Livelihoods of Thai rural households – opportunities and challenges in times of globalization and global environmental change

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Kurzzusammenfassung

Durch eine zunehmend globalisierte Welt und nach Jahrzenten schnellen Wachstums, hat sich Thailand zu einem Land im Bereich des oberen-mittleren Einkommen entwickelt. Vormals eine primär landwirtschaftliche Nation, hat Thailand heutzutage eine divers aufgestellte Wirtschaft und der sekundäre und tertiäre Sektor bieten vielfältige Möglichkeiten. Diese Entwicklung betrifft nicht alle Provinzen gleichmäßig. Große Teile des Landes, speziell im Nordosten, sehen sich mit den Herausforderungen einer transformierenden Wirtschaft, Armut, Subsistenz-Landwirtschaft und Starkwetterereignissen konfrontiert. Die Komplexität, der sich dieser neuen Möglichkeiten und Herausforderungen anpassenden Lebensweisen, ist mit traditionellen Maßen für Armut nur unzureichend umschrieben. Ihre wissenschaftliche Analyse sollte somit auf umfassendere Ansätze, wie zum Beispiel das „Sustainable Livelihoods Framework" zurückgreifen. Mittels eines Langzeit-Panel-Datensatzes, werden in dieser Dissertation Schlüsselfaktoren der Existenzgrundlagen im ländlichen Thailand wie Einkommen, Konsum, Schocks und deren Erhebung analysiert. Nach einer Einleitung erkundet diese Dissertation im ersten Artikel die Einkommensstrategien der ländlichen Haushalte in Thailand, sowie deren Determinanten und Erfolg. Trotzdem Haushalte zunehmend außerhalb der Landwirtschaft tätig sind, bleibt diese nach wie vor relevant. Diversifizierte Einkommensstrategien sind, gemessen am Einkommen, am erfolgreichsten, da sie die effizienteste Allokation von Ressourcen erlauben. Zusätzlich wird die Bedeutung von Migration deutlich. Darüber hinaus zeigen die Ergebnisse, dass landwirtschaftliche Haushalte vulnerabel gegenüber zunehmenden Extremwetterereignissen sind. Im zweiten Artikel wird die Wichtigkeit qualitativ hochwertiger Daten herausgearbeitet und Ansätze zur Identifizierung von inkonsistenten Beschäftigungsdaten werden vorgestellt. Der dritte Artikel untersucht die Auswirkungen der Covid-19 Pandemie und zeigt tiefgreifende Effekte in der Zeit nach dem ersten großen Lockdown, die teilweise bis heute andauern. Darüber hinaus wird die Vulnerabilität von Einkommensstrategien außerhalb der Landwirtschaft gegenüber ökonomischen Schocks aufgezeigt. Artikel vier betrachtet den Konsum der Haushalte und identifiziert Typologien, die analog zur Lebensweise des Haushaltes und den Ergebnissen des ersten Artikels sind. Schocks, speziell Extremwetterereignisse sind dabei ein Initiator für den Wechsel der Existenzstrategie. In einem finalen Kapitel werden die Ergebnisse zusammengefasst und Empfehlungen für die Politik sowie zukünftige Forschung ausgesprochen.

Stichworte: Nachhaltige Lebensverhältnisse; Diversifizierung; Migration; Landwirtschaft; Außerlandwirtschaftliche Tätigkeiten; Ungleichheit; Covid-19; Thailand; Datenqualität und -konsistenz

Abstract

In an increasingly globalised world, Thailand has emerged as an upper-middle-income country, following decades of rapid growth. Once an agrarian nation, Thailand nowadays exhibits a diverse economy with the manufacturing and service sector offering opportunities outside of agriculture. This impressive development has not spread homogenously however, leaving large parts of the country, especially in the rural northeast in the gridlock of a transforming economy, subsistence agriculture, poverty, and an increase in natural disasters. Adjusting to these new challenges has created a plethora of livelihoods whose complexity escapes traditional measures of poverty, necessitating an analysis using more holistic approaches, such as the Sustainable Livelihoods Framework. Using a large-scale panel dataset spanning over more than a decade, key factors pertaining to rural livelihoods in Thailand such as income, consumption, shocks, and the measurement thereof are analysed in four articles.

Following an introduction, the first article of this dissertation explores the income strategies of rural households in Thailand, the determinants of their adoption as well as their success.

The results show that agriculture is still retained, even though households increasingly engage in non-farm income strategies. In addition, diversified livelihoods are shown to be the most successful in terms of income, offering the most efficient allocation of resources within a household. Further, the role of migration to exploit opportunities and a lack thereof in rural areas becomes evident. Finally, vulnerability to shocks is particularly notable with households in agriculture, as they experience an increasing frequency of natural disasters. The second article highlights the relevance of good quality data by presenting methodological approaches to identify and eliminate issues in employment data and their collection as well as showcases the impacts of inconsistent data. Article three examines the effects of the Covid-19 pandemic and reveals severe impacts after the first major lockdown, with some lasting until the present day. Further, the vulnerability of non-farm income sources to economic shocks is highlighted. Looking at the households from the perspective of consumption using cluster analysis, article four reveals distinct typologies that are in line with the overall livelihood strategies and the findings of the first article. Shocks, especially natural disasters, are shown to initiate changes in the livelihood strategies, either by diversification or by reducing the dependence on agriculture. In a conclusive chapter, key results are summarised and policy recommendations as well as an outlook for future research is presented.

Keywords: Sustainable livelihoods; Diversification; Migration; Agriculture; Non-Farm employment; Inequality; Covid-19; Thailand; Data quality and -consistency

Acknowledgments

A few years ago, as I started writing my first paper for this dissertation, I had little understanding of the journey that lay ahead. An interest in the topic, access to a great database and some skills in statistics are a good start, I thought, and the rest will fall into place. In hindsight, the reality was quite a bit more challenging and certainly, I would not have arrived at this point without the support and advice of a variety of people. In the interest of brevity, not all can be named, but I hope that those that are not, still know that I appreciate their support immensely.

First, I extend my gratitude to the supervisor of my thesis, Prof. Dr. Kerstin Nolte. Without her continued advice, countless comments, and suggestions as well as her willingness to share her knowledge, my understanding of methodology, academic writing, and the academic world in general would be considerably inferior to what it is today.

Second, I would like to express my sincere appreciation to Prof. Dr. Hermann Waibel. He has not only kindly agreed to be the second examiner for my dissertation but first introduced me to the world of development economics, when I was a young student assistant at his institute many years ago. I owe it to him, that I was able to participate in a variety of projects and got to know the world from a perspective that many will never have a chance to experience.

Third, I thank all my former and current colleagues, for the advice and discussions about research and other matters of life throughout the process of this dissertation. In particular, I appreciate Mark Brooks and Sina Bierkamp who are my Co-Authors on some of the articles presented in this dissertation.

Further, I thank my family and friends for their support as well as bearing with me when I was unavailable or distracted due to the lingering issues of a paper I was working on at the time. Without their support, this dissertation would not have been achievable.

Finally, this dissertation relies on data from the long-term project No. 20220831434900116103, funded by the Deutsche Forschungsgemeinschaft (DFG). For more detailed information, see http://www.tvsep.de.

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Abbreviations

CAPI	Computer Assisted Personal Interviews
DFG	Deutsche Forschungsgemeinschaft
GDP	Gross domestic product
LSMS	Living Standards Measurement Study
OLS	Ordinary Least Squares
PAPI	Pen And Paper Interviews
TVSEP	Thailand Vietnam Socio Economic Panel
UNCTAD	United Nations Conference on Trade and Development
VIF	Variance inflation factor

1 Introduction

1.1 Motivation

Globalization and the integration into global and regional value chains have led a number of formerly low-income countries to begin a process of transformation and development (Dreher et al., 2008). Macroeconomically, large scale changes can be observed, with the primary sector declining and the manufacturing and service sectors emerging (Dreher et al., 2008; Guadagno et al., 2016; Kucera & Roncolato, 2016; Syrquin, 1988, 2008). GDP growth is another side effect of this trend and eventually, countries will transform into middle-income countries. In the interest of economic growth and development, this trend seems quite desirable on the surface, however, it raises a plethora of issues (Dreher et al., 2008; Guadagno et al., 2016). First and foremost, we must ask how inclusive these developments are and if there are entry barriers that may prevent people from exploiting the new opportunities, especially in high-skill sectors. As a result, especially in the rural and agricultural areas of a country, poverty and inequality are further issues to consider (Guadagno et al., 2016). Looking past the macroeconomic statistics on a country level may reveal striking regional disparities that very much regionalize the national growth and have a potential to marginalize agricultural subsistence-based households that fail to transform (Tipayalai & Mendez, 2022). Paired with an increasing occurrence of natural disasters, accelerated through climate change, these trends may result in the improvement and transformation of rural livelihoods in middle-income countries or in increasing poverty and vulnerability to shocks (Thomas & López, 2015).

Using a large-scale panel dataset from Thailand, this dissertation addresses the composition of rural livelihoods and the determinants behind the changes thereof. Livelihood strategies are evaluated, and typologies of households emerge, both as income strategies as well as consumption strategies. Further, the role of shocks is considered beyond natural disasters, intending to reveal vulnerabilities that are specific to the individual livelihoods. Following this brief introduction, key concepts and literature are presented, forming the basis for both the research gaps and the research objectives that this dissertation contributes to. The first chapter closes with a detailed overview of the dataset and methodology used in the research articles that are presented in the four subsequent chapters. Thereafter, a conclusive chapter summarises the main findings and contributions as well as discusses policy recommendations and the limitations of this work. Finally, an outlook for potential future research on the topic is provided.

1.2 Theoretical framework and research gaps

1.2.1 Assessing development, livelihoods, and poverty

Measuring poverty, economic welfare, and vulnerability to poverty, particularly in the rural areas of a country, has long been a popular subject in development economics, as it bears important implications for policy design and allows conclusions about the general development of a region. Commonly conceptualized as a "poverty line", any household below a certain threshold of per capita income or per capita consumption per day is classed as poor, anyone above as non-poor (Ravallion, 2016). Finding a poverty line that accurately reflects the status "poor" is not trivial however, as many different factors, such as demographics and regional characteristics, can place a household at different levels of economic welfare, despite a constant poverty indicator value (Deaton & Muellbauer, 1980; Ravallion, 2001, 2016). This creates the issue of fluctuating poverty figures depending on the poverty line and the measurement of the chosen indicator (Deaton, 2016). The underlying indicators of per capita income and per capita consumption expenditures are not without challenges either. Income for instance, does not include any measures of wealth, such as assets and can fluctuate strongly, making consumption a potentially superior indicator of economic welfare and poverty (Brandolini et al., 2010; Castro et al., 1981; Deaton, 2003; Meyer & Sullivan, 2003; Zimmerman & Carter, 2003). However, other research finds that using income in high-income countries is preferable, highlighting the necessity to select an indicator in line with the conditions in the region (Atkinson, 1991; Foster et al., 1984; Meyer & Sullivan, 2003; Zimmerman & Carter, 2003). Due to its important role as a financial resource, income should not be ignored in any context, however (Castro et al., 1981; Deaton, 2003). A notable constraint to measuring poverty with any indicator is the empirical implementation, as collecting household data has a tendency for inaccuracy and fails to capture reality. Shortcomings range from questionnaire design with badly chosen reference periods to respondent bias (Deaton, 2003, 2016; Ravallion, 2001). With the shortcomings of income- and consumption-based poverty indicators in mind and as progress to eradicate poverty according to these measures is made, other approaches to assess poverty that include a multidimensional perspective and focus on inequalities as well, have been suggested (Alkire et al., 2023; Atkinson, 1991). A further notable approach that diverges from the emphasis on income- or consumption-based development assessments and highlights the individual level, is the capability approach developed by Sen (Alkire, 2005; A. Sen, 1984, 1985, 1993). In this, rather than for instance utility, social welfare is the focus and is assessed by "valuable functioning" and "freedom". The former is a set of "beings" and "doings" that are of value to a person. The latter represents the ability of a person to choose from different configurations of "functioning" and thereby actively having a choice in life.

Starting in the 1990s, a new branch of research emerged that extended its scope past the constraints of traditional poverty indicators and suggested a more holistic view on the intricacies of a household's situation, often referred to as its "livelihood" (Baulch, 1996; Chambers, 1995; Chambers & Conway, 1992; Scoones, 2009). As a result, Ashley and Carney (1999) as well as Scoones (1998) developed a framework to assess livelihoods and decision-making of rural households in low- and middle-income countries, the "Sustainable Livelihoods Framework" (Ashley & Carney, 1999; Scoones, 1998). The key elements of this framework are presented in Figure 1.1.

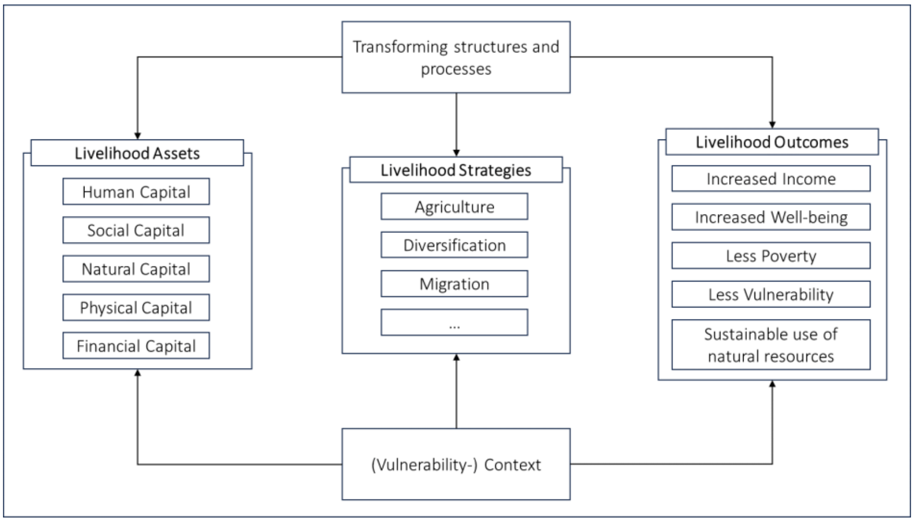

Figure 1.1 Sustainable Livelihoods Framework
(based on Ashley and Carney (1999) and Scoones (1998)).

Receiving widespread use throughout the literature, it aims to provide a dynamic perspective to the livelihood of a household and the factors that make it sustainable, i.e. able to cope with and recover from stressors and shocks (Ashley & Carney, 1999; Chambers & Conway, 1992; Natarajan et al., 2022; Scoones, 1998). At its core, livelihood assets are considered. While income is certainly part of these assets, other factors, such as human capital and physical capital, for instance in the form of land are included. Access to and quantity of these resources are then moderated by transforming structures and processes as well as the livelihood strategies into the sustainable livelihood outcomes. On the livelihood side, this might entail improved wellbeing or reduced poverty. Pertaining to sustainability, it might include a sustainable land use or an increase in resilience against shocks. A further dimension is provided by the (vulnerability-) context a household is situated in. This context includes for instance exposure to shocks,

climate, macro-economic conditions, and policy. It is intimately linked to all other elements of the framework, thereby serving as an important constraint or enabler for a household. As highlighted by Natajaran et al. (2022), in an increasingly globalized economy the framework should also consider a wider context and the transformations of the livelihoods as part of the overall development of the country (Natarajan et al., 2022). The novelty of the sustainable livelihoods approaches is the consideration of poverty as a potential outcome and to provide a framework towards the analysis of its complex and dynamic determinants (Ashley & Carney, 1999; Chambers & Conway, 1992; Natarajan et al., 2022; Scoones, 1998, 2009).
Within the Sustainable Livelihoods Framework, the role of shocks, both as a contextualizing factor and in the form of livelihood outcomes, for example by building resilience and lowering vulnerability, should be highlighted. However, types of shocks, such as idiosyncratic vs. covariate, vary greatly and affect different groups of households. For instance, a predominantly agricultural household will have a higher exposure to natural disasters, whereas a household with plenty of off-farm employed members is at greater risk to suffer from job loss (Hallegatte et al., 2020; Kemper et al., 2013). Like no other element of the Sustainable Livelihoods Framework, shocks are related to all other elements. Shocks can restrict or destroy livelihood assets and influence the strategic decisions in the household, as well as increase inequality, due to heterogenous access to certain strategies, such as off-farm employment. (Cassidy & Barnes, 2012; Datta & Behera, 2022; Reardon & Taylor, 1996). Thereby, increasing resilience and lowering vulnerability are two livelihood outcomes that contribute to the sustainability and stability of a livelihood in the event of crises. (Cassidy & Barnes, 2012; Datta & Behera, 2022; Whitney et al., 2017). Thus, evaluating the role of shocks is integral to any research on rural livelihoods.

1.2.2 Transforming economies and the case of Thailand

With ongoing globalisation, formerly low-income countries subsequently develop and transform into middle-income or even high-income countries. The effects of such transformations are diverse and subsume a variety of changes, for instance the shift from low- to high-productivity sectors and in the longer run, improvements to infrastructure, education and social systems (Bah, 2011; Fan et al., 2013; Guadagno et al., 2016; Kostov & Lingard, 2004; Marjanović, 2015; McMillan et al., 2014; Schlogl & Sumner, 2020; Senadza, 2014; Syrquin, 2008). The consensus in research is, that as a country develops economically and opportunities become available to the individuals, inevitably, labour will move away from agriculture and into income strategies in the secondary or tertiary sector, leading to a decline of the primary sector in macroeconomic figures (Guadagno et al., 2016; Kucera & Roncolato, 2016; Syrquin, 1988, 2008). In addition, productivity in the primary sector might increase, for example due to excess labour leaving the sector or the increased incomes through non-farm activities financing improvements (Kucera & Roncolato, 2016; Reardon et al., 2000; Syrquin, 1988). Some scholars, however, suggest the continued relevance of agriculture to provide food security and stability, for instance, by retention of at least small-scale agriculture as a component of a diversified livelihood, making the role and function of agriculture an important subject of contemporary research (Marjanović, 2015; Senadza, 2014; Timmer, 1988).

Thailand is a particularly good example of a transforming economy, providing an opportunity to examine the development of a country as it transitions from a low-income to an upper-middle income country. Over the past 40 years, Thailand’s economy has transformed from agrarian to industrial (Asian Development Bank, 2015). Since the mid-1980s, Thailand’s economy grew rapidly with up to 9.5% per year (Asian Development Bank, 2015). In the wake of this development, the primary sector’s contribution to the GDP declined, while the contribution of the secondary sector rose, yet a sizable share of the labour force remains in agriculture. (Asian Development Bank, 2015; K. Sen, 2016). Looking at the spatial concentration of this development reveals a pronounced focus on the greater Bangkok area, leaving other parts of the country still primarily involved in agriculture (Ahmad & Isvilanonda, 2003; Browder et al., 1995; Falkus, 1995; Paweenawat & Liao, 2023). Therefore, for the rural population to participate in the opportunities presented by the overall economic development, migration or an increase in productivity of agriculture were the only options available (Ahmad & Isvilanonda, 2003; Disney et al., 2023; Moore & Donaldson, 2016; Paweenawat & Liao, 2023; Thongsawang et al., 2020). Recent years have seen the transformation of formerly rural areas, as urban centres other than Bangkok grow and more domestic opportunities become available to the rural population, however large-scale disparities remain (Ahmad & Isvilanonda, 2003; Falkus, 1995; Moore & Donaldson, 2016; Paweenawat & Liao, 2023; Thongsawang et al., 2020; Tipayalai & Mendez, 2022). Between the new opportunities on the one side and the challenges of traditional agriculture on the other, issues such as inequality, inclusive development and poverty are more pressing than ever (Ahmad & Isvilanonda, 2003; Moore & Donaldson, 2016).

1.3 Research gaps

Summarizing the findings from the literature presented above, several research gaps can be identified. Although generally popular and well used as an approach for research, concepts such as the Sustainable Livelihoods Framework require expansion and adaptation to the realities of transforming economies in middle-income countries (Natarajan et al., 2022). Further, research needs to look past simple one-dimensional measures of poverty to accurately capture the diverseness of livelihoods that follows the integration of a country into global value chains. In this, there is great potential to combine the existing approaches.

Among other topics, such as inequality and sustainability of livelihoods, poverty remains an important issue especially in rural areas, albeit analytically more complex than a simple income or consumption figure might suggest. Understanding the mechanisms behind the livelihood strategies can help to design and implement better support for those most in need.

Another pertinent issue is the role of shocks. Research gravitates towards the analysis of natural disasters in rural areas, implying a predominant affectedness of agriculture. However, with diversified livelihood strategies come diversified risk profiles. These can be a positive factor to build resilience and lower vulnerability to natural disasters, however, they expose rural households to other types of shocks that influence the newly adopted non-farm income sources. In recent years, the effects of Covid-19 would serve as an example. Therefore, conducting research on the workings of shocks in relation to the specific livelihood strategy of a household is another promising field in research.

Finally, researchers tend to frequently collect and use data without sufficiently questioning its validity and completeness. Evaluating data in the context of rural livelihoods and identifying potentials for errors is therefore another research gap.

1.4 Research objectives and structure of this dissertation

Referring to the previously outlined research gaps and based on the literature presented earlier, this cumulative dissertation contributes to the literature by addressing the following four main objectives.

First, a better understanding of diversified livelihoods in low- and middle-income countries is required. Considering the rapidly evolving socio-economic conditions on the macro level, this also necessitates the adoption of a longitudinal perspective.

Second, several attempts have been made to conceptualize and quantify livelihoods. Recent literature highlights the need for holistic approaches to understanding livelihoods, concepts like the Sustainable Livelihoods Framework form the basis for an empirical analysis on the micro-level. Thereby, applying such frameworks to micro-level data can both facilitate a structured analysis and help to advance the overall conceptualization of livelihoods.

Third, the role of shocks should be considered. Global environmental change increases the frequency and severity of natural disasters, while economic and political crises in the global markets can lead to unemployment and other market-based issues. Therefore, shocks need to be regarded as an important factor in the livelihoods of especially rural households in low- and middle-income countries. This is also reflected in the presence of shocks as key components in concepts such as "resilience" or "vulnerability". Lastly, recent years have seen an increase in the availability of large-scale datasets, mostly owing to the advances in data-collection technology. Such data shapes our understanding and analysis of all the above points. It is worthwhile however, to consider the quality and potential shortcomings of such data and develop ways to ensure robustness and better-quality data overall.

Consequently, this dissertation tackles all the aforementioned objectives in four research papers. Presented in Table 1.1 are all articles that are part of this dissertation, their authors, the objective, and the status of submission.

Table 1.1 Papers of this dissertation and status of submission

Title	Author(s)	Research objective	Status	Journal
Income strategies of Thai rural households during economic transformation	Niels Wendt	Diversified Livelihoods (1) Conceptualize Livelihoods (2) Role of Shocks (3)	In preparation for submission	-
Inconsistent responses in household panel surveys: The case of non-farm employment	Mark Brooks, Niels Wendt, Hermann Waibel	Diversified Livelihoods (1) Assessing data quality (4)	Under Review	Survey Research Methods
Rural livelihoods in Thailand after two years of Covid-19	Niels Wendt, Sina Bierkamp	Conceptualize Livelihoods (2) Role of Shocks (3)	Under Review	Journal of Rural Studies
How do vulnerable households navigate current challenges? A consumption typology of Thai rural households	Niels Wendt, Kerstin Nolte	Diversified Livelihoods (1) Conceptualize Livelihoods (2) Role of Shocks (3)	In preparation for submission	-

Source: Own illustration.

Paper 1 is single authored by me and gives an overview over the transformation of rural livelihoods in Thailand. Employing the concept of the "Sustainable Livelihoods Framework", the paper mainly focuses on the income strategies of households as well as the determinants of their adoption. The ongoing trend of diversifying income strategies is evaluated as well as its potential benefits to the adopting households. The analysis in the paper also considers the influence of shocks, both to induce the adoption of a particular livelihood strategy and to expose the vulnerability to shocks that is inherent to some income strategies.

Paper 2 is co-authored with Mark Brooks and Hermann Waibel. The paper is jointly written by Mark Brooks and me, both making equal contributions. Hermann Waibel provided advice, supervision, and edits. The shares contributed to the final paper can be quantified as 40% for Mark Brooks, 40% for me and 20% for Hermann Waibel. Paper 2 is specifically dedicated to the fourth research objective and provides a longitudinal consistency evaluation of employment panel data. In the paper, an approach to identify inconsistencies is developed. Further, factors that will increase the likelihood of inconsistent responses are analysed and quantified in several multilevel-regression models. Finally, implications for income related indicators, such as income-based poverty are evaluated as part of a scenario analysis. Paper 3 is co-authored with Sina Bierkamp. Both authors contributed 50% each to the paper. The paper addresses the third research objective. Using the example of the Covid-19 pandemic and the plethora of shocks that followed in its wake, for instance unemployment due to businesses closing, we evaluate the impact of such shocks on rural households. Referring to the "Sustainable Livelihoods Framework", livelihood assets of the households are utilized to quantify the likelihood of their exposure to the Covid-19 related issues. In particular, the role of public transfers in times of crises becomes visible, as do shortcomings thereof and an overall need for more targeted support. Paper 4 is co-authored with Kerstin Nolte, who provided advice and supervision and contributed to the interpretation of the results as well as the introduction, conceptualization, and methodology. The contribution made by the authors is 80% for Niels Wendt and 20% for Kerstin Nolte. The article is directed at the research objectives one, two and three. Taking a different approach from paper 1, this study examines consumption patterns in households. Although usually preferred to income as an indicator of wellbeing in low- and middle-income countries, measuring and quantifying consumption is not without challenge. Using k-medoids and k-means clustering, we establish a consumption typology for rural households and showcase the determinants of adopting and changing certain types of consumption. In line with the "Sustainable Livelihoods Framework", we contribute to the understanding of how consumption and livelihood assets are related as well as the influence of shocks.

In summary, this dissertation revolves around the analysis of rural livelihoods in transforming environments. Referring to approaches of measuring poverty and the Sustainable Livelihoods

Framework, the four papers provide insights into the diverse nature of livelihoods and the numerous factors they are influenced by.

1.5 Methods and data

Based on the literature review and the research gaps, this dissertation approaches the previously outlined objectives from an empirical point of view. Data driven research provides a valuable contribution by applying theories and concepts to the real world, as well as developing improved methodologies to collect better quality data. Additionally, this dissertation has a regional focus that offers the opportunity to apply and explore rather general concepts and theories in the context of a specific area. Thereby, all articles presented, follow the approach of quantitative research, in which a literature review is followed by extensive empirical analysis, using the methods and data presented in the following sub-chapters.

1.5.1 Dataset

This dissertation is based entirely on a large-scale household panel dataset, namely the Thailand Vietnam Socio Economic Panel (TVSEP), which is funded by the Deutsche Forschungsgemeinschaft (DFG). Established in 2007 as DFG Research Unit (FOR 756) and subsequently formed into the TVSEP, the dataset offers eight waves of household panel data for 2200 households in three provinces of rural Thailand, as well as 2200 households in rural Vietnam. Since this dissertation focuses on Thailand, the latter are not utilized in any of the articles presented. The three Thai provinces, namely Buriram, Ubon Ratchathani and Nakhon Phanom and the households within, were sampled using three-stage cluster sampling, making the sample representative for rural households in the selected provinces as well as similar provinces, as present in rural Northeast Thailand (Hardeweg et al., 2013). In addition to the regular household panel waves, TVSEP offers two waves of migrant surveys, in which the migrant members of the households were tracked and asked a purpose-built questionnaire, village head surveys and a household survey in one Thai- and one Vietnamese province in 2011. Additionally, a special Covid-19 impact survey, that was implemented a few months after the pandemic started, thereby greatly reducing the memory bias of the respondents regarding its impacts. The database is particularly well stocked with data on income, consumption, and individual household members as well as living conditions.
The mission of the TVSEP is to give researchers access to large-scale longitudinal and high-quality datasets to conduct research on all matters of rural livelihoods. The success of this

mission is showcased by over 161 external data users, 8 add-on projects and numerous publications[1].

In addition to utilizing the data from the project for this dissertation, I was also personally involved in the data collection of the 2019, Covid-19 special survey and 2022 waves, being employed at the TVSEP for almost four years. My duties included the conceptualization and implementation of the tablet-based questionnaires, setting up and maintaining the technical infrastructure of the project, the compilation and processing of data, training and supervising the interviewers on location, as well as the staff involved in the quality control of the data. Additionally, I performed automated and manual checks on the incoming data, wrote reports and other analytical outputs, assisted in the project planning and administration, and provided support to data users.

The survey instrument in the TVSEP is conceptualized in the style of the Living Standard Measurement Studies (LSMS) as implemented by the World Bank (Grosh & Glewwe, 2000). In the TVSEP however, the survey instrument contains much greater detail and offers item-level data, even within household members in the applicable sections, such as off-farm employment. Consequently, the questionnaire is extensive and remains consistent in its core sections throughout the panel, with sections on current issues or topics of interest being added or removed over the span of the panel. The only notable exception is the initial questionnaire in 2007 that differs even in some of the core sections from the following waves. The questionnaire starts with some general information about the household, followed by detailed questions about its members, including education, migration, and health. Followed by information regarding monetary transfers from non-household members, trust, and household expenditures, all shocks the household may have experienced since the last wave are recorded. Questions regarding well-being, aspirations as well as risk perceptions for the future follow. The questionnaire then asks for detailed information on all income sources, starting with agriculture (crops, livestock, natural resources), followed by off-farm employment, and concluding with self-employment. Next, the financial situation of the household is assessed by sections on savings, borrowing, lending, public transfers, and insurance. Following the character traits and questions regarding investment and disinvestments, the housing situation and endowment with durable goods (assets) is recorded. In the last section, there is also a module asking for subjective household wealth. In 2022, a final section on the impacts of

[1] For updated statistics and further information, please see: https://www.tvsep.de/.

Covid-19, mimicking the 2020 Covid-19 special survey was added. As an example, Figure 1.2 showcases the questionnaire in its 2019 form with all its sections and subsections. The questionnaires of all years as well as further information are available on https://www.tvsep.de/.

1. Household Information
2. Members
   2.1. Member Details
   2.2. Education
   2.3. Health
   2.4. Household Dynamics
   2.5. Trust
8. Expenditures
3. Shocks, Wellbeing, Aspiration and Risks
   3.1. Shocks
   3.2. Subjective Assessment of Well-Being
   3.3. Risk Games
   3.4. Aspiration
   3.5. Risks
4. Land, Crops, Livestock, Fishing, Hunting, Collecting and Logging
   4.1. Land
   4.2. Crops
   4.3. Livestock
   4.4. Livestock Products
   4.5. Fishing, Hunting, Collecting and Logging
5. Off-Farm Wage Employment
6. Non-Farm Self-Employment, Investment and Disinvestment
   6.1. Non-Farm Self-Employment
7. Borrowing, Lending, Public Transfers, Other Payments and Insurance
   7.1. Borrowing and Lending
   7.2. Savings
   7.3. Public Transfers
   7.4. Insurance
10. Character Traits
6. Non-Farm Self-Employment, Investment and Disinvestment
   6.2. Investment
   6.3. Disinvestment
9. Assets, Household Wealth and Housing
   9.1. Assets
   9.2. Household Wealth
   9.3. Housing Conditions

Figure 1.2 Overview TVSEP questionnaire 2019

Source: Own illustration.

One of the core values of TVSEP always has been to conduct the interviews on-site. Thereby, an interviewer travels to the household and conducts a face-to-face interview using either a paper Questionnaire (PAPI) in earlier years or a tablet-based questionnaire (CAPI) using survey solutions[2] provided by the World Bank, as the technology became available.

Just like any long-term panel, the TVSEP suffers from attrition, as households leave the panel. Reasons are varied and include the household migrating from the village entirely, the last household member passing away or the household outright refusing to be interviewed again.

In Thailand, the overall attrition since 2007 reached 13%, which can be considered quite low. Regardless, a resampling using the original sampling procedure was carried out in 2019, that replenished the sample back to 2199 households. The attrition since has remained below 5% of the households.

[2] More information at: https://mysurvey.solutions.

In summary, the TVSEP dataset is an asset to any researcher in the general field. It provides a rich and detailed database, collected to scientific standards that even allows for longitudinal studies. The strategy of supplementing the core modules with sections on contemporary issues, such as Covid-19, makes it possible to conduct research on a wide variety of current topics, hence the TVSEP data is suitable for use in this dissertation.

1.5.2 Methodology

The articles included in this dissertation apply a variety of quantitative methods, as described below. Present in all papers is a descriptive review of the data as well as evaluation and robustness checks of the utilized methodology, especially in the context of regional factors, for instance by verifying the requirement for a multilevel-regression model with random effects. In addition, all papers reference their analysis to contemporary research through literature reviews and contextualization of the findings inside of frameworks, such as the Sustainable Livelihoods Framework.

The first article employs two types of regression models. First, an ordinary least square regression is conducted, however after evaluating the model, it does not exhibit sufficient quality. Due to the outlier driven characteristics, it is replaced with a robust regression with MM-type estimators and bi-square weighting to model determinants of success of income strategies by using the log per capita income as a dependent variable. Further, paper one uses binary logistic regression to model the odd ratios of adopting certain income strategies with binary indicators for each as the dependent variables.

After developing a procedure to match employments across panel waves and identifying inconsistencies, the second article revolves around a two-level multilevel logistic model that is intended to reveal the factors that increase the odds of an inconsistently reported employment.

The third article places greater emphasis on descriptive analysis and subsequently validates the findings thereof, using a binary logistic regression with a binary indicator of the negative affectedness of the household by Covid-19 as the dependent variable.

The fourth article employs cluster analysis. After careful evaluation, the centroid-based clustering of k-means and k-medoid are selected and exhibit few differences in the assignment of clusters. Further, binary logistic regression is used to model the factors influencing the assignment to each of the clusters, thereby providing evidence towards the typology of households. Another binary logistic regression is then used to model the impact of changes in the livelihood of a household on their consumption typology, presenting the odds to be pulled into another cluster or being pushed out of a given cluster.

1.6 References Chapter 1

Ahmad, A., & Isvilanonda, S. (2003). Rural Poverty and Agricultural Diversification in Thailand. *Working Papers*, Art. 2003:19. https://ideas.repec.org//p/hhs/lunewp/2003_019.html

Alkire, S. (2005). Why the Capability Approach? *Journal of Human Development and Capabilities*, *6*, 115–135. https://doi.org/10.1080/146498805200034275

Alkire, S., Kövesdi, F., Scheja, E., & Vollmer, F. (2023). Moderate Multidimensional Poverty Index: Paving the Way Out of Poverty. *Social Indicators Research*, *168*(1), 409–445. https://doi.org/10.1007/s11205-023-03134-5

Ashley, C., & Carney, D. (1999). *Sustainable livelihoods: Lessons from early experience*. Department for International Development.

Asian Development Bank (Hrsg.). (2015). *Thailand, industrialization and economic catch-up: Country diagnostic study*. Asian Development Bank.

Atkinson, A. B. (1991). Comparing Poverty Rates Internationally: Lessons from Recent Studies in Developed Countries. *The World Bank Economic Review*, *5*(1), 3–21.

Bah, E. (2011). Structural Transformation Paths Across Countries. *Emerging Markets Finance and Trade*, *47*, 5–19. https://doi.org/10.2307/23047440

Baulch, B. (1996). Neglected Trade-offs in Poverty Measurement. *IDS Bulletin*, *27*(1), 36–42. https://doi.org/10.1111/j.1759-5436.1996.mp27001004.x

Brandolini, A., Magri, S., & Smeeding, T. M. (2010). Asset-Based Measurement of Poverty. *Journal of Policy Analysis and Management*, *29*(2), 267–284.

Browder, J., Bohland, J., & Scarpaci, J. (1995). Patterns of Development on the Metropolitan Fringe: Urban Fringe Expansion in Bangkok, Jakarta, and Santiago. *Journal of the American Planning Association*, *61*(3), 310–327. https://doi.org/10.1080/01944369508975645

Cassidy, L., & Barnes, G. D. (2012). Understanding Household Connectivity and Resilience in Marginal Rural Communities through Social Network Analysis in the Village of Habu, Botswana. *Ecology and Society*, *17*(4). https://www.jstor.org/stable/26269205

Castro, A. P., Hakansson, N. T., & Brokensha, D. (1981). Indicators of rural inequality. *World Development*, *9*(5), 401–427. https://doi.org/10.1016/0305-750X(81)90035-8

Chambers, R. (1995). Poverty and livelihoods: Whose reality counts? *Environment and Urbanization*, *7*(1), 173–204. https://doi.org/10.1177/095624789500700106

Chambers, R., & Conway, G. (1992). Sustainable rural livelihoods: Practical concepts for the 21st century. *IDS Discussion Paper*, *296*.

Datta, P., & Behera, B. (2022). Assessment of adaptive capacity and adaptation to climate change in the farming households of Eastern Himalayan foothills of West Bengal, India. *Environmental Challenges*, *7*, 100462. https://doi.org/10.1016/j.envc.2022.100462

Deaton, A. (2003). Household Surveys, Consumption, and the Measurement of Poverty. *Economic Systems Research*. https://doi.org/10.1080/0953531032000091144

Deaton, A. (2016). Measuring and Understanding Behavior, Welfare, and Poverty. *American Economic Review*, *106*(6), 1221–1243. https://doi.org/10.1257/aer.106.6.1221

Deaton, A., & Muellbauer, J. (1980). *Economics and Consumer Behavior*. Cambridge University Press.

Disney, R., McKay, A., & Shabab, C. R. (2023). Household inequality and remittances in rural Thailand: A life-cycle perspective. *Oxford Economic Papers*, *75*(2), 418–443. https://doi.org/10.1093/oep/gpac025

Dreher, A., Gaston, N., & Martens, P. (2008). Introduction. In A. Dreher, N. Gaston, & P. Martens (Hrsg.), *Measuring Globalisation: Gauging Its Consequences* (S. 1–4). Springer. https://doi.org/10.1007/978-0-387-74069-0_1

Falkus, M. (1995). Thai Industrialization: An Overview. In M. Krongkaew (Hrsg.), *Thailand's Industrialization and its Consequences* (S. 13–32). Palgrave Macmillan UK. https://doi.org/10.1007/978-1-349-23909-2_2

Fan, S., Brzeska, J., Keyzer, M., & Halsema, A. (2013). *From subsistence to profit: Transforming smallholder farms* (0 Aufl.). International Food Policy Research Institute. https://doi.org/10.2499/9780896295582

Foster, J., Greer, J., & Thorbecke, E. (1984). A Class of Decomposable Poverty Measures. *Econometrica*, *52*(3), 761–766. https://doi.org/10.2307/1913475

Grosh, M., & Glewwe, P. (2000). *Designing household survey questionnaires for developing countries: Lessons from 15 years of the Living Standards Measurement Study*. World Bank Group.

Guadagno, F., Fortunato, P., Bateman, M., Rada, C., & Vrolijk, K. (2016). *Structural Transformation and Industrial Policy*. United Nations. https://unctad.org/system/files/official-document/gds2016d1_en.pdf

Hallegatte, S., Vogt-Schilb, A., Rozenberg, J., Bangalore, M., & Beaudet, C. (2020). From Poverty to Disaster and Back: A Review of the Literature. *Economics of Disasters and Climate Change*, *4*(1), 223–247. https://doi.org/10.1007/s41885-020-00060-5

Hardeweg, B., Klasen, S., & Waibel, H. (2013). Establishing a database for vulnerability assessment. In *Vulnerability to Poverty: Theory, Measurement and Determinants, with Case Studies from Thailand and Vietnam* (S. 50–79). Springer.

Kemper, N., Klump, R., Menkhoff, L., & Rungruxsirivorn, O. (2013). Financial Shock-Coping in Rural Thailand and Vietnam. In S. Klasen & H. Waibel (Hrsg.), *Vulnerability to Poverty: Theory, Measurement and Determinants, with Case Studies from Thailand and Vietnam* (S. 258–282). Palgrave Macmillan UK. https://doi.org/10.1057/9780230306622_10

Kostov, P., & Lingard, J. (2004). Subsistence Agriculture in Transition Economies: Its Roles and Determinants. *Journal of Agricultural Economics*, *55*, 565–579. https://doi.org/10.1111/j.1477-9552.2004.tb00115.x

Kucera, D., & Roncolato, L. (2016). The manufacturing–services dynamic in economic development. *International Labour Review*, *155*(2), 171–199. https://doi.org/10.1111/j.1564-913X.2015.00052.x

Marjanović, V. (2015). Structural Changes and Structural Transformation in a Modern Development Economy. *Economic Themes*, *53*(1), 63–82. https://doi.org/10.1515/ethemes-2015-0005

McMillan, M., Rodrik, D., & Verduzco-Gallo, Í. (2014). Globalization, Structural Change, and Productivity Growth, with an Update on Africa. *World Development*, *63*, 11–32. https://doi.org/10.1016/j.worlddev.2013.10.012

Meyer, B. D., & Sullivan, J. X. (2003). Measuring the Well-Being of the Poor Using Income and Consumption. *The Journal of Human Resources*, *38*, 1180–1220. https://doi.org/10.2307/3558985

Moore, J. D., & Donaldson, J. A. (2016). Human-Scale Economics: Economic Growth and Poverty Reduction in Northeastern Thailand. *World Development*, *85*, 1–15. https://doi.org/10.1016/j.worlddev.2016.04.004

Natarajan, N., Newsham, A., Rigg, J., & Suhardiman, D. (2022). A sustainable livelihoods framework for the 21st century. *World Development*, *155*, 105898. https://doi.org/10.1016/j.worlddev.2022.105898

Paweenawat, S. W., & Liao, L. (2023). The role of higher education on migration to cities in Thailand. *Cities*, *137*, 104309. https://doi.org/10.1016/j.cities.2023.104309

Ravallion, M. (2001). Growth, Inequality and Poverty: Looking Beyond Averages. *World Development*, *29*(11), 1803–1815. https://doi.org/10.1016/S0305-750X(01)00072-9

Ravallion, M. (2016). Poverty Lines. In *The New Palgrave Dictionary of Economics* (S. 1–8). Palgrave Macmillan UK. https://doi.org/10.1057/978-1-349-95121-5_2541-1

Reardon, T., & Taylor, J. E. (1996). Agroclimatic shock, income inequality, and poverty: Evidence from Burkina Faso. *World Development*, *24*(5), 901–914. https://doi.org/10.1016/0305-750X(96)00009-5

Reardon, T., Taylor, J. E., Stamoulis, K., Lanjouw, P., & Balisacan, A. (2000). Effects of Non-Farm Employment on Rural Income Inequality in Developing Countries: An Investment Perspective. *Journal of Agricultural Economics*, *51*(2), 266–288. https://doi.org/10.1111/j.1477-9552.2000.tb01228.x

Schlogl, L., & Sumner, A. (2020). *Disrupted Development and the Future of Inequality in the Age of Automation*. Springer International Publishing. https://doi.org/10.1007/978-3-030-30131-6

Scoones, I. (1998). *Sustainable Rural Livelihoods: A Framework for Analysis*. https://opendocs.ids.ac.uk/opendocs/handle/20.500.12413/3390

Scoones, I. (2009). Livelihoods perspectives and rural development. *The Journal of Peasant Studies*, *36*(1), 171–196. https://doi.org/10.1080/03066150902820503

Sen, A. (1984). The Living Standard. *Oxford Economic Papers*, *36*, 74–90.

Sen, A. (1985). Well-Being, Agency and Freedom: The Dewey Lectures 1984. *The Journal of Philosophy*, *82*(4), 169–221. https://doi.org/10.2307/2026184

Sen, A. (1993). Capability and Well-Being. In M. Nussbaum & A. Sen (Hrsg.), *The Quality of Life* (S. 0). Oxford University Press. https://doi.org/10.1093/0198287976.003.0003

Sen, K. (2016). The Determinants of Structural Transformation in Asia: A Review of the Literature. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2811507

Senadza, B. (2014). Income Diversification Strategies among Rural Households in Developing Countries: Evidence from Ghana. *African Journal of Economic and Management Studies*, *5*. https://doi.org/10.1108/AJEMS-05-2012-0029

Syrquin, M. (1988). Chapter 7 Patterns of structural change. In *Handbook of Development Economics* (Bd. 1, S. 203–273). Elsevier. https://doi.org/10.1016/S1573-4471(88)01010-1

Syrquin, M. (2008). Structural change and development. *International Handbook of Development Economics*, *Volumes 1 & 2*, 48–67.

Thomas, V., & López, R. (2015). *Global Increase in Climate-Related Disasters* (Working Paper 466). ADB Economics Working Paper Series. https://www.econstor.eu/handle/10419/128585

Thongsawang, S., Rehbein, B., & Chantavanich, S. (2020). Inequality, Sociocultures and Habitus in Thailand. *Sojourn: Journal of Social Issues in Southeast Asia*, *35*(3), 493–524.

