism** OR (SE)
Intercept	0.776*** (0.053)	0.780*** (0.051)	0.778*** (0.051)	0.788*** (0.051)	0.788*** (0.054)
Respondent					
Openness (Scale 1-7: continuous)	0.900* (0.054)				
Conscientiousness (Scale 1-7: continuous)		0.927 (0.071)			
Extraversion (Scale 1-7: continuous)			1.010 (0.073)		
Agreeableness (Scale 1-7: continuous)				0.864** (0.067)	
Neuroticism (Scale 1-7: continuous)					1.020 (0.070)
Random effects	**Variance (SE)**	**Variance (SE)**	**Variance (SE)**	**Variance (SE)**	**Variance (SE)**
Respondent-level variance	1.020 (0.283)	1.100 (0.282)	1.004 (0.273)	1.085 (0.275)	1.234 (0.300)

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Outcome variable is dichotomous and takes on the value of 1 when an employment is inconsistently reported. Odds ratios (OR) reported. Standard errors (ER) in parentheses. Source: Own calculations based on TVSEP (2019).

Individuals that exert high levels of agreeableness are established to be trusting and cooperative in the literature (John & Srivastava, 1999) and are thus hypothesised to be more likely to consistently report. However, our results cannot confirm the literature ($p = 0.12$). In order to further investigate this finding a robustness check was undertaken by utilising an additional variable captured in the survey instrument. The variable captured the degree of trust allocated to different individuals on behalf of the respondent and was transformed to a dichotomous variable that was equal to one if the respondent indicated that they did not trust strangers and was equal to zero otherwise. Thereby, the coefficient is significantly positively correlated with increasing likelihoods of inconsistent reporting and suggests that intrinsic motivation across respondents may indeed be relevant to some extent (Table 3.A1.11).

Generally, comparing all pairs of consecutive survey waves, it can be established that employments that are informal and closely located to the household are less likely to be reported. Further, conversely to other literature, the results suggest that employments with higher incomes are more likely to be reported. In contrast, identification of traits that suggested that the selection of an 'ideal' respondent may be feasible, was not possible although intrinsic motivation and trust seems to play a role. This finding is however constrained, as it can only be examined for one of the models.

3.5.4 Implications of inconsistent reporting for welfare indicators

In order to assess the impact of inconsistently reported employments, a scenario analysis is undertaken. Hereby, we assume that omitted employments in w_{n-1} generate income, which is equivalent to the reported income in w_n. Therefore, measured income in w_{n-1} is adjusted by supplementing income observed in w_n. We recognise that such an approach is likely to overestimate income. In order to ensure that our findings are robust, we additionally control for overestimation of adjusted income. Thereby, following a more moderate approach, we calculate the difference between mean incomes observed by sector and pairs of consecutive survey waves. We substantiate that income supplemented to w_{n-1} is, on average, likely to be overestimated by 15% for off-farm employment and 9% for self-employment and deduct accordingly.

Figure 3.10 displays the mean annual household income in equivalised per capita PPP$ values both as measured and adjusted. Annual equivalised per capita income is observed to increase substantially by an average of 817.29 PPP$ in off-farm employment, while self-employment generates an average additional income of 282.45 PPP$ using unaltered adjusted income[15]. These substantial shifts in income may severely affect the underlying distribution of household income and thus conclusions about related indicators such as poverty rates.

[15] In the moderate approach, annual equivalised per capita income increases by 694.70 PPP$ in off-farm employment and 257.03 PPP$ in self-employment.

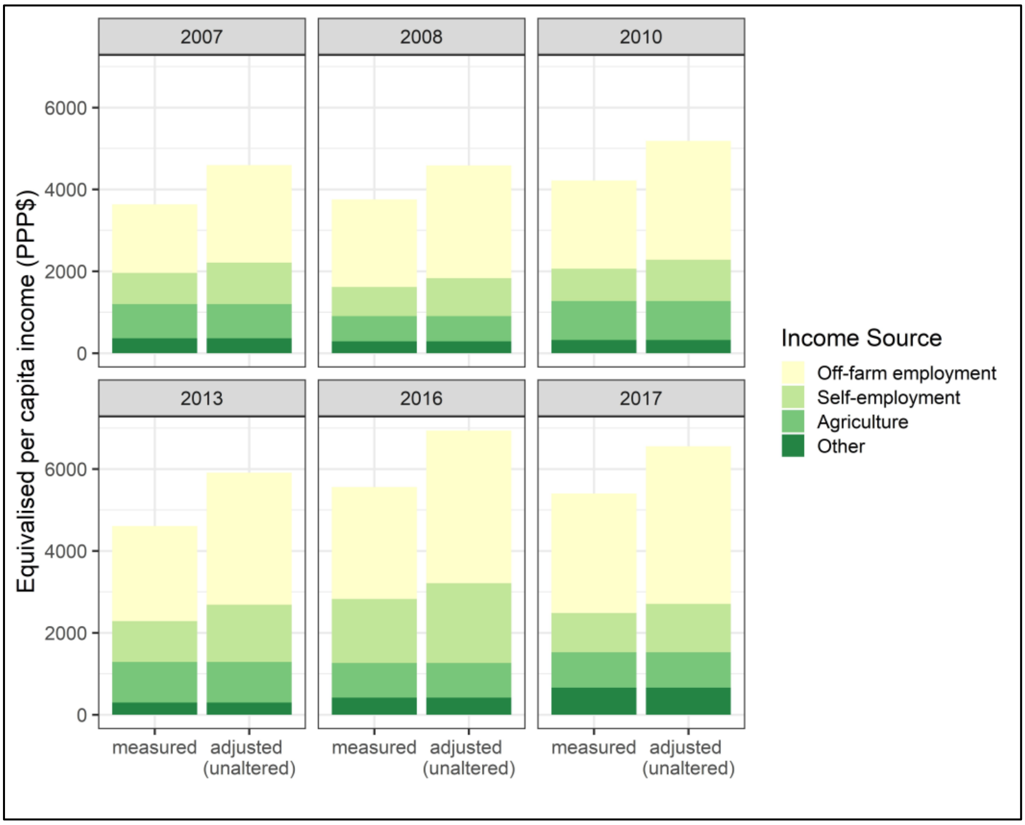

Figure 3.10 Overview of mean equivalised per capita income, by income source and year
Source: Own calculations based on TVSEP (2019).

Figure 3.11 indicates deviations in the number of households that would be considered poor, when applying various poverty thresholds. A substantial number of households that would be considered poor in the measured data are shown to be non-poor when omitted income is taken into consideration. Although the international 1.90 PPP$ poverty line is rather low and less commonly applied in the context of emerging market economies such as Thailand, the issue of inconsistent reporting exists, even at this threshold. The use of a 5.47 PPP$ poverty line (Jolliffe & Prydz, 2016), which is more suitable to upper-middle-income countries, exacerbates this observation. Irrespective of the selected poverty threshold, the issue remains severe, raising questions regarding related distributional issues. Further, deviations between measured income and the two approaches to adjust income are shown to take place at higher levels of income, whilst few households adjacent to the poverty line are impacted.

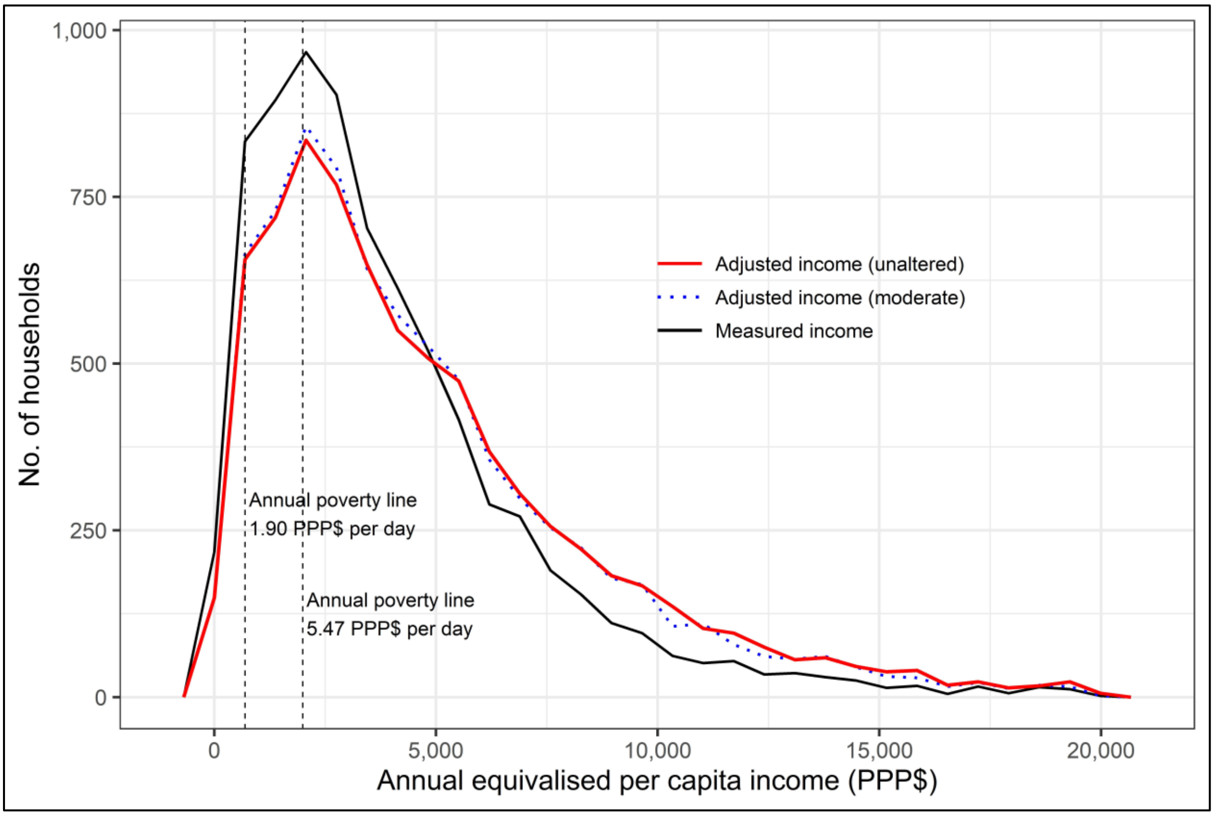

Figure 3.11 Distributions of income in TVSEP sample
Source: Own calculations based on TVSEP (2019).

Subsequent examination of Gini coefficients related to omitted income reveals that the omitted incomes are distributed unequally at the district-level. Coefficients range between 0.39 and 0.45 and further suggest that regional policy implications pertaining to, for example poverty, may be severe.

In recent years, the visualisation of poverty by means of maps has been propagated by the FAO (Davis, 2003) and World Bank as a suitable tool that should be provided to policy-makers to inform policy interventions and assist in their evaluation and assessment (Bedi et al., 2007; Ziulu et al., 2022).

Following this rationale, the Foster-Greer-Thorbecke poverty headcount ratio (FGT0) is calculated at both the district- and provincial-level (Foster et al., 1984) and poverty maps are generated for each survey wave at the district-level:

1) For measured income
2) For adjusted income (unaltered)

Table 3.7 illustrates the distribution of provincial poverty headcounts throughout the span of the panel. The share of households living below the \$5.47 (2011 PPP) poverty line is observed to decrease from an average of 47% in 2007 to 23% by 2017. Irrespective of the selected approach to adjust income for omitted employment, poverty incidence is shown to be substantially lower. Overall, the incidence of poverty is found to be overestimated by on average 6.7 percentage points at the provincial level. Using a paired t-test, means of the two groups of poverty incidence: i) as measured and ii) as modified (unaltered), are demonstrated to differ significantly (p = 0.000) underlining the severity of inconsistently reported employments.

Table 3.7 Overview of mean provincial poverty headcount ratio, by year

Province	**Poverty Incidence***	**2007**	**2008**	**2010**	**2013**	**2016**	**2017**
Buriram	FGT0 (measured)	0.44	0.37	0.22	0.24	0.20	0.23
	FGT0 (moderate)	0.35	0.29	0.16	0.17	0.16	0.19
	FGT0 (unaltered)	0.35	0.28	0.16	0.17	0.16	0.19
Ubon Ratchathani	FGT0 (measured)	0.45	0.37	0.30	0.33	0.28	0.21
	FGT0 (moderate)	0.38	0.32	0.24	0.26	0.22	0.18
	FGT0 (unaltered)	0.38	0.32	0.24	0.26	0.22	0.18
Nakhon Phanom	FGT0 (measured)	0.52	0.45	0.31	0.46	0.28	0.25
	FGT0 (moderate)	0.43	0.35	0.27	0.36	0.24	0.21
	FGT0 (unaltered)	0.43	0.33	0.26	0.34	0.24	0.21

Note: *Poverty indicator is calculated based on the $5.47 (2011 PPP) poverty line. Source: Authors' calculations based on TVSEP (2019).

Figure 3.12 includes poverty maps for each analysed survey wave that display deviations between i) measured income and ii) adjusted income (unaltered) in the calculation of FGT0 at the district-level. Thereby, the $5.47 (2011 PPP) poverty line is selected in order to visualise the prevalence of poverty. The map aims to demonstrate the heterogeneous distribution of the impact of omitted income on observed income-based headcount ratios across districts. On average, poverty headcounts are found to deviate by 6.4 percentage points with extreme cases of over 20 percentage points being observed in some districts.

Such deviations might warrant different approaches in policy on poverty alleviation or may affect existing policies necessitating reassessment of their suitability.

