Essays on Debt, Personality and Well-being in Southeast Asia

Der Wirtschaftswissenschaftlichen Fakultät der

Gottfried Wilhelm Leibniz Universität Hannover

zur Erlangung des akademischen Grades

Doktorin der Wirtschaftswissenschaften

- Doctor rerum politicarum –

genehmigte Dissertation

von

M.Sc. Wiebke Stein,

geboren am 21. Mai 1990 in Hannover

2021

Referent: Prof. Dr. Stephan L. Thomsen

Korreferent: Prof. Dr. Lukas Menkhoff

Tag der Promotion: 18.01.2021

Abstract

Southeast Asian countries, such as Thailand and Vietnam, have made remarkable progress in terms of economic development over the past decades. Yet, rural areas in these countries lag behind. This dissertation studies households in such rural areas in Thailand and Vietnam. It sheds light on (i) the influence of local shocks on individual well-being, (ii) household debt behaviour and expectations towards future income, and (iii) the role of non-cognitive skills on individual labour market outcomes. Hence, it provides rich insights into the factors influencing household perceptions and decision making behaviour as well as the importance of non-cognitive skills in rural areas of Southeast Asia.

The first chapter of this dissertation provides information on the study background, the data and presents an overview of each Chapter. The remainder of the dissertation consists of four essays stretching out over the next Chapters. Chapter 2 analyses the impact of witnessing nearby flood events on a person's individual subjective well-being. While previous studies find a negative effect of directly experienced environmental shocks, this Chapter shows that observing such events also has detrimental consequences for individual well-being. We hereby compare individuals that self-reported a direct flood shock with those who did not. Additionally, it demonstrates that observing traumatic events not only impact current evaluations of subjective well-being but translate into negative future well-being expectations.

Chapter 3 studies the relation between high income expectations and over-in- debtedness. Extensive survey data on households' borrowing behavior and future income expectations were collected for this study. Using indicators of objective and subjective over-indebtedness, a strong positive relation between high income expectations and household over-indebtedness can be shown. An additional lab-in-the-field experiment reveals that over-confidence is related to over-borrowing.

The last two Chapters (Chapter 4 and 5) focus on the importance of non-cognitive skills for individual labour market outcomes in a rural labour market setting. Measures of non-cognitive skills are validated in Chapter 4, studying one of the most commonly used models capturing a person's personality, the Big Five Factor model. The results reveal a five factor structure similar to that found in samples from industrialised countries. In a next step, Chapter 5 analyses the importance of non-cognitive skills for individual occupational attainment and earnings. The findings show that non-cognitive skills are important determinants for labour market outcomes in rural labour markets. A high level of responsibility and efficiency are important characteristics with respect to occupational attainment and emotional stability is associated with higher earnings.

Keywords: Expectations, Household Debt, Local Shocks, Non-cognitive Skills, Southeast Asia, Subjective Well-being

Kurzzusammenfassung

Südostasien hat in den letzten Jahrzehnten ein anhaltendes Wirtschaftswachstum erlebt, das zu einer starken Reduktion der Armut in Ländern wie Thailand und Vietnam geführt hat. Trotz des insgesamt starken Wachstums gibt es in Teilen der Bevölkerung weiterhin unbefriedigende Lebensverhältnisse. Dies ist vor allem in ländlichen Gebieten der Fall. Diese Dissertation untersucht ländliche Haushalte in Thailand und Vietnam. Dabei werden die folgenden Themen erörtert: (i) der Einfluss von lokalen Wetterschocks auf das subjektive Wohlbefinden; (ii) der Einfluss von positiven Einkommenserwartungen auf den Überschuldungsgrad von Haushalten; (iii) die Rolle von nicht-kognitiven Fähigkeiten für die Berufswahl und das Einkommen. Insgesamt untersucht die Arbeit, welche Faktoren sich auf die Wahrnehmung von Haushalten auswirken und welche Entscheidungen damit verbunden sind. Abschließend beleuchtet sie die Bedeutung von nicht-kognitiven Fähigkeiten auf dem Arbeitsmarkt.

Das erste Kapitel dieser Arbeit gibt einen Überblick über den Studienhintergrund, die Datenbasis und einen Überblick über die einzelnen Kapitel. Im Folgenden besteht die Dissertation aus vier Essays zu den oben beschriebenen Themen. Das zweite Kapitel analysiert die Auswirkungen von wahrgenommenen Flutschocks auf das individuelle Wohlbefinden. Studien haben herausgefunden, dass direkt erlebte Umweltschocks negative Folgen für das individuelle Wohlbefinden haben. Dieses Kapitel zeigt, dass allein das Beobachten eines solchen Schocks negative Auswirkungen auf das subjektive Wohlbefinden hat. Dabei werden Individuen, die laut Selbstauskunft im Fragebogen keinen direkten Flutschock erlebt haben, mit solchen verglichen, die eine Schockerfahrung angegeben haben. Diese negativen Konsequenzen wirken sich auch auf zukünftige Einschätzungen in Bezug auf das subjektive Wohlbefinden aus.

Kapitel 3 untersucht den Zusammenhang zwischen hohen Einkommenserwartungen und Haushaltsüberschuldung. Hierzu wurden umfangreiche Daten zum Thema Haushaltsüberschuldung und zukünftigen Einkommenserwartungen erhoben. Anhand der Daten werden zwei verschiedene Überschuldungsindikatoren erstellt: ein Indikator, der sich auf die objektive Überschuldung bezieht und ein zweiter Indikator, welcher die subjektive Haushaltsverschuldung abbildet. In der Analyse kann ein starker Zusammenhang zwischen positiven Einkommenserwartungen und Haushaltsüberschuldung festgestellt werden. In einem sogenannten lab-in-the-field Experiment wird zusätzlich gezeigt, dass Selbstüberschätzung mit Überschuldung zusammenhängt.

Die letzten zwei Kapitel dieser Arbeit (Kapitel 4 und 5) fokussieren sich auf die Bedeutung von nicht-kognitiven Fähigkeiten für den Arbeitsmarkt. Dafür werden in Kapitel 4 zunächst bestimmte Messinstrumente für nicht-kognitive Fähigkeiten validiert. Hierbei handelt es sich um eines der meist verwendeten Messmodelle für nicht-kognitive

Fähigkeiten: das Big Five Faktor Model. Die Ergebnisse zeigen eine Faktorstruktur, die vergleichbar mit Ergebnissen von Stichproben aus Industriestaaten ist. In Kapitel 5 wird die Bedeutung dieser Fähigkeiten für die individuelle Berufswahl und das Einkommen analysiert. Es lässt sich feststellen, dass nicht-kognitive Fähigkeiten eine wichtige Rolle in ländlichen Arbeitsmärkten spielen. Eigenschaften wie Verantwortungsbewusstsein und Effizienz sind wichtige Determinanten bei der Berufswahl. Eine hohe emotionale Belastungsfähigkeit steht im Zusammenhang mit höheren Gehältern.

Schlagwörter: Erwartungen, Haushaltsüberschuldung, lokale Schocks, nicht-kognitive Fähigkeiten, Südostasien, subjektives Wohlbefinden

Acknowledgements

Writing this thesis has been an extraordinary experience and would not have been possible without the help and support of many people.

First of all, I want to thank Andreas Wagener. He gave me the opportunity to pursue my Ph.D. and the freedom to follow the research ideas I am passionate about. His support throughout the first years of my Ph.D. have greatly helped me become the researcher I am today. His unexpected death was challenging and I am very grateful to Stephan Thomsen and Lukas Menkhoff, who supported me during this time and kindly agreed to supervise my thesis. I would not have been able to finish this thesis without your support. I will always be grateful for that. I also want to thank Susan Steiner, Stephan Klasen, Martin Gassebner and Friederike Lenel for their support during this difficult time.

I am grateful to my co-authors, Dorothee Bühler, Theres Klühs, Melanie Koch, Rasadhika Sharma, and Reinhard Weisser. Working with you has been an invaluable experience, and I am thankful to have had the opportunity to work with you.

I also thank the German Research foundation for their financial support during my thesis via the Research Training Group on “Globalization and Development” (RTG 1723) and the Thailand Vietnam Socio Economic Panel (TVSEP). Being part of the Glad was a great opportunity. Likewise, working within the TVSEP group was a great experience and gave me the opportunity to pursue field work in Thailand and Vietnam. Getting to know these two beautiful countries and its people was an invaluable experience. Thanks to the whole TVSEP family.

Thanks to all my colleagues from Hannover, Göttingen and Berlin. Thank you, for all the lunch and coffee breaks and the fruitful discussions. Among them: Stefanos, Alessa, Axel, Björn, Claudia, Daniel, Efi, Helke, Insa, Jana, Johannes, Julia, Kai, Katharina, Lennart, Levke, Marlene, Manuel, Nathalie, Vitus. Thanks to you, the past years have been one of the greatest experience of my life.

I am also grateful for my friends outside university, who always support me, especially my Helgas aka Carmen, Charly, Lena, Lisa, Lisa, Martha, Svea, Svenja. I am fortunate to have you as my friends.

To my parents, Petra and Michael, who have supported me unconditionally for the past thirty years. I am so grateful for your love. This thesis would never have been possible without you. I also thank my brother, Torben, for being my partner in crime, my cousin, Anke, who travelled the world with me and always let me sleep on her couch in Göttingen whenever I needed to, and of course the rest of this big, crazy family. Life would not be so much fun without you.

To my partner David, thank you, for your love, patience and unwavering support in everything I do. You are always there for me, no matter what, which is the best gift anyone could hope for.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

> Development is about transforming the lives of people,
> not just transforming economies.
>
> *Joseph Stiglitz*

Southeast Asian countries have made remarkable progress in terms of economic development over the past decades. Rapid economic growth resulted in a substantial reduction in poverty levels throughout the region (World Bank, 2018). In Thailand and Vietnam, national poverty was reduced from more than 60 percent in the 1980s to under 10 percent in 2018 (Wang et al., 2020; World Bank, 2020). While the majority of the population profited from this overall economic development, inequality between rural and urban areas persists, with poverty concentrated in the rural areas (Amare and Hohfeld, 2016; Pimhidzai, Pimhidzai; ADB, 2020). Such regions do not offer the same diverse earning opportunities as urban centres, like Bangkok or Hanoi, and the majority of households living in rural areas still depend on income from agricultural production or small-scale businesses (Angelsen et al., 2014; Gloede et al., 2015; Parvathi and Nguyen, 2018). These income sources are highly susceptible to external shocks and therefore volatile. Especially, weather shocks, which have increased in recent years due to the impacts of climate change, bear the potential to threaten livelihoods as they can destroy livestock and productive assets. This makes rural households vulnerable to remain poor or being pushed back below the poverty line.

In addition to external factors, increasing household debt puts further pressure on households already struggling to cope with shocks and uncertain incomes (Schicks, 2013). Household debt is rising worldwide, especially in some countries in Southeast

Asia. Thailand, for example, is the emerging economy with the highest household debt to GDP ratio in the world (IMF, 2017). High levels of consumer indebtedness not only pose a threat to the stability of the financial system as a whole, but can be detrimental for household well-being. It is therefore crucial to understand the determinants that lead to households taking too much debt.

Another reason for why people remain vulnerable to poverty is a lack of skills. The formation of skills is a crucial prerequisite to find quality jobs that provide secure incomes (Van Trotsenburg, 2018; World Bank, 2017). In addition to cognitive skills, like education, the importance of non-cognitive skills for occupational outcomes has been highlighted extensively (e.g., Almlund et al., 2011; Heckman and Kautz, 2012) Non-cognitive skills, i.e., a person's personality and preferences, are especially important for individuals with lower levels of education. In settings where education is distributed rather homogeneous, non-cognitive skills may explain why some individuals do better than others (Heckman et al., 2006; Laajaj et al., 2019).

This dissertation contributes to understanding different factors that influence vulnerability to poverty. It consists of four essays that are presented over the next Chapters. While the first two essays focus on the impacts of external shocks and household debt behaviour, the remaining two essays concentrate on the importance of individual skills for development outcomes. In particular, the first essay studies the impact of observing adverse weather events on individual well-being. The second essay studies one possible reason of household over-indebtedness: high income expectations. Essays three and four concentrate on non-cognitive skills and rural labour market outcomes. Measures for non-cognitive skills are first validated for a rural sample in Southeast Asia and then used to analyse the importance for occupational attainment and earnings.

The findings of this thesis are meaningful beyond the context of rural households in Thailand and Vietnam for three reasons: (i) most of the world's poor live in rural areas (IBRD, 2017), therefore, the findings in this thesis provide relevant insights for other rural regions, (ii) household over-indebtedness can be regarded as a global problem. Yet, this field is under researched and lacks answers as to why people are over-indebted (Zinman, 2015). This dissertation provides valuable insights regarding the problem of rising household debt and its determinants, (iii) the increasing frequency of adverse weather events is a worldwide phenomenon and challenges development efforts around the globe.

All chapters are based on empirical data from the Thailand Vietnam Socio Economic Panel (TVSEP)[1] and a TVSEP add-on project conducted in Thailand. The TVSEP sample covers around 4,000 households in three Thai (Buriram, Nakhon Panom, and Ubon Ratchathani) and three Vietnamese (Dak Lak, Ha Tinh, and Thua Thien Hue) provinces. The first wave was collected in 2007, with subsequent waves in 2008, 2010, 2011, 2013, 2016, 2017, and 2019. The sample is representative of the rural population on the household level. This thesis utilises data from the waves collected between 2007 and 2017. While Chapter 2 draws on data from all of these years and combines them with geo-spatial data on local flooding, Chapter 4 and 5 capitalise on the data collected in 2017. Chapter 3 is based on data from a special add-on project conducted in November 2017. These data are complemented with data from previous TVSEP waves. The add-on project took place in Ubon Ratchathani, Thailand. It collected survey data among 750 households and another 604 of those households participated in a lab-in-the-field experiment, complementing the survey data.

Summary of Chapters

Chapter 2, co-authored with Reinhard Weisser, analyses the effects of observing local flood events on individual subjective well-being. Previous studies found a negative effect of directly experienced environmental shocks on subjective well-being levels (e.g., Maddison and Rehdanz, 2011; von Möllendorff and Hirschfeld, 2016; Sekulova and Van den Bergh, 2016). However, evidence on how such events affect individuals merely observing them is lacking. Therefore, we study the impact of local floods on the subjective well-being of individuals who did not report any direct flood shock experience but witnessed a flood event in their close vicinity. Our hypothesis is based on findings from the psychological field which find that witnessing traumatic events can cause severe mental stress, which can ultimately lead to a decrease in quality of life (e.g., Figley, 1995; Potter et al., 2010; Cocker and Joss, 2016).

We link the TVSEP panel data with extensive geo-spatial data from a NASA flood mapping project. This allows us to identify shocks that have been witnessed by respondents that did not report any actual flood experience. We call such events tangential shock events and specify them based on the geo-spatial data that provide precise information on any flood event occurring in a person's sphere of interest.

Employing a multinomial logit model, we show that tangential shock events indeed lower individual subjective well-being for those individuals without a direct shock expe-

[1] More information can be found on the project webpage: `https://www.tvsep.de/overview-tvsep.html`.

rience. These effects also translate into negative expectations regarding person's future well-being evaluations. Overall, we contribute to the literature on the determinants of subjective well-being dynamics and show that not just directly experienced flood shocks but also tangential shock events have negative consequences for well-being levels.

Chapter 3 studies the relationship between positive future income expectations and over-indebtedness. In this essay, which is joint work with Theres Klühs and Melanie Koch, we study one possible driver of household debt: high income expectations. We contribute to the scarce literature on the determinants of household over-indebtedness, offering insights into the role of income expectations. Employing data from the TVSEP add-on project in Thailand, we construct indicators for subjective and objective over-indebtedness as well as a new indicator for income expectations.

We control for a variety of individual and household characteristics, as well as for shock exposure. Finally, we examine data from a lab-in-the field experiment to analyse whether overconfidence acts as a possible channel between expectations and household debt. The results show that positive income expectations are indeed linked to household over-indebtedness. We observe some variation in results with respect to the objective and subjective debt-measures and additionally show that higher certainty regarding expected income is also linked to higher debt levels. Our results are supported by the additional lab-in-the field experiment: Respondents who overspend in the experiment are also more likely to display higher real-life debt levels. Moreover, we find that overconfidence is related to overspending in the experiment.

Chapter 4 and 5 focus on the measurement of non-cognitive skills and their importance for labour market outcomes in rural Thailand and Vietnam. These chapters are joint work with Dorothee Bühler and Rasadhika Sharma. They are motivated by the fact that pre-existing studies on measurement and importance of non-cognitive skills concentrate on samples from western, educated, industrialised, rich, and democratic, also referred to as WEIRD (Heinrich et al., 2010) countries (e.g., Cobb-Clark and Tan, 2011; Thiel and Thomsen, 2013; Wells et al., 2016). Labour markets in emerging and developing countries differ from those in industrialised countries, because they are more labour intensive, credit constrained, and prone to greater earnings instability (Banerjee and Duflo, 2007; Campbell, 2011; Campbell and Ahmed, 2012; Gollin et al., 2014). Therefore, personality traits may be valued differently between labour markets.

Only few studies address the importance of personality in non-WEIRD populations. Existing studies employ data from students and relatively better educated individuals living in urban centers (e.g., Laajaj et al., 2019; Schmitt et al., 2007). We expand the discussion on the validity of the measures on non-cognitive skills and the importance of those skills for labour market outcomes to a rural sample. We thereby contribute to the literature on the factor structure of personality traits as well as their importance for occupational outcomes outside WEIRD populations.

Chapter 4 validates the standard measurement model of personality, the Big Five Factor model, for a rural sample. We test the internal and external validity of the measures, their stability over time and check for measurement bias. We find five factors similar to the structure of the standard Big Five Factor model. The results further show internal and external validity of the measures. The tests for internal consistency of the measures reveal lower values for our rural sample when compared with studies from industrialised countries. This is in line with observations from Laajaj et al. (2019). Analysing the stability of the traits over time reveals stronger stability for higher educated respondents. Overall, we conclude that the measures can be applied for a rural sample in Southeast Asia.

Chapter 5 addresses the importance of non-cognitive skills for occupational attainment and earnings in non-WEIRD populations. To capture a person's personality, we use nine measures (the previously validated measures on the Big Five personality traits, locus of control, risk, trust, and patience). The results reveal that non-cognitive skills are relevant determinants for occupational outcomes in rural Thailand and Vietnam. We observe that being responsible, efficient and hardworking (referred to as conscientiousness in the model) is especially important with respect to occupational attainment. Individuals with higher levels of conscientiousness are more likely to be employed in jobs outside farming. The importance of conscientiousness for occupational attainment has also been highlighted by studies from industrialised countries (e.g., Barrick and Mount, 1991; John and Thomsen, 2014). Findings with regards to occupational earnings differ from those in WEIRD populations. We find that emotional stability, i.e., the ability to cope well with stress, play a vital role for higher earnings. This is in line with findings from Laajaj et al. (2019). Additionally, we show that effects of non-cognitive skills differ across the earnings distribution. This paper is published in *Labour Economics*.

Chapter 2

Observing Traumatic Events: Indirect Effects of Flood Shocks*

with:
Reinhard Weisser

* We thank Lukas Menkhoff, Stephan Thomsen, Susan Steiner, Stefanos Tsikas, Andreas Wagener and seminar participants in Göttingen, Hannover and London for their advice and input on previous versions of this paper. We further acknowledge helpful comments from participants at the Nordic Conference of Development Economics (Gothenburg), the Annual Conference of the International Quality of Life Society (Innsbruck), the World Conference of the Spatial Econometrics Association (Singapore), the Annual Conference of the Scottish Economic Society (Perth), the International Conference on Globalization and Development (Göttingen), and the Annual Congress of the European Economic Association (Köln). Financial support by the German Research Foundation (DFG) via the Research Training Group 1723 and the Thailand Vietnam Socio Economic Panel (Project No. 283672937) is gratefully acknowledged.

2.1 Introduction

Extreme weather events, such as floods and heavy rain, can not only severely affect a person's economic situation but can also have repercussions on a person's subjective well-being.[1] Recent studies address the impact of directly experienced shock events on individual subjective well-being (SWB) and demonstrate that adverse shock events can lower SWB levels (e.g., Maddison and Rehdanz, 2011; von Möllendorff and Hirschfeld, 2016; Sekulova and Van den Bergh, 2016). However, until now, there has been little evidence on how shock events that are witnessed but not directly experienced affect individual SWB. Psychological and medical research, in contrast, has long discussed the impacts of traumatic events on the mental well-being of individuals who observe such events or hear about them from others (e.g., Figley, 1995; Potter et al., 2010; Cocker and Joss, 2016). These studies show that witnessing traumatic events can cause severe stress, consequently resulting in a decrease in quality of life. However, the topic has received little attention in the literature on SWB dynamics or in the economics literature in general. Thus, the potential ramifications of these experiences for economic decision-making are neither known nor incorporated into economic analyses.

We investigate this phenomenon from an economics viewpoint and ask the following question: What are the repercussions of witnessing nearby shock events on the SWB of individuals who did not experience any direct shock exposure? We call such events *tangential shock events (TSEs)* and argue that a recorded decline in well-being may not exclusively reflect shock-related economic losses but may also entail a transitory shift in perceptions.

The scenario we study to demonstrate the impact of TSEs on subjective well-being is flooding in rural villages in Thailand and Vietnam. Floods pose a severe threat to livelihoods, in particular to rural agricultural communities. Their frequency and severity have increased in many regions and will likely become even more prominent in the future (IPCC, 2014). This also suggests an increase in the relevance of TSEs in the future.

To study the influence of witnessing shock events, we use data from an extensive household panel survey in Southeast Asia, as well as high-resolution satellite-based flood data. Within our analysis, we apply a multinomial logit model, which allows us to identify whether TSEs (and other factors) exert a differential effect on positive and negative well-being dynamics. This approach is related to prospect theory (Kahnemann

[1] Subjective well-being can be defined as a function of an individual's personality and his/her reactions to different life events (Stevenson and Wolfers, 2008), or as Diener (2006, p. 400) puts it: "Subjective well-being is an umbrella term for the different valuations people make regarding their lives, the events happening to them, their bodies and minds, and the circumstances in which they live".

and Tversky, 1979) and accounts for different evaluations of SWB above and below a reference point.[2] Ultimately, we find that the mere presence of a flood event can indeed lower individual subjective well-being levels, even if individuals were not affected by the flood itself. Individual behavioural reactions might thus be triggered not only by directly experienced events but also by tangential shocks.

In our sensitivity analysis, we demonstrate that this effect is a robust phenomenon: it is seen even when controlling for potential village network effects, the emergence of coping strategies, unobserved household characteristics, agricultural dependency or indirect psychological effects.

Having established a robust relation between TSEs and subjective well-being, we further investigate whether this is merely a temporary phenomenon or has lasting consequences.

Our research adds to the literature on the determinants of SWB, particularly to a better understanding of the impact of severe weather events. These events will become more prominent in the future due to the effects of climate change. This is especially true for vulnerable households living in rural developing areas of the world. We therefore demonstrate that flood shocks not only have the potential to destroy a person's economic well-being but also may have severe indirect effects on the individuals witnessing these shock events by lowering their subjective well-being. The phenomenon we describe not only results in current evaluations of SWB being altered but it impacts the formation of expected future SWB dynamics.

The paper is organised as follows: We first present a short literature overview (Section 2.2). In Section 2.3, we explain our empirical approach and the derivation of our tangential shock indicators. This is followed by our empirical analysis (Section 2.4), including a detailed sensitivity analysis. We end with a discussion of our results in Section 4.4.

2.2 Related Literature

For our research on the impact of tangential shock events, we built upon the literature on the determinants of subjective well-being, such as sociodemographic and socioeconomic factors. In addition, our research also draws upon the literature on shock events, both from an economic and psychological perspective. To subsequently showcase our

[2] A \$1,000 increase in income might raise SWB to a lesser extent than a \$1,000 decrease would lower SWB. Within our research, the presence of a shock could result in negative SWB dynamics, yet its absence would not necessarily translate into positive SWB dynamics.

contribution, i.e., establishing the relevance of TSEs, we briefly sketch the main lines of thought in the relevant strands of the literature.

Sociodemographic factors Sociodemographic determinants of SWB have been reviewed extensively (e.g., Myers and Diener, 1995; Easterlin, 2003; Helliwell, 2006; Reyes-García et al., 2016). Factors such as age, education, gender, health, and personality explain a substantial degree of the variation in SWB levels (Diener, 1994; van Praag et al., 2003; González et al., 2005). Moreover, close relationships (mostly measured through marital status) and strong religious beliefs have a positive effect on SWB. Poor health, in contrast, is mostly associated with lower levels of SWB (González et al., 2005; Dolan et al., 2008).[3] Many studies address the relationship between SWB and personal life events, such as unemployment, marriage/divorce, educational achievements, or the death of a family member (Clark and Oswald, 1994; Luhmann et al., 2012; Pedersen and Schmidt, 2014). Most of the authors argue that the impacts of such events only prevail in the short run (Diener, 1996; Luhmann et al., 2012).[4]

Socioeconomic factors Another intensively investigated group of determinants are material circumstances, i.e., income or assets. In general, these studies find a positive relationship between income levels and SWB (Easterlin, 2008). Currently, there is some level of consensus that income has positive but diminishing returns (Dolan et al., 2008). In lower-income countries, income plays a more prominent role in individuals' happiness than in wealthier nations (Diener and Biswas-Diener, 2002; Reyes-García et al., 2016). Evidence also suggests that relative income matters for SWB (Luttmer, 2005; Clark et al., 2008; Dolan et al., 2008). In the context of our research (with Thailand and Vietnam being the countries of interest), income plays a significant role in the determination of personal well-being. These economic factors are of particular relevance for our research since they are almost surely affected by flood shocks and are thus correlated with our variables of interest. We therefore include controls for a person's sociodemographic and socioeconomic situation in the analysis.

[3] Although most studies on sociodemographic traits focus on high-income countries, it is worth noting that different studies find a sort of "unique happiness equation" (Veenhoven, 2010; Sarracino et al., 2013; Reyes-García et al., 2016; Markussen et al., 2018). Ultimately, the most essential findings on SWB not only hold in high-income countries but also hold in lower and middle-income countries.

[4] Recent work on panel data has revealed mixed results, showing that the effects of life events are heterogeneous and can have long-lasting repercussions on SWB (Lucas et al., 2003; Lucas, 2005).

Environmental shocks Other recent studies assess the direct impact of severe weather events on SWB levels and have demonstrated that the adverse effects on SWB may also result from unfavourable climate conditions or environmental shocks (Maddison and Rehdanz, 2011). Flooding has an especially persistent and strong negative effect on SWB (Luechinger and Raschky, 2009; Sekulova and Van den Bergh, 2016; von Möllendorff and Hirschfeld, 2016). Sekulova and Van den Bergh (2016) compare data from individuals living in flood-prone regions in Bulgaria to data from those who live in areas without flood occurrence. While they find a strong negative impact of flooding on SWB, they also point out that intangible factors, e.g., psychological damage, explain a large part of the negative effects on SWB levels. They stress that "expecting a flood can be equally traumatic as experiencing the disaster itself" (Sekulova and Van den Bergh, 2016, p.56). We follow this idea of indirect psychological consequences from (flood) shocks and shift the attention from *expecting* to *observing* an environmental shock *without being hit* by it.

Observing traumatic events Our research therefore also relates to psychological and medical studies on the effects of witnessing traumatic events (Figley, 1995; Abendroth and Flannery, 2006; Sabo, 2006; Frančišković et al., 2007; Potter et al., 2010; Patki et al., 2014, 2015; Cocker and Joss, 2016) and the literature on the externalities associated with terrorist attacks (Bozzoli and Müller, 2011; Finseraas and Listhaug, 2013). Psychological studies have revealed, for instance, that caring for traumatized individuals can cause severe mental trauma for the caregiver, such as nurses or social workers, as well as the wives of veterans. Experimental studies have shown that even rats are affected by tangential shocks, i.e., observing other rats being socially defeated by a predator (Patki et al., 2014). Overall, observing traumatic events may increase the risk of developing post-traumatic stress disorder or may raise levels of anxiety, even without direct exposure to the threatening event. Both outcomes are ultimately related to a decrease in quality of life and well-being.

2.3 Study Design

2.3.1 Data

In this paper, we use two types of data. First, we draw upon micro data originating from an extensive household survey in rural Thailand and Vietnam, called the Thailand Vietnam Socio Economic Panel (TVSEP) (Klasen and Waibel, 2013).We link these household data with high-resolution satellite-based flood data to investigate the differential responses of individuals to precisely localised flood shock events.

2.3.1.1 Household data

The TVSEP data have been collected since 2007 in Thailand and Vietnam. For the purposes of this research, we use the data obtained from the six waves between 2007 and 2016.[5] The survey is conducted in six rural provinces, three in each country (cf. Figure A.1). When the survey started in 2007, 4,381 households in 440 villages were interviewed.[6] The same households have been interviewed in each wave.[7] Across the different waves, the respondents within the households have varied in a number of cases. We thus treat the data set as linked cross-sectional observations of individuals in our main analysis and use the full household panel structure in our sensitivity analysis.[8]

Respondents in our sample typically originate from rural, multigenerational households. They are on average 50 years old, and the majority are married (84%) and engaged in subsistence farming (70%). The sample is balanced in terms of gender, and education levels are relatively low-76% have completed primary schooling at best. The information on individual health dynamics is mixed; approximately 30% (11%) of the respondents stated that their health status is worse (better) than one year before. A detailed overview of all variables used in the analysis can be found in Table A.1 in the appendix. For our analysis, we use a pooled sample that includes respondents at least 15 years of age who lived in households that did not move between 2007 and 2016 and for whom the interview date could be identified reliably.[9]

In addition to information on sociodemographic characteristics, the survey's household questionnaire elicits detailed information on agricultural production, income sources and assets, and individual or household well-being. We enrich the basic household dataset with information on household location, which is available from 2016 onward. Household locations are recorded using GPS devices, which provides us with coordinates for most households in the sample. Since the TVSEP survey has a particular focus

[5] The waves took place in 2007, 2008, 2010, 2011, 2013, and 2016.

[6] To identify a group that is representative for the rural population, approximately 2,000 households in each country were selected through a three-stage cluster sampling strategy (cf. Hardeweg et al. (2013)).

[7] In 2011 only one province in each country was surveyed.

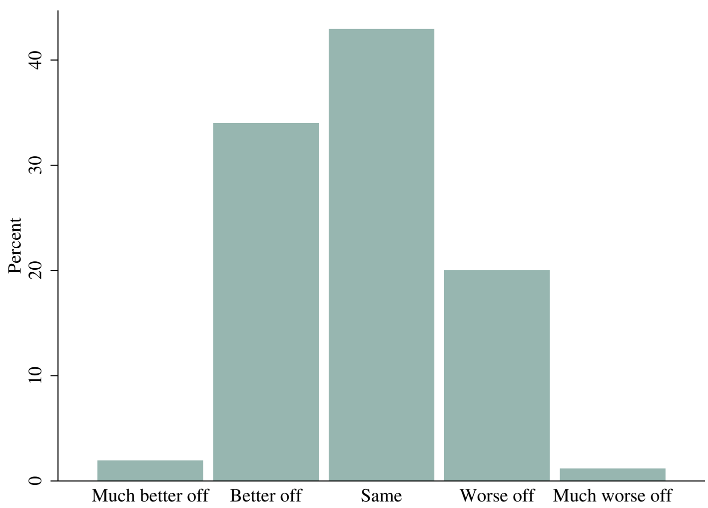
[8] We follow the idea of Ferrer-i Carbonell and Frijters (2004), pointing out the relevance of unobserved, time-invariant factors correlated with likely determinants of subjective well-being. Therefore, we also present random- and fixed-effects specifications (Tables A.9 and A.10).

[9] Sometimes the interview date could not be determined. The household was then excluded from the analysis since we need a precise interview date to link the data with the respective shock events.

on the effects of shocks on vulnerable households in Southeast Asia, respondents also answer detailed questions about their own and their household's shock experience since the last survey. We use this information as our measure of direct flood shock experience. 10% of respondents stated that their household was hit by a flood or heavy rain shock, and more than half of these households were affected by a severe shock event.

Our outcome variable is self-reported subjective well-being.[10] The relevant survey item is formulated such that respondents identify their level of well-being in relation to one year ago. The question posed to the respondent reads: *"Do you think you in person are better off than last year?"*. Each respondent can choose between five answers, namely, *(1) Much better off, (2) Better off, (3) Same, (4) Worse off, and (5) Much worse off.* Only a few respondents chose categories (1) or (5) (see Figure 2.1). We therefore regroup the categories, such that answer options (1) and (2) are summed up in one category and options (4) and (5) form another category, yielding three categories of well-being dynamics: "better off" (ΔSWB^+), "same", and "worse off" (ΔSWB^-).

Figure 2.1: Distribution of subjective well-being on the individual level (5-point scale)



Note: The figure displays the relative frequency of individually reported subjective well-being dynamics. The number of individual-year observations (N=19,901) refers to the unrestricted base sample and includes respondents from all waves from 2007 to 2016.

We also conduct a balance test to evaluate the ex-ante comparability of respondents across a range of sociodemographic variables with respect to both their direct expe-

[10] We focus on individual subjective well-being levels because the respondents' assessment of well-being at the household level would still be the outcome of a cognitive process on the individual level, and thus susceptible to the influence of individual traits and perceptions. Our data also show that reported well-being dynamics at the household and the individual level are highly correlated.

rience of flood shocks and their exposure to tangential shocks (cf. Table A.2). Only in the case of Vietnamese respondents did we observe some differences between those who experienced a direct shock and those lacking such an experience. To address this, we include the respective sociodemographic variables (income measures, age, marital status, health dynamics, educational attainment and occupation) as control variables in all our models, as well as a country dummy.

2.3.1.2 Spatial data on flood events

In addition to the household data, we use derivatives of the NASA/DFO MODIS[11] near-real-time global flood mapping product (Nigro et al., 2014) to identify tangential flood shock events (see Section 2.3.2 for a detailed definition and explanation of our identification approach). Based on the satellite data, the flood mapping algorithm provides information on flood water (FW) events with a relatively high degree of spatiotemporal precision. Flood events are identified if the algorithm detects water-like electromagnetic emissions outside reference water areas, i.e., the sea, lakes or rivers. The information on flood water events is provided at a spatial resolution of approximately 250x250 meters: for each of these tiles (or pixels), the number of flood water days within the observation interval is recorded.[12] Based on the derivation algorithm (Nigro et al., 2014), the day count for flood water can be interpreted as a lower bound.

[11] The measuring instrument on board the satellites is called Moderate Resolution Imaging Spectrodiameter, hence the acronym MODIS.

[12] Since the detection algorithm relies on surface reflections, cloud coverage imposes a severe limitation. To overcome this issue, we use the 14-day composite product. Each daily observation in this interval is included as non-missing if three cloud-free observations originating from the respective reference day or the two previous days are available. In addition, a flood water day is only recorded if water has been detected at least three times among the six satellite transits within this 3-day interval. The corresponding data for Thailand and Vietnam (covering 2004 to 2016) have been kindly provided by NASA on special request. We are grateful for their support. A further merit of flood identification based on multiple water detections is a substantially reduced likelihood of false positives, which can be caused by cloud or terrain shadows, both generating emissions in a wavelength similar to water. Ultimately, recorded flood water days for each tile and each of the 26 yearly observation intervals range from 0 to 14 days (15 or 16 in the case of a year's last interval).

2.3.2 Definition and identification of shock events

In our research, we want to distinguish between the impact of directly experienced shocks and tangential shock events. We define the latter as follows:

> *A tangential shock event (TSE) is an event of potential shock exposure, i.e., a shock event occurring in the local or social vicinity (sphere of interest) of an individual or household. Such an event may be merely observed by an individual without any immediate consequence for the observer's economic well-being or health.*

This implies that tangential shocks should only be *observed*, i.e., their occurrence *could* have been noticed, but actual shocks were not *directly experienced* or reported as an adverse event hitting a household or individual. Relevant direct shock events are those with the potential to reduce levels of well-being in general and in an economic sense, i.e., by causing income or productive factor losses, unforeseen expenditures, or the loss of assets. Ultimately, this *relevance criterion* implies that an individual or household is vulnerable to such a shock, or otherwise well-being should not be affected directly. The *relevance criterion* is met by the households in the TVSEP. Households in the sample are mainly dependent on agricultural or livestock production and thus can be considered vulnerable to shocks (cf. Klasen and Waibel, 2013). Additionally, these data feature detailed information on a wide range of actual shock experiences.

In the context of these vulnerable households, flood shocks are especially harmful because they can diminish crop yields and livestock production, with the potential to be life-threatening. Furthermore, flood and heavy rain shocks have the potential to destroy nonproductive factor assets, such as homesteads.[13] Another characteristic of these shocks is their high degree of visibility: Flooded fields or drowned livestock can be visually detected by respondents. Such a severe event can be recalled easily and reliably at the interview.

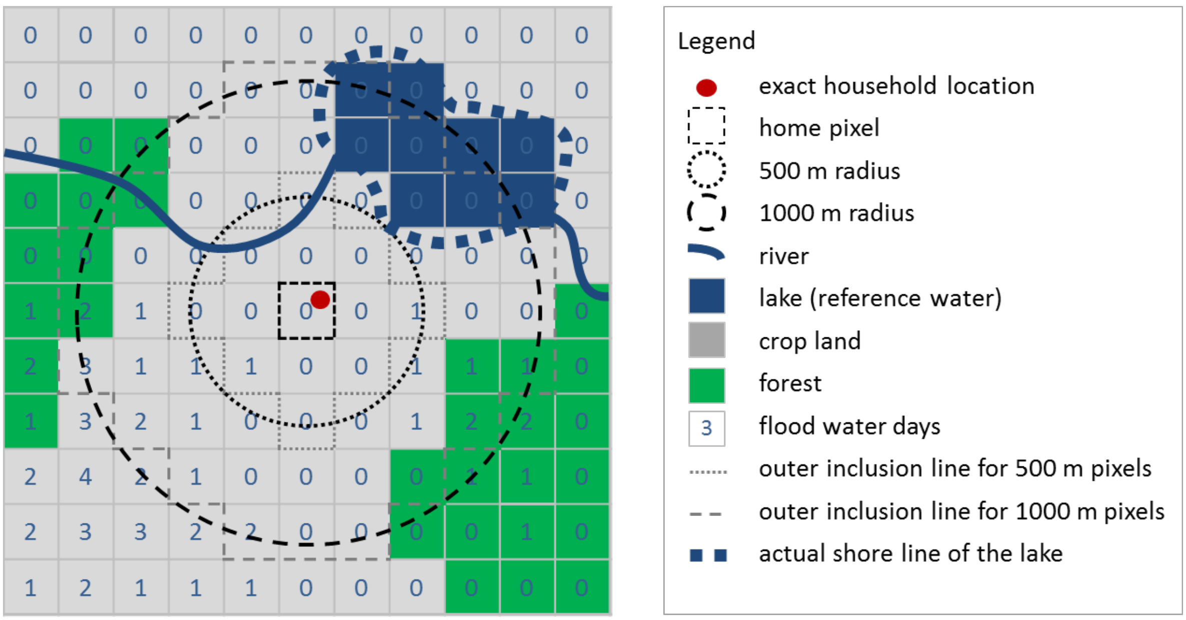
In the analysis, we want to contrast these direct flood shock experiences (as reported in the TVSEP) with tangential flood shock exposure. Therefore, we need to differentiate between the two types of shocks. Whereas direct shock experience can be identified based on the self-reported shock measure from the survey, the identification of tangential shock events is more challenging. Due to their subliminal nature, i.e., they only had

[13] The incorporation of heavy rain shocks is justifiable for two reasons: first, heavy rain may directly cause spontaneous flooding on a localised scale, hence, cause damage to agricultural production. Second, these events tend to coincide, therefore making it hard to discern them when interviewed several months after such an event.

to be potentially observable, reliable information retrieval in a survey is infeasible. To quantify tangential shock exposure, we therefore need an *external measure* of shock occurrences. To precisely evaluate whether any individual could have observed a shock event, i.e., whether such an event happened near the individual's homestead, these data have to be of sufficient spatiotemporal resolution.

The MODIS near-real-time flood mapping product satisfies the criterion of *external measurability* for tangential flood shocks. We therefore use the MODIS data to construct an indicator for tangential shock exposure. Based on households' homestead coordinates from the TVSEP, the closest 250x250 meter tile in the MODIS flood data is identified as the 'home pixel'. In the next step, all relevant tiles within varying radii up to five kilometer are identified. We call this area around a household's homestead the individual's sphere of interest. This five kilometer threshold was chosen because it comprises 95% of a household's cultivation areas and hence comprises the land most relevant for the livelihood of households that are dependent on agricultural production. Figure 2.2 is a stylised representation of the MODIS flood water data for a fictitious household. In addition to the home pixel, it also depicts the relevant pixels in the 500 and 1,000 meter radii.

Figure 2.2: Stylised MODIS flood water data



The TSE indicator captures the highest number of flood days that affected any tile within a certain radius of the home pixel. Such a maximum day count provides an indicator for the maximum local severity of flooding: the longer it lasts or the more events that occur within a given time horizon, the more likely agricultural production will suffer. Maximum local flood severity, i.e., the maximum number of flood days in a pixel, mirrors potentially threatening events in a precise manner.

Conditioning on the exact interview date, we further construct time horizon-specific TSE indicators. Evaluating TSE exposure over the last one-month, three-months or 12-months horizon allows us to test whether any potentially observed tangential shock effects are transitory or more permanent. Table A.3 provides a descriptive overview of the TSE indicator for all three time horizons.

2.3.3 Econometric specification

The premise of our research is to analyse the effects of tangential shock events on individual subjective well-being. The relationship between individual i's subjective well-being (SWB_i), individual characteristics x_i and shocks s_i can be represented by the linear model

$$SWB_i = x_i\beta + s_i'\gamma_1 + s_i^{TSE}\gamma_2 + s_i s_i^{TSE}\theta \tag{2.1}$$

To isolate the effect of TSEs from well-being dynamics induced by direct shock experience and potentially correlated changes in individual circumstances, the vector x_i comprises the set of sociodemographic and socioeconomic SWB determinants known from the literature: age, age squared, health status, marital status, educational attainment, religious beliefs, and occupational status.[14] Economic determinants, i.e., a measure of household income per capita and income dynamics, are represented in x_i as well.

In line with the literature on environmental shocks, experienced adverse shocks (s_i) may not only have an indirect effect, e.g., by lowering income, but may also have an immediate impact on subjective well-being. Being hit by a shock translates into diminished levels of subjective well-being by, for instance, reducing quality of life or deteriorating expectations for the future. The vector s_i includes a binary indicator. This binary indicator reflects whether an individual experienced a flood shock event.