Timmer, C. (1988). The agricultural transformation. *Handbook of development economics. Vol. 1*, *I*.

Tipayalai, K., & Mendez, C. (2022). Regional convergence and spatial dependence in Thailand: Global and local assessments. *Journal of the Asia Pacific Economy*, *0*(0), 1–28. https://doi.org/10.1080/13547860.2022.2041286

Whitney, C. K., Bennett, N. J., Ban, N. C., Allison, E. H., Armitage, D., Blythe, J. L., Burt, J. M., Cheung, W., Finkbeiner, E. M., Kaplan-Hallam, M., Perry, I., Turner, N. J., & Yumagulova, L. (2017). Adaptive capacity: From assessment to action in coastal social-ecological systems. *Ecology and Society*, *22*(2). https://www.jstor.org/stable/26270135

Zimmerman, F. J., & Carter, M. R. (2003). Asset smoothing, consumption smoothing and the reproduction of inequality under risk and subsistence constraints. *Journal of*

Development Economics, *71*(2), 233–260. https://doi.org/10.1016/S0304-3878(03)00028-2

2 Income strategies of Thai rural households during economic transformation

Current version of a paper by Wendt, N., currently in preparation for submission.

Abstract

Thailand's economy has shown impressive growth over the past decades. The subsequent economic transformation with productive resources shifting away from agriculture towards non-farm employments raises the question if rural households participate equally in this development or if they are at a risk of being increasingly marginalized. Moving past one-dimensional poverty measures and utilizing the Sustainable Livelihoods Framework, this study examines the transformation of rural Thai livelihoods. In addition to descriptive statistics, two models assess the success of certain livelihood strategies as well as the factors influencing their adoption. We find a pronounced shift towards diversified income portfolios and our findings confirm this strategy to be the most efficient allocation of household resources. Further, we highlight substantial entry barriers to the pursuit of certain income strategies, as well as a lack of opportunities in the rural areas, often leading to migration. Additionally, we discuss the role of shocks and entrepreneurship and suggest that policy makers increase efforts to build capacity to pursue non-farm income opportunities, for instance through education and to create such opportunities in the rural areas.

2.1 Introduction

It has been a few decades, since Thailand embarked on its journey to become the upper-middle income country that it is today. Impressive GDP-growth of up to 9.5% per year was observed as well as periods of crisis (Asian Development Bank, 2015). Rapid growth is not without challenge however, raising the question if and to what extent this formerly rather agrarian nation changed (socio-) economically.

Historically, agriculture's share in GDP has been decreasing during the course of economic development (Guadagno et al., 2016). Labor and other resources are transferred to the secondary and tertiary sectors of the economy with higher factor productivity (Ellis, 1998). By 2022 agriculture's share of the GDP in Thailand had declined to 8% (World Bank Group, 2022). At the same time however, a large part of the Thai working age population remains in jobs related to agricultural activities, indicating a rather low productivity within that sector (Asian Development Bank, 2015; Sen, 2016; World Bank Group, 2022). Looking at the spatial concentration of the secondary and tertiary sector, a pronounced clustering in some densely populated provinces, including the greater Bangkok area, is revealed (Disney et al., 2023; Grandstaff, 1992; Tipayalai & Mendez, 2022). This begs the question, if households in the rural areas of the country profit and participate in this rapid development and to what extent opportunities to engage in different revenue generating activities are available to them, especially with regards to the role of migration (Disney et al., 2023; Grandstaff, 1992; Tipayalai & Mendez, 2022). Additionally, the role of agriculture as a component of the livelihood strategies of rural households in a changing economy remains to be determined (Abera et al., 2021; Ellis, 1998, 2000).

Research in the rural areas has long focused on poverty, however poverty rates have declined substantially in Thailand over the past years (Tipayalai & Mendez, 2022). A more contemporary topic is to gain a holistic understanding of the livelihoods and the strategies of households in the rural and formerly low-income areas of the country as new opportunities emerge. A prominent concept is the "Sustainable Livelihoods Framework", with the livelihood strategies and livelihood assets of the household at its core (Ashley & Carney, 1999; Natarajan et al., 2022; Scoones, 1998). Regarding income strategies, the literature suggests an increasing diversification, for instance by engaging in off-farm employment while retaining agriculture (Abera et al., 2021; Ellis, 1998, 2000). Another option would be to transform formerly subsistence-based agriculture into a more intensive, commercialized agriculture (Mariyono, 2019).

Although the economic transformation of Thailand is a macro-economic phenomenon, the actions and transformations on the micro-level are still under-researched and the impact of such changes on the livelihoods of households in the rural areas is still widely unknown. Consequently, this study takes a micro-economic perspective and examines the transformations of income strategies and the possible reasons behind them within the regional context.
Drawing on the Sustainable Livelihoods Framework, shocks are considered as accelerators or as potential constraints of transformations. Using a long-term panel dataset, this study aims to provide a longitudinal approach to the factors behind the adoption of income strategies, as well as the success of such strategies over time. First, we discuss the literature on assessing livelihoods, income strategies and transformations as well as the role of shocks. This paper then proceeds with a descriptive analysis, showcasing the evolution of key indicators related to the livelihoods of the panel households. Subsequently, several regression models are fitted to determine which income strategy proved to be most successful and which factors influence the adoption of the respective strategies. All models control for the context of the household by including the province and shocks it may be exposed to. Following the presentation and discussion of the results, a conclusion and outlook are provided, highlighting potentials for early-stage policy interventions as well as challenges for policy makers.

2.2 Transformations, Livelihoods, Income strategies and shocks

In the past decades, many attempts have been made to conceptualize rural livelihoods beyond simple measures of income and consumption, which are common measures for poverty. One approach was suggested by Scoones (1998) as well as Ashley and Carney (1999) with the "Sustainable Livelihoods Framework" (Ashley & Carney, 1999; Chambers & Conway, 1992; Scoones, 1998). It regards a household as an entity, endowed with different resources that acts within a context of regulatory, natural, political, demographical, and social factors by the adoption of livelihood strategies to create and/or maintain sustainable livelihoods. It thereby includes both commonly used living standard and poverty measures, income on the resource side and consumption on the strategic side. The household's resources are utilized within a vulnerability context and transforming structures and processes. A key component of the framework is the interdependency of its elements, in which for example, a given resource endowment of a household can be moderated by context to form a strategy. The success or failure of that strategy may in turn influence the resource endowment or the context. In general, the "Sustainable Livelihoods Framework" offers a compelling approach to facilitate a holistic analysis of a household's actions within a dynamic environment. Furthermore, this concept highlights the interaction between a transforming environment and the availability of new strategic opportunities to combine the given livelihood assets of a household into more efficient strategies, for instance to increase income (Abera et al., 2021; Ellis, 1998, 2000). As a region is integrated into (global-) value chains and starts to develop, the relevance of the primary sector declines, as other income opportunities emerge (Baymul & Sen, 2020; Kuznets, 1955; McMillan et al., 2014; Senadza, 2014). This further emphasizes the need to link the macro-economic developments with observations on the micro-level, as economic actors respond (Barrett et al., 2001; Scoones, 2009). It is important not to confuse an income opportunity with an income strategy, however. While the former is only hypothetically available, the latter describes the adoption or exploitation of such an opportunity by an economic actor. The determinants of the decision to pursue an opportunity can be linked to push- and pull factors, such as the perspective of higher income or accumulation of assets "pulling" or the hardships of the current livelihood "pushing". (Baymul & Sen, 2020; Reardon et al., 2006; Senadza, 2014). Upon review of the literature with regards to additional factors influencing the choice of income strategies by a household, demographic factors such as age, education, prevalence of non-working-age household members and migration are seen as enablers or deterrents to certain strategies (Disney et al., 2023; Ellis, 1998; Estudillo et al., 2019; Habib et al., 2023; Nkedianye et al., 2020; Reardon et al., 1992, 2006). Further, the existing capital of the household, expressed through income, assets, savings, debt and by extension land size, may restrict the opportunities of the household, such as starting a business or investing in a more productive agriculture (Ellis, 1998; Fan et al., 2013; Habib et al., 2023; Hallegatte et al., 2020; Killick, 2001; Kostov & Lingard, 2004; Mariyono, 2019; Reardon et al., 1992, 2006). Especially, rural credit markets can serve as important providers of capital needed to pursue certain strategies such as self-employment but may lead to over-indebtedness (Chantarat et al., 2020; Chichaibelu & Waibel, 2018; Han & Hare, 2013).

Previous research shows that, although the relevance of agriculture declines with ongoing development, it still plays a role for most households, many of which adopt a diversified portfolio of income sources, which can also be called their income strategy (Reardon et al., 2006; Senadza, 2014). Referring to the discussion by Barrett et al., this study defines three main sources of income (Barrett et al., 2001). Agriculture refers to all "on-farm" agricultural activities, such as farming crops or rearing livestock, while off-farm employment encompasses all revenue generating activities in which the subject is employed elsewhere than the household farm. These employments may have an agricultural component but are unrelated to the own household. "Non-farm self-employment" (henceforth referred to as "Self-Employment") contains self-employment that excludes the activities summarised under "Agriculture". The economic transformation of rural areas leads to an increase in availability of opportunities in the latter two income sources, although they might occur elsewhere, necessitating migration (Barrett et al., 2001; Reardon et al., 2000; Schwarze & Zeller, 2005; Wan et al., 2016; Wouterse & Taylor, 2008). The actual exploitation of these and the subsequent changes in income strategies is determined by a complex relation of factors, such as opportunity cost, education, and risk averseness (Barrett et al., 2001; Reardon et al., 2000; Senadza, 2014; Wan et al., 2016). The term "transformation" is ubiquitously used in economics and describes a wide array of changes, be it in process innovation, manufacturing, and many other areas. This study uses the term in line with the Kuznetzian view (Kuznets, 1955, 1967, 1973). The UNCTAD summarizes it as: "Also denoted as structural change, structural transformation refers to the movement of labour and other productive resources from low-productivity to high-productivity economic activities" (Guadagno et al., 2016). It is noteworthy that this term does not mandate sectoral transformations exclusively, as it primarily refers to labour productivity, which can also be achieved intra-sectorial (Christiaensen & Martin, 2018; Kucera & Jiang, 2018; Kucera & Roncolato, 2016; Ocampo et al., 2009; Syrquin, 2008).

Thus far, researchers mostly come to the conclusion that structural transformations are inevitable, as a country's economy develops and are fuelled by said development, forming a circular system (Christiaensen & Martin, 2018; Marjanović, 2015; Schlogl & Sumner, 2020; Syrquin, 2008). Two general directions of transformations are identified in the literature. Firstly, it is observed, that individuals transition or diversify into other, non-primary sector related income strategies, as opportunities emerge. This could for instance be a farmer, who is now seeking higher revenue as a non-farm labourer. The second general direction of transformations involves a specialization and an intensification of efforts in the primary sector, leading to an increase in competitiveness, efficiency and ultimately revenue. Under the consideration of stability and food security, the primary sector still plays an important role, even without such efforts (Christiaensen & Martin, 2018; Marjanović, 2015; Senadza, 2014; Timmer, 1988). Structural transformations usually require an exogenous activator, such as the integration of a region into (global-) value chains. This sparks an economic transformation that is challenging traditional livelihoods, especially subsistence farming, as no longer being competitive (Bah, 2011; Fan et al., 2013; Kostov & Lingard, 2004; McMillan et al., 2014). Adding to that, economic transformations entail other transformations, such as infrastructure, education, etc., which can provide opportunities, but also challenges (Fan et al., 2013; Kostov & Lingard, 2004; McMillan et al., 2014; Senadza, 2014).

External intervention plays a notable role in the occurrence of transformation processes, be it by government policies and/or subsidies or by economic actors, such as multinational corporations buying into the region, or by shocks (Aung et al., 2013; Cotula et al., 2009; Ferraz et al., 2012; Harvey et al., 2014). Especially shocks in the form of natural disasters can serve both as decision accelerators for alternative revenue seeking, but also as decelerators, to take less risk and rather stagnate with traditional, but seemingly safe farming, focusing on subsistence, rather than growth. Research also reveals a higher vulnerability of low-income households to natural disasters, making the consideration of these all the more important (Amare et al., 2018; Chantarat et al., 2019; Grabrucker & Grimm, 2021; Hallegatte et al., 2020; Harvey et al., 2014; Strömberg, 2007). According to literature, the adoption of new income sources is linked to the potential revenue and the income increase they offer over the current income from traditional farming, as well as a chance to provide resilience in times of distress. Yet adopting new strategies comes at an opportunity cost, that not every farmer is willing to risk (Fan & Chan-Kang, 2005; Goulden et al., 2013; Hazell & Haggblade, 1993; Reardon et al., 1992; Scoones, 2009; Senadza, 2014; Vanwambeke et al., 2007; Zhao & Barry, 2013). Shocks or stressors can be seen as accelerators or activators of that decision process, for instance in the way of a coping strategy. Shocks are frequently rather short-term incidents, such as a flood, but can have a big impact in the medium and long term (Chantarat et al., 2019; Grabrucker & Grimm, 2021; Rashid et al., 2006; Tongruksawattana et al., 2009). In recent years, research has focused on the role of natural disasters, also in the context of climate change and has found an impact on farming activities, that require either an adaptation of farming, or might lead to a diminished role of traditional farming in the income system of a household (Amare et al., 2018; Chantarat et al., 2019; Grabrucker & Grimm, 2021; Kubik & Maurel, 2016; Wan et al., 2016). Additionally, these stressors could lead to an increase in the gap of current revenue to expected revenue from alternative sources; not by making new income strategies more profitable, but by reducing the profitability of the current income sources (Barrett et al., 2001; Islam, 1997; Reardon et al., 2000).

According to the Sustainable Livelihoods Framework, another important factor is contributed by the region the household lives in, as any observation is not only the product of itself but is embedded in a spatial context (Brons & Pellenbarg, 2003; Li et al., 2020). Especially when analysing transformations, it is important to understand the way spatial determinants influence these processes. Contemporary research increasingly includes spatial determinants, slowly moving past the "laboratory conditions" of macroeconomic models (Cornett, 1999; Démurger et al., 2010; Li et al., 2020). For the topic of this paper, spatial context will be included in either of two ways. First, it could be seen as an environment for economic actors, which provides a certain variability in resource endowment, opportunities, and exposure to stressors, but plays a passive role in models and decision-making processes by said actors, which only focus on the opportunities as isolated incidence. Second, the spatial context could be seen as an element in the decision making, whose features actively shape the environment the economic actors are placed in. An example for the first way would be to see a natural disaster like a flood, as a one-time event with an impact, while the second approach might include the higher risk exposure of the region to floods, because of its location in the marshes of a river.

Thus far, research is fairly consistent on the fact that transformation processes and shifts in income strategies occur inevitably alongside with the overall economic progress of a country. There are, however, gaps in the literature that motivate our empirical analysis. First, it remains unclear to what extent agriculture is retained. Following the logic of the pull factor of higher revenue income sources, the subsequent decline of agriculture would be inevitable. Also, a more intensified agriculture could provide higher incomes, yet it is limited by productive assets, land, climate, soil, and more. Second, pursuing different income strategies is often seen as “just” a decision driven by monetary considerations, however there is little research on entry barriers and regional availability of opportunities, or more broadly, into the complexities behind the decision. Third, the role of self-employment, interpreted as entrepreneurship is under-researched in rural areas, though it might provide the missing link between diversifying into non-farm income systems and creating such opportunities domestically. Fourth, the role of shocks as a push factor seems obvious, but lacks empirical confirmation beyond descriptive results, just like the two prior points.

Consequently, three hypotheses can be derived. Firstly, the macro-economic transformation of Thailand will cause a decline agriculture within the rural household income strategies. Second, the transition of labour from agriculture into other occupations is severely constrained by entry barriers, such as education. Thirdly and following the rationale behind hypothesis 2, self-employment emerges as a way to stimulate economic growth in the rural areas.

All these research gaps and hypotheses can be linked to elements within the Sustainable Livelihoods Framework, which thereby provides a suitable frame for empirical and causal analysis. The major research subjects addressed in the following chapters are to determine which factors and livelihood assets lead to the adoption of which strategies and which strategies prove to be most successful i.e., yield the highest income, as illustrated in Figure 2.1. Further, the role of the contextual factors will be examined.

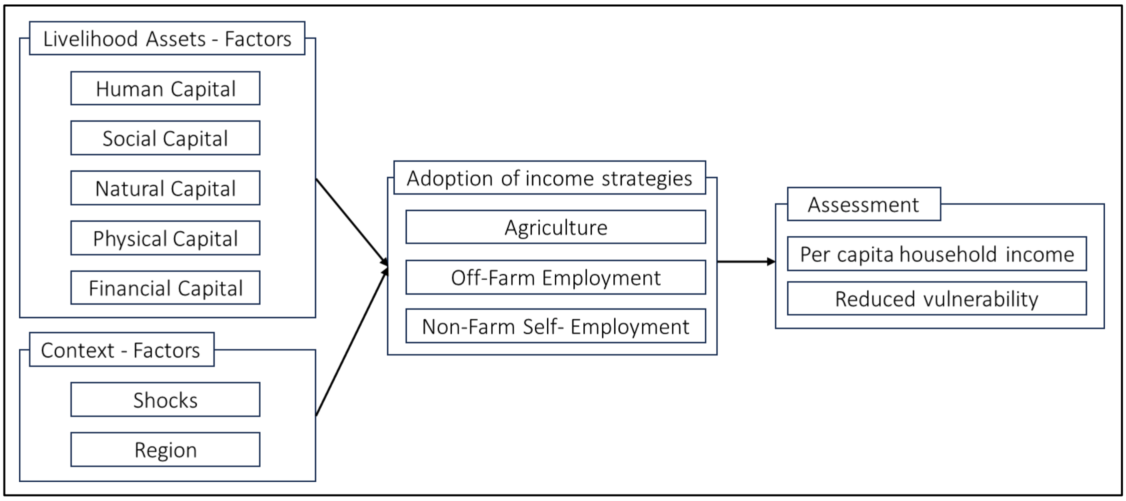

Figure 2.1 Analytical Approach

Source: Own illustration.

2.3 Methodology

2.3.1 Data and Variables

As described in the introduction, this study is based on a panel dataset, provided by the Thailand Vietnam Socio Economic Panel (TVSEP). Started in 2007 with 2200 households each in Thailand and Vietnam, the project has conducted eight waves of data collection up to this point. We focus on Thailand where the survey contains data on households located in three provinces, as showcased in Figure 2.2. The survey instrument used is a LSMS-style questionnaire with extensive sections on all matters of life, including income streams, consumption, assets, demographics and much more. We use five years of data with three-year gaps in between each, namely 2007, 2010, 2013, 2016 and 2019. Due to questionnaire and coding changes between 2007 and 2010, the first year is only used in applicable descriptive comparisons. Further, the data is limited to 1535 consistent households, that were present in all waves (TVSEP, 2022).

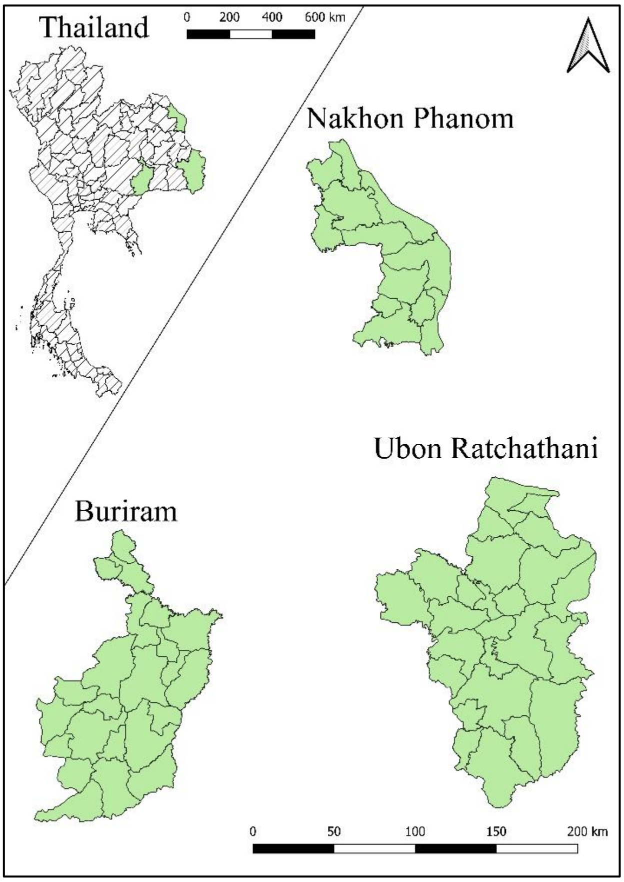

Figure 2.2 TVSEP survey provinces.
Shape source: Humanitarian Data Exchange, 2022

The dependent and independent variables used in subsequent models as well as the data used in the descriptive analysis of this study are based on selected variables from the TVSEP dataset. These were chosen in accordance with the literature presented above and in close relation to the sustainable livelihoods approach. All variables are calculated for the household level. This study considers the complete household with all members indicated by the household head, regardless of migrant status. Independent variables reflect the "livelihood assets". Human capital is considered by the mean age and mean education of the household members. Natural capital is included through the total land size held by the household (incl. rented in/out) and the intensity of its use for farming by the income share the household gains from farming. In few cases, the income from farming is negative, due to the harvest not having taken place at the time of the survey. These cases are included by considering the expenses as hypothetical income that at least needs to be reached upon harvest to break even. Financial capital is proxied through the per capita income of the household as well as savings and debt. Per capita income is defined as the sum of net income from all income sources, returns of savings, transfers from non-household members and public transfers without payments for insurances and taxes being deducted. Physical capital includes the value of all durable assets held by the household. Social Capital is represented by the dependency ratio and the migrant share that limit or enhance potentials for networking to take place. Migrants are defined as household members that stay in the household for 30 days or less during the one-year reference period and are located outside the same sub-district as the household. The vulnerability context is controlled for by including the number of shocks as well as the province. The livelihood strategies and livelihood outcomes are placed on the left-hand side of the models, leaving the transforming structures and processes as the moderating "black box", that the models yield insight into. This selection is also in line with the literature regarding the potential factors behind the decision-making processes of households, as presented in the previous chapter.

2.3.2 Methodology

In a first step, a descriptive analysis is undertaken to gain insight into the household's demographics and actions over time. Table 2.1 provides an overview of tables and figures presented in the descriptive analysis, as well as an association with elements of the Sustainable Livelihoods Framework (SLF).

Table 2.1 Overview of descriptive analysis

Figure/Table	Title	SLF-Element
Table 4	Age, Dependency Ratio, Education, Migrants and Nucleus Household Size	Human and Social Assets
Figure 3	Number of migrants and mean PPP$ remittances	Social and Financial Assets
Table 5	Number of shocks and damages	Context
Figure 4	Income Sources across survey waves	Income Strategies
Figure 5	Per capita income in each survey wave	Financial Assets
Figure 6	Off-farm employment sector by migrant status	Human and Social Assets
Figure 7	Development of income by source	Financial Assets
Figure 8	Distribution of Agriculture by District	Context

Source: Own illustration.

Following this, we delve into the transformations in income strategies by fitting several regressions, namely ordinary least square regressions (OLS), and logistic regressions. The first OLS regression identifies key factors in a household that are conducive to a high per capita income. By the inclusion of income strategies as independent variables, the full causal chain outlined in the "Sustainable Livelihoods Framework" is considered. Thereby, conclusions regarding the overall success of these livelihood strategies and their combination are possible (Model 1). For the analysis in model 1, we measure success by the per capita income. While this is only one of the various livelihood outcomes suggested by the "Sustainable Livelihoods

Framework" (Ashley & Carney, 1999), it is the direct output from the income strategies and an important enabler or constraint to many other livelihood outcomes, for instance food security or vulnerability. A subsequent logistic regression aims to identify factors in a household that might lead to an adoption of a certain strategy (Models 2.1, 2.2 and 2.3). Other model types were evaluated as well. Multinominal logistic regression was deemed unfit for the analytical purpose, as a household might pursue several income strategies, therefore entailing a binary nature of the model with a changing reference category. As a robustness check for the choice of logistic regression, probit regression was evaluated, with the results departing only slightly from those of the logistic regression.

Models 1 and 2 are fitted for each survey year. Table 2.2 provides an overview of all models. Concerning the "Sustainable Livelihoods Approach", Models 1 and 2 allow for insights into the livelihood outcomes and livelihood strategies. Both models control for the relation between the livelihood strategy and the vulnerability context and by extension the ability of the household to enhance its resilience and lower its vulnerability to shocks by the adoption of certain strategies. Table 2.3 provides a detailed overview of the independent variables and transformations, as described in chapter 3.1 and their use in the different models described in Table 2.2. In general, the models are composed in such a way to always reflect the approach of the "Sustainable Livelihoods Framework" and consider the interdependencies between its different elements. Apart from providing a framework for analysis to consider and proxy most elements forming the livelihood of rural Thai households, it allows for conclusions regarding the sustainability of livelihoods in the context of different income strategies and shocks.

Table 2.2 Models and dependent variables

Model	Method	Dependent Variable	Abbreviation	Unit	Transformation
1	OLS/LM	Per Capita Income	Incpc	PPP$	Log
2.1	Logit	Strategy Farming	FarmS	1 = "Yes", 0 = "No"	-
2.2	Logit	Strategy Off-Farm Employment	OffS	1 = "Yes", 0 = "No"	-
2.3	Logit	Strategy Self-Employment	SelfS	1 = "Yes", 0 = "No"	-

Source: Authors' calculations based on TVSEP (2022).

Table 2.3 Independent variables and transformations

Variable	Abbreviation	Unit	Transformation	Models used
Mean Age of household members	MeanA	Years	-	2
Mean Age of household members squared	MeanAsq	Years	squared	2
Dependency Ratio	DepR	Numeric	-	1
Mean Education	MeanE	Years	-	1,2
Migrant Share	MigS	% of all members	-	1,2
Land Area (incl. rented land)	LandA	Rai	Log	1,2
Per Capita Income	Incpc	PPP$	Log	2
Income Share from Farming (incl. Livestock and -products)	IncShF	%	Log	1
Savings	Sav	PPP$	Log	1,2
Debt	Debt	PPP$	Log	1,2
Assets	Asset	PPP$	Log	1,2
Strategy Farming	FarmS	1 = “Yes”, 0 = “No”	-	2
Strategy Off-Farm Employment	OffS	1 = “Yes”, 0 = “No”	-	2
Strategy Self-Employment	SelfS	1 = “Yes”, 0 = “No”	-	2
Strategies	Strat	1 = “More than one”, 0 = “No”	-	1
Shocks (Medium and high severity)	ShockNo	No.	-	1,2
Province	Prov	31 = “Buriram”, 34 = “Ubon Ratchathani”, 48 = “Nakhon Phanom”	-	1,2

Source: Authors’ calculations based on TVSEP (2022).

Model 1 is defined by:

$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_p x_p + \epsilon \quad (1)$$

where β_0 is the intercept, β_p are the model coefficients, x_p is the independent variable and ϵ is the error term.

To establish a linear relationship between the dependent and each independent variable we transformed the latter as indicated in Table 2.3. A correlation matrix showed no signs of excess correlation (Tables A2.9 – A2.12). Further, Table A2.14 and Table A2.15 indicate the one-dimensional GVIF ($GVIF^{\frac{1}{(2*Df)}}$) introduced by Fox and Monette (Fox & Monette, 1992) for all models. All values remain well below the common threshold of 5 and most even stay below or close to the R² dependent criterion of $\frac{1}{1-R^2}$ as proposed by Freund and Wilson and Vatcheva et. al (Freund & Wilson, 1998; Vatcheva et al., 2016).

Model 1 was then first fitted as an Ordinary Least Square Regression (OLS). Autocorrelation of the residuals was not present, however the models tested positive for heteroskedasticity (Breusch-Pagan) and exhibited a non-normal distribution of residuals (Shapiro-Wilk). After investigating the issue, the distribution was mostly outlier driven. Especially when it comes to the diverse livelihoods in the dataset, altering or dropping such outlier cases is not the best practice. Hence, the model was altered to a robust regression with MM-type estimators and bi-square weighting following the approach of Koller and Stahel (2011) and Yohai (1987) with the iterated re-weighted least squares converging (Koller & Stahel, 2011; Yohai, 1987). Robust standard errors are included in the results. Model significance is provided by a robust analysis of variance (ANOVA) against an intercept-only model. The R^2 of model 1 (between 0.3 and 0.398) is satisfactory.

Model 2 is defined as

$$ln\left[\frac{P_i(I=1)}{1-P_i(I=1)}\right] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k \tag{1}$$

$$\text{with } I_i = 1 \; if \; strategy \; was \; pursued \tag{2}$$

$$I_i = 0 \; otherwise$$

with β_0 as a constant and β_k as the coefficients where vector X_k includes the corresponding independent variables. For later interpretation, odd ratios were calculated by

$$\left[\frac{P_i(I=1)}{1-P_i(I=1)}\right] = e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k} \tag{3}$$

For models 2.1, 2.2, and 2.3, the Hosmer Lemeshow goodness-of-fit test did not indicate any concerns. Outliers in deviance residuals and outliers in leverage were assessed and the models were re-fit with the outlier cases excluded. Comparing the results, little deviation was observable, hence no cases were excluded in the final models. In addition, model accuracy was assessed by performing 10-fold cross validations for 10 times as well as calculating the AUC ROC value for 100 times, by which the dataset was randomly split into an 80% train and a 20% test subsample. On average, the results for models 2.1, 2.2 and 2.3 were quite stable and accuracies between 69.3% and 88.8% were achieved (Table A2.16), which, according to Hosmer et. al (2013), can be considered acceptable to excellent (Hosmer et al., 2013). The pseudo-R^2 indicated in the model results is Nagelkerkes/Cragg & Uhlers Pseudo-R^2, which ranges between 0.18 and 0.56, indicating an average to good fit. Further, while it can never be entirely ruled out, the sound theoretical base of the models, their robustness, the correlation coefficients in Appendix 1-4 and the lack of random effects as well as the inclusion of fixed effects in accordance with the literature, suggest little potential for endogeneity. A further consideration was the role of space. Research suggests a rather heterogeneous development across the Thai provinces (Tipayalai & Mendez, 2022), which might be reflected in the three provinces, the underlying dataset is collected in. To account for this potential role of space, two options are possible. One might be a fixed effect, which is included as a control variable in all models. In addition, random effects are tested by fitting a two-level regression with the province of the household as the level-2 random effect. Neither in comparison to a single-level null model nor the single-level full models, any improvement by the inclusion of random effects on the province level could be determined, since both intraclass correlation coefficients (ICC) and differences in AIC remained low, as indicated in Table A2.13. Consequently, the provincial effects were included in the models as fixed effects and no further multilevel regression models were fitted.

2.4 Demographics and trends in households

In line with the literature, we start the descriptive analysis with an overview of the households and the development of key characteristics over the years as displayed in Table 2.4. Fairly consistent conditions in the households are observable in the mean; however small evolutions become visible. Household members are on average older, and the dependency ratio is on an upward trend as well, indicating more members beyond a productive age. In addition, household size is declining, both in terms of migrant members and nucleus members. This trend could be induced by members leaving the household, potentially starting their own households in other locations, a trend that may also be reflected in the savings and debt. Further, the average years of education per member increase. While older household members rarely exceed a primary level education, it is becoming more common amongst younger household members to hold a high school- or even a university degree. In addition, the number of household members that indicate their own agriculture to be their primary occupation declines over the years. Lastly, strong fluctuations in savings and debt become visible, that could be both the result of the above-mentioned demographic shifts, the results of shocks, the need to invest in the upkeep of assets and the willingness to share such information in the presence of frequent scam attempts in Thailand and consequently increased awareness.

Table 2.4 Age, Dependency Ratio, Education, Migrants and Nucleus Household Size

	Mean 2010	**SD 2010**	**Mean 2013**	**SD 2013**	**Mean 2016**	**SD 2016**	**Mean 2019**	**SD 2019**
Age	35.73	10.43	38.1	11.1	40.71	12.13	42.62	12.92
Dependency Ratio	0.53	0.6	0.54	0.65	0.6	0.69	0.67	0.74
Education (Years)	5.98	3.02	6.25	3.43	6.15	2.77	6.35	3.08
Migrants (No.)	1.12	1.31	0.98	1.24	0.98	1.18	0.91	1.07
Nucleus Size (No.)	4.05	1.7	3.91	1.67	3.71	1.66	3.6	1.67
Members with Farming as primary occupation (No.)	2.21	1.05	2.26	1.12	2.02	0.97	1.91	0.86

Savings (PPP$)	1205	3949	1897	7687	2118	8036	1042	7907
Debt (PPP$)	3807	8532	4558	18396	6419	17099	5761	12535

Source: Authors' calculations based on TVSEP (2022).

Table 2.4 indicates a decline in migrants, however referring to the literature review, remittances are an important income source for households. Figure 2.3 presents a more detailed view on the evolution of migrants and remittances over time. In addition to an overall decline of the number of migrant members in each household, it can be observed that especially households with multiple migrant members become less common over time. Interestingly, remittances remain somewhat stable over time, indicating an increase in remittances per migrant. The decline in both remittances and migrant members in 2013 may be a delayed effect of the economic and financial crisis in 2007/2008 as well as an overall weak economic performance between 2013 and 2016.

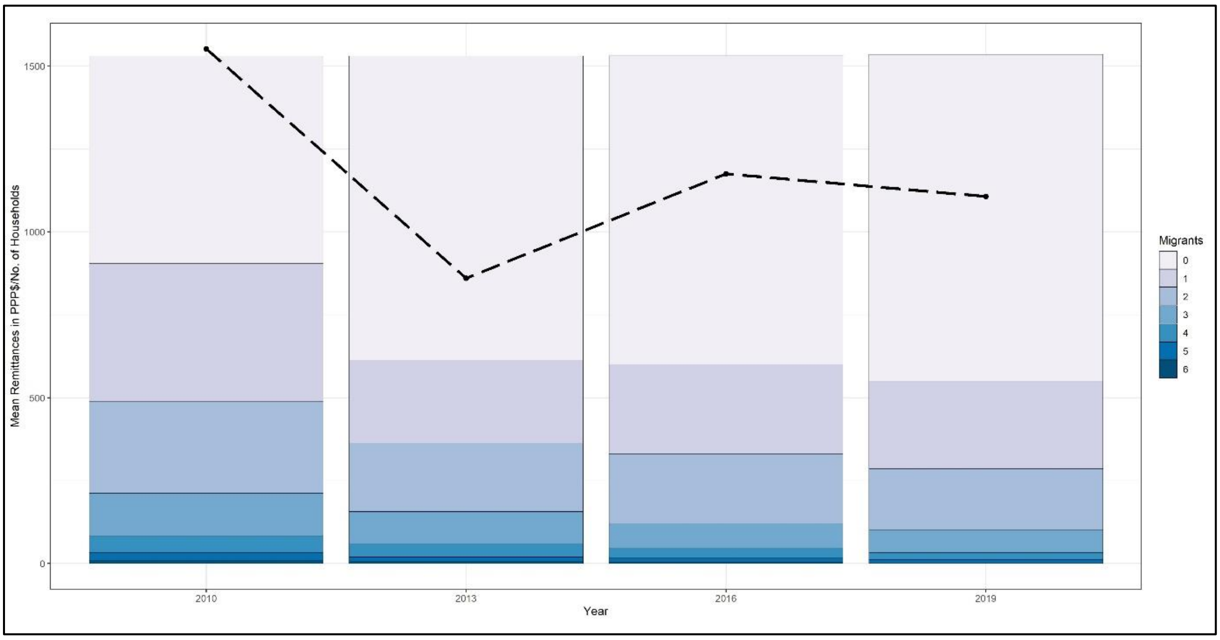

Figure 2.3 Number of migrants and mean PPP$ remittances

Source: Authors' calculations based on TVSEP (2022).

In addition to being exposed to economic shocks, Thai households are also subject to the effects of climate change and other shocks. Table 2.5 presents the average number of medium or high severity shocks, Thai rural households are exposed to, as well as the average damage incurred. The damage is defined as the sum of the damage to assets, extra expenditures, and losses of income due to the shock. Both the mean number of shocks and the average amount of damages as well as the dispersion increase over the years, indicating heterogeneously affected households and an increasing affectedness by shocks overall. The high values in 2010 are capturing the economic shocks of the global financial and economic crisis due to a three-year reference period.

Table 2.5 Number of shocks and damages (medium and severe)

Year	Mean Damage (Log)	SD Damage (Log)	Mean Shocks (No.)	SD Shocks (No.)
2010	2720.3	5917.21	2.27	1.93
2013	931.5	1779.12	1.22	1.24
2016	2848.95	5556.76	1.56	1.35
2019	2939.15	7667.79	1.64	1.69

Source: Authors' calculations based on TVSEP (2022).

Looking at the income strategies pursued by the households, several observations can be made, as presented in Figure 2.4. While fluctuations can be observed, a relatively stable share of households engages in crop production (over 80%), off-farm employment (~70%) and self-employment (over 25%). Livestock on the other hand has seen a decline that is reflected even stronger in the livestock products. Thus, it can be concluded thus that traditional farming of field crops remains an integral part of most household's income strategies.

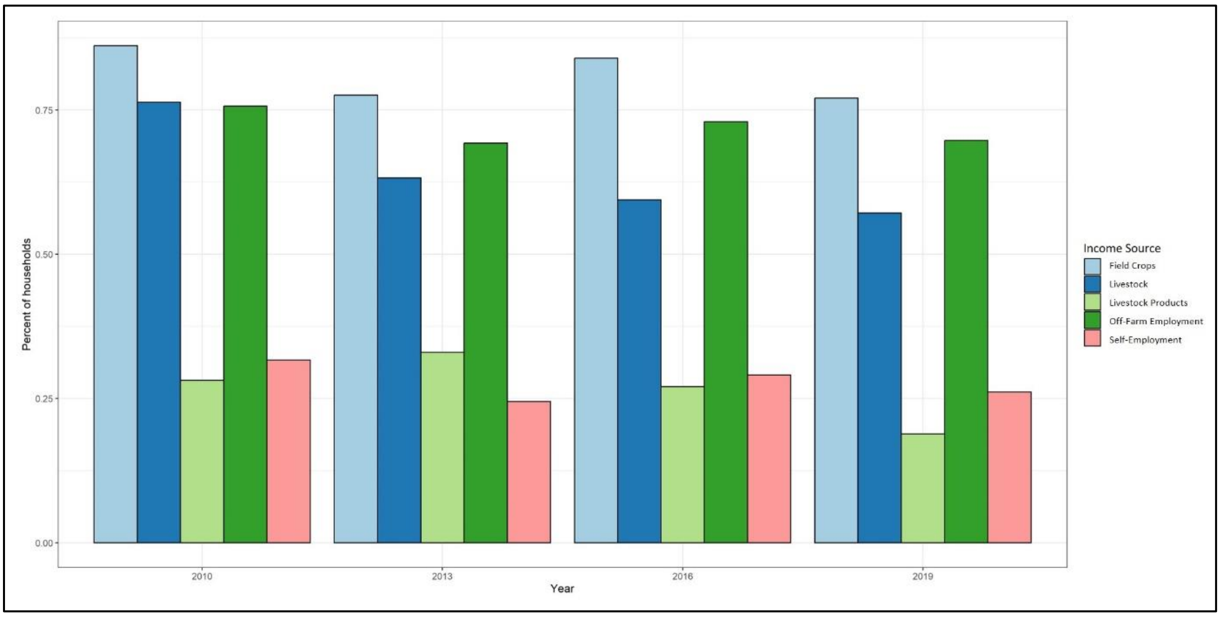

Figure 2.4 Income Sources across survey waves

Source: Authors' calculations based on TVSEP (2022).

Figure 2.5 provides information on the actual incomes from the different sources. As described earlier, agriculture remains prevalent in the household, but the income from it declines substantially after an initial increase. Income from off-farm employment on the other hand is constantly increasing and while showcasing a large spread, still reveals its tremendous importance for the income strategies of the households today. Self-employment is following a similar path and although fewer households engage in it, the relevance as an income strategy is clearly displayed. The trends shown in Figure 2.5 are also reflected in income shares within the households. Figure 2.6 illustrates the average share of the household income generated by each of the major income strategies. As can be observed, the mean share of income derived from agriculture has declined to under 15% in 2019, while until 2013 it remained over 20%. Off-Farm employment on the other hand has increased its average income share by around 7%. The contribution of self-employment remains at a rather stable level just shy of 10%.

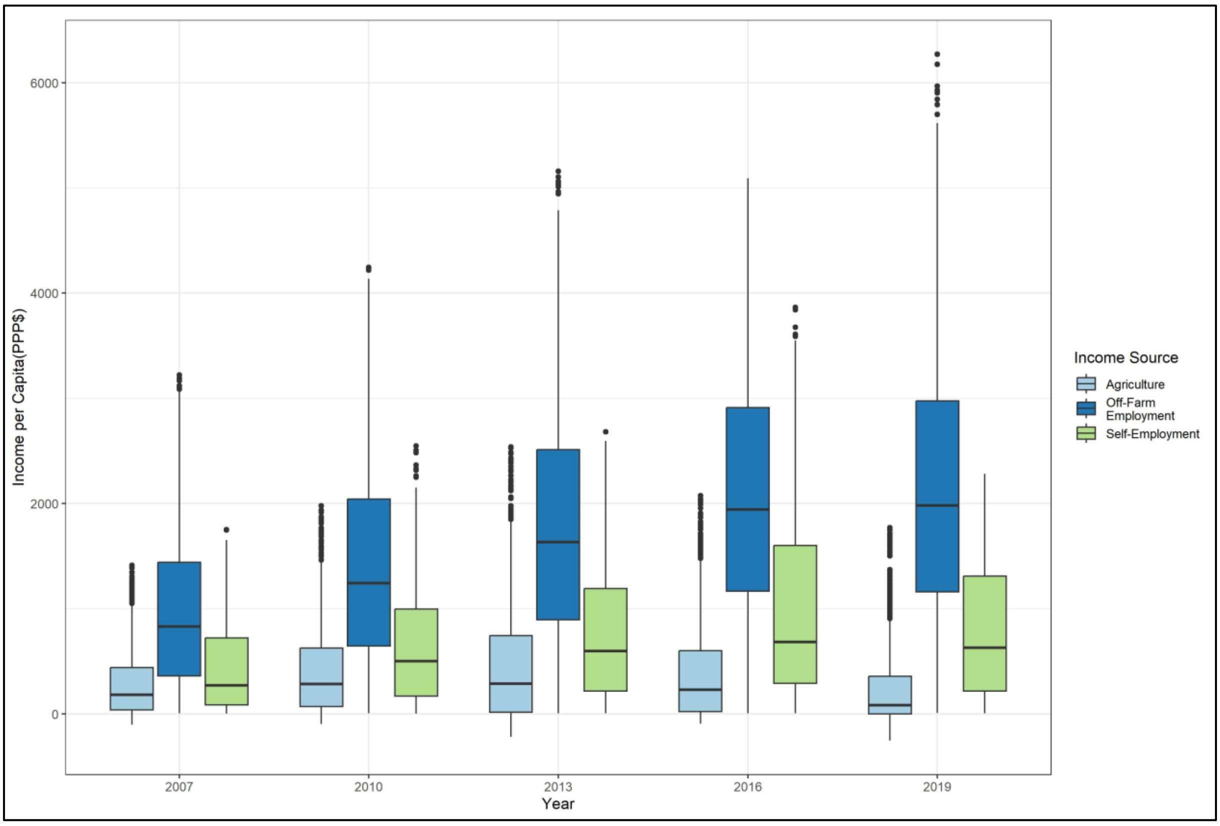

Figure 2.5 Per capita income in each survey wave

Source: Authors' calculations based on TVSEP (2022).