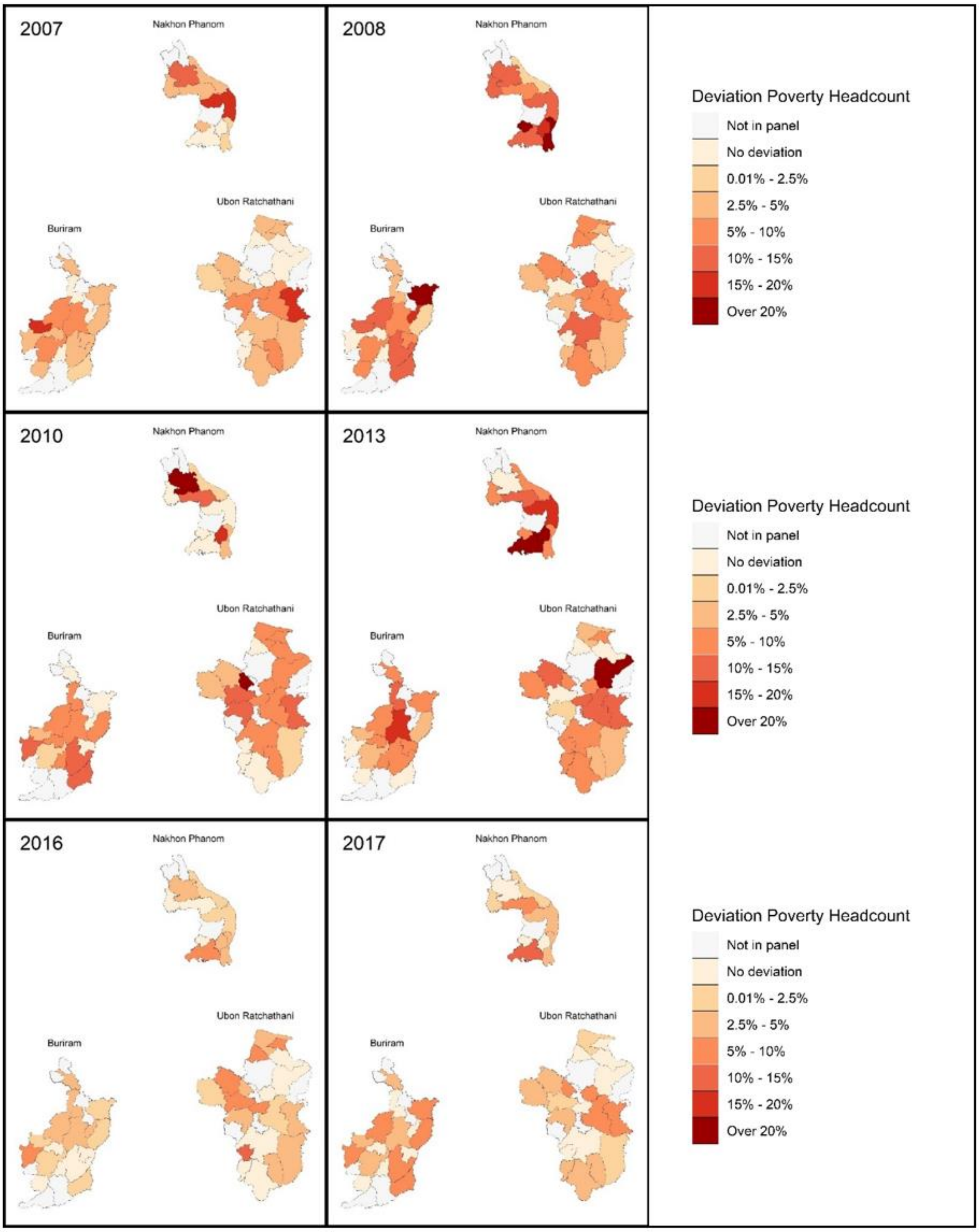

Figure 3.12 Distribution of income in TVSEP sample
Source: Own calculations based on TVSEP (2019). Shape source: HDX (2022).

3.6 Conclusions and recommendations

Using a comprehensive, long-term household panel data set that encompasses 7 waves of data from 2007 to 2019, we identify systematic inconsistencies in reporting of off-farm wage and self-employment.

We demonstrate that large fluctuations in employment observed in the dataset are driven by inconsistent responses. Given the structure of modules on labour throughout many household survey instruments, it is unsurprising that employments are not consistently reported. Employment histories are infrequently controlled for and thus omission of employments is likely to bypass quality assurance. Many feasible steps could be taken to improve the consistency of reported employments. First, expanding modules on labour by inquiring about previously reported employments will likely increase the internal consistency of household panel surveys. Second, the importance of informal activities, as evidenced in the literature and this study, necessitates improvements of survey instruments to better account for particularities of such employments. Third, methods such as dependent or independent interviewing, while being critically discussed, are evidenced to improve the consistency of underlying data sets. Careful implementation of independent interviewing, for example, is considered to minimise biases in reporting on behalf of the respondent while increasing reliability of responses (Lugtig & Jäckle, 2014; Lynn et al., 2006; Lynn et al., 2012; Perales, 2014). Fourth, the utilisation of external validation datasets from, for example, administrative sources, has become more prominent (Epland & Kirkeberg, 2012; Mathiowetz et al., 2002; Meyer et al., 2019). While this is one way to improve data quality, we argue that retrospective internal validation of data sets based on previously collected waves and baseline surveys is being underutilised. For example, large household surveys such as the British Household Panel Survey (BHPS) have taken steps in this direction in order to improve internal consistency of data (Halpin, 1998; Maré, 2006). Nonetheless, survey providers must carefully weigh the benefits of internal consistency against increases in biased reporting.

Using a multilevel logistic approach, we identify that inconsistent reporting, while driven by differences between respondents, is not driven by their socio-economic characteristics. This raises the discussion of whether improving the respondent selection process based on such characteristics is likely to improve the quality of data collection. Extending the model with proxies for intrinsic motivation of the respondent suggests that motivation plays a role in obtaining consistent responses. Thus, we raise the issue whether household surveys should strive to implement tools to improve respondent motivation and retention that exceed exclusively monetary incentives (i.e., payment for participation in the interview).

As derived from our scenario analysis, inconsistencies in employment data are demonstrated to have a substantial impact on policy indicators related to poverty, especially should policy be required to focus on lower-level administrative boundaries.

The findings of this study raise the question whether employment data suffer similar issues across other survey contexts. The underlying survey instrument closely follows the LSMS approach to collecting employment data. The depth and disaggregated nature of modules on employment in the underlying (TVSEP) dataset, allows for a response-level analysis of inconsistently reported employment data. The results of this study substantiate a problem that has recently been raised by researchers using LSMS household survey data (e.g., Alkire, 2007; Ambler et al., 2021; Desiere & Costa, 2019; Jeong et al., 2023).

While one limitation of this study is that it utilises only one source of data, we argue that similarities between household survey instruments make a compelling case for extending our approach to other data sets.

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Appendix 3.A1 – Tables and figures

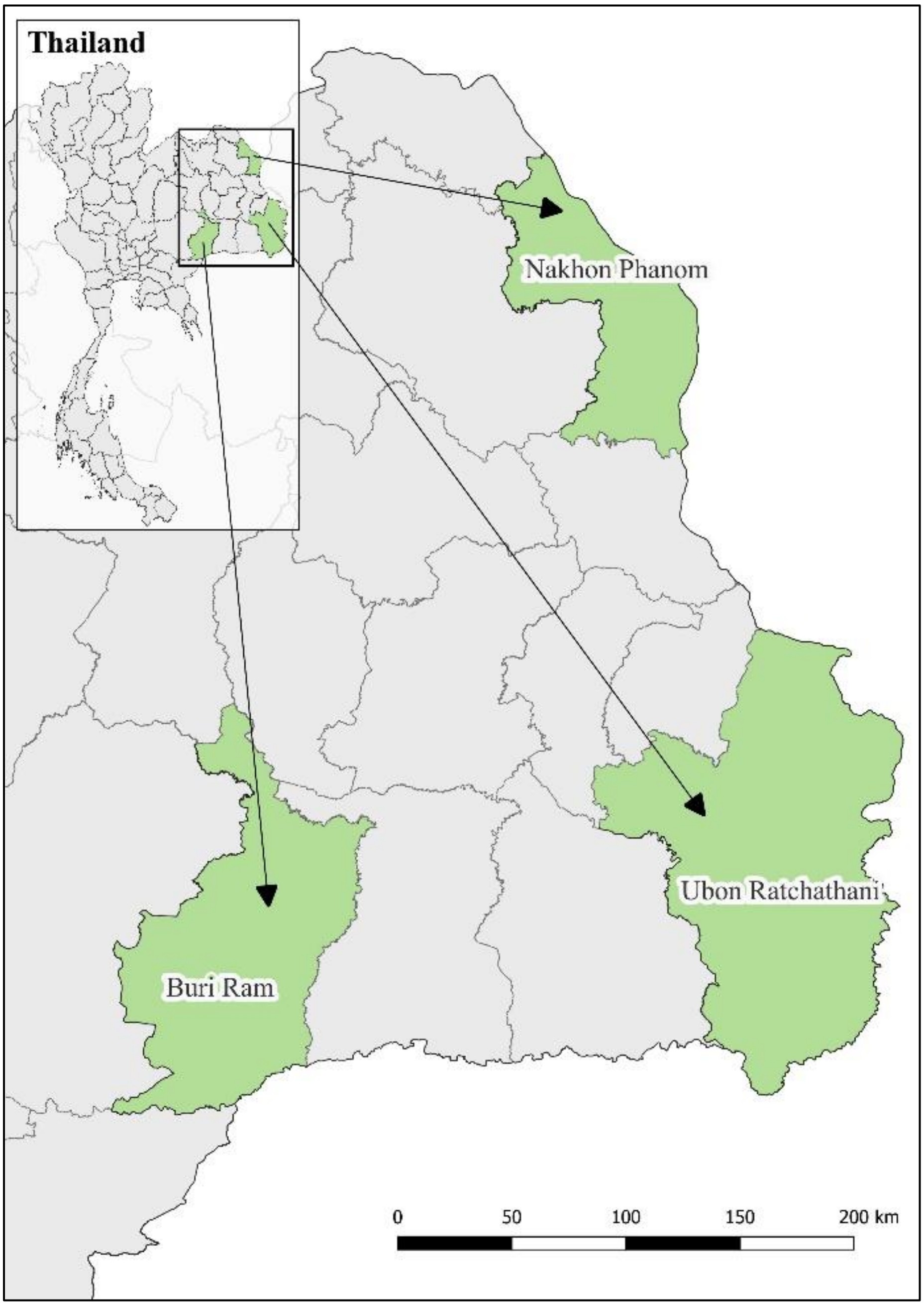

Figure 3.A1.1 Map of study area.
Source: Own illustration. Shape source: HDX (2022).

Table 3.A1.1 Summary of mean respondent- and response-level characteristics

	2008	2010	2013	2016	2017	2019
*Respondent**						
Age	49.73	50.26	52.36	53.21	55.74	56.41
Gender	0.53	0.60	0.61	0.62	0.67	0.67
Secondary education	0.12	0.13	0.13	0.18	0.19	0.18
Head of household	0.60	0.52	0.54	0.52	0.53	0.54
Panel continuity	-	1.72	2.30	2.69	3.30	4.00
*Household**						
Household Size	5.16	5.51	5.87	6.03	6.28	5.22
Engaged in agriculture	0.86	0.89	0.87	0.86	0.84	0.82
*Employment***						
Location	0.52	0.47	0.50	0.43	0.48	0.44
Employment type	0.77	0.72	0.71	0.71	0.77	0.73
Formal registration	0.19	0.15	0.18	0.18	0.19	0.18
Log yearly income (in PPP$)	4,502.62	4,824.95	6,708.31	8,181.45	7,239.95	7,117.37

Note: * Calculated based on unique respondents; ** Calculated based on unique responses. Source: Own calculations based on TVSEP (2019).

Table 3.A1.2 Multilevel logistic regression results of status – 2008

	Model 1: Null Random	**Model 2: Logistic Regression**	**Model 3: Random Intercept: Level 1**	**Model 4: Random Intercepts: Level 1 & 2**
	OR	OR	OR	OR
	(SE)	(SE)	(SE)	(SE)
Intercept	0.875**	0.620***	0.584**	0.528**
	(0.048)	(0.101)	(0.130)	(0.141)
Respondent				
Age		0.995	0.995	1.001
(continuous)		(0.004)	(0.005)	(0.005)
Gender		1.062	1.032	0.960
(1=female, 0=male)		(0.109)	(0.144)	(0.135)
Secondary education		1.077	1.117	1.276
(1=yes, 0=no)		(0.141)	(0.199)	(0.233)
Head of household		1.284**	1.322*	1.204
(1=yes, 0= no)		(0.147)	(0.204)	(0.188)
Panel continuity				-
(continuous)				
Household				
Household Size		1.049**	1.058**	1.107***
(continuous)		(0.020)	(0.029)	(0.031)
Engaged in agriculture		1.274**	1.281	1.174
(1=yes, 0=no)		(0.147)	(0.202)	(0.186)
Employment				
Location				1.527
(1=same district, 0=other)				(0.403)
Employment type				2.436***
(1=off-farm, 0=self)				(0.386)
Location#Employment type				0.308***
(Same district.|Off-farm)				(0.088)
Formal registration				1.127
(1=yes, 0=no)				(0.165)
Log yearly income				0.769***
(continuous in PPP$)				(0.032)
Provinces				
Ubon Ratchathani				0.770**
(ref. Buriram)				(0.093)
Nakhon Phanom				1.147
(ref. Buriram)				(0.193)
Random effects	**Variance**	**Variance**	**Variance**	**Variance**
	(SE)	**(SE)**	**(SE)**	**(SE)**
Respondent-level variance	1.039	-	1.005	0.878
	(0.209)		(0.207)	(0.205)
Goodness-of-fit				
AIC	3,387.87	3,445.93	3,389.40	3,158.50
ICC	0.240	-	0.234	0.211

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Outcome variable is dichotomous and takes on the value of 1 when an employment is inconsistently reported. Odds ratios (OR) reported. Standard errors (SE) in parentheses. Source: Own calculations based on TVSEP (2019).

