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Coping with Covid-19 in rural India: Did financial strategies help to maintain wellbeing?

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Abstract

This thesis examines the direct impact of the Covid-19 pandemic on psychological wellbeing and explores the mediating role of financial coping strategies for this association. Using four waves of representative panel data, collected in 2018, 2020 and 2021 from 2 997 households living across 294 villages in the state of Odisha, India, we find that stress increased whilst depression decreased, resulting in psychological wellbeing being unchanged during the pandemic. This may be because livelihoods were not affected immediately and accumulated stress tends to result in depression. Using only the last survey wave, we find that adopting financial coping strategies was associated with lower stress as the pandemic intensified, whilst receiving instalments from the state government was associated with higher depression during the pandemic. These findings highlight the importance of financial coping strategies as complements to financial state government support. However, as the choice of coping strategy is highly endogenous, these findings should be interpreted with caution.

Keywords: Psychological Wellbeing, Financial Coping, Unconditional Cash Transfer, Covid-19, Panel Data, Propensity Score Matching, Low-and Middle Income Countries

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All errors are our own.

Table of Contents

1. Introduction

The Covid-19 pandemic has adversely affected both lives and livelihoods, especially in low- and middle-income countries (LMIC). India is one of those countries and had one of the most restrictive (Bhalotia et al., 2020) and largest (Karaban & Mozumder, 2020; University of Oxford, 2022) lockdowns in the world, and suffered a larger economic contraction (IMF, 2021a) and higher unemployment (ILO, 2022) than comparable countries. As highlighted in several studies, India's economy has been severely impacted by the lockdown measures (Ray et al., 2020). Yet, the additional budgetary allocation to various social safety measures were lower than in comparable countries (Gentilini et al., 2020; IMF, 2021b), and the scope for containment policy responses and transfers were limited (Feuerbacher et al., 2021).

The adverse impact on living standards of the pandemic translated into lower wellbeing. It is well-documented that the pandemic decreased wellbeing (e.g., Bao et al., 2020; Brodeur et al., 2021a; Bueno-Notivol et al., 2021; Gao et al., 2020; Goularte et al., 2020; Gupta et al., 2021b; Rajkumar, 2020; Trudeau et al., 2020) and affected already vulnerable demographic groups and countries more than other groups and countries (Banks & Xu, 2020; Brodeur et al., 2021b; Gomez et al., 2020; Proto & Quintana-Domeque, 2021). Such findings resonate with more recent literature on vulnerability to climate change and other natural disasters (Bennett et al., 2016; Fischer & Chhatre, 2016; McDowell & Hess, 2012; Sapkota et al., 2016).

Despite the dominance of self-sufficient agriculture and the low exposure to the virus, the livelihood conditions of farmers in India were deteriorating as production, sales, prices, employment and incomes were negatively affected (Bundervoet et al., 2021; Harris et al., 2020). Farmers were especially vulnerable due to their already high levels of poverty, declining incomes and high dependence on migratory wage labour (Gupta et al., 2021a; Mukhopadhyay, 2020; Ranscombe, 2020). Moreover, it is worth noting that the first complete nationwide lockdown coincided with the peak of harvesting season which, in addition to farmers limited intra-temporal substitution of farm labour, imposed significant losses to the farmers (Cariappa et al., 2021; Feuerbacher, et al., 2021; Jaacks et al., 2021; Kesar et al., 2021; Kumar et al., 2020; Lowe et al., 2021), even for the ones that were more well-off (Gentilini et al., 2020; Gupta et al., 2021b). We expect these adverse impacts on farmers' livelihoods to affect their wellbeing, as in line with evidence from rural settings in other LMICs (Cevher et al., 2021; Ragasa et al., 2021; Shafi et al., 2021).

To cope with the impacts on wellbeing, agricultural households adopted different strategies. Since the financial support from the government was neither particularly efficient, sufficient (Ceballos et al., 2020; Goyal et al., 2021) nor something that many farmers were aware of or used (Ceballos et al., 2020), they had to find other ways to smooth their income. Evidence from rural India documented coping strategies such as asset diversification, migration, specialisation into low-risk activities, dissaving, insurance, borrowing, selling assets and receiving transfers from friends and family for climate aberrations (Patnaik & Narayanan, 2015). These mechanisms are in line with those adopted in other crises and contexts (e.g., Cinner et al., 2018; Ellis, 2000; Forsyth & Evans, 2013; Friedline et al., 2021; Hossain et al., 2020a; Mortimore & Adams, 2001; Rahut et al., 2021; Yilma et al., 2014). In the case of the pandemic, however, many existing strategies to mitigate risk were limited as a result of restrictions on mobility, trade and exchange, and opportunities for diversification (Gupta et al., 2021b). Hence, the importance of financial support from governments might be more accentuated for this crisis.

Against this background, there is a need to obtain further evidence on how the pandemic affected psychological wellbeing (PWB) for Indian rice farmers and how they used different financial strategies to cope with this shock. Therefore, we investigate three research questions: i) whether the pandemic affected the psychological wellbeing of Indian farmers, ii) whether financial coping strategies were associated with higher psychological wellbeing as the intensity of the pandemic increased, and iii) whether financial state government support was associated with higher psychological wellbeing during the pandemic.

We contribute to the literature in the following ways. First, existing studies focusing on the impact on wellbeing of the pandemic mostly used cross-sectional data and were conducted only when strict social distancing measures were in place (e.g., Allen et al., 2020; Cénat et al., 2021; Goularte et al., 2020; Grover et al., 2020; Raju et al., 2021; Shamoon et al., 2020), sometimes using retrospective questions about the respondent's wellbeing (e.g., Boateng et al., 2021; Majumdar et al., 2020) or different samples pre- and post-Covid-19 (e.g., Anglim & Horwood, 2021). We are, however, able to use high-quality panel data with many observations both before and after the pandemic to assess the impact on PWB of rural households in a LMIC, in which PWB has not been properly assessed before. This is beneficial as it allows us to control for fixed effects (Di Maio & Fiala, 2020; Ferrer-i-Carbonell & Frijters, 2004; Frey & Stutzer, 2002; Himelein, 2016; Luttmer 2005) and assess the impact over time (e.g. Bundervoet et al., 2021; Joshanloo, 2019). Second, the current literature either focus on coping strategies adopted during the pandemic (e.g., Bundervoet et al, 2021; Gentilini et al., 2020; Hammond et al., 2022; Hill & Narayan, 2020) or the impact on wellbeing of the pandemic (Allen et al., 2020; Bau et., 2021; Boateng et al., 2021; Durizzo et al., 2022; Hamadani et al., 2020). We reconcile these streams of research by examining the mediating role of financial coping strategies on PWB during the pandemic. This allows us to better understand their importance for maintaining wellbeing during crises.

The research questions are assessed by using a large survey data set following Indian rice farmer households in the state of Odisha between 2018 and 2021 in four waves. We use all four waves for assessing the first research question and the last wave for assessing the remaining two research questions. Using this data, we find that the pandemic had an insignificant impact on PWB as depression decreased whilst stress increased. We also find that adopting a financial coping strategy in times of higher intensity of the pandemic was not significantly associated with PWB, but with lower stress ($p < .01$), and that receiving the KALIA instalments had a negative association with PWB ($p < .01$), partly driven by higher depression ($p < .01$).

The thesis is structured as follows: In section 2, we present the existing literature on wellbeing and the pandemic, coping strategies and financial state government support in LMIC. Section 3 provides an overview of our hypotheses, theory, data, the sociodemographic characteristics of our sample, as well as the variables and models used for our analysis. The results are presented in section 4 along with robustness checks, and section 5 concludes this thesis by discussing possible explanations for the findings, policy implications and limitations of this thesis and the methods used.

2. Literature review

2.1. Wellbeing

Ryan and Deci (2001) suggest that the research within the field of wellbeing could be divided into two traditions: the hedonic tradition and the eudaimonic tradition. The former tradition grew from the philosophy of Aristippus, who believed that the goal of life was to experience maximum amount of pleasure and happiness. Within this tradition, most research has estimated and measured wellbeing through subjective wellbeing (SWB), which is an individual's own evaluation of his or her overall quality of life (Diener, 2000; Keyes, 2006) and has been introduced as a proxy for individual utility (Dolan et al., 2008; Frey & Stutzer, 2002). The latter tradition, on the other hand, grew from the philosophy of Aristotle, who argued that hedonic happiness makes humans slavish followers of desires, and that true happiness instead lies in doing what is meaningful for oneself. Here, focus lies on personal growth, self-realisation and living up to one's full potential, and wellbeing is thus usually estimated through psychological wellbeing (PWB) (Abbott et al., 2006; Ryan & Deci, 2001).

Even though PWB and SWB are closely related (Burns et al., 2011; Diener & Seligman, 2004; Dolan et al., 2008), and correlate with other measures of wellbeing (Clark & Senik, 2011; Diener, 2000; Kahneman, 1999; Keyes, 2006; Stiglitz et al., 2009; Urry et al., 2004; Van Praag & Ferrer-i-Carbonell, 2010), suggestions have been made that PWB and SWB are in fact distinct measures (Ryff & Keyes, 1995). Some researchers also argue that PWB constitutes a more robust and consistent predictor of wellbeing in the long-run, as PWB is not as sensitive to variable feelings (Joshanloo, 2019), sociodemographic factors or personality (Keyes et al., 2002), like SWB is, leading to a greater longitudinal stability for PWB (Joshanloo, 2019). Moreover, PWB is also an important element of mental health (Salsman et al., 2014), and has been shown to be negatively associated with depression (Burns et al., 2011; Edmondson et al., 2015; Qingbo et al., 2009; Wood & Joseph, 2010) and stress (Siddique & D'Arcy, 1984), both being highly interrelated (Hammen, 2005; Siddique & D'Arcy, 1984) and important to dimensions of PWB (Erfani & Abedin, 2018).

In developing countries, PWB tends to be low and poverty tends to be high (Kremer et al., 2019; Sawyer et al., 2010). Poverty is consistently suggested to be broadly related to poor PWB, unhappiness, depression and anxiety (Haushofer & Fher, 2014; Kremer et al., 2019), which have shown to lead to lower productivity among farmers (Pailler & Tasaneva, 2018) and, in turn, thus lead to a vicious circle of poverty and low wellbeing (Hill & Narayan, 2020). Of all mental health issues, depression is one of the most important causes of morbidity and disability in developing countries (Patel et al., 2001).

India is not an exception with regards to the low PWB. Previous studies have estimated the prevalence of depression (PHQ-9 score ≥ 10) among the rural population in India to be 11-14.6 percent, depending on socioeconomic factors (Ramesh, 2018; Shidhaye et al., 2016). In a drought affected region, the prevalence was as high as 67 percent (Viswanathan & Kumarasamy, 2019) and the prevalence of mental disorders in general has been found to be higher in poorer states (Pailler & Tsaneva, 2018; Patel et al., 2012).

One of the most vulnerable groups in India in terms of PWB is farmers. Many studies also highlight the already high prevalence of mental health issues in this group (e.g., Ahmed & Jadhav, 2019; Behere & Bhise, 2009; Hossain et al., 2020c; Mukhopadhyay, 2020; Siddique & D'Arcy, 1984). Indian farmers typically experience high levels of stress due to financial stressors (Ramesh & Madhavi, 2009) and have amongst the highest suicide rates in India (Bhise & Behere, 2016; Hossain et al., 2020b; Merriott, 2016), partly due to stress (Kennedy & King, 2014), but also lack of government support, environmental problems, issues related to crops, family problems and economic concerns related to debt and prices, lack of agricultural investments and credit constraints (Behere & Bhise, 2009; Behere & Bhise, 2016; Dongre & Deshmukh, 2012; Kennedy & King, 2014; Merriott, 2016; Yazd et al., 2019). This suggests that the farmers might be more vulnerable to shocks, such as Covid-19.

2.2. The impact of Covid-19

Thus far, the experience of the pandemic on mental health suggests that it has been negatively and quickly affected worldwide (Banks & Xu, 2020; Bao et al., 2020; Proto & Quintana-Domeque, 2021). The spread of the virus has generated fear, anxiety, economic problems, and disturbances in daily life which might have translated into adverse mental health outcomes, including post-traumatic stress, depression, sleep disorders, and reduced overall wellbeing (e.g., Brodeur et al, 2021b; Goularte et al., 2020; Rajkumar, 2020; Verma & Mishra, 2020). Moreover, numerous studies suggest that mental health effects have been growing since the beginning of the pandemic (e.g., Gao et al., 2020; Perez-Arce et al., 2021; Trudeau et al., 2020) and that the prevalence of depression, stress, post-traumatic stress and sleep disorders has been substantially increased, both in developed and developing countries (Bueno-Notivol et al., 2021; Rajkumar, 2020; Xiao et al., 2020).

The impact on wellbeing has, however, been shown to differ across countries and demographic groups. Covid-related worries and depression levels were found to be higher in LMIC than in high-income countries at the onset of the Covid-19 outbreak (Gomez et al., 2020). Several literature reviews on studies conducted in LMIC demonstrate a strong negative impact on mental health of the pandemic (e.g., Bau et al., 2021; Boateng et al., 2021; Bundervoet et al., 2021; Hamadani et al., 2020; Kumar & Kumar, 2020; Rajkumar, 2020; Torales et al., 2020). Meta-analysis, however, highlights the heterogeneity in impact across studies and contexts (Prati & Mancini, 2021). A more detailed study found greater negative mental health effects for wealthier households, since these are more reliant on enterprise and salaried income (Mahmud & Riley, 2021). Other studies found age, occupation, existing mental health illnesses (Das, 2011; Roy et al., 2021) and gender (Afridi et al., 2020) to influence the impact on wellbeing. In addition, more intense experiences of fear and uncertainty have been highlighted amongst the already poor (Gupta et al., 2021b), and larger increases in domestic violence (Ravindran & Shah, 2020), sadness, depression and hopelessness (Bau et al., 2021) in areas with the strictest lockdown rules have been observed.

Other factors, such as economic concerns, job loss (e.g., Akay 2022) and financial stressors (e.g., Kremer et al., 2019; Ramesh & Madhavi, 2009) have been suggested to impact mental health and demonstrated in LMIC during the pandemic. Large studies in LMIC found steep declines in income and employment (Khamis et al., 2021) as well as in remittances (Gupta et al., 2021a), leading to food insecurity (Bundervoet et al., 2021) and declines in non-food consumption (Egger et al., 2021). Interestingly, the effects on income and employment affected the richer population as well (e.g., Egger et al., 2021), implying that even the well-off could not "buy" their way out of the crisis, which is in line with literature from other contexts (Shi et al., 2020; Wenning et al., 2020).

A group that was specifically and negatively affected by the pandemic, in multiple ways, are farmers. Bundervoet et al. (2021) argues that whilst this group had a low exposure to the virus (given the population density in rural areas) and low labour impact (given the engagement in own-account agriculture) in the short run, farm incomes might be adversely affected as purchasing power and demand decrease in the longer run. This prediction is in line with Harris et al. (2020), who found that a clear majority of farmers in India either faced disruptions of production and sales, that prices were too low for continuing production, and that they could not find buyers. Whilst no high-quality studies on the impact of the pandemic on farmers' wellbeing have been conducted in India, evidence from other LMIC in rural settings found vulnerable farmer households to report higher increases in stress (Ragasa et al., 2021; Shafi et al., 2021) and higher anxiety levels (Cevher et al., 2021) during the pandemic compared to other groups.

2.3. Coping strategies during the pandemic

One possible reason that some households were able to cope better during the pandemic is access to coping strategies. Studies have highlighted that the defining aspects of the pandemic are uncertainty (Stiglitz & Guzman, 2021) and anxiety (Sockin, 2021) which induced precautionary behaviour amongst households as they tried to cope with this crisis.