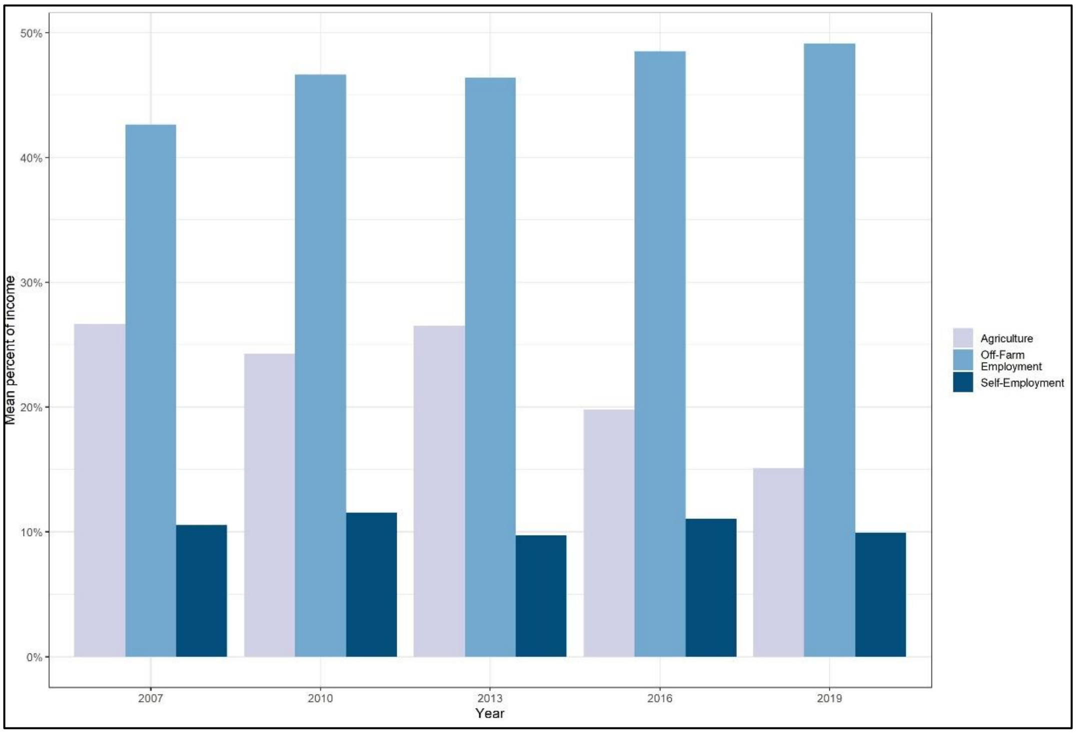

Figure 2.6 Per capita income share in each survey wave

Source: Authors' calculations based on TVSEP (2022).

Wage employment outside the own household agriculture (off-farm wage employment) can be characterised into agricultural and non-agricultural occupations. The prevalence of these occupations among migrant- and non-migrant household members is illustrated in Figure 2.7. As expected, non-migrant members in rural areas show a greater dependency on jobs in agriculture, while migrant members are predominantly occupied in the secondary and tertiary sector. However, even for the non-migrant members, employments in the primary sector are the exception, indicating an overall greater reliance on the secondary and tertiary sector. This is further confirmed by the average number of off-farm wage employments per household member, which declined from 1.046 in 2010 to 1.011 in 2019. Consequently, the models in the following chapter will control for the share of migrant members, although differences in the actual employments sought are confined to less than 25% in the primary sector.

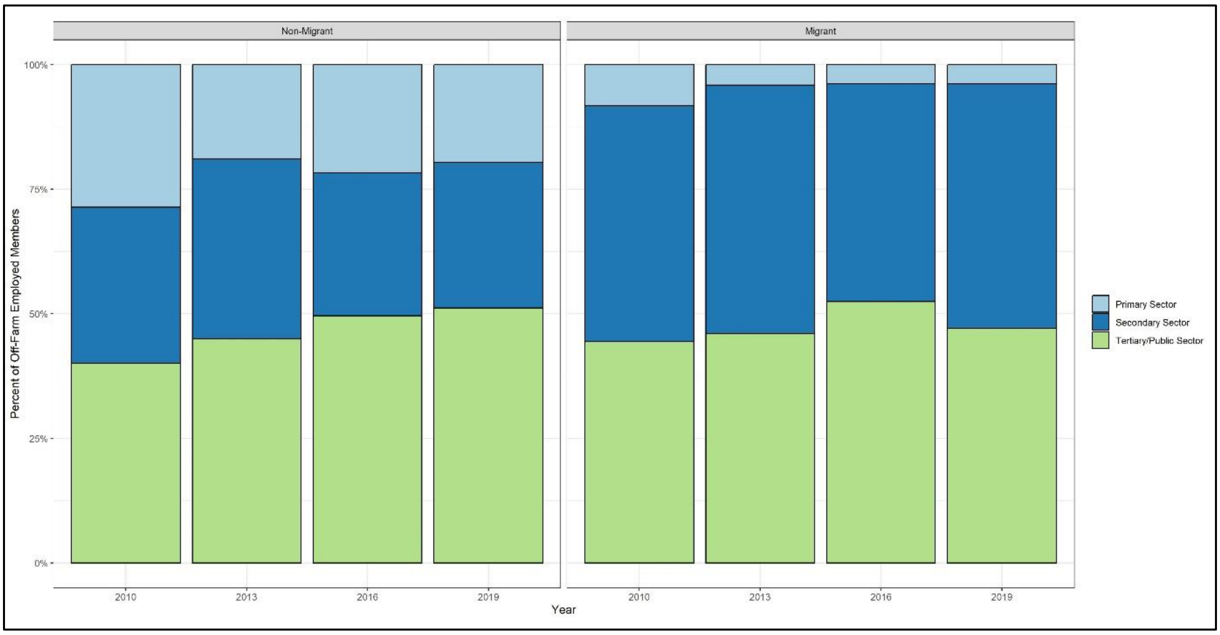

Figure 2.7 Off-farm employment sector by migrant status

Source: Authors' calculations based on TVSEP (2022).

Literature and descriptives alike suggest fluctuations and confirm a transforming environment for the households in rural Thailand. Keeping in mind the spatial heterogeneity of economic advance in Thailand however, this raises the question if all areas are affected to the same extent. Figure 2.8 presents the share of households in all surveyed districts that are engaged in agriculture, with all non-surveyed districts being indicated in white. While an overall high share of agriculturally engaged households remains observable, some areas begin to exhibit dwindling numbers. This points towards a still high relevance of agriculture as well as towards a potential issue in spatial distribution that needs to be controlled for in the following models. On the provincial level, these observations hold true as well, as indicated in Table 2.6.

Table 2.6 Share of households engaged in agriculture.

Year	Buriram	Ubon Ratchathani	Nakhon Phanom
2010	0.961	0.923	0.967
2013	0.931	0.896	0.9
2016	0.891	0.885	0.895
2019	0.884	0.824	0.857

Source: Authors' calculations based on TVSEP (2022).

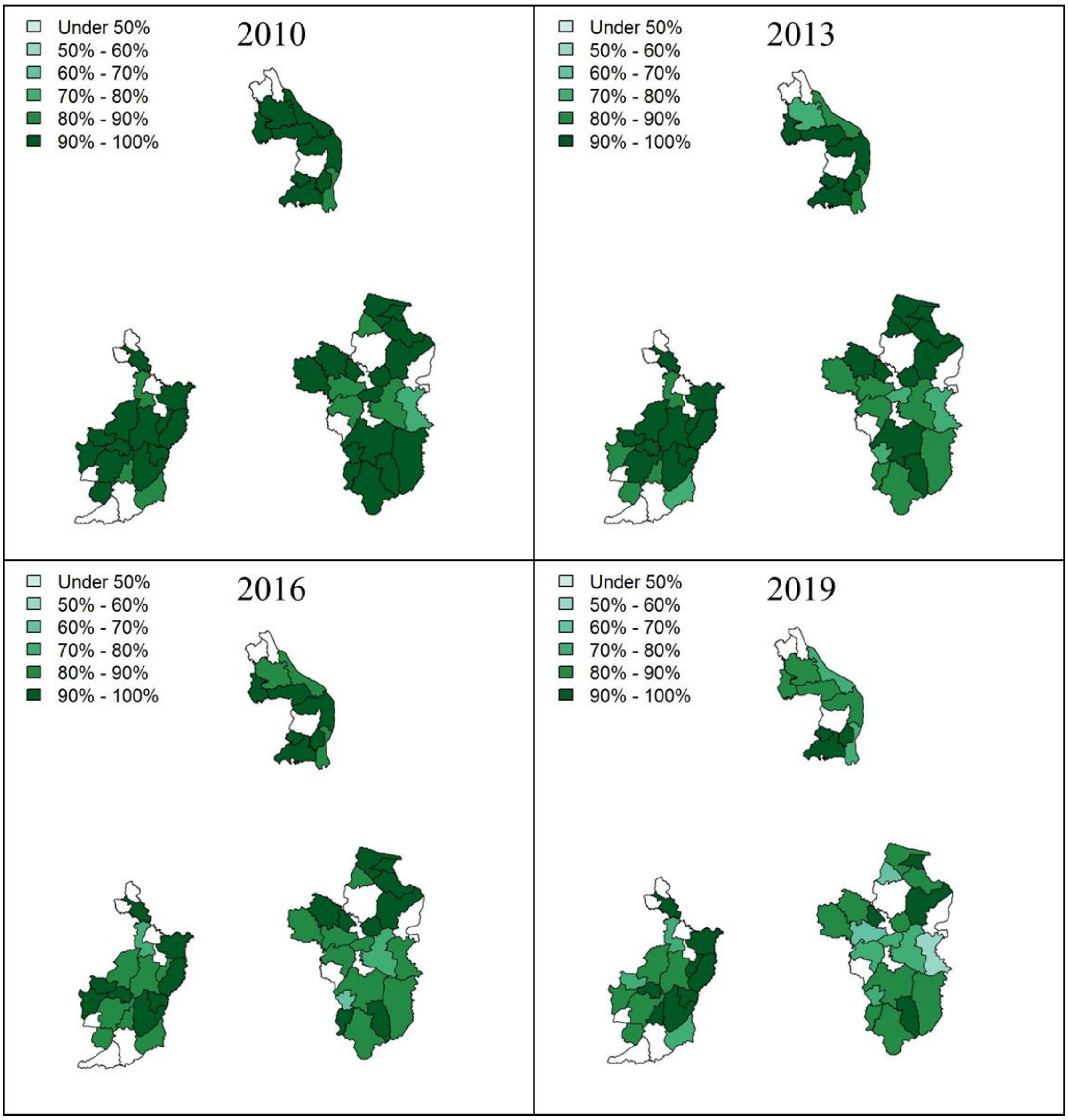

Figure 2.8 Distribution of Agriculture by District

Source: Authors' calculations based on TVSEP (2022).

In summary, the descriptive results presented in this chapter reveal a highly dynamic environment for rural Thai households. Households undergo a demographic change with decreasing numbers of members as well as migrants and an increasing average age. Agriculture becomes less relevant as an income strategy for the households. This is reflected in fewer members that primarily engage in it, lower income generated from it in absolute and relative terms and the increasing popularity of other income strategies, such as off-farm employment. In terms of shocks, the households are exposed to an increasing number of severe shocks with increasing damages as well. This highlights the need to lower vulnerability and increase resilience to enhance the sustainability of the transforming livelihoods revealed above.

2.5 Model Results

The purpose of the models and their results presented in this chapter is to approach the composition of income strategies of a household from several angles. The idea is to determine which strategy is most successful, why a household chooses and changes strategies and to what extent shocks play a role. The log per capita household income as defined earlier is utilized as the dependent variable in model 1. The results of model 1 (Table 2.7) highlight which factors lead to an increase in income, one of the most important pull-factors according to literature. As discussed earlier, other measures than income could be used in the context of a rural population, however, for model 1 this study is mainly concerned with the role of income strategies of which income is the direct output measure. As expected, a lower dependency ratio will lead to an increase in income. Also showcased is the role of education, which serves as a significant enabler for a higher household income. Similarly, the value of assets and savings held by a household will enable higher incomes and vice versa, while indebtedness does not seem to have much effect. Notably, shocks seem to have a strong impact on the overall income and due to the nature of shocks can influence the sustainability of a livelihood.

The choice of strategies indicate that a diversification will yield higher incomes than a focus on one income strategy. In addition, agriculture does seem to be less profitable than other sources of income, with an increasing log share in the household income leading to a lower income overall, regardless of land size. Due to multicollinearity, it is not possible to include the income share of off-farm employment and non-farm self-employment in the same model, however, as a robustness check, the model was rerun with income shares from off-farm income sources instead of the income share from agriculture, confirming the results. Lastly, migrants play a significant role with increasing effects, indicating a strong pull factor of opportunities at the migrants' location and signalling and increasing dependency on remittances. The size of effects varies throughout the years and variables. However, some constantly impactful values can be observed. The dependency ratio will lower the log per capita income by 8.9% to 10.3% per year with each unit increase. Additionally, a unit increase in income share through agriculture leads to a reduction of per capita income by 14.2% to 16.4%, with the largest impact being observed in 2019. Remarkably, the choice to pursue several income strategies increases income by 29.2% to 50.7%, highlighting the monetary benefits of income diversification.

Table 2.7 Influencing factors on the per capita income (Model 1 OLS)

	Model 1:2010	Model 1:2013	Model 1:2016	Model 1:2019
DepR	-0.089** (0.039)	-0.103*** (0.039)	-0.085*** (0.029)	-0.083** (0.035)
MeanE	0.035*** (0.008)	0.027*** (0.008)	0.04*** (0.008)	0.039*** (0.009)
MigS	0.006*** (0.001)	0.006*** (0.001)	0.008*** (0.001)	0.01*** (0.001)
LandA	0.049*** (0.014)	0.088*** (0.019)	0.04** (0.016)	0.083*** (0.021)
IncShF	-0.142*** (0.017)	-0.138*** (0.022)	-0.136*** (0.016)	-0.164*** (0.021)
Sav	0.055*** (0.008)	0.044*** (0.009)	0.027*** (0.006)	0.009 (0.007)
Debt	0.01* (0.005)	0.01 (0.006)	0.002 (0.005)	0 (0.005)
Asset	0.158*** (0.019)	0.053** (0.022)	0.12*** (0.015)	0.082*** (0.015)
Strat	0.387*** (0.063)	0.507*** (0.081)	0.292*** (0.053)	0.358*** (0.061)
ShockNo	-0.017 (0.011)	-0.042** (0.021)	-0.024* (0.013)	-0.026** (0.013)
Prov: Buriram	0.199*** (0.053)	0.353*** (0.082)	0.089* (0.049)	0.234*** (0.057)
Prov: Ubon Ratchathani	0.14*** (0.052)	0.337*** (0.081)	-0.05 (0.048)	0.161*** (0.057)
R^2	0.398	0.3	0.368	0.374
Obs.	1277	1180	1490	1393
P-Value	0	0	0	0

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; Standard errors (SE) in parentheses;
Source: Authors' calculations based on TVSEP (2022).

Overall, model 1 exhibits rather consistent results over the years with key points being highlighted. With emerging opportunities, agriculture evolves to be the inferior choice to off-farm and self-employment. In the context of sustainability of the livelihood, the role of shocks is indicated with a diversification of income sources potentially being an option to diversify risk and reduce vulnerability.

As indicated by the variable "Strat", a combined strategy leads to the highest income, as productive resources of a household can be allocated most efficiently. Model 1 does also hint at the significance of migration and education. However, it cannot explain why households might elect to pursue certain strategies. Entry barriers and other factors remain to be determined in model 2. This model is split into three sub-models (2.1, 2.2 and 2.3), with one being dedicated to each major income strategy of agriculture, off-farm employment and self-employment respectively. Model results are presented in Table 2.8. In model 2, the dependency ratio is replaced with the mean age of the household members and the squared mean age of household members, to proxy the entry barrier of age and determine if there is a cut-off point of being "too old" to pursue a certain strategy.

Table 2.8 Influencing factors on the probability (odd ratios) of adopting Farming, Off-Farm Employment or Self-Employment as Strategy (Model 2 Logit)

	2010			2013			2016			2019		
	2.1:FarmS	**2.2:OffS**	**2.3:SelfS**	**2.1:FarmS**	**2.2:OffS**	**2.3:SelfS**	**2.1:FarmS**	**2.2:OffS**	**2.3:SelfS**	**2.1:FarmS**	**2.2:OffS**	**2.3:SelfS**
MeanA	1.065 (0.065)	1.098** (0.043)	0.986 (0.037)	1.034 (0.054)	1.123*** (0.041)	1.061 (0.042)	0.961 (0.047)	1.187*** (0.04)	1.101*** (0.037)	1.015 (0.042)	1.038 (0.04)	1.058 (0.036)
MeanAsq	0.999 (0.001)	0.998*** (0.001)	1 (0)	0.999 (0.001)	0.998*** (0)	0.999* (0)	1 (0)	0.998*** (0)	0.999*** (0)	1 (0)	0.999*** (0)	0.999** (0)
MeanE	0.9** (0.047)	1.078** (0.037)	1.008 (0.024)	0.888*** (0.029)	1.038 (0.028)	1.011 (0.022)	0.936* (0.038)	1.053 (0.035)	0.991 (0.025)	0.881*** (0.031)	1.147*** (0.035)	0.994 (0.024)
MigS	0.992 (0.007)	1.068*** (0.007)	0.992** (0.004)	0.99 (0.006)	1.066*** (0.007)	1.008* (0.004)	0.991 (0.006)	1.052*** (0.006)	0.996 (0.004)	0.993 (0.005)	1.05*** (0.006)	0.996 (0.004)
LandA	1.955*** (0.087)	0.849** (0.064)	0.834*** (0.048)	2.055*** (0.075)	0.723*** (0.07)	0.817*** (0.057)	2.186*** (0.065)	0.68*** (0.073)	0.762*** (0.057)	2.401*** (0.065)	0.715*** (0.078)	0.81*** (0.059)
Incpc	0.874 (0.22)	2.673*** (0.115)	1.965*** (0.101)	1.422*** (0.1)	2.476*** (0.094)	1.811*** (0.093)	0.834 (0.133)	2.144*** (0.092)	2.089*** (0.089)	0.848 (0.11)	2.939*** (0.098)	1.743*** (0.08)
Sav	1.129** (0.058)	0.908*** (0.036)	1.007 (0.028)	1.001 (0.04)	0.96 (0.03)	1.044 (0.027)	0.993 (0.033)	0.984 (0.025)	1.039* (0.021)	1.019 (0.03)	1.036 (0.026)	1.035* (0.02)
Debt	1.002 (0.044)	0.98 (0.024)	1.015 (0.019)	1.09*** (0.032)	1.015 (0.022)	1.004 (0.019)	1.031 (0.026)	1.056*** (0.019)	1.006 (0.016)	1.046* (0.024)	0.955** (0.021)	0.998 (0.016)
Asset	1.187 (0.132)	0.835** (0.084)	1.578*** (0.068)	1.064 (0.096)	0.994 (0.071)	1.511*** (0.066)	1.135 (0.079)	0.877** (0.061)	1.352*** (0.053)	0.947 (0.054)	0.888** (0.051)	1.275*** (0.046)
FarmS		1.58 (0.462)	0.848 (0.339)		0.708 (0.357)	0.695 (0.294)		1.367 (0.305)	1.576* (0.256)		1.782** (0.289)	1.215 (0.229)
OffS	1.278 (0.447)		0.276*** (0.188)	0.619 (0.347)		0.217*** (0.205)	1.139 (0.3)		0.322*** (0.17)	1.559 (0.273)		0.315*** (0.183)
SelfS	0.821 (0.337)	0.274*** (0.192)		0.619* (0.287)	0.187*** (0.212)		1.374 (0.255)	0.312*** (0.173)		1.072 (0.227)	0.277*** (0.193)	
ShockNo	1.617*** (0.118)	1.097** (0.046)	0.985 (0.037)	1.346** (0.116)	1.163** (0.074)	1.111* (0.062)	1.642*** (0.105)	1.063 (0.059)	1.04 (0.048)	1.328*** (0.081)	0.947 (0.049)	0.953 (0.043)
Prov: Buriram	1.134 (0.563)	0.85 (0.283)	0.69* (0.201)	1.273 (0.353)	1.623* (0.262)	0.751 (0.242)	0.839 (0.305)	0.631** (0.23)	0.668** (0.188)	0.981 (0.294)	1.068 (0.24)	1.092 (0.193)
Prov: Ubon Ratchathani	0.561 (0.518)	0.422*** (0.261)	0.569*** (0.195)	0.941 (0.321)	1.081 (0.234)	0.699 (0.227)	0.688 (0.298)	0.661* (0.22)	0.861 (0.181)	0.881 (0.277)	0.695 (0.226)	0.723* (0.193)
R^2 (Nagelkerke)	0.36	0.47	0.23	0.35	0.49	0.22	0.41	0.46	0.21	0.42	0.56	0.18

Obs.	1278	1278	1278	1182	1182	1182	1492	1492	1492	1398	1398	1398
K-Fold CV	0.95	0.827	0.735	0.908	0.821	0.789	0.903	0.822	0.751	0.888	0.841	0.767

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; Standard errors (SE) in parentheses;
Source: Authors' calculations based on TVSEP (2022).

As can be observed, age ultimately is the cap to all income strategies but agriculture, highlighting the necessity for retirement funds. The results also indicate the role of education as an entry barrier for off-farm employment as the odds rise with the level of education, while agriculture exhibits the opposite effect. Further, self-employment seems to be elected regardless of educational level, highlighting potentials in entrepreneurship for people with lower formal educational attainments. Model 2.2 confirms the impression from model 1 in which migrants primarily pursue off-farm employment. While this might seem logical in comparison to agriculture, it does also indicate a more domestic form of self-employment. Controlling for income again verifies the results of model 1, with the addition of off-farm employment outperforming self-employment. Reflected in the savings and assets are the entry barriers for self-employment to occur, as businesses usually demand some initial investment and asset accumulation. People with fewer valuable assets deviate more towards off-farm employment, whilst savings do not show much impact here. Curiously, in 2019 it can be observed that pursuing off-farm employment also increases the chance of pursuing agriculture, however not vice versa. This might hint to an ongoing process towards diversified income sources and not the subsequent decline of agriculture. Similarly, the model shows that households either pursue self-employment or off-farm employment with either lowering the odds of also pursuing the other. The advancing stability of income through off-farm employment or self-employment is highlighted by the decline in significant impacts of shocks. Only agriculture remains highly affected. Similarly, provincial effects decline, indicating a somewhat even availability of income strategies throughout the panel, although not in terms of income, as indicated in model 1. Interpreting the size of effects, in 2019, a strong effect of the mean years of schooling becomes apparent, with the odd ratio of engaging in agriculture being 11.9% lower, while a 14.7% increase for off-farm employment is observed. The results also show a very strong relation between land area and agriculture, the odd ratio increasing by a factor of up to 2.4 in 2019. Simultaneously an increase in land area lowers the odd ratio to engage in either off-farm employment or self-employment by up to 28.5%. Further strong effects include the mutual exclusivity of off-farm employment and self-employment. Pursuing one of the two, lowers the odd ratio to pursue the other as well by up to 82.3%, an effect that is not present with agriculture. Finally, the impact of shocks is noteworthy. A high number of shocks raises the odds to be engaged in agriculture by up to 64.2%, far outnumbering any such effect in off-farm- or self-employment. Overall, results of model 2 point towards a clear set of requirements and entry barriers that make households eligible for the pursuit of self-employment and even more pronounced, off-farm employment. Finally, models 1 and 2 exhibit the relevance of shocks as contextual factors, with the literature also pointing to a benefit of diversified income strategies for household resilience.

To ensure robustness and motivate the approach of fitting each model for each survey wave, all models were fitted again, using a dataset containing all waves of data with an added control variable for the year. The effect on the coefficients was limited, however, the significance of independent variables was frequently impacted. Combined with the consistent significance of the control variable for the survey wave, this indicates a significant impact of the year, warranting both the overall longitudinal approach of this study as well as a separation of the models by year. Additionally, model 1 was subjected to further robustness checks, by which the change in coefficients, when removing each of the independent variables individually, was assessed. The model exhibited sufficient robustness with an average deviation of coefficients below 0.05. This approach is infeasible for model 2, as for logistic regressions, changes in the coefficients cannot be clearly attributed to the exclusion of a variable (Karlson et al., 2012).

2.6 Conclusion and discussion

In summary, this study confirms the existence of large-scale transformations in the income strategies of the households in rural Thailand. Consistent with the literature, a clear trend towards higher paid off-farm employment is observed with incomes from this source steadily increasing over the past years. The results however partly reject the assumption of hypothesis 1 that households shift to these new income sources, while entirely abandoning agriculture. Instead, a very dynamic environment can be observed, with diversified livelihood strategies being the prevalent – and most successful – choice. Opportunities for alternative income sources present themselves, however entry barriers rise with expectable income, especially regarding education, confirming hypothesis 2. As a result, opportunities may be recognized by households, yet an exploitation is not possible due to intra- household limitations. Similarly, the relevance of migration is highlighted, indicating a lack of opportunities in the rural areas themselves. Conclusively, a diversified income portfolio allows a household to place all its members in their most efficient revenue-generating activities, be it the younger and better educated member as a work-migrant, or the older parental generation as farmers on the household land. In addition, diversifying risk may increase the sustainability of the livelihood and reduce vulnerability. Our results suggest that this process of diversification and allocation is not the result of a conscious strategy, but rather intuitive and according to the household’s endowment with human and physical resources. Coming back to the Sustainable Livelihoods Framework, this study confirms the empirical relevance of all its elements and highlights the interconnectedness. Further, the importance of the livelihood assets is confirmed. Additionally, this study revealed a clear preference for off-farm employment, however it is self-employment in the form of entrepreneurship that might be more accessible to rural households and thus contribute more to rural development by creating more domestic opportunities. Rejecting hypothesis 3, self-employment remains less popular than off-farm employment, which might be due to the higher opportunity costs of self-employment. Within the scope of this study, few distinctions between different kinds of farming, be it large scale or small scale, could be identified. It may however be an underexploited opportunity to further intensify agriculture to generate more income, placing it competitively to the income generated by off-farm employment. This comes at high opportunity costs however and may be a subject for future studies, as financial resources start to trickle into the rural areas.

Finally, shocks showed effects on the strategic choices of a household. With increasing effects of climate change, agriculture could severely suffer from shocks and income diversification may be a way to increase resilience and lower vulnerability. Another benefit, especially from subsistence agriculture, may be the provision of the essentials to survive, serving as a fallback position in case of job loss, bankruptcy, and other non-natural disaster related shocks.

The results of this study bear implications for policy design. First, capacity building and education are emphasized. This does not only extend to the education of children but also to the training of adults. Second, the focus on migration suggests a lack of domestic non-farm income opportunities. Since migration will only contribute to a reduction of regional disparities through remittances, it is important to build more regional employment. This may also be achieved by promoting self-employment and, to an extent, entrepreneurship. Generally speaking, these first two points address capacity building and opportunity recognition in light of fostering a regional and demographic convergence. Finally, shocks have been identified as a key detriment to agriculture. With agriculture still being retained as an income source by most households, targeted disaster alleviation schemes can help to integrate agriculture into diversified household income strategies, as well as encourage investments and intensification in the future.

While the study may have contributed to a better understanding to rural transformation in an emerging economy in Asia one limitation should be mentioned. Considerable uncertainty exists regarding the contribution of migrants to household income. Remittances, as reported in household surveys, is a poor measure of income by non-resident household members. This is because the actual support of migrants for their natal households is difficult to capture and may change over time. Some migrants may return to their village while others may gradually get more detached from their rural household and stay in the urban areas. Therefore, migration is controlled for, but remittances are not explicitly analysed beyond descriptive results in this study.

Expanding this approach taken in this study would certainly be possible for any transforming rural area in an emerging economy but also requires substantial data collection efforts. Finally, the topic of this study is highly dynamic and a regular revisit of the topic with ongoing data collection as part of panel studies seems advisable.

2.7 References Chapter 2

Abera, A., Yirgu, T., & Uncha, A. (2021). Determinants of rural livelihood diversification strategies among Chewaka resettlers' communities of southwestern Ethiopia. *Agriculture & Food Security*, *10*(1), 30. https://doi.org/10.1186/s40066-021-00305-w

Amare, M., Jensen, N., Shiferaw, B., & Cissé, J. (2018). Rainfall shocks and agricultural productivity: Implication for rural household consumption. *Agricultural Systems*, 79–89. https://doi.org/10.1016/j.agsy.2018.07.014

Ashley, C., & Carney, D. (1999). *Sustainable livelihoods: Lessons from early experience*. Department for International Development.

Asian Development Bank (Hrsg.). (2015). *Thailand, industrialization and economic catch-up: Country diagnostic study*. Asian Development Bank.

Aung, M., Shah, W. A., & Oliva, M. B. (2013). *Asia's Economic Transformation: Where to, How, and How Fast?* 106.

Bah, E. (2011). Structural Transformation Paths Across Countries. *Emerging Markets Finance and Trade*, *47*, 5–19. https://doi.org/10.2307/23047440

Barrett, C. B., Reardon, T., & Webb, P. (2001). Nonfarm income diversification and household livelihood strategies in rural Africa: Concepts, dynamics, and policy implications. *Food Policy*, *26*(4), 315–331. https://doi.org/10.1016/S0306-9192(01)00014-8

Baymul, C., & Sen, K. (2020). Was Kuznets Right? New Evidence on the Relationship between Structural Transformation and Inequality. *The Journal of Development Studies*, *56*(9), 1643–1662. https://doi.org/10.1080/00220388.2019.1702161

Brons, L., & Pellenbarg, P. (2003). *Economy, culture and entrepreneurship in a spatial context* (S. 11–36).

Chambers, R., & Conway, G. (1992). Sustainable rural livelihoods: Practical concepts for the 21st century. *IDS Discussion Paper*, *296*.

Chantarat, S., Lamsam, A., Samphantharak, K., & Tangsawasdirat, B. (2020). *Household Debt and Delinquency Over the Life Cycle* (SSRN Scholarly Paper 3555403). https://papers.ssrn.com/abstract=3555403

Chantarat, S., Oum, S., Samphantharak, K., & Sann, V. (2019). Natural Disasters, Preferences, and Behaviors: Evidence from the 2011 Mega Flood in Cambodia. *Journal of Asian Economics*, *63*, 44–74. https://doi.org/10.1016/j.asieco.2019.05.001

Chichaibelu, B. B., & Waibel, H. (2018). Over-indebtedness and its persistence in rural households in Thailand and Vietnam. *Journal of Asian Economics*, *56*, 1–23. https://doi.org/10.1016/j.asieco.2018.04.002

Christiaensen, L., & Martin, W. (2018). Agriculture, structural transformation and poverty reduction: Eight new insights. *World Development*, *109*, 413–416. https://doi.org/10.1016/j.worlddev.2018.05.027

Cornett, A. (1999). *Regional Integration and regional development? - Concepts and empirical relevance*.

Cotula, L., International Institute for Environment and Development, Food and Agriculture Organization of the United Nations, & International Fund for Agricultural Development. (2009). *Land grab or development opportunity?: Agricultural investment and international land deals in Africa*. IIED ; FAO : IFAD. ftp://ftp.fao.org/docrep/fao/011/ak241e/ak241e.pdf

Démurger, S., Fournier, M., & Yang, W. (2010). *Rural households' decisions towards income diversification: Evidence from a township in northern China*. 29.

Disney, R., McKay, A., & Shabab, C. R. (2023). Household inequality and remittances in rural Thailand: A life-cycle perspective. *Oxford Economic Papers, 75*(2), 418–443. https://doi.org/10.1093/oep/gpac025

Ellis, F. (1998). Household strategies and rural livelihood diversification. *The Journal of Development Studies, 35*(1), 1–38. https://doi.org/10.1080/00220389808422553

Ellis, F. (2000). The Determinants of Rural Livelihood Diversification in Developing Countries. *Journal of Agricultural Economics, 51*(2), 289–302. https://doi.org/10.1111/j.1477-9552.2000.tb01229.x

Estudillo, J. P., Cureg, E. F., & Otsuka, K. (2019). Transformation of Rural Economies in Asia and Africa. In K. Otsuka & K. Sugihara (Hrsg.), *Paths to the Emerging State in Asia and Africa* (S. 219–251). Springer. https://doi.org/10.1007/978-981-13-3131-2_10

Fan, S., Brzeska, J., Keyzer, M., & Halsema, A. (2013). *From subsistence to profit: Transforming smallholder farms* (0 Aufl.). International Food Policy Research Institute. https://doi.org/10.2499/9780896295582

Fan, S., & Chan-Kang, C. (2005). Is small beautiful? Farm size, productivity, and poverty in Asian agriculture. *Agricultural Economics, 32*(s1), 135–146. https://doi.org/10.1111/j.0169-5150.2004.00019.x

Ferraz, J., Coutinho, L., & Nassif, A. (2012). *Industrial Policy and Economic Transformation*.

Fox, J., & Monette, G. (1992). Generalized Collinearity Diagnostics. *Journal of the American Statistical Association, 87*(417), 178–183. https://doi.org/10.2307/2290467

Freund, R. J., & Wilson, W. J. (1998). *Regression Analysis: Statistical Modeling of a Response Variable*. Academic Press.

Goulden, M. C., Adger, W. N., Allison, E. H., & Conway, D. (2013). Limits to Resilience from Livelihood Diversification and Social Capital in Lake Social—Ecological Systems. *Annals of the Association of American Geographers, 103*(4), 906–924.

Grabrucker, K., & Grimm, M. (2021). Is There a Rainbow after the Rain? How Do Agricultural Shocks Affect Non-Farm Enterprises? Evidence from Thailand. *American Journal of Agricultural Economics, 103*(5), 1612–1636. https://doi.org/10.1111/ajae.12174

Grandstaff, S. (1992). Income Disparities: What Can be Done? *Pacific Viewpoint, 33*(2), 121–127. https://doi.org/10.1111/apv.332002

Guadagno, F., Fortunato, P., Bateman, M., Rada, C., & Vrolijk, K. (2016). *Structural Transformation and Industrial Policy*. United Nations. https://unctad.org/system/files/official-document/gds2016d1_en.pdf

Habib, N., Rankin, P., Alauddin, M., & Cramb, R. (2023). Determinants of livelihood diversification in rural rain-fed region of Pakistan: Evidence from fractional multinomial logit (FMLOGIT) estimation. *Environmental Science and Pollution Research, 30*(5), 13185–13196. https://doi.org/10.1007/s11356-022-23040-6

Hallegatte, S., Vogt-Schilb, A., Rozenberg, J., Bangalore, M., & Beaudet, C. (2020). From Poverty to Disaster and Back: A Review of the Literature. *Economics of Disasters and Climate Change, 4*(1), 223–247. https://doi.org/10.1007/s41885-020-00060-5

Han, L., & Hare, D. (2013). The link between credit markets and self-employment choice among households in rural China. *Journal of Asian Economics, 26*, 52–64. https://doi.org/10.1016/j.asieco.2013.04.008

Harvey, C. A., Rakotobe, Z. L., Rao, N. S., Dave, R., Razafimahatratra, H., Rabarijohn, R. H., Rajaofara, H., & MacKinnon, J. L. (2014). Extreme vulnerability of smallholder farmers to agricultural risks and climate change in Madagascar. *Philosophical Transactions of the Royal Society B: Biological Sciences, 369*(1639). https://doi.org/10.1098/rstb.2013.0089

Hazell, P., & Haggblade, S. (1993). Farm-nonfarm growth linkages and the welfare of the poor. *Including the Poor*.

Hosmer, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). Assessing the Fit of the Model. In *Applied Logistic Regression* (S. 153–225). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781118548387.ch5

Humanitarian Data Exchange. (2022). *Thailand – Subnational Administrative Boundaries. Available at https://data.humdata.org/dataset/cod-ab-tha.*

Islam, N. (1997). *The nonfarm sector and rural development* (2020 vision briefs 47). International Food Policy Research Institute (IFPRI). https://econpapers.repec.org/paper/fpr2020br/47.htm

Karlson, K. B., Holm, A., & Breen, R. (2012). Comparing Regression Coefficients Between Same-sample Nested Models Using Logit and Probit: A New Method. *Sociological Methodology*, *42*(1), 286–313. https://doi.org/10.1177/0081175012444861

Killick, T. (2001). Globalisation and the Rural Poor. *Development Policy Review*, *19*(2), 155–180. https://doi.org/10.1111/1467-7679.00129

Koller, M., & Stahel, W. A. (2011). Sharpening Wald-type inference in robust regression for small samples. *Computational Statistics & Data Analysis*, *55*(8), 2504–2515. https://doi.org/10.1016/j.csda.2011.02.014

Kostov, P., & Lingard, J. (2004). Subsistence Agriculture in Transition Economies: Its Roles and Determinants. *Journal of Agricultural Economics*, *55*, 565–579. https://doi.org/10.1111/j.1477-9552.2004.tb00115.x

Kubik, Z., & Maurel, M. (2016). Weather Shocks, Agricultural Production and Migration: Evidence from Tanzania. *The Journal of Development Studies*, *52*, 1–16. https://doi.org/10.1080/00220388.2015.1107049

Kucera, D., & Jiang, X. (2018). Structural transformation in emerging economies: Leading sectors and the balanced growth hypothesis. *Oxford Development Studies*, 1–17. https://doi.org/10.1080/13600818.2018.1533934

Kucera, D., & Roncolato, L. (2016). The manufacturing–services dynamic in economic development. *International Labour Review*, *155*(2), 171–199. https://doi.org/10.1111/j.1564-913X.2015.00052.x

Kuznets, S. (1955). Economic Growth and Income Inequality. *The American Economic Review*, *45*(1), 1–28.

Kuznets, S. (1967). Population and Economic Growth. *Proceedings of the American Philosophical Society*, *111*(3), 170–193.

Kuznets, S. (1973). Modern Economic Growth: Findings and Reflections. *The American Economic Review*, *63*(3), 247–258.

Li, T., Cao, X., Qiu, M., & Li, Y. (2020). Exploring the Spatial Determinants of Rural Poverty in the Interprovincial Border Areas of the Loess Plateau in China: A Village-Level Analysis Using Geographically Weighted Regression. *ISPRS International Journal of Geo-Information*, *9*, 345. https://doi.org/10.3390/ijgi9060345

Mariyono, J. (2019). Stepping up from subsistence to commercial intensive farming to enhance welfare of farmer households in Indonesia. *Asia & the Pacific Policy Studies*, *6*(2), 246–265. https://doi.org/10.1002/app5.276

Marjanović, V. (2015). Structural Changes and Structural Transformation in a Modern Development Economy. *Economic Themes*, *53*(1), 63–82. https://doi.org/10.1515/ethemes-2015-0005

McMillan, M., Rodrik, D., & Verduzco-Gallo, Í. (2014). Globalization, Structural Change, and Productivity Growth, with an Update on Africa. *World Development*, *63*, 11–32. https://doi.org/10.1016/j.worlddev.2013.10.012

Natarajan, N., Newsham, A., Rigg, J., & Suhardiman, D. (2022). A sustainable livelihoods framework for the 21st century. *World Development*, *155*, 105898. https://doi.org/10.1016/j.worlddev.2022.105898

Nkedianye, D. K., Ogutu, J. O., Said, M. Y., Kifugo, S. C., de Leeuw, J., Van Gardingen, P., & Reid, R. S. (2020). Comparative social demography, livelihood diversification and land tenure among the Maasai of Kenya and Tanzania. *Pastoralism*, *10*(1), 17. https://doi.org/10.1186/s13570-020-00165-2

Ocampo, J. A., Rada, C., Taylor, L., & Parra, M. (2009). Economic Structure, Policy, and Growth. In *Growth and Policy in Developing Countries* (S. 1–24). Columbia University Press; JSTOR. https://doi.org/10.7312/ocam15014.6

Rashid, D., Langworthy, M., & Aradhyula, S. (2006). Livelihood Shocks and Coping Strategies: An Empirical Study of Bangladesh Households. *American Agricultural Economics Association (New Name 2008: Agricultural and Applied Economics Association), 2006 Annual meeting, July 23-26, Long Beach, CA*.

Reardon, T., Berdegué, J., Barrett, C. B., & Stamoulis, K. (2006). *Chapter 8 Household Income Diversification into Rural Nonfarm Activities: Bd. Transforming the Rural Nonfarm Economy*. Johns Hopkins University Press.

Reardon, T., Delgado, C., & Matlon, P. (1992). Determinants and Effects of Income Diversification Amongst Farm Households in Burkina Faso. *Journal of Development Studies*, *28*, 264–296. https://doi.org/10.1080/00220389208422232

Reardon, T., Taylor, J. E., Stamoulis, K., Lanjouw, P., & Balisacan, A. (2000). Effects of Non-Farm Employment on Rural Income Inequality in Developing Countries: An Investment Perspective. *Journal of Agricultural Economics*, *51*(2), 266–288. https://doi.org/10.1111/j.1477-9552.2000.tb01228.x

Schlogl, L., & Sumner, A. (2020). *Disrupted Development and the Future of Inequality in the Age of Automation*. Springer International Publishing. https://doi.org/10.1007/978-3-030-30131-6

Schwarze, S., & Zeller, M. (2005). *Income diversification of rural households in Central Sulawesi, Indonesia*. *1*, 13.

Scoones, I. (1998). *Sustainable Rural Livelihoods: A Framework for Analysis*. https://opendocs.ids.ac.uk/opendocs/handle/20.500.12413/3390

Scoones, I. (2009). Livelihoods perspectives and rural development. *The Journal of Peasant Studies*, *36*(1), 171–196. https://doi.org/10.1080/03066150902820503

Sen, K. (2016). The Determinants of Structural Transformation in Asia: A Review of the Literature. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2811507

Senadza, B. (2014). Income Diversification Strategies among Rural Households in Developing Countries: Evidence from Ghana. *African Journal of Economic and Management Studies*, *5*. https://doi.org/10.1108/AJEMS-05-2012-0029

Strömberg, D. (2007). Natural Disasters, Economic Development, and Humanitarian Aid. *The Journal of Economic Perspectives*, *21*(3), 199–222. JSTOR.

Syrquin, M. (2008). Structural change and development. *International Handbook of Development Economics, Volumes 1 & 2*, 48–67.

Timmer, C. (1988). The agricultural transformation. *Handbook of development economics. Vol. 1*, *I*.

Tipayalai, K., & Mendez, C. (2022). Regional convergence and spatial dependence in Thailand: Global and local assessments. *Journal of the Asia Pacific Economy*, *0*(0), 1–28. https://doi.org/10.1080/13547860.2022.2041286

Tongruksawattana, S., Schmidt, E., & Waibel, H. (2009). *Shocks and Coping Strategies of Agricultural Households: First Results from Three Provinces in Thailand*. 20.

TVSEP. (2022). *Thailand Vietnam Socio Economic Panel – Poverty Dynamics and Sustainable Development (Version 2022). Dataset available upon request from: Https://www.tvsep.de/en/tvsep-data-access*.

Vanwambeke, S., Somboon, P., & Lambin, E. F. (2007). Rural transformation and land use change in northern Thailand. *Journal of Land Use Science*, *2*, 1–29.

Vatcheva, K. P., Lee, M., McCormick, J. B., & Rahbar, M. H. (2016). Multicollinearity in Regression Analyses Conducted in Epidemiologic Studies. *Epidemiology (Sunnyvale, Calif.)*, *6*(2), 227. https://doi.org/10.4172/2161-1165.1000227

Wan, J., Li, R., Wang, W., Liu, Z., Chen, B., & Rosen, M. (2016). Income Diversification: A Strategy for Rural Region Risk Management. *Sustainability*, *8*, 1–13. https://doi.org/10.3390/su8101064

World Bank Group. (2022). *Thailand Rural Income Diagnostic: Challenges and opportunities for Rural farmers*. World Bank, Bangkok.

Wouterse, F., & Taylor, J. E. (2008). Migration and Income Diversification: Evidence from Burkina Faso. *World Development*, *36*(4), 625–640. https://doi.org/10.1016/j.worlddev.2007.03.009

Yohai, V. J. (1987). High Breakdown-Point and High Efficiency Robust Estimates for Regression. *The Annals of Statistics*, *15*(2), 642–656.

Zhao, J., & Barry, P. (2013). Implications of different income diversification indexes: The case of rural China. *Economics and Business Letters*, *2*, 13. https://doi.org/10.17811/ebl.2.1.2013.13-20

2.8 Appendix Chapter 2

Table A2.9 Correlation Matrix of independent variables 2010

	MeanA	DepR	MeanE	MigS	LandA	IncShF	Sav	Debt	Asset	Strat	ShockNo	Incpc
MeanA												
DepR	0.163***											
MeanE	-0.057**	-0.354***										
MigS	-0.068**	-0.230***	0.193***									
LandA	-0.027	-0.028	0.091***	-0.042								
IncShF	-0.085***	0.037	-0.049*	-0.266***	0.408***							
Sav	-0.021	-0.040	0.211***	0.000	0.234***	0.152***						
Debt	-0.132***	-0.165***	0.132***	0.012	0.032	0.051*	0.046*					
Asset	-0.171***	-0.147***	0.303***	0.001	0.276***	0.159***	0.396***	0.190***				
Strat	-0.282***	-0.236***	0.134***	0.243***	0.075***	-0.072***	0.116***	0.075***	0.189***			
ShockNo	-0.048*	-0.041	-0.033	-0.049*	0.117***	0.094***	0.000	0.041	0.019	0.090***		
Incpc	0.061**	-0.224***	0.314***	0.261***	0.111***	-0.200***	0.298***	0.121***	0.351***	0.333***	-0.064**	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; Source: Authors' calculations.