Table 3.A1.3 Multilevel logistic regression results of status – 2010

	Model 1: Null Random OR (SE)	**Model 2: Logistic Regression** OR (SE)	**Model 3: Random Intercept: Level 1** OR (SE)	**Model 4: Random Intercepts: Level 1 & 2** OR (SE)
Intercept	0.623***	0.507***	0.442***	0.198***
	(0.038)	(0.093)	(0.110)	(0.060)
Respondent				
Age		0.996	0.995	0.999
(continuous)		(0.004)	(0.006)	(0.006)
Gender		1.101	1.099	1.009
(1=female, 0=male)		(0.120)	(0.162)	(0.153)
Secondary		0.835	0.794	1.186
education		(0.113)	(0.145)	(0.229)
(1=yes, 0=no)				
Head of household		1.165	1.203	1.068
(1=yes, 0= no)		(0.138)	(0.192)	(0.176)
Panel continuity		1.113	1.125	1.219
(continuous)		(0.112)	(0.153)	(0.172)
Household				
Household Size		1.042**	1.043	1.057*
(continuous)		(0.020)	(0.028)	(0.030)
Engaged in		1.247	1.291	1.263
agriculture		(0.175)	(0.245)	(0.250)
(1=yes, 0=no)				
Employment				
Location				1.252
(1=same district,				(0.412)
0=other)				
Employment type				4.333***
(1=off-farm,				(0.726)
0=self)				
Location				0.593
#Employment type				(0.205)
(Same district|Off-				
farm)				
Formal registration				0.700**
(1=yes, 0=no)				(0.117)
Log yearly income				0.770***
(continuous in				(0.037)
PPP$)				
Provinces				
Ubon Ratchathani				0.836
(ref. Buriram)				(0.113)
Nakhon Phanom				1.197
(ref. Buriram)				(0.202)
Random effects	**Variance (SE)**	**Variance (SE)**	**Variance (SE)**	**Variance (SE)**
Respondent-level	1.095	-	1.058	1.038
variance	(0.232)		(0.243)	(0.242)
Goodness-of-fit				
AIC	3,061.45	3,115.32	3,067.12	2,848.62
ICC	0.250	-	0.243	0.240

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Outcome variable is dichotomous and takes on the value of 1 when an employment is inconsistently reported. Odds ratios (OR) reported. Standard errors (SE) in parentheses. Source: Own calculations based on TVSEP (2019).

Table 3.A1.4 Multilevel logistic regression results of status – 2013

	Model 1: Null Random	**Model 2: Logistic Regression**	**Model 3: Random Intercept: Level 1**	**Model 4: Random Intercepts: Level 1 & 2**
	OR (SE)	OR (SE)	OR (SE)	OR (SE)
Intercept	0.750*** (0.053)	0.929 (0.185)	0.880 (0.245)	0.322*** (0.107)
Respondent				
Age (continuous)		1.005 (0.005)	1.009 (0.007)	1.009 (0.007)
Gender (1=female, 0=male)		1.027 (0.129)	1.069 (0.188)	0.986 (0.176)
Secondary education (1=yes, 0=no)		0.655*** (0.104)	0.604** (0.133)	0.875 (0.199)
Head of household (1=yes, 0= no)		1.014 (0.136)	0.959 (0.180)	0.910 (0.173)
Panel continuity (continuous)		0.955 (0.060)	0.958 (0.084)	0.972 (0.086)
Household				
Household Size (continuous)		1.047** (0.023)	1.052 (0.033)	1.046 (0.034)
Engaged in agriculture (1=yes, 0=no)		0.904 (0.130)	0.887 (0.179)	0.820 (0.170)
Employment				
Location (1=same district, 0=other)				1.503 (0.504)
Employment type (1=off-farm, 0=self)				4.865*** (0.979)
Location #Employment type (Same district|Off-farm)				0.559 (0.208)
Formal registration (1=yes, 0=no)				0.458*** (0.088)
Log yearly income (continuous in PPP$)				0.845*** (0.047)
Provinces				
Ubon Ratchathani (ref. Buriram)				1.096 (0.165)
Nakhon Phanom (ref. Buriram)				1.932*** (0.422)
Random effects	**Variance (SE)**	**Variance (SE)**	**Variance (SE)**	**Variance (SE)**
Respondent-level variance	1.371 (0.315)	-	1.304 (0.308)	1.107 (0.297)
Goodness-of-fit				
AIC	2,354.00	2,399.61	2,352.90	2,142.60
ICC	0.294	-	0.284	0.252

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Outcome variable is dichotomous and takes on the value of 1 when an employment is inconsistently reported. Odds ratios (OR) reported. Standard errors (SE) in parentheses. Source: Own calculations based on TVSEP (2019).

Table 3.A1.5 Multilevel logistic regression results of status – 2016

	Model 1: Null Random OR (SE)	**Model 2: Logistic Regression** OR (SE)	**Model 3: Random Intercept: Level 1** OR (SE)	**Model 4: Random Intercepts: Level 1 & 2** OR (SE)
Intercept	1.107* (0.068)	1.298 (0.232)	1.410 (0.343)	0.529** (0.152)
Respondent				
Age (continuous)		0.995 (0.004)	0.996 (0.006)	0.999 (0.006)
Gender (1=female, 0=male)		0.871 (0.101)	0.821 (0.128)	0.782 (0.125)
Secondary education (1=yes, 0=no)		0.676*** (0.087)	0.637*** (0.111)	0.830 (0.150)
Head of household (1=yes, 0= no)		1.155 (0.144)	1.139 (0.191)	1.086 (0.186)
Panel continuity (continuous)		0.944 (0.040)	0.932 (0.053)	0.958 (0.056)
Household				
Household Size (continuous)		1.051** (0.022)	1.059** (0.030)	1.065** (0.031)
Engaged in agriculture (1=yes, 0=no)		0.904 (0.116)	0.896 (0.157)	0.921 (0.165)
Employment				
Location (1=same district, 0=other)				1.298 (0.381)
Employment type (1=off-farm, 0=self)				4.683*** (0.782)
Location #Employment type (Same district|Off-farm)				0.520** (0.165)
Formal registration (1=yes, 0=no)				0.518*** (0.082)
Log yearly income (continuous in PPP$)				0.831*** (0.045)
Provinces				
Ubon Ratchathani (ref. Buriram)				1.231 (0.169)
Nakhon Phanom (ref. Buriram)				1.344 (0.250)
Random effects	**Variance (SE)**	**Variance (SE)**	**Variance (SE)**	**Variance (SE)**
Respondent-level variance	1.174 (0.264)	-	1.093 (0.256)	0.992 (0.260)
Goodness-of-fit				
AIC	2,730.98	2,767.89	2,726.81	2,531.65
ICC	0.263	-	0.249	0.232

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Outcome variable is dichotomous and takes on the value of 1 when an employment is inconsistently reported. Odds ratios (OR) reported. Standard errors (SE) in parentheses. Source: Own calculations based on TVSEP (2019).

Table 3.A1.6 Multilevel logistic regression results of status – 2017

	Model 1: Null Random OR (SE)	**Model 2: Logistic Regression** OR (SE)	**Model 3: Random Intercept: Level 1** OR (SE)	**Model 4: Random Intercepts: Level 1 & 2** OR (SE)
Intercept	0.812*** (0.044)	0.612*** (0.104)	0.566*** (0.120)	0.288*** (0.075)
Respondent				
Age (continuous)		1.000 (0.004)	1.002 (0.005)	1.005 (0.005)
Gender (1=female, 0=male)		1.040 (0.113)	1.043 (0.139)	1.019 (0.140)
Secondary education (1=yes, 0=no)		0.723*** (0.089)	0.711** (0.108)	0.820 (0.129)
Head of household (1=yes, 0= no)		1.232* (0.137)	1.242 (0.170)	1.158 (0.162)
Panel continuity (continuous)		0.974 (0.033)	0.974 (0.040)	0.957 (0.041)
Household				
Household Size (continuous)		1.033* (0.019)	1.035 (0.024)	1.029 (0.025)
Engaged in agriculture (1=yes, 0=no)		1.317** (0.158)	1.401** (0.208)	1.502*** (0.230)
Employment				
Location (1=same district, 0=other)				1.626 (0.530)
Employment type (1=off-farm, 0=self)				2.014*** (0.301)
Location #Employment type (Same district|Off-farm)				0.666 (0.227)
Formal registration (1=yes, 0=no)				0.618*** (0.087)
Log yearly income (continuous in PPP$)				0.766*** (0.039)
Provinces				
Ubon Ratchathani (ref. Buriram)				1.281** (0.156)
Nakhon Phanom (ref. Buriram)				1.243 (0.190)
Random effects	**Variance (SE)**	**Variance (SE)**	**Variance (SE)**	**Variance (SE)**
Respondent-level variance	0.698 (0.195)	-	0.635 (0.188)	0.629 (0.196)
Goodness-of-fit				
AIC	3,022.12	3,035.34	3,016.86	2,903.76
ICC	0.175	-	0.162	0.161

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Outcome variable is dichotomous and takes on the value of 1 when an employment is inconsistently reported. Odds ratios (OR) reported. Standard errors (SE) in parentheses. Source: Own calculations based on TVSEP (2019).

Table 3.A1.7 Multilevel regression results of status – 2019

	Model 1: Null Random OR (SE)	**Model 2: Logistic Regression** OR (SE)	**Model 3: Random Intercept: Level 1** OR (SE)	**Model 4: Random Intercepts: Level 1 & 2** OR (SE)
Intercept	0.796***	0.833	0.782	0.373***
	(0.050)	(0.151)	(0.190)	(0.105)
Respondent				
Age		0.995	0.995	0.996
(continuous)		(0.005)	(0.006)	(0.006)
Gender		0.891	0.857	0.818
(1=female, 0=male)		(0.105)	(0.135)	(0.131)
Secondary education		0.740**	0.711*	0.867
(1=yes, 0=no)		(0.100)	(0.128)	(0.160)
Head of household		1.032	1.045	0.988
(1=yes, 0= no)		(0.124)	(0.167)	(0.159)
Panel continuity		0.968	0.964	0.966
(continuous)		(0.030)	(0.040)	(0.040)
Household				
Household Size		0.987	0.984	0.995
(continuous)		(0.024)	(0.032)	(0.033)
Engaged in agriculture		1.157	1.212	1.388*
(1=yes, 0=no)		(0.142)	(0.201)	(0.235)
Employment				
Location				1.650
(1=same district, 0=other)				(0.578)
Employment type				3.285***
(1=off-farm, 0=self)				(0.558)
Location				0.373***
#Employment type				(0.139)
(Same district|Off-farm)				
Formal registration				0.446***
(1=yes, 0=no)				(0.076)
Log yearly income				0.770***
(continuous in PPP$)				(0.043)
Provinces				
Ubon Ratchathani				1.150
(ref. Buriram)				(0.159)
Nakhon Phanom				0.959
(ref. Buriram)				(0.177)
Random effects	**Variance (SE)**	**Variance (SE)**	**Variance (SE)**	**Variance (SE)**
Respondent-level variance	1.080	-	1.058	0.811
	(0.268)		(0.266)	(0.259)
Goodness-of-fit				
AIC	2,565.09	2,602.90	2,568.69	2,304.80
ICC	0.247	-	0.245	0.198

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Outcome variable is dichotomous and takes on the value of 1 when an employment is inconsistently reported. Odds ratios (OR) reported. Standard errors (SE) in parentheses. Source: Own calculations based on TVSEP (2019).

Table 3.A1.8 Summary statistics – Off-farm employment

	No. of off-farm employments						
	Mean	**Std. dev.**	**25% Quartile**	**50% Quartile**	**75% Quartile**	**95th Percentile**	**Max**
2007	2.1	1.24	1	2	3	4	12
2008	2.22	1.38	1	2	3	5	16
2010	2.18	1.22	1	2	3	4	12
2013	2.02	1.16	1	2	3	4	8
2016	2.05	1.1	1	2	3	4	7
2017	1.88	1.02	1	2	2	4	7
2019	1.90	1.02	1	2	2	4	6

Note: This table includes only households that stated that at least one member of the household participates in off-farm employment. Source: Own calculations based on TVSEP (2019).

Table 3.A1.9 Summary statistics – Non-farm self-employment

	No. of non-farm self-employments						
	Mean	**Std. dev.**	**25% Quartile**	**50% Quartile**	**75% Quartile**	**95th Percentile**	**Max**
2007	1.24	0.65	1	1	1	2	8
2008	1.23	0.52	1	1	1	2	5
2010	1.27	0.53	1	1	1	2	5
2013	1.36	0.72	1	1	2	3	6
2016	1.28	0.64	1	1	1	3	5
2017	1.24	0.51	1	1	1	2	4
2019	1.23	0.57	1	1	1	2	7

Note: This table includes only households that stated that at least one member of the household owns a non-farm self-employment. Source: Own calculations based on TVSEP (2019).