Usually, households are expected to save their money to cope with income shocks in order to smooth their consumption over the life cycle (e.g., Alem & Colmer, 2022; Modigliani & Brumberg, 1954). Using saved money and cutting household expenses are the most prevalent methods of overcoming financial stress (Friedline et al., 2021; Varcoe, 1990). This was demonstrated amongst rural households in India as they were shown to be more prone to compromise spending and other forms of savings during the pandemic in order to have more emergency savings (Gopal & Malliasamy, 2022). However, whilst income smoothing was difficult during the pandemic due to limited migration and casual work (Gupta et al., 2021a), consumption smoothing was difficult due to limited savings, access to credit, (Gerard et al., 2020) or insurance (Goyal et al., 2021) or high alcohol consumption (Schilbach, 2019). Thus, this coping strategy was not accessible to every household.

Another common financial coping strategy is to sell assets. The opportunity to sell assets in times of crisis to smooth consumption depends on the liquidity constraints and might be harmful for the household's productive potential in the long run (Bundervoet et al, 2021; Gentilini et al., 2020; Hill & Narayan, 2020) and lead to a vicious cycle (De Quidt & Haushofer, 2016; Mainali & Periscope, 2019; Swift, 1989; Wisner et al., 2004). However, some studies found that many households in LMIC perceived the fall in income due to lockdown as temporary and were hence unwilling to compromise their assets or livestock (Mahmud & Riley, 2021; Rahman & Matin, 2020), whilst other studies found that it was more common to sell livestock and household durable assets (Ceballos et al., 2021; Kansiime et al., 2021; Mahmud & Riley, 2021) as well as spending stored cash to maintain essential food intake (Hammond et al., 2022).

Besides saving money and selling assets, borrowing has also been shown to be a prevalent and important financial coping strategy in times of crisis. As for previous health shocks (Dhanaraj, 2016; Yilma et al., 2014), the pandemic prompted a reliance on borrowing amongst farmers in India (Ceballos et al., 2020; Gupta et al., 2021b) and Bangladesh (Rahman & Matin, 2020). This was however not the case amongst low-income households in rural Kenya, which could be due to credit constraints and reduced peer-to-peer lending (Janssens et al., 2021). Evidence from previous health shocks also demonstrated reductions in formal lending (Dhanaraj, 2016; Yilma et al., 2014), making borrowing even more difficult.

The choice of financial coping strategy has shown to vary across context and crisis. For Tajikistan, a benchmark country in a sense as they did not have any lockdowns, borrowing as well as reducing food and health expenses were significant coping strategies, whilst dissaving and selling assets were not (Murakami, 2022). One explanation could lie in the severity of the health shock. As income from different sources decreases significantly, there is less room for helping others in order to keep food expenditures at par (Janssens et al., 2021). It has also been shown that deaths in poor households reduce the likelihood that they will save, and increase the likelihood that they will dissave (Lundberg et al., 2003). This contradicts the buffer-stock precautionary savings model and points at the importance of social protection or insurance in such contexts.

2.4. Cash transfers during the pandemic

During the pandemic, different policies were introduced to mitigate the negative economic impacts in LMIC. One interesting study that was conducted in rural Kenya found that universal basic income significantly decreased hunger, sickness and depression during the pandemic and that these transfers induced recipients to take on more income risk, and thereby mitigate the most harmful consequences of adverse shocks (Banerjee et al., 2020). Consistently, conditional cash transfers in Malawi were shown to have positive effects on wellbeing, with larger positive effects on the lower quantiles of the mental health distribution (Ohrnberger et al., 2020). These examples are in line with the findings of large positive impacts on PWB of asset and unconditional cash transfers in recent literature reviews (Ridley et al., 2020; Romero et al., 2021; Zimmerman et al., 2021) suggesting positive impacts on PWB also in the longer run by increasing productivity (Kaur et al., 2021) without increasing consumption of temptation goods (Evans & Popova, 2017).

In India, both the national and state governments prompted several measures to provide relief for vulnerable groups during the pandemic under the PMGKY package (Gentilini et al., 2020). This package included direct cash transfers to farmers under the PM-KISAN scheme, and in-kind assistance for other vulnerable groups through the PMJDY, PMUY and PMAVY schemes (Sonkar et al., 2022), which represent about 70% of the total budget of the PM-GKY package (Varshney et al., 2021).[1;2;3] Whilst some of these schemes were shown to increase income and provide food security to farmers (Gupta et al., 2021a), they did not significantly decrease the likelihood of income loss during the pandemic (Sonkar et al., 2022) and many Indians did not experience that they were financially helped by the government during the pandemic (Goyal et al., 2021). These schemes did, however, alleviate credit constraints and increase agricultural investments in inputs (Varshney et al., 2021).

[1] The PMJDY-scheme encourages women to open savings bank accounts for receiving benefits through this account (Gentilini et al., 2020).
[2] The PMUY-scheme aims to provide clean cooking fuel solutions to poor households (Varshney et al., 2021).
[3] The PMAVY-scheme provides free food rations through existing public distribution infrastructure (PDS) (Varshney et al., 2021).

In Odisha, the state from which the data used in this thesis is collected, the government specifically targeted vulnerable farmers with the "Krushak Assistance for Livelihood and Income Augmentation" (KALIA) scheme in order to "accelerate agricultural prosperity and reduce poverty in the state" (Government of Odisha, 2022).[4] The support was mainly provided in the form of direct benefit transfers, but also in the form of life insurance and interest free crop loans (Ahya et al., 2019). According to the Government of Odisha (2022), the support is estimated to cover 92% of all farmer households in the state in 2019-2021. However, the households need to apply to this scheme in order to be considered in the draft list of beneficiaries, and have an internet connection so that the amount could be transferred online, directly to the beneficiary. From this scheme, all "small and marginal agricultural households" will then receive Rs 10 000 (1 292 SEK) per family as assistance for cultivation during five cropping seasons in 2018-2019 and 2021-2022, and Rs 5 000 (646 SEK) separately in the kharif and rabi seasons.[5] Landless and vulnerable agricultural households are provided Rs 10,000 per year to enable them to take care of their sustenance, and the landless also received assistance of Rs 12 500 (1 614 SEK) once to stimulate cultivation.[6]

3. Methodology

3.1. Hypotheses and theory

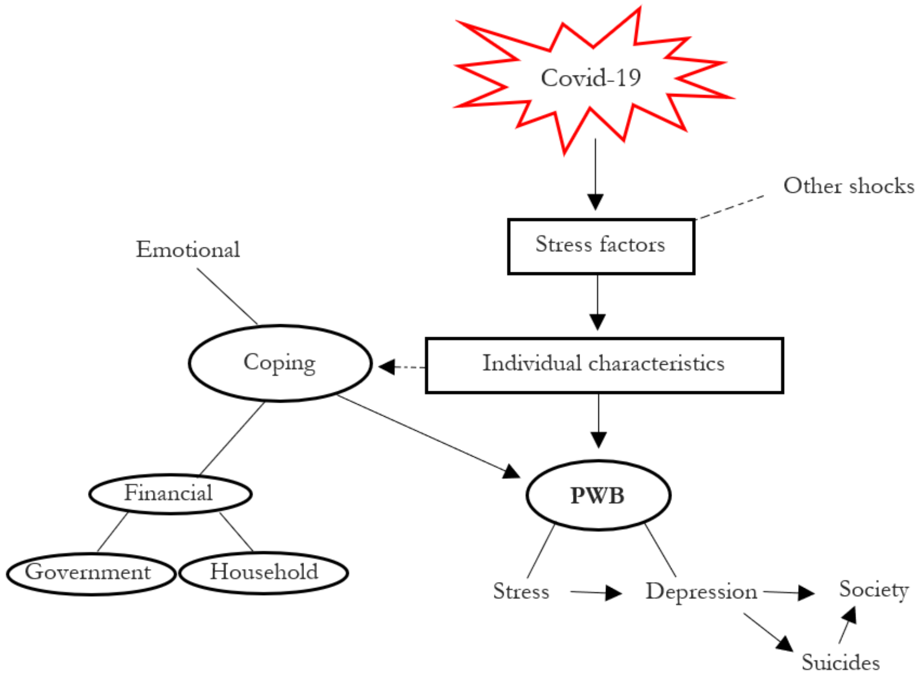
As outlined in the literature review, the Covid-19 pandemic negatively affected PWB (Banks & Xu, 2020; Bao et al., 2020; Proto & Quintana-Domeque, 2021). We argue that this impact was mediated through the increase in financial stress (e.g., Ridley et al., 2020) which induced coping behaviour amongst households, depending on the individual characteristics of the households. The mechanisms through which the pandemic affected PWB are illustrated in Figure 1.

[4] Small and marginal farmers (owning less than 5 acres of land), landless agricultural households (not owning land but engaging in agricultural activities for more than six months) or labourers, and vulnerable sharecroppers or cultivators (due to old age, disease or disability) are targeted if permanent residents or domiciles of Odisha (Government of Odisha, 2022).

[5] As of the exchange rate on 4 May 2022.

[6] As of the exchange rate on 4 May 2022.

Figure 1. Theory illustration



Just as with other shocks, the pandemic induced stress (Cariappa et al., 2021; Jaacks et al., 2021; Kumar et al., 2020; Lowe et al., 2021) and uncertainty (Gupta et al., 2021b; Stiglitz & Guzman, 2021) which individuals tend to react to differently. It has been shown that the perceived severity of the financial threat is more important in forming the way individuals cope with financial hardship (Greenglass & Mara, 2012; Marjanovic et al., 2013, 2015) and that those with greater psychological (Gasiorowska, 2014; Yazdanpanah et al., 2021) and financial resources (Fahey et al., 2016; Friedline et al., 2021; Gomez et al., 2020; Powell-Jackson et al., 2016; Rahut et al., 2021) experience and handle financial hardship better.

As illustrated in the model, we hypothesise that PWB was not only affected directly, through individual characteristics (mainly fixed, but also variable), but also indirectly through the choice of coping strategy (Alem & Colmer, 2022; Caplan & Schooler, 2007). We focus on financial coping strategies in this thesis and argue that households adopted such strategies to a larger extent as the intensity of the pandemic increased. The financial coping strategies that we examine in this thesis are either such where households try to help themselves (by reducing consumption, selling assets, borrowing or receiving money from one's community) or to seek financial help from the state government (by applying for direct cash benefits). We also hypothesise that this impact could have spillover effects on society as long term stress would induce depression (Hou et al., 2020; Ozer et al., 2011; Siddique & D'Arcy, 1984; Van Praag, 2004; Ventevogel et al., 2015), which tends to predict suicides (Das, 2011) and lower productivity (Pailler & Tsaneva, 2018).

Against this background, we test the following alternative hypotheses, where the first hypothesis examines the direct impact of the pandemic, whilst the second and third hypotheses explore the indirect impact.

HA_1: The pandemic had a negative impact on PWB
HA_2: Adopting financial coping strategies as the intensity of the pandemic increased was positively associated with PWB
HA_3: Receiving financial state government support during the pandemic was positively associated with PWB

There are, however, some issues with causation in this model as we could not rule out the possibility of bias and reverse causality. The potential omitted variable bias stems from the fact that we disregard other shocks and are not able to control nor correct for the inherent endogeneity of chosen coping strategies. Furthermore, the literature has highlighted the impact on PWB of political (Behere & Bhise, 2009), health-related, family-related (Behere & Bhise, 2009), or climate-related (Bahinipati & Venkatachalam, 2015; Bhise & Behere, 2006; Lawrence-Bourne et al., 2020) shocks, where especially the last mentioned has been affecting the state of the study, Odisha, as well as the agricultural sector significantly (Bahinipati & Venkatachalam, 2015). It has also highlighted that those facing credit constraints, poverty and vulnerability to repeated shocks (Clarke & Dercon, 2009; de Hoop et al., 2020; Merriott, 2016; Ranscombe, 2020) or are less able to adopt any financial coping strategies. Lastly, the potential of reversed causation for coping strategies has been raised (Durante & Laran, 2016; Koan et al., 2021; Pozzato et al., 2022). Hence, we are aware that our study is exploring rather than establishing causation.

3.2. Data

The data used in this study was collected in Odisha, India. Odisha is a rural state (Government of Odisha, 2021a) where 90% of the farmers are small and marginal (Government of Odisha, 2017) with an average land holding of 2.3 acres (Government of Odisha, 2021). In addition, 29% of the population in the state are classified as multidimensionally poor, which is higher than the average in India (Niti Aayong, 2021).

The data was collected in 2018, 2020 and 2021 from 2 997 rice farmer households living across 294 villages in the state by the International Rice Research Institute.[7] The sample was selected as follows. 15 districts out of 30 districts in Odisha were randomly selected to participate in the study. From each of these 15 districts, 20 villages were randomly selected. In each village, 10 farming households were randomly selected, resulting in a sample of 2 997 households.

[7] The data was collected to understand the impact of an agricultural education and psychological training program on rice farmer decision making.

The dates and the number of observations for each survey wave are presented in Table 1. We have four different waves, where the first three waves were conducted face to face, whilst the last one (wave 4) was conducted by phone. The first wave was collected in 2018, resulting in 2 997 observations. The first Covid-19 case in Odisha was confirmed on 16 March, 2020 (Swain et al., 2020), and soon after, the first nationwide lockdown was announced on 25 March, with some exemptions for agricultural activities and businesses (Ceballos et al., 2020). The second wave was collected in 2020, before this lockdown, resulting in 1 582 observations, and the third wave was collected in 2020 and 2021, right after this lockdown and at the end of the first Covid-19 wave in Odisha (Indian Institute of Technology Hyderabad, 2022), resulting in 1 634 observations. The final wave was collected during summer, at the downturn of Odisha's second Covid-19 wave in 2021 (Indian Institute of Technology Hyderabad, 2022), resulting in 2 950 observations.

As we note in Table 1, the second wave contains half of the households of our whole sample, and the third wave contains the other half (splitted randomly). Thus, these waves could be seen as sub-samples to the whole sample. With regards to the observations before and after Covid-19, we note that the first and second waves were collected pre-Covid-19 and constitute almost 50% of the whole sample, whilst the third and fourth wave were collected post-Covid-19 and constitute the other half of the whole sample. Finally, comparing the sample in the first wave with the sample in the fourth wave, we note that the attrition rate is 2%, which is very low for a sample of this size (Jansson et al., 2021).

Table 1. Waves of survey data

Survey ID	Starting date	End date	Year	Covid-19	Observations	Percent
Wave 1	May	December	2018	Pre	2 997	32.71
Wave 2	February	March	2020	Pre	1 582	17.27
Wave 3	December	March	2020/ 2021	Post	1 634	17.83
Wave 4	July	August	2021	Post	2 950	32.19
		Total			9 163	100.00

In order to assess the research questions, different survey waves have to be used. For the first research question, we use all survey waves as we have the needed data in all these waves, allowing us to control for fixed effects. For the two remaining research questions, only survey wave 4 is used as the questions on the pandemic intensity and coping were only asked in this wave.