Table A2.10 Correlation Matrix of independent variables 2013

	MeanA	DepR	MeanE	MigS	LandA	IncShF	Sav	Debt	Asset	Strat	ShockNo	Incpc
MeanA												
DepR	0.206***											
MeanE	-0.072**	-0.278***										
MigS	-0.156***	-0.198***	0.150***									
LandA	-0.063**	-0.020	0.062**	-0.031								
IncShF	-0.063**	0.012	-0.067**	-0.293***	0.440***							
Sav	-0.034	-0.042	0.180***	-0.046	0.164***	0.103***						
Debt	-0.133***	-0.135***	0.119***	0.070**	0.098***	0.022	0.126***					
Asset	-0.229***	-0.123***	0.219***	-0.024	0.329***	0.150***	0.344***	0.202***				
Strat	-0.258***	-0.182***	0.095***	0.292***	0.121***	-0.067**	0.064**	0.146***	0.175***			
ShockNo	-0.024	-0.049*	0.010	0.024	0.069**	0.026	-0.012	0.103***	0.025	0.102***		
Incpc	0.023	-0.166***	0.198***	0.264***	0.141***	-0.130***	0.214***	0.147***	0.196***	0.364***	0.004	

Note: * p < 0.1, ** p < 0.05, *** p < 0.01; Source: Authors' calculations.

Table A2.11 Correlation Matrix of independent variables 2016

	MeanA	DepR	MeanE	MigS	LandA	IncShF	Sav	Debt	Asset	Strat	ShockNo	Incpc
MeanA												
DepR	0.279***											
MeanE	-0.234***	-0.363***										
MigS	-0.188***	-0.230***	0.261***									
LandA	-0.152***	-0.109***	0.143***	0.013								
IncShF	-0.080***	-0.038	-0.054**	-0.248***	0.519***							
Sav	-0.103***	-0.104***	0.169***	0.042	0.203***	0.100***						
Debt	-0.237***	-0.159***	0.228***	0.066**	0.218***	0.134***	0.076***					
Asset	-0.281***	-0.203***	0.333***	-0.006	0.376***	0.221***	0.299***	0.293***				
Strat	-0.356***	-0.266***	0.202***	0.263***	0.184***	-0.012	0.083***	0.203***	0.208***			
ShockNo	-0.135***	-0.081***	0.028	0.053**	0.259***	0.177***	0.105***	0.167***	0.158***	0.120***		
Incpc	-0.025	-0.226***	0.314***	0.330***	0.076***	-0.235***	0.196***	0.138***	0.272***	0.319***	0.000	

Note: * p < 0.1, ** p < 0.05, *** p < 0.01; Source: Authors' calculations.

Table A2.12 Correlation Matrix of independent variables 2019

	MeanA	DepR	MeanE	MigS	LandA	IncShF	Sav	Debt	Asset	Strat	ShockNo	Incpc
MeanA												
DepR	0.278***											
MeanE	-0.260***	-0.357***										
MigS	-0.223***	-0.268***	0.227***									
LandA	-0.154***	-0.094***	0.158***	0.080***								
IncShF	-0.002	0.017	-0.096***	-0.230***	0.442***							
Sav	-0.068**	-0.081***	0.155***	0.066**	0.146***	0.045*						
Debt	-0.230***	-0.134***	0.160***	0.035	0.218***	0.100***	0.080***					
Asset	-0.315***	-0.151***	0.368***	0.028	0.357***	0.124***	0.203***	0.207***				
Strat	-0.393***	-0.297***	0.255***	0.322***	0.277***	-0.033	0.144***	0.181***	0.235***			
ShockNo	-0.126***	-0.057**	0.048*	0.048*	0.243***	0.121***	0.055**	0.164***	0.079***	0.129***		
Incpc	-0.067**	-0.231***	0.335***	0.363***	0.146***	-0.241***	0.138***	0.113***	0.250***	0.367***	0.010	

Note: * p < 0.1, ** p < 0.05, *** p < 0.01; Source: Authors' calculations.

Table A2.13 Multilevel Evaluation by AIC and ICC

Model	AIC Difference	ICC
Model 1: 2010	3.388	0.006
Model 2.1: 2010	2.111	0.013
Model 2.2: 2010	6.26	0.035
Model 2.3: 2010	4.718	0.009
Model 1: 2013	6.969	0.026
Model 2.1: 2013	-0.75	0
Model 2.2: 2013	2.794	0.004
Model 2.3: 2013	0.444	0
Model 1: 2016	3.729	0.006
Model 2.1: 2016	-0.171	0
Model 2.2: 2016	2.51	0
Model 2.3: 2016	3.08	0.003
Model 1: 2019	6.016	0.016
Model 2.1: 2019	-1.661	0
Model 2.2: 2019	2.917	0.006
Model 2.3: 2019	3.7	0.006
Model 1: 2010	3.388	0.006
Model 2.1: 2010	2.111	0.013
Model 2.2: 2010	6.26	0.035
Model 2.3: 2010	4.718	0.009

Source: Authors' calculations.

Table A2.14 Variance Inflation Factor Model 1

Variable	2010	2013	2016	2019
DepR	1.17	1.135	1.216	1.153
MeanE	1.18	1.144	1.169	1.174
MigS	1.231	1.247	1.219	1.209
LandA	1.186	1.234	1.32	1.408
IncShF	1.316	1.345	1.355	1.362
Sav	1.13	1.164	1.052	1.028
Debt	1.048	1.049	1.096	1.11
Asset	1.177	1.227	1.193	1.146
Strat	1.093	1.129	1.127	1.164
ShockNo	1.038	1.085	1.089	1.063
Prov	1.025	1.115	1.044	1.062
R2 Criterion	1.661	1.428	1.582	1.598

Source: Authors' calculations.

Table A2.15 Variance Inflation Factor Model 2.1, 2.2 and 2.3

	2010			2013			2016			2019		
Variable	**2.1**	**2.2**	**2.3**	**2.1**	**2.2**	**2.3**	**2.1**	**2.2**	**2.3**	**2.1**	**2.2**	**2.3**
MeanA	6.3	5.699	5.405	6.301	5.929	5.691	6.622	6.403	6.068	6.515	6.313	6.036

MeanAsq	6.456	5.762	5.442	6.444	5.999	5.743	6.819	6.52	6.169	6.647	6.417	6.117
MeanE	1.162	1.091	1.119	1.114	1.047	1.069	1.195	1.136	1.135	1.21	1.13	1.142
MigS	1.163	1.021	1.14	1.157	1.037	1.172	1.188	1.041	1.16	1.176	1.028	1.163
LandA	1.051	1.114	1.131	1.079	1.181	1.19	1.074	1.267	1.291	1.125	1.335	1.294
Incpc	1.363	1.205	1.23	1.227	1.177	1.19	1.193	1.16	1.191	1.277	1.165	1.226
Sav	1.152	1.145	1.105	1.103	1.114	1.083	1.076	1.079	1.054	1.041	1.031	1.032
Debt	1.079	1.042	1.021	1.073	1.076	1.055	1.074	1.078	1.08	1.059	1.118	1.072
Asset	1.268	1.259	1.155	1.193	1.21	1.155	1.245	1.28	1.193	1.257	1.287	1.177
FarmS		1.075	1.087		1.109	1.131		1.163	1.175		1.213	1.205
OffS	1.353		1.203	1.318		1.258	1.329		1.205	1.354		1.273
SelfS	1.08	1.119		1.079	1.147		1.101	1.115		1.072	1.12	
ShockNo	1.029	1.027	1.038	1.033	1.059	1.049	1.017	1.069	1.064	1.044	1.068	1.065
Prov	1.034	1.019	1.032	1.048	1.043	1.055	1.021	1.015	1.021	1.029	1.031	1.038
R2 Criterion	1.556	1.888	1.302	1.54	1.97	1.285	1.705	1.862	1.27	1.732	2.26	1.212

Source: Authors' calculations.

Table A2.16 Mean AUC ROC with Standard Deviation for Models 2.1, 2.2 and 2.3

Model	Mean (SD): 2010	Mean (SD): 2013	Mean (SD): 2016	Mean (SD): 2019
2.1	0.871 (0.048)	0.85 (0.044)	0.868 (0.033)	0.847 (0.033)
2.2	0.867 (0.021)	0.875 (0.025)	0.859 (0.024)	0.888 (0.022)
2.3	0.731 (0.028)	0.732 (0.028)	0.723 (0.029)	0.693 (0.032)

Source: Authors' calculations.

3 Inconsistent responses in household panel surveys: The case of non-farm employment

Current version of a paper by Brooks, M., Wendt, N. & Waibel, H., currently under review at "Survey Research Methods".

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. 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 highlighted by examining deviations in the composition of household income and calculating poverty head counts at the district and provincial levels, whereby income from omitted employments is shown to have severe implications for 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.

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, Asian economies have transitioned from predominantly agricultural societies to more diversified, emerging market economies (Haraguchi et al., 2019; Stiglitz, 1996; World Bank, 2018). Hence, the share of agriculture in rural household income declined while reliance on off-farm wage employment and non-farm self-employment increased (Devereux et al., 2012; Gödecke & Waibel, 2011; Hayami & Ruttan, 1971; Hohfeld & Waibel, 2013; Schultz, 1964). Collecting income data on employment coincides with a considerable challenge, namely obtaining information on the substantial number of informal or semi-formal arrangements (Charmes, 2012; ILO, 2018; Lee et al., 2020). These 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). Thus, employment data in household surveys are subject to considerable uncertainty, especially when it comes to the consistency of their reporting throughout the entire span of panels. To date, this issue has rarely been investigated in papers on data quality and non-sampling error.

This study aims to fill this gap in the literature by assessing the consistency of reported employments across panel waves in household surveys using a unique data set from the Thailand Vietnam Socio Economic Panel (TVSEP), consisting of seven waves, collected between 2007-2019. Thereby, 1,542 identical households interviewed throughout all survey waves are considered to identify inconsistent responses between pairs of consecutive waves. We implement a multilevel logistic regression that examines 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.

This study yields three major results. First, both off-farm and non-farm self-employments exhibit substantial cases of inconsistent reporting with informal employments being most likely to be inconsistently reported. Second, although the respondent level explains 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. Third, considering the growing importance of income obtained from off-farm wage employment and self-employment in rural Thailand, misreporting thereof results in faulty income data and accordingly also income-based indicators such as household income compositions and poverty headcount ratios.

The remainder of the paper is structured as follows: Section 2 provides an overview of data quality identified in the literature in the context of employment upon which our hypotheses are derived. Section 3 describes our study area and introduces the dataset. Section 4 introduces the empirical strategy used to identify inconsistently reported employments and model factors thereof. Section 5 contains an empirical analysis pertaining to inconsistencies of reported employments using a long-term household panel data set. Further, the impact of inconsistent reporting on income-based indicators is visualised using poverty headcount. 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 errors 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, was 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; Pyy-Martikainen & Rendtel, 2009; 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 (Alkire, 2007; Desiere & Costa, 2019; Hussmanns, 2004).

Based on this 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 such as 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 agrarian, rice dominated, 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 income than farming (Chawanote & Barrett, 2013), which further drives internal migration to urban centres (Harris & Todaro, 1970; Lall & Selod, 2006; Todaro, 1980). Furthermore, 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[3] (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 A3.12). 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 identical 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 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 wage employment and non-farm self-employment, which provides in-depth information on individual employments. Most LSMS-style surveys collect detailed information for primary employments of household members, but often only provide aggregates on all additional employments (Durazo et al., 2021; UN, 2005). This also applies to derivatives of LSMS, for example, the Integrated Surveys on Agriculture (LSMS(-ISA)), and national Labour Force Surveys (LFS) (Desiere & Costa, 2019). In contrast, the TVSEP survey instrument captures

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

each employment individually, thus not relying on reported aggregates. This allows for the verification of each reported employment throughout the panel in TVSEP, whereas this is infeasible in LSMS. Solely the primary employment in LSMS can be verified if it remains the primary employment throughout all waves. Further, LSMS frequently utilises a reference period spanning the last seven days prior to the date of interview. Accordingly, detailed employment information is confined to this period (e.g., Desiere & Costa, 2019; Durazo et al., 2021). In contrast, the reference period spans 365 days in TVSEP, thus providing a more complete annual overview of employment. In addition, TVSEP further facilitates the analysis of inconsistent reporting in this study due to availability of additional information, such as the geographic location of employment, the household member's work experience and disaggregated sources of income.

3.4 Empirical strategy

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 inconsistency, 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. We modify this approach to accommodate for the informal nature of employment in rural Thailand and availability of supplemental information provided in the questionnaire. This allows 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 have occurred 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 3.1, 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[4].

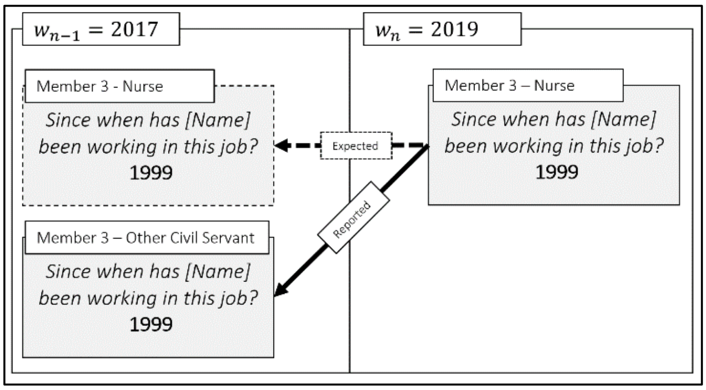

Figure 3.1 Identifying expected employments

Source: Own illustration.

[4] An example of inconsistent reporting is provided in Appendix – Case study 2; whereas an example of consistent reporting is provided in Appendix – 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.[5], 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[6]. 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

[5] To ensure robustness of results, an analysis of the consistency of reported household member I.Ds. throughout the panel was undertaken. On average, 0.30% of household members were found to have issues related to their reported I.D. with at most 0.46% having matching issues in an individual wave. Therefore, inconsistencies in reported employments based on, amongst other criteria, the household member I.D. can be considered to not be driven by inconsistently panelled household members.

[6] 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.

assumed to be unlikely in the context of our study area. Employments are then matched based on the highest 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 3.2 and Table A3.8 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.

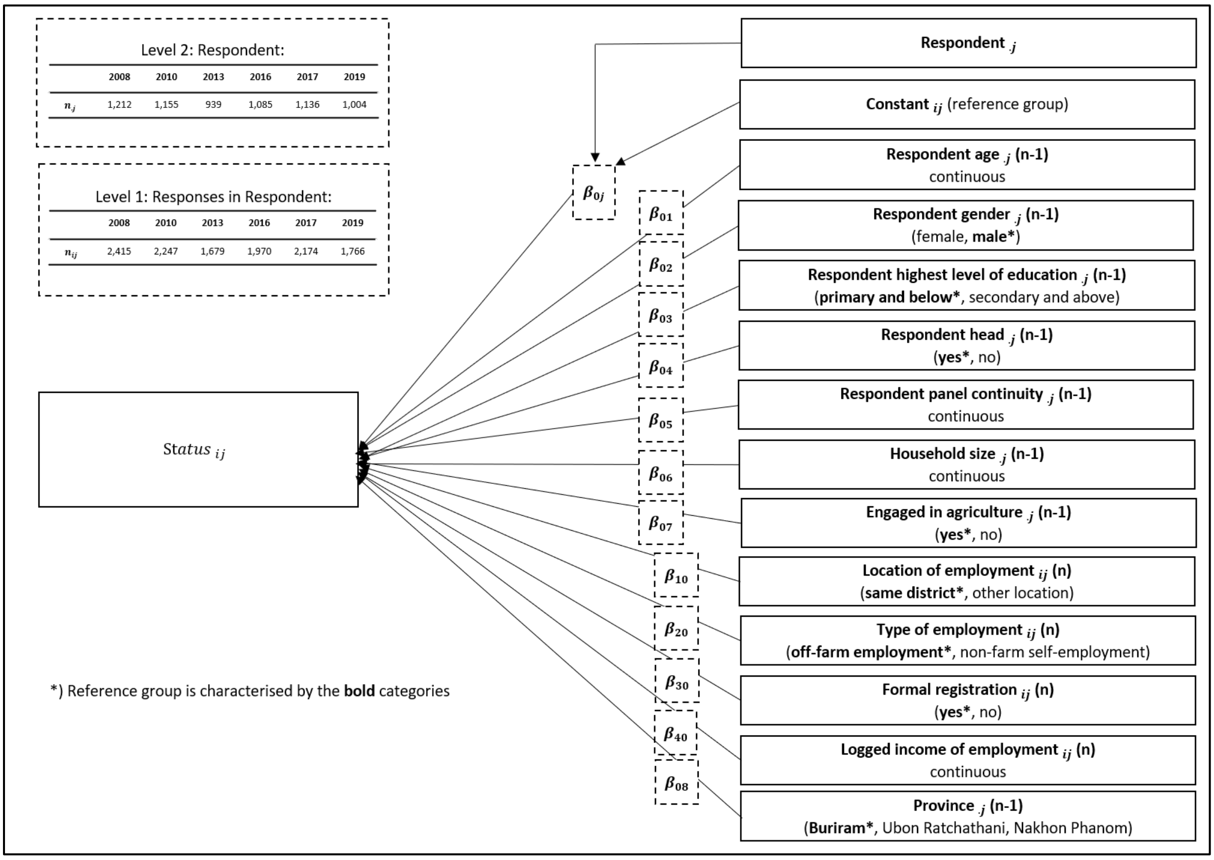

Figure 3.2 Overview of respondent- and response-level explanatory variables

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 A3.8-A3.14). Additionally, for all model variants, the chosen levels are shown to provide sufficient variation in the outcome variable[7].

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

[7] 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).

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 3.3). 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.

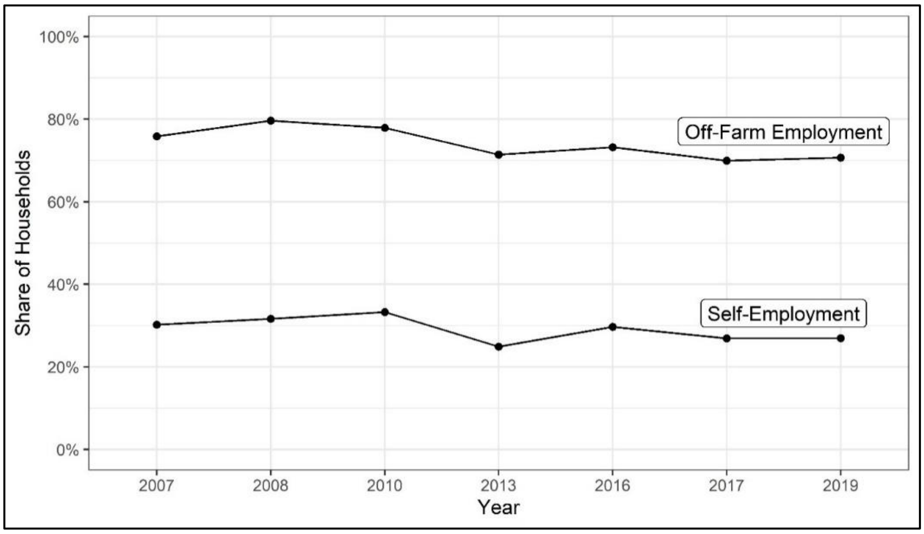

Figure 3.3 Overview – Share of households with at least one member in off-farm wage employment, 2007-2019

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 3.4). 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 A3.15). 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 3.4).

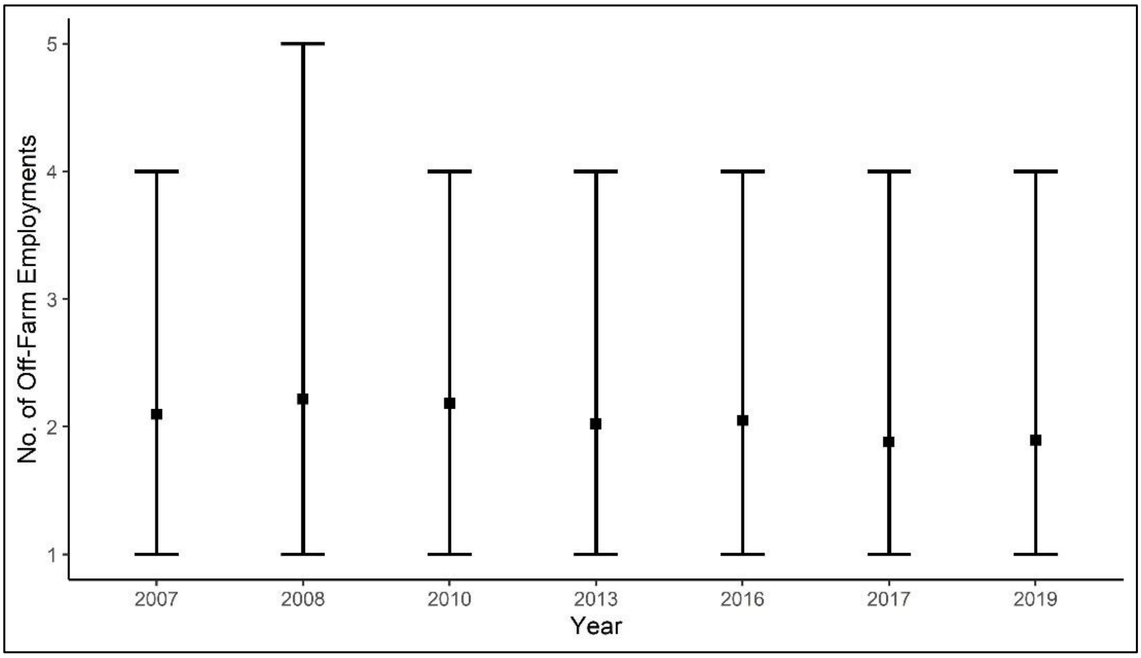

Figure 3.4 Overview of distribution of off-farm employment
Note: The upper and lower thresholds represent the 95th percentile and 25th quartile of the distribution. The mean is displayed as a square point. Source: Own calculation based on TVSEP (2019).

When taking into consideration reported income from off-farm activities in the form of equivalised per capita income[8], 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%) and is shown to increase over time (Figure 3.5). By 2019, the share of off-farm employment increased to 56.3% of total household income.

[8] 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.

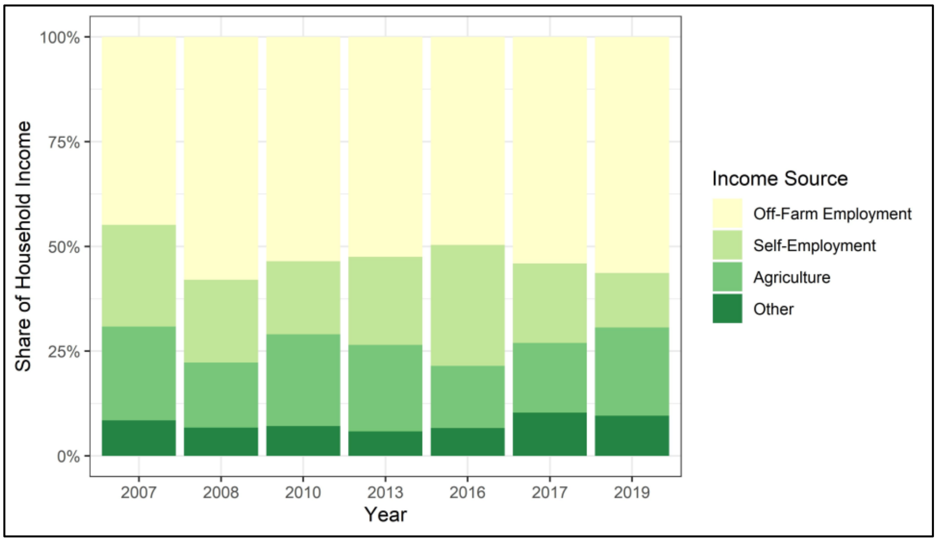

Figure 3.5 Overview – Income composition (total income).

Source: Own calculations based on TVSEP (2019).

In almost one third of households, members are engaged in self-employment (Figure 3.3). The overwhelming majority of such households indicate that they operate one business (Figure 3.6). However, some households report multiple businesses. Notably, households engaged in more than three cases of self-employment represent outliers in the panel (Table A3.16). 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.

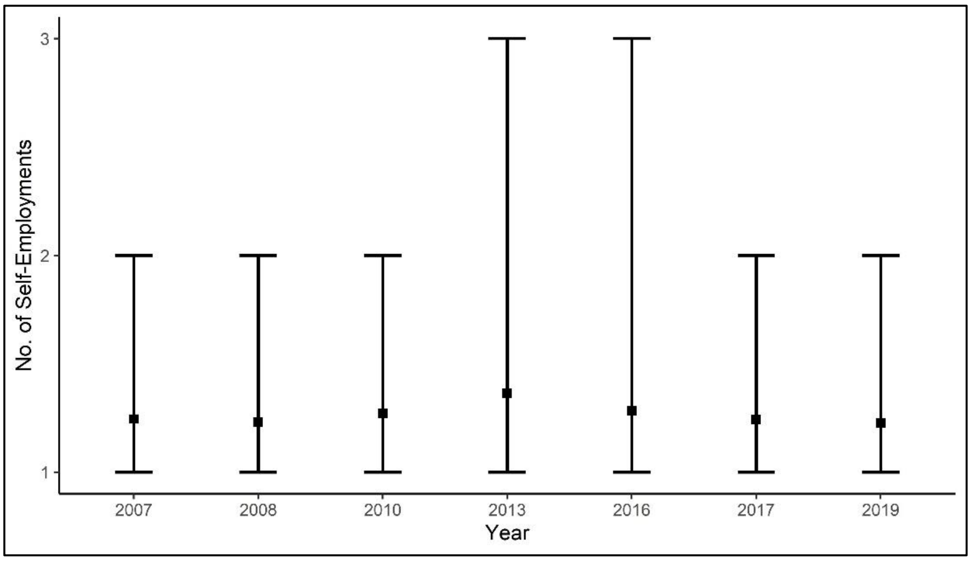

Figure 3.6 Overview of distribution of self-employment

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 3.5 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 3.7. While initially almost 50% of households reported a consistent number of employments (incl. reports of zero employment), 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.

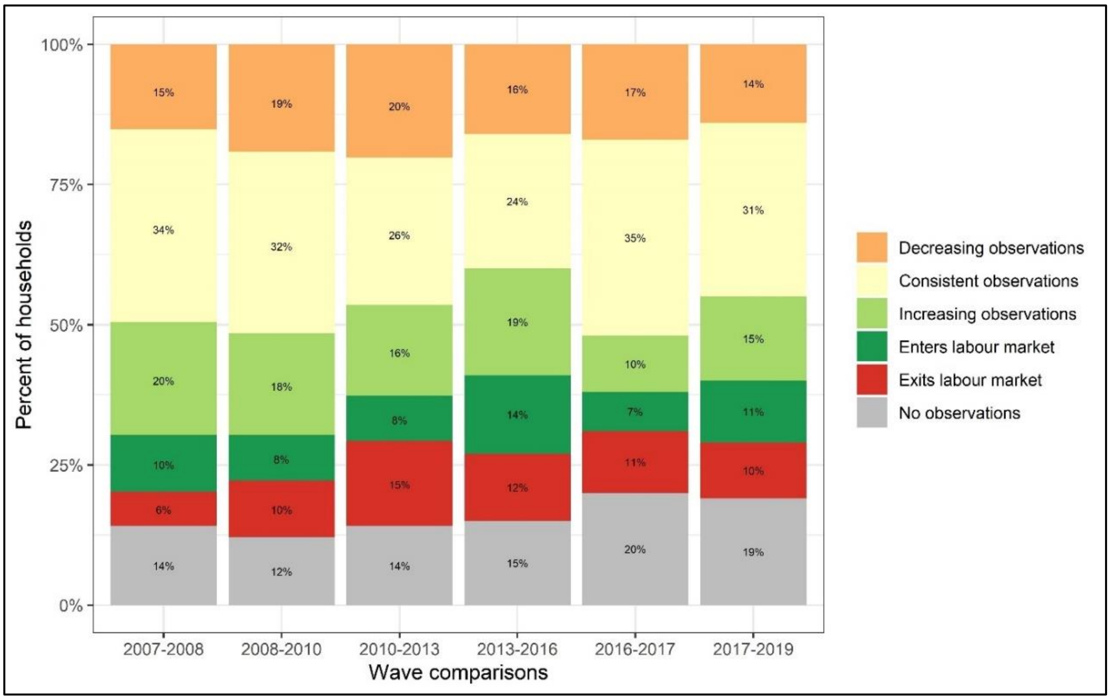

Figure 3.7 Consistency of no. of reported activities over time – Off-farm employment

Source: Own calculations based on TVSEP (2019).

Figure 3.8 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.

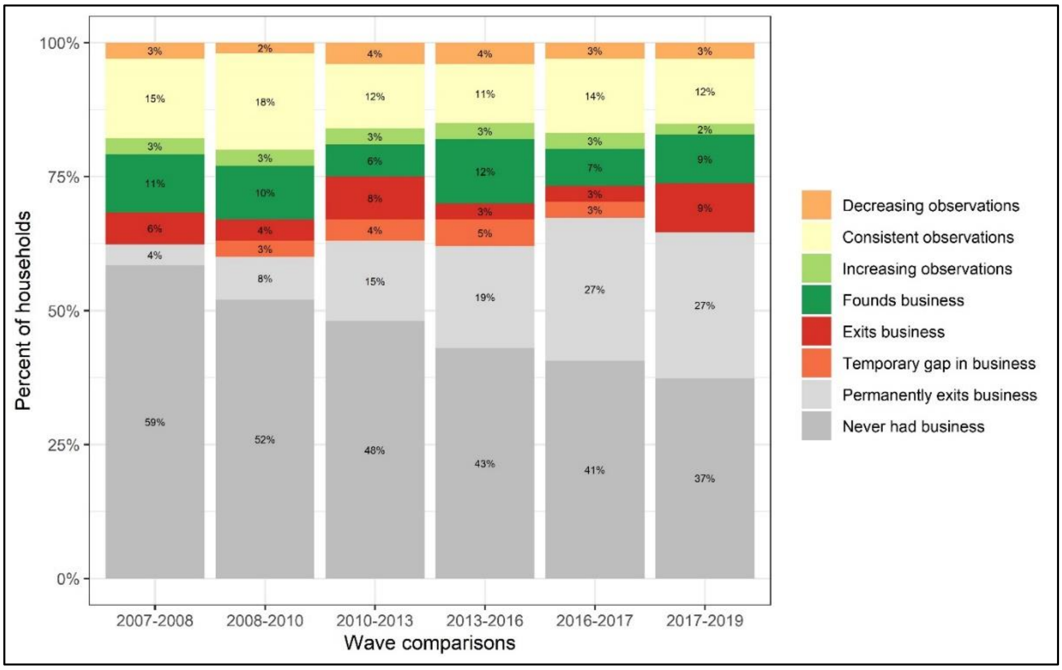

Figure 3.8 Consistency of no. of reported activities over time – Self-employment.

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 magnitude 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 the 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. Main results of the six model variants are reported in Table 3.5 with the model labels denoting 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[9], 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

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

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 A3.17), 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 significant and 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.

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 A3.17. 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***	0.780***	0.778***	0.788***	0.788***
	(0.053)	(0.051)	(0.051)	(0.051)	(0.054)
Respondent					
Openness	0.900*				
(Scale 1-7: continuous)	(0.054)				
Conscientiousness		0.927			
(Scale 1-7: continuous)		(0.071)			
Extraversion			1.010		
(Scale 1-7: continuous)			(0.073)		
Agreeableness				0.864**	
(Scale 1-7: continuous)				(0.067)	
Neuroticism					1.020
(Scale 1-7: continuous)					(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 A3.18).

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, our 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 income-based 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 3.9 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[10]. These substantial shifts in income may severely affect the underlying distribution of household income and thus conclusions about related indicators such as poverty rates.

[10] 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.

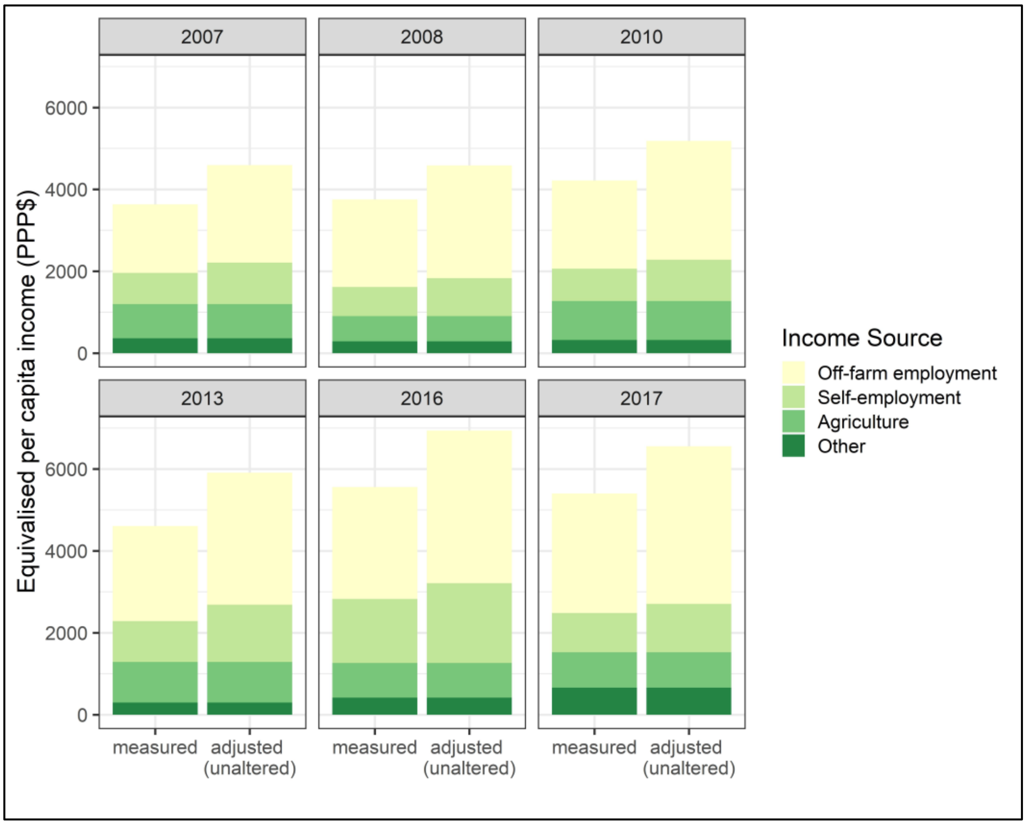

Figure 3.9 Overview of mean equivalised per capita income, by income source and year

Source: Own calculations based on TVSEP (2019).

Figure 3.10 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 based on 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.

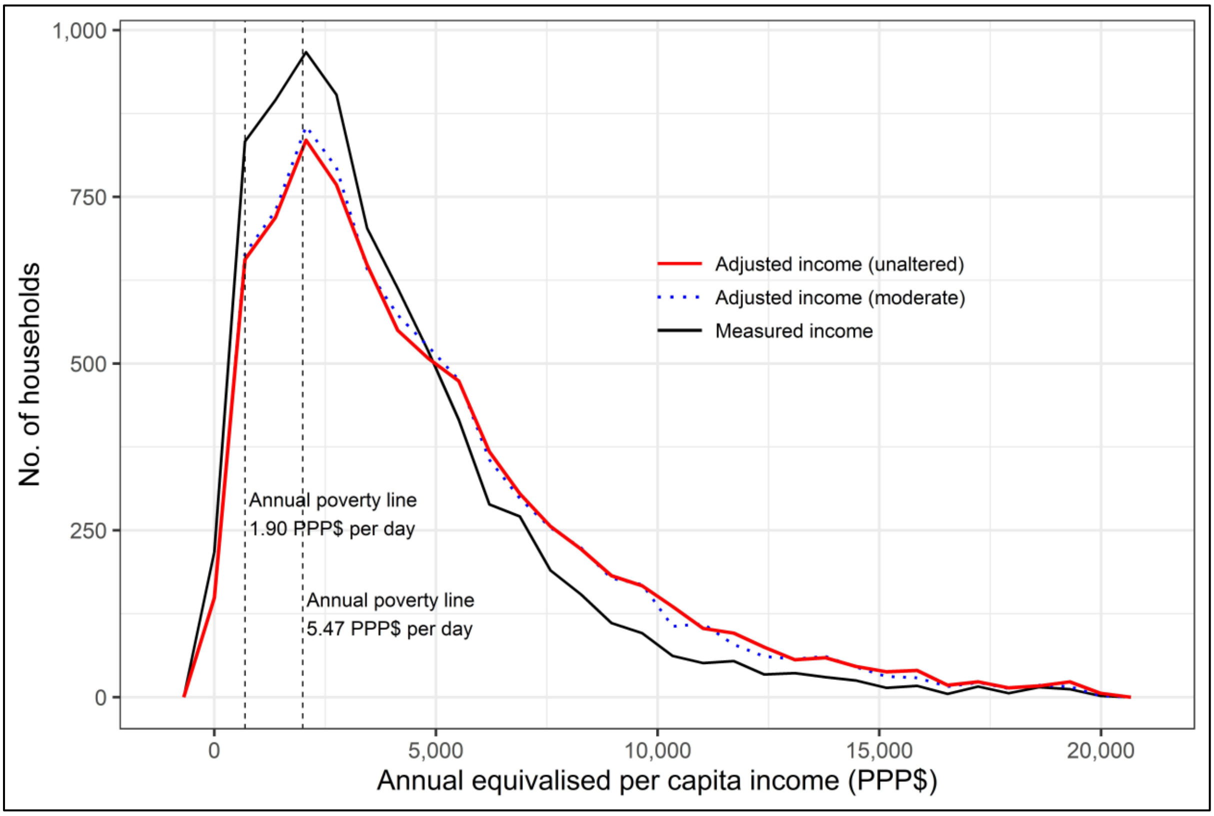

Figure 3.10 Distributions of income in TVSEP sample

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 3.11 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.

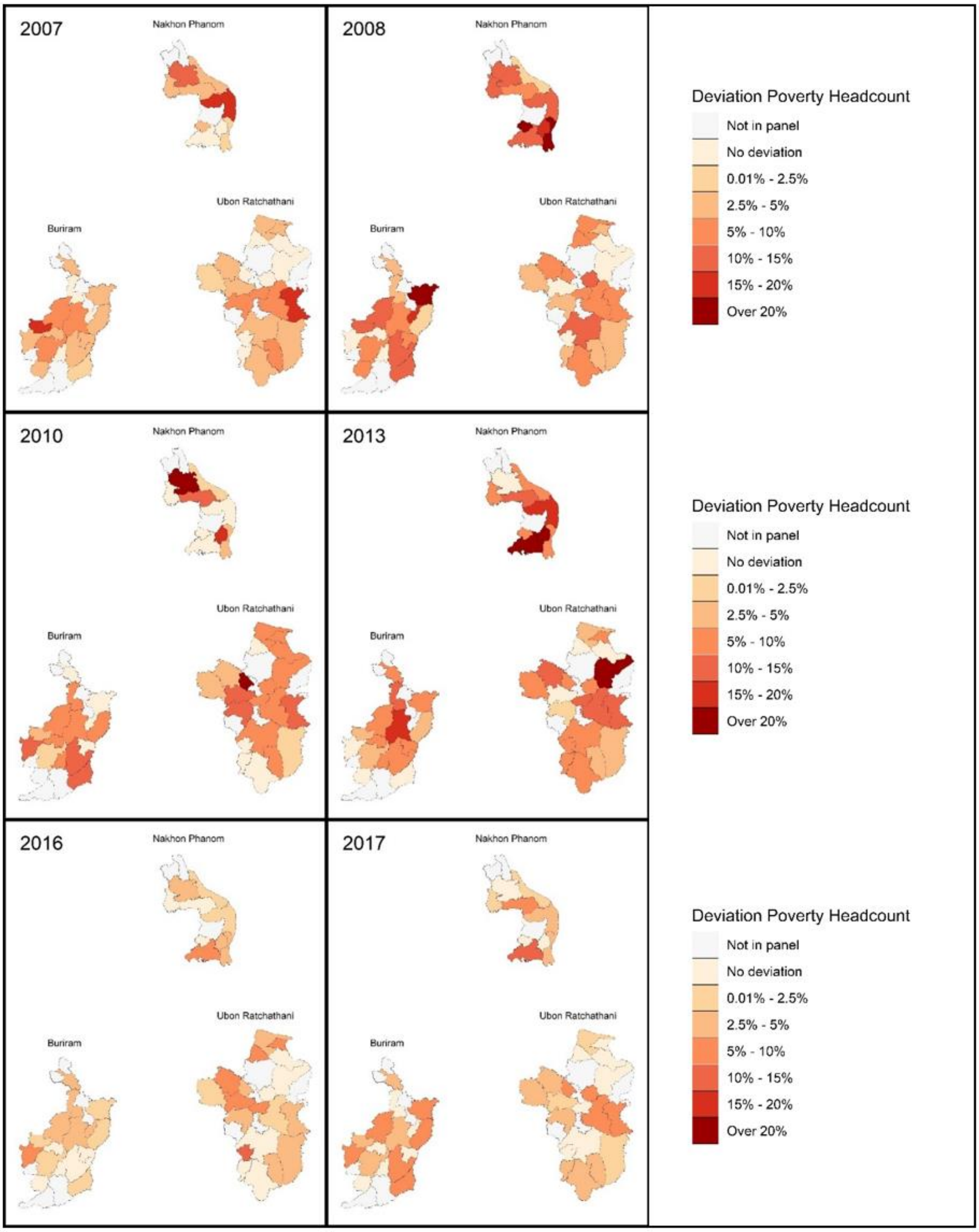

Figure 3.11 Distribution of deviation from poverty headcount

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.

By means of a multilevel logistic regression model, we identify that inconsistent reporting, while driven by differences between respondents, is not driven by their socio-economic characteristics. Our findings raise the question 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, tools to improve respondent motivation and retention beyond exclusively monetary incentives, i.e., payment for participation in the interview, could be helpful.

As derived from our scenario analysis, inconsistencies in employment data are demonstrated to have a substantial impact on income-based policy indicators such as poverty, which is exacerbated should policy be required to focus on lower-level administrative boundaries.

Several steps could be taken to improve the consistency of reported employments in household surveys. First, expanding modules on labour by inquiring about previously reported employments could 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 interviewing (i.e., reactively, or proactively, using previously collected information to assist in the response process), while being critically discussed, are evidenced to improve the consistency of underlying data sets. Careful implementation of reactive dependent interviewing, for example, is considered to minimise biases in reporting on behalf of the respondent while increasing reliability of responses (Eggs & Jäckle, 2015; Lugtig & Jäckle, 2014; Lynn et al., 2006; Lynn et al., 2012; Perales, 2014; Pankowska et al., 2021). 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 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.

The results of this study substantiate a problem that has been raised by researchers using LSMS household survey data (e.g., Alkire, 2007; Ambler et al., 2021; Desiere & Costa, 2019; Jeong et al., 2023), namely inconsistent responses in non-farm employment. Due to the close similarity of the underlying survey instrument with the LSMS, this makes a compelling case for extending our approach to other data sets and highlights the importance of utilising previously collected data as an instrument of validation in future survey waves.

3.7 References Chapter 3

Ahmad, A., & Isvilanonda, S. (2005). "Rural poverty and agricultural diversification in Thailand." In Toriyama (Ed.). Rice is life: scientific perspectives for the 21st century. Los Banos: International Research Institute.

Alkire, S. (2007). "The missing dimensions of poverty data: Introduction to the special issue." Oxford development studies, 35(4), 347-359.

Amare, M., Hohfeld, L., Jitsuchon, S., & Waibel, H. (2012). "Rural-urban migration and employment quality: A case study from Thailand." Asian Development Review, 29(1), 58-80.

Ambler, K., Herskowitz, S., & Maredia, M. K. (2021). "Are we done yet? Response fatigue and rural livelihoods." Journal of Development Economics, 153, Article 102736.

Bardasi, E., Beegle, K., Dillon, A., & Serneels, P. (2011). "Do labor statistics depend on how and to whom the questions are asked? Results from a survey experiment in Tanzania." The World Bank Economic Review, 25(3), 418-447.

Barth, A., & Schmitz, A. (2021). "Interviewers' and Respondents' Joint Production of Response Quality in Open-ended Questions. A Multilevel Negative-binomial Regression Approach." Methods, Data, Analyses, 15(1), 43-76.

Bedi, T., Coudouel, A., & Simler, K. (Eds.). (2007). "More than a pretty picture: using poverty maps to design better policies and interventions." World Bank Publications.

Biemer, P. P. (2010). "Total survey error: Design, implementation, and evaluation." Public opinion quarterly, 74(5), 817-848.

Booth, A. (2019). "Measuring poverty and income distribution in Southeast Asia." Asian-Pacific Economic Literature, 33(1), 3-20.