Table 3.A1.10 Multilevel logistic regression results of status: Random intercepts level 1 & 2, by year

	2008			**2010**			**2013**			**2016**			**2017**			**2019**		
	OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI	
	(SE)	Lower	Upper	(SE)	Lower	Upper	(SE)	Lower	Upper	(SE)	Lower	Upper	(SE)	Lower	Upper	(SE)	Lower	Upper
Respondent																		
Age	1.001	0.990	1.011	0.999	0.987	1.010	1.009	0.995	1.023	0.999	0.988	1.011	1.005	0.995	1.016	0.996	0.983	1.008
(continuous)	(0.005)			(0.006)			(0.007)			(0.006)			(0.005)			(0.006)		
Gender	0.960	0.728	1.266	1.009	0.749	1.359	0.986	0.695	1.398	0.782	0.571	1.070	1.019	0.779	1.333	0.818	0.598	1.119
(1=female, 0=male)	(0.135)			(0.153)			(0.176)			(0.125)			(0.140)			(0.131)		
Secondary education	1.276	0.892	1.823	1.186	0.813	1.730	0.875	0.561	1.366	0.830	0.583	1.182	0.820	0.602	1.116	0.867	0.604	1.245
(1=yes, 0=no)	(0.233)			(0.229)			(0.199)			(0.150)			(0.129)			(0.160)		
Head of household	1.204	0.887	1.635	1.068	0.773	1.475	0.910	0.627	1.320	1.086	0.777	1.518	1.158	0.880	1.523	0.988	0.721	1.354
(1=yes, 0= no)	(0.188)			(0.176)			(0.173)			(0.186)			(0.162)			(0.159)		
Panel continuity				1.219	0.925	1.607	0.972	0.817	1.157	0.958	0.854	1.074	0.957	0.881	1.041	0.966	0.890	1.048
(continuous)				(0.172)			(0.086)			(0.056)			(0.041)			(0.040)		
Household																		
Household size	1.107***	1.048	1.169	1.057*	1.000	1.118	1.046	0.982	1.115	1.065**	1.007	1.127	1.029	0.982	1.079	0.995	0.933	1.061
(continuous)	(0.031)			(0.030)			(0.034)			(0.031)			(0.025)			(0.033)		
Engaged in agriculture	1.174	0.860	1.602	1.263	0.857	1.861	0.820	0.546	1.231	0.921	0.648	1.309	1.502***	1.112	2.027	1.388*	0.996	1.935
(1=yes, 0=no)	(0.186)			(0.250)			(0.170)			(0.165)			(0.230)			(0.235)		
Employment																		
Location	1.527	0.910	2.561	1.252	0.657	2.385	1.503	0.778	2.901	1.298	0.730	2.308	1.626	0.858	3.080	1.650	0.831	3.278
(1=same district,	(0.403)			(0.412)			(0.504)			(0.381)			(0.530)			(0.578)		
0=other)																		
Employment type	2.436***	1.786	3.322	4.333***	3.120	6.017	4.865***	3.279	7.217	4.683***	3.376	6.496	2.014***	1.502	2.701	3.285***	2.355	4.582
(1=off-farm, 0=self)	(0.386)			(0.726)			(0.979)			(0.782)			(0.301)			(0.558)		
Location#Employment	0.308***	0.176	0.539	0.593	0.301	1.167	0.559	0.270	1.160	0.520**	0.279	0.967	0.666	0.342	1.297	0.373***	0.179	0.774
type	(0.088)			(0.205)			(0.208)			(0.165)			(0.227)			(0.139)		
(Same distr.|Off-farm)																		
Formal registration	1.127	0.845	1.502	0.700**	0.505	0.971	0.458***	0.315	0.668	0.518***	0.380	0.707	0.618***	0.470	0.814	0.446***	0.320	0.621
(1=yes, 0=no)	(0.165)			(0.117)			(0.088)			(0.082)			(0.087)			(0.076)		
Log yearly income	0.769***	0.709	0.834	0.770***	0.701	0.846	0.845***	0.758	0.942	0.831***	0.747	0.924	0.766***	0.692	0.847	0.770***	0.690	0.860
(continuous in PPP$)	(0.032)			(0.037)			(0.047)			(0.045)			(0.039)			(0.043)		

Table 3.A1.10 Multilevel logistic regression results: Random intercepts level 1 & 2, by year (cont.)

	2008			2010			2013			2016			2017			2019		
	OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI		OR	95% CI	
	(SE)	Lower	Upper	(SE)	Lower	Upper	(SE)	Lower	Upper	(SE)	Lower	Upper	(SE)	Lower	Upper	(SE)	Lower	Upper
Provinces																		
Ubon Ratchathani	0.770**	0.608	0.975	0.836	0.642	1.088	1.096	0.815	1.472	1.231	0.940	1.612	1.281**	1.009	1.625	1.150	0.878	1.507
(ref. Buriram)	(0.093)			(0.113)			(0.165)			(0.169)			(0.156)			(0.159)		
Nakhon Phanom	1.147	0.825	1.596	1.197	0.859	1.667	1.932***	1.259	2.966	1.344	0.934	1.935	1.243	0.921	1.679	0.959	0.669	1.376
(ref. Buriram)	(0.193)			(0.202)			(0.422)			(0.250)			(0.190)			(0.177)		
Intercept	0.528**	0.313	0.893	0.198***	0.109	0.359	0.322***	0.169	0.616	0.529**	0.301	0.928	0.288***	0.174	0.479	0.373***	0.241	0.649
	(0.141)			(0.060)			(0.107)			(0.152)			(0.075)			(0.105)		
Random effects	**Variance**	**95%CI**		**Variance**	**95% CI**		**Variance**	**95% CI**		**Variance**	**95% CI**		**Variance**	**95% CI**		**Variance**	**95% CI**	
	(SE)	**Lower**	**Upper**	**(SE)**	**Lower**	**Upper**	**(SE)**	**Lower**	**Upper**	**(SE)**	**Lower**	**Upper**	**(SE)**	**Lower**	**Upper**	**(SE)**	**Lower**	**Upper**
Respondent-level	0.878	0.556	1.386	1.038	0.658	1.639	1.107	0.655	1.872	0.992	0.594	1.656	0.629	0.341	1.160	0.811	0.433	1.517
variance	(0.205)			(0.242)			(0.297)			(0.260)			(0.196)			(0.259)		
Goodness-of-fit																		
AIC	3,158.50			2,848.62			2,142.60			2,531.65			2,903.76			2,304.80		
R^2 (Respondent-level)	0.112			0.148			0.174			0.161			0.077			0.124		
N Respondents	1,212			1,155			939			1,085			1,136			1,004		
R^2 (Response-level)	0.177			0.213			0.243			0.221			0.113			0.170		
N Employments	2,415			2,247			1,679			1,970			2,174			1,766		

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Notes: Outcome variable is dichotomous and takes on the value of 1 when an employment is inconsistently reported. All continuous variables have been standardised using general mean centering. Odds ratios (OR) reported. Standard errors (SE) in parentheses. R^2 represents McKelvey&Zavoina-Pseudo-R^2. Source: Own calculations based on TVSEP (2019).

Table 3.A1.11 Extension of multilevel regression results, by agreeableness/trust – 2019

	2019 – Agreeableness			**2019 – Trust**		
	OR	95% CI		OR	95% CI	
	(SE)	Lower	Upper	(SE)	Lower	Upper
Respondent						
Age	0.996	0.984	1.009	0.996	0.984	1.008
(continuous)	(0.006)			(0.006)		
Gender	0.801	0.583	1.099	0.797	0.583	1.089
(1=female, 0=male)	(0.129)			(0.127)		
Secondary education	0.893	0.620	1.286	0.875	0.611	1.254
(1=yes, 0=no)	(0.166)			(0.161)		
Agreeableness	0.885	0.759	1.032			
(Scale 1-7: continuous)	(0.069)					
Distrusts others				1.281*	0.978	1.677
(1=yes, 0=no)				(0.176)		
Head of household	0.992	0.719	1.368	0.988	0.722	1.352
(1=yes, 0= no)	(0.163)			(0.158)		
Panel continuity	0.972	0.895	1.055	0.966	0.891	1.047
(continuous)	(0.041)			(0.040)		
Household						
Household size	0.995	0.933	1.062	0.993	0.931	1.058
(continuous)	(0.033)			(0.032)		
Engaged in agriculture	1.352*	0.963	1.897	1.403**	1.007	1.954
(1=yes, 0=no)	(0.234)			(0.237)		
Employment						
Location	1.423	0.703	2.880	1.609	0.811	3.191
(1=same district, 0=other)	(0.512)			(0.562)		
Employment type	3.142***	2.243	4.401	3.296***	2.364	4.594
(1=off-farm, 0=self)	(0.540)			(0.558)		
Location	0.428**	0.202	0.906	0.378**	0.182	0.785
#Employment type	(0.164)			(0.141)		
(Same district|Off-farm)						
Formal registration	0.452***	0.323	0.632	0.442***	0.317	0.616
(1=yes, 0=no)	(0.077)			(0.075)		
Log yearly income	0.778***	0.695	0.870	0.768***	0.689	0.858
(continuous in PPP$)	(0.044)			(0.043)		
Provinces						
Ubon Ratchathani	1.126	0.855	1.484	1.107	0.844	1.454
(ref. Buriram)	(0.158)			(0.154)		
Nakhon Phanom	0.969	0.672	1.398	0.941	0.678	1.391
(ref. Buriram)	(0.181)			(0.178)		
Intercept	0.397***	0.226	0.696	0.323***	0.182	0.575
	(0.114)			(0.095)		
Random effects	**Variance**	**95%CI**		**Variance**	**95% CI**	
	(SE)	**Lower**	**Upper**	**(SE)**	**Lower**	**Upper**
Respondent-level variance	0.802	0.422	1.524	0.786	0.415	1.489
	(0.263)			(0.256)		
Goodness-of-fit						
AIC	2,2222.16			2,303.56		
R^2 (Respondent-level)	0.121			0.127		
Obs. Resp.	967			1,004		
R^2 (Response-level)	0.166			0.170		
Obs. Occ.	1,699			1,766		

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Outcome variable is dichotomous and takes on the value of 1 when an employment is inconsistently reported. Odds ratios (OR) reported. Standard errors (SE) in parentheses. Source: Own calculations based on TVSEP (2019).

Appendix 3.A2 – Case studies

In the following section, two case studies will be presented that will further underline the issue of inconsistent reporting as illustrated in section 3.2. Each case study will examine patterns in responses related to off-farm employment and non-farm self-employment using an individual household as an example to underline the differences between consistent and inconsistent reporting.

Case study 1 – Consistent reporting

The household selected in this case study is located in the province of Buriram and consists of a core of three household members. The data display sporadic activity in off-farm employment and an absence of non-farm self-employment (Table 3.A2.1).

Both the household head and his spouse are in their fifties in the initial panel wave with the household head being employed in casual agricultural wage labour, an activity, which he has been active in for five years. Otherwise, the adults in the household allocate their labour to their own agriculture. In 2008, the household head permanently retired from this off-farm employment to focus on the household's own agricultural activities jointly with his spouse. The third member of the household is the granddaughter of the household head, who is being raised in the village. In the 2007 wave, she is seven years old and by 2019 is reported as being twenty. Throughout the panel, the granddaughter is consistently reported as being a full-time student. Uniquely to the 2013 wave, her mother is reported as being a household member. She is in her late thirties and stated as having returned to the village, where she was employed as a teacher, for the entirety of the 2013 reference period. Prior to and following the 2013 wave, the daughter is not reported as a member of the household and migrated to another location.

Table 3.A2.1 Overview of employment – Case study 1

I. Off-farm Employment(s)	Member I.D.	2007	2008	2010	2013	2016	2017	2019
Agricultural Wage Labourer [Ploughing&Casual Labour] (Started in 2002)	1							
Government Official [Teacher] (Started in 2005)	4							

Note: Green refers to consistently reported data. Source: Own illustration.

Case study 2 – Inconsistent reporting

The household in case study 2 is located in the province of Ubon Ratchathani and consists of three members in the initial wave of the survey and four in the most recent available survey wave in 2019. An overview of off-farm employment and non-farm self-employment activities throughout the panel is provided in Table 3.A2.2.

Both the household head and his spouse are in their mid-fifties and employed as teachers in 2007 and 2008 – an employment, in which they have been active since the mid-1970s. After 2008, both household members retired from their position and took up "occasional light work", work in own agriculture and work in various household owned businesses for the remainder of the panel.

The third member is their daughter and is present from 2007 onwards. She is in her early thirties and has been a nurse since 1999. While all available survey data suggests that the daughter has consistently been employed as a nurse, albeit in different locations throughout the panel, individual wave data is inconsistent. The daughter worked in Bangkok from 2007-2010 and she returned to the household as a permanent member in 2011 after finding employment as a nurse in proximity to the household. Up to this point, she consistently remains in the same field of employment as a nurse, albeit in different locations.

A slight inconsistency is observed in 2016 and 2017, which originates from her employment being recorded as "Other civil servant" instead of "Nurse". Some researchers may interpret this as a change in employment. However, key variables match between both employments, which raises the issue of mislabelling of employments.

Using supplemental data from a partial survey in 2011, a more consequential inconsistency can be observed in 2013, as no off-farm employment is recorded. By consulting later waves of data, no such gap should exist in 2013. Further, intra-wave observations in 2013 provide evidence that she was indeed employed – following the member section her main employment was reported as "government official". This information is consistent with prior waves and therefore, we can conclude that employment as a nurse was implausibly not reported in the 2013 wave. Thereby, the aggregate household income of 340,000 THB should have been supplemented by between 215,000 THB and 360,000 THB based on consecutive waves of survey data.

The fourth member married into the household in 2016 and is the spouse of the daughter. In 2016, no off-farm employment activity was reported, but information on an employment in the service sector was provided in 2017. According to the 2017 wave, the member had been active in this field of employment since 2010. Therefore, we can conclude that this employment was implausibly not reported in 2016.

Regarding non-farm self-employments, the household founded two businesses in 2010 after the household head and his spouse retired from their employment as teachers. Thereafter, the household began to run a guesthouse – a business that is still present to date. A second-hand car dealership was introduced with the entry of the fourth member in 2016 and is consistently observed until 2019.

Table 3.A2.2 Overview of employment – Case study 2

I. Off-farm Employment(s)	Member I.D.	2007	2008	2010	2011	2013	2016	2017	2019
Government Official [Teacher] (Started in 1975)	1								
Government Official [Teacher] (Started in 1976)	2								
Government Official [Nurse] (Started in 1999)	3								
Service Sector [Other] (Started in 2010)	4								

II. Non-farm Self-employment(s)	2007	2008	2010	2011	2013	2016	2017	2019
Wholesale (Started in 2008)								
Retail Shop (Started in 2009)								
Guesthouse (Started in 2012)								
Other, specify [2nd hand car sales] (Started in 2015)								

Note: Green refers to consistently reported data; orange to consistently reported, but mislabelled data; red to inconsistently reported data. Source: Own illustration.

CHAPTER 4: EXITING THE FARM: AN ADVISABLE STRATEGY FOR POVERTY ALLEVIATION IN RURAL NORTHEAST THAILAND?

Abstract

Following substantial and rapid rural transformation, rural areas in Northeast Thailand have been observed to remain engaged in agriculture to a degree that exceeds expectations of the literature. Using three waves of panel data that span 12 years, the continued role of agriculture in both non-agriculture-based (NAB) and agriculture-based (AB) households is examined. Thereby, the share of agricultural income related to total household income is observed to remain stable. Further, agricultural productivity is observed to increase despite out-migration of working-age individuals with demographic change resulting in high levels of dependency of an increasingly ageing rural population. Poverty incidence is observed to have declined significantly, in particular, for AB households, which in 2019 are as likely to be poor as those households characterised as non-agricultural-based. In order to assess factors influencing rural poverty, we develop a logistic regression approach that is run disaggregated by type of household. Our results highlight that the education of the household head plays a key role and that diversified livelihood strategies are key to reducing poverty in the area. The key driver of rural poverty in a population that remains reliant on agriculture is found to be climate-based shocks in the form of droughts, which implies that poverty makers must focus on improving resilience of rural households rather than focusing on deagrarianisation.