3.3. Sociodemographic characteristics

Descriptive statistics on sociodemographic characteristics are presented in Table 2. The average age in the sample is 51 years. As this study specifically targeted those responsible for farming, the share of women is only 6%. The average *annual* income in the sample is approximately Rs 134 288 (17 344 SEK).[8] The average years of education is approximately 6 years. Whilst general socioeconomic caste constitutes 8% of the sample, 14% of the individuals are classified as "Scheduled Castes" (SC) and 24% as "Scheduled Tribes" (ST). As many as 45% of the individuals come from "Other backward classes" (OBC) and 9% belong to "Socially and economically backward classes" (SEBC). 99% of the individuals in the sample identify as "Hindu". The average cultivated area in the sample is 2.9 acres and 93% has a cultivated area of 5 acres or smaller.[9] With regards to representativeness, we note that the average farmer in the sample is somewhat richer and owns more land than the average farmer in Odisha. An average farmer in Odisha has an average income of Rs 92 772 (11 982 SEK) (Government of Odisha, 2021b) and an average cultivated area of 2.6 acres (International Rice Research Institute, 2022).[10]

Table 2. Sociodemographics

Sociodemographics	
	Baseline
Males (%)	93.8
	(0.241)
Age	50.865
	(12.89)
Years of education	5.94
	(4.650)
Income	134 288.5
	(138 018.2)
Hindu (%)	99.2
	(0.0891)
Cast category General (%)	7.6
	(0.266)
Cast category SC (%)	14.4
	(0.352)
Cast category ST (%)	23.5
	(0.424)
Cast category OBC (%)	45.2
	(0.498)
Cast category SEBC (%)	9.2
	(0.289)
N	**2 997**

Mean values; standard deviation in parentheses

[8] As of the exchange rate on 4 May 2022.

[9] Having a cultivated area of 5 acres or smaller is one of the requirements for receiving the KALIA instalments.

[10] As of the exchange rate on 4 May 2022.

3.4. Variables

3.4.1. Dependent variable

The feeling of having control over one's own life, a meaningful existence and positive relations with others typically determine PWB (Abbott et al., 2006; Ryan & Deci, 2001). Even though the literature on PWB is growing, there is no consensus on how to estimate PWB (Linley et al., 2009; Winefield et al., 2012). Many studies suggest both depression and stress to be negatively associated with PWB (Burns et al., 2011; Edmondson & MacLeod, 2015; Quingbo et al., 2009; Siddique & D'Arcy, 1984). Whilst depression has been found to reduce the perceived meaning in life (Hedayati & Khazaei, 2014), stress was found to be associated with lower perceived control over important matters in life (Cohen et al., 1983). Hence, using both depression and stress could give a good sense of PWB.

In order to assess PWB, we use thirteen questions in total: nine questions to measure depression, and four questions to measure the perceived level of stress.[11] All questions ask the respondent to rate their experienced prevalence of symptoms over the last month, where higher values indicate more often whereas lower values indicate more seldom. Thus, higher values indicate more severe depression and higher levels of perceived stress.

To measure depression, we use the depression module of the Patient Health Questionnaire (PHQ-9) (Manea et al., 2015; Thombs et al., 2014), which is shorter than many depression questionnaires, yet suggested comparable, or even superior in measuring the severity of depression (Kroenke et al., 2009; Martin et al., 2006). The Cronbach's Alpha between the answers for the PHQ-9 survey are 0.85, 0.87, 0.76 and 0.81, respectively for each of the survey waves, which are all high and indicate acceptable internal consistency (Taber, 2018).

To measure the perceived level of stress, we use the Perceived Stress Scale (PSS-4), which has been suggested to provide both reliability and validity in different settings (Warttig et al., 2013). Important to note, however, is that the correlation between the answers constituting the scale is not very high. The Cronbach's Alpha between the answers for the PSS-4 survey are 0.63, 0.67, 0.62 and 0.38, respectively for each of the survey waves. The very low value for the phone survey raises concerns about the reliability of this scale, as previously highlighted by Andreou et al. (2001), but also about the quality of the phone survey.

Table 3 presents the severity of depression and perceived level of stress amongst the respondents. By comparing the mean levels before and after the pandemic, using paired t-tests, we note that the depression first *decreased* right after the first lockdown and then *increased* significantly in the fourth wave, whilst stress *increased* consistently during pandemic.

[11] These questions measuring depression and stress are available in the Appendix A.

Table 3. Depression and stress

	Pre-Covid-19	Pre-Covid-19 - Post Covid-19 F2F	Post Covid-19 F2F	Post Covid-19 F2F - Post Covid-19 phone	Post Covid-19 phone	Full sample
Depression scale	3.996	***	2.697	***	4.447	3.689
Ranging from 0 - 27; high values indicates more severe depression	*(4.432)*		*(2.879)*		*(3.902)*	*(4.052)*
Stress scale	8.537	*	8.722	***	10.556	9.241
Ranging from 4 - 20; high values indicates higher level of perceived stress	*(3.123)*		*(3.064)*		*(3.003)*	*(3.210)*
N	4 579		1 634		2 950	9 163

Mean values; standard deviation in parentheses
Paired t-test was used to test significant differences between the mean values;
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Looking at the pre-Covid-19 (survey wave 1 and 2) PHQ-9 scores in Table 3, we see that the mean depression score is 4, whilst it was 2.7 after the first lockdown, both indicating minimal level of depression (Kroenke et al., 2001). Before the first lockdown, 13.69% were classified as at least moderately depressed (i.e., having a PHQ-9 score of 10 or above), which is fairly representative of the Indian rural population for which Shidhaye et al. (2016) found 11-14.6% to have PHQ-9 scores of 10 or above. Right after the first lockdown, however, only 2.7% had this score, whilst 9.36% had it in the last survey wave. This trend is presented in Table A3.

With regards to stress, which farmers are highly exposed to (Behere & Bhise, 2009), we see in Table 3 that the mean stress score is 8.5 in the pre-Covid-19 sample (survey wave 1 and 2), 8.7 right after the first lockdown (survey wave 3), and 10.6 in the last survey wave. These scores are higher than those found in other studies conducted in similar contexts (Patwary et al., 2021).

Figure 2. PHQ-9 by survey wave

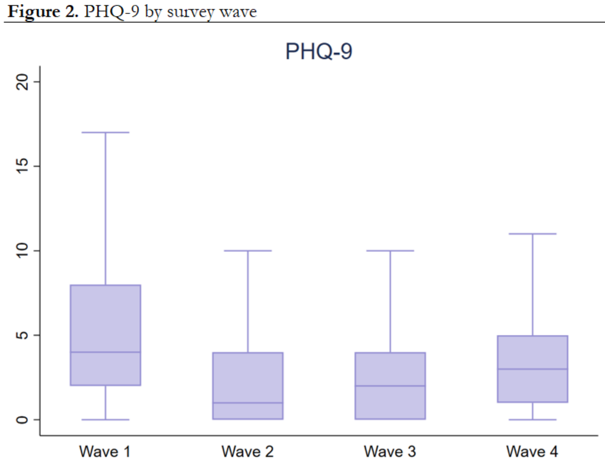


Figure 3. PSS-4 by survey wave

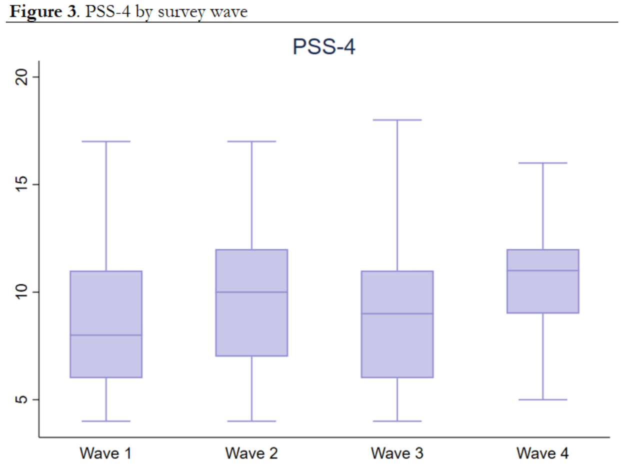


Figure 2 shows a boxplot of the depression scale with 95 percent confidence interval. Interestingly, the confidence interval for the first wave was much wider than for the other waves. Figure 4 shows how the mean depression level varied across the survey waves. It was at its highest in the first wave, probably following recent pest attacks, drought and the cyclone in the state that were shown to induce suicide amongst rural communities during that growing season (Carleton, 2017; Government of Odisha, 2019). Depression decreased significantly in the second wave, right before the first lockdown. Right after the first lockdown, depression increased slightly, between the second and third wave, as in line with what previous studies observed in India (Gopal et al., 2020). As the pandemic proceeded, the depression continued to increase in the fourth wave.

Figure 3 shows a boxplot of the stress scale with 95 percent confidence interval. We note that, compared to the depression scale, the stress scale has a larger range across all waves. Figure 5 shows how the mean stress level varied across the survey waves. The mean stress level was the lowest in the first wave and increased in the second wave, right before the pandemic. In the third wave, right after the first lockdown, the mean stress level decreased slightly and then largely increased as the pandemic proceeded.

Figure 4. Depression Scale

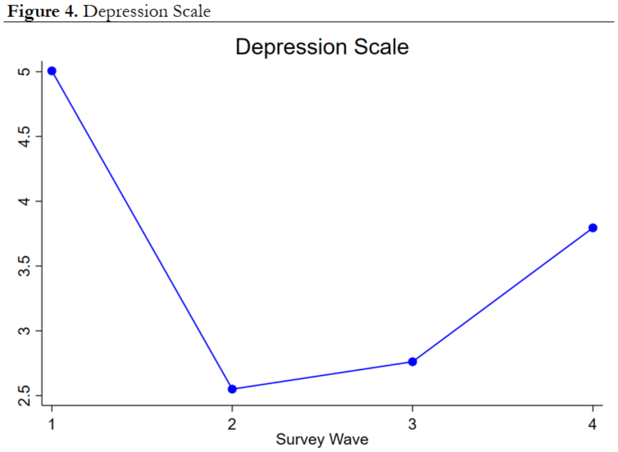
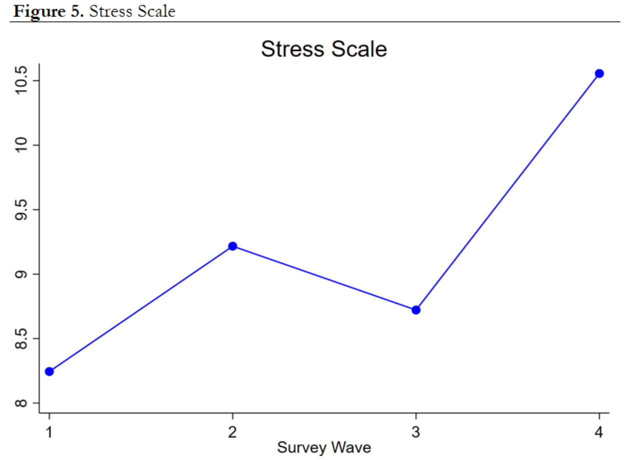


Figure 5. Stress Scale



For our main regressions, we use an unweighted PWB index, in which the two measures of depression and perceived level of stress are recoded so that they are on the same scale, all starting from 1, and high values correspond to low levels of depression and perceived stress. As the depression scale contains nine questions, it ranges from 9 to 36. The stress scale, on the other hand, contains four questions and ranges from 4 to 20. The two scales are then combined in order to create the unweighted index of PWB, which ranges from 13-56 and in which higher values correspond to higher levels of PWB. The Cronbach's Alphas for this index are on average 0.77 and 0.85, 0.78, 0.71 and 0.70 for each of the different survey waves respectively, indicating acceptable internal consistency (Taber, 2018).

To test the robustness of the unweighted PWB index, we later conduct the same analyses, but with other dependent variables such as a separated stress scale and depression scale, and then a weighted index. The weighted index is constructed through principal component analysis (PCA), which creates a few principal components out of the questions and thereby weights the questions in accordance with how much of the variance that they account for. This is a common method for measuring wellbeing as it addresses the issue with multicollinearity and reduces the dimensionality in the data (Mazziotta & Pareto, 2018).

For the first research question, the PCA is conducted for each of the four waves and is then summed into a weighted PWB index. We do this as the weights computed by the PCA change for each data matrix over time and as this allows us to treat each wave separately. For the two remaining research questions, the same procedure is repeated, although using only the last wave for the reasons mentioned in section 3.2.

Figure 6 shows how the mean unweighted PWB index varies across the survey waves. Figure 7 shows how the mean weighted PWB index varies across the survey waves. The unweighted PWB within the sample was high in the first survey wave but decreased significantly during the second wave. For the weighted PWB, the opposite was true, probably because this index weights the answers on depression higher. Right after the first lockdown, we saw that the unweighted and weighted PWB increased, and then later decreased as the pandemic progressed.

Figure 6. Unweighted PWB

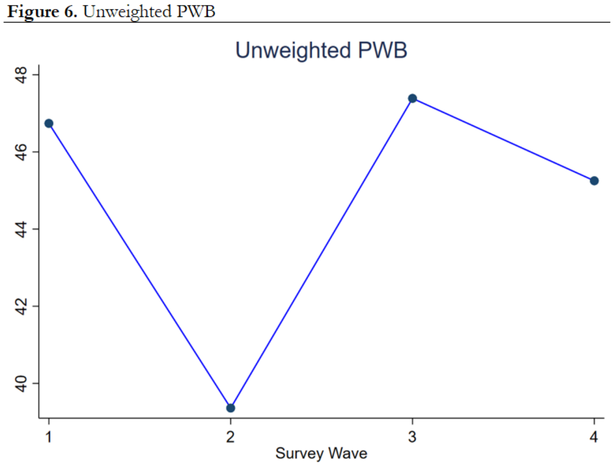
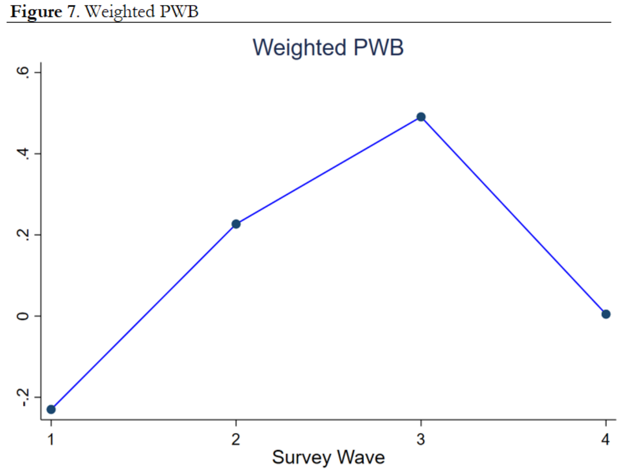


Figure 7. Weighted PWB



The decrease in unweighted PWB as the pandemic progressed can also be seen in Table 4 by comparing the mean levels before and after the pandemic, using paired t-tests.

Table 4. PWB unweighted

	Pre-Covid-19	Pre-Covid-19 - Post Covid-19 F2F	Post Covid-19 F2F	Post Covid-19 F2F - Post Covid-19 phone	Post Covid-19 phone	Full sample
PWB	47.190	***	48.517	***	45.653	46.920
Ranging from 13 - 56; high values indicates better PWB	*(6.456)*		*(4.774)*		*(5.361)*	*(5.904)*
N	4 288		1 596		2 925	8 808

Mean values; standard deviation in parentheses
Paired t-test was used to test significant differences between the mean values;
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We note that the unweighted PWB significantly *increased* in the beginning of the pandemic, but significantly *decreased* shortly after, which might be driven by higher stress, as noted in Table 2.

3.4.2. Variables of interest

For the first research question, the variable of interest is a dummy taking the value of 1 if the respondent was surveyed after the first lockdown (i.e., 25 March 2020), and 0 otherwise (i.e., before 25 March, 2020). Here, we use all four waves. We argue that this variable could be seen as an intervention in a natural experiment, as argued by similar studies (e.g., Bergenholtz et al., 2021; Prati & Mancini, 2021). When inferring relationships, this type of panel research design is preferred over cross-sectional design, because the former is enhanced by temporal ordering and can rule out the effects of unobserved individual differences (Frees, 2004).