In our data, subjective well-being is measured as a change over the preceding 12 months. This yields a difference interpretation for reported subjective well-being in year t, i.e., a well-being dynamic. Our dependent variable (ΔSWB) has three cate-

[14] Individual educational attainment may also be correlated with (individual or household) income. This supports its inclusion into a model of individual well-being.

gories: Subjective well-being may have increased, decreased or stayed the same–the final option being a natural reference point. A valid modelling approach to estimate such a categorical dependent variable (with a natural reference point) is to fit a multinomial logit model (cf. Greene, 2012, p.763), given by

$$\mathrm{P}(\Delta SWB_{i,t} = j | x_{i,t}, s_{i,t}, s_{i,t}^{TSE}) = \frac{\exp(x_{i,j,t}\beta_j + s'_{i,j,t}\gamma_{1,j} + s_{i,j,t}^{TSE}\gamma_{2,j} + s_{i,j,t}s_{i,j,t}^{TSE}\theta_j)}{1 + \sum_{k=1}^{2}\exp(x_{i,k,t}\beta_k + s'_{i,k,t}\gamma_{1,k} + s_{i,k,t}^{TSE}\gamma_{2,k} + s_{i,k,t}s_{i,k,t}^{TSE}\theta_k)} \tag{2.2}$$

For each of the two nonreference response categories (worse off and better off), we obtain a distinct set of parameter estimates. This approach is more flexible than other estimation approaches for categorical variables, e.g., an ordered logit model: it allows for modelling asymmetric effects of the explanatory variables across the response categories.

In contrast to other studies that analyse the impacts of directly experienced flood shocks on well-being, our research is guided by the hypothesis that tangential shocks may also sway perceptions of well-being.[15] Thus, tangential shocks may be interpreted as important externalities. The impact of observing such a local tangential shock s^{TSE} is modelled by an interaction with the reported shock experience (s_i). The respective interaction coefficient θ allows us to retrieve the influence of tangential shocks as the relative SWB difference between individuals from households not reporting any actual shock experience and those having suffered a relevant shock. Tangential shocks play a role if we observe $\theta \neq 0$.

With respect to our analysis, we expect that the overall effect will differ between those with and those without a direct shock experience. Referring to the multinomial logit specification in equation (2.2) with the two categories "better off" (b) and "worse off" (w), we anticipate $\theta^b < 0$ and $\theta^w > 0$. The presence of a tangential shock will reduce (increase) the probability someone without direct shock experience will be better (worse) off. This is then evidence in favour of a divergence in subjective and economic well-being induced by the mere perception of shocks.

Apart from our main analysis in Section 2.4.1, we present a sensitivity analysis in which we run several modifications of our model to test the robustness of our results. The results are presented in Section 2.4.2.

After we establish a robust relation between tangential shocks and SWB dynamics, we examine the consequences of TSE for respondents' future subjective well-being

[15] Our research relates to Guiteras et al. (2015) pointing out the limitation of focusing solely on self-reported shock measures.

expectations in Section 2.4.3.

2.3.4 The distribution of well-being dynamics and flood shocks

Figure A.1 provides insight into the distribution of flood shock exposure for the year 2013. It illustrates the locations of villages in Thailand and Vietnam where at least three households have been interviewed. For each enlarged province, the left panel reports the share of villagers (in blue) who were exposed to a satellite-detected flood shock occurring in a radius of 5,000 meters around their homestead and a time horizon of 12 months. The right panel displays negative well-being dynamics, i.e., the shares of respondents in a village reporting that they are worse off (in red).

We observe that households in villages close to the Mekong River and those situated in river deltas are more likely to have witnessed a flood event. The occurrence of adverse, unconditional well-being dynamics, however, does not seem to be systematically related to satellite-detected flood shock exposure. On the one hand, villagers in these areas might witness such a shock more frequently. On the other hand, they should also be more familiar with recurring flooding and their judgement less sensitive to tangential shocks. We account for past shock exposure in our sensitivity analysis.

Table A.3 presents descriptive statistics for our tangential shock indicator for all considered time horizons and a selection of sphere-of-interest radii (1 km, 3km, and 5 km). The tangential shock indicators display a substantial degree of variation. While the mean values for smaller radii or shorter time horizons can be relatively small, extending the time horizon or the radius reveals a notable share of households that might have observed severe flood events in their vicinity. The sample average for the largest sphere of interest amounts to 4.5 days of flooding over three months and 21 days for the 12-month horizon. These values reflect a substantial likelihood that one longer or several shorter flood events occurred during the growing season. This measure also captures the fact that longer (or more frequent) events increase the likelihood that a flood event is observed by an individual and thus might impinge on subjective well-being.

In the subsequent econometric analysis, we examine whether this variation allows us to detect any robust micro-founded conditional interdependencies. This would be evidence confirming the relevance of tangential shocks in the evaluation of subjective well-being.

2.4 Econometric Analysis

2.4.1 Main Results

In this section, we analyse our main research question: Do tangential shocks shift subjective well-being? To answer this question, we estimate different versions of our multinomial logit model, as given by equation (2.2). Due to an unbalanced panel at the respondent level and to exploit a sufficient number of person-year observations, we use a pooled sample, as described in Section 3.2.[16] To account for systematic (measurement) error at the household level, we cluster our standard errors at the household level. Potential year- and country-specific effects are absorbed by wave and country fixed effects. We include controls for individuals' demographic and economic background in all our estimations.

The first analysis of subjective well-being determinants is presented in Table A.4 in the Appendix. The results from the baseline specification (Columns (1) and (2)) show the expected effects of our control variables on subjective well-being. Higher per-capita household income is associated with an increased likelihood of reporting a positive well-being dynamic (Δ^+), and analogously, it translates into a lower probability of reporting a negative well-being dynamic (Δ^-). Higher income fluctuations reduce (raise) the probability of being better (worse) off. In line with the literature, we document a direct effect of actual flood shock experience on subjective well-being: those without such an experience are less likely to report negative SWB dynamics.

Having established the basic determinants of subjective well-being dynamics in our sample, we now include our tangential shock indicator in the analysis. Since we are interested in differentiating the effects of TSE for those with and without an actual shock experience, we interact the binary flood experience indicator ($s_{i,t}$) and the tangential shock measure (s^{TSE}). This allows for differentiation of the likely impact of tangential shocks on those individuals who reported an actual shock experience (the reference group) and those who were merely observers. We concentrate on this interaction effect in our main analysis and run several multinomial logit regressions using the tangential shock indicator with various time horizons and radii, as described in Section 2.3.4. Coefficient estimates for the tangential shock interactions θ are reported in Table 2.1.[17]

[16] We account for household fixed effects in our sensitivity analysis. We also run alternative specifications controlling for common effects on the province level.

[17] Table A.4 in the appendix exemplifies further details on control variables and model fit using the tangential shock indicator with our baseline thresholds (i.e., 5 km radius and a 12-month time horizon). We abstain from presenting full regression outputs for all specifications for the sake of simplicity.

Table 2.1: TSE interaction estimates for θ (various time horizons and spheres of interest)

	1 Month		3 Months		12 Months	
SWB response category	Δ^{+}	Δ^{-}	Δ^{+}	Δ^{-}	Δ^{+}	Δ^{-}
1 km	-0.063	-0.052	-0.015	-0.010	-0.003	-0.000
	(0.067)	(0.067)	(0.024)	(0.026)	(0.005)	(0.005)
2 km	0.023	0.021	0.004	0.016	0.000	0.004
	(0.038)	(0.039)	(0.013)	(0.016)	(0.003)	(0.003)
3 km	0.034	0.034	0.009	**0.021***	0.003	**0.006****
	(0.030)	(0.029)	(0.010)	(0.012)	(0.002)	(0.003)
4 km	0.019	**0.041***	0.007	**0.021****	0.002	**0.006****
	(0.022)	(0.023)	(0.008)	(0.010)	(0.002)	(0.002)
5 km	0.018	**0.043****	0.007	**0.021*****	0.002	**0.005*****
	(0.019)	(0.019)	(0.007)	(0.008)	(0.002)	(0.002)

*** p<0.01, ** p<0.05, * p<0.1

Note: All specifications include sociodemographic (age, age squared, gender, health dynamics, marital status, religion, educational attainment and occupational status) and socioeconomic (relative income, income dynamics) controls, as well as year and country FE. Standard errors (in parentheses) are clustered at the household level. All estimations are based on the identical sample comprising of 17,346 observations.

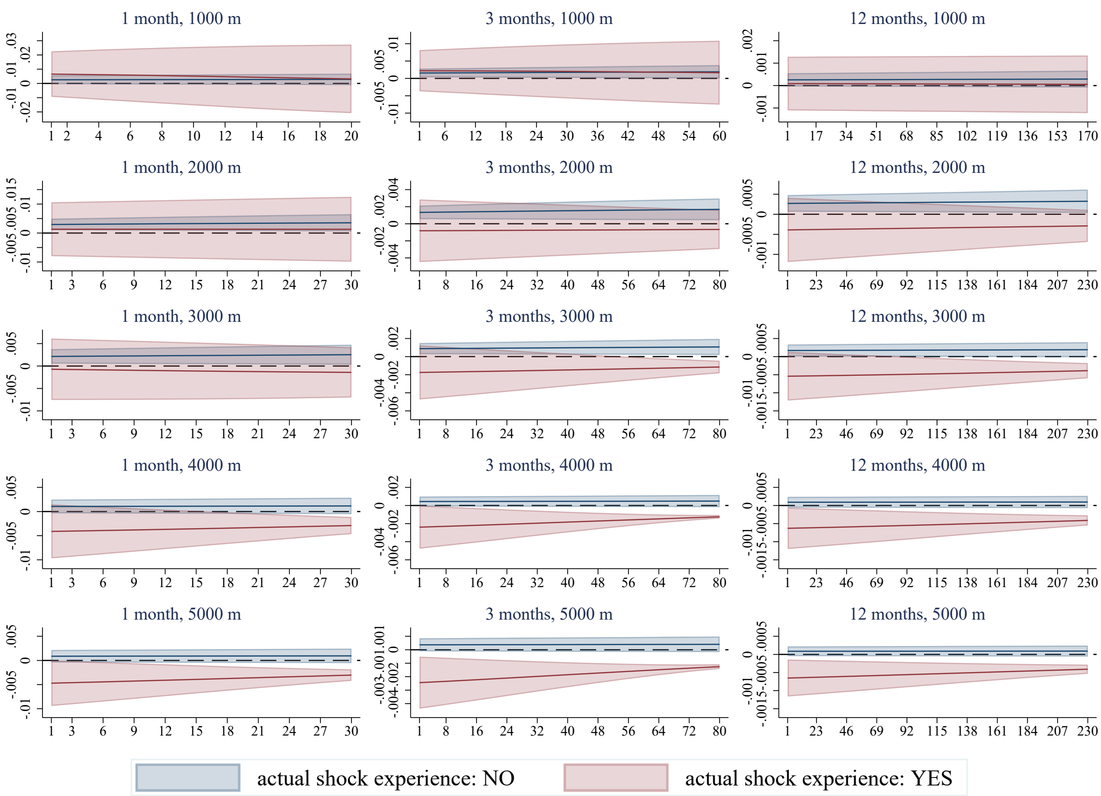
The results in Table 2.1 document significant interaction effects, mostly for larger radii (with a radius of at least 3 km). We also see that these findings are asymmetric, i.e., restricted to negative well-being dynamics (Δ^{-}). A positive interaction coefficient θ implies that the well-being dynamics of individuals without any shock experience are indeed sensitive to exposure to a tangential shock: they seem more likely to report a decline in subjective well-being than those who reported a shock experience in the last 12 months.

To provide a more refined interpretation of the results for the tangential shock indicator, we transform coefficient estimates from the nonlinear multinomial logit model, displayed in Table 2.1, into directly interpretable average marginal effects (AME). This allows us to investigate the overall relevance of the observed effects based on the significant coefficient estimates in Table 2.1. Figure 2.3 therefore illustrates the corresponding average marginal effects in the negative SWB domain.[18]

[18] Figure A.2 in the Appendix provides an overview of both the positive and negative SWB dynamics. There we also account for different effects depending on the intensity of the tangential shock; AMEs are evaluated at the TSE indicator's mean, 90^{th} and 95^{th} percentile.

A first comparison of the absolute sizes of the average marginal effects reveals a more differentiated picture than the previous coefficient estimates suggested. Average marginal effects decrease with higher radii and increasing time horizons; i.e., the effect of tangential shocks is stronger for events that occur closer to a respondent's residence and in the more recent past.

Figure 2.3: Average marginal effects for negative SWB dynamics



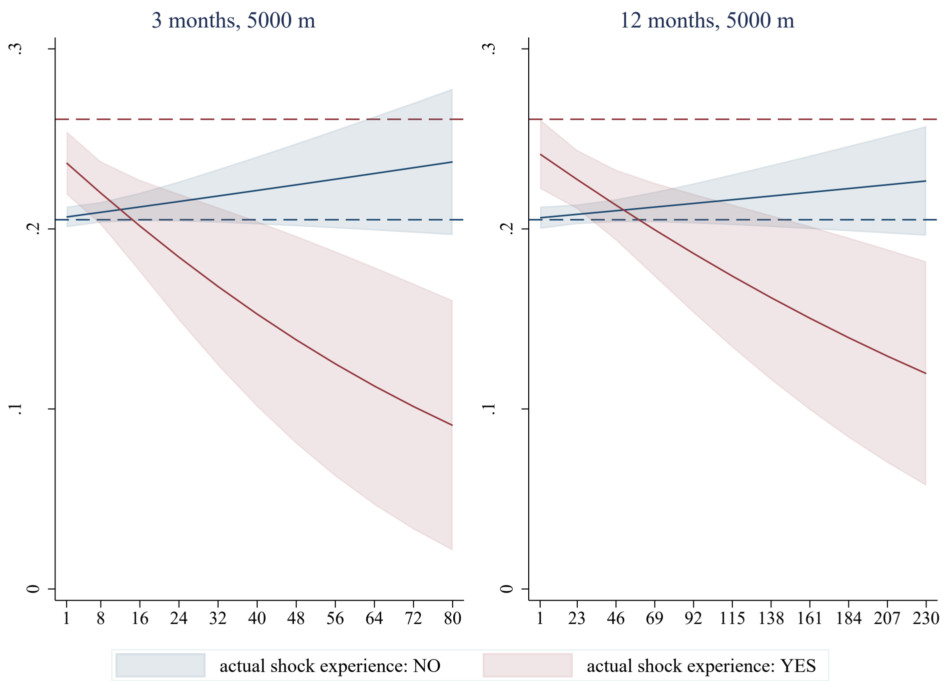
Note: All marginal effects draw upon the same sample comprising of 17,346 observations. The depicted response and shock-experience-specific average marginal effects have been evaluated over the range of the tangential shock measure, depicted on the x-axis. The shaded areas indicate the 90% confidence intervals.

With the 90% confidence band being just above zero (dashed line), the results suggest that individuals without any shock experience (blue graph) are on average more likely to report negative well-being dynamics only for smaller spheres of interest (up to 2,000 m). In the case of at least intermediate radii or time horizons, the confidence bands of the two groups (those with and without actual shock experience) do not overlap–the average marginal effects, and thus perceptions of SWB, differ notably between these groups.

The average marginal effects for those with an actual shock experience (red graph) are inverted and significantly negative for more severe tangential shock events: given an actual shock experience, prolonged tangential shock exposure does not increase the likelihood a respondent reports a negative subjective well-being dynamic. In fact, those who suffered an actual shock seem less affected by an incremental increase in tangential shock exposure since they are less likely to report a deterioration of their SWB. This could be interpreted as a form of resilience to such an adverse condition. Yet, ever-increasing TSE exposure has a dampening effect on negative SWB dynamics for individuals with actual shock experience. The positive slope of the AME curve for this group, gradually converging towards zero, indicates that more intensive tangential shocks may increase resilience only up to a certain point.

To demonstrate the size of the observed effects, Figure 2.4 shows the predicted probabilities of negative SWB dynamics for different levels of TSE intensities on the x-axis.

Figure 2.4: Predicted probabilities for negative SWB dynamics



Note: Horizontal dashed lines represent the group-specific in-sample probabilities for negative SWB dynamics. The x-axis depicts the intensity of TSE.

We see a mild increase in the probability of a negative SWB dynamic for those without actual shock experience if the intensity of the TSE increases. This reflects our initial expectation that those without any actual shock experience will still feel worse off if they are exposed to tangential shock events. For those actually suffering a shock, predicted negative SWB dynamics are substantially dampened and notably below the group-specific unconditional probability (26%, depicted as a dashed red line): exposure to a tangential shock event lasting for a cumulative month (30 days) in the last quarter reduces the expected probability of a negative SWB dynamic by almost 10 percentage points relative to the unconditional probability. A similar TSE in the last 12 months would still result in a 4 percentage-point reduction in negative SWB dynamics.

These findings have an important implication: if SWB is measured during a season with frequent TSE exposure, individuals not hit by a shock may report more negative outcomes, whereas those actually hurt by the shock may develop resilience due to the additional TSE exposure. Thus, the reporting of subjective well-being might be distorted. Interviewing individuals and asking for their subjective evaluations directly after they *observed* a shock or traumatic event may result in a misrepresentation of well-being levels.

2.4.2 Sensitivity analyses

This section describes various robustness tests for our main analysis, addressing concerns about control variables, attrition and unobserved heterogeneity. Output tables are presented in the Appendix.

Shock severity Our analysis builds on different intensities of TSE exposure. So far, however, we have not accounted for variation in the intensity levels of actual flood shock experiences; respondents were either affected or not. In the first sensitivity analysis, we demonstrate that our findings are upheld if we allow actual shock experience to vary in its severity. Table A.4 (Models 2 and 4) shows that both the magnitude and precision of our TSE estimate remain comparable for different specifications of the actual shock indicator variable.[19]

Exposure to other environmental shocks The households in our sample are largely involved in agricultural activities, which explains their overall responsiveness to an environmental shock such as flooding. However, other (possibly correlated) environmental shocks could also be impacting on SWB dynamics. To this end, we integrate three additional environmental shock experiences during the last 12 months: drought, storm, and snow or freezing rain. This does not impact our TSE estimate. However, all three

[19] We show results for the 5 km- and 12-month TSE indicator.

environmental shocks are relevant predictors for negative SWB dynamics (cf. Table A.5, model 1).[20] The same robustness can be observed in the specification where we control for a full set of shocks, including falling victim to a property crime, experiencing a job loss, adverse financial shocks, the death of a household member, etc. (see Table A.5, model 2).

Network effects We also control for the potential transfer of shock-related well-being dynamics between households in the village network. This transfer may be the result of household interdependencies or communication within the village community. The network variable corresponds to the log distance-weighted share of in-sample households (in the same village) who were exposed to a tangential flood shock during the corresponding time horizon.[21] Shock exposure of neighbouring households is weighted more heavily than shock exposure of remote households. With a range between zero and one, our network variable is a proxy for the likelihood of interacting with a fellow villager exposed to a tangential shock. Table A.6 (Model 2) documents the robustness of our findings for various time horizons (3 and 12 months) and spheres of interest (3 and 5 km). Notably, our network variable is significant across specifications with a time horizon of 12 months, yet only for positive well-being dynamics: the larger the share of other households exposed to a tangential shock, the lower is the likelihood a respondent reported an improvement in well-being. Intra-village shock correlation seems to play a relevant role in the formation of subjective well-being, although it does not affect our main results.

Coping strategies Next, we account for the emergence of coping strategies. Households with frequent past exposure to flood shocks might have adapted, and their well-being could be unaffected by tangential shocks. Model 3 in Table A.6 displays the robustness of our findings to controlling for flood history. Accounting for the yearly average exposure to tangential shocks (based on the history from 2004 to the last year prior to the interview in a survey year) does not alter our findings. The same holds for an alternative measure (results not reported) where we only focus on the flood history in the two years prior to the 12-month pre-interview time horizon.

[20] As a type of falsification test, we run a further set of estimations where we interacted all environmental shock experiences with the tangential flood shock measure (model 3). The only significant TSE interaction for negative SWB dynamics is the interaction with the actual flood shock experience.

[21] We also applied equal and linear distance weights. The results were unaffected. We selected the log-distance weights due to a specific desirable feature, i.e., partially reducing the dominance of one very close neighbour over a number of more distant neighbours.

Land usage In another specification (Table A.6, Model 4), we investigate the robustness of our results depending on how households make their livelihoods. In principle, we account for respondents' main occupation in our main analysis; this accounts for the fact that farming households might be more susceptible to (tangential) flood shocks in general. Next, we further account for households' land use, i.e., the overall number of cultivation plots (or the cultivation area) used or owned by the household. Eventually, this could yield a refined interpretation of our results if individuals from farming households with productive assets at stake were particularly sensitive with respect to tangential shock events. Although individuals with more farmland at stake (i.e., those that are relatively better off) display positive well-being dynamics more frequently, we still observe the familiar impact of tangential shocks on negative well-being dynamics.

Psychological factors Another important sensitivity check investigates the extent to which observed well-being dynamics are driven by psychological factors. Since our research examines the impact of potentially traumatic events on subjective well-being, these factors could be a potential source of omitted variable bias: both direct shock experience and tangential shock exposure might adversely impact mental health (e.g., Sekulova and Van den Bergh, 2016; von Möllendorff and Hirschfeld, 2016). Simultaneously, we expect worsening mental health to affect subjective well-being levels. To investigate the relevance of indirect psychological effects, we integrate measures of mental health into our analysis. Since there are no direct measures available for our sample, we resort to the self-reported prevalence of *mental issues* and *headaches* as predictors for underlying mental health conditions.[22] This specific sensitivity analysis comes with two additional caveats: first, the sample is reduced by ca. 10% due to a substantial share of missing values in the underlying health-related variable. Another issue is the low general prevalence of both conditions: only 0.3% of respondents declare mental issues, and only 1.2% report headaches.

Table A.7 illustrates that there is no strong correlation between TSE exposure and mental issues or headaches. The retrieved TSE interaction coefficient for the negative well-being domain corresponds to our earlier results. The last two columns of Table A.7 present the direct correlation structure between flood shock experience and exposure and our mental health proxies. We see a minor but significant correlation between men-

[22] The TVSEP questionnaire does not include specific questions on a person's mental health but rather asks the respondent to report on any impairment over the past year. We chose the answer options most closely related to mental health, i.e., mental issues (including unspecified mental disease or depression) and headaches, which have been found to be a comorbidity of anxiety or psychic disorders (Baskin et al., 2006; Mercante et al., 2011; Lampl et al., 2016).

tal issues and TSE exposure. However, this effect does not translate into a differential effect of mental issues on SWB between those with and those without direct shock experience. Overall, we do not find evidence that our previously uncovered TSE effects are driven by unobserved psychological conditions.

Sample attrition A further sensitivity analysis assesses whether sample attrition might invalidate our findings. Overall sample attrition is relatively low, with a rate of approximately 2% between each wave. We re-estimate our baseline model, including only respondents from households that are represented in all waves.[23] This approach, following Gröger and Zylberberg (2016)[24], reduces our sample by 140 households (corresponding to 537 respondent-year observations). Our main results in this zero-attrition sample (cf. Table A.8) are highly comparable to the overall sample.[25] We thus conclude that sample attrition does not bias our general findings.

Unobserved heterogeneity Our last robustness check assesses the reliability of our previous estimation results with respect to unobserved heterogeneity. Thus far, our estimations were based on a multinomial logit framework in a cross-sectional pooled sample where observations are linked at the household level. This allowed us to examine asymmetric relations between potentially relevant factors across the positive and negative well-being domains. These dynamics, however, are rooted in the cognitive evaluation processes of a responding household member. If certain unobserved household characteristics or respondent traits were correlated with our variables of interest and, at the same time, relevant to the formation of subjective well-being, our previously presented estimates might be biased.

We investigate the influence of such unobserved characteristics, both on the household and the respondent level, by re-estimating our benchmark models (3 km/5 km spheres of interest and 1-/3-/12-month time horizons) in a panel setting. We run fixed-effect multinomial logit models (Pforr, 2014) and panel fixed- and random-effect models. The latter corresponds to a more conventional panel setting and is based on a binary dependent variable, with negative well-being dynamics coded as one. Positive well-being dynamics and stable well-being levels are combined in the reference category. Tables A.9

[23] The 2011 wave was run in two provinces only. For a respondent from these provinces to be included, we thus require that their household is represented in six waves in our dataset. For all other provinces, the zero attrition condition requires a household to be present in five waves.

[24] Gröger and Zylberberg (2016) use the Vietnam TVSEP data.

[25] As in our previous findings, we do not obtain any significant shock estimates for positive SWB dynamics.

and A.10 report the results from our panel models on the respondent level (Panel A) and the household level (Panel B) respectively. In the respondent panel, by controlling for unobserved heterogeneity on the respondent level, significant interaction coefficients can be retrieved from the fixed-effects multinomial logit and the random-effects model when larger spheres of interest and longer time horizons are considered but not from the standard panel fixed-effects model. Controlling for unobserved heterogeneity at the household level, however, we once more establish a familiar set of TSE interaction coefficients (Table A10, Panel B). In accordance with our earlier results, coefficient estimates are significant and of a similar size across all three types of panel estimation models. For the maximum sphere of interest and a time horizon of 3 months, for instance, we obtain an estimate of 0.0029 (corresponding to a 0.29 percentage-point change) in both the panel FE and RE specifications: in these linear models, an additional flood exposure episode of one week translates into a 2 percentage point (7×0.29) increase in the probability that a respondent without actual shock experience reports being worse off. Given their baseline response behaviour (20% stating they are worse off), this implies a 10% increase over baseline.

Ultimately, we are confident that controlling for unobserved, potentially correlated factors at the individual or household level in a panel model supports our findings in the linked cross-sectional analysis: the distortionary effects of tangential shocks impinge on the formation of subjective well-being in an asymmetric manner, e.g., by prompting negative well-being dynamics.

2.4.3 The propagation of TSE into future expectations

In the previous sections, we have shown that tangential shock exposure may sway current SWB dynamics such that respondents without actual shock experience are more likely to report deteriorating SWB (cf. Figure 2.4). This effect is more pronounced for more recent TSEs, and thus timing matters. In the next step, we are interested in the consequences of this effect. Therefore, a related question is whether this distortionary impact of TSE exposure is restricted to evaluations of current well-being dynamics or if it propagates into the formation of well-being expectations for the future.

To investigate a potential forward-carrying effect of TSE exposure, we first examine whether TSE exposure is associated with an update to beliefs about future flood shocks, i.e., respondents are more likely to expect flooding in the future.[26] Subsequently, we investigate whether belief updates are relevant drivers of expectations for future well-being.

Table 2.2 (Model 1) presents coefficient estimates from a linear probability model predicting a respondent's update to flood shock beliefs. Here, the dependent variable is one if an individual expects a flood shock to occur in the next five years.[27] Individuals without an actual flood shock experience are 51 percentage points less likely to expect a flood shock event in the future than those who experienced a flood shock. Individuals' belief updates seem to be in line with their actual experience. Insignificant TSE estimates, on the other hand, highlight that their exposure to TSEs does not impact their belief formation.

Model (2) presents results for future SWB expectations, which include the full set of our standard controls.[28] We obtain a significant positive TSE interaction coefficient for expected negative SWB dynamics (Δ_F^-). Interestingly, there is also a significant negative interaction estimate for expected positive SWB dynamics (Δ_F^+): compared to those with actual shock experience, individuals without such an experience seem to be less optimistic about their future prospects when their TSE exposure is more pronounced. Furthermore, expectations of SWB dynamics are conditional on current SWB evaluations. Individuals reporting positive SWB dynamics over the last year are also more likely to expect future SWB improvement, as signified by the positive coefficient estimate. Those displaying negative past SWB dynamics expect a further downward spiral in the future.

Turning to model (3), which accounts for belief updating in regard to the future occurrence of flood shocks (s_F), we find two interesting insights: (i) flood shock belief updates do not translate into changing SWB expectations, since all estimates related to future flood shock expectations (s_F) are insignificant, and (ii) the influence of tangential shock exposure also remains prevalent in this setting.

[26] The household questionnaire includes a section on expected future shocks. The question posed to respondents is: "Do you think that (event xyz) will occur in the next 5 years?" We use this question to measure a respondent's belief updates. A respondent updates his/her belief if he/she becomes more likely to expect a future flood shock in response to a past flood shock experience or TSE exposure.

[27] The full set of variables is only available for the years 2008 to 2016, hence the smaller sample.

[28] Future SWB expectations are captured through the following question: "Do you think you personally will be better off next year?"

Table 2.2: Belief updates and future SWB expectations (maximum flood exposure, 5km, 12 months)

	(1) FW shock believe update	(2) Future SWB expectations		(3) Future SWB expectations + belief updating	
	s_F	Δ_F^+	Δ_F^-	Δ_F^+	Δ_F^-
s	-0.5119^{***}	0.0903	0.0936	-0.0222	-0.0507
	(0.0135)	(0.0760)	(0.1185)	(0.1480)	(0.2355)
s^{TSE}	-0.0002	0.0042^{***}	-0.0061^{**}	0.0042^{***}	-0.0060^{**}
	(0.0003)	(0.0016)	(0.0030)	(0.0016)	(0.0029)
$s \times s^{TSE}$	0.0003	-0.0037^{**}	0.0063^{**}	-0.0037^{**}	0.0062^{**}
	(0.0003)	(0.0017)	(0.0031)	(0.0017)	(0.0031)
Present SWB Δ^+		1.4270^{***}	-0.0587	1.4269^{***}	-0.0587
		(0.0469)	(0.1011)	(0.0469)	(0.1011)
Present SWB Δ^-		-0.0247	1.2130^{***}	-0.0246	1.2131^{***}
		(0.0532)	(0.0714)	(0.0532)	(0.0714)
s_F				-0.1405	-0.1858
				(0.1562)	(0.2531)
$s \times s_F$				0.1339	0.1696
				(0.1652)	(0.2636)
N	13692	13692		13692	

*** p<0.01, ** p<0.05, * p<0.1

Note: All specifications include sociodemographic (age, age squared, gender, health dynamics, marital status, religion, educational attainment and occupational status) and socioeconomic (relative income, income dynamics) controls, as well as year and country FE. Standard errors (in parentheses) are clustered at the household level.

Future SWB expectations are hence highly sensitive to TSE exposure. Thus, TSE exposure has the potential to be carried over into the future by lowering an individual's outlook on future well-being dynamics. Most importantly, this is not a result of rationally updated beliefs based on newly acquired information of flood shock frequency or severity in one's sphere of interest. Observing a flood shock, even without being hit or updating beliefs regarding underlying flood risks, is sufficient to trigger negative expectations of future well-being.

2.5 Conclusion

Employing a unique household sample from Southeast Asia, we investigate the sensitivity of subjective well-being dynamics to the observation of environmental shocks. We investigate the implications of such tangential shock exposure by studying flood events in rural villages in Thailand and Vietnam.

Capitalising on satellite-based, near-real-time flood event data, we compare the well-being dynamics of individuals reporting an actual flood shock experience with the dynamics of those who were not directly hit but lived in close proximity to the flood event.

In the analysis, we establish two essential findings. (i) In our main analysis, we document that merely witnessing a flood event can be sufficient to trigger negative well-being dynamics. The effects of these tangential shocks are found to be heterogeneous across households and depend on the relative position of a household as well as the timing of the interview. Moreover, the analysis of marginal effects shows that individuals with direct actual flood experience are more resilient to the occurrence of more severe flood events. Once an individual is directly affected by a flood shock of any severity, more extreme flood events do not further depress the subjective well-being dynamics of that individual. For individuals who were not hit by a flood shock, on the other hand, it seems that the lack of direct self-experience translates into an overemphasis on potentially adverse, yet not experienced, consequences. (ii) Our results demonstrate that TSEs not only affect contemporary outcomes but they may also further distort the formation of expectations for the future. We find that witnessing flood shocks without actually being hit translates into less optimistic expectations with respect to the future development of SWB. Notably, we establish that this outcome is not the consequence of a rational belief update.

In conclusion, our findings show that present and future subjective well-being are determined not only by direct (shock) experiences but also by subjective perceptions related to the observation of tangential shock events. Our findings are in line with psychological research on witnessing traumatic events. However, we illustrate that the impacts of such events are also relevant in regard to adverse environmental shocks and individuals' subjective well-being dynamics. Hence, we add a new dimension to the research on subjective well-being determinants and provide new insights into individuals' behavioural patterns in the aftermath of a shock event. While we draw upon a sample taken from a rural population in Thailand and Vietnam, we argue that the relevance of our results may extend beyond this population. Various studies (Sarracino et al., 2013; Markussen et al., 2018; Reyes-García et al., 2016) have identified a so-called 'unique happiness function' and have found that determinants of subjective well-being hold for individuals across countries and cultures.

Our findings therefore call for a more cautious interpretation of behavioural responses and well-being measures, as well as a more thorough consideration of the circumstances in which individuals were encountered. Traditional survey instruments do not capture such tangential events. However, in light of our results, researchers might want to consider the dynamic environment respondents face and how they interact with changing conditions in their surroundings.

Moreover, our findings have implications for policy design in the aftermath of (environmental) shock events. Policies designed to alleviate the ramifications of adverse shocks may yield an inefficient usage of resources if target groups are not directly identified based on their true shock experience. Instead, it might be worthwhile to differentiate between individuals who actually suffered a decline in economic well-being due to the shock and those displaying transitory negative well-being dynamics. The former would require material relief, whereas the latter might benefit from information on how to cope with the risk of a recurring shock event.

Chapter 3

Don't Expect Too Much - High Income Expectations and Over-Indebtedness*

with:
Theres Klühs
Melanie Koch

* We thank Anik Ashraf, Jana Friedrichsen, Antonia Grohmann, Stefan Klonner, Friederike Lenel, Lukas Menkhoff, Marina Schröder, Lisa Spantig, Susan Steiner, Sidiki Soubeiga, Fabian Stöckl, Stephan Thomsen, Andreas Wagener, Georg Weizsäcker, and seminar participants in Berlin, Göttingen, Hannover, Potsdam and, Tutzing for helpful comments. The paper also profited from discussions with participants at ESA World 2018 (Berlin), GLAD Conference 2018 (Göttingen), the 2019 AEL-FHM Doctoral Meeting (Mannheim), the 6th PhD Workshop on Experimental Development Economics at UEA (Norwich), SSES Annual Congress 2019 (Geneva), NCDE 2019 (Kopenhagen), the 5th Dial Conference on Development Economics (Paris), EEA 2019 (Manchester), VfS Annual Conference 2019 (Leipzig), IAREP/SABE 2019 (Dublin) and ASSA 2020 (San Diego). We are grateful to Hanh Le Van, Inka Nozinski, and Theerayuth Labooth, who provided excellent research assistance. Financial support by the German Research Foundation (DFG) via the Research Training Group 1723, the TVSEP Project (Project No. 283672937) and CRC TRR 190 (Project No. 280092119) is gratefully acknowledged.

3.1 Introduction

For households, taking out debt is a valuable tool to smooth consumption and often a necessary precursor of private investments. However, as consumer indebtedness is significantly increasing worldwide, there is widespread concern that it may turn detrimental. Specifically, when households face increasing difficulties to repay their debts, household well-being and consumption are threatened. Moreover, household over-indebtedness poses a serious threat to the stability of the financial system as a whole; for example, as experienced during the U.S. financial crisis in 2007-08.

Emerging market economies are especially at risk of low growth and even financial crises when the level of household debt is high, as not only are their institutions and financial regulations weaker, but income inequality is also higher (IMF, 2017). Therefore, understanding the factors and reacting to the consequences of over-indebtedness are crucial for improving living conditions while also ensuring a stable development of emerging economies. Building on the "permanent income hypothesis", where income expectations determine current consumption and borrowing, this paper studies one potential driver of over-indebtedness: too high income expectations. Although being positive about the future might have a net positive effect on lifetime utility (see Brunnermeier and Parker, 2005), being too positive might lead to serious financial distress and over-indebtedness.

In general, households' borrowing behaviour around the world is still puzzling in various aspects and often hard to reconcile with standard neoclassical and behavioural models. Zinman (2015) argues that one reason for many unresolved puzzles is that household debt is vastly under-researched within household finance. In the last decade, a vibrant literature on measuring over-indebtedness has emerged (e.g., D'Alessio and Iezzi, 2013; Keese, 2012; Schicks, 2013). In contrast, its determinants are still mostly unidentified. Our paper contributes to closing this gap by focusing on high income expectations as one likely cause. To the best of our knowledge, we are the first to study the relationship between real income expectations and over-indebtedness.

We investigate the relationship between positive expectations and over-indebtedness using extensive survey data on the financial situation and financial behaviour of one of the most vulnerable populations in Thailand: rural households in the north-east. A crucial part of our survey was to collect objective and subjective data on potential symptoms of over-indebtedness.

This allows us to construct different objective and subjective over-indebtedness indicators.[1]

Additionally, we quantify households' predictions of their future income. Instead of relying on qualitative Likert scale measures, we elicit individual distributions of expected household income and set these in relation to actual income. Hence, a major contribution to the literature is that we relate the over-indebtedness indicators to a sophisticated measure of subjective income expectations. In our regression analysis, we control for relevant household characteristics and unexpected shocks faced by households, thereby reducing reverse causality concerns. In order to further strengthen the contribution of our paper, we delve deeper into the causal effect of positively biased expectations on overborrowing by carrying out a lab-in-the-field experiment with the exact same respondents. In the experiment, we concentrate on one particular expectation bias: overconfidence. We exogenously bias income expectations via two treatments that vary the level of self-confidence of the respondents and, thereby, their expected earnings. Subsequently, we investigate if participants spend more on goods they can buy in the experiment and, as a consequence, potentially overborrow.

Thailand is, on the one hand, an exemplary emerging market, but, on the other, outstanding when it comes to household finances: Financial inclusion is comparatively high, with four out of five persons participating in the formal financial system. Simultaneously, household debt has increased to over 78.03% of the country's GDP. This makes it the emerging market with the highest household debt to GDP ratio in the world (IMF (2017), see Figure B.1). Given these numbers, it is hardly surprising that both local policy makers and international institutions agree that over-indebtedness is a growing problem in Thailand (Tambunlertchai, 2015). Additionally, there are circumstances that make our sample especially vulnerable to over-indebtedness and to struggle with financial hardship. This part of the population faces higher uncertainty regarding their future incomes in two ways: through the generally high level of macroeconomic volatility in emerging markets and through individual, mostly weather-related shocks, common to poor, small-scale agricultural households (see Loayza et al., 2007; Klasen and Waibel, 2015).

Our survey results show that there is a strong and robust relationship between high expectations and over-indebtedness. Those who have positive expectations are more likely to be over-indebted than those with neutral or negative expectations, which we interpret as a sign that these expectations are truly too high for some households. The

[1] It is still a highly debated topic how to measure over-indebtedness and there is no clear-cut answer on the right method of elicitation, which is why we construct a variety of over-indebtedness measures.

results vary slightly with respect to different debt indicators. The relationship between high expectations and the objective over-indebtedness indicator is more pronounced in comparison to the subjective indicator, but both relationships are significant. Our results indicate that the subjective indicator is not only driven by actual debt levels but also by personal characteristics and perceptions, such that it measures a different dimension of over-indebtedness. In an additional exercise, we can show that the subjective over-indebtedness indicator is highly correlated to a qualitatively assessed income forecast (error) measure. Eventually, we find that being more certain about the future income realization, which can be another form of forecast error, is also positively related to our objective over-indebtedness indicator. Rural households are exposed to a highly uncertain environment; hence, being too certain about ones future income may be harmful. Our results are robust to various sample specifications and become more precise if we exclude parts of the sample that may have had difficulties understanding the questions on eliciting future income expectations.

In the supplemental experiment, we find that overconfidence is related to more spending and overborrowing. However, our treatments themselves have no impact on overborrowing, which is why we cannot claim a causal relationship of overconfidence on overborrowing. These results are not driven by presumably confounding factors that the treatments could have affected and are relatively robust. Rather, we find evidence for "sticky" overconfident beliefs, which also points to a high level of perceived certainty in our sample. Furthermore, participants who overspend in the lab are also those who experience over-indebtedness in real life. This shows that our experiment is not "too artificial" to capture real life behaviour.

Our study touches on three strands of literature: First, the literature on eliciting and using subjective expectations data; second, research on potential behavioural biases in financial decision-making and debt illiteracy; and, third, the literature on households' (over-)indebtedness in emerging economies. There are at least two reasons why the relationship between income expectations and over-indebtedness should be explicitly studied in an emerging market setting and why findings from "WEIRD"[2] populations might not translate to rural populations. First, financial literacy is substantially lower. This implies lower debt literacy, which might hamper expectation formation on financial matters. For example, Lusardi and Tufano (2015) find that debt illiteracy is related to higher debt burdens and the inability to evaluate the own debt position. Burke and Manz (2014) experimentally show that economic illiteracy increases financial forecast errors. Second, the higher uncertainty that respondents are facing distinguishes this

[2] Western, educated, industrialised, rich and democratic (Heinrich et al., 2010)

research from work done in "WEIRD" societies. A more volatile economic environment requires more individual belief formation, which makes biased expectation formation more likely (see for example Johnson and Fowler, 2011) and at the same time more dangerous. In any case, the empirical evidence from WEIRD countries on the relationship between income expectations and over-indebtedness is sparse as well. To the best of our knowledge, there is no study that explicitly concentrates on real-life income expectations.

Our work is most closely related to Hyytinen and Putkuri (2018) and Grohmann et al. (2019). The former find a correlation between Finnish households' overborrowing and extreme positive forecast errors about the financial situation of the household. They do not analyse the effect of income expectations on overborrowing but the effect of financial expectations in general, which gives more rise to issues of reverse causality. Furthermore, the forecast errors are constructed using Likert scales and hence, cannot be quantified. They show that households exhibiting high positive forecast errors are more likely to overborrow than households exhibiting smaller errors. Grohmann et al. (2019) conduct a lab experiment among students in Germany that is similar to ours and link the experiment data with data from the German Socio-Economic Panel. They find a causal link between overconfidence and debt taking in the lab and a correlation between a simple measure for overconfidence and the level of household debt in the panel sample. Our study differs from these two studies in that it contributes to the literature by (i) explicitly eliciting and quantifying real income expectations and precisely measuring over-indebtedness; and (ii) analyzing the research question in a setting where expectation formation is generally difficult and over-indebtedness bears severe consequences.

The paper proceeds as follows: Section 3.2 presents the survey data, discusses the setting, and explains how our variables of interest are constructed. In Section 3.3, the estimation strategy is outlined and survey results are presented. Section 3.4 describes the experiment and its results. Section 4.4 concludes.

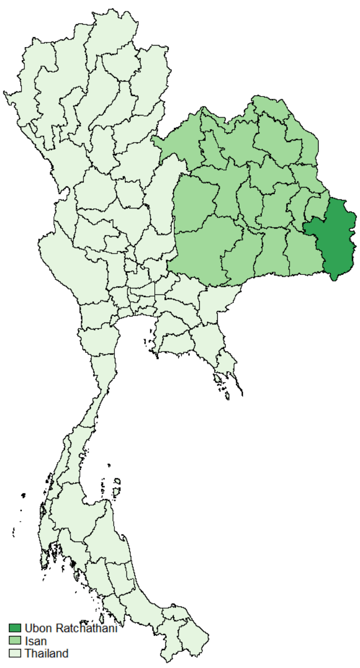
3.2 Data

This section introduces the data collected during the survey and explains how the main variables of interest are derived. We develop a measure that approximates future income expectations, which we call the quantitative income forecast. Further, we construct various over-indebtedness indicators to capture the different dimensions of household debt.