Keywords: Rural development, agriculture, poverty, Thailand, agricultural policy

JEL: Q18, 018, R14

4.1 Introduction

Following the substantial achievements of the Millennium Development Goals (MDGs) in global poverty reduction, the proportion of households living in extreme poverty ($2.15 measured in 2017 PPP) declined from 29.1% in 2000 to 10.8% by 2015 (World Bank, 2023). Subsequently, a shift to the SDGs took place, which hence formulated the goal of eradicating poverty globally by 2030. The proportion of households living in extreme poverty has since declined further and reached 8.4% by 2019 (World Bank, 2023). Progress was largely driven by achievements across every subregion in Asia (Asian Development Bank, 2019). Nonetheless, poverty remains a pressing issue (Asian Development Bank, 2022) that is predominantly concentrated in rural areas of lower- and middle-income countries (Ravallion et al., 2007).

To date, the role of agriculture in economic development and poverty reduction has been subject to debate. Foremost, the belief that the agricultural sector plays a more passive role in development by transferring superfluous labour to more productive sectors was omnipresent throughout the early- to mid-twentieth century (Kuznets 1957; Lewis 1954). Therefore, structural transformation and rapid industrialisation were considered key and expected to result in a decline in the importance of the agricultural sector (Fisher, 1939). Shortly thereafter, a paradigm shift that substantiated a more active role of agriculture took place (Johnston & Mellor, 1961; Ranis & Fei, 1961), which argued that agriculture exhibited high potential for increasing levels of productivity following intensification and adoption of technological innovations (Schultz, 1964; Hayami & Ruttan, 1971). Indeed, structural transformation in its early stages was argued to necessitate a modernisation of the existing low-productivity agricultural sector and expected to have a strong initial effect on poverty alleviation. This school of thought was substantiated by considerable economic development that took place with the onset of the Green Revolution in the 1970s, in particular in Southeast Asia (Pingali, 2012).

In recent decades, Southeast Asia has experienced a substantial reduction in rural poverty with rapid rural structural transformation often being cited as a key driver thereof (Huang, 2018; Liu et al., 2020; Shirai & Rambo, 2017). However, Southeast Asia, despite attempts of deagrarianisation, has been and continues to be characterised by the propensity of rural households to be engaged in small-scale farming with both the expected exodus from agriculture and consolidation of multitudinous small-scale farms failing to materialise (Rigg et al., 2016). Further contradicting economic theory of agricultural intensification following economic development, small-scale farms that comprise less than two hectares of land have been observed to further decline in size (Hazell & Rahman, 2014; Yamauchi et al., 2021).

Whether this phenomenon is detrimental to development is subject to debate. Policy has historically been focused on development of urban regions and thereby the industrial and service sector, while the potential of the rural economy is less frequently considered. On the one hand, continuously decreasing agricultural landholdings and agricultural production raises the issue whether rural households will be able to subsist without access to alternative sources of off-farm income (Hayami, 2007; Liu et al., 2020; World Bank, 2007). On the other hand, it has been observed that improving the situation of smallholders may have a disproportionately strong effect on poverty alleviation (Deininger & Byerlee, 2012; Henley, 2012). Further, in economies characterised by low wages, labour-intensive production is more efficient, thus substantiating small-scale farms as advantageous in such systems (Otsuka et al., 2016). Further, recent research suggests that agricultural labour productivity may be understated and that growth in productivity is not limited to the consolidation of small-scale farms (Fuglie et al., 2019). While the seasonal nature of the agricultural sector results in stark contrasts of productivity throughout the year, seasonal peaks are argued to indicate that agriculture is not intrinsically less productive than alternative sectors. Therefore, seeking new sources of income from non-farm activities should be considered as complementary to agricultural income rather than as a substitute (Christiaensen & Martin, 2018; Fuglie, 2018).

In order to ensure that gaps in collected data are equidistant, three waves of a comprehensive household panel data set that spans 12 years of survey data are examined. Thereby, data from 2007, 2013, and 2019, which encompass 1,160 identical, rural households in Northeast Thailand form the basis of our analyses, which strive to contribute to the literature debating the continued role of agriculture in development. This paper has three objectives. First, to investigate whether, over the course of more than a decade, panel households: i) give up own agriculture, or ii) diversify their sources of livelihood while remaining based in agriculture. The second objective is to undertake a descriptive analysis of the contribution of small-scale agriculture to rural household livelihoods is undertaken. Thereby, changes in agricultural productivity and the contribution of agriculture to rural household income are examined. Third, we investigate factors influencing poverty incidence and differentiate between households that focus on agriculture and those who have reduced their focus on agricultural activities.

The essay is structured as follows: In section 4.2, following a description of the study area, an approach is developed to differentiate between different types of households based on their selected livelihood strategies. Further, our empirical model is developed. Section 4.3 describes the underlying dataset. Section 4.4, summarises and discusses the main results. The final section provides a summary and draws conclusions for policy.

4.2 Methodology

4.2.1 Defining typologies of households in Northeast Thailand

As observed throughout Southeast Asia, Thailand also underwent a period of rapid structural transformation and development beginning in the 1980s (Haraguchi et al., 2019; Stiglitz, 1996; World Bank, 2018) and transitioned from a low-income country with predominantly agricultural production to a more diversified, emerging market economy. Following rapid economic growth, diversification of livelihoods was not confined to urban areas only. In addition, rural households began to diversify their sources of income by pursuing non-farm self-employment and off-farm wage employment, which often coincided with a modernisation of agricultural activities (Schultz, 1964; Hayami & Ruttan, 1971; Devereux et al., 2012).

The Northeast region of Thailand constitutes the largest and simultaneously poorest region in Thailand, which has historically lagged behind the other regions of the country (World Bank, 2016). This stems, in part, from the region's reliance on rainfed agriculture and the generally low quality of soil (Rambo, 2017; Viriya, 2001). The environmental conditions in Northeast Thailand, which is characterised by erratic rainfall and limited availability of surface water poses severe constraints to rainfed agricultural production. Such constraints prompted households to adopt diversified livelihood strategies, which remain focused on agriculture, but also include natural resource extraction and out-migration (Grandstaff et al, 2008). Harris & Orr (2014) conclude that small-scale farms in such regions are unlikely to be lifted above the poverty line by agriculture alone. Rather, they argue that the role of agriculture lies in the provision of direct benefits in the form of improved household food security. Nevertheless, Northeast Thailand experienced rapid rural development beginning in the late 1980s, which resulted in declining rates of poverty (Barnaud et al., 2006; Rambo, 2017). Thereby, the predominantly subsistence-oriented households, which focused primarily on production of glutinous rice, intensified agricultural activities and in some regions diversified crop production (e.g., cash crops such as cassava and sugarcane) whilst simultaneously pursuing off-farm wage employment, which (Fukui, 1996; Grandstaff et al, 2008; Hohfeld & Waibel, 2013). Consequently, agricultural productivity was observed to increase with rice yields increasing from 1.5 t/ha in the 1980s to 2 t/ha by the early 2000s (Grandstaff et al, 2008; Rambo, 2017). One of the effects of rapid economic growth, in the region was that indebtedness of rural households increased substantially (Chichaibelu & Waibel, 2017). Due to their diverse sources of income, rural households in Isaan[16] have been coined as part-time farmers in the literature (e.g., Grandstaff et al, 2008; Rigg et al., 2018; Shirai & Rambo, 2017). Despite the availability of non- and off-farm opportunities and geographic constraints, rural livelihoods remain embedded in agriculture.

Due to the high propensity of agriculture in Northeast Thailand, most households can be characterised as being engaged in agricultural activities, although the intensity thereof varies between individual households. Agricultural activities are considered to be comprised of the production of crops and crop products, livestock and livestock products, natural resource extraction, and agricultural wage employment that takes place outside of the household's own farm (Hill & Cook, 2002). Approaches used to define households as agriculture-based include categorising based on a minimum threshold of: (i) income derived from agricultural sales; (ii) dependency on agriculture production; (iii) farm size; (iv) household labour allocated to agricultural activities. As established in the literature review, in Northeast Thailand, most households are engaged in agriculture, are highly dependent on agriculture and are small-scale farmers that cultivate less than 2 hectares of land. It is argued that in such contexts, utilisation of labour allocation data in order to define household typologies is the most feasible option (Wye Group, 2011). However, using commonly applied definitions, which utilise a broad outlook in defining household typologies (Hill & Karlsson, 2005), such as reference person systems, which consider households as agricultural if at least one member is engaged in own agriculture (Handbook of Household Surveys, 1984), is deemed infeasible as it likely results in all Isaan households being considered as agricultural households. Further, this may result in the categorisation of households that are engaged in home gardening as agriculture-based (Wye Group, 2011). While, defining households based on labour allocation and using person hours with a minimum threshold of hours being required to be defined as agriculture-based households likely represents a robust approach, such data are rarely available in household survey datasets and in the case of our study data were not available for all survey waves. Therefore, this study defines agricultural households based on their dependence on agriculture by determining whether a household is "primarily" engaged in agriculture. Thereby, agriculture-based (AB) households are defined as households in which at least one nucleus[17] member is primarily engaged in agriculture. In contrast, households that have no such members

[16] the Thai term for the Northeast of the country.

[17] This study considers the nucleus unit of the household. Thereby, a household is considered to consist of all household members, which stay in the respective household for at least 180 days during a one-year reference period.

primarily engaged in agriculture, although they may indeed be engaged in own agriculture, albeit as a secondary occupation, are defined as non-agriculture-based (NAB) households.

In order to further examine changes in the livelihoods of rural households, a household income framework is defined, which considers all income-generating activities of nucleus household members. While income generated by household members that are external to the household is not considered, remittance payments received from such members are included. Overall, income is measured by deducting only the variable costs of production from gross income (fixed costs are ignored) and the framework differentiates between agricultural and non-agricultural income. Agricultural income is derived from farm activities including crop activities, livestock, livestock products, natural resource extraction, and wages earned in the agricultural sector. Non-agricultural income stems from non-farm wage employment, self-employment, remittances, and other sources of income such as government transfer payments. Thereby, wage income includes both cash and in-kind payments, while net revenues are calculated for self-employment. Additionally, income generated from renting-out land is considered as non-agricultural income.

4.2.2 Empirical strategy

In order to meet our first two objectives, a descriptive analysis is undertaken that investigates how rural transformation that took place over a twelve-year period has affected rural households in Northeast Thailand. Thereby, its impact is differentiated based on two types of households, namely AB and NAB households. First, changes to the composition of rural households and their livelihoods are examined, including determining whether households remain AB or transition to follow NAB livelihood strategies. Second, based on the pervasiveness of small-scale agriculture in Northeast Thailand, the role of agriculture and the impact of rural transformation thereon is illustrated in order to facilitate the discussion whether the role of agriculture has changed following economic development.

In order to address the third objective of this study, we strive to examine whether the household-level decision to remain engrained in agriculture is beneficial to the economic well-being of rural households. In a first step, the approach of this study focuses on the incidence of rural poverty as measured by the Foster-Greer-Thorbecke poverty headcount ratio (FGT0) (Foster et al., 1984). In order to assess the incidence of poverty, two poverty lines were applied, namely: (i) the international poverty line (IPL) of 1.90 PPP$ and (ii) a 5.47 PPP$ poverty line, which is applicable in the context of upper-middle-income country (UMIC) such as Thailand (Joliffe & Prydz, 2016).

A logit model is applied separately for each of the two types of households, namely: (1) NAB households and (2) AB households. The model is specified as follows:

$$P(Y_{ji} = 1) = \alpha_{j0} + \beta_{kj}X_{ki} + \delta_{mj}Z_{mi} + \vartheta_j S_i + \varepsilon_{ji} \quad (1)$$

where Y_{ji} is indicative of the household type j, which can be either (a) non-agriculture-based; or (b) agriculture-based, and household i (i=1, 2, …, n), respectively. Thereby, Y_{ji} is a dichotomous variable that is equal to one if the household is classified as poor based on the application of a 5.47 PPP$ poverty line and 0 if the household is non-poor. X_{ki} are characteristics of the household head; and Z_{mi} encompasses household characteristics including characteristics pertaining to agricultural activities of the household; and S_i captures whether a household has been affected by a climate-related shock.

Table 4.1 provides an overview and description of explanatory variables that are included in the model. Thereby household head socio-economic characteristics such as age, gender, and education as well as the dependency ratio and characteristics of the household such as its physical assets are included, which have been widely applied to examine poverty incidence (e.g., De Silva, 2008; Imai et al., 2015; Klasen et al., 2015; Malik, 1996; Sekhampu, 2013). Further, household characteristics on economic activities of the household pertaining to agricultural activities are considered based on the context of our study area as described in Section 4.2.1. Due to the high prevalence of environmental shocks, we further control for the impact of drought on the poverty incidence, whereby vulnerability to climate-related shocks has been identified as driving poverty (e.g., Gloede et al., 2015; Hallegatte et al., 2020; Hill & Porter, 2017). Finally, we control for provincial differences in order to ascertain whether there are fundamental differences in poverty incidence experienced based on geographic location of the household.