For the second research question, the variable of interest is an interaction term between the intensity of the pandemic and the adoption of financial coping strategies. Here, we only use the fourth wave of the data, and create an intensity variable to explore the influence of the pandemic. We define the intensity of Covid-19 as the respondent's experienced problems with input access, agricultural income, non-agricultural income, medical/health emergencies, psychological stress/issues or any food shortage due to the pandemic.[12] The intensity variable is an index composed of six binary variables (taking the value of 1 if the respondent experienced any of the problems, and 0 otherwise) with equal weights. Thus, the index ranges from zero to six, where zero indicates that the respondent did not experience any of these problems at all, whilst six indicates that the respondent experienced all the problems. These variables are used to measure the perceived negative impact on the livelihoods of households. This index is then interacted with a dummy on adoption of a financial coping strategy, taking the value of 1 if the respondent adopted any of these strategies: reducing their consumption, selling liquid assets, borrowing cash loans or getting financial assistance from relatives, and 0 otherwise. The variables are interacted to examine how the adoption of such strategies as the perceived intensity of the pandemic increases is associated with PWB.

The different financial coping strategies adopted by the farmers are presented in Table 5, section A. We learn that only 8% adopted a financial coping strategy, where the most common one was to receive assistance from relatives (3%) followed by reducing consumption (3%), borrowing cash or taking a loan (3%) and selling liquid assets (1%). In Table 5, section B, we note that 4% had problems with input access, and that 7% experienced reductions in agricultural income, 13% experienced reductions in non-agricultural income, 9% experienced medical/health emergencies, 16% experienced psychological stress and 6% experienced food shortage. Amongst the respondents, 22% faced at least one of these problems and only 0.4% faced all of these problems.

For the third research question, the variable of interest is a dummy, taking the value of 1 if the respondent received any instalments of the KALIA scheme (either the first or second or both), and 0 otherwise. This variable is seen as treatment. The questions on the instalments were mainly

[12] These questions measuring the intensity of Covid-19 are available in the Appendix A.

asked in the third wave, but also in the fourth wave. Hence, the average treatment effect could be seen as the long-term impact of the direct benefit transfers in the main analysis. Table 5, section C, presents the share of the respondents that received the KALIA instalments during the pandemic in the third and fourth wave. We note that during the third survey wave, 20% received the first instalment whilst 25% received two instalments. In the last survey wave, only 13% received the first instalment and 17% received two instalments.

Table 5. Financial coping strategies and intensity

Section A: Financial coping strategies	Wave 4
Reduced consumption (%)	2.8 *(0.165)*
Sold liquid assets (%)	0.9 *(0.0967)*
Borrowed cash / loan (%)	2.8 *(0.165)*
Assistance from relatives (%)	3.3 *(0.178)*
Adopted a financial coping strategy (%)	7.56 *(0.264)*
Did not adopted a financial coping strategy (%)	92.44 *(0.264)*
N	2 940

Section C: KALIA	Wave 3	Wave 4
Received first instalment of KALIA (%)	20.38 *(0.403)*	12.58 *(0.332)*
Received both instalments of KALIA (%)	25.34 *(0.435)*	17.02 *(0.376)*
N	1 634	2 950

Section B: Intensity	Wave 4
Reduced production due to limited input access (%)	3.864 *(0.193)*
Reduced agricultural income due to marketing restrictions (%)	7.356 *(0.261)*
Reduced non-agricultural income due to reduced opportunities (%)	12.847 *(0.335)*
Medical/Health emergencies (%)	9.525 *(0.294)*
Psychological stress/issues (%)	16.441 *(0.371)*
Food shortage (if any) (%)	5.831 *(0.234)*
Intensity level 1 (%)	22.381 *(0.416)*
Intensity level 2 (%)	*7.517* *(0.263)*
Intensity level 3 (%)	2.687 *(0.161)*
Intensity level 4 (%)	*1.429* *(0.118)*
Intensity level 5 (%)	0.442 *(0.066)*
Intensity level 6 (%)	*0.442* *(0.066)*
N	2 950

Mean values; standard deviation in parentheses

3.4.3. Control variables

For the first research question, we control for important variables, that vary across individuals over time, like income, education (Deb, 2020; Egger et al., 2019; Helliwell, 2003; Hossain et al., 2020c; Prasad et al., 2006) and age (Fontaine & Yamada, 2014; Gupta & Coffey, 2020). In order to account for the skewness of income in the sample, we use the logarithm of income. We are aware that caste is an important determinant of PWB, but since it tends to correlate strongly with both income and education (e.g., Banerjee et al., 2009; Deshpande, 2000; Linssen et al., 2011), we only control for income and education in order to avoid multicollinearity.

For the second research question, we control for multiple individual factors. As the sample predominantly consists of Hindu men, we avoid controlling for gender and religion. We do, however, control for self-efficacy (see e.g., Cattelino et al., 2021; Janker et al., 2021; Strobel et al., 2011; Vesala & Vesala, 2021) and personality (Khosla, 2021; Lecic-Tosevski et al., 2011;Tanksale, 2015) to capture some important individual variation. In addition, we control for age, education and the logarithm of income as previously, for the land area used for cultivation (Barrett 1996; Gregoire, 2002; Molnar, 1985) and for the reduction in food consumption (Egger et al., 2019; McMichael et al., 2021; Trudell et al., 2021), which have been shown to affect PWB. The full set of control variables used for the first and second research questions can be found in Appendix B, Table B1.

For the third research question, we do not include any control variables as we match the observations on variables that predict participation in the KALIA scheme, such as total cultivated area, log income and years of education, which will be explained further in section 3.5.

3.5. Model

For the first research question, we use the whole sample (all waves) and estimate β_1, which could be seen as the impact of the pandemic on PWB, in (a). Since we have panel data, we use a linear fixed effects model specification as it allows for direct interpretation of the coefficients.

$$PWB_{i,t,e} = \beta_0 + \beta_1 Post\ Covid + \lambda_{i,t} + \theta_i + E_e + \varepsilon_{i,t,e} \qquad \text{(a)}$$

We control for individual fixed effects through θ_i , a vector of household dummies, in order to control for the impact stemming from factors that are typically fixed within individuals during this short period of time such as gender, personality, genetic predispositions, caste and religion, and have been shown to affect wellbeing the most (see e.g., Ferrer-i-Carbonell & Frijters, 2004; Frey & Stutzer, 2002; Luttmer, 2005). $\lambda_{i,t}$ is a matrix of control variables on years of education, age and log income, since these variables could explain some of the variation in PWB that is not captured by individual fixed effects. We also control for enumerator fixed effects through E_e, which is a vector of enumerator dummies. These fixed effects have also been shown to be important as there is evidence of large enumerator biases for sensitive questions (Di Maio & Fiala, 2020; Himelein, 2016). Finally, the error term, $\varepsilon_{i,t}$, captures the variation in PWB across households that could not be explained by the variables in the model. Since we have a large panel data set, and the pandemic could be seen as a natural experiment (e.g., Bergenholz et al., 2021; Prati & Mancini, 2021), we could be more confident in making causal claims for this research question.

For the second research question, we use the fourth wave of the sample (the phone survey) and interact the adoption of financial coping strategies with the intensity of Covid-19.[13] For this

[13] All the questions constituting this variable can be seen in Table A12

research question, we aim to estimate γ_1 in (b), which could be interpreted as the *correlation* between PWB and the adoption of coping strategies in times of higher intensity of the pandemic. We could merely interpret a correlation as the choice of coping strategy and the perceived intensity are endogenous. Also, since this data is cross-sectional, we could not control for fixed effects and hence try to control for some of these factors using observables instead, as explained in section 3.4.3.

$$PWB_i = \beta_0 + \beta_1 Intensity + \gamma_0 Cope + \gamma_1 Cope \times Intensity + \lambda_i + \varepsilon_i \quad \text{(b)}$$

λ_i is a vector of control variables on age, education, log income, total cultivated area, reduced food consumption during the pandemic, agricultural self-efficacy and personality, since we have data on these variables for a large majority of households in this wave and we believe that they could explain some of the variation in PWB that is not related to the pandemic nor coping strategies adopted. For both the first and second research question, we use heteroskedasticity-consistent robust standard errors and cluster the standard errors at the household level as households are randomly sampled and followed over time in the data.

For the third research question, we use the fourth survey wave and aim to estimate α in (c), which could be interpreted as the average treatment effect (ATE) of previous financial state government support. As for financial coping strategies, it is difficult to establish any causal inference in this case due to self-selection into the scheme. However, as we have many observations and data on observables, which we argue determine participation in the scheme, we conduct propensity score matching (PSM) analyses to mimic randomisation (Rubin, 2001) and reduce bias in the estimation of the ATE (Rosenbaum & Rubin, 1983).[14]

$$\alpha(p(X)) = E(PWB^1 | T = 1, p(X)) - E(PWB^0 | T = 0, p(X)) \quad \text{(c)}$$

When conducting PSM, the ATE is estimated by taking the difference of the expected PWB for the treated households, PWB^1, and untreated households, PWB^0, with similar propensity scores, p_i, which is the conditional probability of treatment (receiving the KALIA instalments) given covariates X_i.

$$p_i = p(X_i) = Prob[T_i = 1 | X_i]$$

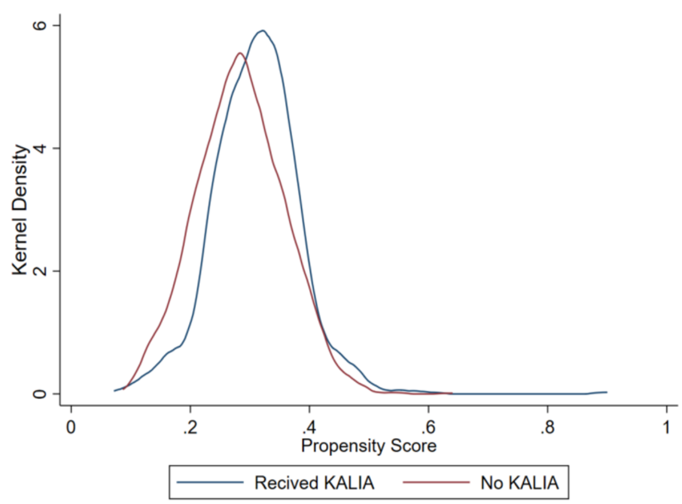
In order to be able to interpret the ATE, we need to have selection on observables and common support for being able to match the observations (Caliendo & Kopeinig, 2008). We argue that by matching on these variables, we have matching on observables since the criterias for receiving KALIA depend on the total cultivated area (Odisha Government, 2022) and we expect

[14] Using estimated likelihood (i.e., propensity) of receiving treatment as a function of observables to match the treated and the control observations (Abadie & Imbens, 2016).

households with lower income and higher education (Ferro et al., 2010; Sadoulet et al., 2001) to self-select into these schemes to a higher degree. Thus, one could argue that these variables predict participation in the scheme. There are theoretical arguments in favour of including only such variables in PSM (see e.g., Austin et al., 2007; Brookhart et al., 2006). However, we are aware of that this condition is rarely fulfilled in social science (Heckman & Navarro-Lozano, 2004) and that PSM eliminates some but not all selection-bias, making it impossible to reliably estimate the ATE for values outside the common support (Heckman et al., 1996).

With regards to common support, we see in Figure 8 that the overlap between the treatment and control group is large.[15] Hence, we could argue that the treatment group and the control group are almost the same on average after PSM. Thus, any observed differences between the treatment and control group are more likely to be due to the treatment effect rather than other confounding factors.

Figure 8. Kernel Density of the propensity score after matching



We estimate the ATE of receiving the KALIA instalments during the pandemic through one-to-one propensity score matching with no replacement (PSM) and kernel based matching (KBM), using a logit model as a treatment model.[16;17] For both methods, the standard errors are heteroskedasticity-consistent (Abadie & Imbens, 2016; Jann, 2017).

[15] We use a Kernel-based matching estimator. With this method, the treated are matched with the untreated with greater weight the more similar the propensity scores of the groups are (Heckman et al., 1997).

[16] For the PSM, we use the Stata program *teffects psmatch*. Here, each participant is matched once to the control with the closest propensity score.

[17] For the KBM, we use the Stata program *kmatch* (Jann, 2017). Here, each participant is matched to a weighted average of all controls, instead of matching a unique control to each participant (Heckman & Vytlacil, 2007).

4. Results and Robustness

4.1. Did the pandemic affect the psychological wellbeing of Indian farmers negatively?

4.1.1. Main analysis

Table 6 shows the regression output for the first research question using regression equation (a) and sequentially adding the confounders. In Model 1, nothing is controlled for, in Model 2, we include individual fixed effects, Model 3 includes the control variables and in Model 4, both individual fixed effects and the controls are included to control for confounders that are fixed and variable over time. In Model 5, we also include enumerator fixed effects. This procedure of presenting the result by sequentially adding control variables in this order is repeated in the robustness checks for this research question.

Table 6. Regression results for Research Question 1

PWB	Model 1	Model 2	Model 3	Model 4	Model 5
Post Covid-19	-0.534***	-0.470***	-0.507***	0.799	-0.718
	(0.125)	*(0.164)*	*(0.125)*	*(0.499)*	*(0.503)*
Years of education			-5.24e-05	0.651	0.516
			(0.0155)	*(1.194)*	*(0.928)*
Age			-0.0374***	-0.901***	-0.719**
			(0.00540)	*(0.329)*	*(0.297)*
Log income			0.469***	0.472*	0.248
			(0.0965)	*(0.267)*	*(0.238)*
Individual fixed effects	No	Yes	No	Yes	Yes
Enumerator fixed effects	No	No	No	No	Yes
Constant	47.19***	47.16***	43.71***	87.94***	85.43***
	(0.0975)	*(0.0546)*	*(1.046)*	*(16.76)*	*(15.24)*
Observations	8 807	8 807	8 797	8 797	8 792
R-squared	0.002	0.350	0.011	0.366	0.570

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

We find that the seemingly negative impact of the pandemic, as seen for Model 1-3, disappears when controlling for both individual fixed effects and the control variables, as seen for Model 4. Whilst a negative impact has been demonstrated in the literature (e.g. Cevher et al., 2021; Ragasa et al., 2021; Shafi et al., 2021), the finding of an insignificant impact is not very common. With regards to the enumerator fixed effects, as seen for Model 5, we note that these effects did not have any significant impact on the result of Model 4.[18]

As expected, we find that the R-squared increased strongly when controlling for individual fixed effects, suggesting that these effects explain a significant portion of the variation in PWB. The importance of individual fixed effects for PWB has been highlighted in the literature (see e.g., Ferrer-i-Carbonell & Frijters, 2004; Frey & Stutzer, 2002; Luttmer, 2005), and supports our

[18] We argue that this is an impact and not just an association as the pandemic could be regarded as a natural experiment, we are able to control for fixed effects and have a large panel data set of high quality.

theory that the impact of stressors on PWB is highly dependent on factors that are fixed over time within households. In addition, the R-squared increased significantly when controlling for enumerator fixed effects, suggesting some enumerator bias to be present (Di Maio & Fiala, 2020).