3.2.1 The Thailand Vietnam Socio Economic Panel

The survey was conducted in Thailand in November 2017 and is an add-on project of the Thailand Vietnam Socio Economic Panel (TVSEP).The TVSEP has conducted panel surveys in rural Thailand and Vietnam on a regular basis since 2007, with recurrent surveys in 2008, 2010, 2011, 2013, 2016, 2017, and 2019, so far. The TVSEP survey captures the living conditions of households in rural areas that are largely engaged in agriculture. It focuses on factors affecting households' vulnerability to poverty. Among others, the survey includes socioeconomic characteristics of every household member, sections on household consumption and savings, crop farming, livestock rearing, and, in particular, questions on exposure to shocks and anticipated risks. Furthermore, each wave captures topics of current research interest. About 4000 rural households in 440 villages across six provinces in Thailand and Vietnam are interviewed for the survey. The sample is set to represent the rural population in these two countries while urban households are deliberately excluded. To obtain a representative sample, a three-stage cluster sampling is used. The procedure is described in Hardeweg et al. (2013).

Our study is conducted in only one of the TVSEP provinces in Thailand, Ubon Ratchathani, which borders Cambodia and Laos (Figures 3.1 and 3.2). The sample consists of about 750 households in 97 villages. For the majority of our analysis, we concentrate on our own survey, adding data from the 2016 and 2017 general TVSEP survey as necessary.



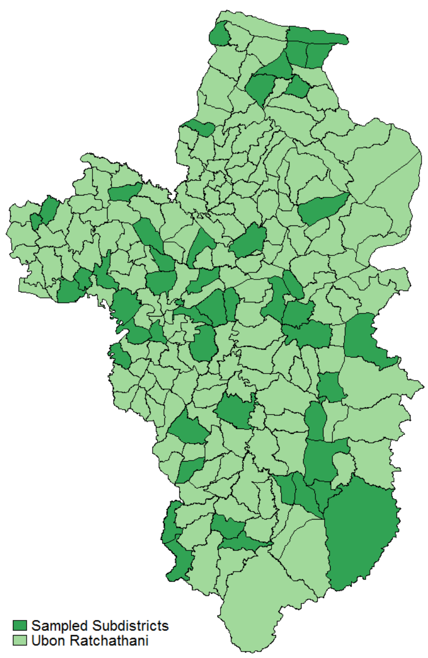


Figure 3.1: Study Site, Ubon Ratchathani Figure 3.2: Sampled Subdistricts

With our study, we want to gain new insights into the determinants of debt induced financial distress within a vulnerable population. Therefore, our survey includes extensive question batteries on objective and subjective over-indebtedness (see Sub-Section 3.2.4), savings, financial literacy, borrowing behaviour in general, and income expectations (see Sub-Section 3.2.3). In addition, we collect data on health, subjective well-being, personality traits, and risk preferences. We use established items to assess these data. For example, personality traits are measured using the short version of the Big Five Inventory "BFI-S" (John and Srivastava, 1999; Gerlitz and Schupp, 2005). We develop a broad financial literacy score, which not only encompasses numeracy but also questions on financial behaviour and attitude. The score is similar in style to that developed by the OECD (OECD, 2018). Furthermore, we construct a score for risk preference out of two questions: The first one asks whether the person is generally fully prepared to take risks and the second question specifically asks for risk-taking behaviour in financial decision-making (i.e., investing and borrowing). Self-control is assessed using the well-established scale of Tangney et al. (2004). Given the low numeracy within the sample, we add a phrase to each numerical value on questions involving scales.[3]

We use a restricted sample for the analysis in Section 3.3 and exclude outliers by the following means: We exclude (i) the 1 percent highest monthly household incomes in 2016 and 2017, (ii) households who have a debt service to income ratio greater than four, and (iii) those whose income is negative in general. For the latter case, we trim them as we do not know whether a negative income itself means that the households are in financial distress. Regression results without trimming are very similar to those with trimming. In any case, trimming (marginally) downward biases our results.

In our trimmed sample, the average respondent is 57 years old, female, the spouse of the household head, and has 5.7 years of education. Our financial literacy score indicates a relatively low level of financial literacy. On average, respondents answered four out of seven knowledge questions correctly, reached five out of nine possible points concerning financial behaviour, and three out of seven possible points with regard to financial attitude. This is in line with findings from the OECD/INFE study for Thailand from 2016 (OECD, 2016). While 57.27% of our respondents are the sole financial decision makers in their households, 28.05% share this task with someone else. Hence, when sometimes using respondent- and not household-specific characteristics or perceptions in the analysis, we are still confident that these individual traits determine the household's state of indebtedness because the majority of respondents is in charge of making financial

[3] Our main questionnaire can be downloaded here.

decisions.[4]

3.2.2 The Thai Rural Credit Market

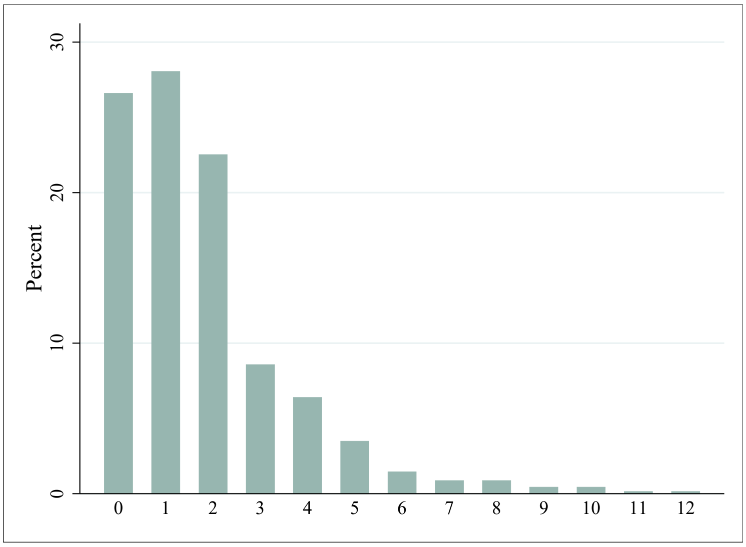
In Thailand, over 80% of the population has a bank account and over 60% uses it for digital payments. The gaps in financial inclusion between women and men as well as between the rural and urban population have declined and are now relatively small (Demirguc-Kunt et al., 2018). Financial inclusion in our sample is similar: 78.34% of our sample households have an account with a formal banking institution.

Simultaneously, the rural credit market has evolved extensively, providing manifold loan options for consumers. This is mainly due to heavily subsidized government programmes. The market is dominated by government-financed institutions (Chichaibelu and Waibel, 2017). The most important ones are the Bank for Agriculture and Agricultural Cooperatives (BAAC) and the Village and Urban Community Fund (VF) programme,[5] with the former reaching approximately 95% of all farm households (Terada and Vandenberg, 2014). This massive expansion can also be observed in our sample, where the majority (73.4%) of households has a loan that is either still owed or has been paid back within the last 12 months. Figure 3.3 provides a graphic overview of the loan situation. Conditional on having a loan, households have on average 2.4 loans. Households borrow from formal and informal sources alike. In fact, loan sources are diverse, with the two most important credit sources being the BAAC and the VF. This lending pattern is similar across all districts we consider. Households also borrow from other sources, for example, from agricultural cooperatives, business partners, money lenders, relatives, and friends. Loans are taken out for various reasons. Most loans are primarily used for agricultural related goods like fertilizer or pesticides (23.96%), for consumption goods (22.39%), and for agricultural investments, e.g., farm land or agricultural machines (16.58%). Loans are also used for paying back another loan (9.87%), buying durable household goods (6.72%), and for education (3.15%).

[4] Still, as a robustness check, we re-run the analysis without respondents who are not at all in charge of financial decision-making within the household.

[5] The aim of the VF is to improve financial access in rural areas in Thailand. It is one of the largest microfinance programmes in the world (Menkhoff and Rungruxsirivorn, 2011).

Figure 3.3: Number of Loans



3.2.3 Income Expectations

Households can form positive or negative income expectations. We are interested in studying households that exhibit high (positive) income expectations. In order to obtain a positive income expectation measure, we must elicit income expectations in the first place. Expectations play a central role in the economic theory of household decision-making, for example, with respect to determining saving, borrowing, and consumption (Friedman, 1957), or with respect to occupation choices (Becker, 1964). Manifold research has tried to predict this choice behaviour based on expectations. Yet, expectations are challenging to elicit empirically.

3.2.3.1 Eliciting Income Expectations

Expectations from Former Income Realizations The traditional way of elicitation - referred to as revealed preference analysis - assumes that individuals have *rational expectations* (Dominitz and Manski, 1997; Manski, 2004) and infers expectations from data on past income realizations. For this approach, strong assumptions on the expectation formations process are needed, with both the researcher and the respondent needing to have the same information set (Guiso et al., 2002). Given these strong assumptions and our conjecture that mistakes in expectation formation are likely to occur in our setting, we decide for two alternative elicitation methods, which are explained in what follows.

Qualitative Expectations Questions The first way is to elicit expectations via qualitative questions, e.g., using Likert scales for questions on future expected events. We use this method in the appendix to replicate the results of Hyytinen and Putkuri (2018), who use Likert scales to elicit financial expectations. However, this approach suffers from two main drawbacks: First, answers might not be comparable across respondents and, second, response options may be too coarse and leave room for responses different from what is proposed.

Subjective Probabilistic Income Expectations Dominitz and Manski (1997) suggest to elicit *probabilistic expectations*. This approach is particularly useful for calculating individual cumulative distribution functions and moments of the relevant variable (Attanasio, 2009). By allowing researchers to retrieve different moments of the expected income distribution, it becomes possible to algebraically study the internal consistency of elicited expectations (e.g., apply the laws of probability) and to use these probabilistic expectations as actual probabilities describing how respondents assess future outcomes. We use this approach in our main analysis to retrieve positive expectations.

As we elicit expectations within a rural sample in an emerging economy, we rephrase percent change questions in a way similar to "how sure are you" and use visual aids to make the concept of probability more comprehensible.[6] Thereby, we address the concerns of Attanasio (2009) and Delavande et al. (2011), who state that the concept of probability might be hard to convey in contexts where people have low levels of education.[7]

To check whether respondents adhere to the basic laws of probability, we first ask them how sure they are that it will rain tomorrow and how sure they are that it will rain within the next two weeks. They can indicate their answer by putting between zero and ten marbles that we gave them beforehand into a cup, with zero marbles meaning they are absolutely sure it will not rain and ten marbles meaning they are absolutely sure it will rain. There are 182 out of 748 respondents (24.33 %) who do not obey the laws of probability: they set a zero chance that it will rain within the next two weeks but a positive probability that it will rain tomorrow. This is a substantial share

[6] Studies dealing with these kind of expectation elicitation include, among others, Attanasio and Augsburg (2016), who study income processes in India, McKenzie et al. (2013), who investigate income expectations of Tongans, and Attanasio and Kaufmann (2014), who elicit income expectations among high school students in Mexico.

[7] The average respondent in our sample only attended school for six years.

of respondents, most likely caused by the low educational level in our sample. In the subsequent analysis, we run our regression both with and without these individuals.

After this "warm-up" exercise, we ask respondents how sure they are that their monthly household income in the next twelve months will be in a predefined range. We use income quartiles from the 2013 TVSEP wave to predetermine the four bins to which respondents allocate their ten marbles. The four bins range between 0 - 3,300 Thai Baht (THB), 3,300 - 8,100 THB, 8,100 - 16,590 THB, and 16,590 - 921,000 THB.[8] Respondents distribute their ten marbles based on how likely they think it is that their future monthly income will lie in each specific bin.[9] Hence, we are able to calculate the individual cumulative distribution function (CDF) for the expected monthly income as we interpret the number of marbles distributed between the cups as points on their individual CDFs.

We then fit a subjective income distribution following Attanasio and Augsburg (2016) and assume a piecewise (i.e., per cup) uniform probability distribution. This enables us to calculate a specific expected mean and median income, as well as the standard deviation, for each household.

Table 3.1: Probabilities Assigned to Sections of the Income Distribution

	Observations	Minimum	Maximum	Median	Mean	S.D.
0-3300 THB	737	0	100	20	32.18	35.1
3301-8100 THB	737	0	100	30	30.71	29.27
8101-16590	737	0	100	20	24.03	28.38
16591-300000	737	0	100	0	13.08	24.08

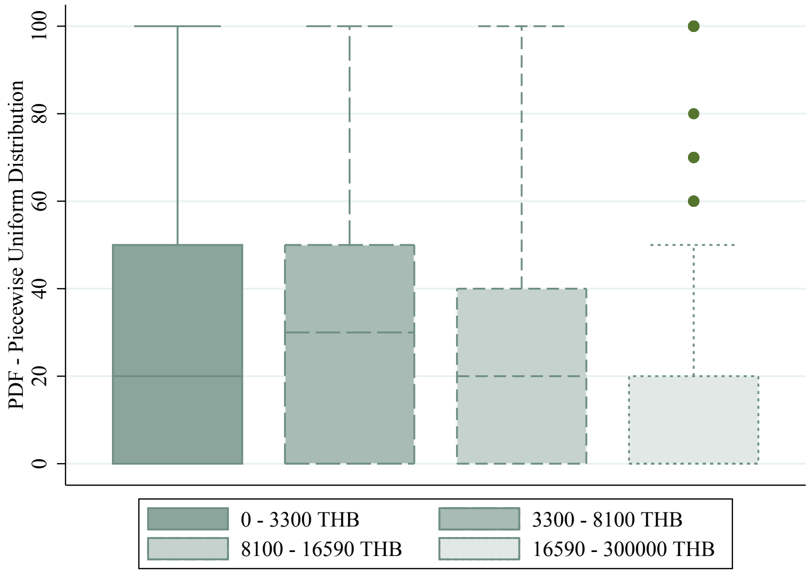
Respondents allocate the number of marbles to the cups as a function of their underlying subjective probability to earn income in the specific income range. The average distribution of marbles per cup, i.e., the average implied probabilities to earn income in the respective income quartile is shown in Table 3.1. Additionally, Figure 3.4 presents the probability density function of expected income in our sample. The average respondent's expected income distribution is skewed to the right; that is, on average,

8 The range of the last bin is very broad. Compared to the maximum monthly income respondents state, we find that only two respondents expect an income as high as 921,000 THB. All other maximum income guesses range between 0 - 300,000 THB. In order to avoid artificially high expected median incomes, we restrict the range of the last bin in our calculation of expected median income to a maximum of 300,000 THB.

9 The enumerator places four cups in front of them, each labelled with a different income range and makes sure that all marbles are allocated at the end of the exercise.

respondents believe it is more probable that their average monthly future income is in the lower cups.

Figure 3.4: Probability Density Function of Expected Income



We also ensure that the elicited expected income is not completely at odds with the actual income process. As measure for the income process, we use the realized income in 2016 and a measure averaging the self-reported income in a very bad and a very good month. Correlations between these and our expected income measure are always statistically significant and range between 0.27 and 0.33, which is encouragingly high given that the correlation between actual income in 2016 and 2017 is 0.48. Furthermore, as Attanasio (2009) proposes, we check how the subjective expected median income co-varies with household characteristics, particularly with the composition, education, and realized income (results available upon request). Beyond the already stated relationship with income, household total education is significantly, positively related to the expected median income. A little ambiguous is the correlation to household composition: While a larger number of elders in the household is associated with lower expected income (albeit not significantly), more workers in the household also seem to decrease it.[10]

[10] Reflecting on this last result, we assume that households with more working members are, in general, poorer and have less stable incomes. There is a tendency in Thailand to abolish multi-generational households for small family homes, which is, however, only possible if income is high enough and stable.

3.2.3.2 Defining Positive Income Expectations

We develop a new kind of positive income expectation measure that is based on the expected future monthly income and the current income. To derive a *quantitative income forecast (Quant. IF)*, we first calculate the percentage change between actual monthly income generated in t and future expected monthly income in $t+1$, which is elicited by the procedure explained in this Section. Specifically, t refers to the year 2017, for which we have actual income data. Consequently, $t+1$ considers income expectations for 2018.

$$Quantitative\ Income\ Forecast\ (Quant.\ IF) = \frac{E_t(Inc_{i,t+1}) - Inc_{i,t}}{Inc_{i,t}} \times 100 \qquad (3.1)$$

In a second step, we divide the quantitative income forecast into quintiles such that our outcome measure allows for five categories ranging from a very negative, negative, mildly negative income forecast, via a neutral income forecast to a positive quantitative income forecast. Thus, the negative (positive) forecasts capture households that expect relatively less (more) future monthly income as compared to their actual earned income in the current year. Each quintile enters the regression via a dummy variable where households with a mildly negative quantitative income forecast (i.e., respondents that range in the third quintile) serve as the omitted group.

In general, respondents are rather pessimistic with regard to their future income. The distribution of changes in expected future income ranges from -98.6% to 19528.6% whereas the maximum is a clear outlier, which also drives the average increase of expected future income of about 35%. If we exclude this household the average shrinks to 6.9%.[11] The median household expects a 51% decrease of future income relative to actual income. Thus, the distribution is skewed to the right. In total, 75% of the sample expect their future income to be lower than the one in the year of the survey. This explains why three of the quintiles clearly range in the negative scope of the distribution and are thus coined “negative income forecast.” Only the highest quintile is composed of households that have a clearly positive outlook.[12] The negative outlook on future income may be explained by two developments: First, respondents may fear further political turmoil following the 2014 military coup. Second, the negative outlook may be due to the persistent, regional, economic inequality. People from north eastern Thai-

[11] The corresponding respondent has a very low income in 2017, but - in the cup game - used all ten balls for the highest income range. We suspect the respondent had not fully grasped the elicitation game.

[12] Variables that covary with each respective forecast group can be found in the Online Appendix.

land still earn substantially less than people from other regions and, thus, might feel disadvantaged throughout (Lao et al., 2019). According to the World Bank, inequality in Thailand has increased between 2015 and 2017, despite overall economic growth in the country (World Bank, 2019).

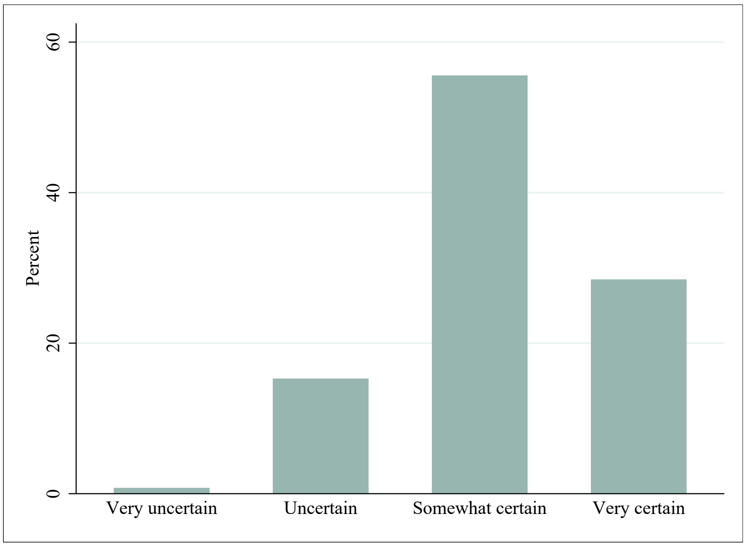
While we cannot formally test accuracy of expectations with our subjective expected income data,[13] we assume that a high and positive relative difference between expected income in 2018 and realized income in 2017 is partly due to respondents being too optimistic regarding what they will earn in the future. This assumption is based on studies finding that expectations about various future outcomes may tend toward being positively biased (see for example Zinman, 2015). Furthermore, considering the median household's negative expectation on future monthly income, we are confident that we capture very optimistic households with regard to income development in the highest quintile of the distribution.

We also account for perceived income uncertainty in our analysis. In addition to asking respondents how they think that their income will develop over the next 12 months, we ask how certain they are that this income development will truly become reality. Being potentially too certain about future realizations of stochastic processes can be a form of biased expectation called "overprecision" (Moore and Healy, 2008).

Figure 3.5 provides a graphic overview of the results on our measure for perceived income certainty: 55.56% of respondents are at least somewhat certain about their income development and 28.44% are very certain. The survey took place during the harvest season, so that respondents might have an idea about the harvest outcome and, therefore, perceive their expected future income as rather certain or they truly suffer from overprecision.

[13] For example, because we lack data about realized income in 2018, the year after we asked for expected income, and we do not know (yet) about shocks households endured during that time.

Figure 3.5: Income Certainty



Last, we derive a measure of expectation accuracy following Souleles (2004) and Hyytinen and Putkuri (2018). It is based on a coarser assessment of a household's future income. We can actually determine its accuracy, which is why we call this measure the *qualitative forecast error*. The derivation and estimation results are found in Appendix B2.

3.2.4 Over-indebtedness Indicators

There is no consensus regarding a single set of indicators measuring indebtedness precisely, even less so for over-indebtedness.[14] In general, all measures share economic, social, temporal, and psychological dimensions such as that the amount of debt exceeds income over a medium- to long-term time horizon and the household is not able to fulfill its debt commitments without increasing its income or lowering its standard of living, which might lead to stress and worry (D'Alessio and Iezzi, 2013). Furthermore, so-called objective debt measures relate to the household's debt service capacity, subjective measures rather emphasize the psychological consequences of being indebted (Keese, 2012).

Based on the existing literature, we decide to construct two measures of over-indebtedness. The first index captures different dimensions of being "objectively" over-indebted (based on best practices from the literature) while the second index rather refers to "subjectively" felt factors related to financial distress.

[14] Among others, D'Alessio and Iezzi (2013) provide a summary on different indebtedness indicators, their usage, and possible drawbacks.

Objective Over-Indebtedness Index The objective over-indebtedness measure is an aggregated and standardized index that combines four indicators. We include the following components in the index: an indicator variable if the debt service to income ratio (DSR) is greater than 0.4, an indicator variable if the overall remaining debt service to income ratio exceeds 0.4, an indicator for if the household holds more than two loans at the same time, and one indicator for if the household paid late or defaulted on a loan in the last 12 months. Each component is well established in the literature (see, for example D'Alessio and Iezzi, 2013). Among these variables, the DSR is widely recognized as standard measure to capture indebtedness. The threshold we set for the DSR to indicate over-indebtedness is based on considerations from the literature where a range between 0.3 and 0.5 is used (Chichaibelu and Waibel, 2017; D'Alessio and Iezzi, 2013). In constructing the objective over-indebtedness index we follow Kling et al. (2007). We explain how the index and its components are derived in the Online Appendix. When deriving our debt measures, we include all types of loans that households report. Those can be formal or informal loans, as well as loans taken from friends and family members. During the interview, respondents were highly encouraged to report all loans regardless of the source. Hence, we are confident that we capture a household's true debt level.

Subjective Over-Indebtedness Index While objective debt indicators provide numerically accurate debt measures, they are sometimes criticized for failing to account either for the reasons why households overborrow or for the household's undisclosed ability to pay back debt. Therefore, we also include subjective, "respondent driven" over-indebtedness measures in our analysis. As before, we derive a standardized index aggregating different indicators of subjective over-indebtedness. The indicators include an assessment identifying if the household feels it has too much debt, if it has difficulties paying debt off, and the so-called "sacrifice index."[15] The index and its components are explained in detail in the Online Appendix. Schicks (2013) prefers to use subjective over objective debt measures in her work analyzing over-indebtedness from a customer-protection point of view in microfinance. D'Alessio and Iezzi (2013) also rely heavily on a subjective measure to study over-indebtedness in Italy. In line with Keese (2012) and Lusardi and Tufano (2015), we argue that subjective measures describe a situation of financial distress for the respective households but are, naturally, highly subjective to the respondent such that these measures should not be used without considering objective indicators as well. For all indices derived, higher scores point at a higher value of accumulated debt.

[15] We closely follow Schicks (2013) in constructing the sacrifice index.

Table 3.2 depicts the summary statistics of the objective and subjective over-indebtedness indices. The objective index ranges from -1 to 3 with higher values indicating a more severe level of over-indebtedness. While the average DSR lies at 0.23, about 18% of the households have a DSR that is higher than 0.4. More strikingly, about 23% of our sample households have more than two loans. The range of the subjective index is between -2 and 3, again oriented in a way that higher numbers point to higher indebtedness. On average, households state that they have the "right amount of debt" (Mean = -0.02 for the debt position variable) and that they have no difficulties paying off debt. However, the average household admits to have made at least some sacrifices regarding household needs due to lack of money as the average value is -0.08 and a household with no sacrifices would be found at the lowest end of the sacrifice index distribution.

Furthermore, Table B.1 presents correlations between all our debt indicators. Naturally, the objective and subjective indices are significantly correlated with their respective sub-indicators. However, our objective and subjective measures also correlate significantly with each other. This is encouraging, since it rebuts criticism with respect to objective over-indebtedness measures neglecting important dimensions of financial distress.

Table 3.2: Summary Statistics - Over-Indebtedness Variables

	Mean	S.D.	Min	Max	Observ.
Objective Index	0.00	0.99	-1	3	688
DSR $>$ 0.4 (=1)	0.18	0.39	0	1	688
Holds $>$ 2 Loans (=1)	0.23	0.42	0	1	688
RDSR $>$ 0.4 (=1)	0.40	0.49	0	1	688
Paid Late/Default (=1)	0.15	0.36	0	1	685
Subjective Index	-0.02	0.98	-1	4	688
Debt Position	-0.02	0.86	-1	1	688
Diff. Paying Debt (=1)	0.06	0.25	0	1	686
Sacrifice Index	-0.08	1.19	-2	4	688

Note: The debt index variables are standardized. The components of the indices are given in non-standardized real terms.

3.3 Survey Results

In the following, we relate the quantitative income forecast to the over-indebtedness indices by running OLS regressions, estimating correlations between the respective variables.

3.3.1 Estimation Strategy

The regressions we run take the following form:

$$Over\text{-}Indebtedness\ Index_i = \beta_0 + \beta_1 Quant.\ IF_i + X_i^{'}\beta_2 + \epsilon_i \qquad (3.2)$$

The dependent variable $Over\text{-}Indebtedness\ Index_i$ represents the debt measures we apply to mirror financial distress of the household. It contains either the objective over-indebtedness index,[16] or the subjective over-indebtedness index.[17] The main variables of interests are captured in $Quant.\ IF_i$. It comprises the income forecast groups (quantitative income forecast) we derived in Section 3.2.3, where the mildly negative

[16] Standardized average of a dummy equaling one if the debt service to income ratio is greater than 0.4, a dummy equaling one if the remaining debt to income ratio is greater than 0.4, a dummy regarding whether the household paid late or defaulted on a loan, and a dummy equaling one if the household has more than two loans.

[17] Standardized average of the sacrifice index, answers to questions on debt position and whether the household has difficulties paying off debt.

forecast group serves as reference group. We cluster our standard errors at the district level.[18]

The vector X_i controls for household and respondent characteristics that are likely to influence household over-indebtedness: dummies for farming, self-employment, and wage employment, monthly household income in 2016 and 2017, the number of children between the age of 0-6, 7-10, and 11-16 years, the number of elders and working members, total household education (sum of all educational levels in the hh), age and age squared of the respondent, and respondent's financial literacy score. The vector also captures the monetary loss from past shocks. We use detailed information from 2016 and 2017 about monetary losses directly related to a shock. We differentiate between losses from farming related shocks, environmental shocks, economic shocks, crime shocks, and other shocks.

3.3.2 Main Results

To begin with, we relate the quantitative income forecast groups to each over-indebtedness index (OI-Index). In a second step, we add the aforementioned control variables to our regression as the indices depend on other respondent and household specific characteristics as well. Tables 3.3 and 3.4 provide results for the objective and subjective OI-Indices. The tables show results for the four income forecast groups as well as for the shock loss control variables. Tables presenting results for all covariates included in the regression analysis are presented in the Online Appendix. The first column in each table represents the standardized and averaged index whereas the subsequent columns depict results for the single non-standardized components of the indices.

Objective Over-Indebtedness We find a strong, statistically significant, relationship between positive income forecasts and the objective OI-Index. Households with high future income expectations compared to their actual income are more likely to be over-indebted. The over-indebtedness index increases by 0.29 - 0.31 points for positive income expectations (columns (1) and (2), Table 3.3). This relationship is mainly driven by the remaining debt ratio and the dummy on if the household paid late or defaulted on a loan. The debt service to income ratio is only marginally significantly related to positive expectations and having more than two loans shows no relation at all. The RDSR increases by 18.7 - 20.7 percentage points (columns (5) and (6)) and the probability

[18] Cameron and Miller (2015) advise to cluster at least at the primary sampling unit, which is the district level in our case. Since this gives us a small number of clusters, as a robustness check, we use wild cluster bootstrap. This does not change our main findings.

that a household paid late or defaulted on a loan increases by 10.9 - 12.4 percentage points for households whose expected future median income is greater than the current income (columns (7) and (8)). Furthermore, the coefficient of the dummy indicating a DSR greater than 0.4 increases by 8.4 - 9.8 percentage points (columns (3) and (4)) for those households.

With regard to the other income forecast groups, we do not find consistent results. While the probability of a household defaulting or paying late slightly increases for households with a negative forecast, overall, results for the non-positive income forecast groups are insignificant, if not showing a negative sign. A significant and robust link to over-indebtedness can only be found for households with positive future income expectations.

Table 3.3: Objective Over-Indebtedness

	Obj. Index		DSR > 0.4		RDSR > 0.4		Paid Late/Default		> 2 Loans	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Very Negative	−0.125	−0.017	−0.097*	−0.022	−0.073	0.011	0.017	−0.015	0.001	0.010
	(0.151)	(0.143)	(0.047)	(0.050)	(0.081)	(0.079)	(0.033)	(0.036)	(0.059)	(0.060)
Negative	0.050	0.058	−0.067	−0.054	0.075	0.100*	0.081**	0.066**	−0.029	−0.037
	(0.134)	(0.132)	(0.045)	(0.048)	(0.058)	(0.057)	(0.032)	(0.029)	(0.057)	(0.058)
Neutral	0.153	0.135	0.025	0.002	0.079	0.067	0.074	0.095*	−0.002	−0.010
	(0.153)	(0.168)	(0.050)	(0.060)	(0.058)	(0.064)	(0.045)	(0.051)	(0.061)	(0.063)
Positive	0.289**	0.333**	0.098**	0.087*	0.187**	0.210***	0.109***	0.133***	−0.054	−0.037
	(0.134)	(0.136)	(0.042)	(0.047)	(0.072)	(0.069)	(0.038)	(0.041)	(0.055)	(0.060)
Farming Shocks		−0.000		−0.000		0.000		−0.000		0.000
		(0.002)		(0.000)		(0.001)		(0.001)		(0.001)
Environ. Shocks		0.005***		−0.000		0.002***		0.002**		0.002***
		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
Economic Shocks		0.003***		0.000		0.002***		0.001*		0.000
		(0.001)		(0.000)		(0.001)		(0.001)		(0.001)
Crime Shocks		−0.016*		−0.004*		−0.013***		−0.002		−0.001
		(0.009)		(0.002)		(0.003)		(0.004)		(0.004)
Other Shocks		−0.000		−0.000		−0.000		0.000**		−0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Constant	−0.073	−1.425**	0.189***	0.119	0.343***	−0.617**	0.099***	−0.016	0.245***	−0.291
	(0.144)	(0.576)	(0.048)	(0.296)	(0.072)	(0.286)	(0.019)	(0.243)	(0.063)	(0.280)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	688	676	688	676	688	676	685	673	688	676
Adj. R-squared	0.014	0.099	0.025	0.046	0.025	0.125	0.007	0.044	-0.003	0.053

*** p<0.01, ** p<0.05, * p<0.1

Note: Clustered standard errors in parentheses. The variables *very negative, negative, neutral*, and *positive* represent the income forecast groups. Households with a mildly negative income forecast serve as the reference group. Additional controls: age, age squared, children (0-6), children (7-10), children (11-16), financial literacy score, main income farming, main income employed, main income self-employed, main income remittances, monthly household income 2017, no. of elders in hh, no. of working members in hh, risk preference, self-control, social status, total hh education.

We account for monetary losses from various shock events, because a shock might influence both the level of over-indebtedness and income expectations at the same time (i.e., an expectation to return to pre-shock-level income). The results show that higher losses are associated with higher debt levels. However, while we find statistically significant effects, these effects are economically rather small. For example, if an environmental shock loss increases by 1000 Thai Baht (ca. 26€ in 2017), the objective OI-Index increases by 0.05 points. Even when accounting for monetary losses induced by shocks, the relationship between positive income forecasts and over-indebtedness remains significant, confirming a robust relationship between the two. Concerning additional covariates, household income and the perceived social status are significantly negatively related to household over-indebtedness. Age is positively and age squared negatively significant, suggesting a hump-shaped pattern in line with life-cycle-income-smoothing. Furthermore, over-indebtedness remains largely unaffected by household composition and education.

Subjective Over-Indebtedness Our analysis of subjective over-indebtedness reveals that the relationship to the positive income forecast group is less pronounced than for the objective over-indebtedness index but still significant for the index and all its components.

Table 3.4: Subjective Over-Indebtedness

.	**Subj. Index**		Debt Position		Diff. Pay off Debt		Sacrifice Index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Very Negative	0.182	0.215*	0.040	0.036	0.065**	0.058	0.118	0.245**
	(0.112)	(0.122)	(0.114)	(0.110)	(0.029)	(0.039)	(0.106)	(0.103)
Negative	0.157	0.150	0.096	0.046	0.037	0.033	0.108	0.178
	(0.135)	(0.110)	(0.111)	(0.109)	(0.025)	(0.026)	(0.174)	(0.154)
Neutral	−0.007	0.048	−0.021	0.008	0.022	0.031	−0.098	−0.035
	(0.104)	(0.092)	(0.096)	(0.094)	(0.021)	(0.019)	(0.128)	(0.095)
Positive	0.144	0.258**	0.113	0.181**	0.024	0.041*	0.113	0.245*
	(0.086)	(0.101)	(0.071)	(0.084)	(0.021)	(0.023)	(0.120)	(0.122)
Farming Shocks		−0.001		0.002		−0.000*		−0.002
		(0.001)		(0.001)		(0.000)		(0.002)
Environmental Shocks		0.007***		0.003***		0.002**		0.003
		(0.001)		(0.001)		(0.001)		(0.002)
Economic Shocks		0.001		0.003**		−0.000		−0.000
		(0.001)		(0.001)		(0.000)		(0.002)
Crime Shocks		0.000		−0.006		0.003		−0.005
		(0.014)		(0.007)		(0.003)		(0.014)
Other Shocks		0.002***		0.000		0.001***		0.002***
		(0.001)		(0.000)		(0.000)		(0.000)
Constant	−0.115	−0.482	−0.064	−1.480***	0.035**	0.140	−0.131	0.344
	(0.082)	(0.593)	(0.081)	(0.514)	(0.016)	(0.155)	(0.111)	(0.591)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	688	676	688	676	686	674	688	676
Adj. R-squared	0.001	0.133	-0.002	0.094	0.002	0.073	-0.001	0.119

*** p<0.01, ** p<0.05, * p<0.1

Note: Clustered standard errors in parentheses. The variables *very negative, negative, neutral*, and *positive* represent the income forecast groups. Households with a mildly negative income forecast serve as the reference group. Households with a mildly negative income forecast serve as the reference group. Additional controls: age, age squared, children (0-6), children (7-10), children (11-16), financial literacy score, main income farming, main income employed, main income self-employed, main income remittances, monthly household income 2017, no. of elders in hh, no. of working members in hh, risk preference, self-control, social status, total hh education.

As shown in Appendix 5, the qualitative forecast error is more strongly related to the subjective OI-Index. This hints at two possible explanations: One, the subjective OI-Index is rather a concept of perceived financial distress and, thus, more related to the "more subjective" qualitative forecast error. Two, financial distress is not only determined by the household's true debt situation but more so by its perception. When analyzing the control variables, we find that risk seeking and the perceived social status of the household are highly significantly related to the subjective OI-Index, much more so than other control variables. Delving deeper into respondent characteristics, we run regressions including the Big Five measures,[19] (results are presented in the Online Appendix). For respondents who score high on openness and neuroticism, the subjective OI-Index and its components are larger than for those who score low. Eventually, shocks are similarly related to subjective over-indebtedness as they are to objective over-indebtedness: Households experiencing an environmental shock have a significantly higher perceived debt level.

Income Certainty In an additional exercise, we investigate whether being potentially too certain about the future income development is related to over-indebtedness. As shown in Tables 3.5 and 3.6, there is no relation between certainty about future income and subjective over-indebtedness, although we find that higher income certainty is related to objective over-indebtedness. If a respondent is very certain about the development of future household income, this is linked to an augmented over-indebtedness index. This result is mainly driven by the debt to service ratio and by having more than two loans (columns (2) and (5), Table 3.5). Thus, certainty is likely to constitute a part of the positive forecast we derived.

[19] The Big Five comprise the following personality traits: openness, conscientiousness, extraversion, agreeableness, and neuroticism. More details on their construction are found in the Online Appendix.

Table 3.5: Certainty Measure - Objective Over-Indebtedness

.	**Obj. Index**	DSR > 0.4	RDSR > 0.4	Paid Late	> 2 Loans
	(1)	(2)	(3)	(4)	(5)
Very Negative	−0.017	−0.023	0.012	−0.017	0.013
	(0.144)	(0.050)	(0.079)	(0.036)	(0.061)
Negative	0.047	−0.062	0.104*	0.057*	−0.034
	(0.129)	(0.044)	(0.054)	(0.030)	(0.057)
Neutral	0.122	−0.002	0.062	0.092*	−0.013
	(0.167)	(0.060)	(0.064)	(0.051)	(0.063)
Positive	0.323**	0.084	0.201***	0.131***	−0.037
	(0.140)	(0.051)	(0.070)	(0.043)	(0.061)
Certainty	0.129**	0.052**	0.046*	−0.008	0.061**
	(0.061)	(0.022)	(0.026)	(0.024)	(0.022)
Constant	−1.564**	0.074	−0.705**	0.064	−0.413
	(0.552)	(0.299)	(0.284)	(0.268)	(0.276)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	664	664	664	661	664
Adj. R-squared	0.101	0.054	0.125	0.042	0.060

*** p<0.01, ** p<0.05, * p<0.1

Note: Clustered standard errors in parentheses. The variables *very negative, negative, neutral*, and *positive* represent the income forecast groups. Households with a mildly negative income forecast serve as the reference group. Households with a mildly negative income forecast serve as the reference group. Additional controls: age, age squared, children (0-6), children (7-10), children (11-16), financial literacy score, loss from crime shocks, loss from economic shocks, loss from environmental shocks, loss from other shocks, main income farming, main income employed, main income self-employed, main income remittances, monthly household income 2017, no. of elders in hh, no. of working members in hh, risk preference, self-control, social status, total hh education.

Table 3.6: Certainty Measure - Subjective Over-Indebtedness

.	**Subj. Index**	Debt Position	Diff. Pay off Debt	Sacrifice Index
	(1)	(2)	(3)	(4)
Very Negative	0.220	0.049	0.057	0.247**
	(0.133)	(0.117)	(0.041)	(0.108)
Negative	0.144	0.045	0.032	0.168
	(0.109)	(0.108)	(0.026)	(0.150)
Neutral	0.043	0.010	0.030	−0.048
	(0.092)	(0.095)	(0.019)	(0.097)
Positive	0.238**	0.177*	0.035	0.227*
	(0.110)	(0.098)	(0.023)	(0.125)
Certainty	0.069	0.092	0.006	0.031
	(0.086)	(0.066)	(0.020)	(0.104)
Constant	−0.673	−1.802***	0.143	0.273
	(0.651)	(0.578)	(0.165)	(0.699)
Controls	Yes	Yes	Yes	Yes
Observations	664	664	662	664
Adj. R-squared	0.133	0.098	0.072	0.115

*** p<0.01, ** p<0.05, * p<0.1

Note: Clustered standard errors in parentheses. The variables *very negative, negative, neutral*, and *positive* represent the income forecast groups. Households with a mildly negative income forecast serve as the reference group. Households with a mildly negative income forecast serve as the reference group. Additional controls: age, age squared, children (0-6), children (7-10), children (11-16), financial literacy score, loss from crime shocks, loss from economic shocks, loss from environmental shocks, loss from other shocks, main income farming, main income employed, main income self-employed, main income remittances, monthly household income 2017, no. of elders in hh, no. of working members in hh, risk preference, self-control, social status, total hh education.

Overall, we conclude, (i) that there is indeed a significant positive and robust relationship between positive quantitative income forecasts and objective as well as subjective over-indebtedness; (ii) We are also reassured that, although correlated to each other, subjective and objective over-indebtedness indicators measure different dimensions of indebtedness. The "hard" objective OI-Index is much stronger related to positive income forecasts than the subjective OI-Index; (iii) Certainty about the household's income development is also related to over-indebtedness, primarily to objective over-indebtedness.

3.3.3 Robustness

Excluding Possibly Confounding Observations. Before eliciting the subjective expected income of respondents, we ask two questions testing the understanding of the concept of probability. We re-run the analysis including only those respondents who do not violate the laws of probability and examine whether our main results hold. Results are presented in Tables B.2 and B.3 in the Appendix. The coefficients for this subsample stay highly significant and almost all coefficients increase in size emphasizing the link between a positive income forecast and objective over-indebtedness.

In order to verify that respondents have an actual understanding of their household's finances, we again re-run the regressions, including only those individuals who are in charge of the household's financial decisions either alone or together with someone else (see Appendix Tables B.4 and B.5). Overall, the results stay virtually unchanged with regard to the significance of our coefficients of interest. Point estimates change slightly.

Interacting the Income Forecast with Personality Traits. We do not claim to show a causal effect because - among other reasons - we acknowledge that the relation between over-indebtedness and positive income expectations may also work in the reverse. For example, if people are indebted, they might have a great bias regarding future expected income as they plan to work harder in the future to pay down their debt. We expect such people to exhibit a high level of conscientiousness, the personality marker describing achievement oriented (McClelland et al., 1953), hard-working, effective, and dutiful characters (Barrick and Mount, 1991). Hence, we interact our income forecast measure with this character trait, expecting to find significant effects for conscientious people. Results for the aggregated indices as dependent variables are presented in Appendix Table B.6. The interaction is not significant for the positive income forecast and any of the OI-Indices. This counteracts the assumption that the achieving respondents with distorted expectations drive the relationship between our positive income forecast and debt status.