Borgers, N., Sikkel, D., & Hox, J. (2004). "Response effects in surveys on children and adolescents: The effect of number of response options, negative wording, and neutral mid-point." Quality and Quantity, 38(1), 17-33.

Bound J., Brown, C., & Mathiowetz, N. (2001), "Measurement error in survey data". In
Heckman, J.J., & Leamer, E. (Eds.), Handbook of Econometrics. Volume 5, Amsterdam: Elsevier Science.

Charmes, J. (2012). "The informal economy worldwide: Trends and characteristics." Margin: the journal of applied economic research, 6(2), 103-132.

Chawanote, C., & Barrett, C. B. (2013). "Non-farm occupational and earnings dynamics in rural Thailand." Cornell University Charles H. Dyson School of Applied Economics and Management, Ithaca: New York. Retrieved from: http://barrett.dyson.cornell.edu/Papers-/NonfarmDynamics_ChawanoteBarrett%2025%20March%202013%20Revisions.pdf. Accessed on: 23.12.2022.

Costa, J., Paul T., & McCrae, R. R. (1997). "Personality trait structure as a human universal." American Psychologist, 52, 587–596.

Dang, H. A. H., & Carletto, C. (2018). "The Seemingly Underappreciated Role of Panel Data in Measuring Poverty and Economic Transformation." World Economics, 19(3), 45-60.

Dang, H. A. H., & Serajuddin, U. (2020). “Tracking the sustainable development goals: Emerging measurement challenges and further reflections.” *World Development*, *127*, Article 104570.

Davis, B. (2003). “Choosing a method for poverty mapping.” Rome: Food & Agriculture Organization of United Nations.

Desiere, S., & Costa, V. (2019). “Employment data in household surveys: Taking stock, looking ahead. Looking Ahead.” World Bank Policy Research Working Paper 8882, World Bank.

Devereux, S., Sabates-Wheeler, R., & Longhurst, R. (2012). “Seasonality, rural livelihoods and development.” London and New York: Routledge.

Durazo, J., Costa, V., Palacios-Lopez, A., & Gaddis, I. (2021). “Employment and Own-Use Production in Household Surveys: A Practical Guide for Measuring Labor.” Washington DC: World Bank.

Eggs, J., & Jäckle, A. (2015). “Dependent Interviewing and Sub-Optimal Responding.” Survey Research Methods, 9(1), 15-29.

Epland, J., & Kirkeberg, M. I. (2012). “Wealth distribution in Norway. Evidence from a new register-based data source.” Oslo: Statistics Norway.

Falkus, M. (1995). “Thai industrialization: an overview.” In Medhi, K. (Ed.), Thailand's industrialization and its consequences, New York: St Martin's Press.

Fleischer, L., Bogiatzis, A., Asada, H, & Koen, V. (2018), “Making growth more inclusive in Thailand.” OECD Economics Department Working Papers, No. 1469, Paris: OECD Publishing. http://dx.doi.org/10.1787/263a78df-en.

Foster, J., Greer, J., & Thorbecke, E. (1984). “A class of decomposable poverty measures.” Econometrica: journal of the econometric society, 761-766.

Galesic M., & Bosnjak, M. (2009). “Effects of questionnaire length on participation and indicators of response quality in a web survey.” Public opinion quarterly, 73(2), 349-360.

Gibson, J. (2016). “Poverty measurement: we know less than policy makers realize.” Asia & the Pacific Policy Studies, 3(3), 430-442.

Gottschalk, P., & Huynh, M. (2010). “Are earnings inequality and mobility overstated? The impact of nonclassical measurement error.” The Review of Economics and Statistics, 92(2), 302-315.

Grimm, M., Krüger, J., & Lay, J. (2011). “Barriers to entry and returns to capital in informal activities: evidence from sub-Saharan Africa.” Review of Income and Wealth, 57, S27-S53.

Gödecke, T., & Waibel, H. (2011). “Rural–urban transformation and village economy in emerging market economies during economic crisis: empirical evidence from Thailand.” Cambridge Journal of Regions, Economy and Society, 4(2), 205-219.

Grosh, M., & Glewwe, P. (2000). “*Designing household survey questionnaires for developing countries.”* Washington, DC: World Bank.

Groves, R. M. (1989). “Survey Errors and Survey Costs.” New York: Wiley.

Groves, R. M, & Couper. M. (1998). “Household Survey Nonresponse.” New York: John Wiley & Sons.

Groves, R. M., & Lyberg, L. (2010). “Total survey error: Past, present, and future.” Public opinion quarterly, 74(5), 849-879.

Hagenaars, A., de Vos, K., & Zaidi, M.A. (1994). "Poverty Statistics in the Late 1980s: Research Based on Micro-data." Luxembourg: Office for Official Publications of the European Communities.

Halpern-Manners, A., & Warren, J. R. (2012). "Panel conditioning in longitudinal studies: Evidence from labor force items in the current population survey." Demography, 49(4), 1499-1519.

Halpin, B. (1998). "Unified BHPS work-life histories: combining multiple sources into a user-friendly format." Bulletin of Sociological Methodology, 60(1), 34-79.

Haraguchi, N., Martorano, B., & Sanfilippo, M. (2019). "What factors drive successful industrialization? Evidence and implications for developing countries." Structural Change and Economic Dynamics, 49, 266-276.

Hardeweg, B., Klasen, S., & Waibel, H. (2013). "Establishing a database for vulnerability assessment." In Klasen, S., & Waibel, H. (Eds.), Vulnerability to Poverty. London: Palgrave Macmillan.

Harris, J. R., & Todaro, M. P. (1970). "Migration, unemployment and development: a two-sector analysis." The American economic review, 60(1), 126-142.

Hayami, Y., & Ruttan, V. W. (1971). "Agricultural development: an international perspective." Baltimore, Md/London: The Johns Hopkins Press.

Heerwegh, D., & Loosveldt, G. (2008). "Face-to-face versus web surveying in a high-internet-coverage population: Differences in response quality." Public opinion quarterly, 72(5), 836-846.

Henley, A., Arabsheibani, G. R., & Carneiro, F. G. (2009). "On defining and measuring the informal sector: Evidence from Brazil." World development, 37(5), 992-1003.

Hohfeld, L., & Waibel, H. (2013). "Investments of rural households in northeast Thailand and the future of small scale farming." Quarterly Journal of International Agriculture, 52(892-2016-65180), 217-236.

Hox, J. J., de Leeuw, E. D., & Kreft, G. G. (1991). "The effect of interviewer and respondent characteristics on the quality of survey data: a multilevel model." In Biemer, P. P., Groves, R. M., Lyberg, L. E., Mathiowetz, N.A., & Sudman, S. (Eds.). Measurement Errors in Surveys. New York: Wiley & Sons.

Hox, J. J., & de Leeuw, E. D. (1994). "A comparison of nonresponse in mail, telephone, and face-to-face surveys." Quality and Quantity, 28(4), 329-344.

Hox, J. J., Borgers, N., & Sikkel, D. (2003). "Response quality in survey research with children and adolescents: the effect of labeled response options and vague quantifiers." International Journal of Public Opinion Research, 15(1), 83-94.

Hox, J. J., Moerbeek, M., & Van de Schoot, R. (2017). "Multilevel analysis: Techniques and applications." New York: Routledge.

Huber, M., & Schmucker, A. (2009). "Identifying and explaining inconsistencies in linked administrative and survey data: The case of German employment biographies." Historical Social Research, 34(3), 230-241.

[Dataset] Humanitarian Data Exchange. (2022). "Thailand – Subnational Administrative Boundaries", tha_adm_rtsd_itos_20210121_SHP.zip, Downloaded from: https://data.humdata.org/dataset-/cod-ab-tha. Accessed on: 28.12.2022.

Hurst, E., Li, G., & Pugsley, B. (2014). “Are household surveys like tax forms? Evidence from income underreporting of the self-employed.” Review of economics and statistics, 96(1), 19-33.

Hussmanns, R. (2004). “Measuring the informal economy: From employment in the informal sector to informal employment.” Working Paper No. 53. Geneva: Policy Integration Department, Bureau of Statistics, International Labour Office.

International Labour Office. (2018). “Women and men in the informal economy: a statistical picture.” Geneva.: International Labour Office.

Jaeger, C. M., & Pennock, J. L. (1961). “An analysis of consistency of response in household surveys.” Journal of the American Statistical Association, 56(294), 320-327.

Jeong, D., Aggarwal, S., Robinson, J., Kumar, N., Spearot, A., & Park, D. S. (2023). “Exhaustive or exhausting? Evidence on respondent fatigue in long surveys.” Journal of Development Economics, 161, Article 102992.

John, O.P. and Srivastava, S. (1999). “The Big Five Trait Taxonomy: History, Measurement,
and Theoretical Perspectives.” In John, O. P., & Pervin, L. A. (Eds.). Handbook of Personality: Theory and Research. New York: Guilford Press.

Jolliffe, D., & Prydz, E. B. (2016). “Estimating international poverty lines from comparable national thresholds.” The Journal of Economic Inequality, 14(2), 185-198.

Knäuper, B., Belli, R. F., Hill, D. H., & Herzog, A. R. (1997). “Question difficulty and respondents' cognitive ability: The effect on data quality.” Journal of Official Statistics-Stockholm, 13, 181-199.

Knäuper, B. (1999). “The impact of age and education on response order effects in attitude measurement.” Public Opinion Quarterly, 63, 347-370.

Krosnick, J. A. (1991). “Response strategies for coping with the cognitive demands of attitude measures in surveys.” Applied Cognitive Psychology, 5, 213-236.

Lall, S. V., & Selod, H. (2006). “Rural-urban migration in developing countries: A survey of theoretical predictions and empirical findings.” World Bank Publications.

Langer, W. (2017). “How to assess the fit of multilevel logit models with Stata?” German Stata Users’ Group Meeting 2017 05, Stata Users Group.

Lee, B. H., Swider, S., & Tilly, C. (2020). “Informality in action: A relational look at informal work.” International Journal of Comparative Sociology, 61(2-3), 91-100.

Lugtig, P. & Jäckle, A. (2014). “Can I just check...? Effects of edit check questions on measurement error and survey estimates.” Journal of Official Statistics, 30(1), 1-19.

Lynn, P., & Clarke, P. (2002). “Separating refusal bias and non-contact bias: evidence from UK national surveys.” Journal of the Royal Statistical Society: Series D (The Statistician), 51(3), 319-333.

Lynn, P., Jäckle, A., Jenkins, S. P., & Sala, E. (2006). “The effects of dependent interviewing on responses to questions on income sources.” Journal of Official Statistics, 22(3), 357-384.

Lynn, P., Jäckle, A., Jenkins, S. P., & Sala, E. (2012). “The impact of questioning method on measurement error in panel survey measures of benefit receipt:

evidence from a validation study." Journal of the Royal Statistical Society Series A (Statistics in Society), 175(1), 289-308.

Maré, D. C. (2006). "Constructing consistent work-life histories: A guide for users of the British Household Panel Survey (No. 2006-39)." ISER Working Paper Series 2006-39. Colchester: University of Essex.

McCall, B. P. (1990). "Occupational matching: A test of sorts." Journal of Political Economy, 98(1), 45-69.

Mathiowetz, N. A., Brown, C., & Bound, J. (2002). "Measurement Error in Surveys of the Low-Income Population." Ver Ploeg, M., Moffitt, R. A., & Citro, C. F. (Eds.). In Studies of Welfare Populations: Data collection and research issues. Washington, DC: National Academy Press.

Meyer, B. D., Mok, W. K., & Sullivan, J. X. (2015). "Household surveys in crisis." *Journal of Economic Perspectives, 29*(4), 199-226.

Meyer, B. D., & Mittag, N. (2019). "Using linked survey and administrative data to better measure income: Implications for poverty, program effectiveness, and holes in the safety net." American Economic Journal: Applied Economics, 11(2), 176-204.

Meyer, B. D., Mittag, N., & Goerge, R. M. (2022). "Errors in survey reporting and imputation and their effects on estimates of food stamp program participation." Journal of Human Resources, 57(5), 1605-1644.

Miller, R. A. (1984). "Job matching and occupational choice." Journal of Political economy, 92(6), 1086-1120.

Moore, J. C., Stinson, L. L., & Welniak, E. J. (2000). "Income Measurement Error in Surveys: A Review." Journal of Official Statistics, 16 (4), 331-361.

Pankowska, P., Bakker, B., Oberski, D., & Pavlopoulos, D. (2021). "Dependent interviewing: A remedy or a curse for measurement error in surveys?" Survey research methods, 15(2), 135-146.

Perales, F. (2014). "How wrong were we? Dependent interviewing, self-reports and measurement error in occupational mobility in panel surveys." Longitudinal and Life Course Studies, 5(3), 299-316.

Pickery, J., Loosveldt, G., & Carton, A. (2001). "The effects of interviewer and respondent characteristics on response behavior in panel surveys: A multilevel approach." Sociological Methods & Research, 29(4), 509-523.

Phung, T. D., Hardeweg, B., Praneetvatakul, S., & Waibel, H. (2015). "Non-sampling error and data quality: what can we learn from surveys to collect data for vulnerability measurements?" World Development, 71, 25-35.

Pyy-Martikainen, M., & Rendtel, U. (2009). "Measurement errors in retrospective reports of event histories. A validation study with Finnish register data." Survey Research Methods, 3(3), 139-155.

Reid, G., Zabala, F., & Holmberg, A. (2017). "Extending TSE to Administrative Data: A Quality Framework and Case Studies from Stats NZ." Journal of Official Statistics (JOS), 33(2), 477-511.

Sanna, V. & Mc Donnell, I. (2017), "Data for development: DAC member priorities and challenges." OECD Development Co-operation Working Papers No. 35, Paris: OECD Publishing.

Schultz, T. W. (1964). "Transforming traditional agriculture." New Haven, Conn: Yale University Press.

Serajuddin, U., Uematsu, H., Wieser, C., Yoshida, N., & Dabalen, A. L. (2015). "Data deprivation: another deprivation to end." Policy Research working paper, no. WPS 7252. Washington, DC: World Bank Group.

Silber, H., Danner, D., & Rammstedt, B. (2019). "The impact of respondent attentiveness on reliability and validity." International Journal of Social Research Methodology, 22(2), 153-164.

Stiglitz, J. E. (1996). "Some lessons from the East Asian miracle." The World Bank Research Observer, 11(2), 151-177.

Sun, H., Conrad, F. G., & Kreuter, F. (2021). "The relationship between interviewer-respondent rapport and data quality." Journal of Survey Statistics and Methodology, 9(3), 429-448.

Todaro, M. (1980). "Internal migration in developing countries: a survey." In Easterlin, R. A. (Ed.). Population and economic change in developing countries. University of Chicago Press.

[Dataset] Thailand Vietnam Socio Economic Panel (2019). "Thailand Vietnam Socio Economic Panel – Poverty Dynamics and Sustainable Development (Version 2019)." [Data set]. Retrieved 06.12.2019, from https://www.tvsep.de/en/tvsep-data-access.

Uhrig, S. N., & Watson, N. (2020). "The impact of measurement error on wage decompositions: evidence from the British Household Panel Survey and the Household, Income and Labour Dynamics in Australia Survey." Sociological Methods & Research, 49(1), 43-78.

United Nations. (2005) "Guide to Producing Statistics on Time Use: Measuring Paid and Unpaid Work". New York: United Nations.

Vaessen, M., Thiam, M., & Le, T. (2005). "Household sample surveys in developing and transition countries." United Nations, Department of Economic and Social Affairs, Statistics Division. Studies in Methods, Series F, (96).

Weisberg, H.F. (2005). "The total survey error approach: A guide to the new science of survey research." Chicago, IL: University of Chicago Press.

World Bank. (2018). "Riding the Wave: An East Asian Miracle for the 21st Century." World Bank East Asia and Pacific Regional Report. Washington, DC: World Bank.

Ziulu, V., Meckler, J., Licona, G. H., & Vaessen, J. (2022). „Poverty Mapping: Innovative Approaches to Creating Poverty Maps with New Data Sources." IEG Methods and Evaluation Capacity Development Working Paper Series. Independent Evaluation Group. Washington, DC: World Bank.

3.8 Appendix Chapter 3

3.8.1 Figures and tables

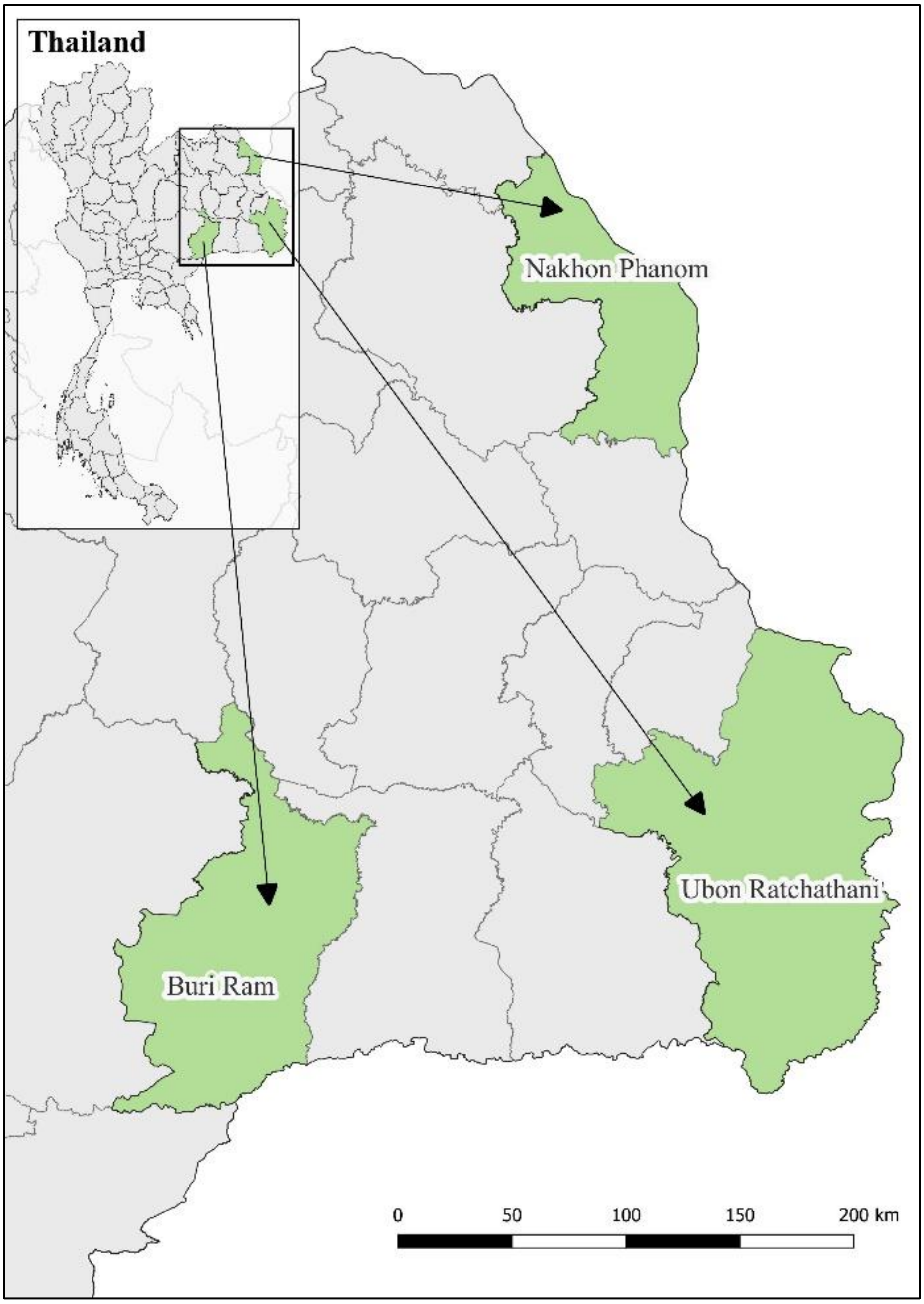

Figure A3.12 Map of study area.

Source: Own illustration. Shape source: HDX (2022).

Table A3.8 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 A3.9 Multilevel logistic regression results of status – 2008

	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	0.875**	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 (SE)**	**Variance (SE)**	**Variance (SE)**	**Variance (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 A3.10 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*** (0.038)	0.507*** (0.093)	0.442*** (0.110)	0.198*** (0.060)
Respondent				
Age (continuous)		0.996 (0.004)	0.995 (0.006)	0.999 (0.006)
Gender (1=female, 0=male)		1.101 (0.120)	1.099 (0.162)	1.009 (0.153)
Secondary education (1=yes, 0=no)		0.835 (0.113)	0.794 (0.145)	1.186 (0.229)
Head of household (1=yes, 0= no)		1.165 (0.138)	1.203 (0.192)	1.068 (0.176)
Panel continuity (continuous)		1.113 (0.112)	1.125 (0.153)	1.219 (0.172)
Household				
Household Size (continuous)		1.042** (0.020)	1.043 (0.028)	1.057* (0.030)
Engaged in agriculture (1=yes, 0=no)		1.247 (0.175)	1.291 (0.245)	1.263 (0.250)
Employment				
Location (1=same district, 0=other)				1.252 (0.412)
Employment type (1=off-farm, 0=self)				4.333*** (0.726)
Location #Employment type (Same district|Off-farm)				0.593 (0.205)
Formal registration (1=yes, 0=no)				0.700** (0.117)
Log yearly income (continuous in PPP$)				0.770*** (0.037)
Provinces				
Ubon Ratchathani (ref. Buriram)				0.836 (0.113)
Nakhon Phanom (ref. Buriram)				1.197 (0.202)
Random effects	**Variance (SE)**	**Variance (SE)**	**Variance (SE)**	**Variance (SE)**
Respondent-level variance	1.095 (0.232)	-	1.058 (0.243)	1.038 (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 A3.11 Multilevel logistic regression results of status – 2013

	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	0.750*** (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 A3.12 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 A3.13 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***	0.612***	0.566***	0.288***
	(0.044)	(0.104)	(0.120)	(0.075)
Respondent				
Age (continuous)		1.000	1.002	1.005
		(0.004)	(0.005)	(0.005)
Gender (1=female, 0=male)		1.040	1.043	1.019
		(0.113)	(0.139)	(0.140)
Secondary education (1=yes, 0=no)		0.723***	0.711**	0.820
		(0.089)	(0.108)	(0.129)
Head of household (1=yes, 0= no)		1.232*	1.242	1.158
		(0.137)	(0.170)	(0.162)
Panel continuity (continuous)		0.974	0.974	0.957
		(0.033)	(0.040)	(0.041)
Household				
Household Size (continuous)		1.033*	1.035	1.029
		(0.019)	(0.024)	(0.025)
Engaged in agriculture (1=yes, 0=no)		1.317**	1.401**	1.502***
		(0.158)	(0.208)	(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	-	0.635	0.629
	(0.195)		(0.188)	(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 A3.14 Multilevel logistic 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 A3.15 Summary statistics – Off-farm employment

	No. of off-farm employments						
	Mean	**Std. dev.**	**25% Quartile**	**50% Quartile**	**75% Quartile**	**95^{th} 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 A3.16 Summary statistics – Non-farm self-employment

	No. of non-farm self-employments						
	Mean	**Std. dev.**	**25% Quartile**	**50% Quartile**	**75% Quartile**	**95^{th} 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 A3.17 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=other)	(0.403)			(0.412)			(0.504)			(0.381)			(0.530)			(0.578)		
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 type	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
(Same distr.|Off-farm)	(0.088)			(0.205)			(0.208)			(0.165)			(0.227)			(0.139)		
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 A3.17 Multilevel logistic regression results of status: Random intercepts level 1 & 2, by year (cont.)

	2008			2010			2013			2016			2017			2019		
	OR (SE)	95% CI Lower	Upper	OR (SE)	95% CI Lower	Upper	OR (SE)	95% CI Lower	Upper	OR (SE)	95% CI Lower	Upper	OR (SE)	95% CI Lower	Upper	OR (SE)	95% CI 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 (SE)**	**95%CI Lower**	**Upper**	**Variance (SE)**	**95% CI Lower**	**Upper**	**Variance (SE)**	**95% CI Lower**	**Upper**	**Variance (SE)**	**95% CI Lower**	**Upper**	**Variance (SE)**	**95% CI Lower**	**Upper**	**Variance (SE)**	**95% CI 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 A3.18 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).

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.

3.8.2 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 A3.19).

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 A3.19 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.

3.8.3 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 A3.20.

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 A3.20 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.

4 Rural livelihoods in Thailand after two years of Covid-19

Current version of a paper by Wendt, N. & Bierkamp, S., currently under review at the "Journal of Rural Studies".

Abstract

The Covid-19 pandemic was expected to have profound and long-lasting negative effects on livelihoods in low- and middle-income countries. We test this claim by analysing the impact of Covid-19 on rural households in Thailand two years after the outbreak of the pandemic, using a long-term dataset from three provinces. By conducting descriptive analyses, we investigate how severely households are impacted. Additionally, applying a binary logistic regression, we identify which livelihood strategies are most likely to be affected. From the results, we assess whether the policy interventions adequately supported and reached those most in need. Our data indicate primarily short-term disruptions in the initial phase of the pandemic. Furthermore, the findings emphasize that households that are involved in global value chains through domestic markets tend to be more negatively affected. To cope with other types of shocks, livelihood diversification remains important. In preparation for future global crises, it is required to find ways to implement sustained and targeted policy interventions that reach the people most in need.

4.1 Introduction

The Covid-19 pandemic evoked an unprecedented global crisis with far-reaching implications for health, economies, and societies (Bundervoet et al., 2022; Pokhrel & Chhetri, 2021; Workie et al., 2020). In a globalized world, it is likely that such crises will occur more frequently and with increased severity in the future (Rasul, 2021; Workie et al., 2020). The pandemic has exposed the weaknesses of economic and social systems (Dandekar & Ghai, 2020; Rasul, 2021). Poverty and inequality increased, particularly in low- and middle-income countries (Dandekar & Ghai, 2020; Workie et al., 2020; World Bank, 2020a). According to early studies, the pandemic impacted rural livelihoods, with many households experiencing a loss in income (Bhagat et al., 2020; Bundervoet et al., 2022; Nolte et al., 2022). Due to global value chains, a variety of economic sectors are affected, including agriculture which is still the most important component of rural livelihood strategies (Nolte et al., 2022; Rasul, 2021; Workie et al., 2020). At the same time, many households have diversified their livelihoods by engaging in off-farm employment and non-farm self-employment in recent years (Dedehouanou et al., 2018; Waibel et al., 2020; Zhang et al., 2018). However, these income sources are most affected by Covid-19 (Bundervoet et al., 2022). In the short-term, the pandemic led to a decline in household consumption due to lower purchasing power and preventive measures (Chen et al., 2021; Turner et al., 2021; Workie et al., 2020). In addition, school closures and shortcomings in health systems can lead to long-lasting effects (Pokhrel & Chhetri, 2021; World Bank, 2020a).

The severity and extent of negative impacts from Covid-19 vary among countries and regions depending on policy, resilience, and capacity. Especially financial resources, but also social and state support, determine how successfully households cope with the crisis (Barrett & Constas, 2014; Laborde et al., 2020; Marome & Shaw, 2021). Additionally, households in low- and middle-income countries are already experiencing a variety of shocks, such as natural disasters (Waibel et al., 2020).

In recent decades, Thailand has rapidly evolved from a low-income to an upper middle-income country (Lin & Liang, 2019; World Bank, 2020b). Rural Thai households increasingly diversify their livelihoods and fewer people rely solely on subsistence farming (Nguyen et al., 2017). However, the disparities between rural and urban areas remain prevalent and rural households frequently send working migrants to the urbanized regions (World Bank, 2020b). Even within cities, migrants experience poverty and inequality which is likely to increase due to Covid-19 (Bundervoet et al., 2022; World Bank, 2020b). During the pandemic, the Thai government took extensive measures to prevent the spread of the virus and to avert the negative impact of Covid-

19 on the population (Marome & Shaw, 2021). These measures encompass both financial support and restrictions.

The aims of this study are to (1) investigate how severely households in rural Thailand are affected by Covid-19 during the two years after the onset of the pandemic. (2) Based on the Sustainable Livelihoods Framework (Ashley & Carney, 1999; Scoones, 1998), we analyse which livelihood platforms and strategies are most likely to be affected. (3) Consequently, we assess whether the implemented policy interventions adequately supported and reached those most in need. The first objective will be analysed descriptively, the second draws on a binary logistic regression model, and the third combines the results of both methods.

This study contributes to the research on the effects of the pandemic in low- and middle-income countries, using the example of rural Thailand. Although most Covid-19 studies provide useful insights, they are often based on literature reviews or own expertise (Pokhrel & Chhetri, 2021; Waibel et al., 2020; Workie et al., 2020). Empirical studies are mostly limited to closed-ended questions or cover a short period of time only (Bundervoet et al., 2022). Long-term effects of the pandemic are difficult to predict, but panel data, which remain sparse in low- and middle-income countries, can provide useful insights (Klasen & Povel, 2013; World Bank, 2020a). These are of great relevance for future crises since understanding the underlying mechanisms behind the effects of Covid-19 can form the basis for swiftly implemented good governance.

Extending on previous research, we use a comprehensive long-term panel dataset from Thailand, provided by the Thailand Vietnam Socio Economic Panel (TVSEP) project. We rely on the household surveys from July 2019 and May 2022 as well as a Covid-19 special survey conducted in November and December 2020. This dataset covers the period before, during, and after the pandemic and allows for a closer look at different aspects of rural livelihoods as the pandemic unfolded.

The paper is organized as follows: Section 2 reviews the literature on the impact of Covid-19 in rural Thailand and introduces the Sustainable Livelihoods Framework as the basis for the further analysis. Section 3 describes the data and methodology. Section 4 presents and discusses the findings. Section 5 summarizes and provides policy implications.

4.2 Literature review

4.2.1 The impact of Covid-19 on rural Thailand

The first case of the Corona Virus Disease 19 (Covid-19) was discovered at a seafood market in Wuhan, China, in December 2019. The virus is transmitted via droplets and aerosols, with globalization and urbanization facilitating a rapid spread all over the world. The severity and extent of the pandemic in each country also depend on political, climatic, and socio-economic characteristics (Marome & Shaw, 2021; Tantrakarnapa et al., 2022). For instance, societies with a higher proportion of elderly and vulnerable people are more severely affected (Tantrakarnapa et al., 2022). In response, governments enforced a range of similar – yet differently implemented – preventive measures such as physical distancing, travel restrictions, face masks, school closures, no mass gatherings, and lockdowns (Hale et al., 2021).

In mid-January 2020, the first Covid-19 case outside of China was reported in Thailand. Due to early and cautious measures, Thailand was at first very effective in limiting the spread of the virus (Marome & Shaw, 2021; Tantrakarnapa et al., 2022; Turner et al., 2021). The measures focused on reducing Covid-19 cases, but initially paid little attention to the long-term economic and social costs (Marome & Shaw, 2021; World Bank, 2020a). Thus, according to the expertise of researchers and early-stage data collection, poverty and inequality will increase as the pandemic impacts the main livelihood strategies of many households (Bundervoet et al., 2022; Sapbamrer et al., 2022; Turner et al., 2021; Workie et al., 2020; World Bank, 2020a). In agriculture, the interruption of global value chains reduced the supply of inputs such as pesticides and labour. With lower demand for agricultural outputs and less transportation, households also have limited opportunities to sell their products (Nolte et al., 2022; Sapbamrer et al., 2022; Waibel et al., 2020). Those engaged in off-farm employment like in manufacturing, commerce, and other services were at greater risk to temporarily or permanently stop their work and suffer a loss of income (Bundervoet et al., 2022; Komin et al., 2021). In recent decades, rural households increased their dependence on remittances generated by labour migration (Waibel et al., 2020). With the outbreak of the Covid-19 pandemic, researchers therefore assumed more return migration which puts additional pressure on migrant sending households (Dandekar & Ghai, 2020; Waibel et al., 2020).

The Thai government provided large-scale aid packages for the population in order to mitigate the negative implications of Covid-19 (Marome & Shaw, 2021; Turner et al., 2021). Nevertheless, households have to adapt their livelihoods. For instance, researchers note that rural households use natural resources as a safety net (Angelsen et al., 2014; Dokken & Angelsen, 2015). However, increasing extraction of already degraded forests, rivers, and lakes additionally strains these environments (Nguyen et al., 2015; Waibel et al., 2020). Further, households may temporarily return to subsistence agriculture as a coping measure (de Janvry & Sadoulet, 2011; Rudolf, 2019). Other strategies are to reduce consumption, sell assets, deplete savings, or borrow money. However, all of these strategies worsen the situation of rural households in the medium- and long-term (Turner et al., 2021; World Bank, 2020a).

4.2.2 Sustainable Livelihoods Framework

The Sustainable Livelihoods Framework, originally developed by Ashley and Carney (1999) as well as Scoones (1998), allows for a better understanding of how households in low- and middle-income countries make decisions concerning their livelihoods. According to Chambers and Conway (1992), livelihoods involve the capabilities, assets, and activities that are necessary to sustain certain means of living. Figure 4.1 illustrates how the combination of livelihood platforms enables different livelihood strategies, resulting in various livelihood outcomes. Livelihood platforms include human capital (e.g. education), social capital (e.g. migrant networks), natural capital (e.g. land), financial capital (e.g. savings), as well as physical capital (e.g. assets).

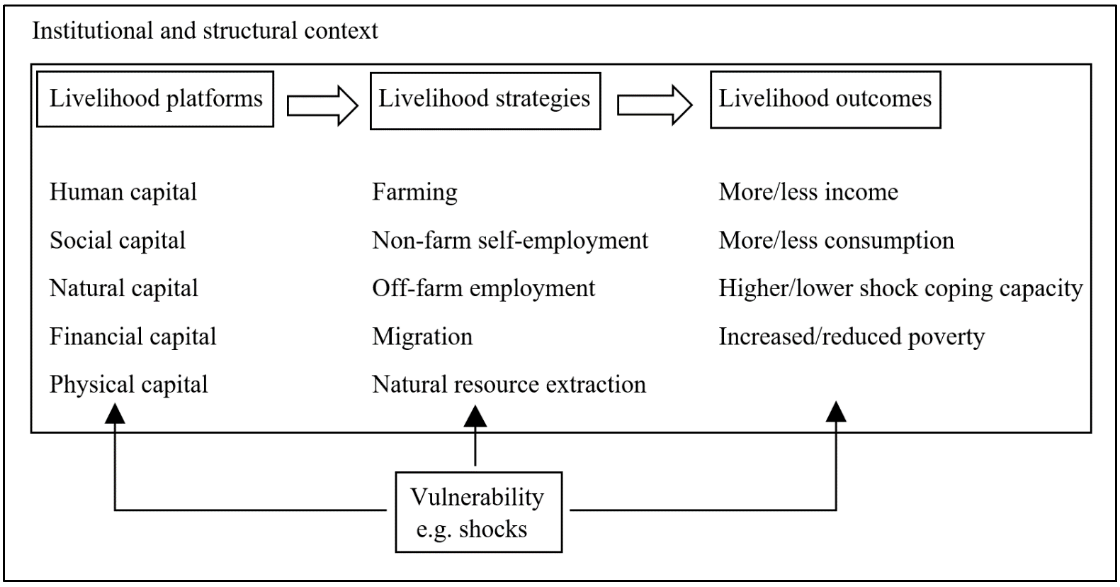

Figure 4.1 Sustainable Livelihoods Framework
(based on Ashley and Carney (1999) and Scoones (1998)).

The Sustainable Livelihoods Framework is characterised by its dynamic nature. Hereby, it accounts for changes that are introduced through shocks and other influencing factors. For instance, if in the short-run income decreases, a household has to reduce consumption or to use savings. However, financial and physical capital is finite because savings, for example, might be depleted the longer a stressor is applied or the more frequently a stressor occurs. In the medium-run, the household might seek alternative livelihood strategies or increase its livelihood diversification. Another main feature of the Sustainable Livelihoods Framework is that it combines the macro-level politics with the micro-level reality of people in low- and middle-income countries. Therefore, the institutional and structural context influences which livelihood strategies and outcomes can be achieved or not. For instance, governmental transfers and borrowing money can help to overcome income shortfalls. However, sustainable livelihoods are characterised by independence from external support, resilience to shocks, and a responsible interaction with other people and the environment.

4.2.3 Impact of Covid-19 on rural livelihoods in Thailand

Covid-19 differs from other types of shocks (Bundervoet et al., 2022; Pokhrel & Chhetri, 2021; Workie et al., 2020). It is not an isolated stressor to a household, but entails multitudinous effects on the global and national economy, trickling down further to rural households. Following the Sustainable Livelihoods Framework of Figure 4.1, Covid-19 is likely to impact livelihood platforms and livelihood strategies of these rural households. In this context, it has to be highlighted that human beings do not behave rationally, leading to heterogeneous responses to the crisis (Gasiorowska, 2014; Tan et al., 2020). This further has an impact on livelihoods since a household makes different decisions if it subjectively perceives a crisis as more severe than it is objectively. Nevertheless, Covid-19 has the potential to affect all livelihood strategies the households have, be it through fluctuations in the availability of agricultural input factors, unemployment, or lack of demand for household businesses (Laborde et al., 2021, 2020; Swinnen & McDermott, 2020; Waibel et al., 2020; World Bank, 2020b). Some of these effects will reach the households with a time lag, for instance remittance transfers. Additionally, Covid-19 can directly affect livelihood outcomes, by e.g. draining funds to maintain consumption. To cushion the negative effects of the pandemic, governments in Thailand and all over the world implemented preventive and supportive measures (Fajardo-Gonzalez et al., 2021; Hale et al., 2021; Marome & Shaw, 2021).

Following the literature, our study hence focuses on the following research questions: (1) How severely are households in rural Thailand affected by Covid-19 during the two years after the onset of the pandemic? (2) Which livelihood platforms and strategies are most likely to be affected? Hereby, we focus on the subjectively perceived impacts. (3) Did the policy interventions adequately support and reach those most in need?

4.3 Data and Methodology

4.3.1 Study site and data collection

This study uses a dataset from Thailand provided by the Thailand Vietnam Socio Economic Panel (TVSEP), a long-term panel survey conducted in three provinces of Thailand since 2007. The aim of this project is to deepen the understanding of income and poverty dynamics in rural areas of this emerging economy. By applying a stratified random sampling, the sample is representative for the rural population in the survey areas (Hardeweg et al., 2013).

Figure 4.2 TVSEP survey provinces.
Shape source: Humanitarian Data Exchange (2022).

With the onset of the Covid-19 pandemic, TVSEP implemented a Covid-19 special survey in Thailand during November and December 2020. The household and village head survey covers 2141 households in 220 villages in the three TVSEP provinces of Buri Ram, Ubon Ratchathani, and Nakhon Phanom (Figure 4.2). The survey was conducted as face-to-face interviews by enumerators on location, with the same households as in the regular household surveys.

For this study, household data from the household surveys in 2019 and 2022, household and village head data from the Covid-19 special survey as well as data from the village head survey in 2022 are used. Four reference periods are considered as shown in Table 4.1. These are named and defined consistently with the respective questionnaires by the TVSEP.

Table 4.1 Reference periods

Reference periods	Timeframe	Description	Source
"Before Covid-19"	05/2019 – 02/2020	Reference for values of income, consumption, etc.	Covid-19 special survey (2020)
"Lockdown"	03/2020 – 05/2020	First national lockdown in Thailand	Covid-19 special survey (2020)
"Post-Lockdown"	06/2020 – 10/2020	"Lockdown" until the Covid-19 special survey in 11/2020	Covid-19 special survey (2020)
"Post-Survey"	11/2020 – 04/2022	Covid-19 special survey until the household survey in 05/2022	Household survey (2022)

Source: Own illustration.

These datasets are well suited for the topic of this study, as modules on both economic and behavioural impacts of Covid-19 are included. Of particular interest are numerical questions that allow to quantify the effects of the pandemic beyond the scope of closed-ended questions.

4.3.2 Identifying and modelling the impact of Covid-19

This study analyses the impact of Covid-19 on rural livelihoods in Thailand and the factors thereof from multiple angles. In order to assess the severity in accordance with the Sustainable Livelihoods Framework (Figure 4.1) and with the findings of the literature review, we conduct an extensive descriptive analysis. The statistics therein cover the major issues commonly associated with rural livelihoods, such as household income, transfer payments, migration, and consumption.

Further, we fit a binary logistic regression to model the effect of household characteristics on the likelihood of suffering financial losses during the pandemic. The dependent variable is a dichotomous indicator I, capturing whether a household i reported a negative impact of Covid-19 on the household's financial situation at any point during the pandemic. Accordingly, the model is specified as:

$$ln\left[\frac{P_i(I=1)}{1-P_i(I=1)}\right] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k \qquad (1)$$

$$\text{with } I_i = 1 \; if \; negative \; impact \qquad (2)$$

$$I_i = 0 \; otherwise$$

where β_0 is a constant, vector X_k includes the independent variables with β_k as the corresponding coefficients. Interpreting the model requires the calculation of odds ratios as follows:

$$\left[\frac{P_i(I=1)}{1-P_i(I=1)}\right] = e^{\beta_0+\beta_1 X_1+\beta_2 X_2+\ldots+\beta_k X_k} \quad (3)$$

with the odds ratio as the likelihood of a household to suffer a negative impact on its financial situation due to Covid-19. It can be hypothesized that this likelihood is influenced by several predictors (Table 4.2). Referring to the literature in Table 4.2 as well as the framework presented in Figure 4.1, this study considers human capital such as mean age, nucleus size, and the mean education of all members that have concluded their education. In addition, the share of working migrants in relation to all household members is used to account for a diversification of the household's livelihood as well as for social networks that go beyond the nucleus household. Further, the total land held by a household represents its natural capital. Different components of financial capital are included: The monthly household per capita income before the pandemic, savings before the pandemic, and the amount of debt at the onset of the pandemic reflect the household's initial situation. Per capita public transfers reflect additional support during Covid-19. The value of assets is incorporated as physical capital. To consider the impact of different livelihood strategies, a dichotomous variable each for farming, off-farm employment, and non-farm self-employment is used. The interaction between total land area and the variable for farming may reveal nuances in farming-based households. A dichotomous variable for natural resource extraction accounts for the opportunity of extraction as a safety net in times of crises. To control for the potential bias and the exacerbated impacts by a parallel occurrence of additional shocks unrelated to Covid-19, the reported number of such shocks is included. In addition, the province of the household controls for location specific effects. The impact direction of the independent variables is hypothesized as illustrated in Table 4.2. The calculation of correlation coefficients suggests that endogeneity of independent variables is no serious problem (Table A4.8). In addition, variance inflation factors (VIF) indicate that there is no multicollinearity between independent variables (Table A4.9).

Table 4.2 Independent variables and their hypothesized effects

Variable	**Unit**	**Direction of odds ratio**	**Sources**
Human capital			
Mean Age	Years	-	Bundervoet et al. (2022), World Bank (2020a)
Nucleus Member	No.	-/+	Cassidy and Barnes (2012)
Mean Education	Degree (Primary/None, Secondary, Tertiary)	-	Bundervoet et al. (2022), World Bank (2020a)
Social capital			

Migrant Share	% of all members	+	Bhagat et al. (2020), Dandekar and Ghai (2020)
Natural capital			
Land Area	Rai	-	Carter and Barrett (2006)
Financial capital			
Per Capita Income before Covid-19 (Covid-19 special survey)	Log(THB/month)	-	Bundervoet et al. (2022), World Bank (2020a)
Per Capita Public Transfers	Log(THB)	-	Fajardo-Gonzalez et al. (2021)
Savings (household survey 2019)	Log(THB)	-	Turner et al. (2021), World Bank (2020a)
Debt (household survey 2019)	Log(THB)	+	Turner et al. (2021), World Bank, (2020a)
Physical capital			
Assets (household survey 2019)	Log(THB)	-	Turner et al. (2021), World Bank (2020a)
Livelihood strategies			
Farming	1 = "Yes", 0 = "No"	-/+	de Janvry and Sadoulet (2011), Rudolf (2019), Nolte et al. (2022)
Self-Employment	1 = "Yes", 0 = "No"	+	Bundervoet et al. (2022)., Waibel et al. (2020), Workie et al. (2020)
Off-Farm Employment	1 = "Yes", 0 = "No"	+	Bundervoet et al. (2022)., Waibel et al. (2020), Workie et al. (2020)
Natural Resource Extraction	1 = "Yes", 0 = "No"	-	Angelsen et al. (2014), Dokken and Angelsen (2015)
Other control variables			
Shocks	No.	+	Klasen and Waibel (2013)
Province	31 = "Buriram", 34 = "Ubon Ratchathani", 48 = "Nakhon Phanom"	-/+	Klasen and Waibel (2013)

Source: Authors' calculations based on TVSEP (2022).