4.1.2. Robustness

In order to test the robustness of these results, we first run different double-lasso regressions using cross-validation with 10 folds and controlling for caste, age, log income, years of education, total cultivated area, agricultural self-efficacy and personality to ensure that the chosen control variables in the main regression do not yield biased estimates. We run double-lasso regressions as this method is calibrated to not over-select potentially spurious covariates, whilst reducing error and increasing statistical power when identifying the best covariates (Urminsky et al., 2016). The estimated key coefficient is presented in Table 7 with different selection methods: double-selection (Belloni et al., 2014) in the first column, partialing out-selection (Belloni et al., 2016) in the second column, and cross-fit partialing out-selection (Chernozhukov et al., 2018) in the third column.[19]

Table 7. Results from double-lasso regression

PWB	Double-selection	Partialing out	Cross-fit partialing out
Post Covid-19	-0.336*	-0.336*	-0.373**
	(0.14)	*(0.14)*	*(0.14)*
Observations	8 193	8 193	8 193

Beta coefficients; standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As seen in Table 7, the different methods yield a similar magnitude and direction of the estimated coefficient across selection methods. Compared to Model 3 in the main regression in Table 6, the magnitudes are somewhat smaller. Compared to Model 4 or Model 5 in Table 6, where we control for individual fixed effects, the coefficients are significant in Table 7. This could be due to the fact that controlling for caste, agricultural self-efficacy and personality is not enough to capture the individual fixed effects.

The second robustness check concerns the survey waves. Since the fourth wave survey was conducted by phone, this change of method could give rise to bias (Ambel et al., 2021; Holbrook et al., 2003). Hence, we examine whether this change in methodology had an impact on the estimated coefficients by comparing the first survey wave with the third survey wave and re-run regression (a). We do this instead of comparing the second and the third survey wave as these consist of different households, as explained in section 3.2.

[19] The double-lasso is a commonly used method to prevent over-selection of spurious control variables and studies have found that this method reduces error and increases the statistical power (Urminsky et al., 2006).

Table 8. Robustness Research Question 1: using wave 1 and 3

PWB	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Post Covid-19	-2.721***	-2.544***	-2.731***	-2.545***
	(0.113)	*(0.221)*	*(0.113)*	*(0.221)*
Years of education			-0.0462***	0.103
			(0.0134)	*(0.158)*
Age			0.0311***	0.00213
			(0.00477)	*(0.0307)*
Log income			-0.0888	1.894
			(0.0895)	*(2.341)*
Individual fixed effects	No	Yes	No	Yes
Constant	29.76***	32***	29.48***	10.61
	(0.0711)	*(0)*	*(0.969)*	*(25.31)*
Observations	4 593	4 593	4 592	4 592
R-squared	0.105	0.705	0.122	0.705

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

In Table 8, we note a *negative* impact of the pandemic for all models, as for Model 1-3 of the main regression in Table 6. However, including the individual fixed effects does not change the significance in this regression, suggesting that the change in method (from conducting the survey face to face to conducting it by phone), the duration of the pandemic, or both, significantly affected the estimated impact on PWB. Using the estimated coefficients in Model 4, Table 8, we learn that the pandemic was associated with a 5.4% decrease in PWB. [20]

Finally, as a third robustness check, using all four waves, we test whether depression and stress were differently affected during the pandemic, as suggested by previous studies (e.g., Brodeur et al., 2021b; Verma & Mishra, 2020). Therefore, we split the dependent variable, PWB, into its components: depression and stress, using the original scales where high values indicate higher levels of depression and stress, and where each of the questions in these scales have equal weight, and run the same regressions as previously.

The regression output of this robustness check is found in Table 9 and 10, where we see that whilst depression significantly *decreased* during the pandemic, the perceived level of stress significantly *increased* in all models. Using the estimated coefficients in Model 4 for both depression and stress, we learn that the pandemic was associated with a 41.6% *decrease* in depression, and a 9.7% *increase* in the perceived stress level. [21]

[20] Comparing the pre-Covid-19 value (in Table 4) with the estimated coefficient (in Table 8).
[21] Comparing the pre-Covid-19 values (in Table 3) with the coefficient estimates (in Table 9 and 10).

Table 9. Robustness Research Question 1: using depression

Depression	Model 1	Model 2	Model 3	Model 4
Post Covid-19	-0.839***	-1.102***	-0.862***	-1.663***
	(0.0845)	*(0.110)*	*(0.0846)*	*(0.253)*
Years of education			-0.0134	-0.297
			(0.0104)	*(0.607)*
Age			0.0262***	0.409**
			(0.00371)	*(0.160)*
Log income			-0.376***	-0.516***
			(0.0663)	*(0.179)*
Individual fixed effects	No	Yes	No	Yes
Constant	4.267***	4.367***	7.344***	-10.73
	(0.0663)	*(0.0366)*	*(0.721)*	*(8.221)*
Observations	8 806	8 806	8 791	8 791
R-squared	0.011	0.355	0.023	0.363

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

Table 10. Robustness Research Question 1: using stress

Stress	Model 1	Model 2	Model 3	Model 4
Post Covid-19	1.372***	1.564***	1.358***	0.832***
	(0.0656)	*(0.0851)*	*(0.0658)*	*(0.256)*
Years of education			0.0143*	-0.258
			(0.00847)	*(0.670)*
Age			0.0111***	0.501***
			(0.00289)	*(0.168)*
Log income			-0.0985*	0.00220
			(0.0506)	*(0.147)*
Individual fixed effects	No	Yes	No	Yes
Constant	8.537***	8.479***	9.016***	-17.19**
	(0.0471)	*(0.0284)*	*(0.546)*	*(8.626)*
Observations	8 807	8 807	8 792	8 792
R-squared	0.046	0.386	0.047	0.403

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

Due to this difference in direction, it might be misleading to refer to PWB as a holistic concept. In addition, the directions of impacts also differ between the answers constituting the depression scale and stress scale, as seen in Table A1 and A2. Hence, as yet another robustness check, we weight the answers to each of the questions in accordance with how much of the variation they account for, and create a new, *weighted* index as a dependent variable. The weights are allocated through principal component analysis (PCA), which is a common method for creating weighted indices measuring wellbeing (Mazziotta & Pareto, 2018). The regression output is presented in Table 11.

Table 11. Robustness Research Question 1: using PCA

PWB using PCA	Model 1	Model 2	Model 3	Model 4
Post Covid-19	0.258***	0.202***	0.266***	0.347***
	(0.0542)	*(0.0715)*	*(0.0544)*	*(0.114)*
Years of education			0.00434	0.414
			(0.00680)	*(0.284)*
Age			-0.00931***	-0.108*
			(0.00232)	*(0.0596)*
Log income			0.101**	0.181
			(0.0421)	*(0.115)*
Individual fixed effects	No	Yes	No	Yes
Constant	-0.0770*	-1.023***	-0.786*	2.478
	(0.0427)	*(0.0238)*	*(0.458)*	*(3.258)*
Observations	8 807	8 807	8 797	8 797
R-squared	0.003	0.358	0.006	0.360

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

We find that the pandemic had a *positive* association with the weighted PWB index in all models. Studying the correlations between the questions constituting the scales, we learn that they were higher for the depression scale than for the stress scale, as seen in A4-A11. This indicates that the depression questions had larger weights in the weighted PWB index than the stress questions.

4.2. Were financial coping strategies *associated with higher psychological wellbeing as the intensity of the pandemic increased?*

4.2.1. Main analysis

Table 12 shows the regression output for research question 2 using regression equation (b) and sequentially adding different sets of control variables. In Model 1, only intensity is included, in Model 2, a dummy on financial coping strategy is included, and Model 3 includes an interaction term between intensity and coping. In Model 4, the first set of control variables that vary over time are included, whilst in Model 5, the second set of control variables are included that are rather fixed over time. This procedure of presenting the result by sequentially adding control variables in this order is repeated in the robustness checks for this research question.

Table 12. Regression results for Research Question 2

PWB	Model 1	Model 2	Model 3	Model 4	Model 5
Intensity	-0.544***	-0.551***	-0.645***	-0.613***	-0.619***
	(0.114)	*(0.129)*	*(0.144)*	*(0.138)*	*(0.139)*
Coping		0.0495	-0.649	-0.538	-0.394
		(0.452)	*(0.698)*	*(0.662)*	*(0.666)*
Intensity x Coping			0.369	0.428	0.430
			(0.310)	*(0.292)*	*(0.297)*
Age				-0.0213***	-0.0234***
				(0.00791)	*(0.00799)*
Years of education				-0.0580**	-0.0568**
				(0.0228)	*(0.0231)*
Log income				-0.203	-0.206
				(0.150)	*(0.154)*
Total cultivated area in acre				0.0431	0.0475
				(0.0349)	*(0.0351)*
Reduced food consumption				-3.210***	-3.084***
				(0.195)	*(0.199)*
Agricultural self-efficacy					-0.0708***
					(0.0225)
Extraversion					-0.227***
					(0.0729)
Agreeable					0.0623
					(0.0830)
Conscientiousness					0.128
					(0.0796)
Neuroticism					-0.0649
					(0.0727)
Openness					-0.153**
					(0.0733)
Constant	45.95***	45.95***	45.98***	51.42***	53.17***
	(0.114)	*(0.114)*	*(0.117)*	*(1.695)*	*(2.060)*
Observations	2 925	2 925	2 925	2 839	2 761
R-squared	0.010	0.010	0.010	0.102	0.111

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

Estimating regression (b), we find that the adoption of a financial coping strategy did not have any significant association with PWB as the pandemic intensified.

4.2.2. Robustness

It is worth noting that both the intensity variable and the adoption of a coping strategy is highly endogenous. Hence, the variable of interest, which is the interaction term between intensity and the dummy on financial coping strategies, is also highly endogenous. Therefore, as a first robustness check, we redefine the intensity variable and examine whether the redefinitions impact the estimated association between the interaction term and PWB. This will not change the endogeneity problems, but it could provide some insight about the association between the pandemic and PWB. To capture the mechanisms through which the pandemic influenced PWB and the adopted coping strategies, we redefine intensity in two ways. The first way is to define intensity in terms of *difficulties* with livelihood during lockdown. In this case, we create dummy variables taking the value of 1 if the respondent experienced any the following problems; having no job, no access to food, no access to medical services, stranded family members, migration return, high food prices or others, and 0 otherwise, and use these variables in an unweighted index.[22] The second method is to define intensity in terms of local prevalence of *infection*. In this case, we create dummy variables taking the value of 1 if someone in the respondent's family, neighbourhood or village has been infected with the coronavirus or if someone in the respondent's village has died due to the virus.[23] Again, we create an index using these binary variables with equal weights.

The regression results using these alternative measures of intensity are presented in Table 13 and 14. In line with the results from the main regression, we find that the adoption of a financial coping strategy did not have any significant association with PWB as the pandemic intensified in any way.

[22] The questions for the intensity variable measured in terms of *difficulties* are found in the Appendix A.

[23] The questions for the intensity variable measured in terms of *infection* are found in the Appendix A.

Table 13. Robustness Research Question 2: using difficulties

PWB	Model 1	Model 2	Model 3	Model 4	Model 5
Difficulties	-1.362***	-1.353***	-1.394***	-1.051***	-1.165***
	(0.0889)	*(0.0892)*	*(0.0911)*	*(0.0935)*	*(0.0962)*
Coping		-0.640	-1.938**	-1.400	-1.302
		(0.398)	*(0.903)*	*(0.877)*	*(0.885)*
Difficulties x Coping			0.577	0.395	0.447
			(0.400)	*(0.386)*	*(0.385)*
Age				-0.0239***	-0.0265***
				(0.00780)	*(0.00781)*
Years of education				-0.0614***	-0.0622***
				(0.0221)	*(0.0222)*
Log income				-0.0897	-0.116
				(0.148)	*(0.150)*
Total cultivated area in acre				0.0188	0.0330
				(0.0346)	*(0.0344)*
Reduced food consumption				-2.297***	-1.967***
				(0.192)	*(0.203)*
Agricultural self-efficacy					-0.138***
					(0.0228)
Extraversion					-0.253***
					(0.0711)
Agreeable					0.0765
					(0.0804)
Conscientiousness					0.159**
					(0.0774)
Neuroticism					-0.0146
					(0.0695)
Openness					-0.122*
					(0.0713)
Constant	48.35***	48.38***	48.46***	51.67***	53.47***
	(0.182)	*(0.182)*	*(0.185)*	*(1.665)*	*(2.010)*
Observations	2 924	2 924	2 924	2 838	2 760
R-squared	0.107	0.108	0.109	0.150	0.169

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

Table 14. Robustness Research Question 2: using infection

PWB	Model 1	Model 2	Model 3	Model 4	Model 5
Infection	-0.225*	-0.203	-0.232*	-0.242*	-0.207
	(0.130)	*(0.130)*	*(0.132)*	*(0.128)*	*(0.130)*
Coping		-1.023**	-1.213***	-0.900**	-0.760*
		(0.403)	*(0.445)*	*(0.428)*	*(0.438)*
Infection x Coping			0.985	1.061	1.006
			(1.003)	*(0.975)*	*(0.963)*
Age				-0.0206***	-0.0226***
				(0.00798)	*(0.00806)*
Years of education				-0.0585**	-0.0580**
				(0.0229)	*(0.0232)*
Log income				-0.202	-0.212
				(0.153)	*(0.156)*
Total cultivated area in acre				0.0497	0.0538
				(0.0349)	*(0.0351)*
Reduced food consumption				-3.259***	-3.125***
				(0.195)	*(0.199)*
Agricultural self-efficacy					-0.0775***
					(0.0224)
Extraversion					-0.230***
					(0.0730)
Agreeable					0.0550
					(0.0830)
Conscientiousness					0.132*
					(0.0799)
Neuroticism					-0.0620
					(0.0727)
Openness					-0.140*
					(0.0729)
Constant	45.82***	45.88***	45.90***	51.32***	53.09***
	(0.141)	*(0.142)*	*(0.144)*	*(1.712)*	*(2.068)*
Observations	2 924	2 924	2 924	2 838	2 760
R-squared	0.001	0.004	0.004	0.099	0.108

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

To test the robustness of these results and reduce the risk of multicollinearity (Urminsky et al., 2006) we run different double-lasso regressions. We use cross-validation with 10 folds and control for age, years of education, reduced food consumption during the pandemic, personality, total cultivated area, log income and agricultural self-efficacy as our second robustness check. The output from the double-lasso regressions is found in Table 15, where the first column shows the estimated coefficient from a double-selection, the second from a partialing out-selection and the third from a cross-fit partialing out-selection.

Table 15. Results from double-lasso regression

PWB	Double-selection	Partialing out	Cross-fit partialing out
Intensity	-0.610***	-0.562***	-0.563***
	(0.14)	*(0.14)*	*(0.14)*
Coping	-0.118	-0.111	-0.252
	(0.67)	*(0.66)*	*(0.67)*
Intensity x Coping	0.412	0.330	0.346
	(0.30)	*(0.29)*	*(0.30)*
Observations	2 761	2 761	2 761

Beta coefficients; standard errors in parentheses
* p < 0.05, ** p < 0.01, *** p < 0.001

The different selection methods yield non-significant associations between the interaction term and PWB. This is in line with the main regression result in Model 4, Table 12, and suggests that the choice of control variables and number of observations did not notably influence the significance.

The third robustness check concerns the dependent variable. Since depression and stress moved in opposite directions during the pandemic, as shown in the results for research question 1, we once again split the index measuring PWB into its components: depression and stress. The outcomes of the regressions are presented in Table 16, where the regression output for depression is reported, and Table 17, where the regression output for stress is reported.