Exchanging the Forecast Groups with One Single Indicator. We apply a coarser indicator measuring positive future income expectations to counteract the possible criticism that our results hinge on the choice of the reference category with respect to our income forecast groups. In lieu of the five quantitative income forecast groups, we define an indicator variable to turn one if the relative difference between expected future and actual income is greater than zero. Results for the objective and subjective over-indebtedness indices as well as for the certainty measure are presented in Appendix Tables B.7, B.8, B.9, and B.10. Probably due to the broader category that we use as the main explanatory variable, point estimates gain in significance, but are numerically a little smaller when compared to the positive income forecast group. This actually supports our finding that it is exactly those respondents with high expectations about their future income who are also relatively more indebted. Generally, this robustness check confirms that our results remain significant and similar in size with respect to the objective and subjective over-indebtedness indicators when using a broader income expectation indicator. Hence, it is not the choice of the reference group that drives our results.[20]

3.4 The Experiment

The preceding section shows that high expectations and over-indebtedness are strongly related to each other in our rural Thai population, even when controlling for important socioeconomic characteristics and shocks. However, methodologically, the implemented regression analysis only represents correlations. Furthermore, we are specifically interested whether overconfidence, a systematic behavioural bias that might be responsible for having too high expectations in the first place, can actually cause overspending and overborrowing. In what follows, we analyse if overconfidence is one potential *cause* why households in our sample spend more than they can actually afford.

Theoretically, upward biased expectations can arise for two reasons; either an individual is overly optimistic or overly confident. We follow Heger and Papageorge (2018) in defining overoptimism as the tendency to overestimate the probability of preferred outcomes and overconfidence as the tendency to overestimate one's own performance. We acknowledge that in our rural, agricultural setting, overoptimism might occur as frequently if not more than overconfidence. Since agricultural activities and the exposure to weather shocks are rather homogeneous in our sample and less driven by personal abilities, a more positive view on the future might originate from an optimistic view on the world in general. Still, there is scope for overconfidence as the adoption of new agricultural technologies and crops, the working pace (that can influence agricultural output) and the bargaining power in selling crops is strongly dependent on beliefs about individual performance and might lead to positive income expectations as well. For our experiment, we concentrate on overconfidence because numerous studies show that over-

[20] Additionally, we also used different reference groups in the first place and our regression results remain similar. Results are available upon request.

confidence is related to important life and financial decisions, while overoptimism is less so.[21]

3.4.1 Experimental Design

As final part of the survey, we play a "market game" in which respondents can buy different kinds of goods for a discounted price with money they earn in the experiment. They can buy packs of coffee, chips, dried mango, or detergent for 10 THB (ca. 0.25€) each instead of the 20 THB list price.[22] Each participant receives an endowment of 40 THB. Additional money can be earned by answering questions in a trivia game. Earnings depend on how many questions the participant answers correctly in comparison to the other participants. We rank them from 1-10, where rank ten corresponds to answering the most questions correctly and rank one to answering the least number of questions correctly.[23] People ranked 1-4 do not earn anything on top of their endowment, those ranked 5-6 earn 10 THB, those ranked 7-8 20 THB, and those ranked 9-10 earn 40 THB additionally. Thus, participants can earn up to 80 THB and can buy at most eight goods.

We make expectations a crucial factor in the game by requiring participants to decide how much and what to buy before they take the pay-off relevant quiz, i.e., before they know their final payoff. We divide participants in two treatment groups; one group faces a "hard" quiz and the other one an "easy" trivia quiz. To convey the difficulty of each quiz and to exogenously vary expectations about relative performance, participants do a test quiz with seven questions upfront where difficulty again depends on treatment. Based on the test quiz, participants infer how good they will be in the pay-off relevant main quiz and form expectations about the performance of the others

[21] For example, Camerer and Lovallo (1999), who experimentally test the effect of overconfidence on entrepreneurial decision-making (this relationship is a well-researched field of study), conclude that excess entry in a market game is strongly related to overconfidence and not to overoptimism.

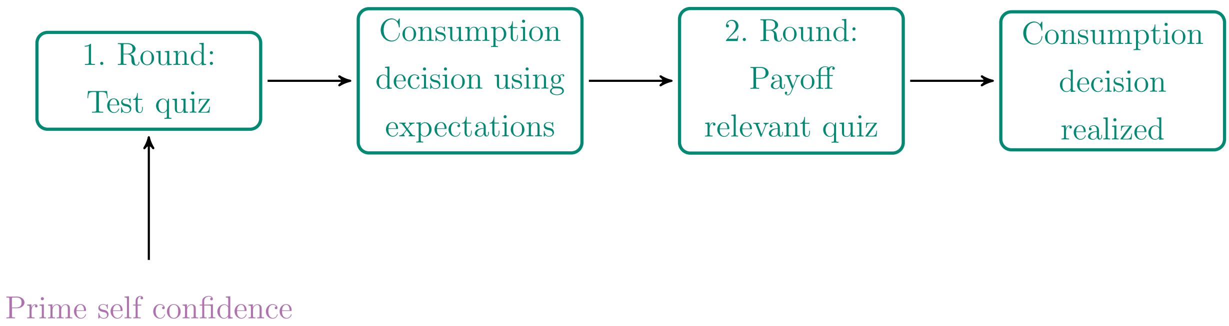
[22] At least for the bag of chips, it is common knowledge that they usually cost 20 THB as, for a long time, they had the price printed on their front. To further convince participants that the products are truly discounted, we attached "20 THB" price tags to each product.

[23] In the field, participants from the first villages were ranked against participants from our pilot villages and our interviewers who also took the quizzes. For later villages, we replaced our interviewer data with data from the previous villages and told participants that they are ranked against ten persons who live in a village similar to theirs. For the final analysis, we use all the observations to create a ranking. In each treatment, we have two accumulation points in the number of correctly answered questions that are next to each other and around the mean. We set these two points as rank five and six. Each one point deviation in correctly answered question then constitutes a one point deviation in rank (e.g., if rank five means nine questions answered correctly, rank four means eight questions answered correctly). Since there are more questions than possible ranks, we have some bunching of correctly answered questions around rank one and rank ten, the boundaries of the ranking.

and, thereby, their relative rank. They are ranked within each treatment group and they are told that everybody they are ranked against took the exact the same quiz. With this design, we can exploit the so-called hard-easy gap analogous to Dargnies et al. (2019) and very similar to Grohmann et al. (2019). Much research finds that people tend to overplace themselves in easy tasks and to underplace themselves in hard tasks (for example Merkle and Weber, 2011; Hartwig and Dunlosky, 2014; Benoit et al., 2015). Over-(under-)placing is a form of over-(under-)confidence in which individuals over-(under-)estimate their relative performance in comparison to others. Thus, by assigning participants to two different treatments, we exogenously vary their expectations through varying self-confidence (see Figure 3.6).[24] We subsequently measure confidence as the difference between expected rank and actual rank:

$$confidence = rank_{exp} - rank_{act} \tag{3.3}$$

Figure 3.6: Experimental Flow



Except for the difference in difficulty, the procedure is the same for every participant: If participants agree to play the game, the interviewer prepares the set-up and starts reading the instructions. The instructions include comprehension questions to test whether participants understand how their rank is determined and how much they can earn. If participants do not answer these questions correctly, the interviewer does not continue with the instructions.[25]

[24] The exogenous variation is one reason why we do not include this measure for self-confidence in our survey regressions as a measure for expectation bias. Another reason is that self-confidence is domain dependent.

[25] Still, there are participants who had serious difficulties in understanding the game such that we exclude them from the main analysis

After they have finished the instructions, the participants start answering the test quiz, which has seven trivia questions. They have five minutes to answer all the questions. For each question, four possible answers are given. When the time is up or participants have finished answering, they receive a decision sheet. On the decision sheet, they first have to write down the rank and the earnings they expect to reach in the following main quiz. Then, they must indicate their buying decision based on their expected earnings. Afterwards, participants continue with the main quiz where they have to answer 15 questions in ten minutes. Following the quiz, there are three debriefing questions including a question on the expected rank after the second quiz has actually taken place (such that we can check for belief updating). Finally, the interviewer calculates the rank and earnings, then hands over the products and money, if applicable.

In most cases, participants could read, write, and answer the quizzes on their own. Sometimes, people, in particular the elderly, needed assistance in reading and writing, which was provided by the interviewer. The supplemental material for the experiment is found in the Online Appendix in English (for the experiment everything was translated to Thai).

Rational Decisions

If participants want to buy more than they can afford, including their endowment, their consumption has to be restricted. They receive at most as many goods as they can buy with their earnings and nothing beyond that amount. Participants are aware of this fact.

We implicitly assume that expectations influence buying decisions. If this does not hold, the aforementioned design feature seriously distorts our results as follows. If it was the case that "rational" participants strictly prefer goods over money because, for example, they are cheaper than list price and can be stockpiled, expectations would become meaningless for the consumption decision. Indicating to buy eight goods is weakly dominating any other number of goods for this kind of participants, since they clearly prefer goods over money independent of the budget.[26]

Eventually about 4% of our participants decided to buy eight goods even though they expect to earn less. An additional 3% wanted to buy more than they expected to earn but less than eight goods. In our main analysis, these observations are excluded because i) we already know that expectations do not impact consumption in this setting for them

[26] If the participant expects less than 80 THB, there is a potential loss in indicating to buy less than eight goods because the prediction might be underconfident. However, given our setting, there is no loss if she indicates buying eight goods but actual earnings are less than 80 THB.

and ii) they could artificially inflate our results. We present additional analyses on this sub-sample in the Appendix Section "The Rationals" (B.3.4) and discuss whether they truly acted in a rational way or rather had difficulties understanding the game.

For the other 93%, we still assume that respondents generally prefer a bundle of products and cash. The exact composition depends on individual preferences but also expected earnings. Thus, being overconfident (or underconfident) creates a distortion in utility. Following these reflections, we derive the following hypotheses:

Hypothesis 1: *On average, individuals in the easy treatment will buy more than individuals in the hard treatment.*
Hypothesis 2: *A great level of overconfidence will lead to excessive spending.*

Hypothesis 1 is implied by the finding on the hard-easy gap. Hypothesis 2 follows from the fact that we define respondents to be overconfident if their expected rank is higher than their actual rank, which implies that they earn less than expected. Since we cannot allow respondents to pay from personal money if experimental money is insufficient, restricting consumption in some cases is necessary. Therefore, people cannot accumulate debt. Still, we try to mimic real life financial decision making with this design, especially the fact that sometimes (and optimally) consumption decisions must be made before income is realized. In that sense, participants still have to take a loan, although only for a short time and without serious consequences, if they want to consume. Further, if they have biased beliefs, they might end up with a consumption bundle that is sub-optimal, thus overborrowing. The process can also be seen as a form of household budgeting; however, we prefer the term overborrowing as participants have to plan with money they do not have in the moment of planning. In real life those who overborrow accumulate more debt than optimal, perhaps more than they are able to repay.

3.4.2 Experimental Results

Overall, 604 respondents participated in the game. Since participation is self-selected, participants and non-participants are compared in Table B.3.1 in the Appendix. As can be seen, participants and non-participants differ significantly in some variables.[27] In all these variables, the difference is in the expected direction: female, older, less occupied, less educated, financial illiterate and less numerate, and more financial risk

[27] A complete list of all variables and their explanation is provided in the Online Appendix.

averse respondents are less likely to participate in the game. Several of these variables are significantly correlated with each other. Running a simple regression on the likelihood to participate, we find that some of these variables are insignificant and that the time of day is one of the strongest predictors of game participation (see B.3.2). Since the time of day at which we visited households for the interviews is mostly exogenous,[28] self-selection into the game is less pronounced than initially expected.

Out of the 604, seven observations are excluded because either treatments for them are mixed up, personal information is missing, or a third person helped them answer the questions. We exclude 44 observations that are also excluded from the survey regression analysis because they are outliers in income or the debt service to income ratio (see Section 3.2.1).[29] Additionally, 84 observations are excluded because it can be inferred from the data that comprehension was insufficient[30] or because they want to buy more than they expect to earn in total (see previous Sub-Section on these special cases). Those 84 cases differ only in their number of children between 7-10 years.

In Table 3.7 characteristics of the remaining 471 participants are compared across treatments. The significantly unequal number of participants per treatment is due to fact that we slightly over-sampled the easy treatment. Results from previous studies suggest that the effect of easy tasks on self-confidence is generally stronger than the effect of hard tasks (see for example Dargnies et al., 2019). The characteristics depicted here might be important for the general level of self-confidence and the willingness to buy products. Given the sample size and the number of variables analysed, randomizing participants into the treatments worked well; the two groups only significantly differ with regard to their health status, their monthly household income, and their (objective) over-indebtedness index. Controlling for these variables leaves our results virtually unchanged and a f-test on joint orthogonality finds that controls do not jointly determine the treatment group.

[28] We interviewed households according to a schedule we designed together with our interview team manager, which tried to minimize travel distances for each interview team. Hence, this schedule was exogenous to individual household characteristics, except for the village that the household resides in. However, a few houses were empty the first time we visited them and we had to reschedule another date with the household itself.

[29] The results are robust to this exclusion.

[30] For example, one participant writes that he expects to earn 30 Baht from the game, which is, however, not an possible option. Another one wants to buy 35 products although the maximum affordable number is eight.

Table 3.7: Descriptive Statistics across Treatments

	Full Sample	Hard Treatment	Easy Treatment	Difference
Sex	1.64	1.60	1.67	−0.07
Age	56.16	55.23	56.93	−1.70
Relation to HH Head	1.70	1.69	1.71	−0.02
Marital Status	2.13	2.09	2.16	−0.07
Main Occupation	4.79	4.29	5.20	−0.90
Years of Schooling	5.92	6.08	5.79	0.28
Children (0-6 years)	0.33	0.37	0.29	0.08
Children (7-10 years)	0.26	0.26	0.26	0.01
Numeracy	2.14	2.09	2.19	−0.10
Health Status	1.38	1.32	1.43	−0.11**
BMI	23.58	23.25	23.86	−0.61
Fin. Decision Maker	1.57	1.55	1.59	−0.03
Self Control	20.94	21.19	20.75	0.44
Risk Taking	4.02	3.96	4.07	−0.12
Fin. Risk Taking	4.06	3.99	4.12	−0.13
FL-Score	5.66	5.55	5.75	−0.20
Monthly Inc. 2017	18653.06	20802.79	16893.44	3909.35**
Obj. OI-Index	0.01	−0.09	0.09	−0.18**
Subj. OI-Index	−0.04	−0.03	−0.06	0.03
Morning	0.53	0.51	0.54	−0.03
Midday	0.27	0.26	0.28	−0.02
Read Alone	1.44	1.44	1.44	−0.00
Difficulties in Game	1.14	1.15	1.13	0.01
Observations	471	212	259	471

*** p<0.01, ** p<0.05, * p<0.1

Shift in Beliefs

On average, participants answered 9.07 out of 15 trivia questions correctly in the easy treatment and 5.09 out of 15 in the hard treatment. Thus, it can be assumed that, for our sample, the easy treatment is truly "easier" than the hard treatment. The average expected rank in the hard treatment is 6.89 whereas the average expected rank in the easy treatment is 7.22. In Figure 3.7 the cumulative distribution functions of the expected ranks for both treatments are plotted. It seems that there is only a small shift in beliefs, since the distributions are still almost overlapping.[31] Indeed, if we compare the distributions of the "second" expectations that are elicited after respondents actually

[31] We focus on the expected rank in our analysis but everything holds analogously for expected earnings.

took the main quiz, we find a much larger shift (see Appendix Figure B.3.1). Thus, either our test quizzes are not as hard or easy as the main quizzes and, therefore, the shift in first beliefs is smaller or participants have such strong beliefs that they only gradually update their beliefs. Still, the distributions of first beliefs are significantly different from each other (Kolmogorov-Smirnov one-sided p=0.056; Wilcoxon rank-sum two-sided p=0.041). The t-test for mean expectations is significant at the 5% level (one-sided) as well (Figure 3.10).

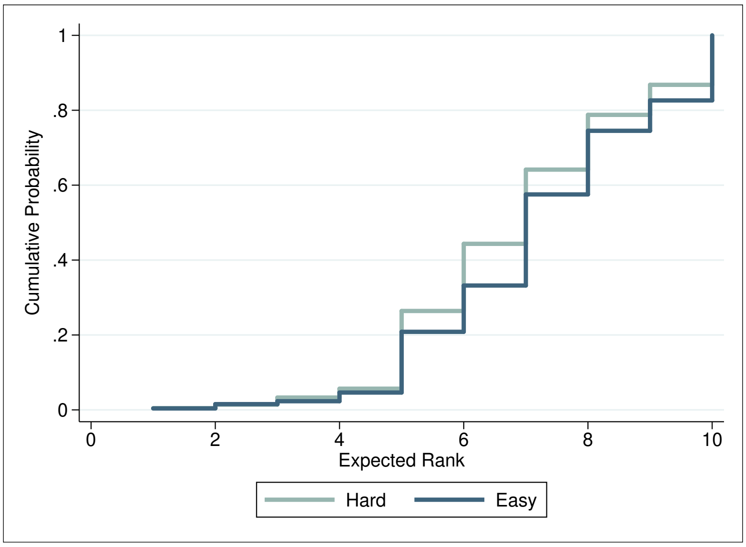


Figure 3.7: Cumulative Density Distribution of Expected Rank by Treatment

The difference in self-confidence is larger than the difference in expected rank (see Figure 3.8). This might be driven by our ranking procedure or by the fact that the easy quiz is not a perfect shift of the hard quiz with respect to the number of questions answered correctly. In any case, this suggests that our manipulation via the treatments to shift the level of beliefs and thereby self-confidence worked.

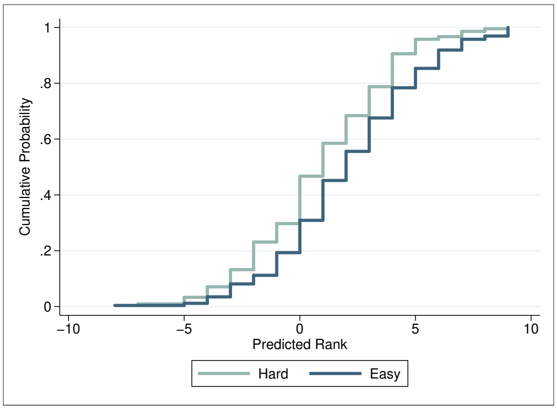


Figure 3.8: CDFs of Self-Confidence

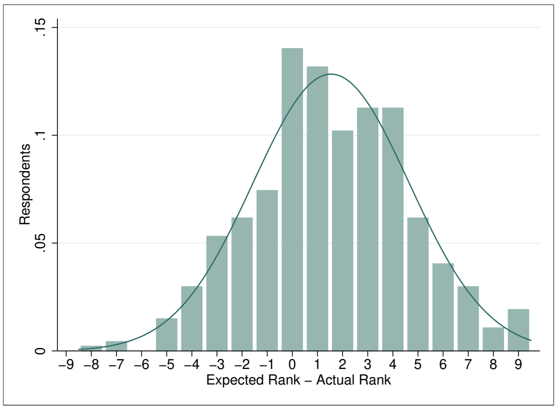


Figure 3.9: Histogram for Self-Confidence

As seen in Figure 3.9, across both treatments, the mean and median respondents are slightly overconfident (even in the hard treatment). The whole distribution is a little bit skewed to the left but still resembles a normal distribution. Over 14% of the sample have perfectly accurate beliefs and have a self-confidence of "0." Small deviations from 0 could be considered accurate as well because they could present a form of Bayesian updating.[32] Still, a substantial fraction of participants seems to be tremendously overconfident.

Buying Decision

We find a significant positive correlation between expected rank (earnings) and the number of goods participants want to buy. However, there is no significant relation between the treatment itself and mean desired consumption as presented in Figure 3.11.

[32] On this discussion, see Merkle and Weber (2011).

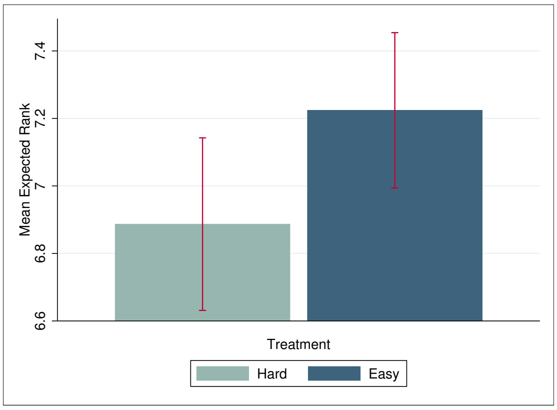


Figure 3.10: Mean Expected Rank by Treatment

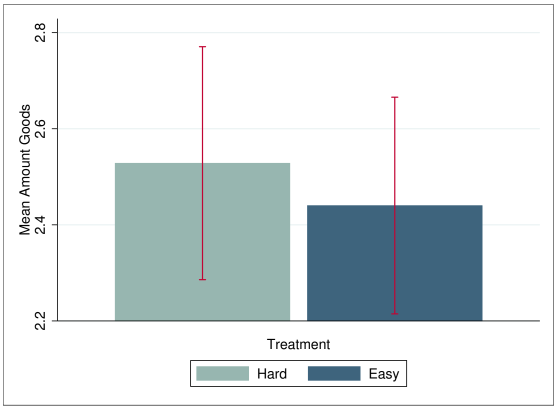


Figure 3.11: Mean Consumption by Treatment

If we run regressions where we can control for the variables that are unbalanced across treatments, the picture stays the same: the treatment is positively related to the expected rank, the expected rank is positively related to the desired amount of goods, but the treatment is not related to the amount of goods (see Table 3.8).

Table 3.8: Consumption Decision

.	Exp. Rank	No. Goods		
	(1)	(2)	(3)	(4)
Treatment	0.377**	−0.133		−0.189
	(0.175)	(0.173)		(0.171)
Exp. Rank			0.144***	0.149***
			(0.046)	(0.046)
Controls	Yes	Yes	Yes	Yes
Observations	470	470	470	470

*** p<0.01, ** p<0.05, * p<0.1

Note: Robust standard errors in parentheses. Treatment: 0=Hard Quiz, 1=Easy Quiz; A higher expected rank corresponds to a higher expected performance. Controls: Health Status, Monthly HH income and Objective OI-Index.

A similar pattern emerges if we look explicitly at spending behaviour (see Table 3.9). We distinguish *overborrowing*, meaning buying more than actual earnings including endowment can pay for, from *overspending*, meaning buying more than actual game earnings can pay for, but the spending can still be paid with the endowment. The expected rank as well as confidence have a significant effect on both variables, but treatment does not.[33]

Table 3.9: Overborrowing and Overspending

.	Overconfidence	Overborrowing		Overspending
	(1)	(2)	(3)	(4)
Treatment	1.217***	0.010	−0.007	−0.034
	(0.284)	(0.019)	(0.019)	(0.045)
Overconfidence			0.014***	0.044***
			(0.004)	(0.007)
Controls	Yes	Yes	Yes	Yes
Observations	470	470	470	470

*** p<0.01, ** p<0.05, * p<0.1

Note: Robust standard errors in parentheses. Treatment: 0=Hard Quiz, 1=Easy Quiz; Controls: Health Status, Monthly HH income and Objective OI-Index.

Summarized, our treatments shifted expectations in hypothesised directions; expectations are positively related to spending behaviour, but the treatment has no impact on the latter. Therefore, we cannot claim that there is a causal link between expectations and overborrowing in our experiment.

3.4.3 Confounding Factors

The previous findings are robust to various restrictions. For example, they are not driven by participants who are very old or have mild comprehension difficulties (we already excluded those with large difficulties in the main analysis). It is also not the case that the treatments only affect expected ranks but not expected earnings.[34] This suggests that there are confounding factors or "noise" interfering with our treatments. We run further analyses to rule out that the treatments affected factors other than expectations:

Frustration and Gratification. One of the most likely confounds could be that participants in the hard treatment feel frustrated because of the difficult questions and want

[33] The level of significance is higher not lower when we exclude possibly "rational" participants who want to buy more than they expect to earn in total.

[34] This could happen if there is a piecewise treatment effect (shifting expectations only within the same earnings category) because earnings are only piecewise increasing in ranks and not equidistant.

to treat themselves with “shopping.” In contrast, some others might be proud of mastering such a hard quiz and also want to reward themselves. Both motives should lead to the result that, specifically, participants with extreme expectations behave differently across treatments. Participants who are frustrated should rank themselves rather low whereas participants that are proud should rank themselves rather high. Subsequently, the buying behaviour of participants with the same expected rank across treatments should be significantly different for the lowest and highest ranks. However, the only (marginally) significant difference we can detect is for the five participants who expected to reach rank two: here, participants in the hard treatment want to buy more than participants in the easy treatment. Excluding these observations does not change our results. For all other ranks, participants in both treatments exhibit the same spending pattern. This finding does not favour frustration and gratification as being possible confounding factors.

Temptation. Another possibility is that participants in the hard treatment are more susceptible to temptation goods. They have to exercise more cognitive effort, which decreases their self-control, so-called “ego depletion” (see, for example, Hagger et al., 2010). Running separate regressions on each product, we find a significantly different treatment effect only for dried mango. Still, self-control (measured with the scale from Tangney et al., 2004) and BMI do not have significant effects on buying mango, which opposes the ego depletion interpretation. We also do not find evidence that frustrated (more depleted) participants are more likely to buy mango. Furthermore, detergent is the most popular product and the share of detergent in all goods desired is not different across treatments, whereas mango is the least popular. Detergent is the one product we would expect to be least related to self-control issues. Summarized, we do not find convincing evidence that persons in the hard treatment are more likely to give in to temptation.

Based on these tests, we argue that we can rule out the most probable factors interfering with our treatment. We believe that the reason we do not find a treatment effect on spending and borrowing is that the shift in beliefs was not strong enough to eventually be reflected in spending. We find additional evidence for this proposition when employing IV estimation, where we instrument expected rank with treatment. Several tests indicate that treatment is a weak instrument for expected rank.

3.4.4 Behaviour in the Lab and in Real Life

A supplementary result we find worth mentioning is that being over-indebted in "real life" is actually related to spending behaviour in our experiment (see Table 3.10). Those respondents who have problems controlling their spending in real life are also those who spend less carefully in the game. Eventually, we see this as evidence that our experiment, although highly artificial, still captures aspects of real life behaviour.

Table 3.10: Overborrowing in the Game and in Real Life

.	No. Goods		Overborrowing		Overspending	
	(1)	(2)	(3)	(4)	(5)	(6)
Obj. OI-Index	−0.000		−0.001		0.050**	
	(0.077)		(0.008)		(0.021)	
Subj. OI-Index		0.105		−0.005		0.043*
		(0.078)		(0.008)		(0.022)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	471	471	471	471	471	471

*** p<0.01, ** p<0.05, * p<0.1

Note: Robust standard errors in parentheses. Controlled for confidence as defined in Equation 3.3.

We can only speculate why the well-established hard-easy gap is so small in our setting. Consulting our interviewers, we have no reason to believe that participants did not perceive the test quizzes as hard or easy when they should. Several other studies find larger shifts in beliefs, although participants had less exposure to manipulation.[35] The rural Thai population may have more persistent beliefs than WEIRD populations. This makes changing these beliefs more difficult. Given the tremendous level of overconfidence we find in the lab, this circumstance might not be beneficial for our participants. It relates to our regression result that being too certain about future income is related to over-indebtedness. "Sticky," biased expectations, bear implications for policy making and must be taken into account when measures to reduce over-indebtedness are designed.

[35] For example, Grohmann et al. (2019) only use four questions they frame as "example questions" and find larger treatment effects on expectations.

3.5 Conclusion

Over-indebtedness can pose a serious threat to households' welfare and the financial stability of a country, especially in emerging markets. However, the determinants underlying over-indebtedness globally are, so far, not well understood. Theoretically, as modelled in various permanent income hypotheses, higher income expectations should lead to a higher level of borrowing.

In this study, we analyse the relationship between high income expectations and over-indebtedness using data from an extensive household survey and a lab-in-the-field experiment. Low levels of financial knowledge and high income uncertainty demand for explicit research in emerging countries because relying on results for Western populations is insufficient. Our sample belongs to a panel survey of relatively poor and rural households in Thailand. Indeed, we can confirm a low level of financial literacy in several dimensions and find substantial uncertainty in income expectations for our sample. While over-indebtedness is increasingly recognized as a growing problem in Thailand, our study sheds light on one potential driver.

In our regression analysis, we find a strong and robust positive relationship between high expectations concerning future income and over-indebtedness controlling for various household characteristics and shocks. We think this is a sign that these expectations are actually too high for some households. This finding holds for various measures of over-indebtedness. They are stronger for objective measures, if we use a quantitative elicitation method for positive income expectations based on probabilistic expectations and stronger for subjective over-indebtedness, if we use a qualitative, more subjective forecast error. In any case, they are always significant. The results reflect that subjective over-indebtedness indicators are likely to be influenced more heavily by personal perceptions on the household's financial situation as well as by respondents' personality traits and that objective and subjective measures capture different dimensions of over-indebtedness. Eventually, higher certainty about the future household income development is also related to more household over-indebtedness, which might be the case because being too certain is not optimal given the highly uncertain environment. The results are robust to a diverse set of different sample specifications and we do not find evidence of reverse causality issues.

We attempt to establish a causal relationship between overconfidence as a form of biased expectation and overborrowing in our experiment by exogenously biasing self-confidence via the so-called hard-easy gap. Thereby, we change expectations about the future payout in the game. Our results show that, in the experiment, overconfidence is related to more spending and overborrowing, but we cannot claim causality. The most probable reason why our treatments do not affect spending behaviour are too "sticky" beliefs. This also suggests that rural households are indeed too certain about their income expectations. Interestingly, we find that overspending in the experiment is related to overspending in real life, which confirms that the artificial experiment still captures real life behaviour.

As we will never know the true income generating process, we cannot know whether the expectations of our respondents are systematically biased or positive for other reasons. A systematic overestimation of future income would have much more devastating effects than a random, one-shot, inaccurate guess. Nevertheless, we find reassuring evidence that even one-time high expectations are positively related to household over-indebtedness, thus pushing households into severe poverty. One of the potential channels through which high expectations are related to over-indebtedness is being too certain about own expectations in the highly uncertain environment that rural households in emerging markets are living in. Given the supplemental evidence for sticky beliefs from our experiment, to change beliefs or their certainty seems to be challenging. More appropriate policy measures might reduce vulnerability and uncertainty with the expansion of assistance and insurance schemes, especially for households engaged in agriculture.

Chapter 4

Validation of the Big Five Model in Rural Developing Economies – Evidence from Thailand and Vietnam*

with:
Dorothee Bühler
Rasadhika Sharma

* We thank Ulrike Grote, Lukas Menkhoff, Susan Steiner, Stephan Thomsen, and Andreas Wagener for their helpful comments. Financial support by the German Research Foundation (DFG) via the Research Training Group 1723 and the Thailand Vietnam Socio Economic Panel (Project No. 283672937) is gratefully acknowledged.

4.1 Introduction

The importance of personality traits for economic research has been highlighted extensively over the past two decades. However, the measurement of personality is a complex endeavour, since context and sub-group characteristics can hamper the applicability of existing models. The standard measurement model of personality is the Big Five Factor model by Costa and McCrae (1992) that defines personality along five dimensions. The typology and measurement of this model were developed and tested mainly in industrialised countries among highly educated samples.[1] Therefore, it is not self-evident that the structure of this model is universally applicable, i.e., that it also holds in non-WEIRD populations. A handful of recent studies from developing countries provide further ground to these concerns. For instance, Gurven et al. (2013) find only two personality factors instead of the usual five in their data from rural Bolivia. Other papers highlight more issues such as lack of internal consistency, wrong factor loadings and measurement errors (Schmitt et al., 2007; Cheung, 2009; Ludeke and Larsen, 2017). Evidence from Laajaj et al. (2019) shows that the survey mode, i.e., whether the survey is self-administered or not, also plays an important role.

Our study contributes to this string of literature on the measurement and factor structure of personality traits outside WEIRD populations. While studies such as Laajaj et al. (2019) and Schmitt et al. (2007) employ data from students and relatively better educated individuals living in urban centers, we expand the discussion to a rural sample. In particular, we introduce and validate the Big Five measure of personality traits for individuals in rural Southeast Asia. Using a rich panel data set from rural Thailand and Vietnam of some 4,000 individuals,[2] we analyse the internal and external validity of the Big Five factor structure. Therewith, we specifically address whether the factor structure holds, and, if survey measures can be applied in rural samples in Southeast Asia. We further provide insights into the stability of the traits over time using individual-level data.

In this paper, we (i) test the scales for internal consistency; (ii) test the stability of personality traits over time; (iii) test the scales for external validity; (iv) correct our scales for acquiescence bias. The results reveal that the underlying factor structure in our sample population from rural Southeast Asia is similar to the structure of the standard Big Five model. We find five factors that can be largely mapped to the Big Five factors. Results further suggest that the survey measure is internally and externally valid

[1] These are also often referred to as western, educated, industrialised, rich, and democratic (WEIRD) countries (Heinrich et al., 2010).

[2] The data were collected under the Thailand Vietnam Socio Economic Panel (TVSEP).

in the context of rural households in Thailand and Vietnam. In line with Laajaj et al. (2019), measures of internal consistency are lower for our sample compared to expected values from WEIRD populations. Additionally, results show that retest stability across different survey waves is stronger among higher educated respondents, which matches findings from other studies (e.g., Schmitt et al. (2007)).

The remainder of the paper is organised as follows: Section 4.2 introduces the data and measurement of personality traits. Section 4.3 presents the econometric methods and discusses the results. Section 4.4 concludes.

4.2 Data and Measurement

We analyse Big Five data from the 7th wave of the Thailand Vietnam Socio Economic Panel (TVSEP), collected in the summer of 2017.[3] The data were collected in three rural provinces in each country. In Thailand, these are the provinces of Buriram, Nakhon Panom and Ubon Ratchathani and in Vietnam the data are gathered in the provinces of Thua Thien Hue, Ha Tinh and Dak Lak. Figure C.1 in the Appendix exhibits an overview of the survey region. For the purpose of this study, we utilise data on 3,811 individual respondents - 1,913 Thais and 1,898 Vietnamese, who answered the subsection on personality traits.

In both countries, an almost identical household survey is applied. It consists of nine sections covering individual information on household members (e.g., age, education, health, and employment) as well as household-level information (such as household income, housing conditions and experienced shocks). In wave 7 of the TVSEP database, an additional module asking for the established psychological personality inventories was included. These questions allow to study personality traits and their consequences on a large sample of individuals living in rural Thailand and Vietnam, and, to relate them to a rich set of socioeconomic variables.

The survey questionnaire includes items that measure personality following the Big Five model developed by Costa and McCrae (1992, 1997). This model is the most cross-culturally validated model of personality traits (Stuetzer et al., 2018). It defines personality along the five following factors: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. The survey questions included in the TVSEP are based

[3] The TVSEP is a panel survey that runs since 2007 and regularly administers surveys among rural households in Thailand and Vietnam. Until now, eight waves have been conducted. The survey covers some 4,400 households in 440 villages. The household sample in each province was randomly drawn based on a stratification process considering the heterogeneous agro-ecological conditions within the regions. Please refer to Hardeweg et al. (2013) for a detailed review of the sampling strategy.

on the Big Five personality inventory questions used in the German Socio Economic Panel (SOEP). Similar questions are used in the British micro panel survey and World Bank surveys across different countries (Guerra et al., 2016). In the respective TVSEP questionnaire section, respondents are asked how much they agree with different statements about themselves. They rank their answers on a 7 point Likert scale ranging from 1 to 7, where 1 means "Does not apply to me at all" and 7 means "Applies to me perfectly". Respondents are presented with 15 survey questions in total. Each factor is captured by three questions. Table C.1 in the appendix illustrates the relation between the personality traits and survey questions. To obtain the Big Five traits, we construct simple averages using three questions for each respective trait.

Additional Data for Stability Testing In Section 4.3.2 we test stability of the data over time and compare data from wave 7 to the 8th TVSEP wave, that was conducted in the summer of 2019.[4] For this wave, data were collected in Thailand only. Therefore, comparison data for Vietnam are not available. The questions and answer options are identical to the ones in the wave 7 questionnaire. The dataset includes data on personality traits for all three Thai provinces. We identify 933 households with the same respondent in 2017 and 2019. While the same households are interviewed for every TVSEP wave, the respondent within the household may vary over time, e.g., if the household head is not available his or her spouse might answer the survey. Therefore, we only include cases, where the respondent was the same in both years. Hence, the lower sample size. The questions and scales on personality traits in the 2019 survey are identical to the ones in the 2017 survey.

4.3 Results

4.3.1 Internal Validity

We conduct a series of psychometric indicators to document the internal validity and consistency of our survey measures. Following Laajaj et al. (2019) these indicators include: (i) the within correlation that is the average correlation within the items belonging to one personality trait, (ii) the between correlation that is the average correlation between items of different personality traits, and (iii) the Cronbach's itemized alpha coefficient which tests for the internal consistency of scales across the survey questions and

[4] These data sets are used only in this specific Section. Throughout the rest of the paper, we use the full data set from wave 7 for both countries.

the personality traits. We compute the psychometric indicators separately for Thailand and Vietnam as well as jointly for the whole database.

Within and Between Correlation Table 4.1 provides the results for the within and between correlations. A strictly positive correlation either in the within or the between correlation coefficient suggests that the indicator captures something that the tested items have in common rather than just noise. If the expected factor structure exists, the correlation within items belonging to one trait should be positive. Further, the correlation between items of different personality traits should be close to zero. The results show that the within correlation is strictly positive and varies between between 19% to 21%. The between correlation is significantly lower and ranges between 4% to 6%. Other studies using data from developing countries such as Laajaj et al. (2019) report higher within correlations. However, since the between correlation shows there is very little correlation across items belonging to different factors, the factor structure still holds.

Table 4.1: Psychometric Indicators

	No. of Items	No. of Observations	Within Correlation	Between Correlation	Cronbach's Alpha*
All	15	3090	0.21	0.048	0.45
Thailand	15	1447	0.19	0.040	0.41
Vietnam	15	1643	0.21	0.064	0.43

Note: Own calculations with TVSEP data from wave 7. * average for five character traits.

Cronbach's Alpha The Cronbach's itemized alpha coefficient (Cronbach, 1951) is one of the most widely used tests of internal consistency (Gosling et al., 2003). It tests the internal consistency of scales across the survey questions and across the five personality traits. The coefficient can take values between 0 and 1 and increases with higher correlation between the items of the same personality trait. Thus, the higher the alpha coefficient, the better the items measure the same underlying factor (Laajaj et al., 2019). The minimum threshold for the alpha coefficient is often set at 0.7. However, the threshold also depends on the extend of the applied measure, with alpha usually increasing with more items (Gosling et al., 2003).[5] The TVSEP questionnaire includes a

[5] Gosling et al. (2003) suggest to also look at the test-retest correlation as a further reliability check, which we do in the Section 4.3.2.

short measure of 15 questions, which is standard for most household surveys.[6] Therefore, we expect alpha values below 0.7.

The results of the Cronbach's alpha coefficient for each factor are displayed in Table 4.1 and Table C.2. The individual coefficients range between 0.25 and 0.62 across the different items and factors. As expected, the coefficients are below the 0.7 benchmark. However, the results are similar to that of other Big Five surveys using a short version of the measure (e.g., Schäfer (2016); Laajaj et al. (2019)). The average reliability for the five factors for the whole sample is 0.44. The values per country are slightly lower. Table C.2 in the Appendix displays detailed results per trait. The factors openness, conscientiousness and agreeableness display higher values of internal consistency, while the values for neuroticism and extraversion are lower.

4.3.2 Stability

In order to further check the reliability of the data, we test the congruence of the survey results over time. We do so by: (i) comparing the two sample means for each factor; (ii) calculate the test-retest correlation; (iii) present superimposed histograms to take a closer look at the answer distributions. The time difference between the two survey waves is two years. While personality traits are regarded as relatively stable for adults (Cobb-Clark and Schurer, 2012), certain life events as well as changes in demographic factors can lead to a change in personality traits over the course of a lifetime. We would therefore expect to see somewhat stable results.

The results for the mean comparison between wave 7 and wave 8 are presented in Table 4.2. We observe significant differences in the means between both waves for all five factors. However, these differences are relatively small and mean values are still similar. We also provide results for the test-retest correlations in Table C.3 in the Appendix. The test-retest correlation ranges between 0.21 and 0.25. Other studies observe higher test-retest correlations (see for example Gosling et al. (2003)). We therefore look at sub-samples of the data set and see that our results improve when excluding possible confounding factors, i.e., respondents that may had difficulties understanding the questions.[7] We also see some differences between the three survey provinces, with Ubon Rathchathani pertaining a lower retest correlation for openness, neuroticism and

[6] Surveys centering on the assessment of the Big Five model often use the 44-item Big-Five Inventory (see for example John and Srivastava (1999)) or the the 60-item NEO Five-Factor Inventory (Costa and McCrae, 1992).

[7] We defined these as respondents with a difference between the test and the retest that is greater than two points on the Likert scale

extraversion. We also test the correlations and means per province, but do not find strong provincial effects. To get a more comprehensive understanding of the differences between waves, we present superimposed histograms in the appendix. They show that answers in wave 8 are on average more moderate, i.e., respondents choose less extreme values, than in wave 7. We think that this might indicate that respondents are getting used to the questions and therefore slightly alter there answer patterns.

Table 4.2: Comparison of Sample Means

	Thailand Wave 7	**Thailand Wave 8**	**Difference**
Openness	4.610	4.384	0.225***
Conscientiousness	5.688	5.564	0.124**
Extraversion	4.521	4.410	0.111**
Agreeableness	5.801	5.634	0.167***
Neuroticism	3.313	3.411	-0.098**
Observations	933	933	933

*** p<0.01, ** p<0.05, * p<0.1

Note: Own calculations with 2017 and 2019 TVSEP data. First two columns show results for the sample means. Column three displays results from the two-sided ttests. Own calculation with TVSEP data from wave 7 and wave 8 in Thailand.

Furthermore, we delve deeper into the causes of differences in results between the two waves. We find that males and more educated individuals are less likely to alter their responses over the two years. Studies from other data sets also observe that a higher level of education and literacy in the survey population favours replication and reliability of the Big Five model (e.g., Schmitt et al. (2007); Laajaj et al. (2019)).

Overall, the results show that answers vary over the medium run. However, the differences in are still small and we would expect some variation over a time period of two years, since respondents are exposed to different life events that could possibly change answers. We further see that demographic factors have an influence on the answer stability. Therefore, we recommend to run robustness checks for different subgroups when using the data in an analysis.