Table 4.1 Description and overview of explanatory variables

Variable	Type	Description	NAB households Mean (Std. Dev.)	AB households Mean (Std. Dev.)
Household head				
Age	Continuous	Age in years	61.89 (13.21)	58.35 (12.49)
Gender	Dummy	1 if female, 0 otherwise.	0.43 (0.49)	0.28 (0.45)
Secondary education	Dummy	1 if head has at least completed secondary education, 0 otherwise.	0.20 (0.40)	0.09 (0.28)
Main occupation in agriculture	Dummy	1 if head's main occupation is agriculture, 0 otherwise.	-	0.80 (0.40)
Household				
No. of members in off-farm wage employment	Continuous	Number of members engaged in off-farm wage employment.	0.68 (0.97)	0.73 (1.00)
No. of members in self-employment	Continuous	Number of members engaged in self-employment.	0.53 (0.84)	0.26 (0.55)
Dependency ratio (%)	Continuous	Share of dependent household members.	94.06 (92.70)	71.68 (79.33)
Share of rice expenditures	Continuous	Share of rice expenditures in relation to total household expenditure.	8.17 (10.45)	4.48 (8.67)
Affected by drought	Dummy	1 if household was affected by drought, 0 otherwise.	0.15 (0.35)	0.35 (0.48)
Agriculture				
Farm size	Continuous	Farm size in rai.	2.23 (1.11)	2.65 (0.85)
Mechanised agriculture	Dummy	1 if household used mechanised agricultural devices (rented and/or owned), 0 otherwise.	0.29 (0.46)	0.88 (0.32)
No. of crops planted	Continuous	Number of crops planted by household.	1.16 (1.85)	2.53 (2.11)
Perennial crops planted	Dummy	1 if household cultivates perennial crops, 0 otherwise	0.16 (0.36)	0.17 (0.38)
Other annual crops planted	Dummy	1 if household cultivates other annual crops, 0 otherwise	0.13 (0.34)	0.24 (0.42)
Provinces				
Ubon Ratchathani (ref. Buriram)	Categorical	1 Buriram 2 Ubon Ratchathani 3 Nakhon Phanom	-	-

Note: all continuous variables are transformed as mean-centered in later analyses; values displayed in this table are based on their uncentered values. Source: Own calculations based on TVSEP (2019).

4.3 Data

The survey data used in this study stem from a long-term household panel survey, the Thailand Vietnam Socio Economic Panel (TVSEP), which deals with the subject of poverty dynamics of rural households. The panel encompasses three provinces and 2,200 household located in Northeast Thailand, namely Buriram, Ubon Ratchathani and Nakhon Phanom. These provinces were selected and the households sampled with the goal of being representative of rural populations of Northeast Thailand following a three-stage cluster sampling design (Hardeweg et al., 2013). The sampled provinces were purposively selected due to being characterised by low per capita income, inequality in village-level wealth distribution, a high-share of household income stemming from agriculture, poor infrastructure, and high development potential, which makes this panel particularly suitable for our purposes. In total, seven waves of data are available to data with the first household survey having been conducted in 2007 and the most recently conducted survey being in 2019. In order to facilitate our research objectives, we focus on a consistent base of 1,160 households for which income data was available and which were interviewed in all seven consecutive waves of the panel. Using data from 2007, 2013, and 2019 the role of agriculture is examined using equidistant 6-year gaps.

The survey instrument contains standard components of Living Standard Measurement Studies (LSMS) as conducted by the World Bank (Grosh & Glewwe, 2000). Thereby, detailed modules on agriculture, off-farm wage employment and self-employment facilitate the analysis undertaken in this study. In addition to the typical components of LSMS survey instruments, modules that facilitate research on vulnerability to poverty such as modules on shocks and risks as well as behavioural aspects of development are available. In accordance with standard procedures in LSMS style surveys, interviews are structured as in-person interviews in which a member of the household responds, in proxy, on behalf of their household.

4.4 Results

4.4.1 Descriptive analysis

In a first step, rural livelihoods are analysed in order to determine how they have changed between 2007 and 2019. In congruence with the literature, most rural households in Northeast Thailand are characterised as being primarily engaged in agriculture throughout the twelve-year span of available data (Grandstaff et al, 2008; Rigg et al., 2018; Shirai & Rambo, 2017). The overall share of AB households is high at almost 90% in 2007 (Table 4.2). Households gradually transition out of primarily focusing on agriculture with 76.7% of households remaining AB in 2019. Nonetheless, agriculture continues to play an important, albeit smaller role, for households characterised as NAB with more than 10% of household members remaining in agriculture. Further, almost 60% of NAB households continue to generate income from agricultural sources, while some 40% exit agriculture entirely and focus on other income-generating activities. While over 60% of household members are engaged in agriculture in AB households, households not primarily engaged in agriculture nonetheless an average of over 10% of household members remain in agriculture. AB households, on average, have almost twice as much land at their disposal when compared with NAB households. While average household income differs moderately between the two types of households in all waves of collected data, per capita income is substantially lower in AB households due to their higher average household size.

Table 4.2 Overview of household characteristics, by year

	Non-agriculture-based households			**Agriculture-based households**		
	2007 Mean (s.d.)	**2013 Mean (s.d.)**	**2019 Mean (s.d.)**	**2007 Mean (s.d.)**	**2013 Mean (s.d.)**	**2019 Mean (s.d.)**
Household size	3.20 (1.40)	3.34 (0.45)	3.27 (1.80)	4.20 (1.66)	4.08 (1.59)	3.76 (1.60)
Members engaged in agriculture (No.)	0.47 (0.80)	0.45 (0.92)	0.41 (0.68)	2.37 (1.05)	2.34 (1.02)	2.06 (0.87)
Share of Members engaged in agriculture (%)	15.83 (28.38)	11.53 (23.03)	13.50 (25.33)	60.01 (22.17)	61.66 (23.67)	60.68 (25.21)
Members engaged in wage employment	0.42 (0.70)	0.65 (0.99)	0.83 (1.03)	0.96 (1.12)	0.65 (0.95)	0.59 (0.88)
Size of land plots (Rai)	10.64 (16.58)	12.08 (17.00)	9.75 (14.87)	20.98 (18.86)	21.32 (19.42)	19.18 (16.32)
Total household income (PPP$)	7,774.73 (9,694.84)	10,541.31 (23,133.27)	11,564.91 (29,474.04)	7,408.15 (30,115.33)	9,230.01 (26,891.56)	11,039.70 (45,634.80)
No. of households	132	155	270	1,028	1,005	890

Source: Own calculations based on TVSEP (2019).

Demographic change in rural Northeast Thailand

Economic development in Thailand resulted in increasing rural-urban out-migration of working age individuals. Figure 4.1 illustrates the changing composition of rural households in Northeast Thailand using population pyramids. While an expansive pyramid form can be observed in 2007, with a wide base of individuals in younger age groups, the base is observed to contract over the next twelve years. Notably, the number of individuals in the middle categories of the population pyramid, i.e., individuals between the age of 20 and 40, are shown to decline substantially, irrespective of gender. This observation reflects the overall trend of rural-urban out-migration in Thailand with individuals exiting the village in order to seek alternative income-generating activities either within the boundaries of their home province, other nearby provinces, or the Bangkok Metropolitan Region (Amare et al., 2012). In congruence with literature on population economics in lower- and middle-income countries, households in rural Thai villages are often observed to consist of elderly household members, who are left behind alongside younger household members (Knodel et al., 2010; Rigg, 2020).

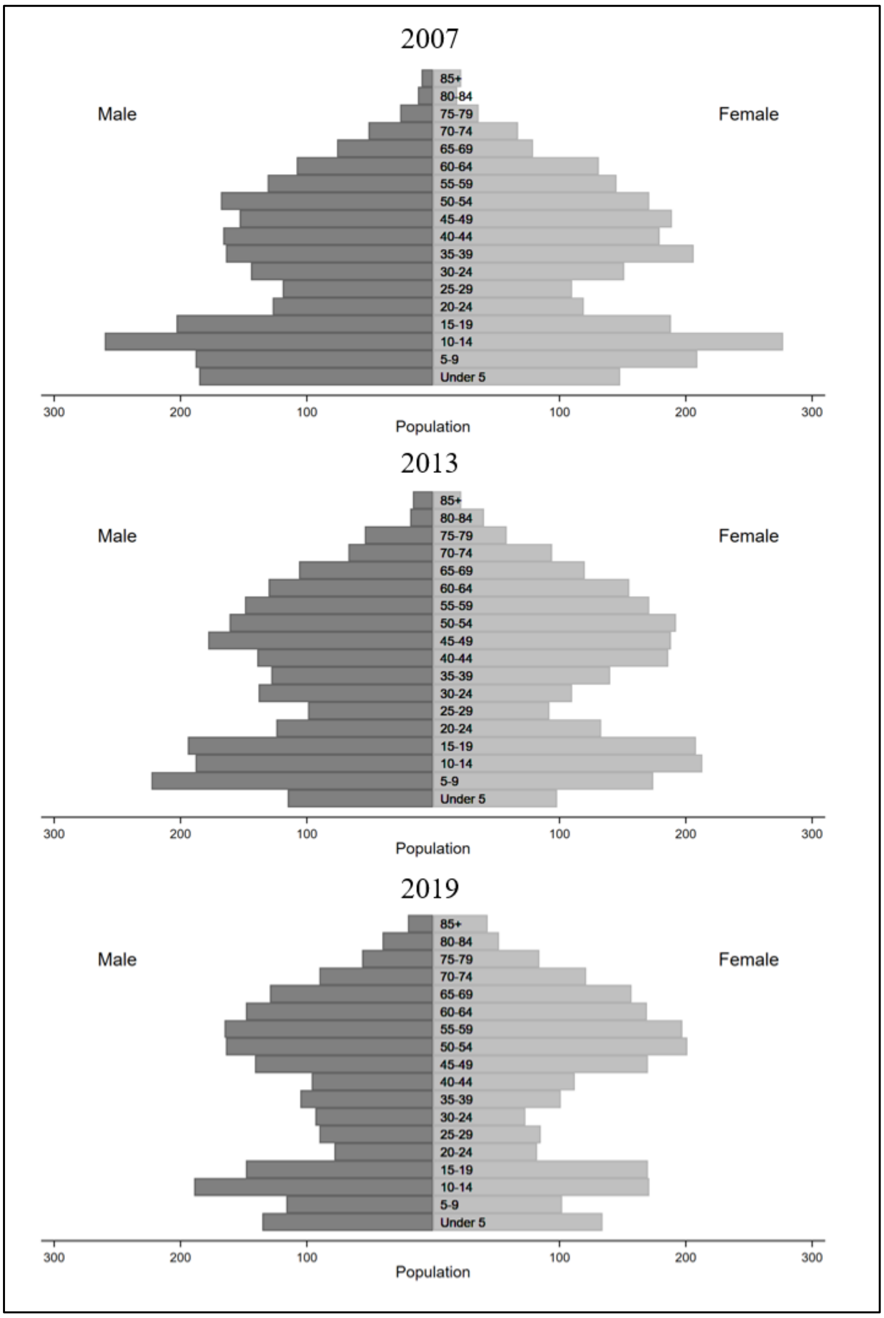

Figure 4.1 Sample population pyramids, by year
Source: Own calculation based on TVSEP (2019).

A distinct consequence of the thriving rural-urban migration is an increasing reliance of rural household members on a dwindling group of working-age nucleus household members. In the first wave of data, the burden of nucleus working-age members situated in NAB households is high and the average dependency ratio is found to be over 100% (Figure 4.2). Conversely, the dependency ratio of AB households is substantially lower at ~60% in 2007, which is driven by a larger proportion of young dependents in NAB households that declines from ~60% in 2007 to below 40% by 2013. A similar, albeit less pronounced decline in youth dependency is observed in AB household. Simultaneously, both types of households experience an increase in the dependency ratios of elderly household members, which is observed to counteract the declining child dependency ratio for both types of households. Overall, dependency is observed to converge as the panel progresses with NAB households exhibiting an average dependency ratio that is 9% higher than that of AB households by 2019.

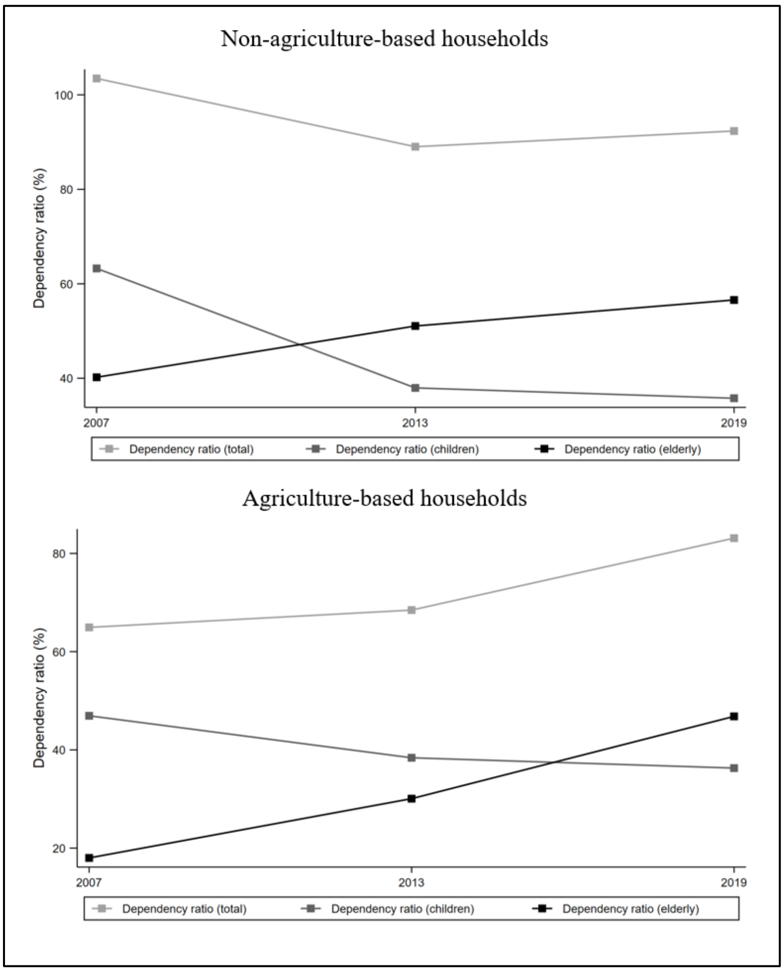

Figure 4.2 Dependency ratio, by household type and year
Source: Own calculations based on TVSEP (2019).

In NAB households, household members engaged in agriculture mostly stem from the older age cohorts and are above the age of 40 (Table 4.3). Conversely, the agricultural workforce of AB households is spread across all age cohorts in 2007. However, as the panel progresses, the majority of agricultural workers are drawn from an ever-increasing share of older cohorts. In particular, the share of workers above the age of 60 almost triples by 2019, whereas younger and middle-aged cohorts increasingly cease to participate in agricultural activities of the household. Despite the exodus of younger cohorts in AB households, the overall share of nucleus household members engaged in agriculture remains stable and lies between 55% to 57% across all waves.