Table 16. Robustness Research Question 2: using depression

Depression	Model 1	Model 2	Model 3	Model 4	Model 5
Intensity	0.275***	0.241**	0.174	0.167	0.160
	(0.0855)	*(0.0976)*	*(0.111)*	*(0.105)*	*(0.105)*
Coping		0.230	-0.261	-0.392	-0.468
		(0.343)	*(0.521)*	*(0.503)*	*(0.509)*
Intensity x Coping			0.259	0.202	0.202
			(0.234)	*(0.220)*	*(0.226)*
Age				0.00922	0.00936
				(0.00582)	*(0.00584)*
Years of education				0.0393**	0.0355**
				(0.0165)	*(0.0166)*
Log income				-0.169	-0.135
				(0.106)	*(0.108)*
Total cultivated area in acre				-0.0453*	-0.0553**
				(0.0245)	*(0.0255)*
Reduced food consumption				2.190***	2.021***
				(0.140)	*(0.141)*
Agricultural self-efficacy					0.0833***
					(0.0158)
Extraversion					0.137**
					(0.0543)
Agreeable					-0.0887
					(0.0598)
Conscientiousness					-0.0968*
					(0.0577)
Neuroticism					0.0358
					(0.0538)
Openness					0.0772
					(0.0541)
Constant	3.641***	3.643***	3.670***	3.858***	3.028**
	(0.0817)	*(0.0816)*	*(0.0835)*	*(1.201)*	*(1.464)*
Observations	2 924	2 924	2 924	2 838	2 760
R-squared	0.005	0.005	0.005	0.091	0.103

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

Table 17. Robustness Research Question 2: using stress

Stress	Model 1	Model 2	Model 3	Model 4	Model 5
Intensity	0.273***	0.314***	0.477***	0.452***	0.466***
	(0.0553)	*(0.0647)*	*(0.0738)*	*(0.0742)*	*(0.0753)*
Coping		-0.281	0.920**	0.941***	0.875**
		(0.241)	*(0.367)*	*(0.360)*	*(0.358)*
Intensity x Coping			-0.634***	-0.638***	-0.640***
			(0.143)	*(0.142)*	*(0.141)*
Age				0.0124***	0.0143***
				(0.00453)	*(0.00461)*
Years of education				0.0211	0.0237*
				(0.0133)	*(0.0136)*
Log income				0.364***	0.333***
				(0.0902)	*(0.0929)*
Total cultivated area in acre				-0.00155	0.00355
				(0.0240)	*(0.0246)*
Reduced food consumption				1.042***	1.082***
				(0.113)	*(0.117)*
Agricultural self-efficacy					-0.0111
					(0.0132)
Extraversion					0.0843**
					(0.0420)
Agreeable					0.0225
					(0.0486)
Conscientiousness					-0.0351
					(0.0481)
Neuroticism					0.0266
					(0.0419)
Openness					0.0707
					(0.0434)
Constant	10.40***	10.40***	10.34***	4.768***	3.984***
	(0.0646)	*(0.0646)*	*(0.0666)*	*(0.999)*	*(1.207)*
Observations	2 924	2 924	2 924	2 838	2 760
R-squared	0.008	0.008	0.014	0.055	0.059

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

In Model 5, Table 16, we note that the association between the adoption of a financial coping strategy as the intensity of the pandemic increases and depression is insignificant. For stress, we note that the association is significant and negative, as seen in Model 5, Table 17. This suggests that adopting a financial coping strategy as the pandemic intensified by one level was associated with a decrease in stress by 7.5%, on average.[24] However, due to the low internal consistency of the stress scale in this wave, as shown and discussed in section 3.4.1., we have reasons for being careful in interpreting this result.

As a fourth robustness check, we use a weighted index of PWB (allocating the weights through

[24] Comparing the pre-Covid-19 value (in Table 3) with the estimated coefficient (in Table 17).

PCA) as a dependent variable where high values indicate higher PWB, as previously. The regression output from this robustness check is presented in Table 18.

Table 18. Robustness Research Question 2: using PCA

PWB using PCA	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Intensity	-0.0379*	-0.0390	-0.0199	-0.0301	-0.0334
	(0.0231)	*(0.0258)*	*(0.0283)*	*(0.0276)*	*(0.0281)*
Coping		0.00708	0.148	0.165	0.161
		(0.0805)	*(0.133)*	*(0.129)*	*(0.128)*
Intensity x Coping			-0.0744	-0.0555	-0.0568
			(0.0649)	*(0.0620)*	*(0.0611)*
Age				-0.00303**	-0.00328**
				(0.00148)	*(0.00149)*
Years of education				-0.00162	-0.00206
				(0.00429)	*(0.00438)*
Log income				0.127***	0.145***
				(0.0293)	*(0.0302)*
Total cultivated area in acre				0.00634	0.00307
				(0.00530)	*(0.00534)*
Reduced food consumption				-0.235***	-0.258***
				(0.0370)	*(0.0387)*
Agricultural self-efficacy					0.0172***
					(0.00413)
Extraversion					-0.0104
					(0.0139)
Agreeable					0.0140
					(0.0151)
Conscientiousness					-0.00293
					(0.0144)
Neuroticism					-0.0158
					(0.0138)
Openness					-0.0238*
					(0.0135)
Constant	0.0212	0.0213	0.0135	-1.170***	-1.188***
	(0.0216)	*(0.0216)*	*(0.0220)*	*(0.331)*	*(0.399)*
Observations	2 924	2 924	2 924	2 838	2 760
R-squared	0.001	0.001	0.002	0.031	0.038

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

We note that the association between the interaction term and the weighted measure on PWB is not significant, which is in line with the estimated coefficient for the unweighted measure on PWB.

4.3. Were KALIA instalments associated with higher psychological wellbeing during the pandemic?

4.3.1. Main analysis

Table 19 shows the estimated ATE on unweighted PWB of the KALIA instalments during the pandemic, which was estimated through both propensity score matching (PSM) and kernel based matching (KBM) using a logit model as a treatment model. We match the households on log income, education and total cultivated area.

Table 19. Matching estimates for Research Question 3, KALIA

PWB	PSM	KBM
Average Treatment Effect of KALIA	-1.487***	-1.406***
	(0.357)	*(0.335)*
Treated	833	784
Untreated	2 023	1 889
Observations	2 856	2 856

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Overall, the different matching estimates suggest that receiving the KALIA instalments had a negative ATE on PWB. This means that those who received the instalments, and are similar in terms of income, education and total cultivated area, had lower PWB on average.

4.3.2. Robustness

The chosen matching variables could have had an impact on the estimated ATE. Hence, as robustness check, we match the households on log income and total cultivated area only. This is because education might not be as explanatory for participation in the KALIA scheme as income and land are, since these are implicit criterias for the KALIA scheme, whilst education is not. In addition, we note in Table B5 that the years of education are lower on average for the treatment group than for the control group, which contradicts our initial hypothesis that those with higher education self-select into government benefit schemes.

Table 20. Matching estimates for Research Question 3, KALIA: Robustness matching on log income and total cultivated area

PWB	PSM	KBM
Average Treatment Effect of KALIA	-1.095***	-1.193***
	(0.307)	*(0.291)*
Treated	837	800
Untreated	2 029	1 920
Observations	2 866	2 866

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 20 shows the estimated ATE on unweighted PWB of the KALIA instalments during the pandemic when matching only on log income and total cultivated area, which was estimated, as previously, through PSM and KBM matching using a logit model as a treatment model.

The different matching estimates in Table 20 are in line with that of the main estimates in Table 19, suggesting that matching on education did not significantly change the ATE of the KALIA instalments during the pandemic.

As our second robustness check, we run the same estimations but with other dependent variables: a weighted index of PWB, a depression scale and a stress scale, and matching on the same observables as in the main analysis (log income, education and total cultivated area). The estimated ATEs for these variables are presented in Table 21.

Table 21. Matching estimates for Research Question 3, KALIA: Robustness using different dependent variables

	PWB using PCA		**Depression**		**Stress**	
	PSM	**KBM**	**PSM**	**KBM**	**PSM**	**KBM**
Average Treatment Effect of KALIA	0.020	0.003	0.990***	0.998***	0.236	0.181
	(0.045)	*(0.046)*	*(0.211)*	*(0.190)*	*(0.157)*	*(0.140)*
Treated	828	781	828	774	828	773
Untreated	2 010	1 878	2 010	1 878	2 010	1 880
Observations	2 838	2 838	2 838	2 838	2 839	2 839

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Table 21, we note that the ATE on stress and on the weighted PWB is insignificant, whilst it was significant for depression. This suggests that the negative association between receiving the KALIA instalments and PWB, as seen in the main regression in Table 19, was partly driven by higher depression, but is not necessarily robust.

Some additional robustness checks are performed concerning the matching algorithm and the instalment. These are presented in Appendix B in Tables B2, B3 and B4. The findings suggest that the change of matching algorithm to caliper matching did not affect the estimated ATE, that the negative ATE on unweighted PWB was partly driven by receiving only the first instalment, and that the negative ATE on the unweighted PWB was also prevalent in the shorter run.[25]

[25] Caliper matching provides a limit on the quality of the matches. If no controls are available with a propensity score within the value of a case, that case is not matched (Smith & Todd, 2005). We use a radius of 0.1 which is common in similar studies (e.g. Covarrubias, Davis & Winters, 2012; Arau Pontones, 2014). This means that the matching takes place within 10 percentage points of each treated household's propensity score. We also tested a caliper width of 0.01 and obtained the similar results.

5. Discussion

5.1 Results

In this thesis, three research questions were examined. First, we asked if the pandemic affected the psychological wellbeing of Indian rice farmers. To investigate this, we used a linear fixed effects model specification and found that the pandemic did not seem to have any significant impact on PWB. This could be explained by the fact that depression decreased, whilst stress increased. Moreover, excluding the phone survey was shown to influence the results, suggesting that the change in method or/and the duration of the pandemic were important confounders for PWB.

Relating these findings to the literature, we note that previous research has generally shown a negative association between the pandemic and different measures of overall wellbeing, such as depression, anxiety and stress, in different contexts (e.g., Allen et al., 2020; Bau et al., 2021; Boateng et al., 2021; Bueno-Notivo et al., 2021; Goularte et al., 2020; Grover et al., 2020; Hamadani et al., 2020; Rajkumar, 2020; Raju et al., 2021). Hence, the decrease in depression is not in line with the literature. However, we should remember that very few of these studies were conducted in India (Gaidhane et al., 2020) or focused on farmers (Ceballos et al., 2020; Gaidhane et al., 2020; Kumar et al., 2021; Menon & Schidt-Vogt, 2022). Moreover, few of these studies have data surveying as many households and spanning from 2018 to the end of 2021, with observations both before and after the outbreak of Covid-19 (e.g., Allen et al., 2020; Grover et al., 2020; Raju et al., 2021), like we have. Thus, we could say that our findings are reliable. However, it is worth noting that depression was relatively high in 2018, whilst stress was low, as seen in Figure 4 and 5, which clearly affected the results. If omitting this wave, we would probably see an increase in both depression and stress during the pandemic, as in line with other studies. It should also be noted that the livelihoods of Indian rice farmers were especially affected in the longer run and indirectly (Bundervoet et al., 2020) and that stress eventually results in depression (Hou et al., 2020; Ozer et al., 2011; Siddique & D'Arcy, 1984; Van Praag, 2004; Ventevogel et al., 2015), which could imply that depression levels might increase further in the future, despite economic recovery, as found by Durizzo et al., (2022).

Second, we asked if financial coping strategies were associated with higher psychological wellbeing as the pandemic intensified. Here, we used a linear interaction specification where the intensity of the pandemic was interacted with the adoption of financial coping strategies. Using this specification and only the last survey wave, we found that the adoption of financial coping strategies was not significantly associated with PWB as the pandemic intensified, regardless of how we defined intensity. However, when splitting up the index, we note that whilst the adoption of such strategies did not affect depression, it significantly reduced stress in all models. Since this study is the first to explore this association, we lack benchmark studies.

Related research mostly focuses on the prevalence of different financial coping strategies (e.g Hammond et al., 2022; Hill & Narayan, 2020; Kansiime et al., 2022; Murakami, 2022; Rahman & Matin, 2020) or how psychological factors affected the choice of coping strategy during the pandemic (Haushofer et al., 2020; Yazdanpanah et al., 2021). Thus, our results, showing that adopting financial coping strategies significantly reduced stress, provide an important addition to the literature and highlight the need for further investigations, preferably using panel data, to be able to explore the causal mechanisms.

Lastly, we asked if financial state government support had a positive association with psychological wellbeing during the pandemic. Here, we used a propensity score matching model specification where we matched the farmers on income, education and land. We found that receiving the instalments were negatively associated with PWB during the pandemic, even when only matching on income and land. This negative association was partly driven by higher depression and receiving only the first instalment, and was evident even in the shorter run. The findings are not in line with the broad literature on the impact of cash transfers on PWB suggesting mainly positive, if any, associations, as discussed in section 3.4.3 and highlighted in Hjelm et al. (2017). Worth noting, however, is that depressive symptoms are not as responsive to cash transfers like other dimensions of PWB (Ohrnberger et al., 2020; Romero et al., 2021; Zimmerman et al., 2021) and that trust in political institutions mediates the association between wellbeing and benefit transfers (Gassmann et al., 2021). However, as we could not possibly match on all important observables predicting participation, it could be that we had matching on unobservables and that more depressed respondents self-selected into the scheme. It could also be that the respondents were affected by something else, that was not related to the pandemic nor income, land or education, which might have elevated depression in the treatment group. In Table B5, we learn that those who received the instalments had significantly higher depression, reduced their food consumption more, had lower income and higher self-efficacy, compared to the control group. This suggests that we might have had some selection on unobservables.

We note that this study is also the first to explore the association between PWB and receiving the KALIA instalments during the pandemic, as well as examining the role of the number of instalments and the persistence of the mental health impacts for the treated. Studies on financial government support in LMIC during the pandemic do not generally suggest a negative impact on PWB (Banerjee et al., 2020; Gupta et al., 2021a; Ohrnberger et al., 2020; Romero et al., 2021; Zimmerman et al., 2021). There is, however evidence suggesting that the financial government support in India during the pandemic was insufficient (Gentilini et al., 2020; IMF, 2021b) and inadequate (Ceballos et al., 2020; Goyal et al., 2021; Irudaya et al., 2020) and that there was significant variation in local government response to the livelihood threats of the pandemic in India and Nepal (Gupta et al., 2021b). These findings point at the role of institutions' political will and capacity to provide sufficient livelihood support and maintain wellbeing during crises.

5.2 Policy implications

The policy implications of these results are several. First, the findings of this thesis highlight the heterogeneous impacts on stress and depression, in shorter and longer run. This is important to better understand the dynamics of policy impacts on PWB. Second, the findings emphasise the resilience of households in times of crisis and show that they are willing to adopt mostly problem-focused coping strategies and thereby optimise their utility. This is in line with Adamus and Grežo (2021) and points at the role of individual response to shocks, and the need to further explore this association and how this response could be enhanced by reducing constraints. Third, with regards to financial state government support, the findings of this thesis suggest policymakers to investigate and evaluate the KALIA scheme and its design in order to assess its efficiency. This is important as household-level coping mechanisms are unlikely to be enough to mitigate the economic harm of pandemics in the longer run (Adamus & Grežo, 2021; Feuerbacher et al., 2021; Gupta et al., 2021b; Marjanovic et al., 2015), especially for the rural poor as they have been found unable to adopt active financial coping strategies during previous idiosyncratic and covariate shocks (Alem & Colmer, 2022; Pradhan & Mukherjee, 2018; Yilma et at., 2014).