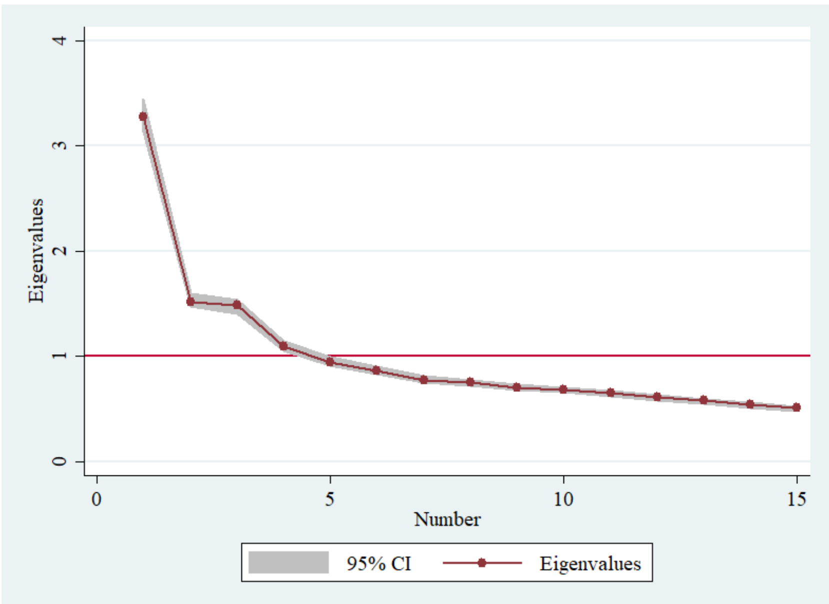
4.3.3 External Validity

We test for the underlying structure of personality traits and the external validity of our survey measures. In particular, we (i) perform a Principal Component Analysis to explore the underlying factor structure in our sample, (ii) correlate our factors to the conventional Big Five personality traits, and (iii) compare our findings with SOEP (Germany), HILDA (Australia) and SAPA (United States of America).

Principal Component Analysis We conduct a Principal Component Analysis (PCA) to analyse the factor structure in our sample. A PCA is advantageous when data sets contain a large number of variables. It uses the dependencies between the input variables to reduce the dimensionality and creates groups which are homogeneous within themselves and heterogeneous between each other (Backhaus et al., 2011). We base the PCA on the 15 questions on personality traits administered to respondents in the household questionnaire (see Section 4.2). To conclude that the factor structure of the Big Five model can be applied to our sample, the PCA should produce five factors and the underlying 15 items should load on the expected factors.

Figure 4.1 clearly shows the presence of a five-factor structure. The Kaiser criterion (K1) (Ford et al., 1986) which retains all factors with eigenvalues greater or equal to one, is used to determine the number of factors to be retained. Together, these factors explain a total of 56 % of the variance.

Figure 4.1: Scree Plot of Eigenvalues after PCA



Note: Own illustration with 2017 TVSEP data.

Factor loadings from the PCA are shown in Table 4.3. Following Hair et al. (2009), only the factors with loadings greater than 0.30, i.e., meeting the minimum practical significance level, are interpreted.

Table 4.3: Factor Loadings according to PCA

BFI-Items	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Artistic	**0.30**	-0.27	-0.10	0.01	0.08
New ideas	**0.31**	-0.12	0.12	**0.31**	**-0.35**
Active imagination	**0.32**	-0.26	0.10	0.05	-0.14
Work thoroughly	**0.30**	0.22	0.10	0.04	**-0.39**
Efficient	**0.35**	0.11	-0.08	-0.06	**-0.30**
Lazy (reversed)	0.10	**0.53**	-0.08	0.05	**-0.31**
Talkative	0.24	-0.12	-0.03	**0.45**	0.22
Sociable	**0.32**	-0.02	0.00	**0.30**	**0.30**
Reserved (reversed)	-0.15	0.24	-0.12	**0.65**	0.15
Forgiving	0.28	0.25	0.04	-0.19	**0.48**
Kind	**0.35**	0.23	0.00	-0.18	**0.33**
Rude (reversed)	0.00	**0.53**	-0.14	-0.04	0.06
Worries	0.00	0.15	**0.67**	0.01	-0.01
Nervous	0.00	0.01	**0.66**	-0.02	0.12
Relaxed	**-0.31**	0.12	0.17	**0.32**	0.00

Note: Own calculations with 2017 TVSEP data. We only interpret variables that have factor loadings greater than or equal to 0.30.

Factor 1 has a positive loading in relation to seven items and a negative loading from one item. The positive loading includes all three questions related to the Big Five factor of openness - artistic, new ideas and active imagination and two items related to conscientiousness - work thoroughly and efficient. In addition, the positive loadings also include the items sociable and kind. Further, this factor loads negatively on the item relaxed. Thus, Factor 1 is a mix of two Big Five traits. Factor 2 loads positively on two items, hard working and polite. This factor cannot be directly mapped to one of the conventional traits in the Big Five with respect to the items. Factor 3 loads positively on two items, worries and nervous. Therewith, the factor falls into the same category as the Big Five factor of neuroticism. Factor 4 loads positively on five items. Of these, the three items with the highest positive loadings, talkative, sociable and reserved (reversed), belong to the Big Five factor extraversion. In addition, this factor also loads positively on the items new ideas and relaxed. While there is a clear congruence with extraversion, this factor slightly overlaps with Factor 1. Factor 5 loads positively on three and negatively on four items. Among the positive loadings are forgiving and kind. The factor loads negative on the items new ideas, work thoroughly, efficient, and lazy (reversed). Thus, the factor describes a mix of searching for social acceptance while at the same time avoiding hard work. The factor does not seem to be directly related to any of the Big Five factors per se. Overall, the results from the PCA reveal a five factor structure similar to that of the Big Five Factor model. However, we observe that the items do not always load on the expected factors. This finding is largely in line with a meta study from Schmitt et al. (2007) showing that populations from Asia might diverge from the factor structure as well as the average scores per factor, in relation to other areas of the world. In the next section, we therefore take a closer look at the obtained factors and compare them to the Big Five factors.

Correlations with Big Five Factors In this part of the analysis, we compare factors obtained from the PCA with the Big Five factors to assess their similarity. As explained in section 4.2, we construct the Big Five factors using simple averages of the three questions for each respective trait. Table 4.4 shows the correlations between the two sets of factors.

Table 4.4: Correlation between Big Five and Factors from PCA

	Openness	**Conscientiousness**	**Extraversion**	**Agreeableness**	**Neuroticism**
Factor 1	**0.76**	**0.63**	0.38	0.50	-0.23
Factor 2	-0.37	**0.51**	0.12	**0.64**	-0.12
Factor 3	-0.02	0.13	-0.06	0.09	**0.92**
Factor 4	0.22	0.08	**0.75**	-0.24	0.11
Factor 5	-0.21	-0.42	0.46	0.32	0.07

Note: Own calculations with 2017 TVSEP data.

Factor 1 is significantly correlated to the factor openness from the Big Five model. Similarly, Factor 3 can be clearly mapped to the factor neuroticism, and, Factor 4 to the Big Five factor, extraversion. However, the trait structure differs with respect to Factor 2, which comprises hard working and polite individuals. Therefore, it correlates with both Big Five factors of conscientiousness and agreeableness. Our analysis reveals that these qualities are a particular feature of personality traits in our sample population. Overall, we find that the PCA factors are relatively close to the Big Five factors.

Comparison with other surveys In general, Southeast Asians score lower on extraversion and conscientiousness, and higher on agreeableness compared to their Western counterparts. The scores reported are very similar in case of openness and neuroticism (Schmitt et al., 2007). We inspect if the same patterns are observed in case of our sample. We compare our results for personality traits means with those from three other surveys, namely – the German Socio-Economic Panel (SOEP), the Australian Household Income and Labour Dynamics in Australia (HILDA) and the American Synthetic Aperture Personality Assessment (SAPA) 2015.

Table 4.5: Comparison between TVSEP and other surveys

Trait	**Thailand (rural)**	**Vietnam (rural)**	**Germany (SOEP)**	**Australia (HILDA)**	**USA (SAPA)**
Openness	4.60a,b	4.04a,b	4.49	4.24	x
	(1.26)	(1.37)	(1.169)	(1.052)	
Conscientiousness	5.66a,b,c	5.79a,b,c	5.93	5.15	4.20
	(1.01)	(0.89)	(0.872)	(1.005)	(1.02)
Extraversion	4.48a,b,c	4.55a,b,c	4.82	4.40	3.84
	(1.05)	(1.09)	(1.134)	(1.087)	(0.08)
Agreeableness	5.76a,b,c	5.89a,b,c	5.35	5.40	4.69
	(0.96)	(0.89)	(0.965)	(0.888)	(0.06)
Neuroticism	3.31	4.41	x	x	x
	(1.12)	(1.08))			

Note: Thailand and Vietnam means are calculated by authors based on TVSEP 2017 (NTH = 1,913, NVN = 1,898). German SOEP means are taken from Schäfer (2016) (N = 17,028). Australian HILDA means are taken from Cobb-Clark and Schurer (2012) (N = 6,104). American SAPA 2015 means are taken from Elleman et al. (2018) (N = 134,858). x - Schäfer (2016), Cobb-Clark and Schurer (2012) and Elleman et al. (2018) use a different factor, called Emotional Stability and do not calculate neuroticism. a – Independent ttest comparison with SOEP.b – Independent ttest comparison between HILDA. c – independent ttest comparison with SAPA 2015.

The results are broadly in line with the aforementioned proposition. The rural population in Thailand reports the highest levels of openness. However, Germans are more conscientious than all other samples. On average, Thais and Vietnamese tend to be less extroverted and score highest on agreeableness.

4.3.4 Acquiescence Bias

Acquiescence is a common bias, where the respondent agrees or disagrees with a question irrespective of the content (Ferrando et al., 2004). For instance, in the TVSEP questionnaire, the questions *"Do you see yourself as someone who does tasks efficiently?"* and *"Do you see yourself as someone who tends to be lazy?"*, capture conscientiousness.

The second question is coded reversely. If an individual strongly agrees to both these questions, this contradiction indicates Acquiescence Bias (AB). This systematic error can affect the mean levels in item responding, factor structure and hence the overall validity of personality questionnaires (Rammstedt et al., 2017; Danner et al., 2015).

To test for AB in our sample, we construct personality trait factors corrected for AB. This requires that at least one of the questions measuring each factor is reversed. The TVSEP questionnaire does not contain reversed questions for openness and agreeableness. Therefore, we estimate the AB for the other factors and subsequently apply the correction to all items. This method is also illustrated in Laajaj et al. (2019). These AB corrected factors are compared to our Big Five factors. Table 4.6 shows that all factors are statistically different from each other. This highlights that there is evidence of acquiescence bias in our data. As this could affect our factorial structure and other aspects pertaining to validity, we also execute internal and external validity tests with the Big Five factors corrected for acquiescence bias.

Table 4.6: Comparison between Sample means and AB corrected sample means

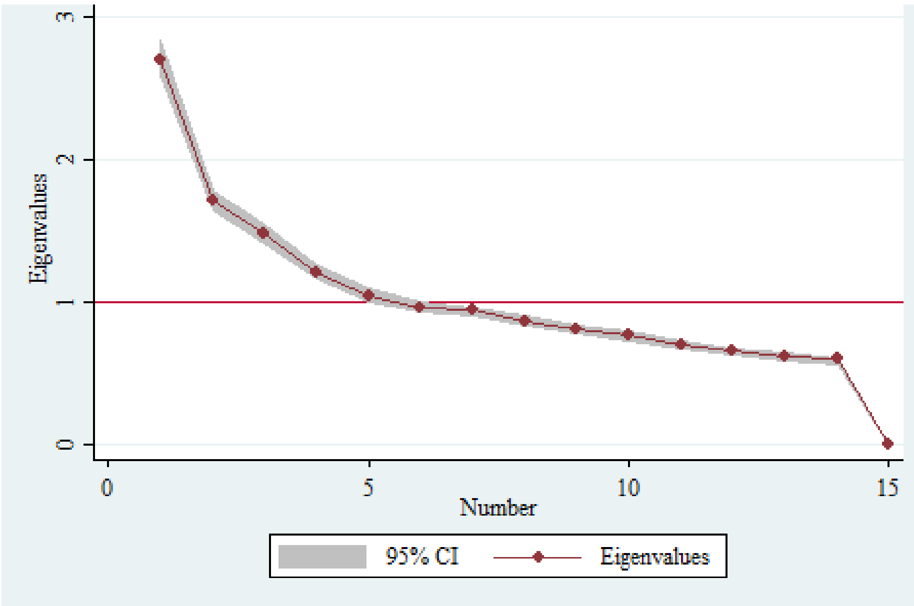
	Mean Sample	**Mean AB corrected**	**Mean Difference**
Openness	4.32	4.04	0.28***
Conscientiousness	5.71	5.62	0.09***
Extraversion	4.52	4.42	0.09***
Agreeableness	5.83	5.73	0.09***
Neuroticism	3.86	3.77	0.09***

*** p<0.01, ** p<0.05, * p<0.1

Note: Own calculation with TVSEP wave 7 data. First two columns show the means. Column three displays results from the two-sided ttests.

We find that the scree plot in Figure 4.2 and the PCA (refer to table C.4) reveal a five factor structure. The Chronbach's alpha lies at 0.51, which is similar to the original value (refer to Table C.5). Hence, we can conclude that the acquiescence bias does not impact the internal and external validity of our results.

Figure 4.2: Scree Plot of Eigenvalues after PCA - Acquiescence Bias corrected



Note: Own illustration with 2017 TVSEP data.

4.4 Conclusion

This paper validates the Big Five model in a rural developing country setting. Our results suggest that the survey measure is internally and externally valid in the context of rural households in Thailand and Vietnam. We further find that the underlying factor structure is similar to the structure of the Big Five model. In particular, (i) we test the scales for internal consistency, (ii) we test the stability of personality traits over time, (iii) we test the scales for external validity, (iv) we correct our scales for acquiescence bias. For this, we use data on 3,811 individuals collected under the Thailand Vietnam Socio Economic Panel.

The first research objective relates to the internal validity of the sample measures. The psychometric indicators (within correlation, between correlation, and Cronbach's alpha) estimated for the sample indicate that the factor structure holds. Results show very low between correlations. In terms of the alpha values, we see that the factors openness, conscientiousness and agreeableness display higher alpha values and neuroticism and extraversion relatively lower values. The fact that the alpha values range below 0.7 is not unusual in sample with a short version of the Big Five measures and is also observed in other data sets with short measures.

Our second research objective examines the stability of the results over time. We compare results from wave 7 and 8 of the TVSEP. We find significant differences in the means between the two waves, with relatively lower values reported in the wave 8. Here, we also show that respondents education level is vital. Individuals with higher education exhibit more stable personality traits over time.

The third research objective was checks the external validity of the model. The PCA and the scree plot reveal a five-factor structure. However, the groups of input variables do not always load on the expected traits. Still, we find high correlations between the factors obtained from the PCA and the factors created using weighted averages of items according to the common Big Five structure. A comparison of sample means for traits from our sample with those from other surveys conducted in other countries further shows that Southeast Asians are less conscientious but more agreeable than their counterparts from WEIRD countries.

Last, we construct acquiescence bias corrected factors and compare these with our Big Five factors. We find evidence for acquiescence bias in our results. However, the bias does not render substantial effects on the internal and external validity of our estimations.

While we acknowledge that we cannot reject all the concerns highlighted by existing studies (e.g., with respect to stability), our results provide substantial evidence on the validity of the Big Five model in a developing country setting. Specifically, they demonstrate that the model is applicable in the context of rural households in Southeast Asia.

Chapter 5

Occupational Attainment and Earnings in Southeast Asia: The Role of Non-cognitive Skills*

with:

Dorothee Bühler

Rasadhika Sharma

This paper has been published as:
Bühler, D., Sharma, R., and Stein, W. (2020). "Occupational Attainment and Earnings in Southeast Asia: The Role of Non-cognitive Skills", *Labour Economics (67, 101913).*

DOI: https://doi.org/10.1016/j.labeco.2020.101913

* We thank Mathias Bühler, Ulrike Grote, Olaf Hübler, Lukas Menkhoff, Helke Seitz, Susan Steiner, Stephan Thomsen, Andreas Wagener, and seminar participants in Göttingen and Hannover for their helpful comments. The paper also profited from discussions with workshop and conference participants at the 3rd IZA/HSE Workshop in St. Petersburg, the AASLE 2019 in Singapore and the Annual Congress of the European Economic Association (EEA) 2020. Financial support by the German Research Foundation (DFG) via the Research Training Group 1723 and the Thailand Vietnam Socio Economic Panel (Project No. 283672937) is gratefully acknowledged.

Bibliography

Abendroth, M. and J. Flannery (2006). Predicting the risk of compassion fatigue. A study of hospice nurses. *Journal of Hospice and Palliative Nursing 8*(6), 346–356.

ADB (2020). *Key Indicators for Asia and the Pacific.* Manila, Philippines: Asian Development Bank.

Almlund, M., A. L. Duckworth, J. J. Heckman, and T. D. Kautz (2011). Chapter 1 - Personality psychology and economics. In E. A. Hanushek, S. Machin, and L. Woessmann (Eds.), *Handbook of the Economics of Education*, Volume 4, pp. 1–181. Elsevier.

Amare, M. and L. Hohfeld (2016). Poverty transition in rural Vietnam: The role of migration and remittances. *The Journal of Development Studies 52*(10), 1463–1478.

Angelsen, A. Jagger, P., R. Babigumira, B. Belcher, S. Hogarth, N. J.and Bauch, J. Börner, C. Smith-Hall, and S. Wunder (2014). Environmental income and rural livelihoods: A global-comparative analysis. *World Development 64 (Supplement 1)*, S12–S28.

Attanasio, O. and B. Augsburg (2016). Subjective expectations and income processes in rural india. *Economica 83*(331), 416–442.

Attanasio, O. P. (2009). Expectations and perceptions in developing countries: Their measurement and their use. *American Economic Review 99*(2), 87–92.

Attanasio, O. P. and K. M. Kaufmann (2014). Education choices and returns to schooling: Mothers' and youths' subjective expectations and their role by gender. *Journal of Development Economics 109*, 203–216.

Backhaus, K., B. Erichson, W. Plinke, and R. Weiber (2011). *Multivariate Analysemethoden: Eine anwendungsorientierte Einführung* (13$^{\text{th}}$ ed.). Berlin, Heidelberg, New York: Springer-Verlag.

Banerjee, A. V. and E. Duflo (2007). The economic lives of the poor. *Journal of Economic Perspectives 21*(1), 141–167.

Barrick, M. R. and M. K. Mount (1991). The big five personality dimensions and job performance: A meta-analysis. *Personnel Psychology 44*(1), 1–26.

Baskin, S. M., G. L. Lipchik, and T. A. Smitherman (2006). Mood and anxiety disorders in chronic headache. *Headache 46*, 76–87.

Becker, G. (1964). *Human capital: A theoretical and empirical analysis, with special reference to education*. University of Chicago Press for the National Bureau of Economic Research.

Benoit, J.-P., J. Dubra, and D. A. Moore (2015). Does the better-than-average effect show that people are overconfident?: Two experiments. *Journal of the European Economic Association 13*(2), 293–329.

Bozzoli, C. and C. Müller (2011). Perceptions and attitudes following a terrorist shock: Evidence from the UK. *European Journal of Political Economy 27*, 89–106.

Brunnermeier, M. K. and J. A. Parker (2005). Optimal expectations. *American Economic Review 95*(4), 1092–1118.

Burke, M. A. and M. Manz (2014). Economic literacy and inflation expectations: Evidence from a laboratory experiment. *Journal of Money, Credit and Banking 46*(7), 1421–1456.

Camerer, C. and D. Lovallo (1999). Overconfidence and excess entry: An experimental approach. *The American Economic Review 89*(1), 306–318.

Cameron, A. C. and D. L. Miller (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources 50*(2), 317–372.

Campbell, D. (2011). *The Global Crisis: Causes, Responses and Challenges*. Geneva: International Labour Office.

Campbell, D. and I. R. Ahmed (2012). The labour market in developing countries. *Perspectives on Labour Economics for Development (Geneva, ILO)*.

Cheung, F. M. (2009). The cultural perspective in personality assessment. In J. N. Butcher (Ed.), *Oxford Library of Psychology. Oxford Handbook of Personality Assessment*, pp. 44–56. Oxford University Press.

Chichaibelu, B. B. and H. Waibel (2017). Borrowing from "pui" to pay "pom": Multiple borrowing and over-indebtedness in rural thailand. *World Development 98*, 338–350.

Clark, A. E., P. Frijters, and M. A. Shields (2008). Relative income, happiness, and utility: An explanation for the easterlin paradox and other puzzles. *Journal of Economic Literature 46*(1), 95–144.

Clark, A. E. and A. J. Oswald (1994). Unhappiness and unemployment. *The Economic Journal 104*(424), 648–659.

Cobb-Clark, D. A. and S. Schurer (2012). The stability of big-five personality traits. *Economics Letters 115*, 11–15.

Cobb-Clark, D. A. and M. Tan (2011). Non-cognitive skills, occupational attainment, and relative wages. *Labour Economics 18*, 1–13.

Cocker, F. and N. Joss (2016). Compassion fatigue among healthcare, emergency and community service workers: A systematic review. *International Journal of Environmental Research and Public Health 13*(6), 618.

Costa, P. T. J. and R. R. McCrae (1992). Revised neo personality inventory (neo-pi-r) and neo five factor inventory (neo-ffi) professional manual. Technical report, Odessa, FL, USA.

Costa, P. T. J. and R. R. McCrae (1997). Personality trait structure as a human universal. *American Psychologist 52*, 587–596.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika 16*(3), 297–334.

D'Alessio, G. and S. Iezzi (2013). Household over-indebtedness: Definition and measurement with italian data. Questioni di Economia e Finanza (Occasional Papers) 149, Bank of Italy, Economic Research and International Relations Area.

Danner, D., J. Aichholzer, and B. Rammstedt (2015). Acquiescence in personality questionnaires: Relevance, domain specificity, and stability. *Journal of Research in Personality 57*, 119–130.

Dargnies, M.-P., R. Hakimov, and D. Kübler (2019). Self-confidence and unraveling in matching markets. *Management Science 65*(12), 5603–5618.

Delavande, A., X. Giné, and D. McKenzie (2011). Measuring subjective expectations in developing countries: A critical review and new evidence. *Journal of Development Economics 94*(2), 151–163.

Demirguc-Kunt, A., L. Klapper, D. Singer, S. Ansar, and J. Hess (2018). *Global Findex Database 2017: Measuring Financial Inclusion and the Fintech Revolution.* Washington, DC: World Bank.

Diener, E. (1994). Assessing subjective well-being: Progress and opportunities. *Social Indicators Research 31*(2), 103–157.

Diener, E. (1996). Events and subjective well-being: Only recent events matter. *Journal of Personality and Social Psychology 70*(5), 1091.

Diener, E. (2006). Guidelines for national indicators of subjective well-being and ill-being. *Journal of Happiness Studies 7*(4), 397–404.

Diener, E. and R. Biswas-Diener (2002). Will money increase subjective well-being? *Social Indicators Research 57*(2), 119–169.

Dolan, P., T. Peasgood, and M. White (2008). Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being. *Journal of Economic Psychology 26*, 94–122.

Dominitz, J. and C. F. Manski (1997). Using expectations data to study subjective income expectations. *Journal of the American Statistical Association 92*(439), 855–867.

Easterlin, R. A. (2003). Explaining happiness. *Proceedings of the National Academy of Sciences 100*(19), 11176–11183.

Easterlin, R. A. (2008). Income and happiness: Towards a unified theory. *The Economic Journal 111*(473), 465–484.

Elleman, L. G., D. M. Condon, S. E. Russin, and W. Revelle (2018). The personality of U.S. states: Stability from 1999 to 2015. *Journal of Research in Personality 72*, 64–72.

Ferrando, P., L. Condon, and E. Chico (2004). The convergent validity of acquiescence: An empirical study relating balanced scales and separate acquiescence scales. *Personality and Individual Differences 37*, 1331–1340.

Ferrer-i Carbonell, A. and P. Frijters (2004). How important is methodology for the estimates of the determinants of happiness? *The Economic Journal 114*(497), 641–659.

Figley, C. R. (1995). *Compassion fatigue: Coping with secondary traumatic stress disorder in those who treat the traumatized: An Overview.* New York: Taylor Francis Group.

Finseraas, H. and O. Listhaug (2013). It can happen here: the impact of the mumbai terror attacks on public opinion in western europe. *Public Choice 156*(1-2), 213–228.

Ford, J. K., R. C. MacCallum, and M. Tait (1986). The application of exploratory factor analysis in applied psychology: A critical review and analysis. *Personnel Psychology 39*(2), 291–314.

Frančišković, T., A. Stevanović, I. Jelušić, B. Roganović, M. Klarić, and J. Grković (2007). Secondary traumatization of wives of war veterans with posttraumatic stress disorder. *Croatian Medical Journal 48*(2.), 0–184.

Friedman, M. (1957). *A Theory of the Consumption Function.* National Bureau of Economic Research, Inc.

Georgarakos, D., A. Lojschova, and M. E. Ward-Warmedinger (2010). Mortgage indebtedness and household financial distress. ECB Working Paper 1156, European Central Bank.

Gerlitz, J.-Y. and J. Schupp (2005). Zur Erhebung der Big-Five-basierten Persönlichkeitsmerkmale im SOEP. *DIW Research Notes 4*, 2005.

Gloede, O., L. Menkoff, and H. Waibel (2015). Shocks, individual risk attitude, and vulnerability to poverty among rural households in Thailand and Vietnam. *World Development 71*, 55–78.

Gollin, D., D. Lagakos, and M. E. Waugh (2014). The agricultural productivity gap. *The Quarterly Journal of Economics 129*(2), 939–993.

González, J. L., B. Moreno, E. H. Garrosa, and C. Penacoba (2005). Personality and subjective well-being: Big five correlates and demographic variables. *Personality and Individual Differences 38*(7), 1561–1569.

Gosling, S. D., P. J. Rentfrow, and W. B. Swann (2003). A very brief measure of the Big-Five personality domains. *Journal of Research in Personality 37*(6), 504–528.

Greene, W. H. (2012). *Econometric Analysis* (7^{th} ed.). Prentice Hall, New Jersey.

Gröger, A. and Y. Zylberberg (2016). Internal labor migration as a shock coping strategy: Evidence from a typhoon. *American Economic Journal: Applied Economics 8*(2), 123–153.

Grohmann, A., L. Menkhoff, C. Merkle, and R. Schmacker (2019). Earn more tomorrow: Overconfident income expectations and consumer indebtedness. Discussion Paper 152, CRC TRR 190.

Guerra, N., K. Modecki, and W. Cunningham (2016). Developing socio-emotional skills for the labor market - the practise model. Policy Research Working Paper No. 7123, World Bank, Washington D.C., USA.

Guiso, L., T. Jappelli, and L. Pistaferri (2002). An empirical analysis of earnings and employment risk. *Journal of Business and Economic Statistics 20*(2), 241–53.

Guiteras, R., A. Jina, and A. M. Mobarak (2015). Satellites, self-reports, and submersion: exposure to floods in bangladesh. *American Economic Review 105*(5), 232–36.

Gurven, M., C. von Rueden, M. Massenkoff, H. Kaplan, and M. Vie (2013). How universal is the big five? testing the five-factor model of personality variation among forager-farmers in the bolivian amazon. *Journal of Personality and Social Psychology 104*(2), 354–370.

Hagger, M. S., C. Wood, C. Stiff, and N. L. Chatzisarantis (2010). Ego depletion and the strength model of self-control: A meta-analysis. *Psychological Bulletin 136*(4), 495–525.

Hair, J. F., W. C. Black, B. J. Babin, and R. E. Anderson (2009). *Multivariate Data Analysis* (7^{th} ed.). Harlow, Essex, UK: Pearson Education Limited.

Hardeweg, B., S. Klasen, and H. Waibel (2013). Establishing a database for vulnerability assessment. In S. Klasen and H. Waibel (Eds.), *Vulnerability to Poverty: Theory, Measurements and Determinants with Case Studies from Thailand and Vietnam*, pp. 50–79. Basingstoke, UK: Palgrave Macmillan.

Hartwig, M. K. and J. Dunlosky (2014). The contribution of judgment scale to the unskilled-and-unaware phenomenon: How evaluating others can exaggerate over-(and under-) confidence. *Memory and Cognition 42*(1), 164–173.

Heckman, J. J. and T. Kautz (2012). Hard evidence on soft skills. *Labour Economics 19*(4), 451–464.

Heckman, J. J., J. Stixrud, and S. Urzua (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor Economics 24*(3), 411–482.

Heger, S. A. and N. W. Papageorge (2018). We should totally open a restaurant: How optimism and overconfidence affect beliefs. *Journal of Economic Psychology 67*, 177–190.

Heinrich, J., S. J. Heine, and A. Norenzayan (2010). The weirdest people in the world? *Behavioral and Brain Sciences 33*, 61–135.

Helliwell, J. F. (2006). Well-being, social capital and public policy: What's new? *The Economic Journal 116*, C34–C45.

Hyytinen, A. and H. Putkuri (2018). Household optimism and overborrowing. *Journal of Money, Credit and Banking 50*(1), 55–76.

IBRD (2017). *Growing the rural nonfarm economy to alleviate poverty - An evaluation of the contribution of the World Bank Group.* Washington, D.C., U.S.: International Bank for Reconstruction and Development and The World Bank.

IMF (2017). *Global Financial Stability Report: Is Growth at Risk?* Washington, DC: International Monetary Fund.

IPCC (2014). Climate change 2014: Synthesis report. *Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*.

John, K. and S. L. Thomsen (2014). Heterogeneous returns to personality: The role of occupational choice. *Empirical Economics 47*, 553–592.

John, O. P. and S. Srivastava (1999). The Big Five Trait Taxonomy: History, Measurement, and Theoretical Perspectives. In L. Pervin and O. P. John (Eds.), *Handbook of Personality: Theory and Research*, pp. 102–138. New York, US: Guilford Press.

Johnson, D. D. P. and J. H. Fowler (2011). The evolution of overconfidence. *Nature 477*, 317–320.

Kahnemann, D. and A. Tversky (1979). Prospect theory: An analysis of decision under risk. *Econometrica 47*(2), 263–291.

Keese, M. (2012). Who feels constrained by high debt burdens? subjective vs. objective measures of household debt. *Journal of Economic Psychology 33*(1), 125–141.

Klasen, S. and H. Waibel (2013). *Vulnerability to Poverty.* London Palgrave Macmillan.

Klasen, S. and H. Waibel (2015). Vulnerability to poverty in south-east asia: Drivers, measurement, responses, and policy issues. *World Development 71*, 1–3.

Kling, J. R., J. B. Liebman, and L. F. Katz (2007). Experimental analysis of neighborhood effects. *Econometrica 75*(1), 83–119.

Kolenikov, S. and G. Angeles (2009). Socioeconomic status measurement with discrete proxy variables: Is principal component analysis a reliable answer? *Review of Income and Wealth 55*, 128–165.

Laajaj, R., K. Macours, D. A. Pinzon Hernandez, O. Arias, S. D. Gosling, J. Potter, M. Rubio-Codina, and R. Vakis (2019). Challenges to capture the big five personality traits in non-WEIRD populations. *Science Advances 5*(7), eaaw5226.

Lampl, C., H. Thomas, C. Tassorelli, Z. Katsarava, J. M. Laínez, M. Lantéri-Minet, D. Rastenyte, E. R. de la Torre, L. J. Stovner, C. Andrée, and T. J. Steiner (2016). Headache, depression and anxiety: associations in the eurolight project. *The Journal of Headache and Pain 17*(59).

Lao, R., T. I. Parks, C. Sangvirojkul, A. Lek-Uthai, A. Pathanasethpong, P. Arporniem, T. Takkhin, and K. Tiamsai (2019). *Thailand's Inequality: Myths & Reality of Isan.* The Asia Foundation.

Loayza, N. V., R. Rancière, L. Servén, and J. Ventura (2007). Macroeconomic volatility and welfare in developing countries: An introduction. *The World Bank Economic Review 21*(3), 343–357.

Lucas, R., A. Clark, and Y. Georgellis (2003). Reexamining adaptation and the set point model of happiness. *Journal of Personality and Social Psychology 84*(3), 527–539.

Lucas, R. E. (2005). Time does not heal all wounds: A longitudinal study of reaction and adaptation to divorce. *Psychological Science 16*(12), 945–950.

Ludeke, S. G. and E. G. Larsen (2017). Problems with the Big Five assessment in the World Values Survey. *Personality and Individual Differences 112*, 103–105.

Luechinger, S. and P. A. Raschky (2009). Valuing flood disasters using the life satisfaction approach. *Journal of Public Economics 93*(3-4), 620–633.

Luhmann, M., W. Hofmann, M. Eid, and R. Lucas (2012). Subjective well-being and adaptation to life events. *Journal of Personality and Social Psychology 102*(3), 592–615.

Lusardi, A. and P. Tufano (2015). Debt literacy, financial experiences, and overindebtedness. *Journal of Pension Economics and Finance 14*(04), 332–368.

Luttmer, E. (2005). Neighbors as negatives: Relative earnings and well-being. *Quarterly Journal of Economics 120*(3), 963–1002.

Maddison, D. and K. Rehdanz (2011). The impact of climate on life satisfaction. *Ecological Economics 70*, 2437–2445.

Manski, C. F. (2004). Measuring expectations. *Econometrica 72*(5), 1329–1376.

Markussen, T., M. Fibæk, F. Tarp, and N. D. A. Tuan (2018). The happy farmer: Self-employment and subjective well-being in rural vietnam. *Journal of Happiness Studies 19*(6), 1613–1636.

McClelland, D. C., J. W. Atkinson, R. A. Clark, and E. L. Lowell (1953). *The Achievement Motive.* East Norwalk, CT, US: Appleton-Century-Crofts.

McKenzie, D., J. Gibson, and S. Stillman (2013). A land of milk and honey with streets paved with gold: Do emigrants have over-optimistic expectations about incomes abroad? *Journal of Development Economics 102*, 116–127.

Menkhoff, L. and O. Rungruxsirivorn (2011). Do village funds improve access to finance? evidence from thailand. *World Development 39*(1), 110–122.

Mercante, J. P. P., M. F. P. Peres, and M. A. Bernik (2011). Primary headaches in patients with generalized anxiety disorder. *The Journal of Headache and Pain 12*(3), 331–338.

Merkle, C. and M. Weber (2011). True overconfidence: The inability of rational information processing to account for apparent overconfidence. *Organizational Behavior and Human Decision Processes 116*(2), 262–271.

Moore, D. A. and P. J. Healy (2008). The trouble with overconfidence. *Psychological Review 115*(2), 502–517.

Myers, D. G. and E. Diener (1995). Who is happy? *Psychological Science 6*(1), 10–19.

Nigro, J., D. Slayback, F. Policelli, and G. R. Brakenridge (2014). Nasa/dfo modis near real-time (nrt) global flood mapping product evaluation of flood and permanent water detection. Report october 2014.

OECD (2016). *OECD/INFE international survey of adult financial literacy competencies.* Paris: Organisation for Economic Co-operation and Development.

OECD (2018). *OECD/INFE toolkit for measuring financial literacy and financial inclusion.* Paris: Organisation for Economic Co-operation and Development.

Parvathi, P. and T. T. Nguyen (2018). Is environmental income reporting evasive in household surveys? Evidence from rural poor in Laos. *Ecological Economics 143*, 218–226.

Patki, G., A. Salvi, H. Liu, and S. Salim (2015). Witnessing traumatic events and post-traumatic stress disorder: Insights from an animal model. *Neuroscience Letters 600*, 28–32.

Patki, G., N. Solanki, and S. Salim (2014). Witnessing traumatic events causes severe behavioral impairments in rats. *International Journal of Neuropsychopharmacology 17*(12), 2017–2029.

Pedersen, P. J. and T. D. Schmidt (2014). Life events and subjective well-being: The case of having children. IZA Discussion Paper No. 8207, Institute of Labor Economics, Bonn, Germany.

Pforr, K. (2014). femlogit—implementation of the multinomial logit model with fixed effects. *The Stata Journal 14*(4), 847–862.

Pimhidzai, O. *Climbing the Ladder: Poverty Reduction and Shared Prosperity in Vietnam.* Washington, D.C., U.S.: The World Bank.

Potter, P., J. Divanbeigi, J. Berger, L. Norris, and S. Olsen (2010). Compassion fatigue and burnout: Prevalence among oncology nurses. *Clinical Journal of Oncology Nursing 14*(5), 56–62.

Rammstedt, B., D. Danner, and M. Bosnjak (2017). Acquiescence response styles: A multilevel model explaining individual-level and country-level differences. *Personality and Individual Differences 107*, 190–194.

Reyes-García, V., R. Babigumira, A. Pyhälä, S. Wunder, F. Zorondo-Rodríguez, and A. Angelsen (2016). Subjective wellbeing and income: Empirical patterns in the rural developing world. *Journal of Happiness Studies 17*(2), 773–791.

Sabo, B. M. (2006). Compassion fatigue and nursing work: can we accurately capture the consequences of caring work? *International Journal of Nursing Practice 12*(3), 136–142.

Sarracino, F. et al. (2013). Determinants of subjective well-being in high and low income countries: Do happiness equations differ across countries. *The Journal of Socio-Economics 42*(3), 51–66.

Schäfer, K. C. (2016). The influence of personality traits on private retirement savings in germany. Soep papers no. 867, German Institute for Economic Research (DIW), Berlin, Germany.

Schicks, J. (2013). The sacrifices of micro-borrowers in ghana - a customer-protection perspective on measuring over-indebtedness. *The Journal of Development Studies 49*(9), 1238–1255.

Schmitt, D. P., J. Allik, R. R. McCrae, and V. Benet-Martínez (2007). The geographic distribution of big five personality traits: Patterns and profiles of human self-description across 56 nations. *Journal of Cross-Cultural Psychology 38*(2), 173–212.

Sekulova, F. and J. C. Van den Bergh (2016). Floods and happiness: Empirical evidence from bulgaria. *Ecological Economics 126*, 51–57.

Smits, J. and I. Günther (2017). Financial distress in microcredit borrowers: Overindebtedness or a symptom of poverty? Mimeo.

Souleles, N. (2004). Expectations, heterogeneous forecast errors, and consumption: Micro evidence from the michigan consumer sentiment surveys. *Journal of Money, Credit and Banking 36*(1), 39–72.

Stevenson, B. and J. Wolfers (2008). Economic growth and subjective well-being: Reassessing the easterlin paradox. CESifo Working Paper No. 2394.

Stuetzer, M., D. B. Audretsch, M. Obschonka, S. D. Gosling, P. J. Rentfrow, and J. Potter (2018). Entrepreneurship culture, knowledge spillovers and the growth of regions. *Regional Studies 52*(5), 608–618.

Tambunlertchai, K. (2015). Financial inclusion, financial regulation, and financial education in thailand. ADBI working paper 537, Asian Development Bank Institute, Tokyo.

Tangney, J. P., R. F. Baumeister, and A. L. Boone (2004). High self-control predicts good adjustment, less pathology, better grades, and interpersonal success. *Journal of Personality 72*(2), 271–324.

Terada, Y. and P. Vandenberg (2014). Thailand's state-led approach to financial inclusion. In A. D. B. Institute (Ed.), *Financial Inclusion in Asia: Country Surveys*, Chapter 5, pp. 89–110. Tokyo: Asian Development Bank Institute.

Thiel, H. and S. L. Thomsen (2013). Noncognitive skills in economics: Models, measurement, and empirical evidence. *Research in Economics 67*(2), 189–214.

van Praag, B. M. S., P. Frijters, and A. Ferrer-i Carbonell (2003). The anatomy of subjective well-being. *Journal of Economic Behavior & Organization 51*, 29–49.

Van Trotsenburg, A. (2018). More and better jobs for developing nations. `https://www.worldbank.org/en/news/opinion/2018/05/11/more-and-better-jobs-for-developing-nations`. [Online; accessed 6-September-2019].

Veenhoven, R. (2010). How universal is happiness? In E. Diener, D. Kahneman, and J. Helliwell (Eds.), *International differences in well-being.* New York, U.S.: Oxford University Press.

von Möllendorff, C. and J. Hirschfeld (2016). Measuring impacts of extreme weather events using the life satisfaction approach. *Ecological Economics 121*, 108–116.

Wang, S., B. Hansl, P. K. Milne, S. Zaidi, and J. Yang (2020). *Taking the pulse of poverty and inequality in Thailand.* Washington, D.C., U.S.: The World Bank.

Wells, R., R. Ham, and P. N. R. Junankar (2016). An examination of personality in occupational outcomes: Antagonistic managers, careless workers and extroverted salespeople. *Applied Economics 48*(7), 636–651.

World Bank (2017). Skills development - Overview. `https://www.worldbank.org/en/topic/skillsdevelopment`. [Online; accessed 22-September-2020].

World Bank (2018). *Riding the wave: An east asian mircale for the 21st century.* Washington, D.C., U.S.: The World Bank.

World Bank (2019). The World Bank in Thailand. `https://www.worldbank.org/en/country/thailand/overview`. [Online; accessed 21-October-2019].

World Bank (2020). The World Bank in Vietnam - Overview. `https://www.worldbank.org/en/country/vietnam/overview#1`. [Online; accessed 22-September-2020].

Zinman, J. (2015). Household debt: Facts, puzzles, theories, and policies. *Annual Review of Economics 7*(1), 251–276.