Table 4.3 No. of members engaged in agriculture, by year and age group

	Non-agriculture-based households			**Agriculture-based households**		
	2007	**2013**	**2019**	**2007**	**2013**	**2019**
15-20	1	1	3	121	97	19
21-30	5	6	3	352	242	116
31-40	15	13	10	593	396	187
41-50	29	24	30	579	583	389
51-60	10	18	42	513	577	547
>60	2	8	23	280	457	573
∑	62	70	111	2,438	2,352	1,831
No. of household members	422	518	882	4,314	4,103	3,345
No. of households	132	155	270	1,028	1,005	890

Source: Own calculations based on TVSEP (2019).

Changing livelihood strategies

The composition of household income is illustrated in Figure 4.3 and displays the overall share of household income derived from agriculture, off-farm employment, self-employment, remittances, and other sources of income such as public transfers. In 2007, 10% of household income of NAB households is obtained from agricultural activities. The share thereof is observed to remain somewhat stable in 2013 and decline by almost 50% in 2019. The preferred source of income for such households is off-farm wage employment and self-employment, which jointly make up over 70% of income in 2007, which further increases in later waves. However, the role of agriculture is more pronounced in AB households and the share of total income remains somewhat stable with some 40% of household income being derived from agriculture. Income from off-farm wage employment remains comparable between 2007 and 2019, whereas income attained from small-scale household businesses decreases substantially between 2013 and 2019. Notably, other income constitutes a substantial share of income for

AB households in 2019, which is mainly driven by recipients of public transfer payments. Remittances from non-nucleus household members play a key role for both types of households and the share thereof is comparable across waves.

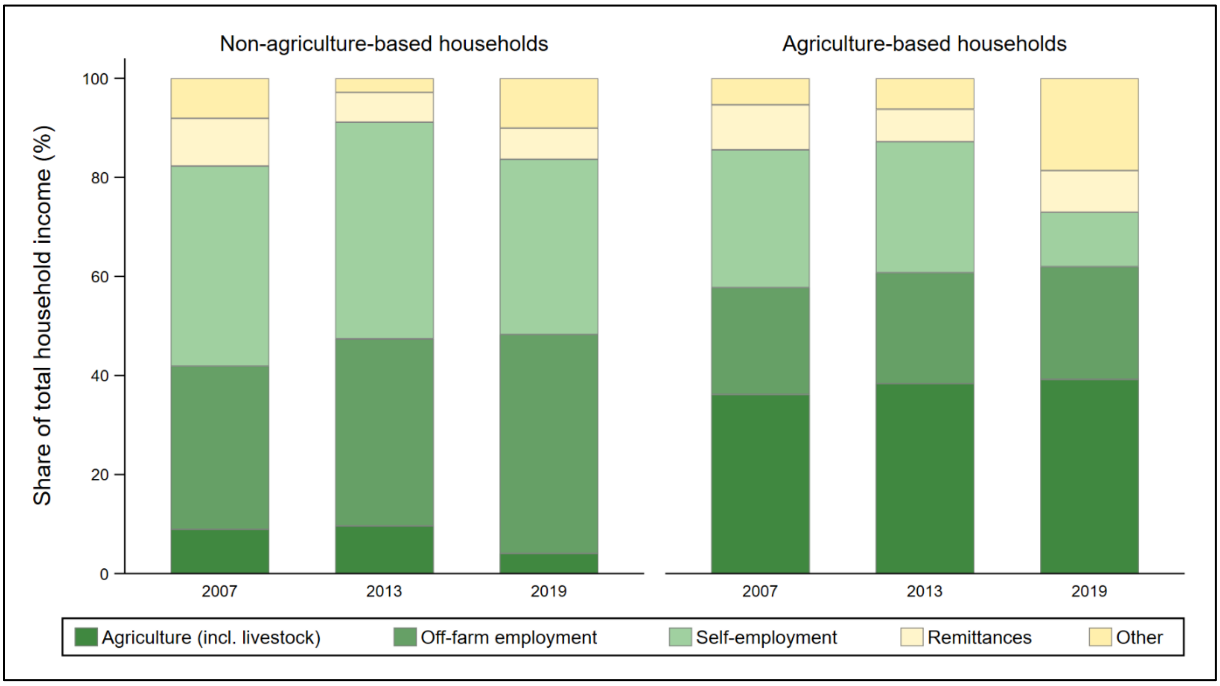

Figure 4.3 Income composition of households, by year
Source: Own calculations based on TVSEP (2019).

Table 4.4 illustrates transitions made by both AB and NAB households pertaining to their focus on agriculture as a primary component of their livelihoods. Notably, the share of AB households declines over time with a large transition of AB households taking place between 2013 and 2019. While most households are observed to remain in their initial state, one in five households transition between the two livelihood strategies with the majority thereof transitioning to the category of NAB households.

Table 4.4 Overview of transitioning livelihood strategies

	2007/2013	2013/2019	2007/2019
Remain			
Agriculture-based	936	830	837
Non-agriculture-based	63	95	79
Transition			
Agriculture-based to non-agriculture based	92	175	191
Non-agriculture-based to agriculture based	69	60	53

Source: Own calculations based on TVSEP (2019).

In summary, the rural landscape is observed to change substantially from 2007 to 2019, particularly regarding the demographic structure of households, which results in higher dependencies on those working-age individuals that remain in the village. Most households are observed to remain reliant on agriculture, including those that consider a more diversified approach to their livelihoods, albeit to a lesser degree. This finding necessitates further in-depth analysis of shifts in agricultural production, which are expected to generate further insights needed to discuss the question whether promoting an exit from agriculture is beneficial to rural households.

The changing role of agriculture?

Having illustrated changes in household compositions and livelihood strategies in Northeast Thailand throughout a 12-year span, using a six-year interval, the next step is to examine how rural transformation has affected agricultural production.

Throughout the period of time encapsulated in the underlying dataset and across the two types of households, differences in terms of land use can be observed (Table 4.5). Households that are not based in agriculture are shown to own less land than their counterparts. Notably, the share of total land that is utilised for agricultural purposes in NAB households remains high and ranges between 30-50%, which is, however, substantially lower than in AB households that are found to allocate over 80% of their land to agriculture. Additionally, the majority of households operate as small-scale farms that cultivate less than 12.5 rai (2 ha) of land. Further, 98% of households cultivate less than 10 hectares of agricultural land, which further substantiates the characterisation of small-scale farming households as opposed to consolidated rural farms in Northeast Thailand. Further, no clear indication of an onset of consolidation of farm land can be observed with neither the area of rented-out land increasing substantially, nor there being a higher share of rented-in agricultural land in the case of AB households, which was observed to decline from ~20% in 2007 to ~10% in 2019.

Table 4.5 Overview of household land use, by year

Land (Rai)	Non-agriculture-based households 2007	2013	2019	Agriculture-based households 2007	2013	2019
Agricultural land	3.77	6.14	4.47	17.44	18.20	17.28
	(7.40)	(11.91)	(8.95)	(17.25)	(17.40)	(14.64)
Non-agricultural land	3.77	3.17	2.84	2.42	2.29	1.19
	(7.77)	(7.07)	(6.68)	(5.41)	(6.71)	(3.20)
Vacant land	0.33	0.90	0.22	0.44	0.44	0.21
	(2.38)	(3.78)	(1.26)	(2.74)	(2.11)	(1.48)
Rented-out	2.78	1.87	2.22	0.68	0.39	0.50
	(7.49)	(6.50)	(6.34)	(3.51)	(2.86)	(3.19)
Total land	10.65	12.08	9.75	20.98	21.32	19.18
	(16.58)	(17.00)	(14.87)	(18.86)	(19.42)	(16.32)

Source: Own calculations based on TVSEP (2019).

A distinct difference in the allocation of agricultural land to specific crop varieties can be observed between the two typologies of households. While the majority of land is utilised to cultivate the regional staple crop, namely rice crops, AB households, on average, allocate a higher proportion of their land to rice cultivation than their counterparts (Table 4.6). Both the cultivation of perennial crops (e.g., para rubber, banana, and mango) and other annual crops (e.g., chilies, cassava, and sugarcane) has increased over the 12-year period observed in this study, showcasing a shift to more diversified agricultural production in the region. However, the increased diversification of cultivation of crops other than rice is observed to be more prevalent in NAB households. Notably, in 2013, NAB households increasingly cultivated cassava and sugarcane over perennial crops such as para rubber, resulting in a substantial decline in land allocated to perennial crops. Conversely, in 2019, the planted area of mango cultivation almost doubled across the NAB sample and some households shifted to cultivation of oil palm.

Table 4.6 Overview of land allocation, by year

	Non-agriculture-based households			Agriculture-based households		
Land share (%)	**2007**	**2013**	**2019**	**2007**	**2013**	**2019**
Rice	75.61	70.49	56.65	89.24	86.39	85.22
	(41.28)	(41.91)	(46.87)	(25.06)	(27.72)	(28.58)
Perennial crops	13.35	7.81	19.61	6.47	7.66	8.99
(e.g., para rubber, banana, and mango)	(32.97)	(19.86)	(32.94)	(18.78)	(20.19)	(22.31)
Other crops	11.04	21.70	23.74	4.30	5.96	5.79
(e.g., chilies, cassava, and sugarcane)	(27.41)	(38.07)	(37.30)	(15.85)	(18.92)	(18.01)

Source: Own calculations based on TVSEP (2019).

A further indicator of changes in agricultural production is observed in the mechanisation of agriculture as shown in Table 4.7. In 2007, the ~30% of NAB households made use of machinery throughout the process of agricultural production, whereas most AB households made use of machinery. However, most NAB households rented machinery in the initial survey wave. Throughout the 12-year period of observation, AB households are observed to have increasingly invested in own agricultural machinery, which is supplemented with rented machinery, especially in 2019. This observation is in line with the literature on the mechanisation of rural Thai agriculture, which finds that small-scale agriculture is facilitated by the availability of suitable and affordable machines that can be rented out to farmers (e.g., Cramb & Thepent, 2020; Rigg et al., 2016).

Table 4.7 Mechanisation of agricultural production, by year

	Non-agriculture-based households			Agriculture-based households		
% of households	**2007**	**2013**	**2019**	**2007**	**2013**	**2019**
Mechanised agriculture	29.55	36.13	25.93	89.69	88.66	86.40
(rented and/or owned)	(45.80)	(48.19)	(43.90)	(30.43)	(31.73)	(34.29)
No machinery	70.45	63.87	74.07	10.31	11.34	13.60
	(45.80)	(48.19)	(43.90)	(30.43)	(31.73)	(34.29)

Source: Own calculations based on TVSEP (2019).

Regarding agricultural labourers, most households were observed to hire labour from outside of their household that assisted in land preparation, planting, application of fertilisers and pesticides, and harvesting in the first two waves. Over 75% of NAB households utilised hired labour, whereas over 80% of AB households were observed to do so. However, the propensity to hire labour declined substantially between 2013 and 2019 for both types of households and dropped to below 30%. Figure 4.4 displays the relationship between hired and family labour expressed in person hours, which was available for the 2013 and 2019 survey waves. Notably, an average ratio of 1:1 was applied by NAB households in 2013, while AB households mostly relied on family labour. Overall, the ratio of hired/family person hours is observed to decline in 2019, especially toward the upper end of the distribution of NAB households. While many households are observed to abstain from hiring external labour as the panel progresses, those who maintain their hiring practices, hire agricultural labourers at a similar rate between 2013 and 2019.

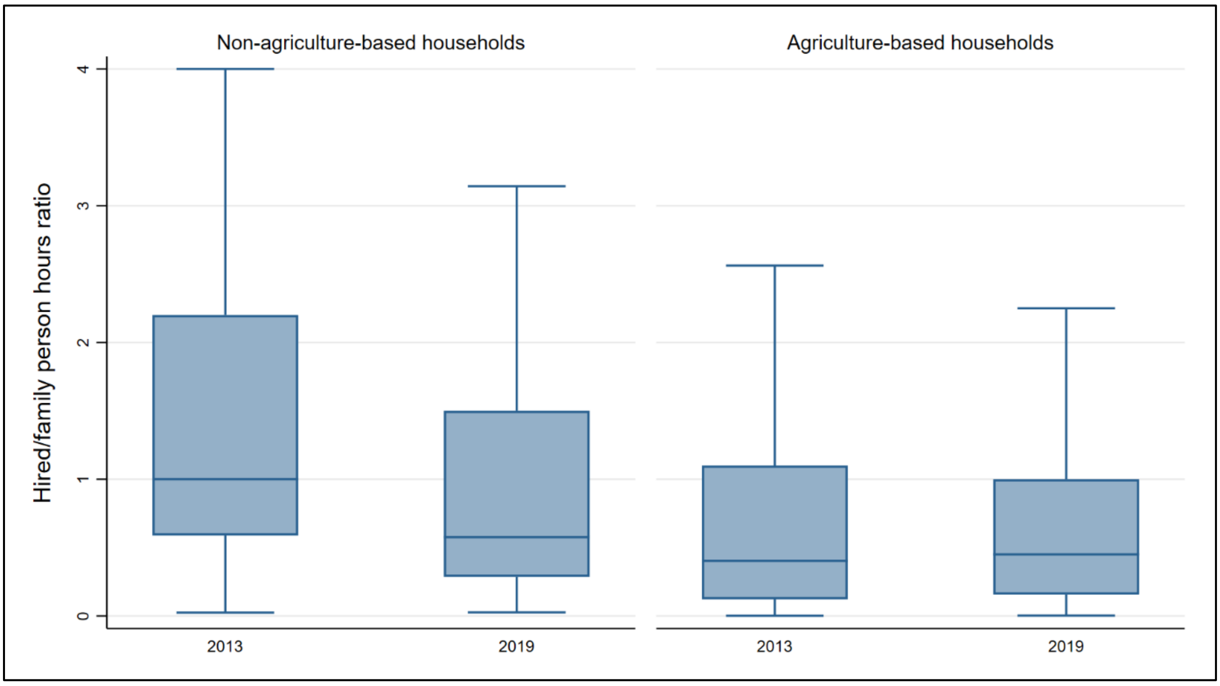

Figure 4.4 Overview of relationship between hired and family labour person hours, by year
Source: Own calculations based on TVSEP (2019).