5.3 Limitations and Future Research

The first limitation of this thesis relates to the interview-administered surveys and the reliance on subjective reports. This affects the reliability of the analyses as there might be a discrepancy between stated behaviours and revealed behaviours, which we could not control for in this study. Another issue with the surveys being interview-administered lies in the increased risk for *social desirability bias* as it has been shown that respondents underreport on depressive symptoms (Latkin et al., 2017) and on other sensitive topics in such surveys (Tourangeau et al., 2000). [26] Some studies suggest that this bias may be larger in phone surveys than face to face as respondents tend to be more suspicious and less cooperative in phone surveys (Holbrook et al., 2003), whilst others challenge these conclusions (e.g., Aneshensel et al., 1982; Novick, 2008; Pinto-Meza et al., 2005).

The second limitation concerns the way the index on PWB was constructed. Referring to the literature, where depression and stress correlate (Hou et al., 2020; Siddique & D'Arcy, 1984) and explain PWB to a large extent (Siddique & D'Arcy, 1984; Qingbo et al., 2009), we used both scales in our (unweighted) index. However, given the estimates from the robustness tests, showing that depression and stress were differently affected during the pandemic, it might be misleading to refer to PWB as a holistic concept of only depression and stress. Moreover, the difference in the estimated impact between the unweighted and weighted index suggests that the way in which one measures and defines PWB matters. The relatively low internal consistency of

[26] Social desirability bias stems from respondents reporting what is socially desirable or what they believe will please the interviewer (Lee & Woodliffe, 2010; Leggett et al., 2003).

the stress scale (Taber, 2018) in the phone survey, as discussed in section 3.4.1, also raises concerns and suggests that the significant positive association between the PWB and the adoption of financial coping strategies as the pandemic intensifies is not very robust.

The third limitation concerns omitted variable bias, which is an issue in most of our models. Especially as we do not control for other shocks causing stress and depression in our context such as input price fluctuations (Addison et al., 2016; Feuerbacher et al., 2021), other diseases, pests, conflicts, political shocks (Clarke & Dercon, 2009) or climate change (Birthal & Hazrana, 2019; Lawrence-Bourne et al., 2020; Rasul, 2021). This bias is stronger for the second and third research questions, where we use cross-sectional data from the phone survey, and have highly endogenous variables of interest. Even though we try to overcome this issue using relevant control variables and quasi-experimental methods such as matching, the endogeneity still persists as we could not control for fixed effects or apply other quasi-experimental methods. We also disregard other coping strategies, such as emotional (Mayo et al., 2022) or psychological (Mayo et al., 2022; Mumtaz et al., 2021) coping, migration (Feuerbacher et al., 2021), off-farm employment (Gupta et al., 2021b) and other sources of support, both from the government and elsewhere, that were common during the pandemic (Chen et al., 2021; Ohrnberger et al., 2020; Romero et al., 2021; Zimmerman et al., 2021). Hence, we could not make any causal claims for the last two research questions.

Finally, we note that there might be a risk of reverse causality in the second and third research questions. Individuals with lower PWB might be more likely to experience the pandemic as more intense and less likely to adopt financial coping strategies due to lack of hope, leading to avoidance (Holmgren et al., 2019; Marjanovic et al., 2015; Rand & Cheavens, 2009). Besides limitations concerning the internal validity, the fact that the sample is richer than the average of Odisha questions the external validity of our results, especially since richer households are more able to adopt financial coping strategies (Pradhan & Mukherjee, 2018; Yilma et at., 2014).

Given these limitations and the lack of literature exploring these associations, there is certainly room for future research to better understand the mediating role of financial coping strategies for psychological wellbeing in times of crisis. More specifically, future studies could make sure to ask households about their financial coping behaviour over time, use longer time periods to distinguish short-term and long-term impact, and study revealed rather than stated behaviour, symptoms and severity of crisis. Finally, as depression and stress are distinct measures, future research could focus on these separately. Considering that the pandemic, and other crises, are prevalent and evident, our thesis could be valuable in informing future research on how wellbeing and the resilience of households in LMIC, and elsewhere, could be maintained.

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Appendix A

Depression and stress

The PHQ-9 survey is used to estimate the depression severity within the sample. The questions asked in the survey are the following: *Over the last month, how often have you been bothered by any of the following problems?*

1. Feeling tired or having little energy
2. Poor appetite or overeating
3. Trouble falling or staying asleep, or sleeping to much
4. Moving or speaking so slowly that other people could have noticed. Or the opposite – being so fidgety or restless that you have been moving around a lot more than usual
5. Trouble concentrating on things such as reading the newspaper or watching television or any work
6. Little interest or pleasure in doing things
7. Feeling down, depressed or hopeless
8. Feeling bad about yourself or that you are a failure or have let yourself or your family down
9. Thoughts that you would be better off dead, or of hurting yourself in some way

The respondent answers these questions on a scale where 0 indicates not at all (0 days), 1 indicates several days (1-10 days), 2 indicates more than half of the time (16-10 days) and 3 indicates nearly every day (more than 20 days) in the last month. Each answer is then summed into an unweighted index ranging from 0 to 27, which can be translated into the following levels of depression severity (Kroenke et al., 2001):

- 0 - 4: Minimal depression
- 5 - 9: Mild depression
- 10 - 14: Moderate depression
- 15 - 19: Moderately severe depression
- 20 - 27: Severe depression

For the stress scale, the Perceived Stress Scale-4 (PSS-4) is used, and the following questions are asked: *In each of the questions, how often have you felt or thought in a certain way?*

1. How often have you felt that you were unable to control the important things in your life?
2. How often have you felt confident about your ability to handle your personal problems?
3. How often have you felt that things are going your way?

4. How often have you felt difficulties were piling up so high that you could not overcome them?

The respondent answers on a scale where 1 indicates never, 2 almost never, 3 sometimes, 4 fairly often and 5 very often. Question 2 and 3 are asked in such a way that high values indicate low stress whereas for the remaining questions, high values indicate high stress. Therefore, the answers to question 2 and 3 are recoded so that 1 indicates very often, 2 indicates fairly often, 3 indicates sometimes, 4 indicates almost never. Hence, high values indicate higher levels of perceived stress for all questions.

All questions on depression and stress are asked in all waves, which could be seen in Table A1 and A2. The first two waves constitute the pre-Covid-19 sample, and are collected in 2018 and 2020, i.e., pre-Covid-19, face to face. The two remaining waves constitute the endline, and are collected in 2020 and 2021, post-Covid-19. As complement to our main analysis, we conducted paired t-test to test whether there was a significant difference between the mean values of depression and stress before and after the outbreak. We found that whilst most indicators on depression have significantly lower means in the post Covid-19 sample, the opposite is true for indicators on stress. For some indicators, the difference was not significant, such as having troubles with concentration, thinking that one would be better off dead or feeling unable to control important things in life.

Table A1. Answers PHQ-9

Questions depression scale answers on a scale from 0 - 3	Baseline	Baseline- Post Covid-19 F2F	Post Covid-19 F2F	Post Covid-19 F2F - Post Covid-19 phone	Post Covid-19 phone	Full sample
Feeling tired or having little energy	0.633	***	0.380	***	0.568	0.566
	(0.664)		*(0.577)*		*(0.694)*	*(0.666)*
Poor appetite or overeating	0.547	***	0.400	***	0.508	0.507
	(0.745)		*(0.592)*		*(0.792)*	*(0.738)*
Trouble falling or staying asleep, or sleeping too much	0.584	***	0.412	***	0.517	0.531
	(0.799)		*(0.640)*		*(0.745)*	*(0.757)*
Moving or speaking so slowly that other people could have noticed? Or being so fidgety or restless that you have been moving around a lot more than usual?	0.411 *(0.719)*	***	0.302 *(0.576)*	*	0.267 *(0.555)*	0.344 *(0.647)*
Trouble concentrating on things	0.441	***	0.298		0.325	0.376
	(0.739)		*(0.571)*		*(0.624)*	*(0.677)*
Little interest or pleasure in doing things	0.586	***	0.387	***	0.548	0.537
	(0.750)		*(0.591)*		*(0.854)*	*(0.764)*
Feeling down, depressed, or hopeless	0.528	***	0.283	***	0.707	0.543
	(0.765)		*(0.537)*		*(0.869)*	*(0.781)*
Feeling bad about yourself or that you are a failure or have let yourself or your family down	0.415 *(0.733)*	***	0.187 *(0.459)*	***	0.258 *(0.559)*	0.321 *(0.642)*
Thoughts that you would be better off dead, or of hurting yourself in some way?	0.124 *(0.466)*		0.114 *(0.353)*		0.097 *(0.340)*	0.113 *(0.408)*
N	4 288		1 596		2 925	8 809

Mean values; standard deviation in parentheses
Paired t-test was used to test significant differences between the mean values;
* p < 0.05, ** p < 0.01, *** p < 0.001

Table A2. Answers SPSS-4

Questions stress scale answers on a scale from 1 - 5	Baseline	Baseline - Post Covid-19 F2F	Post Covid-19 F2F	Post Covid-19 F2F - Post Covid-19 phone	Post Covid-19 phone	Full sample
How often have you felt that you were unable to control the important things in your life?	1.835 *(0.989)*		1.826 *(0.977)*	***	2.698 *(1.213)*	2.120 *(1.142)*
How often have you felt confident about your ability to handle your personal problems?	2.395 *(1.148)*	***	2.242 *(1.184)*	***	2.796 *(1.265)*	2.500 *(1.213)*
How often have you felt that things were going your way?	2.348 *(1.198)*	***	2.510 *(1.224)*	***	2.245 *(1.176)*	2.343 *(1.199)*
How often have you felt difficulties were piling up so high that you could not overcome them?	1.960 *(1.116)*	***	2.143 *(1.084)*	***	2.817 *(1.328)*	2.278 *(1.247)*
N	4 288		1 596		2 925	8 809

Mean values; standard deviation in parentheses
Paired t-test was used to test significant differences between the mean values;
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3 shows the sample's depression rate classified according to the PHQ-9, for all waves separately and an average classification for the full sample, i.e., all waves.

Table A3. Depression severity

Classification according to PHQ-9	Pre-Covid-19		Post Covid-19 F2F		Post Covid-19 phone		Full Sample	
	N	%	N	%	N	%	N	%
Minimal, 0-4	3 020	65.95	1 276	78.09	2 067	70.07	6 363	69.44
Mild, 5-9	932	20.35	314	19.22	607	20.58	1 853	20.22
Moderate, 10-14	505	11.03	37	2.26	222	7.53	764	8.34
Moderately severe, 15–19	99	2.16	6	0.37	42	1.42	147	1.6
Severe, 20–27	23	0.5	1	0.06	12	0.41	36	0.39
Total	4 579	100	1 634	100	2 950	100	9 163	100

Correlation matrices for depression and stress

Table A4 - A11 presents the correlation between each of the depression questions constituting the PHQ-9 and each of the stress questions constituting the PSS-4 for each of the survey waves.

Table A4. Correlations: Answers PHQ-9 survey wave 1

	Feeling tired	Appetite	Sleep status	Speaking	Concentrating	Interest	Feeling down	Feeling bad	Hurting yourself
Feeling tired	1.0000								
Appetite	0.4810	1.0000							
Sleep status	0.4442	0.5188	1.0000						
Speaking	0.3372	0.4706	0.4852	1.0000					
Concentrating	0.3180	0.4669	0.5044	0.5369	1.0000				
Interest	0.3390	0.3801	0.3954	0.4601	0.4699	1.0000			
Feeling down	0.2458	0.3498	0.4615	0.4731	0.4782	0.4378	1.0000		
Feeling bad	0.1821	0.3575	0.4153	0.4707	0.4860	0.4183	0.5704	1.0000	
Hurting yourself	0.1474	0.1902	0.2077	0.2334	0.2447	0.1875	0.2604	0.3069	1.0000

Table A5. Correlations: Answers PSS-4 survey wave 1

	Unable to control the important things	Confident about your ability	Felt that things were going your way	Difficulties were piling up
Unable to control important things	1.0000			
Confident about your ability	0.2554	1.0000		
Felt that things were going your way	0.2673	0.3345	1.0000	
Difficulties were piling up	0.4107	0.2916	0.2741	1.0000

Table A6. Correlations: Answers PHQ-9 survey wave 2

	Feeling tired	Appetite	Sleep status	Speaking	Concentrating	Interest	Feeling down	Feeling bad	Hurting yourself
Feeling tired	1.0000								
Appetite	0.4338	1.0000							
Sleep status	0.5086	0.5376	1.0000						
Speaking	0.3710	0.4161	0.4794	1.0000					
Concentrating	0.3394	0.4330	0.4680	0.5513	1.0000				
Interest	0.4001	0.4036	0.4921	0.4650	0.4463	1.0000			
Feeling down	0.3800	0.4093	0.3923	0.3733	0.4366	0.4761	1.0000		
Feeling bad	0.3590	0.4789	0.4870	0.4387	0.4623	0.4489	0.5248	1.0000	
Hurting yourself	0.2573	0.3594	0.3828	0.3629	0.3861	0.4058	0.3746	0.5604	1.0000

Table A7. Correlations: Answers PSS-4 survey wave 2

	Unable to control the important things	Confident about your ability	Felt that things were going your way	Difficulties were piling up
Unable to control important things	1.0000			
Confident about your ability	0.2904	1.0000		
Felt that things were going your way	0.2080	0.5924	1.0000	
Difficulties were piling up	0.4148	0.2529	0.2761	1.0000

Table A8. Correlations: Answers PHQ-9 survey wave 3

	Feeling tired	Appetite	Sleep status	Speaking	Concentrating	Interest	Feeling down	Feeling bad	Hurting yourself
Feeling tired	1.0000								
Appetite	0.3773	1.0000							
Sleep status	0.3438	0.3814	1.0000						
Speaking	0.2112	0.1901	0.3177	1.0000					
Concentrating	0.2694	0.2934	0.3717	0.3407	1.0000				
Interest	0.2973	0.2965	0.3220	0.2557	0.2480	1.0000			
Feeling down	0.2616	0.2708	0.2499	0.2627	0.2362	0.2891	1.0000		
Feeling bad	0.1699	0.1635	0.1480	0.1803	0.2184	0.1706	0.1973	1.0000	
Hurting yourself	0.1993	0.1715	0.1749	0.2559	0.2605	0.2091	0.2790	0.3593	1.0000

Table A9. Correlations: Answers PSS-4 survey wave 3

	Unable to control the important things	Confident about your ability	Felt that things were going your way	Difficulties were piling up
Unable to control important things	1.0000			
Confident about your ability	0.2972	1.0000		
Felt that things were going your way	0.1323	0.3825	1.0000	
Difficulties were piling up	0.4062	0.2739	0.2571	1.0000

Table A10. Correlations: Answers PHQ-9 survey wave 4

	Feeling tired	Appetite	Sleep status	Speaking	Concentrating	Interest	Feeling down	Feeling bad	Hurting yourself
Feeling tired	1.0000								
Appetite	0.4580	1.0000							
Sleep status	0.2978	0.3995	1.0000						
Speaking	0.1412	0.1950	0.3574	1.0000					
Concentrating	0.2349	0.3212	0.4215	0.3925	1.0000				
Interest	0.2565	0.3328	0.3820	0.3221	0.6106	1.0000			
Feeling down	0.2718	0.3171	0.3704	0.2848	0.5250	0.7181	1.0000		
Feeling bad	0.1719	0.2432	0.2961	0.2502	0.3134	0.3208	0.3636	1.0000	
Hurting yourself	0.1542	0.2290	0.2163	0.1973	0.2801	0.3026	0.3239	0.3929	1.0000

Table A11. Correlations: Answers PSS-4 survey wave 4

	Unable to control the important things	Confident about your ability	Felt that things were going your way	Difficulties were piling up
Unable to control important things	1.0000			
Confident about your ability	0.1243	1.0000		
Felt that things were going your way	-0.0323	0.0777	1.0000	
Difficulties were piling up	0.5675	0.1282	0.0069	1.0000

The intensity variable

For the second research question, fourth wave data (the endline phone survey) is used to measure the intensity of Covid-19. The intensity variable is an index composed of six binary variables (taking the value of 1 if the respondent experienced a particular problem, and 0 otherwise) with equal weights. Hence, the index ranges from zero to six, where zero indicates that the respondent did not experience any of these risks at all, whilst six indicates that the respondent experienced all the risks. The question used to create the intensity index are the following:

- ❖ Did you face any of these risks related to Covid-19?
  a) Reduced production due to limited input access
  b) Reduced agricultural income due to marketing restrictions
  c) Reduced non-agricultural incomes due to reduced opportunities
  d) Medical / health emergencies
  e) Psychological stress/issues
  f) Food shortage (if any)

From this question six binary variables are created: "*reduced production due to limited input access*", "*reduced agricultural income due to marketing restrictions*", "*reduced non-agricultural incomes due to reduced opportunities*", "*medical/health emergencies*", "*psychological stress/issues*" and "*food shortage*". The variables taking the value 1 if the respondent faced the specific risk and 0 otherwise. These variables are then combined into the intensity index. Table 2 shows how many of the respondents that faced the different risks.