4.4 Results and discussion

4.4.1 Descriptive findings

Figure 4.3 illustrates the effect of Covid-19 on overall household income as estimated by the households compared to before the pandemic. Reduced income is most prevalent in the "Lockdown" period and subsequently declines in severity, although even in the "Post-Survey" period close to 500 households remain strongly affected. Conversely, the number of unaffected households increases throughout the pandemic, however, positive impacts are most frequently observed in the "Post-Lockdown" period. Overall, the pandemic appears to impact households most severely in the first months.

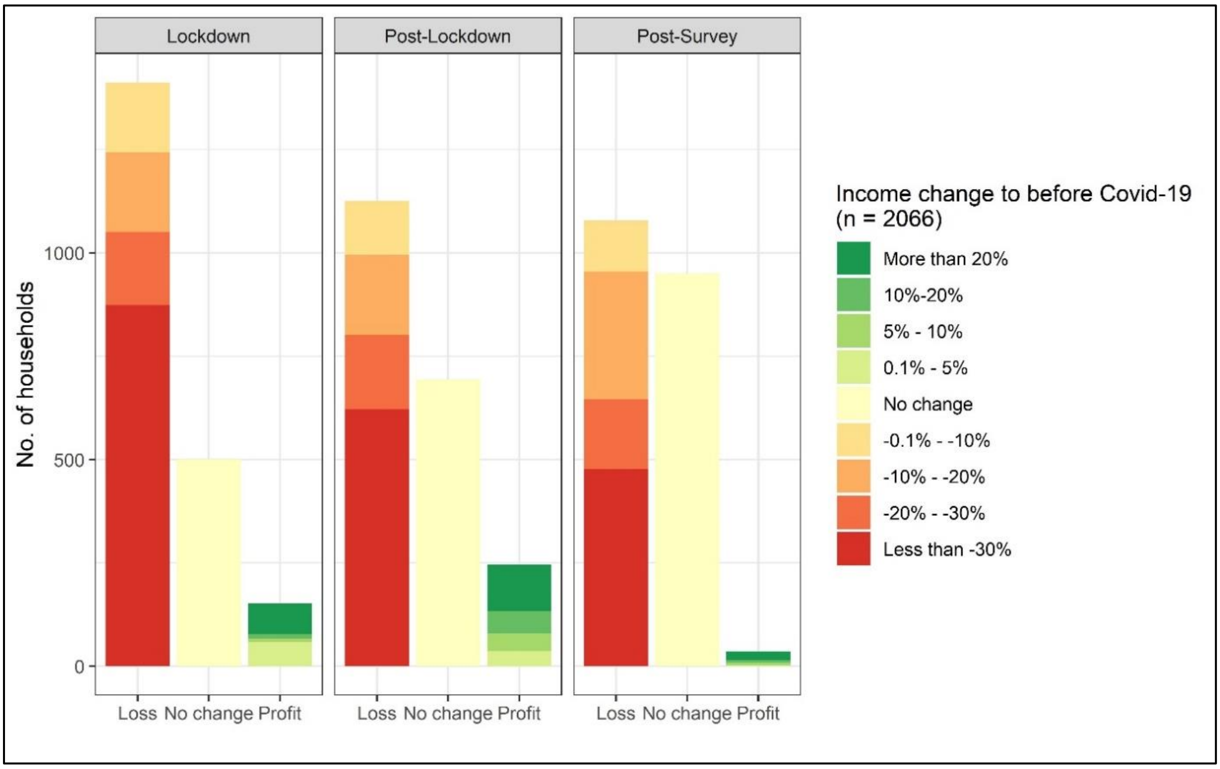

Figure 4.3 Subjective assessment of income effect in comparison to before Covid-19. Source: Authors' calculations based on TVSEP (2022).

The impact of Covid-19 on agriculture, off-farm employment, and self-employment is presented in Table 4.3. Thereby, the effects on agriculture are small in comparison to the effects on off-farm employment and self-employment, with "suffered losses" being the most frequently reported. This could relate to farmers that exhibit stronger ties with global value chains and are therefore more affected by shifts in supply and demand of agricultural inputs and goods (Nolte et al., 2022; Rasul, 2021). Additionally, income streams do not necessarily cease entirely, but reduce by e.g. receiving lower wages. Further, during the initial phases of the pandemic, more severe impacts are observed. In particular, the strong effects on off-farm employment subside after the initial impact. This may be caused by the strict lockdown measures, implemented by the Thai Government as the pandemic unfolded. Consistency with the estimated aggregate income effect in Figure 4.3 is observed.

Table 4.3 Impact of Covid-19 on agriculture, off-farm employment, and self-employment

Agriculture			**Off-Farm Employment**			**Self-Employment**		
	Percent of households			**Percent of households**			**Percent of households**	
Reference period / **Effect**	"Lockdown"/ "Post-Lockdown" (n = 2141)	"Post-Survey" (n = 2101)	**Reference period** / **Effect**	"Lockdown"/ "Post-Lockdown" (n = 2141)	"Post-Survey" (n = 2101)	**Reference period** / **Effect**	"Lockdown"/ "Post-Lockdown" (n = 2141)	"Post-Survey" (n = 2101)
Made Profits	0.33	0.24	Higher wage	0.28	0	Made profits	0.37	0.33
Suffered losses	5.89	5.66	Lower wage	14.11	0.62	Suffered losses	15.6	4.47
Increased Production	2.01	0.76	Work at increased hours	0.09	0	Opened the business	0.33	0
Decreased production	1.77	3.43	Work at reduced hours	17.05	0.57	Had to close business	2.76	0.9
Bought livestock/fish	0.05	0	Temporarily no work	10.32	1	Opened the Covid-19 related business but already closed it	0	0.05
Sold livestock/fish	2.01	0.19	Job loss	9.01	0.52			

Note: Multiple answers are possible; Source: Authors' calculations based on TVSEP (2022).

Table 4.4 illustrates the impact of Covid-19 on the migrant members of the panel households and their subsequent coping measures. Contrary to early predictions, few migrants lost their jobs (4.22%) in the "Lockdown" and "Post-Lockdown" periods, while lower income or reduced work hours were much more common. In coping with the pandemic, the most frequent strategy was observed to be a reduction in consumption. Further strategies were to use savings or to take up an additional occupation. Only a very small share of migrants in the panel were indicated to have moved back to the rural household or to a different place permanently. Figure 4.4 depicts the changes in remittance transfers during "Lockdown" and "Post-Lockdown". As expected, migrants experience increased financial pressure, thus more than 50% of the households report either reduced or entirely stopped remittances during "Lockdown". In the "Post-Lockdown" period, more households return to the usual or an increased level, however, numerous households with reduced and stopped remittances remain.

Table 4.4 Impact of Covid-19 on the migrant members of panel households

	Percent of migrants	
Reference period / **Impact**	"Lockdown"/ "Post-Lockdown" (n = 2248)	"Post-Survey" (n = 1111)
Job loss	4.22	1.08
Had to work reduced hours	12.59	4.05
Lower income	13.97	15.57
Move to a cheaper accommodation	0.89	1.17
Reduce consumption	18.91	16.56
Take up additional occupation	2.98	1.08
Used savings	3.91	2.07

Note: Migrant definition varies between surveys, resulting in a different number of migrants; Source: Authors' calculations based on TVSEP (2022).

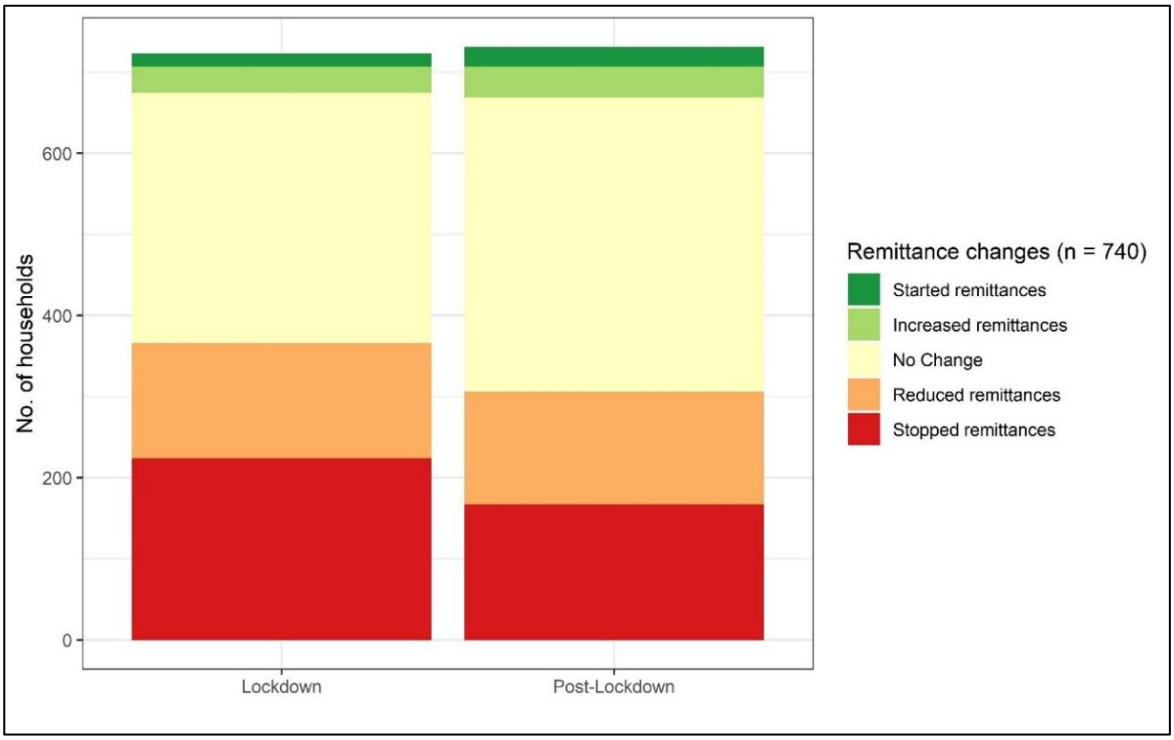

Figure 4.4 Impact of Covid-19 on remittance streams during “Lockdown” and “Post-Lockdown”.

Source: Authors’ calculations based on TVSEP (2022).

Figure 4.5 illustrates the number of households receiving public transfers in each month. The swiftly implemented support schemes by the Thai Government during the first national lockdown are visible between April 2020 and August 2020. These are received by up to 61% of households in the panel in July 2020. Notably, the number of supported households declines as the pandemic progresses. This may be related to the different requirements for support schemes that are potentially less accessible for rural households, e.g. because of the need to register using a smartphone.

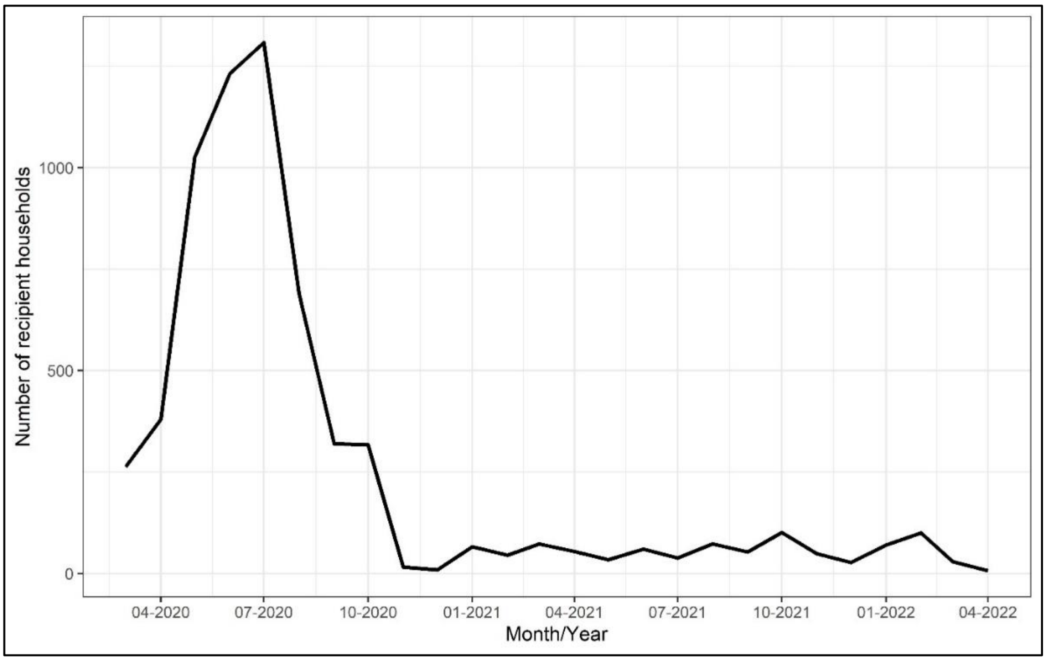

Figure 4.5 Number of households receiving public transfers.
Source: Authors' calculations based on TVSEP (2022).

As observable in Table 4.5, the effect of Covid-19 on the borrowing behaviour of the households in the panel is limited, with only some 16% of households taking up a Covid-19 induced loan in the initial phase of the pandemic. Most of these are recorded during the first lockdown and exhibit a rather low volume of on average 200,000 THB in the Covid-19 special survey and 500,000 THB in the household survey (2022). Those who take up a loan because of Covid-19 mostly use it to pay for everyday consumption. Fewer loans are utilized to sustain current livelihood strategies such as agriculture and businesses. In comparison, the household survey (2019) exhibits an emphasis on investments.

Table 4.5 Usage of borrowed money due to Covid-19

Usage of borrowed money	Percent of households (n = 354)
Used to pay back another loan	10.24
Investment	3.15
Put in savings account	1.18
Pay for everyday consumption	87.8
Used to buy inputs for agriculture	14.17
Used to buy inputs for business	4.33
Other reason	3.15

Note: Multiple answers are possible; Source: Authors' calculations based on TVSEP (2022).

Depicted in Figure 4.6 is the evolution of all first and subsequent vaccinations as well as infections with Covid-19 amongst household members in the panel. Initially, the vaccination campaign progresses slowly and only picks up in the summer of 2021. First, the majority of vaccines used are of Chinese origin (Sinovac and Sinopharm), however, their effectiveness remains controversial (Wee & Londoño, 2021), hence cross-vaccination with other brands upon availability is favoured. Vaccinations of the brand "Astrazeneca" are used in substantial numbers, as these become more available once other countries predominantly shift to using mRNA vaccines. mRNA vaccines are available much later in Thailand and as of 2022 become the main type of vaccine. Thailand reports relatively low numbers of Covid-19 infections for most of the pandemic, only experiencing temporary waves with more regional outbreaks in e.g. the province of Samut Sakhon in late 2020 (Sriring & Perawongmetha, 2020). However, in 2022, infections increase substantially, both in the dataset as well as nationally.

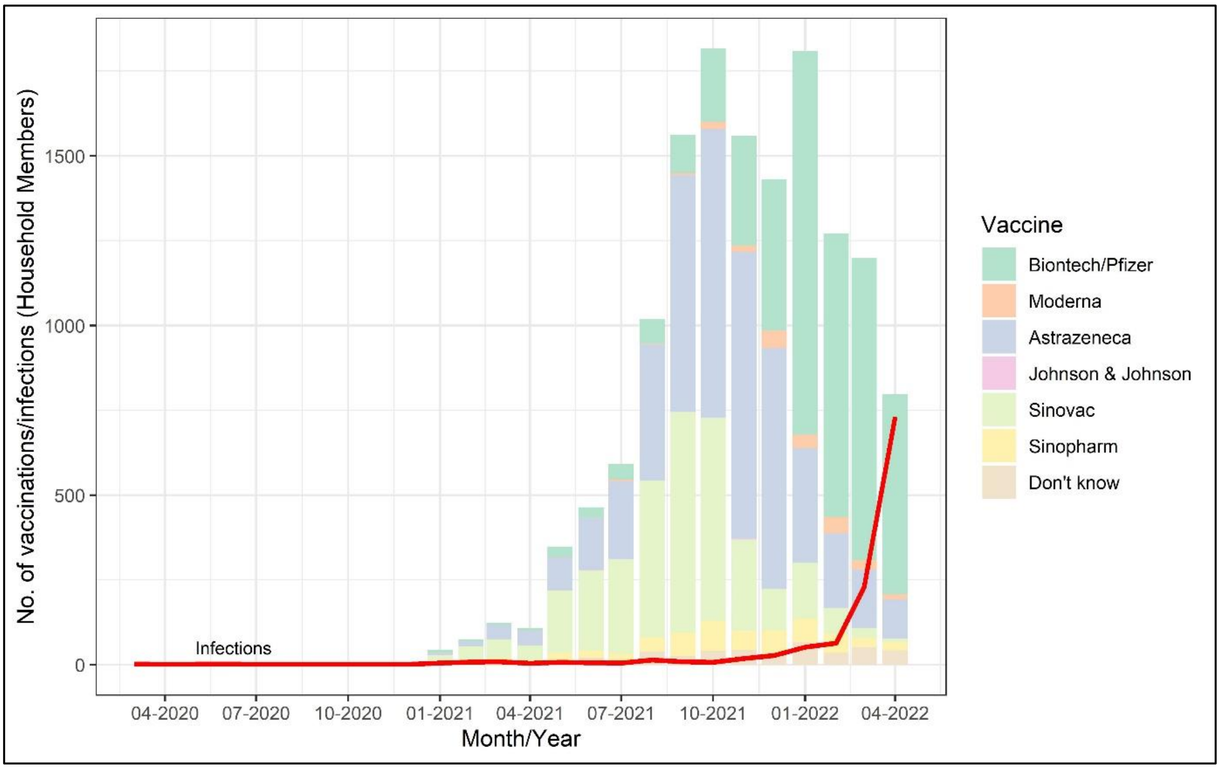

Figure 4.6 Vaccinations and infections with Covid-19 among household members.

Source: Authors' calculations based on TVSEP (2022).

Table 4.6 indicates the changes in consumption expenditures due to Covid-19. Especially during the "Lockdown" and "Post-Lockdown" periods, many households spend less on proteins (meat, fish, milk products), even though in the "Post-Survey" period households tend to increase their protein consumption. With respect to vitamins, households report a decline as well but little increase later on. Unobservable in the table are shifts regarding the quality of purchased items (quantity vs. quality) as well as changes in the share of self-produced items. Additionally, households alter their non-food expenditures. However, the interpretation is impeded as this category includes many different kinds of goods. With the onset of the pandemic, the expenditures for lottery and gambling decline, but swiftly return to the initial level. A persistent increase in expenditures is observable for health.

Table 4.6 Changes in consumption expenditures due to Covid-19

Expenditures	Percent of households			
	"Lockdown"/ "Post-Lockdown" (n = 2141)		"Post-Survey" (n = 2101)	
	Decrease	**Increase**	**Decrease**	**Increase**
Carbohydrates (rice, noodle, root crops)	5.65	5.18	1.48	4.76
Protein (meat, fish, milk products)	16.58	7.43	4.95	13.04
Vitamins (vegetables, fruits)	8.45	2.62	1.86	3.14
Non-food expenditures (care supplies, energy cost, transportation, etc.)	18.82	14.48	3.28	16.18
Lottery and gambling	19.76	1.21	4.47	1.05
Health (preventive and curative)	0.19	16.16	1.24	11.52

Source: Authors' calculations based on TVSEP (2022).

4.4.2 Factors of households financially impacted by Covid-19

In this section, the factors influencing the probability of a negative impact of Covid-19 on a household's financial situation are presented in Table 4.7. The model achieves a McFadden R^2 of 0.13. A ten-fold cross validation, whereby the dataset is randomly split into a training and testing dataset 10 times, yields an accuracy of 78%.

Table 4.7 Influencing factors on the probability of suffering a negative financial impact

	Odds ratio (SE)
Human capital	
Mean Age	0.967*** (0.005)
Nucleus Member	1.056 (0.044)
Mean Education	0.536*** (0.149)
Social capital	
Migrant Share	1.376 (0.508)
Natural capital	
Land Area	0.963** (0.018)
Financial capital	
Per Capita Income before Covid-19 (Covid-19 special survey)	2.334*** (0.174)
Per Capita Public Transfers	1.130*** (0.042)
Savings (household survey 2019)	1.006 (0.028)
Debt (household survey 2019)	1.012 (0.023)
Physical capital	
Assets (household survey 2019)	1.046 (0.064)

Livelihood strategies	
Farming	1.027 (0.169)
Farming#Land Area	1.031* (0.018)
Off-Farm Employment	1.579*** (0.144)
Self-Employment	3.045*** (0.173)
Natural Resource Extraction	0.57 (0.549)
Other control variables	
Shocks	1.346*** (0.059)
Province Buriram (ref. Nakhon Phanom)	0.668** (0.171)
Province Ubon Ratchathani (ref. Nakhon Phanom)	0.621*** (0.166)
Intercept	0.645 (0.742)
R^2 (McFadden)	0.13
Obs.	2062

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; Standard errors (SE) in parentheses;
Source: Authors' calculations based on TVSEP (2022).

The odds of suffering a negative impact of Covid-19 on a household's financial situation are statistically significantly influenced by the household's members mean age and mean education. Households that are on average older are less likely to experience a financial loss due to their rather self-sustained livelihoods that are less involved in the globalized economy (Kassie et al., 2017; Xu et al., 2015). In addition, households with a higher average level of education amongst their members show reduced odds, as it may enable them to manage and mitigate crises more effectively. Mean education and mean age lower the odds by 46% and 3.3% per unit increase respectively.

The household's per capita income before the pandemic, the involvement of the household in off-farm employment and/or self-employment as well as the volume of public transfers show a statistically significant correlation with the odds. Thereby, a household with a higher per capita income before the pandemic is more likely to incur a negative financial impact due to the more globalized nature of higher revenue generating activities. The involvement in either off-farm employment or self-employment increases the likelihood of suffering adverse effects by a factor of 1.57 and a factor of 3 respectively. Conversely, involvement in farming yields no significance, unless interacted with the total land area of the household. Larger-scale farms are more likely to be affected, indicating a higher level of dependence on domestic and global markets. However, land area in households without farming is shown to reduce the odds of negative financial impacts with increasing size. The results from the logistic regression further indicate that receiving more public transfers increases the likelihood of a financial loss. This shows that households that receive more support were indeed those affected most by the pandemic, indicating the relevance of targeted policy interventions.

In addition, both variables controlling for the reported number of other shocks and the location show statistically significant effects. Thereby, a higher number of other shocks experienced by the household also increases the odds ratio of a negative financial effect due to Covid-19 by 35%. This may be related to either a reporting bias or a reduced capacity of the household in coping with multiple stressors. Further, the province in which the household is located, shows a higher likelihood for a negative financial impact in the province of Nakhon Phanom compared to the other two provinces in the survey.

4.5 Sustainable rural livelihoods against the background of Covid-19

Discussing our empirical results in light of the Sustainable Livelihoods Framework presented in Figure 4.1, Covid-19 has long-lasting impacts. Education – which is an important part of human capital – proved to be a statistically significant enabler for households to mitigate the effects of the crisis. However, financial and physical capital, e.g. savings and assets, appeared to be of little relevance. The choice of livelihood strategies has a statistically significant influence on whether households experience a negative financial impact. While diversified livelihood strategies are commonly regarded as desirable in the context of rural livelihoods, Covid-19 particularly impacts those households involved in domestic and global markets. Conversely, small-scale farming reduces negative impacts. In light of these observations, it is noteworthy that Covid-19 is dissimilar from other shocks commonly experienced by households in the study area. In addition, the simultaneous occurrence of different shocks further worsens livelihood outcomes. In response to Covid-19, some households swiftly change their consumption, while others prefer to expend resources, e.g. loans, to uphold consumption. In summary, Covid-19 has affected livelihood platforms, strategies, and outcomes alike.

This exposes the multitudinous weaknesses of rural livelihoods and raises the issue of how better policies can be implemented to cushion the effects of future crises. Our analysis exposes the households that require the most support which in turn could be utilized to better target these. Especially during the initial phase of the pandemic, vast amounts of money were distributed to most of the households in the panel, regardless of their actual situation. Combining the characteristics of the crisis at hand as well as the inclusion of detailed data yields a more targeted and therefore sustainable policy design, ideally aimed at those with the highest likelihood of suffering a financial loss.

4.6 Conclusion

The Covid-19 pandemic was expected to have profound and long-lasting effects on households in low- and middle-income countries. Applying a descriptive approach, we observe that Covid-19 predominantly affects households that already exhibit a degree of involvedness in domestic and global markets, e.g. by pursuing off-farm employment or non-farm self-employment. In summary, our dataset confirms the occurrence of most predicted adverse effects from the literature, albeit with a strong emphasis on the first months of the pandemic. Although improvements can be observed, as the pandemic progresses, even two years after its onset, negative impacts remain notable. These findings are reflected in the binary logistic regression model, particularly, in the correlation between involvement in global value chains and likelihood to be negatively impacted. Conversely, households with a higher average age, lower education, and smaller farm size are less likely to be affected. In the context of rural livelihoods, this points to the differences between various kinds of shocks. While higher income and diversified livelihood strategies increase resilience against natural disasters, precisely these strategies exhibit higher vulnerability to economic shocks. Nevertheless, livelihood diversification remains essential. In any case, the aggregate effects of multiple shocks put additional pressure on households and worsen their livelihood outcomes.

Initially, the governmental transfer payments reach the people most in need. In later stages of the pandemic, households receive substantially lower amounts. Following these observations, it seems more desirable to implement more targeted support policies that are sustainable over a longer period of time. Data collection at an early stage to obtain a better understanding of who is most affected, is key in facilitating such policies.

This study demonstrates the importance of data driven conclusions about the impact of crises. Although our dataset provides detailed information on the household's situation before and during the pandemic, it is not without limitations. Some data about the impact on income and consumption are aggregated estimates by the respondents with inherent inaccuracies. Further, this study only considers two years after the onset of the pandemic, whereby longer-term effects are yet to unfold. However, as the data covers most of the pandemic until April of 2022, whereafter Covid-19 slowly entered a recession, any following impacts on the households may not be clearly attributable to the pandemic but to the general economic situation. At the same time, the availability of data limits the regional scope of this study, with similar large-scale household surveys only being conducted in few countries. Since Covid-19 is a global phenomenon, extending the analysis of this study to other regions may improve the response to future crises.

4.7 References Chapter 4

Angelsen, A., Jagger, P., Babigumira, R., Belcher, B., Hogarth, N. J., Bauch, S., Börner, J., Smith-Hall, C., & Wunder, S. (2014). Environmental Income and Rural Livelihoods: A Global-Comparative Analysis. *World Development*, *64*, S12–S28. https://doi.org/10.1016/j.worlddev.2014.03.006

Ashley, C., & Carney, D. (1999). *Sustainable livelihoods: Lessons from early experience*. Department for International Development.

Barrett, C. B., & Constas, M. A. (2014). Toward a theory of resilience for international development applications. *Proceedings of the National Academy of Sciences*, *111*(40), 14625–14630. https://doi.org/10.1073/pnas.1320880111

Bhagat, R. B., Reshmi, N., Sahoo, H., Roy, A. K., & Govil, D. (2020). *The COVID-19, migration and livelihood in India: Challenges and policy issues*. *17*(5), 705–718.

Bundervoet, T., Dávalos, M. E., & Garcia, N. (2022). The short-term impacts of COVID-19 on households in developing countries: An overview based on a harmonized dataset of high-frequency surveys. *World Development*, *153*, 105844. https://doi.org/10.1016/j.worlddev.2022.105844

Chambers, R., & Conway, G. (1992). Sustainable rural livelihoods: Practical concepts for the 21st century. *IDS Discussion Paper*, *296*.

Chen, H., Qian, W., & Wen, Q. (2021). The Impact of the COVID-19 Pandemic on Consumption: Learning from High-Frequency Transaction Data. *AEA Papers and Proceedings*, *111*, 307–311. https://doi.org/10.1257/pandp.20211003

Dandekar, A., & Ghai, R. (2020). Migration and reverse migration in the age of COVID-19. *Economic and Political Weekly*, *55*(19), 28–31.

de Janvry, A., & Sadoulet, E. (2011). Subsistence farming as a safety net for food-price shocks. *Development in Practice*, *21*(4–5), 472–480. https://doi.org/10.1080/09614524.2011.561292

Dedehouanou, S. F. A., Araar, A., Ousseini, A., Harouna, A. L., & Jabir, M. (2018). Spillovers from off-farm self-employment opportunities in rural Niger. *World Development*, *105*, 428–442. https://doi.org/10.1016/j.worlddev.2017.12.005

Dokken, T., & Angelsen, A. (2015). Forest reliance across poverty groups in Tanzania. *Ecological Economics*, *117*, 203–211. https://doi.org/10.1016/j.ecolecon.2015.06.006

Fajardo-Gonzalez, J., Gray Molina, G., Montoya-Aguirre, M., & Ortiz-Juarez, E. (2021). *Global Estimates of the Impact of Income Support during the Pandemic*. United Nations Development Programme.

Gasiorowska, A. (2014). The relationship between objective and subjective wealth is moderated by financial control and mediated by money anxiety. *Journal of Economic Psychology*, *43*, 64–74. https://doi.org/10.1016/j.joep.2014.04.007

Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S., & Tatlow, H. (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour*, *5*(4), 529–538. https://doi.org/10.1038/s41562-021-01079-8

Hardeweg, B., Klasen, S., & Waibel, H. (2013). Establishing a database for vulnerability assessment. In *Vulnerability to Poverty: Theory, Measurement and Determinants, with Case Studies from Thailand and Vietnam* (S. 50–79). Springer.

Humanitarian Data Exchange. (2022). *Thailand – Subnational Administrative Boundaries. Available at https://data.humdata.org/dataset/cod-ab-tha.*

Kassie, G. W., Kim, S., Fellizar, F. P., & Ho, B. (2017). Determinant factors of livelihood diversification: Evidence from Ethiopia. *Cogent Social Sciences*, *3*(1), 1369490. https://doi.org/10.1080/23311886.2017.1369490

Klasen, S., & Povel, F. (2013). Defining and Measuring Vulnerability: State of the Art and New Proposals. In *Vulnerability to Poverty: Theory, Measurement and Determinants, with Case Studies from Thailand and Vietnam* (S. 17–49). Springer.

Komin, W., Thepparp, R., Subsing, B., & Engstrom, D. (2021). Covid-19 and its impact on informal sector workers: A case study of Thailand. *Asia Pacific Journal of Social Work and Development*, *31*(1–2), 80–88. https://doi.org/10.1080/02185385.2020.1832564

Laborde, D., Martin, W., Swinnen, J., & Vos, R. (2020). COVID-19 risks to global food security. *Science*, *369*(6503), 500–502. https://doi.org/10.1126/science.abc4765

Laborde, D., Martin, W., & Vos, R. (2021). Impacts of COVID-19 on global poverty, food security, and diets: Insights from global model scenario analysis. *Agricultural Economics*, *52*(3), 375–390. https://doi.org/10.1111/agec.12624

Lin, P., & Liang, C. Y. C. (2019). Assessing the Growth Effect of Financial Liberalization in the Presence of Financial Crises: A Case Study of Tiger Cub Economies. *The Developing Economies*, *57*(2), 159–193. https://doi.org/10.1111/deve.12194

Marome, W., & Shaw, R. (2021). COVID-19 Response in Thailand and Its Implications on Future Preparedness. *International Journal of Environmental Research and Public Health*, *18*(3), 1089. https://doi.org/10.3390/ijerph18031089

Nguyen, T. T., Do, T. L., Bühler, D., Hartje, R., & Grote, U. (2015). Rural livelihoods and environmental resource dependence in Cambodia. *Ecological Economics*, *120*, 282–295. https://doi.org/10.1016/j.ecolecon.2015.11.001

Nguyen, T. T., Nguyen, L. D., Lippe, R. S., & Grote, U. (2017). Determinants of Farmers' Land Use Decision-Making: Comparative Evidence From Thailand and Vietnam. *World Development*, *89*, 199–213. https://doi.org/10.1016/j.worlddev.2016.08.010

Nolte, K., Sipangule, K., & Wendt, N. (2022). Agricultural households in times of crisis. The COVID-19 pandemic, livelihoods and land-use decisions. *Journal of Land Use Science*, *17*(1), 134–160. https://doi.org/10.1080/1747423X.2021.2020922

Pokhrel, S., & Chhetri, R. (2021). A Literature Review on Impact of COVID-19 Pandemic on Teaching and Learning. *Higher Education for the Future*, *8*(1), 133–141. https://doi.org/10.1177/2347631120983481

Rasul, G. (2021). Twin challenges of COVID-19 pandemic and climate change for agriculture and food security in South Asia. *Environmental Challenges*, *2*, 100027. https://doi.org/10.1016/j.envc.2021.100027

Rudolf, R. (2019). The impact of maize price shocks on household food security: Panel evidence from Tanzania. *Food Policy*, *85*, 40–54. https://doi.org/10.1016/j.foodpol.2019.04.005

Sapbamrer, R., Chittrakul, J., Sirikul, W., Kitro, A., Chaiut, W., Panya, P., Amput, P., Chaipin, E., Sutalangka, C., Sidthilaw, S., Promrak, P., Kamolsan, P., & Hongsibsong, S. (2022). Impact of COVID-19 Pandemic on Daily Lives, Agricultural Working Lives, and Mental Health of Farmers in Northern Thailand. *Sustainability*, *14*(3), 1189. https://doi.org/10.3390/su14031189

Scoones, I. (1998). Sustainable rural livelihoods: A framework for analysis. *IDS Working Paper*, *72*.

Sriring, O., & Perawongmetha, A. (2020, Dezember 20). Thailand to test thousands after shrimp market COVID outbreak. *Reuters*. https://www.reuters.com/article/us-health-coronavirus-thailand-idUSKBN28U070

Swinnen, J., & McDermott, J. (2020). *COVID-19 and global food security* (0 Aufl.). International Food Policy Research Institute. https://doi.org/10.2499/p15738coll2.133762

Tan, J. J. X., Kraus, M. W., Carpenter, N. C., & Adler, N. E. (2020). The association between objective and subjective socioeconomic status and subjective well-being: A metaanalytic review. *Psychological Bulletin*, *146*(11), 970–1020. https://doi.org/10.1037/bul0000258

Tantrakarnapa, K., Bhopdhornangkul, B., & Nakhaapakorn, K. (2022). Influencing factors of COVID-19 spreading: A case study of Thailand. *Journal of Public Health*, *30*(3), 621–627. https://doi.org/10.1007/s10389-020-01329-5

Turner, S., Langill, J. C., & Nguyen, B. N. (2021). The utterly unforeseen livelihood shock: COVID -19 and street vendor coping mechanisms in Hanoi, Chiang Mai and Luang Prabang. *Singapore Journal of Tropical Geography*, *42*(3), 484–504. https://doi.org/10.1111/sjtg.12396

TVSEP. (2022). *Thailand Vietnam Socio Economic Panel – Poverty Dynamics and Sustainable Development (Version 2022). Dataset available upon request from: Https://www.tvsep.de/en/tvsep-data-access*.

Waibel, H., Grote, U., Min, S., Nguyen, T. T., & Praneetvatakul, S. (2020). COVID-19 in the Greater Mekong Subregion: How resilient are rural households? *Food Security*, *12*(4), 779–782. https://doi.org/10.1007/s12571-020-01069-0

Wee, S.-L., & Londoño, E. (2021, Januar 13). Disappointing Chinese Vaccine Results Pose Setback for Developing World. *New York Times*. https://www.nytimes.com/2021/01/13/business/chinese-vaccine-brazil-sinovac.html

Workie, E., Mackolil, J., Nyika, J., & Ramadas, S. (2020). Deciphering the impact of COVID-19 pandemic on food security, agriculture, and livelihoods: A review of the evidence from developing countries. *Current Research in Environmental Sustainability*, *2*, 100014. https://doi.org/10.1016/j.crsust.2020.100014

World Bank. (2020a). *COVID-19 Crisis Through a Migration Lens* [Brief]. World Bank. https://doi.org/10.1596/33634

World Bank. (2020b). *Poverty and Distributional Impacts of COVID-19: Potential Channels of Impact and Mitigating Policies*. World Bank.

Xu, D., Zhang, J., Rasul, G., Liu, S., Xie, F., Cao, M., & Liu, E. (2015). Household Livelihood Strategies and Dependence on Agriculture in the Mountainous Settlements in the Three Gorges Reservoir Area, China. *Sustainability*, *7*(5), 4850–4869. https://doi.org/10.3390/su7054850

Zhang, L., Dong, Y., Liu, C., & Bai, Y. (2018). Off-farm employment over the past four decades in rural China. *China Agricultural Economic Review*, *10*(2), 190–214. https://doi.org/10.1108/CAER-11-2017-0212

4.8 Appendix Chapter 4

Table A4.8 Correlation coefficients of independent variables (Pearson)

	Mean Age	Nucleus Member	Mean Education	Migrant Share	Land Area	Per Capita Income before Covid-19	Per Capita Public Transfers	Debt	Savings	Assets	Farming	Off-Farm Employment	Self-Employment	Natural Resource Extraction	Shocks
Mean Age															
Nucleus Member	-0.51***														
Mean Education	-0.28***	0.17***													
Migrant Share	-0.14***	-0.13***	0.21***												
Land Area	-0.04*	0.13***	0.10***	0.00											
Per Capita Income before Covid-19	-0.04*	-0.12***	0.22***	-0.17***	0.06***										
Per Capita Public Transfers	-0.15***	0.05**	-0.03	0.03	0.04*	0.05**									
Debt	-0.20***	0.15***	0.08***	0.03	0.10***	0.08***	0.09***								
Savings	-0.03	0.02	0.08***	-0.02	0.09***	0.12***	0.04*	0.05**							
Assets	-0.24***	0.20***	0.30***	0.00	0.25***	0.31***	0.07***	0.16***	0.18***						
Farming	-0.13***	0.13***	-0.01	0.02	0.34***	0.00	0.10***	0.12***	0.12***	0.22***					
Off-Farm Employment	-0.29***	0.17***	0.23***	0.50***	-0.11***	-0.08***	0.06***	0.04*	-0.03	-0.01	-0.09***				
Self-Employment	-0.08***	0.12***	0.16***	-0.02	-0.03	0.20***	0.08***	0.02	0.04*	0.17***	-0.05**	-0.06***			
Natural Resource Extraction	-0.02	0.01	-0.01	0.03	-0.03	0.01	0.00	0.01	0.02	-0.01	-0.02	0.04*	-0.03		
Shocks	-0.08***	0.10***	0.01	-0.01	0.08***	0.01	0.06***	0.06**	0.05**	0.07***	0.18***	0.04*	0.01	0.03	
Province	0.05**	-0.01	0.05**	-0.06**	0.03	0.07***	-0.01	-0.15***	-0.02	0.06***	-0.06***	-0.03	0.03	0.02	0.00

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; Source: Authors' calculations.

Table A4.9 Variance Inflation Factor (VIF) values of independent variables

	VIF
Human capital	
Mean Age	1.292
Nucleus Member	1.314
Mean Education	1.175
Social capital	
Migrant Share	1.301
Natural capital	
Land Area	4.84
Financial capital	
Per Capita Income before Covid-19 (Covid-19 special survey)	1.141
Per Capita Public Transfers	1.023
Savings (household survey 2019)	1.026
Debt (household survey 2019)	1.062
Physical capital	
Assets (household survey 2019)	1.174
Livelihood strategies	
Farming	1.255
Self-Employment	1.036
Off-Farm Employment	1.291
Natural Resource Extraction	1.005
Farming#Land Area	5.077
Other control variables	
Shocks	1.023
Province	1.025

Source: Authors' calculations.

5 How do vulnerable households navigate current challenges? A consumption typology of Thai rural households

Current version of a paper by Wendt, N. & Nolte, K., currently in preparation for submission.

Abstract

Worldwide, rural households are faced with globalization and global environmental change. We explore how Thai rural households navigate these challenges. Finding the optimal way to measure poverty and welfare as well as assessing livelihoods using consumption data has been subject to extensive debate. We develop a household typology based on observed consumption behaviour. Applying k-means and k-medoids clustering to a long-term household panel dataset from Thailand, we demonstrate that clustering is a feasible method to assign households to consumption patterns and identify their characteristics. Further, we investigate factors behind shifts in consumption patterns. Our results confirm that crises, in particular natural disasters, drive households to diversify away from agriculture, even though agriculture remains one important livelihood strategy. We find that the majority of households ends up in a cluster that is more vulnerable. With our approach in mind, future surveys could be implemented more cost effectively and more efficiently, while yielding valuable inputs for policy makers and researchers alike.

5.1 Introduction

In recent decades, the world faced grand challenges. Globalisation and global environmental change have affected all countries in the world but pose particular challenges to vulnerable households in the Global South. These households face significant challenges related to their integration into globalized value chains that dominate the economy as well as natural disasters that become more frequent in times of climate change.

The question of how vulnerable households, particularly those in rural areas, navigate these challenges is pertinent and subject to a large body of literature. Put differently, do more households fall into poverty faced with globalization and global environmental change? Concepts such as resilience and vulnerability are helpful in understanding the dynamic situation of such households.

Consumption is considered an important predictor of livelihoods and poverty. Consumption behaviour is at the end of a complex decision-making process determined by a multitude of factors, both on the individual household level but importantly also on the macro-level, for instance, considering shocks such as draughts or floods.

Thus, better understanding consumption strategies gives us insights into how different households navigate current challenges, and in turn allows us to better design policies to support households in times of crises. We therefore develop a consumption typology of households, based on their observed consumption behaviour. Our analysis draws on data from the Thailand Vietnam Socio Economic Panel collected in three provinces in rural Thailand. The typology identifies different clusters of households that are relatively similar in their consumption behaviour. We then assess what determines households to pursue a certain consumption behaviour, considering household level variables as well as external shocks. Importantly, we then investigate changes in consumption behaviour across time, allowing us to assess what makes households drop out of a certain strategy and what makes them move into a typology.

Our paper contributes to the literature in three ways: 1) We show that a consumption typology of rural households can be achieved with a clustering approach applied to household survey data. 2) Our results confirm that crises, in particular natural disasters, drive households to diversify away from agriculture. We find that the majority of these households ends up in a cluster that is more vulnerable. While we can confirm that diversification is a viable livelihood strategy to increase resilience, most households lack the means to do so. This bears important policy implications: it is crucial to support vulnerable households in times of climate change in their strive to diversify their livelihood strategies. 3) Even though agriculture becomes less important for many households, it remains an important livelihood strategy. Therefore, Thai rural households will also need to move their agricultural production towards climate-smart practices.

On a more practical level, our analysis will allow better targeting policy design, especially when implementing support schemes on a short notice in the aftermath of a salient shock.

This paper is structured as follows: Section 2 contains a literature review, further showcasing the status quo of research as well as the research gap and approaches the classification of consumption strategies based on previous research with particular attention to the relevance of utility maximization. Section 3 then follows with the introduction of the dataset and a cluster analysis which can then be combined with the findings of section 2 to finalize the classification of consumption strategies. In section 4, descriptive statistics about the change in consumption strategies due to shocks are provided, while section 5 seeks to model the determinants of adopting certain strategies and adjusting them in the event of a shock. Section 6 draws a conclusion and includes policy recommendations.

5.2 Consumption and resilience and vulnerability

Consumption is part of everyone’s daily routine and thus, understanding individual consumption can reveal a lot about well-being, inequality and poverty (Deaton, 2016). However, research lacks a precise definition for the terms “consumption” and “consumables.” The scope of definitions ranges from the act of purchase exclusively, to considering any acquisition and use of an item. Thereby, some include almost anything, right down to passive consumption of items such as housing or assets into their considerations, while others only consider commodities or goods. This issue is further complicated by the different institutional traditions in a multidisciplinary research community (Evans, 2019; Graeber, 2011; Pepermans, 1984).

Taking a behavioural stance, no clear distinction can be observed in the literature either. Some regard consumption as the process to maximize utility, others regard consumption from the perspective of the product, that is equal to all consumers (Deaton, 2003; Holt, 1995; Kahneman & Thaler, 2006). More recently, the complexity of consumption analysis as part of an individual’s behaviour has been recognized, with individuals not always acting in a rational manner or being part of a larger entity, such as a household (Deaton, 2003; Kahneman & Thaler, 2006). In reality, there exists a complex network of preferences, capabilities and circumstances, that might distort the rationality of a consumption strategy (Kahneman & Thaler, 2006; Sheth et al., 1991). An important implication from this strand of research is a need for data-driven research, representing the complexity of real-world consumption and at the same time allowing for comparability and validity of results. To achieve this, consistent definitions of consumption among various data-sources are needed, in particular within household surveys. Further, measurements must be sought using consistent reference periods, survey instruments and response levels, e.g. the household or individuals (Pepermans, 1984). In reality, however, consumption data is frequently impacted by biases, survey design shortcomings and measurement errors, such as telescoping error (Abate et al., 2022; Christiaensen et al., 2022; Deaton, 2003, 2016; Gibson et al., 2017; Ravallion, 2001; Stifel & Christiaensen, 2007).