Appendix A - Appendix for Chapter 2

Table A.1: Description of Variables

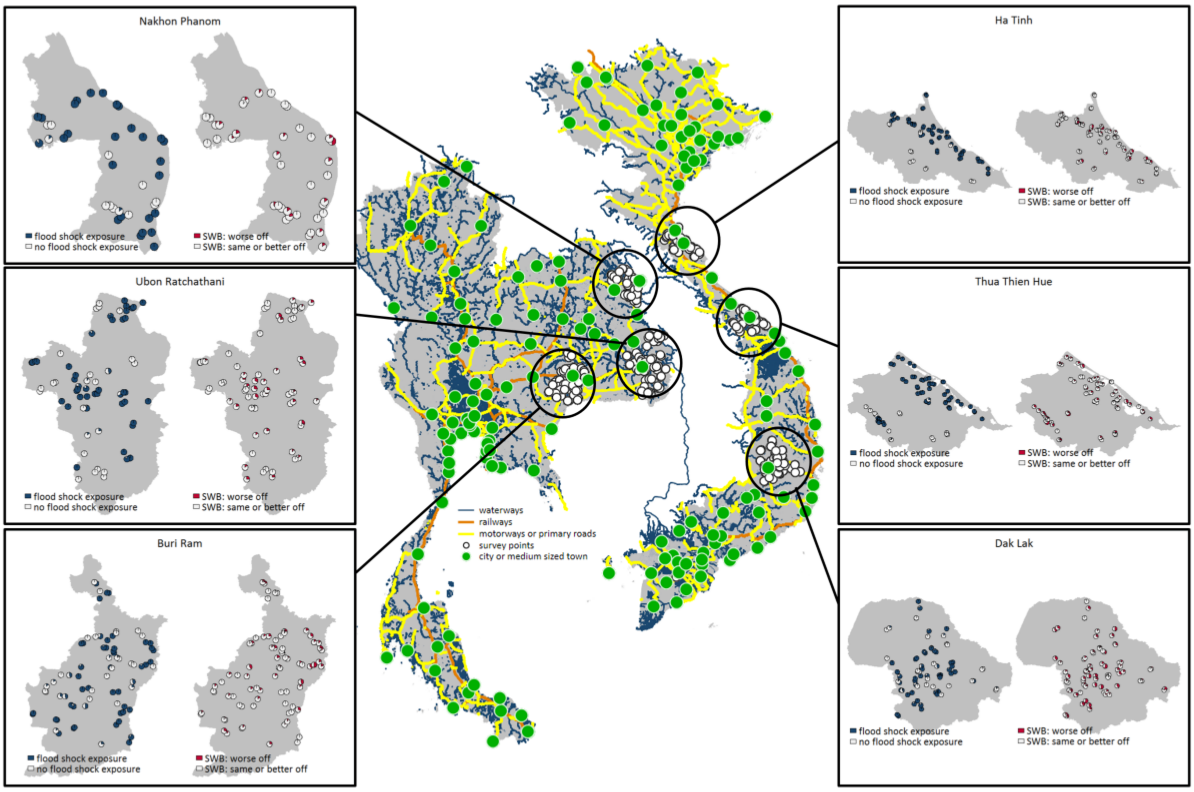
Variable label	Short description	min	max	mean	std.dev.
Dependent variables					
past well-being dynamic	individual well-being compared to last year (1: better off 36.2%, 2: same 42.8%, 3: worse off 21.0%)	1	3	-	-
future well-being dynamic	individual well-being in one year (1: better off 51.3%, 2: same 38.3%, 3: worse off 10.4%)	1	3	-	-
shock expectations	flood shock expected to occur within the next five years	0	1	0.301	-
distributional preferences	support for more government redistribution	0	1	0.626	-
Control variables					
HH income p.c. (log)	HH income (2005 PPP U.S. Dollar) per nucleus HH member relative to province median	0	205.921	1.604	3.338
HH income fluctuation	fluctuation of HH income (1: not at all 39.4%, 2: a bit 49.1%, 3: a lot 11.5%)	1	3	-	-
gender	respondent's gender (0: male, 1: female)	0	1	0.503	-
age	respondent's age	15	93	50.352	13.426
health dynamics	health status compared to one year before (1: worse 32.1%, 2: same 56.9%, 3: better 11.1%)	1	3	-	-
marital status	relationship indicator (1: unmarried 5.3%, 2: married 83.9%, 3: widowed 10.9%)	1	3	-	-
religion	respondent is religious (0: no, 1: yes)	0	1	0.595	-
educational attainment	highest completed educational attainment (0: no schooling 47.8%, 1: primary 27.2%, 2: lower secondary 16.3%, 3: upper secondary 8.6%	0	3	-	-
main occupational status	main occupational status in the last year (0: no occupation 4.4%, 1: housewife/HH-member caretaker 3.1%, 2: casually employed 9.3%, 3: permanently employed 3.6%, 4: own agriculture/hunting 68.8%, 5: own off-farm business 8.7%, 6: government official 2.0%, 7: student/pupil 0.1%)	0	7	-	-
Shock experience variables	(0: no, 1: yes, reversed in estimations for reasons of interpretability				
flood shock	flood shock experience in last 12 months	0	1	0.080	-
flood or heavy rain shock	flood or heavy rain shock experience in last 12 months	0	1	0.090	

Table continues on next page

Variable label	Short description	min	max	mean	std.dev.
severe flood or heavy rain shock	severe flood or heavy rain shock experience in last 12 months	0	1	0.051	
drought shock	drought shock experience in last 12 months	0	1	0.044	-
storm shock	experience of storm shock experience in last 12 months	0	1	0.019	-
ice or snow rain shock	ice or snow rain shock experience in last 12 months	0	1	0.005	-
Sensitivity analyses					
network (r=5000, m=12)	distance weighted share of village HH exposed to TS in r and m	0	1	0.661	0.464
flood history (r=5000)	HH specific average maximum yearly TS exposure in r	0	195.333	20.074	37.336
land-use (r=5000)	number of cultivation plots in r	0	28	3.186	1.857
mental issues	serious incidence of mental disease or depression (0: no, 1: yes)	0	1	0.03	
headache	serious incidence of headache in the last year (0: no, 1: yes)	0	1	0.012	

Note: Descriptive statistics for explanatory variables on the household / individual level and flood exposure variables are conditioned on the sample used in the main analysis (n=17,346). Variables from the sensitivity analyses refer to the corresponding sample of each analysis. The same holds for the variables used in Section 4.2 and 4.3. In case of categorical variables, no means or standard deviations are reported. For binary indicators, the means indicate the share of responses coded as one.

Figure A.1: Distribution of Environmental conditions and well-being dynamics in 2013



Note: The graph provides an overview of the environmental conditions, village-level shares of individuals with potential flood shock exposure and well-being dynamics for the year 2013. The left side shows the Thai provinces and the right side the Vietnamese provinces. Only villages with at least three interviewed households are depicted. The size of the provinces is not necessarily true to scale.

Table A.2: Ex-ante Comparability of Respondents

	Vietnam						Thailand					
	direct experience			TS exposure			direct experience			TS exposure		
	no	yes	P(Test)	no	yes	P(Test)	no	yes	P(Test)	no	yes	P(Test)
N	1,058	447		171	1,334		1,393	243		106	1,530	
Continuous and binary variables												
rel income p.c.	1.76	1.35	0.0050	1.34	1.68	0.1009	1.65	1.26	0.0256	1.28	1.61	0.1814
female	0.36	0.39	0.3117	0.34	0.38	0.3446	0.53	0.55	0.5568	0.58	0.53	0.3319
age	46.02	43.92	0.0052	42.52	45.77	0.0027	50.81	50.35	0.6068	49.91	50.8	0.4838
Categorical variables												
income fluct.			0.0000			0.0430			0.1460			0.366
health fluct.			0.0040			0.8180			0.2400			0.894
marital status			0.0920			0.0060			0.5200			0.661
education			0.0170			0.6540			0.8230			0.946
occupation			0.0000			0.1390			0.8390			0.3370

Note: Table shows ex-ante comparability of respondents in 2007 by direct shock experience and tangential shock exposure. For continuous and binary variables, we report group means and applied a T-test with H_0: Group means are identical. Groups are defined as having ever experienced a direct shock experience or having been exposed to a tangential shock (TS). In case of categorical variables with three or more categories, the samples are evaluated based on a χ^2 test with H_0: Independence of categories and shock experience/exposure.

Table A.3: Overview of Tangential Shock Indicators

		Sphere of interest (Radius in meter)				
Time horizon		1000	2000	3000	4000	5000
1 month	mean	0.21	0.46	0.77	1.14	1.51
	maximum	22	26	26	27	27
	stand. dev.	1.40	2.25	2.97	3.56	4.09
3 months	mean	0.67	1.42	2.32	3.42	4.54
	maximum	59	77	77	77	77
	stand. Dev.	3.63	5.77	7.70	9.27	10.78
12 months	mean	4.57	8.71	13.07	17.29	21.52
	maximum	173	226	226	226	226
	stand. dev.	16.67	24.31	30.86	35.60	40.02

Note: Table is based on the sample used in the main analysis (17,346 observations). Minimum values across indicators, radii and time horizons are zero. The average numbers of included pixels for a given radius are 53, 493 and 1367.

Table A.4: Model Comparison: Flood Shock Experiences and TSE (5 km Radius, 12 Months)

Specification	Main (Section 4.1)								Robustness (Section 5)							
Shock experience	Flood and heavy rain				Flood and heavy rain				Flood only				Severe flood and heavy rain			
TSE exposure	No				Yes				Yes				Yes			
	Δ^+		Δ^-		Δ^+		Δ^-		Δ^+		Δ^-		Δ^+		Δ^-	
	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.	coef.	s.e.
HH Income (p.c., rel.)	0.059***	(0.020)	−0.046**	(0.023)	0.059***	(0.020)	−0.046**	(0.023)	0.059***	(0.020)	−0.045**	(0.023)	0.059***	(0.020)	−0.045*	(0.023)
HH Income fluctutation																
Yes, a bit	−0.103***	(0.038)	0.632***	(0.048)	−0.103***	(0.038)	0.635***	(0.049)	−0.103***	(0.038)	0.634***	(0.049)	−0.102***	(0.038)	0.631***	(0.049)
Yes, a lot	−0.287***	(0.070)	1.623***	(0.066)	−0.287***	(0.070)	1.623***	(0.066)	−0.286***	(0.070)	1.624***	(0.066)	−0.285***	(0.070)	1.621***	(0.066)
Gender (female=1)	−0.001	(0.042)	0.051	(0.050)	−0.001	(0.042)	0.052	(0.050)	−0.001	(0.042)	0.051	(0.050)	−0.001	(0.042)	0.049	(0.050)
Age	0.011	(0.010)	0.026**	(0.011)	0.011	(0.010)	0.027**	(0.011)	0.011	(0.010)	0.027**	(0.011)	0.011	(0.010)	0.026**	(0.011)
Age^2	−0.000*	(0.000)	−0.000**	(0.000)	−0.000*	(0.000)	−0.000**	(0.000)	−0.000*	(0.000)	−0.000**	(0.000)	−0.000*	(0.000)	−0.000**	(0.000)
Health dynamics (1 year)																
worse	−0.003	(0.043)	0.591***	(0.047)	−0.003	(0.043)	0.592***	(0.047)	−0.003	(0.043)	0.591***	(0.047)	−0.002	(0.043)	0.591***	(0.047)
better	0.652***	(0.057)	0.124	(0.081)	0.652***	(0.057)	0.125	(0.081)	0.652***	(0.057)	0.124	(0.081)	0.652***	(0.057)	0.127	(0.081)
Marital status																
married	0.268***	(0.087)	−0.010	(0.098)	0.268***	(0.087)	−0.011	(0.098)	0.268***	(0.087)	−0.012	(0.098)	0.268***	(0.087)	−0.012	(0.098)
widowed	0.236**	(0.107)	0.061	(0.117)	0.236**	(0.107)	0.062	(0.117)	0.236**	(0.107)	0.062	(0.117)	0.236**	(0.107)	0.060	(0.117)
Religion (yes=1)	−0.292***	(0.078)	−0.060	(0.082)	−0.290***	(0.078)	−0.057	(0.082)	−0.291***	(0.078)	−0.058	(0.082)	−0.293***	(0.078)	−0.054	(0.082)
Educational attainment																
primary	0.102*	(0.055)	−0.126**	(0.059)	0.102*	(0.055)	−0.126**	(0.059)	0.102*	(0.055)	−0.127**	(0.059)	0.102*	(0.055)	−0.125**	(0.059)
lower secondary	0.288***	(0.063)	−0.070	(0.073)	0.287***	(0.063)	−0.070	(0.073)	0.286***	(0.063)	−0.071	(0.073)	0.287***	(0.063)	−0.070	(0.073)
upper secondary / tertiary	0.193**	(0.078)	−0.165*	(0.096)	0.191**	(0.078)	−0.166*	(0.096)	0.191**	(0.078)	−0.167*	(0.096)	0.191**	(0.078)	−0.164*	(0.096)
Main occupational status																
housewife / home nursing	0.269*	(0.144)	−0.056	(0.146)	0.270*	(0.144)	−0.053	(0.146)	0.269*	(0.144)	−0.056	(0.146)	0.269*	(0.144)	−0.054	(0.146)
casual labour	0.371***	(0.114)	0.074	(0.113)	0.371***	(0.114)	0.078	(0.113)	0.371***	(0.114)	0.078	(0.113)	0.370***	(0.114)	0.076	(0.113)
permanently employed	0.661***	(0.140)	0.090	(0.163)	0.661***	(0.140)	0.093	(0.163)	0.661***	(0.140)	0.090	(0.163)	0.660***	(0.140)	0.094	(0.163)
agriculture	0.486***	(0.103)	−0.096	(0.103)	0.486***	(0.103)	−0.093	(0.103)	0.486***	(0.103)	−0.094	(0.103)	0.487***	(0.103)	−0.095	(0.103)
own business	0.559***	(0.120)	0.128	(0.126)	0.559***	(0.120)	0.127	(0.126)	0.559***	(0.120)	0.128	(0.126)	0.558***	(0.120)	0.127	(0.126)
government official	0.542***	(0.173)	0.114	(0.208)	0.541***	(0.173)	0.116	(0.208)	0.541***	(0.173)	0.115	(0.208)	0.541***	(0.173)	0.116	(0.208)
student/pupil	0.205	(0.815)	−0.629	(1.172)	0.237	(0.831)	−0.541	(1.201)	0.230	(0.827)	−0.540	(1.201)	0.207	(0.816)	−0.609	(1.181)
no shock experience (s)	−0.011	(0.069)	−0.141**	(0.071)	−0.054	(0.079)	−0.252***	(0.081)	−0.031	(0.084)	−0.279***	(0.085)	0.069	(0.104)	−0.404***	(0.099)
TSE exposure (s^{TSE})					−0.002	(0.002)	−0.005**	(0.002)	−0.001	(0.002)	−0.005**	(0.002)	−0.000	(0.003)	−0.007**	(0.003)
$s \times s^{TSE}$					0.002	(0.002)	0.005***	(0.002)	0.001	(0.002)	0.006***	(0.002)	0.000	(0.003)	0.007**	(0.003)
N (HH cluster)	17,346 (3,543)				17,346 (3,543)				17,346 (3,543)				17,346 (3,543)			
LL	-17329.55				-17325.56				-17325.06				-17320.58			
df_m	56.00				60.00				60.00				60.00			
Wald chi2	1760.45				1768.45				1766.38				1785.54			
p(chi2)	0.0000				0.0000				0.0000				0.0000			

*** p<0.01, ** p<0.05, * p<0.1

Note: All specifications include year and country FE. Standard errors are clustered at the household level. x denotes an interaction.

Table A.5: The Influence of Other Types of Shocks

Model	(1)		(2)		(3)	
	Δ^{+}	Δ^{-}	Δ^{+}	Δ^{-}	Δ^{+}	Δ^{-}
no flood shock experience (s)	−0.0522	−0.2283***	−0.0596	−0.1880**	−0.0668	−0.1866**
	(0.0790)	(0.0815)	(0.0794)	(0.0824)	(0.0799)	(0.0826)
TSE exposure (s^{TSE})	−0.0021	−0.0046**	−0.0019	−0.0041**	0.0048	−0.0063
	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0048)	(0.0055)
$s \times s^{TSE}$	0.0020	0.0052***	0.0019	0.0046**	0.0018	0.0048**
	(0.0019)	(0.0020)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
no drought shock	0.1782***	−0.1050*	0.1708***	−0.0444	0.1780***	−0.0568
	(0.0530)	(0.0601)	(0.0535)	(0.0626)	(0.0576)	(0.0680)
no storm shock	−0.0392	−0.2394**	−0.0386	−0.1931*	−0.0990	−0.1544
	(0.0895)	(0.0979)	(0.0898)	(0.1003)	(0.1050)	(0.1186)
no snow / ice rain shock	0.0013	−0.4923***	−0.0026	−0.4982***	0.2268	−0.5526***
	(0.1448)	(0.1422)	(0.1454)	(0.1447)	(0.1834)	(0.1782)
other shocks	No		Yes		Yes	
env. shock $\times s^{TSE}$	No		No		Yes	
N (HH clusters)	17,346 (3,543)		17,346 (3,543)		17,346 (3,543)	
Wald χ^2 (P $>$ χ^2)	1800.17 (0.0000)		1955.35 (0.0000)		1965.80 (0.0000)	

*** p<0.01, ** p<0.05, * p<0.1

Note: All specifications include the full set of sociodemographic and socioeconomic controls, as well as year and country FE. Standard errors are clustered at the household level. x denotes an interaction.

Table A.6: Sensitivity Analysis - Network Effects, Coping Strategies and Land Usage

	(1)		(2)		(3)		(4)	
	Δ^+	Δ^-	Δ^+	Δ^-	Δ^+	Δ^-	Δ^+	Δ^-
	Panel A: 3000m, 3 months							
s	−0.0360	−0.1342*	−0.0431	−0.0925	−0.0432	−0.0929	−0.0267	−0.0954
	(0.0721)	(0.0755)	(0.0762)	(0.0807)	(0.0762)	(0.0807)	(0.0766)	(0.0808)
s^{TSE}	−0.0079	−0.0138	−0.0112	−0.0150	−0.0106	−0.0177	−0.0099	−0.0177
	(0.0101)	(0.0115)	(0.0108)	(0.0124)	(0.0114)	(0.0132)	(0.0114)	(0.0132)
$s \times s^{TSE}$	0.0088	0.0197*	0.0111	0.0198	0.0110	0.0198	0.0109	0.0195
	(0.0100)	(0.0118)	(0.0104)	(0.0125)	(0.0104)	(0.0125)	(0.0104)	(0.0125)
Network			−0.0047	0.0210	−0.0006	0.0014	−0.0004	−0.0002
			(0.0674)	(0.0743)	(0.0722)	(0.0820)	(0.0722)	(0.0825)
Flood history					−0.0002	0.0010	−0.0001	0.0010
					(0.0015)	(0.0017)	(0.0015)	(0.0017)
Land use							0.0453***	−0.0154
							(0.0119)	(0.0141)
	Panel B: 3000m, 12 months							
s	−0.0522	−0.1601**	−0.0650	−0.1148	−0.0690	−0.1227	−0.0521	−0.1245
	(0.0752)	(0.0790)	(0.0797)	(0.0842)	(0.0797)	(0.0843)	(0.0801)	(0.0844)
s^{TSE}	−0.0028	−0.0043*	−0.0031	−0.0040	−0.0062*	−0.0092***	−0.0059*	−0.0091***
	(0.0024)	(0.0025)	(0.0026)	(0.0027)	(0.0032)	(0.0034)	(0.0032)	(0.0035)
$s \times s^{TSE}$	0.0028	0.0055**	0.0033	0.0051*	0.0035	0.0054*	0.0034	0.0053*
	(0.0024)	(0.0026)	(0.0026)	(0.0027)	(0.0025)	(0.0027)	(0.0026)	(0.0027)
Network			−0.0837*	−0.0134	−0.0871*	−0.0199	−0.0893*	−0.0156
			(0.0470)	(0.0535)	(0.0471)	(0.0538)	(0.0472)	(0.0540)
Flood history					0.0033	0.0055**	0.0033	0.0055**
					(0.0022)	(0.0023)	(0.0022)	(0.0024)
Land use							0.0455***	−0.0155
							(0.0119)	(0.0141)

Table continues on next page.

	Panel C: 5000m, 3 months							
s	−0.0511	−0.1668**	−0.0570	−0.1233	−0.0572	−0.1240	−0.0392	−0.1269
	(0.0752)	(0.0783)	(0.0795)	(0.0837)	(0.0795)	(0.0838)	(0.0800)	(0.0838)
s^{TSE}	−0.0078	−0.0156**	−0.0071	−0.0161**	−0.0087	−0.0181**	−0.0079	−0.0178**
	(0.0070)	(0.0072)	(0.0074)	(0.0078)	(0.0079)	(0.0085)	(0.0079)	(0.0085)
$s \times s^{TSE}$	0.0074	0.0178**	0.0076	0.0172**	0.0076	0.0172**	0.0076	0.0169**
	(0.0070)	(0.0075)	(0.0072)	(0.0079)	(0.0072)	(0.0079)	(0.0072)	(0.0079)
Network			−0.0338	0.0370	−0.0436	0.0242	−0.0485	0.0213
			(0.0577)	(0.0641)	(0.0606)	(0.0684)	(0.0608)	(0.0686)
Flood history					0.0006	0.0008	0.0007	0.0008
					(0.0012)	(0.0014)	(0.0012)	(0.0014)
Land use							0.0472***	−0.0160
							(0.0118)	(0.0144)
	Panel D: 5000m, 12 months							
s	−0.0596	−0.1880**	−0.0749	−0.1390	−0.0767	−0.1429	−0.0572	−0.1444
	(0.0794)	(0.0824)	(0.0842)	(0.0880)	(0.0843)	(0.0880)	(0.0848)	(0.0880)
s^{TSE}	−0.0019	−0.0041**	−0.0017	−0.0038*	−0.0026	−0.0055**	−0.0024	−0.0054**
	(0.0019)	(0.0019)	(0.0020)	(0.0020)	(0.0025)	(0.0026)	(0.0025)	(0.0026)
$s \times s^{TSE}$	0.0019	0.0046**	0.0021	0.0043**	0.0022	0.0043**	0.0021	0.0042**
	(0.0019)	(0.0019)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Network			−0.1066**	0.0090	−0.1075**	0.0070	−0.1111**	0.0168
			(0.0475)	(0.0546)	(0.0475)	(0.0547)	(0.0477)	(0.0550)
Flood history					0.0010	0.0019	0.0010	0.0018
					(0.0016)	(0.0019)	(0.0016)	(0.0019)
Land use							0.0478***	−0.0159
							(0.0118)	(0.0143)
N (HH cluster)	17,346 (3,543)		15,310 (3,159)		15,310 (3,159)		15,230 (3,159)	
Other shocks	Yes		Yes		Yes		Yes	

*** p<0.01, ** p<0.05, * p<0.1

Note: All models include our full set of sociodemographic controls, as well as year and country FE. Standard errors (in parentheses) are clustered at the household level. Network refers to the distance weighted share of in-sample households within a village which have been exposed to a tangential shock in their maximum sphere of interest in the previous year. Flood history represents the household specific average yearly exposure to the corresponding tangential shock since 2004. The land-use control specification accounts for the number of cultivation area plots in a sphere of interest.

Table A.7: Tangential Shocks and Indirect Psychological Effects

	SWB				mental issues	headache
	Δ^+	Δ^-	Δ^+	Δ^-		
TSE radius / time horizon	5km / 3 months		5km / 12 months		5km / 12 months	
no shock experience (s)	−0.0610	−0.2400***	−0.0675	−0.2555***	−0.0004	0.0009
	(0.0779)	(0.0809)	(0.0823)	(0.0850)	(0.0015)	(0.0042)
TSE exposure (s^{TSE})	−0.0052	−0.0138*	−0.0013	−0.0035*	−0.0000*	−0.0001
	(0.0072)	(0.0077)	(0.0020)	(0.0020)	(0.0000)	(0.0001)
$s \times s^{TSE}$	0.0049	0.0170**	0.0013	0.0043**	0.0000	0.0001
	(0.0073)	(0.0080)	(0.0020)	(0.0021)	(0.0000)	(0.0001)
mental issues	0.2370	0.5719	0.2367	0.5735		
	(0.3496)	(0.4118)	(0.3495)	(0.4120)		
headache	−0.1902	0.2340	−0.1900	0.2314		
	(0.1831)	(0.1880)	(0.1832)	(0.1882)		
N	15,885		15,885		15,885	15,885

Note: All models include our full set of sociodemographic and socioeconomic controls, as well as year and country FE. Standard errors are clustered at the household level.

Table A.8: Attrition Analysis: Shock-related Estimates for Negative SWB Dynamics

radius (meter)	3000	4000	4000	5000	5000	5000
months	12	3	12	1	3	12
no shock experience (s)	−0.1994**	−0.1959**	−0.2176***	−0.1937**	−0.2144***	−0.2336***
	(0.0792)	(0.0770)	(0.0807)	(0.0770)	(0.0783)	(0.0824)
TSE exposure (s^{TSE})	−0.0037	−0.0155*	−0.0042*	−0.0314*	−0.0157**	−0.0040**
	(0.0026)	(0.0092)	(0.0022)	(0.0187)	(0.0074)	(0.0019)
$s \times s^{TSE}$	0.0047*	0.0178*	0.0046**	0.0371*	0.0177**	0.0045**
	(0.0027)	(0.0095)	(0.0022)	(0.0194)	(0.0077)	(0.0020)
N	16,809	16,809	16,809	16,809	16,809	16,809

Note: All models include the full set of sociodemographic and socioeconomic controls, as well as year and country FE. Standard errors are clustered at the household level.

Table A.9: Fixed and Random Effects Models for Negative SWB Dynamics - Respondent Level

Model		(1)		(2)	(3)	(4)		(5)	(6)
Radius		3km				5 km			
Estimation		FEMlogit		FE	RE	FEMlogit		FE	RE
		Δ^+	Δ^-	Δ^-	Δ^-	Δ^+	Δ^-	Δ^-	Δ^-
	Month	Panel A: Respondent panel							
s	1	0.0943	−0.1345	−0.0079	0.0012	0.0612	−0.1510	−0.0340**	−0.0343***
		(0.0951)	(0.1033)	(0.0073)	(0.0052)	(0.0981)	(0.1064)	(0.0152)	(0.0130)
s^{TSE}		−0.0328	−0.0667	−0.0314**	−0.0283**	−0.0341	−0.0560*	−0.0074*	−0.0037
		(0.0422)	(0.0484)	(0.0146)	(0.0125)	(0.0252)	(0.0305)	(0.0038)	(0.0030)
$s \times s^{TSE}$		0.0348	0.0527	0.0047	0.0010	0.0368	0.0367	0.0037	0.0048
		(0.0388)	(0.0449)	(0.0069)	(0.0054)	(0.0238)	(0.0276)	(0.0035)	(0.0031)
s	3	0.1041	−0.1561	−0.0042	−0.0015	0.0607	−0.1713	−0.0371**	−0.0386***
		(0.0959)	(0.1035)	(0.0027)	(0.0020)	(0.0997)	(0.1075)	(0.0154)	(0.0132)
s^{TSE}		−0.0039	−0.0299	−0.0360**	−0.0325**	−0.0130	−0.0188	−0.0022	−0.0020*
		(0.0143)	(0.0190)	(0.0148)	(0.0127)	(0.0096)	(0.0121)	(0.0015)	(0.0011)
$s \times s^{TSE}$		0.0057	0.0287*	0.0039	0.0025	0.0117	0.0178	0.0020	0.0026**
		(0.0126)	(0.0173)	(0.0025)	(0.0021)	(0.0087)	(0.0109)	(0.0014)	(0.0012)
s	12	0.0853	−0.1854*	−0.0014**	−0.0006	0.0559	−0.1818	−0.0393**	−0.0430***
		(0.1009)	(0.1077)	(0.0006)	(0.0004)	(0.1064)	(0.1123)	(0.0163)	(0.0140)
s^{TSE}		−0.0033	−0.0096**	−0.0400**	−0.0370***	−0.0025	−0.0046	−0.0007	−0.0006**
		(0.0041)	(0.0046)	(0.0155)	(0.0134)	(0.0030)	(0.0036)	(0.0005)	(0.0003)
$s \times s^{TSE}$		0.0023	0.0071**	0.0009*	0.0008*	0.0027	0.0042	0.0005	0.0007**
		(0.0031)	(0.0036)	(0.0005)	(0.0004)	(0.0024)	(0.0027)	(0.0004)	(0.0003)
N		12,958		15,534	15,534	12,958		15,534	15,534

*** p<0.01, ** p<0.05, * p<0.1

Note: We report results for the 3km (models 1-3) and 5km (models 4-6) radius. Model (1) and (4) report results for the fixed effects multinomial logit model for positive and negative SWB dynamics. Model (2), (3), (5), and (6) show results for fixed effects (FE) and random effects (RE) models, with a binary dependent variable that is coded as one if a respondent reported to be worse off, and zero otherwise. The set of explanatory variables comprises the full set of sociodemographic and socioeconomic controls. Samples comprise those individuals (or households) for which we have at least two observations in the dataset. Standard errors (reported in parentheses) are clustered on the household level.

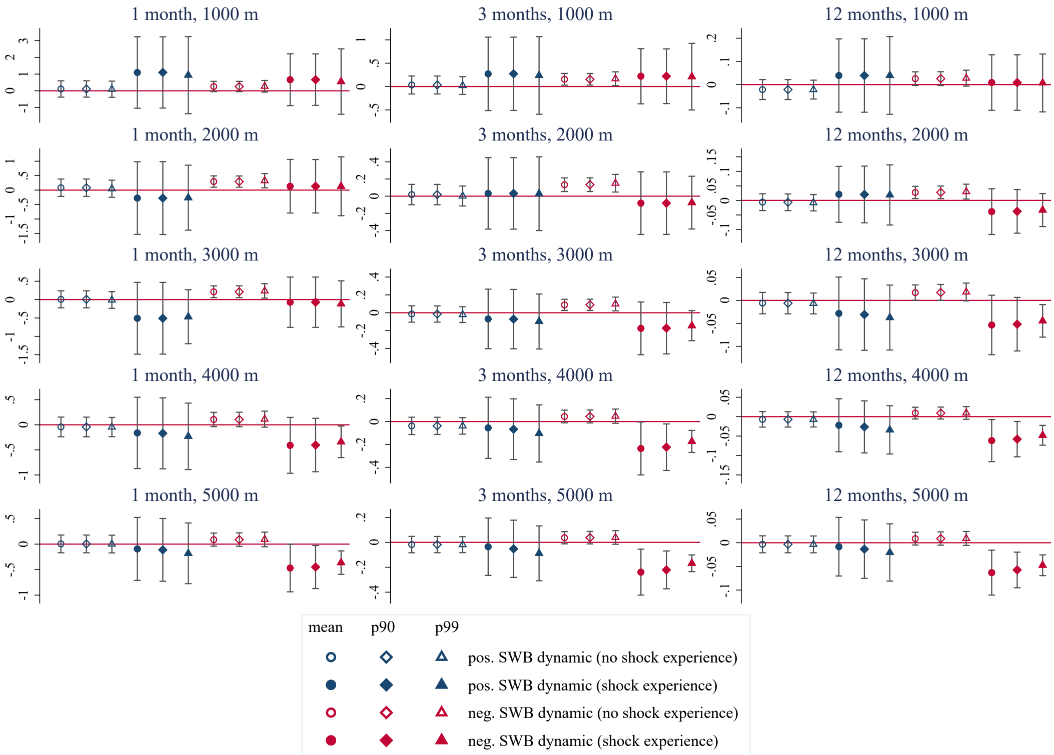
Table A.10: Fixed and Random Effects Models for Negative SWB Dynamics - Household Level

Model		(1)		(2)	(3)	(4)		(5)	(6)
Radius		3km				5 km			
Estimation		FEMlogit		FE	RE	FEMlogit		FE	RE
		Δ^+	Δ^-	Δ^-	Δ^-	Δ^+	Δ^-	Δ^-	Δ^-
	Month	Panel B: Household panel							
s	1	0.0591	−0.1368	−0.0129*	−0.0004	0.0373	−0.1633*	−0.0326**	−0.0332***
		(0.0812)	(0.0896)	(0.0067)	(0.0050)	(0.0845)	(0.0923)	(0.0137)	(0.0122)
s^{TSE}		−0.0227	−0.0888**	−0.0290**	−0.0273**	−0.0275	−0.0701***	−0.0094***	−0.0045
		(0.0358)	(0.0401)	(0.0132)	(0.0118)	(0.0217)	(0.0257)	(0.0036)	(0.0029)
$s \times s^{TSE}$		0.0270	0.0612	0.0080	0.0030	0.0252	0.0500**	0.0063*	0.0057*
		(0.0326)	(0.0376)	(0.0064)	(0.0052)	(0.0200)	(0.0233)	(0.0033)	(0.0030)
s	3	0.0624	−0.1516*	−0.0051**	−0.0018	0.0333	−0.1839*	−0.0358**	−0.0371***
		(0.0821)	(0.0903)	(0.0025)	(0.0019)	(0.0859)	(0.0939)	(0.0140)	(0.0124)
s^{TSE}		−0.0060	−0.0338**	−0.0321**	−0.0311***	−0.0131	−0.0249**	−0.0031**	−0.0023**
		(0.0123)	(0.0169)	(0.0134)	(0.0119)	(0.0086)	(0.0104)	(0.0014)	(0.0011)
$s \times s^{TSE}$		0.0064	0.0297*	0.0044*	0.0029	0.0089	0.0226**	0.0029**	0.0029**
		(0.0106)	(0.0154)	(0.0023)	(0.0020)	(0.0076)	(0.0094)	(0.0013)	(0.0011)
s	12	0.0394	−0.1796*	−0.0014**	−0.0006	0.0228	−0.1958**	−0.0384***	−0.0409***
		(0.0866)	(0.0938)	(0.0006)	(0.0004)	(0.0915)	(0.0982)	(0.0148)	(0.0132)
s^{TSE}		−0.0032	−0.0094**	−0.0358**	−0.0346***	−0.0032	−0.0052*	−0.0008*	−0.0006**
		(0.0035)	(0.0039)	(0.0140)	(0.0125)	(0.0026)	(0.0030)	(0.0004)	(0.0003)
$s \times s^{TSE}$		0.0028	0.0071**	0.0010**	0.0008*	0.0023	0.0052**	0.0007**	0.0008***
		(0.0027)	(0.0030)	(0.0005)	(0.0004)	(0.0021)	(0.0023)	(0.0003)	(0.0003)
N		16,289		17,313	17,313	16,289		17,313	17,313

*** p<0.01, ** p<0.05, * p<0.1

Note: We report results for the 3km (models 1-3) and 5km (models 4-6) radius. Model (1) and (4) report results for the fixed effects multinomial logit model for positive and negative SWB dynamics. Model (2), (3), (5), and (6) show results for fixed effects (FE) and random effects (RE) models, with a binary dependent variable that is coded as one if a respondent reported to be worse off, and zero otherwise. The set of explanatory variables comprises the full set of sociodemographic and socioeconomic controls. Samples comprise those individuals (or households) for which we have at least two observations in the dataset. Standard errors (reported in parentheses) are clustered on the household level.

Figure A.2: Average Marginal Effects (%) for SWB Dynamics - Maximum Days of Flood Exposure Measure



Note: All marginal effects draw upon the main sample of 17,346 observations. The depicted response and shock experience specific average marginal effects have been calculated at the mean, the 90$^{\text{th}}$ and 99$^{\text{th}}$ percentile of the tangential shock variable (maximum days of flood exposure). The whiskers indicate the 90% confidence intervals.

Appendix B - Appendix for Chapter 3

B.1 Survey Appendix

Figure B.1: Household Debt to GDP Ratio, Selected Emerging Markets

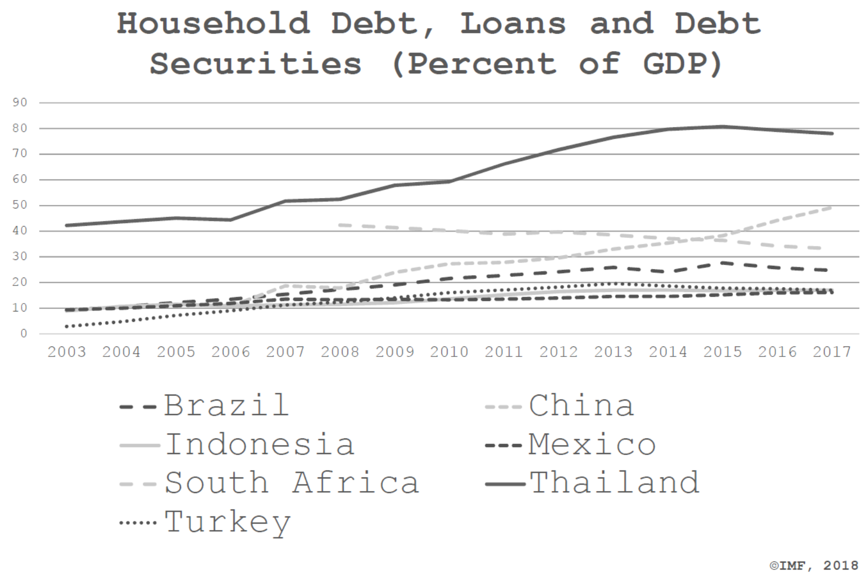


Table B.1: Correlation Matrix - Over-Indebtedness Variables

	Obj. OI-Index	DSR > 0.4 (=1)	RDSR > 0.4 (=1)	Holds > 2 Loans (=1)	Paid Late/ Default (=1)	Subj. OI-Index	Debt Position	Diff. to Pay Debt (=1)	Sacrifice Index
Obj. OI-Index	1								
DSR > 0.4 (=1)	0.733***	1							
RDSR > 0.4 (=1)	0.771***	0.481***	1						
Holds > 2 Loans (=1)	0.725***	0.426***	0.430***	1					
Paid Late/Default (=1)	0.529***	0.111***	0.212***	0.141***	1				
Subj. OI-Index	0.458***	0.193***	0.347***	0.310***	0.417***	1			
Debt Position	0.485***	0.250***	0.439***	0.348***	0.302***	0.763***	1		
Diff. to Pay Debt (=1)	0.298***	0.0922**	0.164***	0.169***	0.398***	0.749***	0.371***	1	
Sacrifice Index	0.240***	0.0881**	0.169***	0.174***	0.233***	0.728***	0.330***	0.305***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The objective and subjective overindebtedness indices are standardized with mean zero and standard deviation of one.

Table B.2: Subsample Probability Question: Objective OI-Indicators

.	**Obj. Index**	DSR > 0.4	RDSR > 0.4	Paid Late	> 2 Loans
	(1)	(2)	(3)	(4)	(5)
Very Negative	−0.088	−0.067	−0.024	−0.003	−0.008
	(0.166)	(0.052)	(0.093)	(0.043)	(0.061)
Negative	0.061	−0.071	0.075	0.079**	−0.009
	(0.178)	(0.064)	(0.075)	(0.038)	(0.066)
Neutral	0.109	0.010	0.033	0.090	−0.014
	(0.196)	(0.076)	(0.066)	(0.060)	(0.068)
Positive	0.373**	0.105**	0.218***	0.141***	−0.025
	(0.137)	(0.047)	(0.063)	(0.043)	(0.058)
Constant	−1.978**	−0.103	−0.914***	−0.008	−0.448
	(0.845)	(0.315)	(0.316)	(0.303)	(0.383)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	525	525	525	522	525
Adj. R-squared	0.092	0.054	0.124	0.044	0.039

*** p<0.01, ** p<0.05, * p<0.1

Note: Clustered standard errors in parentheses. The variables *very negative, negative, neutral*, and *positive* represent the income forecast groups. Households with a mildly negative income forecast serve as the reference group. Households with a mildly negative income forecast serve as the reference group. Additional controls: age, age squared, children (0-6), children (7-10), children (11-16), financial literacy score, loss from crime shocks, loss from economic shocks, loss from environmental shocks, loss from other shocks, main income farming, main income employed, main income self-employed, main income remittances, monthly household income 2017, no. of elders in hh, no. of working members in hh, risk preference, self-control, social status, total hh education.

Table B.3: Subsample Probability Question: Subjective OI-Indicators

.	**Subj. Index**	Debt Position	Diff. Pay off Debt	Sacrifice Index
	(1)	(2)	(3)	(4)
Very Negative	0.210	−0.003	0.059	0.282**
	(0.131)	(0.115)	(0.047)	(0.106)
Negative	0.124	0.044	0.012	0.207
	(0.118)	(0.135)	(0.027)	(0.154)
Neutral	0.019	0.026	0.017	−0.073
	(0.115)	(0.127)	(0.024)	(0.094)
Positive	0.343***	0.213**	0.057**	0.351***
	(0.092)	(0.083)	(0.025)	(0.120)
Constant	−0.872	−1.816**	0.059	0.154
	(0.829)	(0.726)	(0.181)	(0.688)
Controls	Yes	Yes	Yes	Yes
Observations	525	525	523	525
Adj. R-squared	0.109	0.076	0.055	0.119

*** p<0.01, ** p<0.05, * p<0.1

Note: Clustered standard errors in parentheses. The variables *very negative, negative, neutral*, and *positive* represent the income forecast groups. Households with a mildly negative income forecast serve as the reference group. Households with a mildly negative income forecast serve as the reference group. Additional controls: age, age squared, children (0-6), children (7-10), children (11-16), financial literacy score, loss from crime shocks, loss from economic shocks, loss from environmental shocks, loss from other shocks, main income farming, main income employed, main income self-employed, main income remittances, monthly household income 2017, no. of elders in hh, no. of working members in hh, risk preference, self-control, social status, total hh education.

Table B.4: Subsample Financial Decision Makers: Objective OI-Indicators

.	**Obj. Index**	DSR > 0.4	RDSR > 0.4	Paid Late	> 2 Loans
	(1)	(2)	(3)	(4)	(5)
Very Negative	−0.098	−0.024	−0.032	−0.027	−0.031
	(0.154)	(0.055)	(0.085)	(0.040)	(0.067)
Negative	−0.016	−0.064	0.076	0.045	−0.069
	(0.141)	(0.051)	(0.064)	(0.035)	(0.072)
Neutral	0.094	0.002	0.041	0.083	−0.023
	(0.197)	(0.070)	(0.067)	(0.060)	(0.078)
Positive	0.352**	0.093	0.212***	0.132***	−0.023
	(0.153)	(0.055)	(0.073)	(0.042)	(0.064)
Constant	−1.394*	0.082	−0.634**	0.076	−0.299
	(0.676)	(0.340)	(0.292)	(0.236)	(0.308)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	575	575	575	572	575
Adj. R-squared	0.094	0.040	0.141	0.046	0.046

*** p<0.01, ** p<0.05, * p<0.1

Note: Clustered standard errors in parentheses. The variables *very negative, negative, neutral*, and *positive* represent the income forecast groups. Households with a mildly negative income forecast serve as the reference group. Households with a mildly negative income forecast serve as the reference group. Additional controls: age, age squared, children (0-6), children (7-10), children (11-16), financial literacy score, loss from crime shocks, loss from economic shocks, loss from environmental shocks, loss from other shocks, main income farming, main income employed, main income self-employed, main income remittances, monthly household income 2017, no. of elders in hh, no. of working members in hh, risk preference, self-control, social status, total hh education.

Table B.5: Subsample Financial Decision Makers: Subjective OI-Indicators

.	**Subj. Index**	Debt Position	Diff. Pay off Debt	Sacrifice Index
	(1)	(2)	(3)	(4)
Very Negative	0.141	−0.041	0.047	0.204*
	(0.122)	(0.134)	(0.040)	(0.116)
Negative	0.108	−0.042	0.021	0.245
	(0.120)	(0.116)	(0.027)	(0.208)
Neutral	−0.030	−0.053	0.013	−0.074
	(0.115)	(0.114)	(0.018)	(0.135)
Positive	0.252**	0.148**	0.040	0.278*
	(0.100)	(0.069)	(0.026)	(0.156)
Constant	−0.181	−1.442**	0.194	0.848
	(0.710)	(0.563)	(0.179)	(0.787)
Controls	Yes	Yes	Yes	Yes
Observations	575	575	573	575
Adj. R-squared	0.140	0.108	0.065	0.132

*** p<0.01, ** p<0.05, * p<0.1

Note: Clustered standard errors in parentheses. The variables *very negative, negative, neutral*, and *positive* represent the income forecast groups. Households with a mildly negative income forecast serve as the reference group. Households with a mildly negative income forecast serve as the reference group. Additional controls: age, age squared, children (0-6), children (7-10), children (11-16), financial literacy score, loss from crime shocks, loss from economic shocks, loss from environmental shocks, loss from other shocks, main income farming, main income employed, main income self-employed, main income remittances, monthly household income 2017, no. of elders in hh, no. of working members in hh, risk preference, self-control, social status, total hh education.