Alternative intensity variables

For the second research question, two alternative specifications measuring the intensity of the Covid-19 were used.

The first index measure whether the respondent experienced any difficulties during the lockdown, in order to create this index, the following questions were used:

- ❖ Were you able to sustain your life without any difficulties during the lockdown/s?
    a) Yes, no issues
    b) Faced some difficulties
    c) Faced serious difficulties

If the respondent answered b or c, following question were asked:

- ❖ What type of difficulties (multiple options are possible)
    a) No job
    b) Access to food
    c) Access to medical services
    d) Family member stranded
    e) Return migration
    f) High food prices
    g) Others

To create the index we used the latter part of the question that asked the respondents what type of difficulties they experienced. From this question we created binary variables for each of the difficulties (taking the value 1 if the respondent experienced a particular difficulty, and 0 otherwise). These variables were then combined into the intensity (difficulties) index, with equal weights. Hence, the index ranges from zero to seven, where zero indicates that the respondent did not experience any of these difficulties at all, whilst seven indicates that the respondent experienced all the difficulties. Table A12 shows how many of the respondents experienced the different difficulties.

The second index is related to the infection rate of Covid-19 in the respondent's immediate area. In order to crate this index, the following questions were used:

- ❖ In the last 12 month has anyone in your family been infected with the Coronavirus?
    a) Yes
    b) No

- ❖ In the last 12 months has anyone in your village been infected with Coronavirus?
  a) Yes
  b) No

- ❖ How many people died due to the Coronavirus in the village?

The third question was then recoded, taking the value of 1 if the respondent had anyone in their village that had died due to the Coronavirus, and 0 otherwise. From the three binary variables (taking the value 1 if the respondent had experienced any of the scenarios, and 0 otherwise) the index was created, with equal weights to the three questions. Hence, the index ranges from zero to three, where zero indicates that the respondent did not experience any of these scenarios at all, whilst three indicates that the respondent experienced all the escenarios. Table A12 shows how many of the respondents experienced the different scenarios.

Table A12. Alternative specifications of Covid-19 intensity

Section A: Intensity using difficulties	**Wave 4**	**Section B: Intensity using infection**	**Wave 4**
No Job (%)	22.9	Someone in your family been infected with Coronavirus (%)	6.4
	(0.420)		*(0.245)*
Access to food (%)	35.0	Someone in your neigborhood been or village been in infected with Comonavirus (%)	55.1
	(0.477)		*(0.497)*
Access to medical services (%)	22.1	Someone in your village has died due to the Coronavirus (%)	15.1
	(0.415)		*(0.358)*
Family member stranded (%)	14.7	Infection level 1 (%)	35.2
	(0.354)		*(0.478)*
Return migration (%)	13.0	Infection level 2 (%)	17.0
	(0.336)		*(0.376)*
High food price (%)	55.1	Infection level 3 (%)	1.9
	(0.497)		*(0.138)*
Others (%)	35.5		
	(0.479)		
Difficulties level 1 (%)	14.1		
	(0.348)		
Difficulties level 2 (%)	21.6		
	(0.412)		
Difficulties level 3 (%)	31.4		
	(0.464)		
Difficulties level 4 (%)	22.0		
	(0.414)		
Difficulties level 5 (%)	7.4		
	(0.261)		
Difficulties level 6 (%)	2.9		
	(0.167)		
Difficulties level 7 (%)	0.6		
	(0.082)		
N	2 924		2 924

Mean values; standard deviation in parentheses

Reduced food consumption

For the second research question, fourth wave data (the endline phone survey) are used to measure whether the respondent had to reduce their food consumption as a result of Covid-19. The following question are used to create the control variable *reduced food consumption*:

- ❖ In the last 12 month has your family food consumption reduced due to Covid-19?
  a) Significantly reduced
  b) Moderately reduced
  c) Somewhat reduced
  d) Slightly reduced
  e) Not at all

From this question a new binary variable was created. The binary variable takes the value 1 if the respondent had reduced their food consumption, i.e., if the respondent answered a, b, c or d, and 0 if the respondent's food consumption has not been reduced, i.e., the respondent answered c. Table A13 shows that most respondents, approximately 54%, had to reduce their food consumption due to Covid-19.

Table A13. Reduced food consumption

Reduced food consumption (%)	53.9
	(0.499)
No reduced food consumption (%)	46.1
	(0.499)
N	2 950
Mean values; standard deviation in parentheses	

Agricultural self-efficacy

To create the index estimating the agricultural self-efficacy among the farmers, three variables each ranging from 1 to 5 were used and combined. Hence, the agricultural self-efficacy index ranges from 3 to 15, where 3 indicates lowest agricultural self-efficacy and 15 indicates the highest agricultural self-efficacy. The questions used to create the agricultural self-efficacy index was the following:

1. I have little control over what happens to my agricultural production
2. Luck is very important for what happens to my agricultural production
3. My agricultural production does not depend on the amount of effort I put in

The respondents answered in a scale where, 1 indicates strongly agree, 2 indicates agree, 3 indicates neither agree or disagree, 4 indicates disagree and 5 indicates strongly agree. Table A14 presents how the respondents answered on each question, while Table A15 presents the agricultural self-efficacy index.

Table A14. Agricultural self-efficacy

I have little control over what happens to my agricultural production		**Luck is very important for what happens to my agricultural production**		**My agricultural production does not depend on the amount of effort I put in**	
Strongly agree (%)	18.1	Strongly agree (%)	19.0	Strongly agree (%)	5.6
	(0.385)		*(0.392)*		*(0.230)*
Agree (%)	44.4	Agree (%)	46.6	Agree (%)	20.4
	(0.497)		*(0.499)*		*(0.403)*
Neither agree or disagree (%)	17.4	Neither agree or disagree (%)	14.6	Neither agree or disagree (%)	23.8
	(0.379)		*(0.353)*		*(0.426)*
Disagree (%)	16.8	Disagree (%)	16.9	Disagree (%)	36.5
	(0.374)		*(0.375)*		*(0.482)*
Strongly disagree (%)	3.3	Strongly disagree (%)	0.029	Strongly disagree (%)	13.7
	(0.180)		*(0.168)*		*(0.344)*
N	1 612	*N*	1 612	*N*	1 612

Mean values; standard deviation in parentheses

Table A15. Agricultural self-efficacy index

	Agricultural self-efficacy index
Missing (%)	45.4
	(0.498)
Score 3 (%)	0.0
	(0.018)
Score 4 (%)	0.2
	(0.049)
Score 5 (%)	2.7
	(0.162)
Score 6 (%)	10.9
	(0.311)
Score 7 (%)	10.2
	(0.302)
Score 8 (%)	10.8
	(0.311)
Score 9 (%)	6.8
	(0.253)
Score 10 (%)	5.3
	(0.223)
Score 11 (%)	2.2
	(0.147)
Score 12 (%)	3.7
	(0.188)
Score 13 (%)	1.1
	(0.104)
Score 14 (%)	0.6
	(0.080)
Score 15 (%)	0.1
	(0.032)
N	2 950

Mean values; standard deviation in parentheses

The Big Five Personality Traits

To estimate The Big Five Personality Traits, the following questions were asked:

I see myself as someone who…

1. Is reserved, self-restrained
2. Is generally trusting
3. Does a thorough job
4. Is relaxed, handles stress well
5. Has an active imagination
6. Is outgoing and sociable
7. Tends to find fault with others
8. Tends to be lazy
9. Gets nervous easily
10. Has few artistic interests or is uncreative

The respondent answered in a scale where; 1 indicates strongly agree, 2 indicates agree, 3 indicates neither agree nor disagree, 4 indicates disagree and 5 indicates strongly disagree. Table A16 presents the mean value of the respondents' answers.

Table A16. Personality Traits Questions

	Personality Traits Questions
Is reserved, self restrained	2.740 *(0.999)*
Is generally trusting	2.242 *(0.807)*
Does a thorough job	2.404 *(0.881)*
Is relaxed, handles stress well	2.639 *(0.911)*
Has an active imagination	2.628 *(0.923)*
Is outgoing and sociable	2.562 *(0.983)*
Tends to find fault with others	3.437 *(0.982)*
Tends to be lazy	3.571 *(0.945)*
Gets nervous easily	3.427 *(0.949)*
Has few artistic interest, uncreative	3.316 *(0.993)*
N	2 844

Mean values; standard deviation in parentheses

Half of the questions were recoded in order to combine the questions to measure personality traits. The following questions were recoded, generally trusting, does a thorough job, has an active imagination, is outgoing and sociable and gets nervous easily, such that 1 indicates strongly disagree, 2 indicates agree, 3 indicates neither agree nor disagree, 4 indicates agree and 5 indicates strongly agree. The different questions are then combined two and two in order to estimate the personality traits in the following way:

1. **Extraversion** = Is reserved, self-restrained + Is outgoing and sociable
2. **Agreeable** = Is generally trusting + Tends to find fault with others
3. **Conscientiousness** = Does a thorough job + Tends to be lazy
4. **Neuroticism** = Is relaxed, handles stress well + Gets nervous easily
5. **Openness** = Has an active imagination + Has few artistic interests, uncrative

In other words, each of the personality traits is an index, reaching from 2 - 10, where high values indicate that the respondent is better suited for the specific personality traits. Table A17 presents the mean value of each of the respective personality traits.

Table A17. Big Five Personality Traits

	Big Five Personality Traits
Extraversion	6.179
	(1.353)
Agreeable	7.196
	(1.297)
Conscientiousness	7.168
	(1.343)
Neuroticism	5.213
	(1.419)
Openness	6.687
	(1.343)
N	2 844

Mean values; standard deviation in parentheses

Appendix B

Control variables

Table B1 presents the control variables that are used in this thesis. Section A presents the control variables that are used in research question 1 and their mean values and standard deviation for each survey wave. Section B presents the control variables that are used in research question 2, their mean values and standard deviation.

Table B1. Control variables

	Section A: Control variables Research Question 1					Section B: Control variables Research Question 2
	Wave 1	**Wave 2**	**Wave 3**	**Wave 4**	**Full sample**	**Wave 4**
Years of education	5.940	6.100	5.806	5.955	5.945	5.955
	(4.650)	*(4.681)*	*(4.621)*	*(4.648)*	*(4.649)*	*(4.648)*
Age	50.865	50.926	50.815	52.898	51.534	52.898
	(12.89)	*(12.83)*	*(12.95)*	*(12.91)*	*(12.93)*	*(12.91)*
Log income	11.501	11.505	11.499	11.562	11.521	11.562
	(0.750)	*(0.752)*	*(0.748)*	*(0.752)*	*(0.751)*	*(0.752)*
Total cultivated area in acre						2.942
						(2.914)
Reduced food consumption						0.539
						(0.499)
Agricultural self-efficacy						4.446
						(4.341)
Extraversion						6.659
						(1.425)
Agreeable						7.628
						(1.318)
Conscientiousness						7.105
						(1.501)
Neuroticism						5.280
						(1.742)
Openness						6.846
						(1.522)
N	2 997	1 367	1 630	2 945	8 939	2 950

Mean values; standard deviation in parentheses

Robustness for Research Question 3

Table B2 presents the robustness check for the third research question concerning the instalments. As seen in the table, the negative ATE that was demonstrated in Table 19 was mainly driven by the first rather than second instalment.

Table B2. Matching estimates for Research Question 3, divided on instalments

PWB	**PSM**	**KBM**	**PSM**	**KBM**
	One instalment		Two instalments	
Average Treatment Effect	-1.660***	-2.050***	-0.467	-0.348
	(0.433)	(0.276)	(0.325)	(0.282)
Treated	355	336	473	441
Untreated	2 483	2 346	2 365	2 239
Observations	2 838	2 838	2 838	2 838

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B3 presents another robustness check for the third research question, but concerning the matching algorithms. Here, we perform caliper matching and thereby set a "maximum tolerance level" in order to disregard "bad matches" that have a larger propensity score distance from each other (Smith & Todd, 2005). We find that the ATE of the instalments on the unweighted PWB index is still negative, suggesting the main result to be robust.

Table B3. Matching estimates for Research Question 3, with caliper matching

PWB	**PSM**	**KBM**
Average Treatment Effect	-1.050***	-1.255***
	(0.286)	(0.240)
Treated	827	827
Untreated	2 009	2 009
Observations	2 836	2 836

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B4 presents the final robustness check for this research question, using the third survey wave. We find that the short run ATE of KALIA on unweighted PWB is also negative, although somewhat weaker than in the longer run.

Table B4. Matching estimates for Research Question 3, using wave 3

PWB	**PSM**	**KBM**
Average Treatment Effect	-1.001***	-1.041***
	(0.267)	(0.249)
Treated	827	692
Untreated	737	773
Observations	1 564	1 564

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Household characteristics treatment and control group

Table B5 presents the household characteristics of the control group and the treatment group, where the treatment is the KALIA instalments. Paired t-tests were used to test whether there were any significant differences between the two groups in terms of observables. Interestingly, we find that those who received the instalments had significantly lower PWB, higher depression, lower income, fewer years of education, reduced their food consumption more and had higher agricultural self-efficacy on average, compared to those who did not receive any instalments.

Table B5. Household characteristics

	Control group		Treatment group
PWB unweighted	45.982	***	44.861
	(5.107)		*(5.853)*
Depression scale	3.492	***	4.508
	(3.671)		*(4.326)*
Stress scale	10.526		10.632
	(2.986)		*(3.048)*
Age	53.055		52.655
	(12.93)		*(12.83)*
Years of education	6.190	***	5.343
	(4.730)		*(4.338)*
Log income	11.636	***	11.379
	(0.758)		*(0.711)*
Total cultivated area in acre	2.964		2.880
	(2.961)		*(2.763)*
Reduced food consumption (%)	50.7	***	63.1
	(0.500)		*(0.483)*
Agricultural self-efficacy	2.966	***	8.113
	(4.113)		*(2.180)*
Extraversion	6.656		6.662
	(1.450)		*(1.403)*
Agreeable	7.642		7.616
	(1.296)		*(1.338)*
Conscientiousness	7.190	*	7.030
	(1.486)		*(1.512)*
Neuroticism	5.223		5.329
	(1.754)		*(1.731)*
Openness	6.923		6.779
	(1.509)		*(1.530)*
N	2 058		864

Mean values; standard deviation in parentheses

Paired t-test was used to test significant differences between the mean values; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$