In development economics, consumption is frequently utilized as a proxy for poverty. Whilst traditionally, income remains popular, consumption has been suggested to be a more accurate indicator for low- and middle-income countries, although more difficult to measure. It is less susceptible to short term fluctuations and includes benefits that households receive from accumulated assets, thus performing better as an overall long-term indicator. In addition, consumption includes all benefits (e.g. informal transfers) a household may receive and is generally easier to report in low- and middle- income areas, where formalized and steady incomes are less common (Brandolini et al., 2010; Deaton, 2003, 2005; Meyer & Sullivan, 2003; Rahman et al., 2021; Sen, 1976; Zimmerman & Carter, 2003). Further, consumption tends to yield smoother figures over time, as it relies on permanent rather than current income (Campbell & Deaton, 1989; Zimmerman & Carter, 2003). At the same time, consumption is essential to survival, consumption smoothing often taking priority in times of crisis and even being the primary use for borrowed money (Eswaran & Kotwal, 1989).

Consumption is also an essential component in resilience and vulnerability. In times of crisis, household consumption can be viewed as both a strategic option and a constraint, representing the outcome of a resource allocation process facilitated through capabilities (Bellon et al., 2020; Praneetvatakul et al., 2013; Sen, 1985; Zimmerman & Carter, 2003). Vulnerability is the state of a household prior to a shock that determines the degree of potential affectedness if a shock, such as a drought, was to occur. In that, consumption can serve as an important indicator of how close the household is operating at its minimum consumption before falling into poverty and to what extent the household holds the means to smooth the impact, for instance through assets, capital, and general wealth. Commonly, vulnerability to poverty serves as an ex-ante indicator and predictor, regarding potential poverty (Bellon et al., 2020; Bidisha et al., 2021; Praneetvatakul et al., 2013; Zimmerman & Carter, 2003).

Resilience on the other hand is the ability of a household to “bounce back” after a shock or to transfer to a new steady state. Thereby, consumption is a strategic option in the short and medium term, as the household may elect to consume differently or to shift preferences in order to preserve resources. Consuming more efficiently or more frugally, can thus be an option to smooth impacts of shocks, while a failure to do so, can exacerbate the risk for adverse effects (Bellon et al., 2020; Béné et al., 2014; Zimmerman & Carter, 2003).

Within the concepts of resilience and vulnerability, shocks are the primary stressors, that impact the households and serve as contributors to changes in consumption. Shocks can alter the decision-making within the household up to the point of adopting suboptimal strategies to avoid risk (Gloede et al., 2015). Since shocks occur on the micro level, types and impacts of shocks are very diverse, yet they can be broadly summarized into natural disasters and demographic shocks with varying degrees of severity. Natural disasters refer to shocks that occur through extreme weather events or other natural causes, such as storms, droughts, floods, and landslides. Impacts of this type of shock can be very severe to low-income households, both physically and in terms of perceptions and preferences, especially if these are engaged in farming. In the wake of climate change and limited resources, it is worthwhile to examine the role of these shocks, both ex-ante and ex-post for the well-being of people in the affected areas. (Bellon et al., 2020; Gloede et al., 2015; Hallegatte et al., 2020; Kochar, 1995; Nguyen et al., 2020; Stein & Weisser, 2022). In recent years, Covid-19 emerged as a hyper-covariate shock throughout the world (Krauss et al., 2022). However, the pandemic rarely impacts households directly, but rather through secondary effects, such as disruptions of value chains, lower demand or job loss as well as lockdown measures (Bidisha et al., 2021).

As established by now, consumption is an essential strategic option for a household, both in terms of resilience and as a coping measure in times of shocks. Consumption strategies involve several dimensions. An economic actor may resort to home consumption of self-produced items, in its most extreme form subsistence-based livelihood or may adjust the quantity and quality of items purchased. Substitutions are an option as well as the prioritization of certain items, e.g., staple foods. Another dimension would be the share of available resources dedicated to consumption, as some might elect to spend a lower proportion of their disposable resources (Deaton, 1988; Deaton & Muellbauer, 1980; Deaton & Paxson, 1998). Considering the increasing diversity in income strategies, not all options are equally available to all actors, as for instance, a household with exclusively off-farm employed members, may not have sufficient quantities of self-produced items available anymore (Barrett et al., 2001; Deaton, 1988; Meyimdjui & Combes, 2021). Consequently, low- and middle-income countries, especially in rural areas, exhibit a wide variety of consumption patterns, ranging from purely satisfying basic needs to elaborate lifestyles, as increasing incomes open different consumption paths all within a dynamic context of opportunities and shocks (Bhattacharya & Patnaik, 2016; Hubacek et al., 2007; Senauer et al., 1986; Vasileska & Rechkoska, 2012). Subsistence households, for instance, exhibit a more diverse portfolio of crops to optimize land usage and to diversify risks and the diet. However, this may be a limitation to commercialization and participation in the local markets. More generally, the relevance of home consumption must be acknowledged, as any household, that engages in agriculture will have the option to consume its own produce (Mpogole et al., 2023; Polson & Spencer, 1991). Especially in emerging economies, the traditional image of subsistence-based farmers is challenged, as other opportunities emerge. Diversification of income sources, migration, urbanisation, and other trends reduce the relevance of agriculture and raise the question to what extent farmers in these areas retain the ability to satisfy parts of their consumption needs through their own outputs. Additionally, this process reveals elasticities in consumption in response to increased income, including an increase in quality, not just quantity as well as a potential shift to other items as substitutions. As a result, a variety of consumption patterns with smaller intra-household consumption components emerge (Barrett, 2008; Bhattacharya & Patnaik, 2016; Bouis, 1994; Holmelin, 2021; Senauer et al., 1986; Vasileska & Rechkoska, 2012).

A popular approach that contains most of the intricacies and connections of consumption described above is the "Sustainable Livelihoods Framework." Presented in 1998 and 1999 following previous Sustainable Livelihoods approaches, it adopts a complete view on a household's livelihood (Ashley & Carney, 1999; Baulch, 1996; Chambers, 1995; Chambers & Conway, 1992; Natarajan et al., 2022; Scoones, 1998). Thereby, a household is endowed with certain livelihood assets, categorized into financial, physical, social, human, and natural capital. By means of transforming structures and processes, such as laws, policies and livelihood strategies, a livelihood outcome is generated. All of these elements are influenced by contextual factors such as shocks. Regarding the term "Sustainable", vulnerability and resilience play a crucial role in the framework, as they can be detrimental or conducive to the sustainability of the livelihood outcome (Ashley & Carney, 1999; Scoones, 1998). Consumption can be placed at two different points in the framework. For once, consumption can be considered a livelihood strategy, as is converts available resources given the respective context and transforming structures and processes. On the other hand, it is related to several of the livelihood outcomes, for instance poverty and well-being. With regards to the relevance of consumption smoothing, the term "sustainable" is relevant as well.

This study focuses on the example of Thailand, that contains all previously mentioned challenges of an emerging market economy. Thailand saw rapid economic growth in the past years as modern urban centres, like the metropolis of Bangkok and the surrounding provinces developed and both the secondary and tertiary sectors have become large contributors to the GDP (Ahmad & Isvilanonda, 2003; Browder et al., 1995; Falkus, 1995; Paweenawat & Liao, 2023). However, parts of Thailand remain rural, and agriculture still serves an important role, both in policy and in the economic structure of the country. In recent years however, the rural areas began a process of transformation, with new provincial urban centres evolving and job opportunities outside of agriculture emerging. As part of this process, inequality and poverty remain pertinent issues (Ahmad & Isvilanonda, 2003; Falkus, 1995; Moore & Donaldson, 2016; Paweenawat & Liao, 2023; Thongsawang et al., 2020). In addition, migration is a popular strategy, with especially younger people leaving the rural areas to find work elsewhere and support their families back home (Moore & Donaldson, 2016; Paweenawat & Liao, 2023; Thongsawang et al., 2020). In this highly dynamic and transformative environment, it is worthwhile to analyse consumption patterns and determine which factors might incentivise which strategies.

In summary, consumption is a highly relevant component of development research, that remains heterogenous in definitions, approaches and data collection. In an increasingly globalised world and within contextualising factors such as climate change, the importance of micro level studies, that make use of the available data and provide sufficient aggregation while retaining insights at the individual level, is highlighted in the literature. Consequently, the remainder of this study contributes to the understanding and the classification of consumption strategies and the determinants of their adoption and change. Further, the factors influencing the consumption of a household are examined. Finally, all previous results are contextualized by the characteristics of the shocks, a household may be exposed to.

5.3 Methodology

5.3.1 Data

We base our analysis on a long-term panel dataset, provided by the Thailand Vietnam Socio Economic Panel (TVSEP). The panel was established in 2007 and initially covered 2200 Thai households in the provinces of Buriram, Ubon Ratchathani and Nakhon Phanom (Figure 5.1). The questionnaire only shows minor changes in codes and structures of related survey modules over the years, none of which influence the comparability of survey waves. In the following chapters, we use two waves of household survey data from the years 2017 and 2019. To ensure comparability of results, the sample was limited to the 1508 households that were present in both survey waves and showed no missing or outlier data in the sections relevant for clustering.

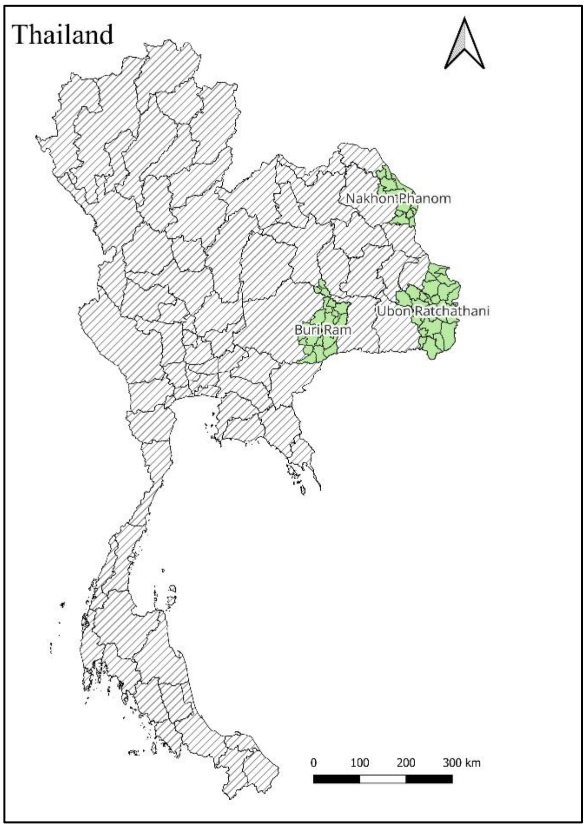

Figure 5.1 Map of the TVSEP survey provinces in Thailand
Shape source: Humanitarian Data Exchange, 2022

5.3.2 Establishing a household consumption typology

Scholars have engaged in extensive debates regarding the best way to capture consumption behaviour. One frequent source are surveys that have, however, a tendency to be inaccurate and heterogenous in methodology (Christiaensen et al., 2022; Deaton, 2005, 2016; Gibson et al., 2017; Holt, 1995). With the context of a survey, the consumption of an individual is often regarded as difficult to assess in all of its depth, requiring a certain degree of aggregation (Bouis, 1994; Christiaensen et al., 2022; Deaton, 2003; Deaton & Zaidi, 1999; Gibson et al., 2017; Holt, 1995). In this aggregation process during the survey, one must be careful however not to lose track of the individual's welfare (Deaton, 2016). This can be achieved by aggregating the individual behaviour into indicators, that capture the general direction of the consumption strategy and yet retain a dataset on the individual level (Deaton & Zaidi, 1999; Paim, 1995; Rahman et al., 2021). While such aggregations are difficult to compute and subject to a plethora of causes for noise introduced by the data, in recent years, clustering has emerged as one way to achieve balance between the retention of the micro-level and the extraction of patterns and profiles, even as part of time-series data (Anthony, 2008; Kaur & Gabrijelčič, 2022; Peng & Law, 2023; Rahman et al., 2021; Zhang et al., 2022). Careful attention must be paid to validate the methodology however, since errors in clustering are common and occur relatively easily (Kaur & Gabrijelčič, 2022; Zhang et al., 2022). In development research, the method of clustering proves helpful for assigning research units to categories, that reflect their overall livelihood strategies, well-being, and other factors, based on multiple indicators of, for instance, poverty. Thereby multidimensional concepts, such as Multidimensional Poverty Indicators become more feasible for quantitative analysis (Anthony, 2008; Peng & Law, 2023; Rahman et al., 2021).

Accordingly, we establish a consumption typology of households in rural Thailand. This allows us to detect common trends in complex and diverse consumption behavior - that are an integral part of rural livelihoods – and identify factors behind changes in and adoption of consumption behavior. We use a typology that assigns households to mutually exclusive categories, that broadly capture their consumption behavior. Several questions and sections in the dataset contain information on household expenditures and quantities consumed, however, the latter is limited to food items as illustrated in Table 5.1. In addition, we use data about the endowment of households with durable goods as well as data on household income. We consistently conduct all the steps described below across both survey waves.

Table 5.1 Consumption data in the TVSEP

Section	Subsection	Quantity	Value
8 – Expenditures	8a – Food	X	X
	8b – Nonfood		X
	8c – Transport and Communication		X
	8d – Education		X
	8e – Health		X
	8f - Social		X
	8g - Other		X
4.2 – Crops	Usage of crops: Home consumption	X	X
4.3.1 - Livestock	Usage of livestock: Home consumption	X	X
4.3.2 – Livestock Products	Usage of livestock product: Home consumption	X	X
4.4 – Natural Resources	Usage of Resource: Home consumption	X	X

Source: Own illustration.

In a first step, we calculate three indicators, that capture the basic consumption behavior and allocation of resources by a household (Table 5.2). These are inspired by consumption-based poverty indicators and draw on the literature presented earlier. “HomeCons” captures consumption of home-produced food, with food being provided through household agriculture, such as crops and livestock. Second, the share of expenditures allocated to food as one of the most essential items is captured in “FoodConsShare”, however we must keep in mind that this indicator is also subject to the chosen quality of food items and the composition of the diet. Further, to capture the endowment with durable goods and to include past and passive consumption behavior thereof, “Asset” summarizes the assets held by the household as well as housing quality. For this indicator, two options were evaluated. First, the present value of all durable assets owned by the household was added up. Second, we used the principal component analysis approach presented by Filmer and Pritchett (2001) to generate a score based on the endowment of the household with different kinds of durable assets as well as the housing quality, measured by toilet facilities, floor material, number of rooms and source of water (Filmer & Pritchett, 2001). Comparing these two options with other household characteristics, the first was determined to better reflect the nuances in household endowment.

Table 5.2 Consumption indicators used for clustering.

Indicator Name	Description	Calculation
HomeCons	Share of home consumption for food	Value of home consumed food divided by total value of consumed food
FoodConsShare	Share of household consumption dedicated to food	Value of consumed food divided by total household expenditures
Asset	Indicator of durable assets	Log of the sum of the present value of all durable assets

Source: Own illustration.

In a second step, we use these indicators to typologize households drawing on cluster analysis, effectively assigning a household to a category containing households with a similar combination of indicator values. Clustering the underlying data is not without challenge, however. As previously discussed, consumption is a complex phenomenon with a plethora of sometimes minute nuances on the household level. Observing clear cut groups, such as a dataset on species of flowers would exhibit, is therefore unrealistic. For this study, three methods of clustering were evaluated, centroid-based clustering, hierarchical clustering, and density-based spatial clustering, with centroid-based clustering proving most suitable. Consequently, k-means with 100 initial configurations and k-medoids clustering were applied, with the assignment of households into the clusters being 97% identical. Precluding clustering, data from both survey waves utilized in this study was appended with each household appearing twice, once with its

2017 indicators and once with its 2019 indicators. Before applying cluster analysis, all indicators are standardized as follows:

$$z = \frac{x - \mu}{\sigma}, \text{ where } \mu \text{ is the mean and } \sigma \text{ is the standard deviation. (1)}$$

The maximum average silhouette width of 0.33 suggests the existence of a structure, although weak and potentially influenced by the fuzzy nature of the clusters, especially in the intersecting areas in between (Kaufman & Rousseeuw, 1990). To ensure further robustness and to account for this, fuzzy c-means clustering was applied. The results thereof suggest that 90% of households can be attributed to a cluster by a margin of at least 10% and over 71% by a margin of more than 25%.

One of the perquisites of k-means and k-medoids clustering is the necessity to define a desired number of clusters beforehand. A common way is the so-called “Elbow method”, by which the number of clusters “k” (1-10) is plotted against the total within sum of squares (WSS) for each. Once a bend (“knee”) in the plot can be observed, there is a diminishing benefit of further increasing the number of clusters. Additionally, to validate the elbow method, silhouette analysis was applied with the goal of choosing the number of clusters with the most separation in-between. Consequently, this study uses three clusters, as illustrated in Table 5.3. Although the elbow method is ambiguous between three or four clusters, the silhouette analysis clearly points towards using three clusters.

Table 5.3 Results of the elbow method and silhouette analysis.

	Total WSS		**Marginal reduction of WSS**		**Mean silhouette width**	
k	**K-Means**	**K-Medoids**	**K-Means**	**K-Medoids**	**K-Means**	**K-Medoids**
1	8861.458	8861.458				
2	6178.937	6185.296	2682.521	2676.162	0.275	0.275
3	4544.53	4556.097	1634.407	1629.199	0.294	0.294
4	3980.67	3962.371	563.86	593.726	0.259	0.255
5	3462.015	3469.089	518.655	493.282	0.254	0.252
6	3014.948	3206.436	447.067	262.653	0.255	0.241
7	2766.499	2764.222	248.449	442.214	0.244	0.257
8	2494.032	2514.406	272.467	249.816	0.238	0.254
9	2327.275	2356.008	166.757	158.398	0.248	0.245
10	2182.972	2233.83	144.303	122.178	0.252	0.239

Source: Authors’ calculations based on TVSEP (2022).

5.3.3 Factors behind consumption strategies

In a third step, we shed more light on the factors influencing the households' allocation to the consumption clusters presented earlier by fitting several logistic regression models for each cluster. Table 5.4 provides an overview of the independent variables used. These variables capture different variables relevant for consumption, as suggested in the literature. We first capture household characteristics using the dependency ratio of non-working-age members in relation to working-age members. Further, the nucleus size of the household as well as the mean age of its members are used. In addition, the years of schooling of the household head, who is key to the decision making in the household are considered. Second, the financial situation of the household is considered by its income and the composition thereof, as well as the endowment of the household with resources. To take diverse income sources into account, we add two dummies that capture whether a household is engaged in off-farm or self-employment, as well as a variable capturing the remittances received. Third, the income share of agriculture is included, as almost all households pursue agriculture to varying intensities. As a potential detriment to the household's financial situation, indebtedness is also included. To proxy the households' endowment with resources, the land area and savings are included. Finally, the clustering indicators only utilize relative numbers that relate to the expenditures of a household. Therefore, we include the z-standardized per capita income and per capita expenditures. Since the values are mean-centered through z-standardization, this approach allows for conclusions regarding an increase of expenditures or an increase of income above the mean. Further, particular attention is paid to shocks that a household may be exposed to. Shocks are defined as exceptional events, such as natural disasters. The reference period for shocks in the questionnaire spans from the previous wave to the current wave, for instance meaning that the 2019 dataset includes all shocks since the 2017 wave. To account for the severity of the shocks, we include the damages of all shocks as well as the number of natural disasters to control for the type of shock. Finally, the province of the household is included to control for provincial and survey team effects.

As discussed earlier, consumption remains a phenomenon influenced by individual decisions and circumstances. Thus, finally, to account for any potential effects of the personality traits, we calculate the respective indicators of agreeableness, conscientiousness, extraversion, neuroticism and openness as part of the Big Five model (Bühler et al., 2023; McCrae & Costa, 1997). In the underlying survey instruments, the related questions are only asked for the respondent, which commonly is the household head or the financial decision maker.

Table 5.4 Independent variables

Variable	Label	Unit
Human Capital		
DepRatio	Dependency ratio	$\frac{No.of\ members\ (0-14\ and\ over\ 65)}{No.of\ members\ (15-65)}$
MeanAge	Mean age of household members	Years
Yearsschool	Years of schooling of the household head	Years
Nucmem	Number of nucleus members	No.
Social Capital		
Remit	Remittances received	PPP$ (Log)
Natural Capital		
LandAr	Land area	Rai (Log)
Livelihood Strategies		
ShareAgri	Share of income from agriculture	%
Offemp	Household engaged in Off-Farm employment	1 = Yes, 0 = No
PCOffemp	Per capita income from Off-Farm employment	PPP$/Capita (z-standardized)
Selfemp	Household engaged in Non-Farm Self-employment	1 = Yes, 0 = No
PCexp	Per capita expenditures	PPP$/Capita (z-standardized)
Financial Capital		
PCInc	Per capita income	PPP$/Capita (z-standardized)
SavVal	Value of savings	PPP$ (Log)
Borr	Total value of outstanding loans	PPP$ (Log)
Other control variables		
Prov	Province of household	31 = "Buriram", 34 = "Ubon Ratchathani", 48 = "Nakhon Phanom"
N_Shocks	Number of Shocks	No.
Natural	Number of natural disasters	No.
Loss	Total losses to shocks	PPP$ (Log)
Personality traits		
Resp_Agree	Respondent Agreeableness	Scale: 1 - 7
Resp_Consc	Respondent conscientiousness	Scale: 1 - 7
Resp_Extra	Respondent extraversion	Scale: 1 - 7
Resp_Neuro	Respondent neuroticism	Scale: 1 - 7
Resp_Openness	Respondent openness	Scale: 1 - 7

Source: Own illustration.

The independent variables presented in Table 5.4 are regressed against the log odds of being allocated to a given cluster (model 1) and against the log odds to change into (model 2) or away (model 3) from a given cluster. An appended dataset containing both survey waves is used for model 1, with the survey year being considered as a control variable. Model 2 and model 3 use both survey waves to determine changes in the cluster allocation as well as changes in the independent variables. Consequently, for models 2 and 3, a percent change between the survey waves which is then z-standardized is calculated for most independent variables, indicated by the prefix of "c" in the model results. This allows to clearly discern which changes in the conditions of a household spark a change in the consumption strategy large enough, to be placed within a different cluster, all while compensating for the natural inter-wave changes. The results of model 1, model 2 and model 3 allow to confirm or falsify the observations from the descriptive analysis of the clusters regarding their underlying socio-economic characteristics. Further, the models will allow for a clear allocation of attributes to the clusters, effectively forming the "typology".

Thereby model 1, model 2 and model 3 are specified as follows:

$$ln\left[\frac{P_i(I=1)}{1-P_i(I=1)}\right] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k \tag{1}$$

where X_k $is\ a\ set\ of\ independent\ variables$ (2)

and $I_i = 1\ if\ cluster\ was\ allocated\ and\ I_i = 0\ otherwise$ for model 1 (3)

and $I_i = 1\ if\ cluster\ was\ changed\ into\ and\ I_i = 0\ otherwise$ for model 2 (4)

and $I_i = 1\ if\ cluster\ was\ changed\ away\ from\ and\ I_i = 0\ otherwise$ for model 3 (5)

For the ease of interpretation, we report odd ratios for all models. A correlation matrix for the independent variables is provided in Table A5.10, exhibiting few signs of problematic correlation. Table A5.11 contains the one-dimensional GVIF by Fox and Monette (Fox & Monette, 1992). Neither the commonly applied threshold of 5, nor the R^2 related threshold introduced by Freund and Wilson and Vatcheva et. al (Freund & Wilson, 1998; Vatcheva et al., 2016) exhibit any concerns. The fit of model 1, model 2 and model 3 was assessed using the Hosmer Lemeshow goodness-of-fit test. Further, leverage and deviance residuals were examined and model results with and without the inclusion of outliers was evaluated. No issues were present, and the final models are presented without the exclusion of any cases. The model accuracy of 81%, as expressed by the Area under the Curve (AUC)/Receiver Operating Characteristics (ROC) can be considered excellent discrimination for model one. For model 2 and 3 the AUC ROC of between 57% and 66% signals rather poor discrimination and is influenced by the rare events nature of these models (Hosmer et al., 2013). The model results presented later indicate Nagelkerke's/Cragg & Uhler's Pseudo-R^2. The R^2 values of model 1 (0.35 – 0.38) suggest a good fit, whilst the R^2 of models 2 and 3 (0.1 – 0.2) is still passable.

5.4 Results

To get an insight into the indicators used for clustering as well as the clusters themselves, we now present selected descriptive statistics. Table 5.5 displays the mean and standard deviation of the indicators used for clustering over the whole dataset and within each cluster in every year. As can be observed, the clusters depart quite notably from the overall mean and exhibit emphasis on certain variables. Additionally, the changes between years within the clusters mirror the overall trend.

Table 5.5 Mean and standard deviation across clusters.

Year	Cluster	Households	HomeCons	FoodConsShare	Asset
2017	1	539	0.451 (0.138)	0.573 (0.122)	7.87 (1.025)
2019	1	376	0.423 (0.131)	0.618 (0.107)	7.944 (1.268)
2017	2	399	0.085 (0.088)	0.555 (0.13)	6.702 (1.09)
2019	2	581	0.069 (0.086)	0.596 (0.12)	6.687 (1.265)
2017	3	570	0.205 (0.147)	0.362 (0.118)	9.282 (1.048)
2019	3	551	0.162 (0.145)	0.409 (0.121)	9.443 (0.985)
2017	Full sample	1508	0.261 (0.198)	0.489 (0.158)	8.095 (1.473)
2019	Full sample	1508	0.191 (0.185)	0.533 (0.151)	8.008 (1.672)

Source: Authors' calculations based on TVSEP (2022).

Thus far, the clusters are formed based on the selected indicators, yet to form a typology, attributes need to be assigned to the clusters. From Table 5.5, we learn, that Cluster 1 has a focus on consumption of home-produced food and a medium endowment with assets. Cluster 2 exhibits the lowest proportion of consumption of home-produced food, consequently, a substantial portion of income is spent on buying food. Moreover, there is a low endowment with assets. Cluster 3 does consume some home-consumed food, but less than the average household in our sample and spends between 36 and 40% of income on food – still a substantial amount. Further, households assigned to cluster 3 exhibit a high endowment with assets. Following these observations, Table 5.6 provides the mean and standard deviation of selected variables, that will also be used as independent variables in the subsequent regression models of this study.

Table 5.6 Mean and standard deviation in parentheses of independent variables across clusters

Year	Cluster	Mean Age	PCInc PPPS$/Cap	DepRatio	Share Agri	Share OffEmp	Share SelfEmp	Nucmem
2017	1	44.189	1996.006	0.675	0.649	0.188	0.045	3.686
		(13.11)	(1748.682)	(0.783)	(0.395)	(0.295)	(0.154)	(1.543)
2019	1	45.032	2081.705	0.653	0.683	0.156	0.062	3.566
		(12.965)	(2352.593)	(0.774)	(0.398)	(0.291)	(0.18)	(1.484)
2017	2	46.074	1975.702	0.757	0.328	0.284	0.072	3.274
		(16.388)	(2053.336)	(0.784)	(0.429)	(0.376)	(0.207)	(1.609)
2019	2	48.653	1750.911	0.75	0.263	0.267	0.075	3.211
		(15.994)	(2033.712)	(0.786)	(0.408)	(0.376)	(0.225)	(1.571)
2017	3	40.787	2914.843	0.519	0.351	0.291	0.187	4.17
		(11.593)	(4121.693)	(0.595)	(0.4)	(0.374)	(0.309)	(1.678)
2019	3	41.28	2746.961	0.573	0.327	0.296	0.18	4.047
		(11.939)	(4005.57)	(0.65)	(0.41)	(0.386)	(0.336)	(1.747)
2017	Full	43.402	2344.964	0.638	0.451	0.252	0.107	3.76
	sample	(13.701)	(2986.204)	(0.724)	(0.432)	(0.351)	(0.245)	(1.65)
2019	Full	45.051	2196.58	0.661	0.391	0.25	0.11	3.606
	sample	(14.227)	(3002.824)	(0.74)	(0.44)	(0.365)	(0.268)	(1.657)

Source: Authors' calculations based on TVSEP (2022).

Even though the means change in absolute terms, they remain relatively robust across survey waves. Overall, Table 5.6 confirms the conclusions from Table 5.5 and a typology can be established as presented in Table 5.7.

Table 5.7 Typology of households

Cluster	Summary	Typology
1	High consumption of home-produced food, high share of food expenditures, medium wealth	Farming based, average age, medium income
2	Low consumption of home-produced food, high share of food expenditure, low wealth	Low productivity farming, diversified, low income, older age, high dependency ratio
3	Medium consumption of home-produced food, medium share of food expenditures, high wealth	Diversified, high income, younger age, low dependency ratio

Source: Own illustration.

Households in cluster 1 are primarily engaged in farming and of average age and size. Their per capita income is lower than that of households in cluster 3, but higher than that of households in cluster 2. Aside from the income, the values for cluster 3 confirm that households within this cluster follow a diversified income portfolio, as indicated by the income shares of agriculture, off-farm employment and self-employment. In addition, the households are the largest and have the lowest mean age and dependency ratio, indicating the presence of children and the younger generation in general. Finally, cluster 2 contains the oldest households with the highest dependency ratio. Despite the low consumption of home-produced food, agriculture is one livelihood strategy, however in combination with off-farm employment. In general, the mean income of households in cluster 2 is below average and the lowest overall.

As presented in the literature review, a household is embedded into a regional context, that will influence its actions by the local conditions and opportunities. Hence, Figure 5.2 shows the relative distribution of clusters across provinces and years. As can be observed, the allocation to clusters is very dynamic with plenty of changes becoming apparent. The strongest shifts are visible by a transfer of households from cluster 1 to cluster 2, especially in the provinces of Buriram and Ubon Ratchathani, a trend that is also reflected in number of assigned households as displayed in Table 5.5. This could indicate a decline in the relevance of agriculture as well as a demographic issue, considering the descriptive values for each cluster presented earlier. The assignment to cluster 3 remains fairly constant. Referring to the term "sustainable" in the Sustainable Livelihoods Framework, these descriptive observations seem to reinforce the sustainability of diversified livelihoods and the vulnerability of agricultural livelihoods.

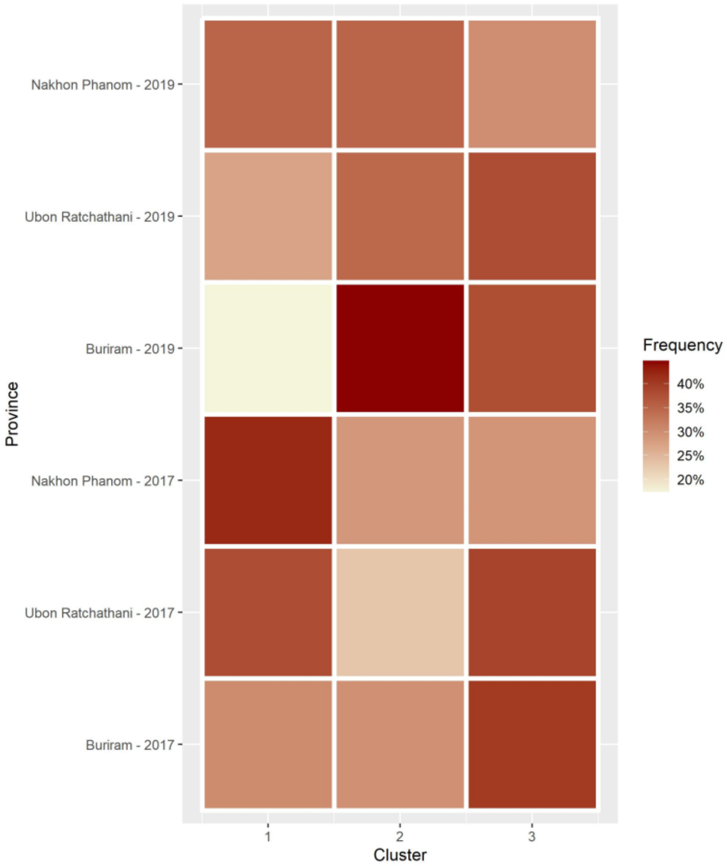

Figure 5.2 Heatmap of cluster selection by year

Source: Authors' calculations based on TVSEP (2022).

The exhibited changes in household cluster allocation, warrant further investigation. As discussed earlier, there is a degree of fuzziness in border regions of the clusters where small changes in the clustering indicators might therefore lead to the assignment to a different cluster. In Figure 5.3, we introduce a measure for "fuzzy" cases, by which the mean change in cluster indicators remained at 15% or below. The number of cases that we classify as fuzzy is negligible, as Figure 5.3 illustrates, with most households either remaining in their cluster or exhibiting large scale changes in the clustering indicators in between survey waves. Conclusively, the reasons behind the changes must lie elsewhere and are explored in subsequent models.

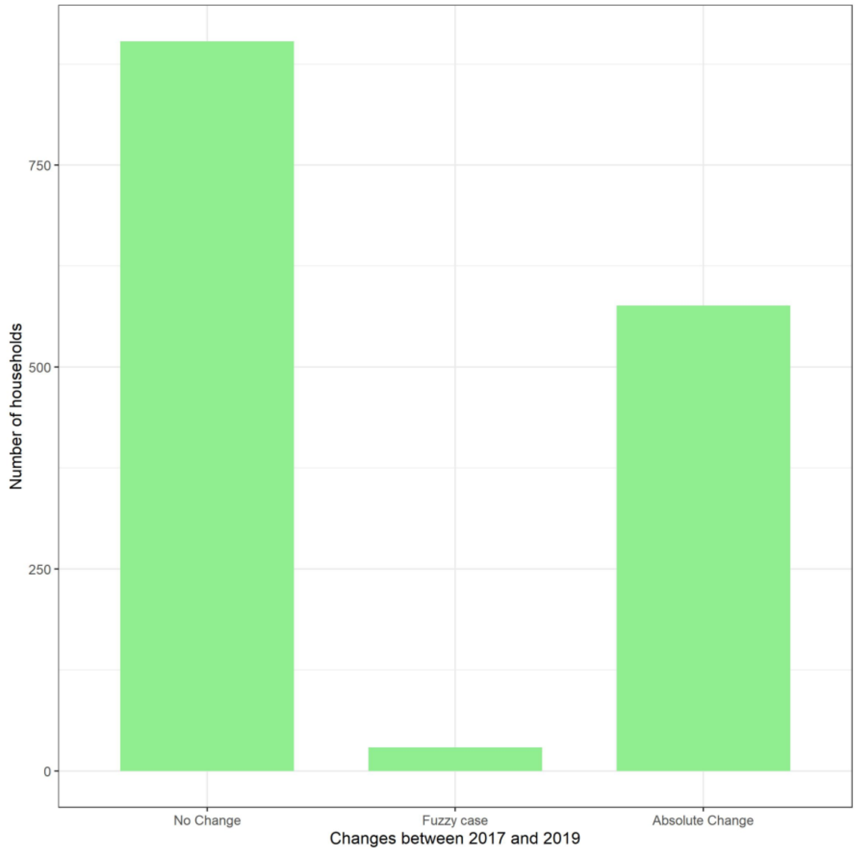

Figure 5.3 Number of households with changed consumption strategy

Source: Authors' calculations based on TVSEP (2022).

Following observations from the descriptive analysis, we conduct several regression models to gain insight into the determinants of being allocated into a certain cluster as well as the determinants that might induce a change in clusters. Model 1 aims to understand determinants of the adoption of a strategy and is presented in Table 5.8.

Table 5.8 Results of model 1 (Determinants of assignment to cluster)

	Cluster 1	**Cluster 2**	**Cluster 3**
Human Capital			
DepRatio	0.976 (0.072)	1.06 (0.072)	0.952 (0.074)
MeanAge	0.996 (0.005)	0.999 (0.005)	0.996 (0.005)
Yearsschool	0.979 (0.022)	0.915*** (0.022)	1.08*** (0.019)
Nucmem	0.749*** (0.045)	0.729*** (0.046)	1.61*** (0.043)
Social Capital			
Remit	1.011 (0.014)	1.017 (0.015)	0.981 (0.014)
Natural Capital			
LandAr	1.952*** (0.055)	0.581*** (0.04)	1.16*** (0.04)
Livelihood Strategies			
ShareAgri	1.019*** (0.002)	0.988*** (0.001)	0.995*** (0.001)
Offemp	2.519*** (0.149)	0.727** (0.136)	0.809 (0.131)
PCOffemp	0.695*** (0.13)	0.941 (0.078)	1.219** (0.084)
Selfemp	0.998 (0.143)	0.476*** (0.138)	1.865*** (0.122)
PCexp	0.442*** (0.067)	0.638*** (0.061)	3.022*** (0.066)
Financial Capital			
PCInc	1.031 (0.072)	0.923 (0.056)	1.002 (0.056)
SavVal	1.015 (0.016)	0.961** (0.016)	1.02 (0.015)
Borr	0.986 (0.013)	0.962*** (0.013)	1.048*** (0.012)
Other control variables			
Prov: Buriram	0.452*** (0.141)	1.438** (0.143)	1.532*** (0.144)
Prov: Ubon Ratchathani	0.766** (0.134)	0.812 (0.143)	1.675*** (0.141)
N_Shocks	0.976 (0.042)	0.997 (0.042)	1.025 (0.039)
Personality traits			
Resp_Openness	1.012 (0.041)	0.967 (0.041)	1.013 (0.039)
Resp_Extra	0.935 (0.049)	1.108** (0.049)	0.961 (0.048)
Resp_Agree	0.945 (0.057)	1.049 (0.057)	1.002 (0.055)
Resp_Neuro	0.928 (0.046)	1.041 (0.046)	1.036 (0.044)
Resp_Consc	0.992 (0.056)	0.881** (0.056)	1.13** (0.055)
Year	0.74*** (0.101)	1.939*** (0.103)	0.756*** (0.098)
R2	0.35	0.38	0.38
N_OBS	2745	2745	2745
K-Fold CV	0.734	0.762	0.755
Hosmer-Lemeshow_Sig	0.16	0.28	0.49

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; Standard errors (SE) in parentheses;
Source: Authors' calculations based on TVSEP (2022).

To structure the interpretation of model 1, we group the independent variables according to the livelihood assets and livelihood strategies, as described in the Sustainable Livelihoods Framework. In terms of human capital, education and the number of nucleus members are of importance, characterizing better educated and larger households in cluster 3. Each additional year of schooling will decrease the odd ratio to be in cluster 2 by 8.5%, while increasing the odds to be in cluster 3 by 8%. A larger nucleus household will increase the odds to be in cluster 3 by 61% per additional member, while it decreases the odd ratio by up to 27.1% for cluster 1 and 2. In terms of social capital, no significant influence can be observed, however the direction of coefficients points towards a higher dependency on remittances in cluster 1 and 2. Natural capital in the form of land holdings, points to smaller land sizes for the households in cluster 2, lowering the odds by 41.9% for each log rai. Especially cluster 1 is very dependent on land, with increased odds of 95.2% per log rai. A major contributor to consumption as a livelihood outcome is the livelihood strategies, which in turn influence the livelihood assets. Households in cluster 1 generate a significant share of their income through agriculture, indicated by the increase in odds of 1.9% per additional percent of agricultural income share. Additionally, households of cluster 1 seem to be very active in off-farm employment. However, as the z-standardized capita income from off-farm employments reveals, pursuing higher revenue jobs in off-farm employment increases the odds by 21.9% to be placed in cluster 3 for each standard deviation above the mean, while lowering the odds for cluster 1 by 30.5%. Another characteristic of cluster 3 is the huge statistically significant increase in odds if the household pursues self-employment. These income strategies are also reflected in the expenditures, that indicate a strong focus on cluster 3 when above the mean, while cluster 1 and 2 exhibit lower odd ratios, once expenditures rise above the mean. The indicators of financial capital are statistically significantly lower in cluster 2, with about 4% reduction in the odd ratio for the log savings and log volume of credits. The latter however is very much present in the households of cluster 3. The control variables confirm the shift from cluster 1 to cluster 2, both in terms of the year and the province. Further, households of cluster 1 show stronger presence in the province of Nakhon Phanom, while households of cluster 3 are more common in Buriram and Ubon Ratchathani, with the odd ratio increasing by up to 67.5%.

Conclusively, the results of model 1 confirm the assessment of the descriptive analysis. Cluster 1 contains households that have larger land holdings and focus on agriculture. Although off-farm employment is present, it is low in wage. The households tend to have lower expenditures for consumption and are most prevalent in Nakhon Phanom. Cluster 2 sees households with considerably less land and a low relevance of agriculture. If these households wanted to intensify their agricultural outputs, they would require additional land or shift to higher-productivity crops. Although not statistically significant, remittances may play a role for these households. The income and consumption shows that these households usually have lower than average spendings that are accompanied by a similar income level. Additionally, households of cluster 2 have less savings and are more prominent in the province of Buriram. Finally, households in cluster 3 pursue diverse income strategies with a focus on high-wage off-farm employment and self-employment, the potentially necessary higher qualification being reflected in the higher education. They do, however, still retain some agriculture and hold the necessary land. The potentially higher opportunity costs are reflected in the amount of loans. Finally, the big-five model shows some statistically significant contributors to be placed either in cluster 2 for extraversion or in cluster 3 for conscientiousness. Especially the latter may reflect the attitude that is necessary to pursue business or work in a higher-skill employment.

The observations of model 1 and the descriptives suggest some mobility between clusters in between the waves, with the most pronounced change into cluster 2. The reasons behind these changes are analyzed in model 2 and 3 drawing on the concept of push- and pull factors. Thereby, model 2 looks into factors leading to a shift into the respective cluster, i.e., pull factors, while model 3 analyzes factors to move out of a given cluster, i.e., push factors. The results of model 2 and model 3 are presented in Table 5.9, with model 2 being labelled as “pull” and model 3 as “push”.

Table 5.9 Results of model 2 and model 3 (Push- and Pull factors to change into/away from a cluster)

	Pull: Cluster 1	**Push: Cluster 1**	**Pull: Cluster 2**	**Push: Cluster 2**	**Pull: Cluster 3**	**Push: Cluster 3**
cDepRatio	0.995	1.018	0.933	0.991	1.07	0.977
	(0.111)	(0.092)	(0.098)	(0.119)	(0.104)	(0.101)
MeanAge	0.995	1.017**	1.028***	0.983*	0.968***	0.99
	(0.009)	(0.007)	(0.008)	(0.01)	(0.009)	(0.008)
Yearsschool	1.097**	0.888***	0.849***	1.117**	1.065	1.03
	(0.044)	(0.045)	(0.049)	(0.046)	(0.042)	(0.04)
cNucmem	0.684**	1.351**	0.867	1.143	1.633***	0.609***
	(0.157)	(0.122)	(0.13)	(0.139)	(0.139)	(0.15)
cShareAgri	1.298**	0.524**	0.86	1.302**	0.874	1.129
	(0.105)	(0.288)	(0.119)	(0.106)	(0.136)	(0.099)
cOffemp	1.028	0.951	0.896	1.02	1.121	0.968
	(0.211)	(0.187)	(0.186)	(0.23)	(0.203)	(0.194)
cSelfemp	0.988	0.913	1.071	1.061	0.911	1.013
	(0.278)	(0.242)	(0.243)	(0.299)	(0.26)	(0.252)
cRemit	0.865	1.168	1.012	0.789*	1.109	0.964
	(0.117)	(0.102)	(0.102)	(0.131)	(0.113)	(0.106)
cSavVal	0.948	0.986	1.012	1.071	1.067	1.001
	(0.116)	(0.099)	(0.098)	(0.129)	(0.111)	(0.104)
cBorr	1.092	0.926	0.84*	1.408***	1.149	0.898
	(0.113)	(0.098)	(0.099)	(0.132)	(0.11)	(0.102)
cLandAr	1.195*	0.701**	0.719*	1.237**	1.022	1.09
	(0.097)	(0.157)	(0.177)	(0.108)	(0.105)	(0.1)
cPCInc	1.037	1.073	0.933	1.229	1.07	0.89
	(0.147)	(0.13)	(0.128)	(0.308)	(0.18)	(0.156)
cPCexp	0.725***	1.465***	0.892	1.148	1.557***	0.588***
	(0.121)	(0.104)	(0.102)	(0.128)	(0.113)	(0.116)
Prov: Buriram	0.979	0.782	1.207	0.982	0.803	1.371
	(0.346)	(0.303)	(0.304)	(0.367)	(0.337)	(0.325)
Prov: Ubon	0.774	1.233	1.108	0.546*	1.088	1.17
Ratchathani	(0.326)	(0.288)	(0.288)	(0.355)	(0.311)	(0.306)

Natural	0.695	1.479**	1.527**	0.73	0.81	0.781
	(0.242)	(0.193)	(0.195)	(0.264)	(0.217)	(0.206)
Loss	0.99	0.999	0.985	1.01	1.025*	0.993
	(0.016)	(0.013)	(0.013)	(0.017)	(0.014)	(0.014)
Resp_Openness	0.935	1.123	0.988	1.033	1.075	0.867*
	(0.091)	(0.078)	(0.079)	(0.102)	(0.088)	(0.082)
Resp_Extra	0.958	0.99	1.169	0.887	0.858	1.073
	(0.111)	(0.095)	(0.097)	(0.126)	(0.108)	(0.101)
Resp_Agree	0.901	1.093	1.031	0.972	1.083	0.934
	(0.126)	(0.11)	(0.109)	(0.142)	(0.125)	(0.115)
Resp_Neuro	1.02	1.057	1.131	0.895	0.845	1.017
	(0.106)	(0.092)	(0.093)	(0.117)	(0.103)	(0.097)
Resp_Consc	1.022	0.873	0.767**	1.169	1.389**	1.058
	(0.132)	(0.115)	(0.116)	(0.153)	(0.136)	(0.12)
R2	0.1	0.16	0.17	0.14	0.2	0.12
N_OBS	505	505	505	505	505	505
K-Fold CV	0.759	0.607	0.615	0.811	0.704	0.679
Hosmer-Lemeshow_Sig	0.85	0.29	0.55	0.21	0.3	0.42

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; Standard errors (SE) in parentheses;
Source: Authors' calculations based on TVSEP (2022).