Average annual crop production is observed to increase from 2007 to 2013. However, production of rice declines substantially in 2019 and is observed for both types of households, which warrants further investigation. Therefore, a measure of productivity is calculated (kg per rai of land) for rice crops in 2007, 2013, and 2019. The average productivity of rice is found to increase from ~300 kg/rai in 2007 to 310 kg/rai in 2013, which matches the observed productivity of rice farmers in Northeast Thailand in other studies (Grandstaff et al, 2008; Rambo, 2017). However, in stark contrast to the growing productivity observed, in particular for NAB households, rice productivity declines to an average of below 250 kg/rai in 2019, which almost corresponds with the productivity observed in the 1980s. Notably, this observation is limited to rice and the 2019 wave of survey data. Climate shocks such as droughts have been observed to significantly impact the productivity of crops, in particular rice in Northeast Thailand (Prabnakorn et al., 2018; Jaretzky et al., 2022), which warrants further examination.

An overview of rice productivity in 2019 is displayed in Table 4.8, which is disaggregated by the three provinces encompassed in the study area. Further the proportion of households affected by droughts is displayed. A high proportion of households located in Buriram are observed to have been affected by drought when compared to the other provinces. In particular, AB households twice as often reported that they had been negatively impacted by climate-based shocks in the form of droughts. Accordingly, rice productivity is observed to have declined substantially in Buriram, whereas the other two provinces are indicated to have been less affected. In Ubon Ratchathani, a province that was seldom reported as having been affected by droughts, the productivity of rice is comparable, if not slightly higher, than that reported in 2013.

Table 4.8 Rice productivity and prevalence of drought, by province – 2019

	Non-agriculture-based households		**Agriculture-based households**	
	Rice productivity (kg/rai)	**Households affected by drought (%)**	**Rice productivity (kg/rai)**	**Households affected by drought (%)**
Buriram	204.92	29.52	208.42	62.47
	(173.12)	(45.83)	(158.00)	(48.49)
Ubon	341.65	2.32	322.22	18.53
Ratchathani	(169.58)	(15.13)	(168.44)	(38.91)
Nakhon	256.63	11.11	269.75	6.96
Phanom	(189.39)	(31.87)	(183.32)	(25.53)

Source: Own calculations based on TVSEP (2019).

The severity of drought events in all three provinces is illustrated in Table 4.9. Notably, households affected by drought are shown to report lower rice productivity when compared with those that were not, which is consistently observed across provinces. This suggests that the decline in rice crop productivity is likely driven by the severity of droughts experienced in 2019 rather than transformation of rural demographics and agriculture. Nonetheless, the productivity of those households that are reportedly unaffected by droughts is observed to have stagnated rather than increased when compared with 6-year preceding data, which is unexpected. The high prevalence of drought events likely also explains the observation of increased shares of household income of AB households stemming from public transfers (Figure 4.3). Indeed, public transfers more than quadrupled in 2019 and increased especially for AB households due to climate-based shocks and payments received from government programmes pertaining to social relief for natural disasters and rice support programmes (e.g., Lebel et al., 2011; Ricks & Laiprakobsup, 2021).

Table 4.9 Average rice productivity (kg/rai), by province and drought status – 2019

	Non-agriculture-based households			Agriculture-based households		
	Buriram	**Ubon Ratchathani**	**Nakhon Phanom**	**Buriram**	**Ubon Ratchathani**	**Nakhon Phanom**
Unaffected by drought	302.02 (199.36)	341.65 (169.58)	308.12 (200.90)	268.17 (165.22)	332.58 (166.72)	271.81 (185.66)
Affected by drought	163.30 (146.63)	-	136.48 (96.89)	171.67 (141.86)	278.47 (169.99)	240.25 (151.42)

Source: Own calculations based on TVSEP (2019).

4.4.2 Poverty incidence and model results

In order to address our third objective and to garner important insights as to whether remaining more engrained in agriculture is detrimental to household well-being, the poverty headcount ratio is calculated. First, the international poverty line (IPL) of 1.90 PPP$ is applied in order to examine the prevalence of extreme poverty in rural Northeast Thailand. Second, given that Thailand is an emerging market economy, a second poverty line of 5.47 PPP$ is applied that is more suited to the context of an UMIC (Jolliffe & Prydz, 2016). The share of households classified as poor based on the IPL of 1.90 PPP$ is mostly comparable between the two types of households across our three points of reference (Figure 4.5). More notable differences are observed in the application of the 5.47 PPP$ poverty line. Thereby, the share of NAB households classified as poor is observed to decrease slightly from 43.9% in 2007 to 41.1% by 2019. Conversely, poverty incidence declines substantially by over 10 percentage points in the case of AB households. While poverty incidence differs greatly in 2007 and 2013, the disparity between household typologies recedes by 2019. However, there is a substantial difference towards the upper end of the distribution of income with almost twice the share of NAB households being categorised as having at their disposal a per capita daily income of over 15.00 PPP$ when compared to their counterparts, which indicates substantial inequality in the distribution of income.

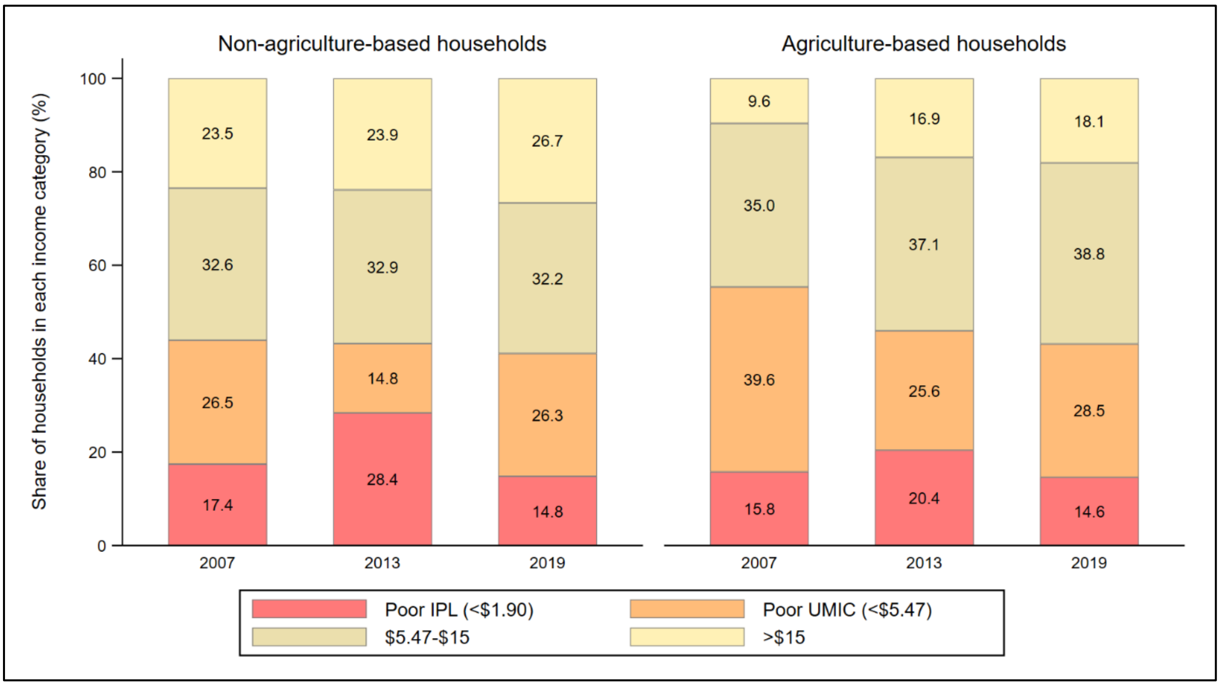

Figure 4.5 Distribution of income over time
Source: Own calculations based on TVSEP (2019).

Based on the observation that poverty incidence has converged between 2007 and 2019 with both NAB and AB households being almost equally as likely to be classified as poor, a logistic regression (Equation (1)) is run separately for each of the two household types in order to analyse factors associated with poverty incidence. The results thereof are reported in Table 4.10.

As expected, characteristics of the household head exhibit highly significant correlations in the model variant on AB households. Thereby, households headed by individuals that are over the sample mean age of 58, or primarily engaged in agriculture, are significantly more likely to be poor. Further, having completed at least a secondary level of education significantly reduce the likelihood of being poor and is mirrored across both types of households underlining the importance of improving access to schooling in rural areas in low- and middle-income countries. An increasing number of members engaged in alternative income-generating activities, i.e., in off-farm wage employment or small-scale household businesses, that exceeds the sample mean is negatively correlated with poverty incidence. This highlights that households in rural Northeast Thailand, which partake in more diversified livelihood strategies and increasingly capitalise on new non-farm opportunities, are more likely to be non-poor. Regarding characteristics of agriculture, AB households with large farm sizes are found to be less likely to be poor, which indicates that medium-size farms are less likely to be poor and likely more resilient than the predominantly observed small-scale farming households in

Northeast Thailand. Notably, and in line with the finding of the descriptive analysis, AB households affected by droughts are significantly more likely to be poor throughout the panel. The results further indicate that as households become less subsistence-oriented in their production of rice, as proxied for by the share of total expenditures devoted to purchasing rice, they are more likely to be poor. Indeed, the share of rice expenditures is highly positively correlated with poverty incidence in the case of AB households. Cultivation of perennial crops in AB households is indicated to increase the likelihood of being poor. This may be explained by perennial crops requiring several growth cycles before they can be harvested, thus delaying sale of products to later periods, while costs must be carried up front. A further explanation my lie in the increasing share of poor households that are found to invest in perennial crops over the 12-year period. For example, over 20% of households that cultivated perennial crops reported a total production of zero in each individual wave. Reportedly being affected by a drought is found to coincide with a higher likelihood of being poor. Thereby, the odds of a household being poor are almost 30% higher when they report that they were negatively affected by a drought. Overall, the model results match the findings of the descriptive analysis that indicated that while AB households were initially more likely to be poor, the likelihood thereof decreased significantly by 2019.

Table 4.10 Logit regression results – poverty headcount (5.47 PPP$ poverty line), by type of household

	Non-agriculture-based households OR (SE)	**Agriculture-based households OR (SE)**
Household head		
Age	1.018*	1.009***
(continuous)	(0.011)	(0.004)
Gender	1.134	1.060
(1 =female, 0=male)	(0.266)	(0.099)
Secondary education	0.383***	0.637***
(1=yes, 0=no)	(0.132)	(0.094)
Main occupation in agriculture	0.339	1.306***
(1=yes, 0=no)	(0.303)	(0.145)
Household		
No. of members in off-farm wage	0.227***	0.644***
employment (continuous)	(0.043)	(0.030)
No. of members in self-employment	0.498***	0.469***
(continuous)	(0.096)	(0.039)
Dependency ratio (%)	0.999	1.000
(continuous)	(0.001)	(0.001)
Share of rice expenditures	1.023*	1.016***
(continuous)	(0.012)	(0.005)
Affected by drought	1.158	1.266***
(1=yes, 0=no)	(0.416)	(0.113)
Agriculture		
Farm size (Rai)	0.997	0.979***
(continuous)	(0.018)	(0.003)
Mechanised agriculture	0.671	0.788*
(1=yes, 0=no)	(0.248)	(0.109)
No. of crops planted	0.973	0.926***
(continuous)	(0.115)	(0.027)
Perennial crops planted	1.703	1.242*
(1=yes, 0=no)	(0.763)	(0.160)
Other annual crops planted	0.526	0.941
(1=yes, 0=no)	(0.237)	(0.108)
Provinces		
Ubon Ratchathani	0.968	1.024
(ref. Buriram)	(0.249)	(0.095)
Nakhon Phanom	1.990*	1.606***
(ref. Buriram)	(0.752)	(0.195)
Survey wave		
2013	1.449	0.612***
(ref. 2007)	(0.462)	(0.059)
2019	1.516	0.546***
(ref. 2007)	(0.441)	(0.055)
Intercept	0.436*	1.124
	(0.211)	(0.201)
R^2	0.291	0.100
Obs.	545	2,899

Note: * p < 0.1, ** p < 0.05, *** p < 0.01. Odds ratios (OR) reported. Standard errors (SE) in parentheses. Source: Own calculations based on TVSEP (2019).

4.5 Conclusions

Overall, our study shows that demographic change is profoundly taking place in rural areas in Northeast Thailand with an increasingly ageing population remaining engaged in agriculture. Nonetheless, we observe little to no decline in terms of agricultural land cultivated and most households remain primarily engaged in agriculture while simultaneously seeking to diversify their incomes by seeking off-farm wage employment or founding small-scale businesses – as is typical for households in Northeast Thailand. Those households that no longer can be classified as primarily being engaged in agriculture are nonetheless observed to earn a substantial share of their income from part-time farming, which, on average, ranges between 5 and 10% of total household income. Indeed, the average crop production of households is increasing when compared with the baseline of 2007. Notably, poverty incidence has decreased by over 10 percentage points during the 12-year period in the case of AB households, whereas poverty declined substantially less for NAB households.

Despite researchers raising concerns over the exit of more productive youths from rural areas and thus also from agriculture, which is argued to potentially result in dire consequences for agricultural productivity (Dolislager et al., 2019), our study provides some contrasting evidence. In our sample, a decline in an already low level of agricultural productivity is not found to coincide with out-migration of working-aged individuals in rural Northeast Thailand. Rather, the unfavourable climate in Northeast Thailand and the dependency on rainfed agriculture continues to constrain agricultural production, as has been the case for many generations. Further, in facing unfavourable environmental conditions, we find that rural AB households are highly dependent on government transfer payments to cope with climate-based shocks, which more than quadrupled during the 12-year period observed in this study.

Regarding policy implications, this study further substantiates that a consolidation of smallholder farms has not taken place in rural Northeast Thailand despite rural development. This phenomenon is not limited to the Thai context with a high proportion of agricultural land being cultivated by small-scale farmers throughout Asia (Hazell & Rahman, 2014; Yamauchi et al., 2021). Additionally, it seems unlikely that this will change in the near future, especially based on the function of rural households as safety nets in times of crisis and their importance for food security of the extended household (e.g., Waibel et al., 2020). Based on the high propensity of environmental shocks in the region, we recommend further development of government interventions in order to ensure resilience of rural households and to facilitate households escaping poverty.

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