Table B.6: Interaction of Over-Indebtedness Indices with Conscientiousness

.	**Obj. Index**	**Subj. Debt Index**
	(1)	(2)
Very Negative	−0.409	1.102
	(0.747)	(0.867)
Negative	−0.767	0.834
	(0.498)	(0.668)
Neutral	−0.184	0.169
	(0.801)	(0.596)
Positive	−0.071	0.909
	(0.773)	(0.592)
Conscientiousness	−0.105	0.077
	(0.069)	(0.085)
Very neg. x Conscient.	0.068	−0.155
	(0.127)	(0.140)
Negative x Conscient.	0.144*	−0.119
	(0.076)	(0.107)
Neutral x Conscient.	0.056	−0.021
	(0.127)	(0.103)
Positive x Conscient.	0.071	−0.113
	(0.122)	(0.106)
Constant	−0.859	−0.942
	(0.777)	(0.769)
Controls	Yes	Yes
Observations	676	676
Adj. R-squared	0.095	0.130

*** p<0.01, ** p<0.05, * p<0.1

Note: Clustered standard errors in parentheses. The variables *very negative, negative, neutral*, and *positive* represent the income forecast groups. Households with a mildly negative income forecast serve as the reference group. Households with a mildly negative income forecast serve as the reference group. Additional controls: age, age squared, children (0-6), children (7-10), children (11-16), financial literacy score, loss from crime shocks, loss from economic shocks, loss from environmental shocks, loss from other shocks, main income farming, main income employed, main income self-employed, main income remittances, monthly household income 2017, no. of elders in hh, no. of working members in hh, risk preference, self-control, social status, total hh education.

Table B.7: Objective Over-Indebtedness, Quantitative Inc. Forecast Dummy

	Obj. Index		DSR > 0.4		RDSR > 0.4		Paid Late/Default		> 2 Loans	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Forecast Dummy	0.269**	0.245**	0.131***	0.095**	0.163***	0.137**	0.058*	0.077**	−0.033	−0.022
	(0.097)	(0.101)	(0.036)	(0.038)	(0.049)	(0.049)	(0.031)	(0.034)	(0.035)	(0.040)
Farming Shocks		−0.000		−0.000		−0.000		−0.000		0.000
		(0.002)		(0.000)		(0.001)		(0.001)		(0.001)
Environ. Shocks		0.005***		−0.000		0.002***		0.002*		0.002***
		(0.001)		(0.001)		(0.000)		(0.001)		(0.001)
Economic Shocks		0.003***		0.000		0.002***		0.001*		0.000
		(0.001)		(0.000)		(0.001)		(0.001)		(0.001)
Crime Shocks		−0.014		−0.003		−0.012***		−0.001		−0.001
		(0.009)		(0.002)		(0.003)		(0.004)		(0.004)
Other Shocks		−0.000		−0.000		−0.000		0.000*		−0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Constant	−0.061	−1.274**	0.150***	0.133	0.358***	−0.518*	0.141***	0.074	0.237***	−0.314
	(0.091)	(0.546)	(0.031)	(0.285)	(0.042)	(0.294)	(0.015)	(0.226)	(0.044)	(0.265)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	686	676	686	676	686	676	683	673	686	676
Adj. R-squared	0.012	0.099	0.020	0.048	0.019	0.121	0.003	0.037	-0.000	0.055

*** p<0.01, ** p<0.05, * p<0.1

Note: Clustered standard errors in parentheses. The variables *very negative, negative, neutral*, and *positive* represent the income forecast groups. Households with a mildly negative income forecast serve as the reference group. Households with a mildly negative income forecast serve as the reference group. Additional controls: age, age squared, children (0-6), children (7-10), children (11-16), financial literacy score, loss from crime shocks, loss from economic shocks, loss from environmental shocks, loss from other shocks, main income farming, main income employed, main income self-employed, main income remittances, monthly household income 2017, no. of elders in hh, no. of working members in hh, risk preference, self-control, social status, total hh education.

Table B.8: Subjective Over-Indebtedness, Quantitative Inc. Forecast Dummy

	Subj. Index		Debt Position		Diff. Pay off Debt		Sacrifice Index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Quant. Inc. Forecast Dummy	0.063	0.172*	0.105	0.165*	−0.005	0.019	0.054	0.146
	(0.097)	(0.093)	(0.094)	(0.086)	(0.020)	(0.024)	(0.079)	(0.087)
Farming Shocks		−0.001		0.001		−0.000**		−0.003
		(0.001)		(0.001)		(0.000)		(0.002)
Environmental Shocks		0.007***		0.003***		0.002***		0.004*
		(0.001)		(0.001)		(0.001)		(0.002)
Economic Shocks		0.000		0.003**		−0.001		−0.000
		(0.001)		(0.001)		(0.000)		(0.002)
Crime Shocks		0.000		−0.006		0.003		−0.006
		(0.014)		(0.008)		(0.003)		(0.015)
Other Shocks		0.002***		0.000		0.001***		0.002***
		(0.001)		(0.000)		(0.000)		(0.000)
Constant	−0.037	−0.430	−0.044	−1.447***	0.066***	0.152	−0.100*	0.377
	(0.040)	(0.566)	(0.045)	(0.504)	(0.011)	(0.147)	(0.050)	(0.584)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	686	676	686	676	684	674	686	676
Adj. R-squared	-0.001	0.133	0.001	0.099	-0.001	0.073	-0.001	0.117

*** p<0.01, ** p<0.05, * p<0.1

Note: Clustered standard errors in parentheses. The variables *very negative, negative, neutral*, and *positive* represent the income forecast groups. Households with a mildly negative income forecast serve as the reference group. Households with a mildly negative income forecast serve as the reference group. Additional controls: age, age squared, children (0-6), children (7-10), children (11-16), financial literacy score, loss from crime shocks, loss from economic shocks, loss from environmental shocks, loss from other shocks, main income farming, main income employed, main income self-employed, main income remittances, monthly household income 2017, no. of elders in hh, no. of working members in hh, risk preference, self-control, social status, total hh education.

Table B.9: Certainty Measure - Objective Over-Indebtedness - Quantitative Inc. Forecast Dummy

.	**Obj. Index**	DSR > 0.4	RDSR > 0.4	Paid Late	> 2 Loans
	(1)	(2)	(3)	(4)	(5)
Quant. Inc. Forecast Dummy	0.242**	0.096**	0.130**	0.079**	−0.023
	(0.103)	(0.040)	(0.050)	(0.035)	(0.041)
Certainty	0.127*	0.053**	0.043	−0.008	0.062**
	(0.061)	(0.023)	(0.027)	(0.024)	(0.022)
Constant	−1.406**	0.080	−0.587*	0.160	−0.443
	(0.526)	(0.286)	(0.299)	(0.247)	(0.262)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	664	664	664	661	664
Adj. R-squared	0.102	0.056	0.121	0.035	0.063

*** p<0.01, ** p<0.05, * p<0.1

Note: Clustered standard errors in parentheses. The variables *very negative, negative, neutral*, and *positive* represent the income forecast groups. Households with a mildly negative income forecast serve as the reference group. Households with a mildly negative income forecast serve as the reference group. Additional controls: age, age squared, children (0-6), children (7-10), children (11-16), financial literacy score, loss from crime shocks, loss from economic shocks, loss from environmental shocks, loss from other shocks, main income farming, main income employed, main income self-employed, main income remittances, monthly household income 2017, no. of elders in hh, no. of working members in hh, risk preference, self-control, social status, total hh education.

Table B.10: Certainty Measure - Subjective Over-Indebtedness - Quantitative Inc. Forecast Dummy

.	**Subj. Index**	Debt Position	Diff. Pay off Debt	Sacrifice Index
	(1)	(2)	(3)	(4)
Quant. Inc. Forecast Dummy	0.156	0.160*	0.014	0.133
	(0.094)	(0.091)	(0.022)	(0.091)
Certainty	0.064	0.090	0.005	0.023
	(0.089)	(0.066)	(0.021)	(0.107)
Constant	−0.609	−1.761***	0.154	0.331
	(0.630)	(0.571)	(0.153)	(0.726)
Controls	Yes	Yes	Yes	Yes
Observations	664	664	662	664
Adj. R-squared	0.133	0.103	0.072	0.112

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: Clustered standard errors in parentheses. The variables *very negative, negative, neutral*, and *positive* represent the income forecast groups. Households with a mildly negative income forecast serve as the reference group. Households with a mildly negative income forecast serve as the reference group. Additional controls: age, age squared, children (0-6), children (7-10), children (11-16), financial literacy score, loss from crime shocks, loss from economic shocks, loss from environmental shocks, loss from other shocks, main income farming, main income employed, main income self-employed, main income remittances, monthly household income 2017, no. of elders in hh, no. of working members in hh, risk preference, self-control, social status, total hh education.

B.2 The Qualitative Forecast Error

Deriving the Qualitative Forecast Error

We develop a measure of expectation accuracy closely following Souleles (2004) and Hyytinen and Putkuri (2018), which enables us to replicate the latter authors' results. We make use of the available panel data and combine categorical answers to the question, "How do you think your average monthly income will develop in the next twelve months?" ($E_{t-1}(Inc_{i,t})$) asked in 2016 (one year prior to our survey) with responses to the question "Do you think your household is better off than last year" asked in 2017 ($A(Inc_{i,t})$).[1] We call the difference between these two questions qualitative forecast error:

$$Qualitative\ Forecast\ Error = A(Inc_{i,t}) - E_{t-1}(Inc_{i,t}) \tag{B.2.1}$$

A positive qualitative forecast error occurs if the expected household situation is better than the realized one and a negative if the opposite is true. We form five categories ranging from a very negative to a very positive qualitative forecast error, which enter the regression analysis as dummy variables. The category with households making no forecast error serves as omitted group.

As the qualitative forecast error is derived at the household level, the respondent may not be the same for all three data points. Therefore, we re-run the analysis for a sub-sample with only identical respondents, which does not change the results. We assume that the household's qualitative assessment regarding its own development stays similar for a time period of two years and, thus, is able to explain indebtedness in 2017. There are two reasons encouraging this view: We are able to control for a rich set of socio-economic variables that capture household formation and, as incomes are rather stationary, expectations may also change slowly.

Results for the Qualitative Forecast Error

The regressions we run for the qualitative forecast error take the same form as the ones for the quantitative income forecast (standard errors are clustered at the district level):

$$Over - Indebtedness\ Index_i = \beta_0 + \beta_1 Qual.FE_i + X_i^{'}\beta_2 + \epsilon_i \tag{B.2.2}$$

Results for the objective and subjective over-indebtedness indices are presented in Tables B.2.1 and B.2.2. With regards to the relationship between the objective OI-Index and the qualitative forecast error, we find that over-indebtedness increases by 0.42 points if respondents exhibit a very positive forecast error. The results are driven by two components: the remaining debt to service ratio (columns (5) and (6), Table B.2.1) and the probability of whether people paid late or defaulted on a loan (columns (7) and (8)). The results are similar to those of the quantitative income forecast. We again find that very positive forecasts are related to a higher probability of being objectively over-indebted. Point estimates are slightly higher for results from the qualitative forecast error. Regarding the impact of losses from shocks as well as additional control variables, results are similar to those of the quantitative

[1] Answer options range on a scale from 1-5. For the question asked in 2016, one means "increase a lot" and five "decrease a lot." The question asked in 2017 ranges from one being "much better off" to five "much worse off."

income forecast. Overall, results from the qualitative forecast error confirm the findings from the quantitative income forecast: positive future income expectations are related to increasing objective over-indebtedness.

Table B.2.1: Qualitative Forecast Error - Main Results Objective OI-Indicators

	Obj. Index		DSR > 0.4		RDSR > 0.4		Paid Late/Default		> 2 Loans	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Very negative	0.130	0.179	−0.089	−0.073	0.118	0.148	0.106	0.109	0.024	0.034
	(0.222)	(0.236)	(0.061)	(0.067)	(0.129)	(0.142)	(0.106)	(0.101)	(0.067)	(0.065)
Negative	−0.158**	−0.055	−0.046	−0.030	−0.033	0.006	−0.026	−0.003	−0.076	−0.033
	(0.063)	(0.069)	(0.032)	(0.035)	(0.040)	(0.044)	(0.028)	(0.029)	(0.047)	(0.048)
Positive	0.165**	0.069	0.007	−0.009	0.087*	0.044	0.035	0.014	0.069	0.034
	(0.064)	(0.070)	(0.031)	(0.034)	(0.045)	(0.040)	(0.036)	(0.035)	(0.041)	(0.039)
Very Positive	0.443**	0.410**	0.070	0.052	0.194***	0.182***	0.151*	0.149**	0.100	0.093
	(0.170)	(0.144)	(0.073)	(0.068)	(0.058)	(0.050)	(0.073)	(0.067)	(0.063)	(0.057)
Farming Shocks		0.000		0.000		−0.000		0.000		0.000
		(0.001)		(0.000)		(0.000)		(0.000)		(0.000)
Environm. Shocks		0.003**		−0.000		0.002***		0.001		0.001**
		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
Economic Shocks		0.003***		0.001**		0.001***		0.001**		0.000
		(0.001)		(0.000)		(0.000)		(0.000)		(0.000)
Crime Shocks		−0.012***		−0.003***		−0.006**		−0.002		−0.003
		(0.004)		(0.001)		(0.002)		(0.002)		(0.002)
Other Shocks		−0.000		−0.000**		−0.000		0.000		−0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Constant	−0.059	−1.264**	0.184***	0.190	0.359***	−0.508*	0.132***	0.059	0.214***	−0.355
	(0.082)	(0.584)	(0.032)	(0.320)	(0.032)	(0.290)	(0.020)	(0.229)	(0.038)	(0.275)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	688	676	688	676	688	676	685	673	688	676
Adj. R-squared	0.022	0.120	0.002	0.044	0.014	0.124	0.013	0.050	0.011	0.063

*** p<0.01, ** p<0.05, * p<0.1

Note: Clustered standard errors in parentheses. The variables *very negative, negative, positive*, and *very positive* represent the forecast groups. Households with no forecast error serve as the reference group. Additional controls: age, age squared, children (0-6), children (7-10), children (11-16), financial literacy score, main income farming, main income employed, main income self-employed, main income remittances, monthly household income 2017, no. of elders in hh, no. of working members in hh, risk preference, self-control, social status, total hh education.

We also find a strongly significant relationship between positive qualitative forecast errors and subjective over-indebtedness. This relationship is much stronger than for the quantitative income forecast. Again, we only find a robust relationship for households in the group with the largest positive forecasts. The subjective OI-Index increases by 0.42 points for respondents who exhibit very positive forecast errors (columns (1) and (2), Table B.2.2). Mainly, this is due to the positive relationship between the forecast error and the "debt position" component of the index and the sacrifice index component. Households with a very positive error tend to state more frequently that they "have too much debt right now" (columns (3) and (4)) and that they make an increasing number of everyday sacrifices to repay their loans (column (7) and (8)). We conclude that the nature of the qualitative forecast error being more "subjectively" elicited than the calculated quantitative income forecast *per se*, might be reflected in more pronounced results regarding subjectively "felt" debt. This is also in line with our analysis from the quantitative income forecast that subjective over-indebtedness may rather be a concept of perceived financial distress affected by not only the household's true debt situation but also by respondent characteristics.

Table B.2.2: Qualitative Forecast Error - Main Results Subjective OI-Indicators

.	**Subj. Index**		Debt Position		Diff. Pay off Debt		Sacrifice Index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Very negative	0.218	0.140	0.064	0.055	0.052	0.027	0.243	0.167
	(0.258)	(0.245)	(0.230)	(0.261)	(0.068)	(0.060)	(0.214)	(0.198)
Negative	−0.025	0.030	−0.091	−0.011	0.030	0.028	−0.096	−0.046
	(0.127)	(0.103)	(0.072)	(0.061)	(0.035)	(0.031)	(0.153)	(0.134)
Positive	0.208**	0.105	0.139*	0.065	0.021	0.011	0.265*	0.134
	(0.077)	(0.083)	(0.072)	(0.069)	(0.016)	(0.019)	(0.150)	(0.133)
Very Positive	0.476**	0.455**	0.351*	0.361**	0.091	0.086	0.352*	0.308*
	(0.208)	(0.186)	(0.177)	(0.155)	(0.053)	(0.053)	(0.187)	(0.160)
Farming Shocks		0.000		0.000		0.000		−0.001
		(0.001)		(0.001)		(0.000)		(0.001)
Environ. Shocks		0.002		0.001		0.001		0.001
		(0.002)		(0.001)		(0.001)		(0.002)
Economic Shocks		0.000		0.002**		−0.000*		0.001
		(0.001)		(0.001)		(0.000)		(0.001)
Crime Shocks		−0.003		−0.000		−0.000		−0.007
		(0.007)		(0.007)		(0.002)		(0.006)
Other Shocks		0.001***		0.000		0.000***		0.001**
		(0.000)		(0.000)		(0.000)		(0.000)
Constant	−0.122**	−0.499	−0.074	−1.459**	0.043***	0.122	−0.176**	0.357
	(0.057)	(0.664)	(0.050)	(0.530)	(0.014)	(0.175)	(0.072)	(0.626)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	688	676	688	676	686	674	688	676
Adj. R-squared	0.019	0.136	0.015	0.102	0.006	0.073	0.012	0.115

*** p<0.01, ** p<0.05, * p<0.1

Note: Clustered standard errors in parentheses. The variables *very negative, negative, positive*, and *very positive* represent the forecast groups. Households with no forecast error serve as the reference group. Additional controls: age, age squared, children (0-6), children (7-10), children (11-16), financial literacy score, main income farming, main income employed, main income self-employed, main income remittances, monthly household income 2017, no. of elders in hh, no. of working members in hh, risk preference, self-control, social status, total hh education.

Furthermore, we again add an income certainty measure to the regression. Results are presented in Tables B.2.3 and B.2.4. There is no relationship between future income certainty on objective and subjective over-indebtedness. For the subjective OI-Indicators, results are in line with those from the quantitative income forecast. However, they differ for objective over-indebtedness. While we find that higher income certainty is related to higher objective over-indebtedness with respect to the quantitative income forecast, we do not find that relationship with the qualitative error. This may be due to the more subjective nature of the qualitative forecast error.

Table B.2.3: Objective Over-Indebtedness - Income Certainty

.	**Obj. Index**	DSR > 0.4	RDSR > 0.4	Paid Late	> 2 Loans
	(1)	(2)	(3)	(4)	(5)
Very negative	0.180	−0.075	0.151	0.110	0.034
	(0.242)	(0.067)	(0.145)	(0.102)	(0.066)
Negative	−0.056	−0.030	0.007	−0.004	−0.034
	(0.068)	(0.035)	(0.044)	(0.029)	(0.048)
Positive	0.070	−0.010	0.045	0.015	0.034
	(0.069)	(0.034)	(0.040)	(0.035)	(0.039)
Very Positive	0.465**	0.093	0.187***	0.153*	0.104*
	(0.164)	(0.078)	(0.059)	(0.074)	(0.058)
Certainty	0.046	0.030	0.008	0.004	0.011
	(0.049)	(0.020)	(0.017)	(0.019)	(0.024)
Constant	−1.481**	−0.001	−0.640**	0.066	−0.297
	(0.551)	(0.295)	(0.280)	(0.262)	(0.261)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	663	663	663	660	663
Adj. R-squared	0.118	0.050	0.122	0.046	0.058

*** p<0.01, ** p<0.05, * p<0.1

Note: Clustered standard errors in parentheses. Households with no forecast error serve as the reference group. The variables *very negative, negative, positive*, and *very positive* represent the forecast groups. Households with no forecast error serve as the reference group. Additional controls: age, age squared, children (0-6), children (7-10), children (11-16), financial literacy score, loss from crime shocks, loss from economic shocks, loss from environmental shocks, loss from other shocks, main income farming, main income employed, main income self-employed, main income remittances, monthly household income 2017, no. of elders in hh, no. of working members in hh, risk preference, self-control, social status, total hh education.

Table B.2.4: Subjective Over-Indebtedness - Income Certainty

.	**Subj. Index**	Debt Position	Diff. Pay off Debt	Sacrifice Index
	(1)	(2)	(3)	(4)
Very negative	0.150	0.063	0.026	0.186
	(0.242)	(0.258)	(0.060)	(0.192)
Negative	0.028	−0.012	0.028	−0.048
	(0.104)	(0.061)	(0.031)	(0.136)
Positive	0.109	0.068	0.011	0.141
	(0.085)	(0.071)	(0.019)	(0.135)
Very Positive	0.578**	0.429**	0.116*	0.400**
	(0.211)	(0.191)	(0.064)	(0.169)
Certainty	−0.035	−0.033	0.010	−0.103
	(0.058)	(0.048)	(0.012)	(0.072)
Constant	−0.356	−1.374**	0.128	0.605
	(0.667)	(0.563)	(0.181)	(0.629)
Controls	Yes	Yes	Yes	Yes
Observations	663	663	661	663
Adj. R-squared	0.143	0.104	0.076	0.121

*** p<0.01, ** p<0.05, * p<0.1

Note: Clustered standard errors in parentheses. Households with no forecast error serve as the reference group. The variables *very negative, negative, positive*, and *very positive* represent the forecast groups. Households with no forecast error serve as the reference group. Additional controls: age, age squared, children (0-6), children (7-10), children (11-16), financial literacy score, loss from crime shocks, loss from economic shocks, loss from environmental shocks, loss from other shocks, main income farming, main income employed, main income self-employed, main income remittances, monthly household income 2017, no. of elders in hh, no. of working members in hh, risk preference, self-control, social status, total hh education.

Overall, results from the qualitative forecast error confirm the main findings from the quantitative income forecast: very positive forecasts are related to a higher level of over-indebtedness. There is no such relationship for negative forecasts and over-indebtedness. The results also support the analysis from the quantitative income forecast that subjective and objective over-indebtedness indicators measure different dimensions of indebtedness. Finally, our results from the qualitative forecast error are in line with those of Hyytinen and Putkuri (2018). They report that households with a very positive forecast error are more likely to be over-indebted and that such a pattern cannot be found for households with negative forecast errors. Our results show the same relationship.

B.3 Experiment Appendix

Table B.3.1: Descriptive Statistics by Participation in Game

	Full Sample	Participating	Non-Participating	Difference
Sex	1.66	1.63	1.76	0.12***
Age	57.01	56.35	59.78	3.43***
Relation to HH Head	1.67	1.66	1.71	0.05
Marital Status	2.15	2.14	2.22	0.09
Main Occupation	4.97	4.66	6.29	1.64*
Years of Schooling	5.74	5.83	5.33	−0.51*
Children (0-6 years)	0.32	0.32	0.33	0.01
Children (7-10 years)	0.24	0.23	0.25	0.02
Numeracy	2.05	2.13	1.69	−0.45***
Health Status	1.40	1.38	1.46	0.08
BMI	23.64	23.70	23.41	−0.28
Fin. Decision Maker	1.57	1.56	1.60	0.03
Self Control	21.26	21.02	22.26	1.24
Risk Taking	3.95	3.99	3.78	−0.21
Fin. Risk Taking	3.94	4.04	3.57	−0.47**
FL-Score	5.50	5.63	4.95	−0.68***
Monthly Inc. 2017	19197.02	19313.71	18704.57	−609.14
Obj. OI-Index	0.00	0.00	−0.00	−0.00
Subj. OI-Index	−0.00	−0.01	0.03	0.04
Morning	0.53	0.53	0.53	0.00
Midday	0.24	0.26	0.17	−0.09***
Observations	748	604	144	748

*** p<0.01, ** p<0.05, * p<0.1

Table B.3.2: Linear Probability Model Participation in Game

.	Participation
Sex	-0.077^{**}
	(0.036)
Age	-0.003^{**}
	(0.002)
Fin. Risk Taking	0.023^{**}
	(0.010)
FL-Score	0.020^{**}
	(0.010)
Morning	0.083^{**}
	(0.040)
Midday	0.144^{***}
	(0.043)
Observations	717

*** p<0.01, ** p<0.05, * p<0.1

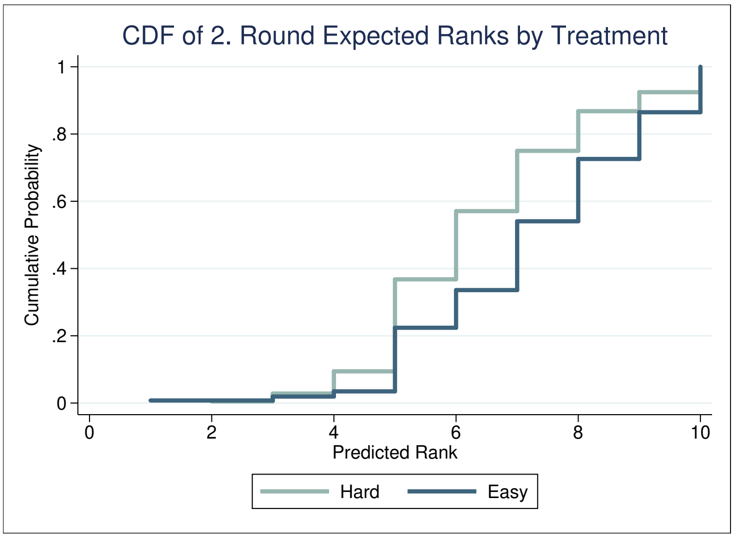
Note: Only significant variables reported, remaining variables are the same as in Table B.3.1.

Table B.3.3: Descriptive Statistics for Excluded Sample

	Full Sample	In	Out	Difference
Sex	1.65	1.64	1.67	−0.03
Age	56.40	56.16	57.75	−1.59
Relation to HH Head	1.68	1.70	1.56	0.14
Marital Status	2.14	2.13	2.24	−0.11
Main Occupation	4.68	4.79	4.08	0.71
Years of Schooling	5.87	5.92	5.60	0.32
Children (0-6 years)	0.31	0.33	0.25	0.08
Children (7-10 years)	0.24	0.26	0.13	0.13***
Numeracy	2.13	2.14	2.04	0.11
Health Status	1.38	1.38	1.38	0.00
BMI	23.69	23.58	24.27	−0.68
Fin. Decision Maker	1.56	1.57	1.52	0.05
Self Control	21.05	20.94	21.62	−0.67
Risk Taking	3.98	4.02	3.74	0.28
Fin. Risk Taking	4.03	4.06	3.90	0.15
FL-Score	5.62	5.66	5.40	0.26
Monthly Inc. 2017	18523.65	18653.06	17798.04	855.02
Obj. OI-Index	0.01	0.01	−0.02	0.03
Subj. OI-Index	−0.03	−0.04	0.05	−0.09
Read Alone	1.45	1.44	1.49	−0.04
Difficulties	1.15	1.14	1.21	−0.08
Observations	555	471	84	555

*** p<0.01, ** p<0.05, * p<0.1

Figure B.3.1: CDF for the Expected Rank by Treatment, After the Main Quiz



The Rationals

As mentioned above, so far we have excluded experiment participants who want to buy more than they expect to earn. We refer to these persons as "rationals." In this section, we discuss whether these participants are actually rational or had difficulties in understanding the experiment and how including these observations change our results. Comparing our main sample against all rationals does not yield results that differ substantially from those presented in Table B.3.3. However, if we divide the rationals into those participants who want to buy more than expected earnings could pay for but less than eight goods and those who want to buy exactly eight goods (which would be the "truly" rational decision), we find interesting differences. The former group has significantly lower education, numeracy, and financial literacy than the main sample (see Table B.3.4). We see this as evidence that they may have had difficulties understanding the game (from here on, we refer to these individuals as non-rationals). It does not seem to be the case, however, that these are persons who generally have problems controlling their own spending behavior (also outside the lab) because their debt to service ratio is significantly smaller compared to the main sample.

Table B.3.4: Descriptive Statistics for Non-Rationals (only significant effects reported)

	Full Sample	Others	Non-Rationals	Difference
Years of Schooling	5.84	5.91	5.00	0.91***
Children (7-10 years)	0.24	0.26	0.12	0.14**
Numeracy	2.10	2.13	1.76	0.36*
FL-Score	5.60	5.64	5.10	0.54*
Observations	532	490	42	532

*** p<0.01, ** p<0.05, * p<0.1

The remaining rationals, however, not only have significantly higher numeracy and financial literacy, but also have a better understanding of the game as perceived by the interviewers (see Table B.3.5) (for non-rationals the difference is in the opposite direction, but not significant). Thus, these participants might have taken advantage of the set-up and reasoned that it is optimal for them to buy as many goods as possible because of the large discount.

Table B.3.5: Descriptive Statistics for Rationals (only significant effects reported)

	Full Sample	Others	Rationals	Difference
Main Occupation	4.70	4.76	3.48	1.28*
Numeracy	2.16	2.13	2.78	–0.66*
FL-Score	5.66	5.64	6.22	–0.58*
Difficulties in Game	1.15	1.16	1.00	0.16***
Observations	513	490	23	513

*** p<0.01, ** p<0.05, * p<0.1

Including these two groups into the analysis, the results change as anticipated: the effect of expected rank on goods turns insignificant and negligible (see Table B.3.6). All other effects are almost unchanged.

Table B.3.6: Consumption Decision including Rationals

.	Exp. Rank	No. Goods		
	(1)	(2)	(3)	(4)
Treatment	0.373**	−0.234		−0.254
	(0.168)	(0.199)		(0.199)
Exp. Rank			0.048	0.054
			(0.052)	(0.052)
Controls	Yes	Yes	Yes	Yes
Observations	511	511	511	511

*** p<0.01, ** p<0.05, * p<0.1

Note: Standard errors in parentheses. Treatment: 0=Hard Quiz, 1=Easy Quiz; A higher expected rank corresponds to a higher expected performance. Controls: Health Status, Monthly HH income and Objective OI-Index.

B.4 Online Appendix

Additional Regression Tables

Table B.4.1: Full Regression Output for Main Regression - Objective Over-Indebtedness

	Obj. Index		DSR > 0.4		RDSR > 0.4		Paid Late/Default		> 2 Loans	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Very Negative	−0.125	−0.017	−0.097*	−0.022	−0.073	0.011	0.017	−0.015	0.001	0.010
	(0.151)	(0.143)	(0.047)	(0.050)	(0.081)	(0.079)	(0.033)	(0.036)	(0.059)	(0.060)
Negative	0.050	0.058	−0.067	−0.054	0.075	0.100*	0.081**	0.066**	−0.029	−0.037
	(0.134)	(0.132)	(0.045)	(0.048)	(0.058)	(0.057)	(0.032)	(0.029)	(0.057)	(0.058)
Neutral	0.153	0.135	0.025	0.002	0.079	0.067	0.074	0.095*	−0.002	−0.010
	(0.153)	(0.168)	(0.050)	(0.060)	(0.058)	(0.064)	(0.045)	(0.051)	(0.061)	(0.063)
Positive	0.289**	0.333**	0.098**	0.087*	0.187**	0.210***	0.109***	0.133***	−0.054	−0.037
	(0.134)	(0.136)	(0.042)	(0.047)	(0.072)	(0.069)	(0.038)	(0.041)	(0.055)	(0.060)
Monthly Inc. 2017		−0.000		−0.000*		−0.000***		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Age		0.061***		0.007		0.031***		0.015*		0.019***
		(0.017)		(0.008)		(0.009)		(0.008)		(0.007)
Age Squared		−0.001***		−0.000		−0.000***		−0.000**		−0.000***
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
FL-Score		0.021		0.008		0.018***		−0.010		0.012
		(0.018)		(0.007)		(0.006)		(0.006)		(0.007)
Risk Preference		0.054***		0.013*		0.026***		0.012		0.013
		(0.018)		(0.007)		(0.008)		(0.008)		(0.008)
Self-Control		0.001		−0.002		−0.001		0.003		0.001
		(0.006)		(0.002)		(0.003)		(0.002)		(0.002)
Main Inc. Farming		−0.122		−0.066		−0.006		−0.090		0.032
		(0.155)		(0.059)		(0.091)		(0.057)		(0.044)
Main Inc. Employed		−0.194		−0.106*		−0.032		−0.022		−0.063
		(0.166)		(0.059)		(0.076)		(0.057)		(0.055)
Main Inc. Self-Emp.		−0.163		−0.087		−0.025		−0.025		−0.053
		(0.212)		(0.089)		(0.099)		(0.068)		(0.061)
Main Inc. Remitt.		−0.151		−0.068		−0.016		−0.070		−0.015
		(0.144)		(0.060)		(0.057)		(0.058)		(0.037)
Children (0-6 yrs)		−0.085*		−0.012		−0.057**		0.007		−0.045**
		(0.047)		(0.017)		(0.026)		(0.027)		(0.020)
Children (7-10 yrs)		0.092		0.012		0.079**		0.008		0.019
		(0.082)		(0.048)		(0.033)		(0.022)		(0.036)
Children (11-16 yrs)		0.030		−0.017		0.017		0.025		0.009
		(0.040)		(0.020)		(0.021)		(0.020)		(0.019)
No. of Elders		0.036		0.003		0.036*		0.034*		−0.032
		(0.040)		(0.024)		(0.018)		(0.020)		(0.023)
No. of Working Mem.		0.072*		0.022		0.008		0.002		0.051**
		(0.042)		(0.015)		(0.019)		(0.019)		(0.021)
Total HH Education		−0.001		−0.000		0.002		−0.000		−0.003
		(0.005)		(0.002)		(0.003)		(0.002)		(0.002)
Farming Shocks		−0.000		−0.000		0.000		−0.000		0.000
		(0.002)		(0.000)		(0.001)		(0.001)		(0.001)
Environ. Shocks		0.005***		−0.000		0.002***		0.002**		0.002***
		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
Economic Shocks		0.003***		0.000		0.002***		0.001*		0.000
		(0.001)		(0.000)		(0.001)		(0.001)		(0.001)
Crime Shocks		−0.016*		−0.004*		−0.013***		−0.002		−0.001
		(0.009)		(0.002)		(0.003)		(0.004)		(0.004)
Other Shocks		−0.000		−0.000		−0.000		0.000**		−0.000
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Social Status		−0.140*		−0.021		−0.028		−0.056***		−0.051
		(0.071)		(0.023)		(0.033)		(0.019)		(0.032)
Constant	−0.073	−1.425**	0.189***	0.119	0.343***	−0.617**	0.099***	−0.016	0.245***	−0.291
	(0.144)	(0.576)	(0.048)	(0.296)	(0.072)	(0.286)	(0.019)	(0.243)	(0.063)	(0.280)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	688	676	688	676	688	676	685	673	688	676
Adj. R-squared	0.014	0.099	0.025	0.046	0.025	0.125	0.007	0.044	-0.003	0.053

*** p<0.01, ** p<0.05, * p<0.1

Note: Clustered standard errors in parentheses.

Table B.4.2: Full Regression Output for Main Regression - Subjective Over-Indebtedness

	Subj. Index		Debt Position		Diff. Pay off Debt		Sacrifice Index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Very Negative	0.182	0.215*	0.040	0.036	0.065**	0.058	0.118	0.245**
	(0.112)	(0.122)	(0.114)	(0.110)	(0.029)	(0.039)	(0.106)	(0.103)
Negative	0.157	0.150	0.096	0.046	0.037	0.033	0.108	0.178
	(0.135)	(0.110)	(0.111)	(0.109)	(0.025)	(0.026)	(0.174)	(0.154)
Neutral	−0.007	0.048	−0.021	0.008	0.022	0.031	−0.098	−0.035
	(0.104)	(0.092)	(0.096)	(0.094)	(0.021)	(0.019)	(0.128)	(0.095)
Positive	0.144	0.258**	0.113	0.181**	0.024	0.041*	0.113	0.245*
	(0.086)	(0.101)	(0.071)	(0.084)	(0.021)	(0.023)	(0.120)	(0.122)
Monthly Inc. 2017		−0.000		−0.000		−0.000		−0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Age		0.061***		0.063***		0.007*		0.042**
		(0.014)		(0.015)		(0.004)		(0.018)
Age Squared		−0.001***		−0.001***		−0.000**		−0.000**
		(0.000)		(0.000)		(0.000)		(0.000)
FL-Score		−0.026**		0.007		−0.007**		−0.047**
		(0.012)		(0.010)		(0.003)		(0.018)
Risk Preference		0.044**		0.057***		0.003		0.023
		(0.017)		(0.018)		(0.005)		(0.019)
Self-Control		0.009**		0.005		0.001		0.015***
		(0.004)		(0.004)		(0.001)		(0.005)
Main Inc. Farming		−0.192**		−0.159		0.007		−0.323**
		(0.078)		(0.100)		(0.032)		(0.140)
Main Inc. Employed		0.042		0.017		0.047		−0.138
		(0.121)		(0.114)		(0.037)		(0.176)
Main Inc. Self-Emp.		−0.019		−0.019		0.031		−0.178
		(0.139)		(0.108)		(0.046)		(0.164)
Main Inc. Remitt.		−0.159		−0.251**		0.020		−0.176
		(0.102)		(0.090)		(0.036)		(0.165)
Children (0-6 yrs)		−0.091		−0.101**		−0.012		−0.046
		(0.062)		(0.048)		(0.016)		(0.063)
Children (7-10 yrs)		−0.084		0.039		−0.026		−0.162
		(0.075)		(0.071)		(0.019)		(0.094)
Children (11-16 yrs)		0.007		−0.002		−0.022		0.123*
		(0.063)		(0.037)		(0.022)		(0.066)
No. of Elders		0.026		0.043		0.012		−0.045
		(0.036)		(0.042)		(0.011)		(0.056)
No. of Working Mem.		0.121***		0.123***		−0.005		0.182***
		(0.042)		(0.033)		(0.014)		(0.045)
Total HH Education		−0.009**		−0.008**		0.001		−0.019***
		(0.004)		(0.003)		(0.001)		(0.005)
Farming Shocks		−0.001		0.002		−0.000*		−0.002
		(0.001)		(0.001)		(0.000)		(0.002)
Environmental Shocks		0.007***		0.003***		0.002**		0.003
		(0.001)		(0.001)		(0.001)		(0.002)
Economic Shocks		0.001		0.003**		−0.000		−0.000
		(0.001)		(0.001)		(0.000)		(0.002)
Crime Shocks		0.000		−0.006		0.003		−0.005
		(0.014)		(0.007)		(0.003)		(0.014)
Other Shocks		0.002***		0.000		0.001***		0.002***
		(0.001)		(0.000)		(0.000)		(0.000)
Social Status		−0.353***		−0.184***		−0.069***		−0.371***
		(0.079)		(0.045)		(0.023)		(0.092)
Constant	−0.115	−0.482	−0.064	−1.480***	0.035**	0.140	−0.131	0.344
	(0.082)	(0.593)	(0.081)	(0.514)	(0.016)	(0.155)	(0.111)	(0.591)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	688	676	688	676	686	674	688	676
Adj. R-squared	0.001	0.133	-0.002	0.094	0.002	0.073	-0.001	0.119

*** p<0.01, ** p<0.05, * p<0.1

Note: Clustered standard errors in parentheses.

Table B.4.3: Additional Regression on Big5 Measures - Objective Over-Indebtedness

	Obj. Index		DSR > 0.4		RDSR > 0.4		Paid Late/Default		> 2 Loans	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Very Negative	−0.125	−0.032	−0.097*	−0.026	−0.073	0.006	0.017	−0.021	0.001	0.008
	(0.151)	(0.137)	(0.047)	(0.050)	(0.081)	(0.076)	(0.033)	(0.036)	(0.059)	(0.059)
Negative	0.050	0.056	−0.067	−0.052	0.075	0.097*	0.081**	0.062**	−0.029	−0.035
	(0.134)	(0.133)	(0.045)	(0.050)	(0.058)	(0.056)	(0.032)	(0.029)	(0.057)	(0.061)
Neutral	0.153	0.111	0.025	−0.001	0.079	0.059	0.074	0.087*	−0.002	−0.019
	(0.153)	(0.160)	(0.050)	(0.058)	(0.058)	(0.060)	(0.045)	(0.050)	(0.061)	(0.063)
Positive	0.289**	0.311**	0.098**	0.084*	0.187**	0.206***	0.109***	0.128***	−0.054	−0.050
	(0.134)	(0.135)	(0.042)	(0.046)	(0.072)	(0.072)	(0.038)	(0.040)	(0.055)	(0.060)
Openness		0.100***		0.028***		0.040**		0.027**		0.022
		(0.030)		(0.008)		(0.016)		(0.012)		(0.016)
Conscientiousn.		−0.083**		−0.016		−0.036**		−0.025		−0.020
		(0.031)		(0.014)		(0.014)		(0.016)		(0.013)
Extraversion		−0.003		0.013		−0.013		−0.018		0.014
		(0.038)		(0.013)		(0.021)		(0.015)		(0.015)
Agreeableness		0.039		0.007		−0.008		0.009		0.034*
		(0.049)		(0.019)		(0.019)		(0.019)		(0.019)
Neuroticism		0.033		0.001		0.008		0.002		0.029*
		(0.034)		(0.010)		(0.018)		(0.017)		(0.015)
Constant	−0.073	−1.493*	0.189***	0.053	0.343***	−0.464	0.099***	0.073	0.245***	−0.539*
	(0.144)	(0.783)	(0.048)	(0.367)	(0.072)	(0.360)	(0.019)	(0.264)	(0.063)	(0.305)
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	688	676	688	676	688	676	685	673	688	676
Adj. R-squared	0.014	0.108	0.025	0.047	0.025	0.129	0.007	0.046	-0.003	0.061

*** p<0.01, ** p<0.05, * p<0.1

Note: Clustered standard errors in parentheses. Households with no forecast error serve as the reference group. Additional controls: age, age squared, children (0-6), children (7-10), children (11-16), financial literacy score, loss from crime shocks, loss from economic shocks, loss from environmental shocks, loss from other shocks, main income farming, main income employed, main income self-employed, main income remittances, monthly household income 2017, no. of elders in hh, no. of working members in hh, risk preference, self-control, social status, total hh education.

Table B.4.4: Additional Regression on Big5 Measures - Subjective Over-Indebtedness

	Subj. Index		Debt Position		Diff. Pay off Debt		Sacrifice Index	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Very Negative	0.182	0.213*	0.040	0.035	0.065**	0.056	0.118	0.252**
	(0.112)	(0.115)	(0.114)	(0.103)	(0.029)	(0.039)	(0.106)	(0.102)
Negative	0.157	0.136	0.096	0.032	0.037	0.034	0.108	0.155
	(0.135)	(0.113)	(0.111)	(0.109)	(0.025)	(0.026)	(0.174)	(0.157)
Neutral	−0.007	0.030	−0.021	−0.003	0.022	0.030	−0.098	−0.061
	(0.104)	(0.089)	(0.096)	(0.090)	(0.021)	(0.020)	(0.128)	(0.100)
Positive	0.144	0.239**	0.113	0.170**	0.024	0.041*	0.113	0.206*
	(0.086)	(0.091)	(0.071)	(0.077)	(0.021)	(0.023)	(0.120)	(0.113)
Openness		0.094**		0.058*		0.012		0.113**
		(0.036)		(0.033)		(0.009)		(0.049)
Conscientiousness		−0.007		0.005		−0.017		0.054
		(0.054)		(0.042)		(0.014)		(0.056)
Extraversion		−0.042		−0.055		0.007		−0.072
		(0.042)		(0.037)		(0.012)		(0.042)
Agreeableness		−0.021		−0.026		−0.001		−0.019
		(0.042)		(0.037)		(0.011)		(0.050)
Neuroticism		0.058*		0.031		−0.002		0.123**
		(0.031)		(0.029)		(0.009)		(0.044)
Constant	−0.115	−0.577	−0.064	−1.401**	0.035**	0.183	−0.131	−0.209
	(0.082)	(0.706)	(0.081)	(0.646)	(0.016)	(0.154)	(0.111)	(0.812)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Observations	688	676	688	676	686	674	688	676
Adj. R-squared	0.001	0.143	-0.002	0.098	0.002	0.072	-0.001	0.141

*** p<0.01, ** p<0.05, * p<0.1

Note: Clustered standard errors in parentheses. Households with no forecast error serve as the reference group. Additional controls: age, age squared, children (0-6), children (7-10), children (11-16), financial literacy score, loss from crime shocks, loss from economic shocks, loss from environmental shocks, loss from other shocks, main income farming, main income employed, main income self-employed, main income remittances, monthly household income 2017, no. of elders in hh, no. of working members in hh, risk preference, self-control, social status, total hh education.