Generally, the results of model 2 and 3 exhibit consistency in the push factors of one cluster and the presence of opposite pull forces on a different cluster. Firstly, a change in the number of nucleus members of a household will lead to an increase in odds to move into cluster 3 by up to 63.3% per standard deviation over the mean. This trend is moderated by the mean age in the household however, with elderly households exhibiting a 2.8% increase in odds to move into cluster 2 with each additional year, while this decreases the odds to move into cluster 3 by 3.2%. If a change in cluster is present, a higher educational level of the household head will increase odds to move into cluster 1 by about 9%, while decreasing the odds to be placed in cluster 2 by 15.1% and even providing evidence to be a push-factor out of there. The relevance of agriculture as a characterizing feature of the clusters becomes visible too, as an increase in the income share from agriculture over the mean change will firmly place and lock households into cluster 1 with odds increasing by about 29.8% per standard deviation in change. This is also reflected in the acquisition of land, that provides a strong push factor out of cluster 2 and a similarly strong pull factor into cluster 1. Acquiring financial means is also important for an exit from cluster 2, as reflected in the remittances and borrowing behavior.

The role of shocks is also apparent. Cluster 1, being heavily involved in agriculture shows the strongest push effects of natural disasters with almost 47% increase in odds to leave the cluster per natural disaster incurred. The equally strong pull factor for this variable into cluster 2 provides some explanation why so many households changed from cluster 1 into cluster 2. Similarly, high losses from shocks provide a pull-factor into cluster 3 with a 2.5% increase in odds per log PPP$ lost. Combined with the increased odds to leave cluster 1 with increased expenditures, this could reflect a diversification process in the income sources of a household with higher means, when faced with natural disasters, while those with lesser means gravitate towards cluster 2. Additionally, the role of the province is not very relevant in these models, which hints at the overall applicability of these results, regardless of the province. Finally, the personality traits exhibit some influence, especially openness and conscientiousness. The former significantly lowers the odds of exiting cluster 3 by 13.3% per step in the scale, the latter increases the odds by 38.9%, while simultaneously lowering the odds to be in cluster 2 by 23.3%.

5.5 Discussion

Following our results and the literature review, we find that it is indeed feasible to assess the complex consumption patterns of rural households using regular household survey data (Anthony, 2008; Kaur & Gabrijelčič, 2022; Peng & Law, 2023; Rahman et al., 2021; Zhang et al., 2022). While it is inevitable some details are lost in the process, clustering seems a promising approach to simplify and analyse otherwise rather individual datasets and condense them into a standardized household typology. This bears implications for data collection as well since detailed consumption survey data can be expensive, rare, and inaccurate. Capturing sufficient data to compute indicators that are then aggregated into clusters on the other hand could be achieved with notably less effort, while retaining the key characteristics of the households.

Moreover, our results demonstrate the embeddedness of consumption into the livelihood of a household as a whole and reject the assumption of income being the only enabler for higher consumption (Brandolini et al., 2010; Deaton, 2003, 2005; Meyer & Sullivan, 2003; Rahman et al., 2021; Sen, 1976; Zimmerman & Carter, 2003). This confirms the crucial role of consumption in many indicators of welfare, poverty, vulnerability, and resilience as conceptualized in the "Sustainable Livelihoods Framework". Referring to the literature as well as the results of model 1, that are presented in line with the Sustainable Livelihoods Framework, the crucial role of consumption both as a livelihood outcome and a livelihood strategy becomes apparent. It is interwoven with the other livelihood outcomes in the framework and is determined by livelihood assets and -strategies just as much. The sensitivity to shocks and a lack of sustainability are also confirmed in our results (Gloede et al., 2015). While for the cluster assignment, the role of shocks seems to be of less importance, we can show that shocks lead to changes in cluster assignment between the survey years. Especially in agriculturally based households, with a higher share of consumption of home-produced food (i.e cluster 1), natural disasters can have a drastic effect on food security and consumption patterns in general, showing a low resilience to shocks (Bellon et al., 2020; Deaton & Muellbauer, 1980; Gloede et al., 2015; Hallegatte et al., 2020; Zimmerman & Carter, 2003). Models 2 and 3 show, that shocks have a particularly pronounced impact on households in cluster 1, pushing them out of this cluster. Especially poor households are “pulled” into cluster 2. Cluster 2 is a cluster that has less emphasis on agriculture but tends to be poor in income and assets, put differently, a cluster that is highly vulnerable. In contrast, cluster 3 as the cluster with the highest income and assets and a high diversification, evidenced by the income shares and the higher incomes from off-farm employment as well as the pronounced involvement in self-employment, seems to be more resilient to shocks, “pulling” wealthier households.

Nevertheless, a predominant trend emerges where most households follow the pattern of transitioning out of cluster 1 (50.4% of all transitions) into the most vulnerable cluster 2 (31.7% of all transitions) or into the more diversified, least vulnerable cluster 3 (18.7% of all transitions). Consequently, during times of crisis in Thailand, there is a noticeable shift towards reduced dependence on agriculture among households. However, this trend places vulnerable households at risk of falling into a poverty trap and challenges the “sustainability” of livelihoods in cluster 1 and 2. Moreover, it is important to note that while the dependence on agriculture reduces, agriculture remains an important livelihood strategy. Accordingly, in order for households to be resilient to the increasing occurrence of shocks, agricultural production must move towards climate-smart production.

5.6 Conclusion

We provide a household typology, based on observed consumption behaviour. As discussed in the literature, consumption is indeed a very complex and individual phenomenon, that cannot be explained entirely by input factors, such as income or by rational assumptions. This study demonstrates that clustering may well be an option to typologize households and offer insights into the individual consumption behaviour based on just a few indicators related to the household, thereby greatly simplifying the complexity of consumption patterns. The statistically significant alignment of the features of households within each cluster with common measures of livelihoods, such as those proposed in the “Sustainable Livelihoods Framework” reinforce the validity of this concept (Ashley & Carney, 1999; Natarajan et al., 2022; Scoones, 1998). This study identifies several key aspects pertaining to household consumption in rural Thailand. First, the relevance of education and diverse income sources become visible. These lead to a higher resource endowment on the one side, and to a diversified risk on the other side. The persistent role of agriculture and the marginalization of older and smaller scale subsistence households becomes apparent, as does their vulnerability to natural disasters and subsequent dependence on other income streams also outside of off-farm employment and self-employment. Thereby, the consumption behaviour of a household is not just the product of its income in absolute terms, but of the living conditions as a whole, including a regional context, as demonstrated by the significant and high impact of the provincial control variable in the models.

These findings convey important policy implications: in an ongoing climate crisis, shocks from natural disasters are likely to increase both in number and severity. In Thailand, agriculture is still an important livelihood strategy for many rural households. Adopting a diversified livelihood maximizes the resilience of a household, while lowering its vulnerability to one type of shock. At the same time, moving agricultural production towards climate-smart approaches is crucial. However, our results confirm that many agriculture-based households lack the means to diversify and change their production patterns and are thus not resilient to shocks. Our approach can help to identify these households and design targeted support for these vulnerable households that are at risk of falling into a poverty trap.

This study also has some limitations. While the underlying dataset offers data on consumption and other characteristics of a household, it is not a purpose-built consumption survey. Therefore, factors such as the change of a respondent in between survey waves – as is frequent in this type of survey - or lack of knowledge on certain household characteristics on behalf of the respondent can greatly influence the results. If for instance, the household head is interviewed, who may be very knowledgeable on all things related to the agricultural activities of the household, but not so much on the expenditures, this could affect the quality of results. If another respondent, more knowledgeable on the expenditures had answered the last survey, this could explain some of the variability exhibited by households in the panel. Thanks to a number of inbuilt quality and consistency checks in the survey, we are confident that this issue is of minor importance and does not drive our results. Additionally, some of the definitions used in the survey instrument, for instance those regarding the membership of the household and participation in consumption as well as contribution to the income, are somewhat flexible. For instance, it may be the case that in one survey year, a migrant was considered a household member, whereas in the next survey year the migrant may not be considered a household member. Obviously, this may introduce some variability between survey years. However, again inbuilt consistency checks aim to reduce such biases and we therefore believe the problem to be of minor importance.

With increasing opportunities for efficient data collection, the implementation of purpose-built and rather short consumption surveys, that capture relevant indicators for clustering would offer new ways of modelling consumption on an individual level for future research.

5.7 References Chapter 5

Abate, G. T., de Brauw, A., Gibson, J., Hirvonen, K., & Wolle, A. (2022). Telescoping Error in Recalled Food Consumption: Evidence from a Survey Experiment in Ethiopia. *The World Bank Economic Review*, *36*(4), 889–908. https://doi.org/10.1093/wber/lhac015

Ahmad, A., & Isvilanonda, S. (2003). Rural Poverty and Agricultural Diversification in Thailand. *Working Papers*, Art. 2003:19. https://ideas.repec.org//p/hhs/lunewp/2003_019.html

Anthony, E. K. (2008). Cluster Profiles of Youths Living in Urban Poverty: Factors Affecting Risk and Resilience. *Social Work Research*, *32*(1), 6–17.

Ashley, C., & Carney, D. (1999). *Sustainable livelihoods: Lessons from early experience*. Department for International Development.

Barrett, C. B. (2008). Smallholder market participation: Concepts and evidence from eastern and southern Africa. *Food Policy*, *33*(4), 299–317. https://doi.org/10.1016/j.foodpol.2007.10.005

Barrett, C. B., Bezuneh, M., Clay, D. C., & Reardon, T. A. (2001). Heterogeneous Constraints, Incentives and Income Diversification Strategies in Rural Africa. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.258371

Baulch, B. (1996). Neglected Trade-offs in Poverty Measurement. *IDS Bulletin*, *27*(1), 36–42. https://doi.org/10.1111/j.1759-5436.1996.mp27001004.x

Bellon, M. M., Pizzinelli, C., & Perrelli, M. R. (2020). Household Consumption Volatility and Poverty Risk: Case Studies from South Africa and Tanzania. *IMF Working Papers*, Art. 2020/051. https://ideas.repec.org//p/imf/imfwpa/2020-051.html

Béné, C., Newsham, A., Davies, M., Ulrichs, M., & Godfrey-Wood, R. (2014). Review Article: Resilience, Poverty and Development. *Journal of International Development*, *26*(5), 598–623. https://doi.org/10.1002/jid.2992

Bhattacharya, R., & Patnaik, I. (2016). Financial Inclusion, Productivity Shocks, and Consumption Volatility in Emerging Economies. *The World Bank Economic Review*, *30*(1), 171–201. https://doi.org/10.1093/wber/lhv029

Bidisha, S. H., Mahmood, T., & Hossain, Md. B. (2021). Assessing Food Poverty, Vulnerability and Food Consumption Inequality in the Context of COVID-19: A Case of Bangladesh. *Social Indicators Research*, *155*(1), 187–210. https://doi.org/10.1007/s11205-020-02596-1

Bouis, H. E. (1994). The effect of income on demand for food in poor countries: Are our food consumption databases giving us reliable estimates? *Journal of Development Economics*, *44*(1), 199–226. https://doi.org/10.1016/0304-3878(94)00012-3

Brandolini, A., Magri, S., & Smeeding, T. M. (2010). Asset-Based Measurement of Poverty. *Journal of Policy Analysis and Management*, *29*(2), 267–284.

Browder, J., Bohland, J., & Scarpaci, J. (1995). Patterns of Development on the Metropolitan Fringe: Urban Fringe Expansion in Bangkok, Jakarta, and Santiago. *Journal of the American Planning Association*, *61*(3), 310–327. https://doi.org/10.1080/01944369508975645

Bühler, D., Sharma, R., & Stein, W. (2023). The Big Five model in rural Southeast Asia: Validation, stability, and its role in household income*. *Journal of Personality*, *91*(6), 1364–1380. https://doi.org/10.1111/jopy.12813

Campbell, J., & Deaton, A. (1989). Why is Consumption So Smooth? *The Review of Economic Studies*, *56*(3), 357–373. https://doi.org/10.2307/2297552

Chambers, R. (1995). Poverty and livelihoods: Whose reality counts? *Environment and Urbanization*, *7*(1), 173–204. https://doi.org/10.1177/095624789500700106

Chambers, R., & Conway, G. (1992). Sustainable rural livelihoods: Practical concepts for the 21st century. *IDS Discussion Paper*, *296*.

Christiaensen, L., Ligon, E., & Sohnesen, T. P. (2022). Consumption Subaggregates Should Not Be Used to Measure Poverty. *The World Bank Economic Review*, *36*(2), 413–432. https://doi.org/10.1093/wber/lhab021

Deaton, A. (1988). Quality, Quantity, and Spatial Variation of Price. *The American Economic Review*, *78*(3), 418–430.

Deaton, A. (2003). Household Surveys, Consumption, and the Measurement of Poverty. *Economic Systems Research*. https://doi.org/10.1080/0953531032000091144

Deaton, A. (2005). Measuring Poverty in a Growing World (Or Measuring Growth in a Poor World). *The Review of Economics and Statistics*, *87*(1), 1–19.

Deaton, A. (2016). Measuring and Understanding Behavior, Welfare, and Poverty. *American Economic Review*, *106*(6), 1221–1243. https://doi.org/10.1257/aer.106.6.1221

Deaton, A., & Muellbauer, J. (1980). *Economics and Consumer Behavior*. Cambridge University Press.

Deaton, A., & Paxson, C. (1998). Economies of Scale, Household Size, and the Demand for Food. *The Journal of Political Economy*, *106*(5), 897–930.

Deaton, A., & Zaidi, S. (1999). *Guidelines for Constructing Consumption Aggregates For Welfare Analysis* (Working Paper 217). Princeton University, Woodrow Wilson School of Public and International Affairs, Research Program in Development Studies. https://econpapers.repec.org/paper/prirpdevs/deaton_5fzaidi_5fconsumption.pdf.htm

Eswaran, M., & Kotwal, A. (1989). Credit as insurance in agrarian economies. *Journal of Development Economics*, *31*(1), 37–53. https://doi.org/10.1016/0304-3878(89)90030-8

Evans, D. M. (2019). What is consumption, where has it been going, and does it still matter? *The Sociological Review*, *67*(3), 499–517. https://doi.org/10.1177/0038026118764028

Falkus, M. (1995). Thai Industrialization: An Overview. In M. Krongkaew (Hrsg.), *Thailand’s Industrialization and its Consequences* (S. 13–32). Palgrave Macmillan UK. https://doi.org/10.1007/978-1-349-23909-2_2

Filmer, D., & Pritchett, L. H. (2001). Estimating Wealth Effects without Expenditure Data-or Tears: An Application to Educational Enrollments in States of India. *Demography*, *38*(1), 115–132. https://doi.org/10.2307/3088292

Fox, J., & Monette, G. (1992). Generalized Collinearity Diagnostics. *Journal of the American Statistical Association*, *87*(417), 178–183. https://doi.org/10.2307/2290467

Freund, R. J., & Wilson, W. J. (1998). *Regression Analysis: Statistical Modeling of a Response Variable*. Academic Press.

Gibson, J., Le, T., & Kim, B. (2017). Prices, Engel Curves, and Time-Space Deflation: Impacts on Poverty and Inequality in Vietnam. *The World Bank Economic Review*, *31*(2), 504–530. https://doi.org/10.1093/wber/lhv082

Gloede, O., Menkhoff, L., & Waibel, H. (2015). Shocks, Individual Risk Attitude, and Vulnerability to Poverty among Rural Households in Thailand and Vietnam. *World Development*, *71*, 54–78. https://doi.org/10.1016/j.worlddev.2013.11.005

Graeber, D. (2011). “Consumption”. *Current Anthropology*, *52*(4), 489–511. https://doi.org/10.1086/660166

Hallegatte, S., Vogt-Schilb, A., Rozenberg, J., Bangalore, M., & Beaudet, C. (2020). From Poverty to Disaster and Back: A Review of the Literature. *Economics of Disasters and Climate Change*, *4*(1), 223–247. https://doi.org/10.1007/s41885-020-00060-5

Holmelin, N. B. (2021). National specialization policy versus farmers’ priorities: Balancing subsistence farming and cash cropping in Nepal. *Journal of Rural Studies*, *83*, 71–80. https://doi.org/10.1016/j.jrurstud.2021.02.009

Holt, D. B. (1995). How Consumers Consume: A Typology of Consumption Practices. *Journal of Consumer Research*, *22*(1), 1–16.
Hosmer, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). Assessing the Fit of the Model. In *Applied Logistic Regression* (S. 153–225). John Wiley & Sons, Ltd. https://doi.org/10.1002/9781118548387.ch5
Hubacek, K., Guan, D., & Barua, A. (2007). Changing lifestyles and consumption patterns in developing countries: A scenario analysis for China and India. *Futures*, *39*(9), 1084–1096. https://doi.org/10.1016/j.futures.2007.03.010
Humanitarian Data Exchange. (2022). *Thailand – Subnational Administrative Boundaries. Available at https://data.humdata.org/dataset/cod-ab-tha.*
Kahneman, D., & Thaler, R. H. (2006). Anomalies: Utility Maximization and Experienced Utility. *The Journal of Economic Perspectives*, *20*(1), 221–234.
Kaufman, L., & Rousseeuw, P. J. (1990). Partitioning Around Medoids (Program PAM). In *Finding Groups in Data* (S. 68–125). John Wiley & Sons, Ltd. https://doi.org/10.1002/9780470316801.ch2
Kaur, R., & Gabrijelčič, D. (2022). Behavior segmentation of electricity consumption patterns: A cluster analytical approach. *Knowledge-Based Systems*, *251*, 109236. https://doi.org/10.1016/j.knosys.2022.109236
Kochar, A. (1995). Explaining Household Vulnerability to Idiosyncratic Income Shocks. *The American Economic Review*, *85*(2), 159–164.
Krauss, J. E., Artur, L., Brockington, D., Castro, E., Fernando, J., Fisher, J., Kingman, A., Moises, H. M., Mlambo, A., Nuvunga, M., Pritchard, R., Ribeiro, N., Ryan, C. M., Tembe, J., & Zimudzi, C. (2022). 'To prevent this disease, we have to stay at home, but if we stay at home, we die of hunger' – Livelihoods, vulnerability and coping with Covid-19 in rural Mozambique. *World Development*, *151*, 105757. https://doi.org/10.1016/j.worlddev.2021.105757
McCrae, R. R., & Costa, P. T. (1997). Personality trait structure as a human universal. *The American Psychologist*, *52*(5), 509–516. https://doi.org/10.1037//0003-066x.52.5.509
Meyer, B. D., & Sullivan, J. X. (2003). Measuring the Well-Being of the Poor Using Income and Consumption. *The Journal of Human Resources*, *38*, 1180–1220. https://doi.org/10.2307/3558985
Meyimdjui, C., & Combes, J.-L. (2021). *Food Price Shocks and Household Consumption in Developing Countries: The Role of Fiscal Policy* (SSRN Scholarly Paper 3799604). https://papers.ssrn.com/abstract=3799604
Moore, J. D., & Donaldson, J. A. (2016). Human-Scale Economics: Economic Growth and Poverty Reduction in Northeastern Thailand. *World Development*, *85*, 1–15. https://doi.org/10.1016/j.worlddev.2016.04.004
Mpogole, H., Kauki, B., Namwata, B., Ngilangwa, E., Mandara, C., & Hauli, E. (2023). Can subsistence farmers commercialize? Evidence from the southern highlands of Tanzania. *Farming System*, *1*(2), 100022. https://doi.org/10.1016/j.farsys.2023.100022
Natarajan, N., Newsham, A., Rigg, J., & Suhardiman, D. (2022). A sustainable livelihoods framework for the 21st century. *World Development*, *155*, 105898. https://doi.org/10.1016/j.worlddev.2022.105898
Nguyen, T. T., Nguyen, T.-T., Le, V.-H., Managi, S., & Grote, U. (2020). Reported weather shocks and rural household welfare: Evidence from panel data in Northeast Thailand and Central Vietnam. *Weather and Climate Extremes*, *30*, 100286. https://doi.org/10.1016/j.wace.2020.100286
Paim, L. (1995). A Consumption Model for Measuring Poverty: An Exploratory Exercise. *Social Indicators Research*, *35*(2), 129–153.
Paweenawat, S. W., & Liao, L. (2023). The role of higher education on migration to cities in Thailand. *Cities*, *137*, 104309. https://doi.org/10.1016/j.cities.2023.104309

Peng, C., & Law, Y.-W. (2023). How Do Consumption Patterns Influence the Discrepancy Between Economic and Subjective Poverty? *Journal of Happiness Studies*, *24*(4), 1579–1604.

Pepermans, R. (1984). The meaning of consumption. *Journal of Economic Psychology*, *5*(3), 281–306. https://doi.org/10.1016/0167-4870(84)90027-8

Polson, R. A., & Spencer, D. S. C. (1991). The technology adoption process in subsistence agriculture: The case of cassava in Southwestern Nigeria. *Agricultural Systems*, *36*(1), 65–78. https://doi.org/10.1016/0308-521X(91)90108-M

Praneetvatakul, S., Phung, T. D., & Waibel, H. (2013). Agricultural Diversification and Vulnerability to Poverty: A Comparison between Vietnam and Thailand. In S. Klasen & H. Waibel (Hrsg.), *Vulnerability to Poverty: Theory, Measurement and Determinants, with Case Studies from Thailand and Vietnam* (S. 189–215). Palgrave Macmillan UK. https://doi.org/10.1057/9780230306622_8

Rahman, M. A., Sani, N. S., Hamdan, R., Othman, Z. A., & Bakar, A. A. (2021). A clustering approach to identify multidimensional poverty indicators for the bottom 40 percent group. *PLOS ONE*, *16*(8), e0255312. https://doi.org/10.1371/journal.pone.0255312

Ravallion, M. (2001). Growth, Inequality and Poverty: Looking Beyond Averages. *World Development*, *29*(11), 1803–1815. https://doi.org/10.1016/S0305-750X(01)00072-9

Scoones, I. (1998). *Sustainable Rural Livelihoods: A Framework for Analysis*. https://opendocs.ids.ac.uk/opendocs/handle/20.500.12413/3390

Sen, A. (1976). Poverty: An Ordinal Approach to Measurement. *Econometrica*, *44*(2), 219–231. https://doi.org/10.2307/1912718

Sen, A. (1985). A Sociological Approach to the Measurement of Poverty: A Reply to Professor Peter Townsend. *Oxford Economic Papers*, *37*(4), 669–676.

Senauer, B., Sahn, D., & Alderman, H. (1986). The Effect of the Value of Time on Food Consumption Patterns in Developing Countries: Evidence from Sri Lanka. *American Journal of Agricultural Economics*, *68*(4), 920–927. https://doi.org/10.2307/1242138

Sheth, J. N., Newman, B. I., & Gross, B. L. (1991). Why we buy what we buy: A theory of consumption values. *Journal of Business Research*, *22*(2), 159–170. https://doi.org/10.1016/0148-2963(91)90050-8

Stein, W., & Weisser, R. A. (2022). Direct Shock Experience vs. Tangential Shock Exposure: Indirect Effects of Flood Shocks on Well-Being and Preferences. *The World Bank Economic Review*, *36*(4), 909–933. https://doi.org/10.1093/wber/lhac012

Stifel, D., & Christiaensen, L. (2007). Tracking Poverty Over Time in the Absence of Comparable Consumption Data. *The World Bank Economic Review*, *21*(2), 317–341. https://doi.org/10.1093/wber/lhm010

Thongsawang, S., Rehbein, B., & Chantavanich, S. (2020). Inequality, Sociocultures and Habitus in Thailand. *Sojourn: Journal of Social Issues in Southeast Asia*, *35*(3), 493–524.

TVSEP. (2022). Thailand Vietnam Socio Economic Panel – Poverty Dynamics and Sustainable Development (Version 2022). Dataset available upon request from: Https://www.tvsep.de/en/tvsep-data-access.

Vasileska, A., & Rechkoska, G. (2012). Global and Regional Food Consumption Patterns and Trends. *Procedia - Social and Behavioral Sciences*, *44*, 363–369. https://doi.org/10.1016/j.sbspro.2012.05.040

Vatcheva, K. P., Lee, M., McCormick, J. B., & Rahbar, M. H. (2016). Multicollinearity in Regression Analyses Conducted in Epidemiologic Studies. *Epidemiology (Sunnyvale, Calif.)*, *6*(2), 227. https://doi.org/10.4172/2161-1165.1000227

Zhang, X., Ramírez-Mendiola, J. L., Li, M., & Guo, L. (2022). Electricity consumption pattern analysis beyond traditional clustering methods: A novel self-adapting semisupervised clustering method and application case study. *Applied Energy*, *308*, 118335. https://doi.org/10.1016/j.apenergy.2021.118335

Zimmerman, F. J., & Carter, M. R. (2003). Asset smoothing, consumption smoothing and the reproduction of inequality under risk and subsistence constraints. *Journal of Development Economics*, *71*(2), 233–260. https://doi.org/10.1016/S0304-3878(03)00028-2

5.8 Appendix Chapter 5

Table A5.10 Correlation matrix of independent variables

	DepRatio	Remit	LandAr	Nucmem	SavVal	Borr	MeanAge	Yearsschool	Year	Resp_Openness	Resp_Extra	Resp_Agree	Resp_Neuro	Resp_Consc	PCexp	PCInc	Offemp	Selfemp	ShareAgri
DepRatio																			
Remit	-0.187***																		
LandAr	-0.078***	0.046**																	
Nucmem	0.038**	-0.060***	0.150***																
SavVal	-0.078***	0.059***	0.157***	0.039**															
Borr	-0.137***	0.079***	0.197***	0.155***	0.079***														
MeanAge	0.183***	-0.090***	-0.092***	-0.606***	-0.049**	-0.213***													
Yearsschool	-0.158***	-0.027	0.028	-0.041**	0.099***	0.124***	-0.144***												
Year	0.014	-0.003	-0.044**	-0.061***	-0.162***	-0.090***	0.064***	0.031											
Resp_Openness	-0.031	0.027	0.047**	0.056***	0.078***	0.086***	-0.064***	0.085***	-0.084***										
Resp_Extra	0.019	0.015	0.043**	0.030	0.009	-0.005	-0.004	0.022	-0.043**	0.203***									
Resp_Agree	0.015	0.007	0.004	-0.022	0.027	0.048**	0.059***	0.023	-0.073***	0.181***	0.119***								
Resp_Neuro	-0.023	-0.017	-0.047**	0.039**	-0.066***	0.008	-0.052***	-0.029	0.023	-0.018	-0.098***	-0.225***							
Resp_Consc	0.011	-0.025	0.016	0.017	0.050***	0.034*	-0.015	0.037*	-0.053***	0.262***	0.185***	0.391***	-0.243***						
PCexp	-0.213***	0.082***	0.132***	-0.318***	0.125***	0.102***	0.112***	0.239***	0.142***	0.067***	0.037*	-0.004	-0.045**	0.039**					
PCInc	-0.142***	0.072***	0.039**	-0.079***	0.121***	0.059***	0.033*	0.176***	-0.023	0.079***	0.034*	0.022	-0.031	0.026	0.244***				
Offemp	-0.170***	-0.099***	-0.126***	0.272***	0.029	0.048**	-0.244***	0.164***	-0.022	0.035*	-0.009	0.030	0.010	0.035*	-0.084***	0.143***			
Selfemp	-0.068***	-0.059***	0.034*	0.136***	0.089***	0.094***	-0.083***	0.058***	-0.002	0.112***	0.023	0.000	-0.033*	0.049**	0.160***	0.176***	-0.049**		
ShareAgri	0.058***	0.071***	0.283***	-0.097***	0.019	0.053***	0.067***	-0.121***	-0.078***	0.008	0.019	-0.006	0.011	0.007	-0.001	-0.065***	-0.470***	-0.265***	
N_Shocks	-0.036*	0.029	0.191***	0.052***	0.086***	0.112***	-0.064***	-0.034*	0.011	0.077***	0.012	-0.022	0.022	-0.017	0.059***	-0.039**	-0.006	0.020	0.024

Source: Authors' calculations based on TVSEP (2022).

Table A5.11 Generalized variance inflation factors

Variable	M1: Cluster 1	M1: Cluster 2	M1: Cluster 3
DepRatio	1.096	1.099	1.082
MeanAge	1.367	1.374	1.316
Yearsschool	1.075	1.084	1.069
Nucmem	1.473	1.44	1.473
ShareAgri	1.359	1.242	1.298
Offemp	1.499	1.389	1.386
PCoffempnuc	1.391	1.306	1.356
Selfemp	1.142	1.126	1.132
Remit	1.06	1.071	1.056
SavVal	1.049	1.03	1.038
Borr	1.084	1.062	1.059
LandAr	1.138	1.065	1.105
PCInc	1.178	1.141	1.176
PCexp	1.237	1.177	1.237
Prov	1.033	1.04	1.034
N_Shocks	1.033	1.048	1.042
Resp_Openness	1.075	1.069	1.074
Resp_Extra	1.041	1.04	1.038
Resp_Agree	1.12	1.111	1.111
Resp_Neuro	1.062	1.051	1.054
Resp_Consc	1.144	1.139	1.143
Year	1.043	1.054	1.046
R2 Threshold	1.54	1.609	1.606

Variable	M2: Cluster 1	M2: Cluster 2	M2: Cluster 3	M3: Cluster 1	M3: Cluster 2	M3: Cluster 3
cDepRatio	1.043	1.032	1.043	1.039	1.047	1.037
MeanAge	1.073	1.057	1.069	1.073	1.076	1.073
Yearsschool	1.042	1.032	1.036	1.037	1.044	1.039
cNucmem	1.173	1.147	1.157	1.168	1.138	1.184
cShareAgri	1.045	1.037	1.025	1.045	1.063	1.039
cOffemp	1.074	1.063	1.056	1.077	1.074	1.07
cSelfemp	1.032	1.032	1.031	1.035	1.038	1.03
cRemit	1.075	1.07	1.078	1.063	1.087	1.07
cSavVal	1.031	1.044	1.044	1.041	1.039	1.038
cBorr	1.015	1.018	1.016	1.022	1.02	1.015
cLandAr	1.058	1.039	1.047	1.053	1.067	1.041
cPCInc	1.022	1.02	1.017	1.019	1.03	1.017
cPCexp	1.098	1.093	1.114	1.101	1.082	1.1
Prov	1.089	1.082	1.087	1.086	1.096	1.083
Natural	1.379	1.448	1.45	1.432	1.451	1.402
Loss	1.337	1.426	1.435	1.401	1.412	1.37
Resp_Openness	1.098	1.099	1.094	1.104	1.094	1.096
Resp_Extra	1.053	1.051	1.05	1.044	1.056	1.053
Resp_Agree	1.147	1.147	1.14	1.153	1.147	1.145
Resp_Neuro	1.081	1.086	1.09	1.085	1.086	1.082
Resp_Consc	1.185	1.174	1.183	1.189	1.182	1.191
R2 Threshold	1.115	1.208	1.25	1.188	1.16	1.141

Source: Authors' calculations based on TVSEP (2022).

6 Conclusion

6.1 Summary

In summary, this dissertation offers an insight into the diverse rural livelihoods in Northeast Thailand and their evolution over the past years.

Article one contains a detailed analysis of the livelihood strategies as well as the livelihood assets available to the households in the panel. Following a descriptive review of the data, robust linear regression highlights the successfulness of diversified income strategies to efficiently allocate the productive resources of a household. Further, household characteristics can be linked to the likelihood to pursue certain income strategies, suggesting the prevalence of entry barriers, for instance education, or the uneven availability of opportunities throughout the regions. In any case, agriculture is mostly retained, even if a household diversifies its income sources. However, the parallel occurrence of off-farm and self-employment in the same household is rare, suggesting a degree of exclusivity to each of these strategies, while agriculture is complementary.

Article two examines the consistency of non-farm employment data, which is key to assessing livelihoods and poverty. Despite other measures being available, income is still one of the most important resources to a household, constraining or enabling consumption and other strategies integral to its livelihood. The paper is structured into three main sections and uses several waves of survey data for a longitudinal approach. First, we develop an approach to match employments over survey waves. Thereby we identify and quantify large scale consistency issues and fluctuations in the off-farm- and non-farm self-employment sections. Second, we apply a multilevel logistic regression model to identify factors leading to the observed inconsistencies. While respondents do play a role, the inconsistencies are largely based on employment characteristics as well as interview length. Including personality traits according to the “Big Five”, we find that intrinsic motivation of the respondent is beneficial for obtaining consistent answers. Thirdly, we conduct a scenario analysis to showcase the potential ramifications of inconsistently reported employments. Using the simple indicator of income-based poverty, we demonstrate a substantial impact, which could raise issues for lower-level policy makers.

Article three focuses on the impact of Covid-19 on rural Thai households. Following a literature review, in which we showcase the expected effects, we present a descriptive analysis, using data from a Covid-19 special survey. We observe that Covid-19 primarily affects households that are already involved in domestic or global markets, for instance by pursuing off-farm or self-employment. While most adverse effects predicted by the literature are indeed observable and still linger, they were most severe in the beginning of the pandemic. These observations are then confirmed by applying a binary logistic regression, modelling the odds to be negatively affected by the pandemic. Following this, we conclude that vulnerability also depends on the kind of shock, as in the case of Covid-19 it was precisely the diversified and non-farm households that were affected, while subsistence-based agricultural households were not affected as much. A further result is the analysis of government transfers. Both the descriptive findings and the regression suggest that although in the beginning large amounts of money were provided in the form of support programs, these could not be sustained for very long and were not sufficiently targeted at those most in need.

Article four establishes a household typology through consumption patterns. Consumption can be seen as a livelihood strategy or as a livelihood outcome, yet it is difficult to quantify, as it is a highly complex and individual phenomenon. Applying cluster analysis, we establish a consumption typology and, using binary logistic regression, we show the characteristics of the households within the clusters to be in line with the livelihood assets as part of the Sustainable Livelihoods Framework. We thereby reinforce the consideration of consumption as a livelihood strategy as well as a livelihood outcome, that is largely determined by the resources available to the household. However, there is no direct relation between factors such as income and consumption, highlighting the complexity of the determinants of consumption decisions. Notably, households that engage in diversified non-farm income activities exhibit the highest volume of consumption and are most stable in their cluster. Further, using binary logistic regression to model the odds of changing away from and into another cluster (push-/pull), we highlight the relevance of natural disasters that drastically increase the odds to shift away from the cluster aligned with mainly agricultural activities and a potential to end up in a more vulnerable cluster. Finally, we discuss the necessity for a policy to build resilience against natural disasters for both agricultural households and households that retain agriculture as part of a diversified livelihood.

6.2 Main findings

Following the introduction, the presentation of the four articles and the summary of this dissertation, this chapter synthesizes all the results into the following combined main findings. The articles show the realities in rural Thailand that depart notably from the image of subsistence agriculture and widespread poverty. In fact, most households in the panel have diversified their livelihood in some way over the past years and seek optimal allocation of their productive resources by pursuing multiple revenue streams. The role of agriculture, however, must not be ignored, as it is still a source of food and income for most of the households and an important element to the consumption strategies of many. The key factor is the intensity of agriculture that determines consumption patterns as well as vulnerability to shocks. In general, a striking diverseness of livelihoods is revealed. This diverseness is present in almost all analytical stages, be it in terms of income strategies, demographic factors, endowment with resources, consumption, or exposure to shocks. Similarly, the disparities between households that adapt well to the transforming economy and the opportunities presented thereby and those that are unable to, are showcased. A more inclusive growth is certainly desirable, but the reality is different. Within this context of diversifying livelihoods and in the absence of opportunities in the rural areas, migration becomes a crucial component to a household's livelihood strategy. Be it for only periods at a time, or permanently, migrants work mostly in jobs outside of agriculture and provide an important income stream to the households.

Further, the results of the papers highlight the relevance of shocks. Here, two factors stand out: One, there is a diverseness in shocks, that affects households very differently and in accordance with their livelihood strategies. Two, the advantages of a diversified livelihood are highlighted again, as greater capacity to cushion the effects of shocks and less affectedness are present. Additionally, the role of natural disasters in the context of climate change becomes apparent for agriculturally based households.

A further result lies in the characterization of a household as a "managing entity" that allocates the resources it is endowed with in the subjectively best way. However, literature and results alike suggest a relevance of individual capability, as for instance expressed by the educational attainments of decision makers, providing evidence for a framework of determinants beyond simple physical resources. One such framework to encompass almost all issues discussed in this dissertation is the "Sustainable Livelihoods Framework". Its implications and causal interactions are confirmed throughout the papers presented in the preceding chapters. However, there is plenty of room for expansion and concretisation in the framework to adapt it to the contemporary challenges of transforming economies.

The final result of this dissertation is the great value of micro-level data. Only with the availability of almost unaggregated comprehensive datasets, research on the individual level becomes possible. The results thereof offer a much more detailed understanding of a subject or a region than any macro-level data ever could, especially when highlighting disparities. However, a word of caution regarding data is in order. Especially as discussed in the second article, it is of crucial importance to use high quality data and consider its accuracy, level of aggregation and consistency before use. Particularly in the context of low- and middle-income countries, data always reflects the challenging and tiresome conditions of its collection as well as budgetary constraints, thereby necessitating the careful evaluation of its usability and quality by the user precluding any research.

6.3 Policy implications

The diverseness of livelihoods and regional disparities in rural Thailand make it challenging to design policy that includes all people and contributes to a convergence of living standards in the future.

Therefore, studying the livelihoods of people can contribute to informing better policy. The first suggestion is to move away from the assumption that rural areas equal small-scale agriculture and poverty. While poverty persists in some cases, more generally it is non-agricultural income opportunities that need to become available. At the same time, agriculture, as an essential component of the rural household's livelihood strategies, needs to be recognized. Thus, capacity building, both for employment outside of agriculture as well as more productive and climate-smart agriculture, is advisable. Such capacity-building could for instance come in the form of training-centres, including those past the school-age. At the moment, migration is a popular choice to generate income elsewhere, especially for those who are better educated, however creating more local opportunities as well could help in reducing regional disparities and remove entry barriers. A rarely studied phenomenon is the occurrence of entrepreneurship in the form of non-farm self-employment. Fostering entrepreneurship could greatly contribute to a more diversified portfolio of opportunities and create economic growth in the more rural areas. The second implication for policy lies in the way shocks are treated. Following the results of this dissertation, households in rural Thailand are subject to different shock exposure, dependent on their livelihood strategy. In that, not all shocks will affect all people equally. A good example is the case of Covid-19, which, although affecting markets for agricultural produce, primarily affected those engaged in non-farm revenue seeking activities. The public support programmes however, distributed money equally, regardless of how affected a person actually was. Similarly, a primarily agricultural household shows large vulnerabilities to natural disasters, while a household with smaller agricultural involvement may not. Designing efficient disaster alleviation schemes in accordance with the risk profiles of the individual people would therefore allow for a more targeted and effective distribution of the limited funds. A side note in this is the immediate effect that shocks have on consumption. Developing efficient measures to smooth consumption, for instance by providing food instead of money that is subject to the intra-household management of resources, could prove effective in mitigating the immediate aftermath of shocks of any kind.

Finally, and thirdly, this dissertation demonstrates the value of accurate and detailed data. In low- and middle-income countries, the public records of employments, taxes, etc. often lack the quality and depth needed to perform the above-mentioned policy design. Implementing high-quality surveys and publicising the data might therefore be a solution to both inform policy and motivate research on the crucial topics of development.

6.4 Limitations and research potentials

This dissertation was written using a single dataset. Although the data is provided by a reputable project and the author was directly involved in the collection thereof, the question if and to what extent the results of this dissertation can be applied to other regions and datasets must be raised. Methodologically, a more universal application should be realistic without issues, as the underlying survey instrument and structure of the database bear large similarities with LSMS style surveys as implemented by the World Bank in regions around the world, such as in many African countries. Therefore, applying the same analytical approaches in a different regional frame is possible, especially pertaining to the issues of data consistency raised in the second paper. The results of this dissertation are of course specific to the context of northeast Thailand. The general history of a transforming economy and the subsequent challenges of integrating the rural areas into the overall development, however, are not. The results presented in this dissertation, especially due to their adherence to universal approaches such as the Sustainable Livelihoods Frameworks should therefore mostly hold true in other contexts as well. One must be careful though to apply the findings of one regional frame to another without supplemental analysis and careful evaluation. Additionally, as the second article presented in this dissertation shows, no dataset is perfect, even despite best efforts. Factors such as respondent bias, interviewer bias and other issues are impossible to eliminate entirely, and in combination with the challenging conditions on location during data collection, can create errors in the underlying dataset. Increasing technical capabilities have allowed to greatly improve data quality, for instance through automated plausibility checks and procedures for validation on location. Yet, although possible, dataset-wide consistency checks are very costly and rarely implemented. However, with advancing technology, this would certainly be an area with great potential for future research.

The results of this dissertation suggest statistically significant differences on the province level. Combined with the implications of the literature, future research should work towards the development of a framework for the analysis of the spatial context of a household, using methods such as multilevel regression models. This would extend and quantify the context factors of the Sustainable Livelihoods Framework and yield a more nuanced view on how different regional levels may have an impact on a household's livelihood.

Another potential for future research could be the development of more standardized survey instruments to accurately capture complex phenomena such as consumption, as discussed, for instance, in chapter 5. Establishing measures that reliable capture the diverse realities of rural households and are comparable across countries is subject to various issues and biases. However, technological advances allow for much more cost-effective and better-quality data to be collected, a wide-spread implementation with scientific standards, producing comparable data, would therefore be a realistic goal in the future.

The results show plenty of implications for policy makers. Building local capacity both in agriculture and non-farm occupations, creating local opportunities, fostering entrepreneurship as well as increasing disaster prevention and targeted alleviation schemes are just a few to name here. A close cooperation between researchers and policy makers in the rural areas of low- and middle-income countries could guide and develop such policy in the most effective and targeted manner. Through this, the people whose livelihoods are being studied, discussed, and assessed could actually receive a tangible benefit and potentially find assistance in navigating the future challenges.

Short Curriculum Vitae

Name:	Niels Wendt
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Secondary Education

2004 – 2011	Gymnasium Bismarckschule Hannover

Higher Education

Since 2020	Leibniz University Hannover (Doctoral student in Economic Geography)
2017 – 2019	Leibniz University Hannover (M. A. in Economic Geography)
2014 – 2017	Leibniz University Hannover (B. A. in Geography)
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Academic Career

Since 04/2023	Research Associate at Institute of Economic and Cultural Geography at Leibniz University Hannover
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List of publications

Published Articles

Nolte, K., Sipangule, K. & **Wendt, N.** (2022) Agricultural households in times of crisis. The COVID-19 pandemic, livelihoods and land-use decisions, Journal of Land Use Science, 17:1, 134-160, DOI: 10.1080/1747423X.2021.2020922

Articles in progress

Wendt, N. (-) Income strategies of Thai rural households during economic transformation. In preparation for submission.

Brooks, M., **Wendt, N.** & Waibel, H. (-) Inconsistent responses in household panel surveys: The case of non-farm employment. Survey Research Methods (Under Peer-Review).

Wendt, N. & Bierkamp, S. (-) Rural livelihoods in Thailand after two years of Covid-19. Journal of Rural Studies (Under Peer-Review).

Wendt, N. & Nolte, K. (-) How do vulnerable households navigate current challenges? A consumption typology of Thai rural households. In preparation for submission.