Table B.4.5: Additional Regression on Predictors for Income Forecast Groups

	Very Negative		Negative		Mildly Negative		Neutral		Positive	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Monthly Inc. 2017	0.000***	0.000***	0.000	0.000	−0.000**	−0.000**	−0.000***	−0.000***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.016**	0.018***	0.003	0.000	0.004	0.006	−0.008	−0.006	−0.015*	−0.019**
	(0.006)	(0.006)	(0.008)	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)
Age Squared	−0.000**	−0.000**	−0.000	−0.000	−0.000	−0.000	0.000	0.000	0.000*	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FL-Score	−0.022***	−0.020***	−0.001	−0.001	0.002	0.003	0.019***	0.017***	0.002	0.001
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.007)
Risk Preference	0.006	0.007	−0.015*	−0.015	0.018**	0.015*	−0.008	−0.007	−0.001	−0.000
	(0.006)	(0.007)	(0.008)	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)
Self-Control	−0.002	−0.002	0.002	0.002	−0.001	−0.000	0.002	0.002	−0.001	−0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Main Inc. Farming	0.131***	0.136***	0.032	0.035	0.008	0.011	0.058	0.053	−0.230***	−0.236***
	(0.034)	(0.037)	(0.041)	(0.044)	(0.053)	(0.055)	(0.060)	(0.062)	(0.069)	(0.070)
Main Inc. Employed	0.184***	0.197***	0.086*	0.089*	0.046	0.034	−0.021	−0.021	−0.295***	−0.298***
	(0.028)	(0.033)	(0.049)	(0.049)	(0.059)	(0.064)	(0.054)	(0.057)	(0.078)	(0.080)
Main Inc. Self-Emp.	0.144***	0.155***	0.116	0.107	−0.146**	−0.145**	0.070	0.073	−0.184*	−0.190**
	(0.046)	(0.047)	(0.071)	(0.071)	(0.062)	(0.061)	(0.068)	(0.071)	(0.091)	(0.087)
Main Inc. Remitt.	0.075*	0.089**	0.001	0.007	0.103	0.094	0.062	0.060	−0.241***	−0.251***
	(0.036)	(0.040)	(0.043)	(0.040)	(0.067)	(0.071)	(0.066)	(0.067)	(0.083)	(0.083)
Children (0-6 yrs)	−0.006	−0.002	0.045	0.044	−0.011	−0.020	−0.022	−0.019	−0.006	−0.003
	(0.021)	(0.020)	(0.028)	(0.030)	(0.023)	(0.023)	(0.028)	(0.029)	(0.030)	(0.028)
Children (7-10 yrs)	−0.038	−0.038	0.004	−0.009	0.094**	0.095**	−0.039*	−0.035	−0.021	−0.014
	(0.031)	(0.032)	(0.031)	(0.029)	(0.035)	(0.034)	(0.021)	(0.022)	(0.025)	(0.025)
Children (11-16 yrs)	0.028	0.027	0.023	0.018	−0.028	−0.028	−0.000	0.004	−0.023	−0.021
	(0.032)	(0.032)	(0.032)	(0.032)	(0.024)	(0.023)	(0.025)	(0.025)	(0.021)	(0.019)
No. of Elders	0.047**	0.045**	0.026	0.024	0.008	0.008	−0.023	−0.017	−0.058**	−0.060**
	(0.018)	(0.019)	(0.019)	(0.020)	(0.019)	(0.018)	(0.017)	(0.019)	(0.022)	(0.023)
No. of Working Mem.	0.021	0.019	0.037*	0.035*	−0.003	0.000	−0.004	−0.004	−0.050**	−0.050**
	(0.016)	(0.016)	(0.018)	(0.019)	(0.019)	(0.018)	(0.016)	(0.017)	(0.018)	(0.018)
Total HH Education	−0.003*	−0.003*	−0.000	−0.000	−0.003	−0.003	0.001	0.001	0.005**	0.005**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Social Status	−0.021	−0.028	−0.015	−0.015	−0.031	−0.034	0.010	0.006	0.057**	0.070**
	(0.018)	(0.018)	(0.027)	(0.028)	(0.023)	(0.025)	(0.021)	(0.021)	(0.023)	(0.025)
Farming Shocks		0.000		−0.000		0.001		−0.000		−0.001**
		(0.001)		(0.001)		(0.001)		(0.001)		(0.000)
Environmental Shocks		0.002		0.001		−0.001		−0.000		−0.002**
		(0.001)		(0.001)		(0.000)		(0.000)		(0.001)
Economic Shocks		−0.000		−0.000		−0.001		0.000		0.001
		(0.000)		(0.001)		(0.001)		(0.001)		(0.001)
Crime Shocks		−0.006**		−0.001		−0.003**		0.000		0.009**
		(0.002)		(0.004)		(0.001)		(0.001)		(0.004)
Other Shocks		0.000*		−0.000		0.000		−0.000		−0.000*
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Certainty		−0.001		−0.012		0.020		0.033		−0.040*
		(0.022)		(0.024)		(0.034)		(0.022)		(0.019)
Constant	−0.286	−0.363*	0.035	0.151	0.209	0.089	0.207	0.075	0.835***	1.047***
	(0.219)	(0.209)	(0.259)	(0.267)	(0.264)	(0.280)	(0.220)	(0.247)	(0.261)	(0.269)
Observations	676	664	676	664	676	664	676	664	676	664
Adj. R-squared	0.221	0.224	0.025	0.017	0.041	0.037	0.063	0.055	0.072	0.087

*** p<0.01, ** p<0.05, * p<0.1

Note: Clustered standard errors in parentheses.

Description of Variables

Debt Indices	
Objective Over-Indebtedness Index	It contains the equally weighted average of z-scores of four debt indicators. The procedure of aggregating these specific outcomes is adapted from Kling et al. (2007). It "improves statistical power" and helps "to detect effects that go in the same direction" among indicators (Kling et al., 2007, p.89). The objective over-indebtedness index captures households with a debt service to income ratio greater than 40%, a remaining debt service to income ratio greater than 40%, households, who defaulted on a loan or paid late in the last 12 months and households with more than two loans. The literature has defined (kind of arbitrary) thresholds for the DSR indicator beyond which a household is over-indebted. A household is deemed over-indebted, for example, if its DSR exceeds - depending on the study - 0.3 to 0.5 (Chichaibelu and Waibel, 2017). Hence, we set the over-indebtedness threshold at a DSR of 0.4 following what we deem is best practice among researchers (Georgarakos et al., 2010).
Subjective Over-indebtedness Index	It contains the equally weighted average of z-scores of three debt indicators: the standardized sacrifice index and two assessments on whether the household has too much debt and whether it has difficulties paying them off.

Debt Measures	
Debt Service to Income Ratio	It is the ratio of all annual interest and principal payments on loans divided by all annual income generating activities of the household.
Debt Position	The question if the household has too much debt right now is asked twice in almost identical fashion. For this reason, we combine both questions by deriving two dummy variables, standardize them and calculate their mean. The exact formulation of both questions is the following: "I have too much debt right now" (Disagree fully, disagree strongly, disagree a little, neither agree nor disagree, agree a little, agree strongly, agree fully) and "Which of the following best describes your current debt position?" (I have too little debt; I have about the right amount of debt; I have too much debt right now.). The first dummy equals 1 if the respondent at least agrees a little and the second equals 1 if they feel they have too much debt right now.
Difficulties to Pay Off Debt	Dummy variable derived from the categorical question with answer options 1-"I have no difficulties paying off my debt", 2-"I have some difficulties [...]", and 3-"I have a lot of difficulties [...]", where 1 and 2 are coded to 0 in the dummy and 3 is coded to 1.

Remaining Debt to Income Ratio	The ratio relates a household's actual, yearly debt burden to the average income of 2016 and 2017.
Sacrifice Index	This index is adapted by Schicks (2013), which asks for several sacrifices households may make because they lack money. Like them, we combine these indicators into one "sacrifice index" applying polichoric principal component analysis such that a continuous index is created giving more weight to more serious sacrifices people have to make and transforming the categorical responses into a continuous measure (Kolenikov and Angeles, 2009; Smits and Günther, 2017). In total, we ask respondents about ten possible sacrifices both for a shorter term (i.e., twelve months) and for a longer term (five years). Unlike Schicks (2013), we do not pose questions about the acceptability of sacrifices made but ask only for the frequency of distress events that occurred in the household. We added two questions introduced by Smits and Günther (2017) and two new questions that are more context-specific to the rural setting in North-East Thailand. Depending on the question asked, respondents could answer on a scale from 1-3 (e.g., had to work much more, more, not more) or from 1-5 (e.g., had to buy less food: never, sometimes, regularly, often, almost always, always).
Income Forecasts	
Quantitative Income Forecast	Relative change between expected median income from the probabilistic expectations elicitation and the actual income in 2017.
Qualitative Forecast Error	Difference between expected income in 2016 and actual welfare of the household as evaluated in 2017.
Expectation Measures	
Actual welfare of the household	Answer to "Do you think your household is better off than last year?", from 1-"much worse off" to 5-"much better off".
Certainty	Answer to "How certain are you that this income development will truly become reality?". The scale ranges from 1-"Very uncertain" to 4 "Very certain".
Expected income	Answer to "How do you think your average monthly income will develop in the next twelve months?", from 1-"Decrease a lot" to 5-"Increase a lot".
Probabilistic expectations	Probabilities assessing how individuals assess future outcomes.

Experiment Measures	
Treatment	1=Hard Quiz, 2=Easy Quiz.
Expected Rank	Rank that participant expects to reach after taking the test quiz from 1-“Least questions answered correctly” to 10-“Most questions answered correctly”.
Number of Goods	Amount of goods participant wants to buy.
Overconfidence	Difference between expected and actual rank of participant.
Overborrowing	Dummy variable, that takes the value 1 if participant wants to buy more than earnings including endowment can pay for.
Overspending	Dummy variable, that takes the value 1 if participant wants to buy more than earnings excluding endowment can pay for.

Controls	
Age	Age of respondent in years.
Age Squared	Squared term of age.
Financial Literacy Score	Our index is based on seven questions eliciting financial knowledge, on nine assessments concerning financial behavior, and on three questions regarding financial attitude. The overall index is composed of the sum of the sub indices and ranges between 0 and 22 with higher numbers indicating a higher level of financial literacy.
Financial Risk Taking	Answer to “Attitudes towards risk change in different situations. When thinking about investing and borrowing are you a person who is fully prepared to take risk or do you try and avoid taking risk?”, from 1-“Fully unwilling to take risks” to 7-“Fully willing to take risks”. Part of our risk preference measure.
Main Income Dummies	We include four income dummies that tell us whether the main income comes from farming, off-farm employment, self employment or remittances.
Monthly Inc. 2017	Monthly household income in 2017
Number of children	This variable is split in three age categories for the analysis. Number of children aged 0-6 years; Number of children aged 7-10 years; Number of children aged 11-16 years.

Number of Elders	Number of elder household members, defined as people older than 60 years.
Shock loss indicators	We include information on monetary losses from various shock events for 2016 and 2017. We hereby separate by five shock categories: Farming Shocks, Environmental Shocks, Economic Shocks, Crime Shocks, Other Shocks.
Number of Working Members	Number of working household members.
Risk Preference	Equally weighted average of risk taking and financial risk taking.
Risk Taking	Answer to "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risk?", from 1-"Fully unwilling to take risks" to 7-"Fully willing to take risks". Part of our risk preference measure.
Self-Control	We use the questions introduced by Tangney et al. (2004) and add up the Likert-Scale answers to one score. The scale ranges from 1-"Disagree fully" to 7-"Agree fully". The final score ranges from 0 to 49 where lower numbers indicate a higher level of self-control.
Total HH Education	Sum of years all working household members went to school.

Big Five - Personality Traits	
Agreeableness	A person, who scores high on Agreeableness (Item scale ranges from 1 to 7 for all items) has a forgiving nature, is considerate and kind and not rude to others.
Conscientiousness	A person, who scores high on Conscientiousnes does a thorough job, works efficiently and is not lazy.
Extraversion	A person, who scores high on Extraversion is communicative, talkative, outgoing and not reserved.
Neuroticism	A person, who scores high on Neuroticism worries a lot, gets nervous easily and is not relaxed.
Openness	A person, who scores high on Openness values artistic experiences, is original and has an active imagination.

Additional Controls Experiment	
BMI	Respondent's Body Mass Index as of 2017.
Difficulties in Game	Answer to "Did the respondent have difficulties answering questions?" with 1-"Not at all", 2-"Yes, a little bit", 3-"Yes, very much". Filled in by the enumerator.
Financial Decision Maker	Answer to question "Who is responsible for making day-to-day decisions about money in your household?" where means 1-"Myself", 2-"Myself and someone else" and 3-"Someone else".
Health Status	Health status of the respondent in 2017: 1-"Good", 2-"Can manage", 3-"Sick"
Marital Status	Respondent's marital status: 1-"Unmarried", 2-"Married", 3-"Widow", 4-"Divorced/separated".
Morning	Dummy variable that takes the value 1 if the interview took place in the morning, i.e., before 11am.
Midday	Dummy variable that takes the value 1 if the interview took place around noon, i.e., between 12am and 2pm.
Numeracy	The numeracy index is based on six questions about simple arithmetic problems. It ranges between zero and six. Zero, if the respondent does not give any correct answer and six if the respondent gives only correct answers.
Read Alone	Dummy variable that takes the value 1 if the participant could read the experimental instructions without help. Filled in by the enumerator.
Relation to HH Head	Respondent's relation to the household head: 1-"Head", 2-"Wife/Husband", 3-"Son/Daughter", 4-"Son/Daughter in law", 5-"Father/Mother", 8-"Grandchild", 9-"Nephew/Niece", 11-"Other relatives".
Sex	Sex of respondent: 1-"Male", 2-"Female".
Years of Schooling	Years respondent went to school.

Experimental Material

Material B.1: Instructions Experiment

Experiment Script

Read out:
We want to play a market game with you. In this game you can earn money and buy goods. The kind of goods you can buy are placed right next to you. Each piece has a value of 20 THB, but we offer them to you for a discounted price of 10 THB. You don't have to buy one kind of product, but can buy different kinds (for example 2 chocolate bars and 1 bag of chips). If you don't like to buy anything you can keep the money you earn.

To earn money, you have to play a quiz which consists of 15 questions. 10 persons from another village, which is similar to your village, took the same quiz before. The amount of money you earn is dependent on how many questions you answered right in comparison to these villagers. In this picture, the person who has given the most correct answers is ranked 10, the person who has given the second most correct answers is ranked 9, the person who has given the third most correct answers is ranked 8, and so on. In the picture you can also see how much money you will earn dependent on your ranking. For example, if you are ranked 7 you will earn 20 THB. Please take your time to understand how you can earn money in this game.

[Show picture of ranks, payoffs and people]

I want you to ask some test question to check whether the procedure of the ranking is clear to you. If not, I will explain it again.

Test Question 1: What does it mean to be ranked 6? [Open answer; enumerator please continue if you think the respondent gave a correct answer]

Test Question 2: How much money do you earn if you are ranked 6? [Answer: 10 THB]

Test Question 3: How many goods you can buy for 10 THB? [Answer: 1]

The money you earn, will be put on your game account which already has 40 THB in it. As you can see from the picture, you can earn up to additional 40 THB. The quiz for which you will receive money will be played in the second round.

In the first round, you will get 7 test questions, which are very similar to the questions you will get in the second round. But again, you can ONLY earn money in the second round.

After you answered this first set of questions, you have to decide how many goods you want to buy. The 40 THB that are already in your account are given you as a credit that you can use to buy the goods. With the money you earn in the second round in the quiz you will pay back your credit. If you spend more money than you earned we will keep the money from your account and give you the goods you have bought. If you earned more than you bought, you pay back your credit and can keep the rest of the money and goods.

If you don't have any further questions we start with the first round. [FAQ]

[Hand respondent the first quiz (green paper). If respondent cannot read, assist in all tasks]

Please read through the questions on the green sheet of paper and try to answer as many questions as you can. You have 5 minutes to answer the questions. I will tell you when the 5 minutes are over. After you have finished the quiz, please have a look on the white piece of paper and answer these questions and make your buying decision. When you have finished the first round, I will collect the white piece of paper. You can keep the green paper with the test quiz. It is only for you, so that you know what kind of questions to expect in the quiz of the second round.

[Set your alarm clock to 5 minutes and tell the respondent to start]

The 5 minutes are over. Please, stop answering the test quiz and make your decisions on the white sheet of paper. Give me a sign when you have made your decisions, then I will collect the white paper.

[During the time the respondent takes the second quiz, evaluate the white sheet of paper and enter the numbers on the tablet]

Now, in the second round, you play the quiz that decides how much money you earn. You have 10 minutes to answer the questions. Afterwards, I will collect the quiz, calculate your earnings and hand you the goods and money.

[Hand the second quiz, set your alarm clock to 10 minutes and tell respondent to start]

The time is up. Please, hand me the second quiz. Before we conclude, I have some final questions for you.

Question 1: After taking the quiz, when 1 is the villager who gave the least correct answers and 10 is the villager who gave the most correct answers, where do you see yourself in this picture?

Question 2 [Only ask if expected earning of respondent was smaller than 40 THB]: Would you have buy more goods, if you thought your earnings would be higher?

Question 3 [Only ask if expected earning of respondent was more than 0 THB]: Would you have buy less goods, if you thought your earnings would be lower?

Thank you very much for your participation, we hope you enjoyed the game. I will now calculate your earnings and inform my STL which will bring you your payment and goods.

[Calculate rank, earnings and cash/goods payoff. Wait for STL to hand the money/goods]

{In the very unlikely case, that more goods were wanted than earnings are generated:}

I calculated your earnings and you cannot afford all the goods you want to buy. You want to buy […] goods but can only afford […] goods. Please, choose which goods you want to keep.

[Please note which goods were finally kept]

Material B.2: Guideline for Interviewers to Answer Questions from Participants

Frequently Asked Questions

Respondent: “What if I don’t want to buy anything?”
You: “You don’t have to buy anything, you can also keep the money.”

Respondent: “Can I spend all my money on buying products?”
You: “Yes you can, but if you do not earn enough money to pay all the products you wanted to buy, you will only get the part of the products you can afford.”

Respondent: “Can I change my buying decision after I took the second quiz?”
You: “No, your decision is fixed. Only in the case where you wanted to buy more products than you have money available, you can decide on which products to keep”

Respondent: “What happens if I spend more money on products than I earn?”
You: “Then we will take the money from the 40 THB that are already on your virtual bank account for the game. If even this is not enough, you only get as many products as you have money. We will NOT take any out of your pocket and we will NOT take money from the 50 THB you get for the questionnaire. We only count the money you get in the game.”

Respondent: “Does being on rank 7 means that I need to get 7 questions correct?”
You: “No! It means that three persons have answered more questions correctly than you and six persons have answered less questions correctly than you. The rank is always dependent on how many questions you have correct in comparison to the other 10 villagers. In this case you are as good as the villager who was ranked 7.”

Respondent: “Does it make a difference which questions I answer correctly?”
You: “No, all questions count the same.”

Respondent: “Do the products really cost 20 THB per piece?”
You: “Yes, if you buy them as presented here, they cost 20 THB.”

[Respondent: “What if I don’t know the answer to a question at all?”
You: “Just take a guess. You don’t receive some sort of minus points for wrong answers.”]

Respondent: “What if I cannot finish the quiz in time?”
You: “That is no problem. Please, try to answer as many questions as you can in the given time frame. There will be no minus points for unanswered questions.”

Respondent: “Who are the other 10 persons who have answered the quiz before?”
You: “They are just some randomly selected persons from another village, that is similar to your village.”

Material B.3: Quiz-Hard Treatment

Test Quiz

1. What is the biggest city in Canada by population?

- [ ] Ottawa
- [ ] Vancouver
- [ ] Montreal
- [ ] Toronto

2. What is the most common blood type in the world?

- [ ] O positive
- [ ] AB positive
- [ ] B positive
- [ ] A positive

3. Which animal cannot fly?

- [ ] Chicken
- [ ] Duck
- [ ] Penguin
- [ ] Squirrel

4. Which fruit contains the most amount of Vitamin C per 100g?

- [ ] Pineapple
- [ ] Mango
- [ ] Banana
- [ ] Passion Fruit

5. How many days does Mercury need to orbit the sun?

- [ ] 144
- [ ] 94
- [ ] 88
- [ ] 126

6. Which animal is not part of the Zodiac?

- [ ] Leo
- [ ] Pisces
- [ ] Dragon
- [ ] Scorpio

7. Which are the Japanese cities that were hit by atomic bombs of the U.S. army during WWII?

- [ ] Hokkaido and Kyushu
- [ ] Shikoku and Hashima
- [ ] Okinawa and Okinoshima
- [ ] Hiroshima and Nagasaki

Quiz

1. What is the national animal of China?

- ☐ Tiger
- ☐ Eagle
- ☐ Lion
- ☐ Panda

2. If Thai currency is THB, what is the currency of Germany?

- ☐ Euro
- ☐ US. Dollar
- ☐ Pound
- ☐ Deutsche Mark

3. How many provinces does Japan have currently?

- ☐ 47 provinces
- ☐ 48 provinces
- ☐ 49 provinces
- ☐ 50 provinces

4. Which is the heaviest insect in the world?

- ☐ Grasshopper
- ☐ Spider
- ☐ Beetle
- ☐ Centipede

5. Which of these countries does NOT border Germany?

- ☐ Austria
- ☐ France
- ☐ Sweden
- ☐ Poland

6. Which is the most drank beverage in the world?

- ☐ Coca Cola
- ☐ Beer
- ☐ Tea
- ☐ Coffee

7. Which country is the origin of pizza?

- ☐ Italy
- ☐ France
- ☐ Spain
- ☐ Portugal

8. Which of these four is the biggest organ of the human body?

- ☐ Lungs
- ☐ Heart
- ☐ Liver
- ☐ Brain

9. Who is the president of Indonesia?

- [ ] Susilo Bambang Yudhoyono
- [ ] Joko Widodo
- [ ] Abdurrahman Wahid
- [ ] Megawati Sukarnoputri

10. What color is traditionally not associated with Christmas Day?

- [ ] Red
- [ ] Gold
- [ ] Green
- [ ] Pink

11. Of which colors is the flag of Germany composed of?

- [ ] Black, Blue and Gold
- [ ] Black, Red and White
- [ ] Black, Red and Gold
- [ ] Black, Red and Blue

12. Which fruit is blue?

- [ ] Blueberry
- [ ] Pear
- [ ] Apple
- [ ] Kiwi

13. What color will you get if you mix blue, red and yellow?

- [ ] Grey
- [ ] Dark green
- [ ] Black
- [ ] Brown

14. How many seasons are there in Germany? And which ones?

- [ ] 4 seasons including spring, summer, autumn and winter.
- [ ] 3 seasons including rainy, winter and spring
- [ ] 2 seasons including rainy and winter
- [ ] 2 seasons including summer and winter

15. Who is the God of Islam?

- [ ] Nabi Muhammad
- [ ] Yahweh
- [ ] Allah
- [ ] Moses

QID: ____________

Material B.4: Quiz-Easy Treatment

Test Quiz

1. What is the biggest city in Thailand?

- ☐ Ubon Ratchathani
- ☐ Chiang Mai
- ☐ Bangkok
- ☐ Surat Thani

2. What color will you get if you mix blue and yellow?

- ☐ Grey
- ☐ Green
- ☐ White
- ☐ Pink

3. Which animal cannot jump?

- ☐ Asian Buffalo
- ☐ Dog
- ☐ Elephant
- ☐ Tiger

4. Which fruit is prohibited in public transport around South-East Asia?

- ☐ Banana
- ☐ Papaya
- ☐ Durian
- ☐ Apple

5. Which of these countries does NOT border Thailand?

- ☐ Vietnam
- ☐ Laos
- ☐ Cambodia
- ☐ Myanmar

6. Which animal is not part of the Chinese Zodiac?

- ☐ Monkey
- ☐ Horse
- ☐ Cat
- ☐ Dragon

7. What is the most common eye color in the world?

- ☐ Blue
- ☐ Brown
- ☐ Green
- ☐ Hazel

Quiz

★

1. What is the national animal of Thailand?

- ☐ Elephant
- ☐ Eagle
- ☐ Lion
- ☐ Naga (Thai Dragon)

2. If Thai currency is THB, what is the currency of USA?

- ☐ Euro
- ☐ US Dollar
- ☐ Pound
- ☐ Franc

3. How many provinces does Thailand have currently?

- ☐ 76 provinces
- ☐ 77 provinces
- ☐ 78 provinces
- ☐ 79 provinces

4. Which is the biggest animal in the world?

- ☐ Blue Shark
- ☐ Killer Whale
- ☐ Blue Whale
- ☐ Elephant

5. How many months have 31 days?

- ☐ 6
- ☐ 5
- ☐ 4
- ☐ 7

6. How many seasons are there in Thailand? And which ones?

- ☐ 3 seasons including summer, rainy and winter
- ☐ 2 seasons including summer and rainy
- ☐ 2 seasons including rainy and winter
- ☐ 4 seasons including summer, rainy, autumn and winter

7. Which of these do you need to make traditional Som Tam Thai?

- ☐ Coconut Milk
- ☐ Tomatoes
- ☐ Oyster Sauce
- ☐ Chili Paste

8. Which is the biggest sense organ of the human body?

- ☐ Skin
- ☐ Eyes
- ☐ Mouth
- ☐ Ears

9. Who is currently the president of the United States of America?

- [ ] Donald Trump
- [ ] Barack Obama
- [ ] Angela Merkel
- [ ] Bill Clinton

10. What is the color of the day on Wednesday?

- [ ] Red
- [ ] Pink
- [ ] Green
- [ ] Light blue

11. Of which colors is the flag of Thailand composed of?

- [ ] Green, White and Red
- [ ] Green, White and Blue
- [ ] Blue, White and Red
- [ ] Blue, Red and Yellow

12. Which fruit does not have thorns?

- [ ] Durian
- [ ] Jackfruit
- [ ] Rambutan
- [ ] Salak

13. Which reign of Thailand abolished slavery?

- [ ] 4th Reign
- [ ] 5th Reign
- [ ] 6th Reign
- [ ] 7th Reign

14. Which country has the highest total rice consumption?

- [ ] Thailan
- [ ] Germany
- [ ] Cambodia
- [ ] China

15. Who is the son of god of Christianity?

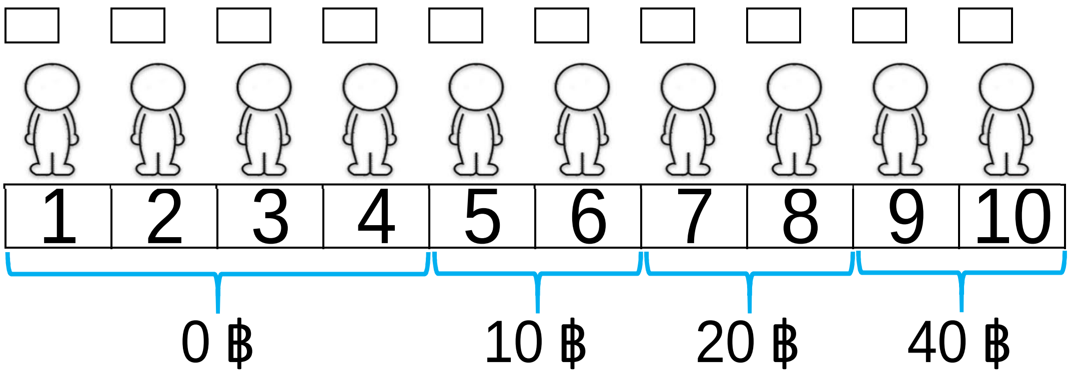
- [ ] Nabi Muhammad
- [ ] Jesus
- [ ] Guanyin
- [ ] Vishu

QID: ______

Material B.5: Decision Sheet

Before you take the second quiz where you can earn money, we have some questions for you and you have to decide which goods and how many you want to buy.

Question 1: As mentioned before, 10 persons from another village took the same quiz as you will have to take now. After taking the test quiz and knowing the second quiz will be similar: When the villager on the left side of this picture is the one who gave the least correct answers and the villager on the right side of this picture is the one who gave the most correct answers, where do you see yourself in this picture? Please cross the respective box.



Question 2: We told you that the money you will earn in the second quiz depends on how you actually are ranked in this picture above. For example if you are ranked 7, which means that 3 villagers gave more correct answers than you and 6 villagers gave less correct answers than you, you will get 20 THB. What do you think, how much money will you earn?

☐ ฿

Question 3: Now, you have to decide how many and which kind of goods you want. You have to think about how much you will possibly earn including your credit and how much you can spend on the goods. You don't have to buy anything at all. But if you want to, remember each piece has a discounted price of 10 THB and you can buy as many different kinds as you want.

> Example: You think you are ranked 7, so you earn 40 THB, and you want to buy one pack of coffee and one bag of chips. That will cost you 20 THB. After you have answered the second quiz, we will calculate your earnings.
>
> If you have earned 40 THB for example, we will give you the goods you wanted to buy and additionally 20 THB.
> All in all, you have two goods then and 60 THB.
>
> If you have earned 10 THB for example, we will give you the goods you wanted to buy and we will deduct 10 THB from the 40 THB credit we gave you. All in all, you have two goods then and 30 THB.

Please indicate here how many of each good you want. If you do not want to buy some kind of good put 0 there:

Coffee		Mango	
Chips		Detergent	

QID:

Appendix C - Appendix for Chapter 4

Figure C.1: Overview of Survey Region

Note: The six TVSEP provinces are highlighted in red. The green dots represent internal migrants from the survey rural regions.
Source: Hardeweg et al. (2013), based on ESRI World Map.

Table C.1: Overview of Survey Questions

Do you see yourself as someone who...	Big Five Factor
...values artistic, aesthetic experiences? ...is original, comes up with new ideas? ...has an active imagination?	Openness
...works thoroughly? ...does tasks efficiently? ...tends to be lazy?	Conscientiousness
...is talkative? ...is outgoing, sociable? ...is reserved?	Extraversion
...has a forgiving nature? ...is considerate and kind to almost everyone? ...is sometimes a bit rude to others?	Agreeableness
...worries a lot? ...gets nervous easily? ...is relaxed, handles stress well?	Neuroticism

Note: Questions from the The TVSEP survey questionnaire. Same questions were administered for wave 7 and 8.

Figure C.2: Item Scale TVSEP questionnaire wave 7 and wave 8

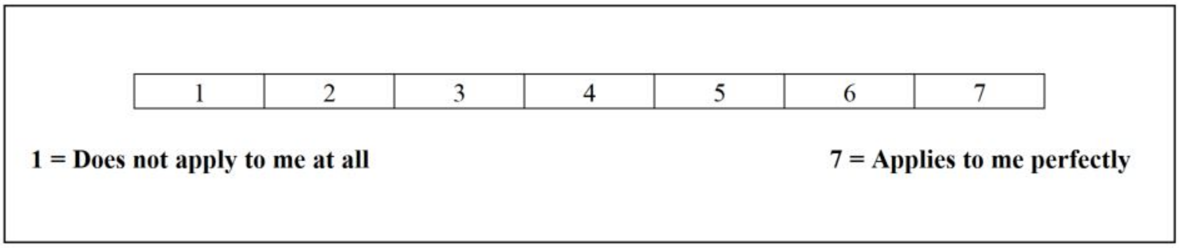


Table C.2: Cronbach's Alpha

Personality Trait	Cronbach's alpha	No. of items
Openness	0.59	3
Conscientiousness	0.48	3
Extraversion	0.29	3
Agreeableness	0.43	3
Neuroticism	0.48	3
Average	0.45	

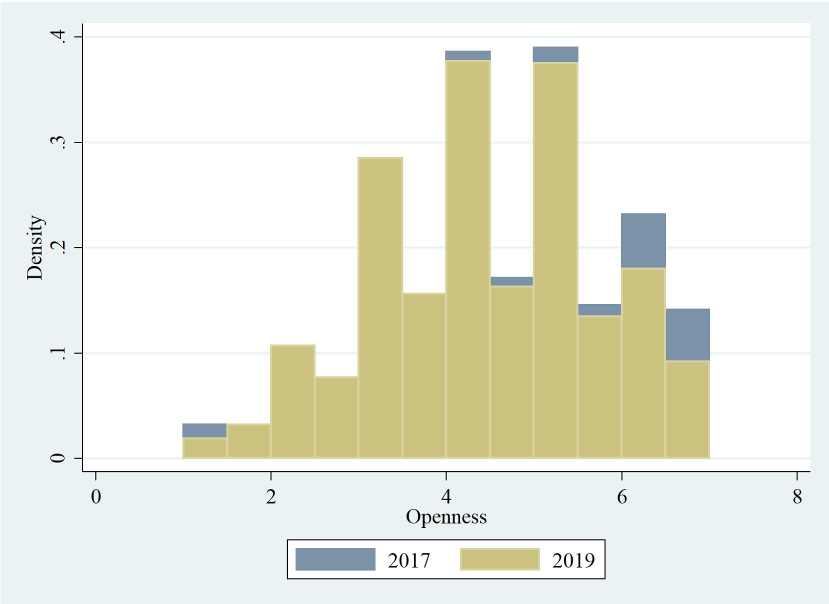
Note: Own calculations with TVSEP data from wave 7.

Table C.3: Test-Retest Correlation

Openness	0.21
Conscientiousness	0.25
Extraversion	0.24
Agreeableness	0.25
Neuroticism	0.23
Average	0.24

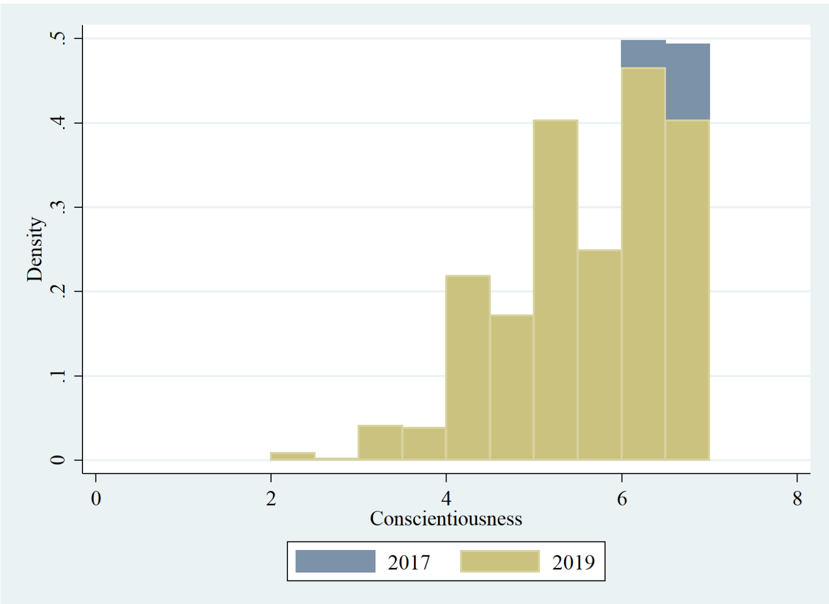
Note: Own calculations with TVSEP data wave 7 and 8. Table shows the test retest correlation between wave 7 and wave 8. N = 933.

Figure C.3: Openness



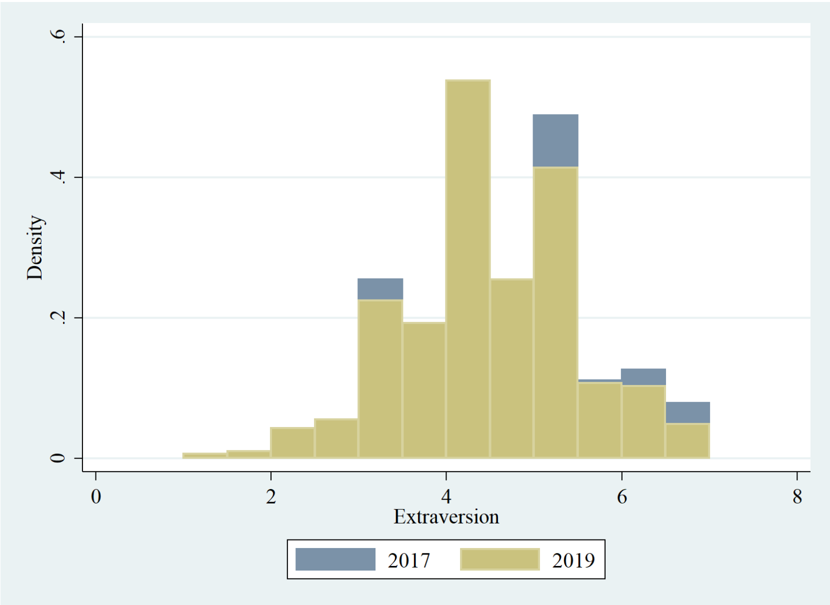
Note: Own illustration with TVSEP wave 7 and wave 8 data.

Figure C.4: Conscientiousness



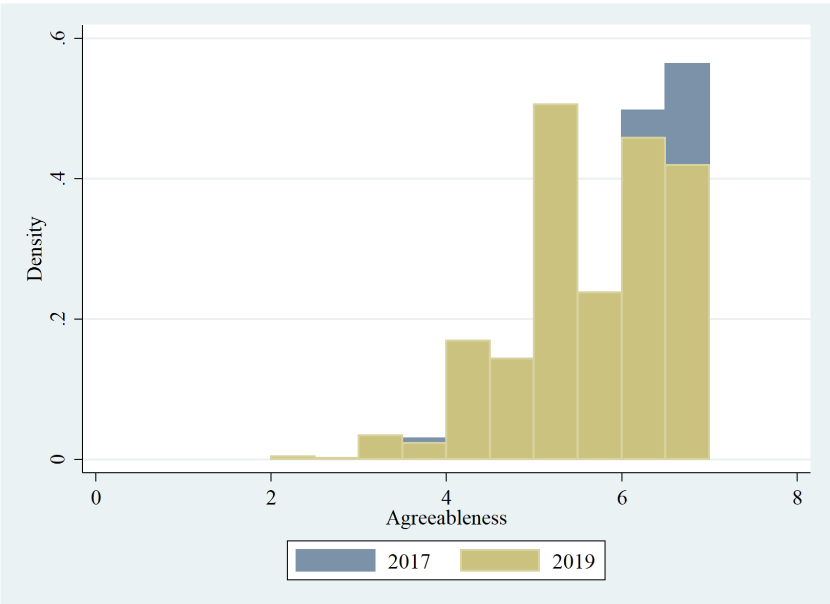
Note: Own illustration with TVSEP wave 7 and wave 8 data.

Figure C.5: Extraversion



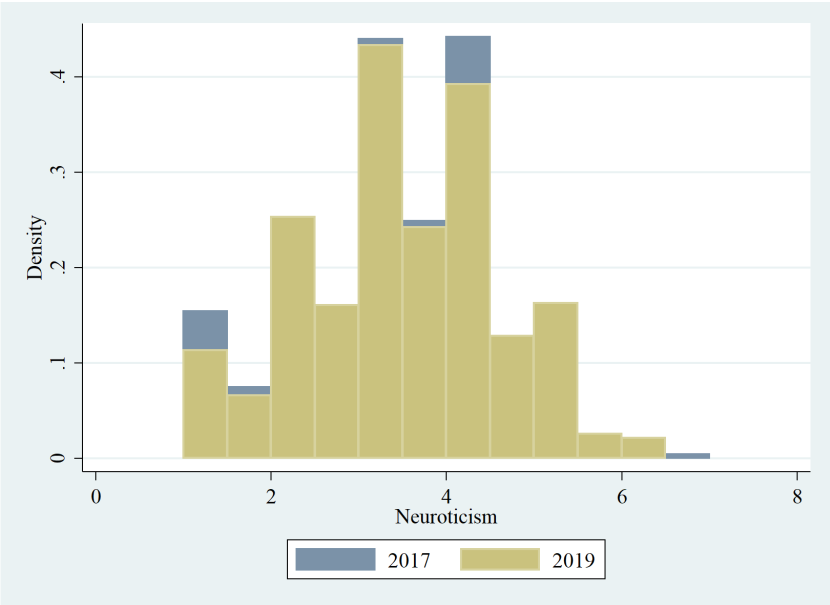
Note: Own illustration with TVSEP wave 7 and wave 8 data.

Figure C.6: Agreeableness



Note: Own illustration with TVSEP wave 7 and wave 8 data.

Figure C.7: Neuroticism



Note: Own illustration with TVSEP wave 7 and wave 8 data.

Table C.4: Factor Loadings according to PCA - Acquiescence Bias corrected

BFI-Items	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Artistic	0.2367	0.2395	0.2417	0.1869	**0.3057**
New Ideas	0.2466	0.0717	**0.3626**	**0.3573**	0.0858
Active Imagination	0.2292	0.1214	**0.3202**	**0.4466**	0.1836
Works thoroughly	**0.2921**	0.2388	0.0027	0.0443	**0.4511**
Efficient	**0.3564**	0.0002	0.0090	0.0724	**0.4057**
Lazy (reversed)	**0.3249**	0.1886	0.2479	0.2162	0.2327
Talkative	0.1796	0.0274	**0.3103**	**0.3223**	0.0243
Sociable	0.2832	0.0112	0.1953	0.1568	**0.3927**
Reserved (reversed)	0.1454	0.2201	**0.4653**	**0.4757**	0.1088
Forgiving	0.2547	0.2096	0.2388	0.2883	0.2105
Kind	**0.3497**	0.1592	0.2045	0.2323	0.1620
Rude (reversed)	0.2848	0.1768	**0.3391**	0.1392	**0.4070**
Worries	0.1368	**0.5655**	0.0617	0.1948	0.0206
Nervous	0.1975	**0.4931**	0.0774	0.1848	0.1789
Relaxed (reversed)	0.2304	**0.3427**	0.2672	0.0257	0.0887

Note: Own calculations with TVSEP data from wave 7. Factor loadings greater than or equal to 0.30 are shown in bold.

Table C.5: Cronbach's Alpha - Acquiescence Bias corrected

Personality Trait	Cronbach's alpha	No. of items
Openness	0.49	3
Conscientiousness	0.55	3
Extraversion	0.36	3
Agreeableness	0.56	3
Neuroticism	0.59	3
Average	0.51	

Note: Own calculations with TVSEP data from wave 7.