TI 2025-005/V
Tinbergen Institute Discussion Paper

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# Daily Struggles, Shifting Moods: The Short-Term Dynamics of Income and Depression in Kenya

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**Abstract**

A bi-directional relationship between poverty and mental health may create a vicious cycle, wherein economic hardship and psychological distress reinforce each other. We examine the short-term dynamics between income fluctuations and mental well-being using 17 months of weekly financial diaries and monthly depression assessments from 669 adults in rural Kenya. Dynamic GMM estimations show that higher weekly incomes correlate with lower depression scores, particularly by improving cognition-related sleep quality and concentration. However, depressive symptoms do not predict subsequent income, challenging the notion of a short-term psychological poverty trap. Additionally, household-level mortality and illness shocks correlate with depression but not income, while job loss predicts immediate income reductions but not depression. COVID-19 containment measures explain both outcomes, slightly weakening the income-depression association. Our findings highlight the potential mental health returns to expanding financial support and safety nets, even if breaking a poverty trap via psychological mechanisms seems unlikely short-term.

We are grateful to Johannes Haushofer, Gabriel Tourek, Stephen L. Ross, Jan Kiviet, Sebastian Kripfganz, Abu Siddique, Hans van Kippersluis, and Hans Bloemen for their valuable comments and feedbacks. We greatly appreciate the continued support and insightful discussions with PharmAccess Foundation, Amref Health Africa, and their i-PUSH program staff. The high-quality data collection efforts of our field research team in Kenya deserve special recognition. We extend our deepest gratitude to our study participants who generously shared their time and provided invaluable insights into their lives. This research benefited from helpful comments from participants at the Royal Economic Society Conference, the European Congress on Tropical Medicine and Internal Health (ECTMIH), the German Development Economics Conference, and the European Health Economics Association PhD Conference (EuHEA), the lowlands Health Economists' Study Group (lolaHESG), and the Joep Lange Chair & Fellows Masterclass. This work was supported by funding from the Dutch National Postcode Lottery, the Joep Lange Institute, the Dutch Ministry of Foreign Affairs through the Health Insurance Fund, and the Turkish Ministry of Education.

# 1 Introduction

Despite significant reductions in global poverty rates during the past two centuries, approximately 10% of the world's population continues to live in extreme poverty on less than $2.15 a day (Roser, 2021). The concept of a "poverty trap" has been suggested to explain why it is so difficult for many households to attain higher standards of living (Bowels et al., 2006). When income falls below a certain threshold, various factors may prevent individuals from escaping poverty, as they both diminish the capacity to generate income and are themselves exacerbated by low income (Balboni et al., 2022). Well-known examples include poor nutrition, credit constraints, and informal social institutions (Ghatak, 2015). This paper explores the potential role of mental health in creating a poverty trap.

Poverty and mental health are strongly correlated. More than one in four people will experience a major depression in their lifetime (Dattani et al., 2023), with low-income individuals facing a 1.5 to 3 times higher risk than their wealthier counterparts (Ridley et al., 2020). Depression, in turn, is associated with reduced labor market participation and increased medical expenses both for physical and mental health care (Arena et al., 2023; Frank et al., 2023; Li et al., 2021). The intersection of poverty and mental health problems suggests that feedback loop might exist: Poverty serves as a significant risk factor for the onset of mental disorders (Lund et al., 2018), while (untreated) mental health problems contribute to the exacerbation of poverty (Haushofer & Fehr, 2014). Theoretically, this sets the stage for a vicious cycle, raising the possibility of a "psychological poverty trap" (Haushofer & Salicath, 2023).

Evidence exists in support of both directions of the relationship. Meta-analyses of (experimental) evaluations of cash transfers or poverty graduation programs find significant improvements in mental well-being (McGuire et al., 2022; Romero et al., 2021). Similarly, financial shocks, e.g. due to economic downturns or extreme weather events, directly affect mental health (Chemin et al., 2013; Christian et al., 2019; McInerney et al., 2013). Conversely, mental health interventions have been shown to substantially enhance economic outcomes (Lund et al., 2024). Some cross-armed field experiments, examining the impact of cash transfers and psychological interventions both separately and combined, have found evidence of a bi-directional relationship (Bossuroy et al., 2022; Orkin et al., 2023), while other experimental studies were less conclusive (Angelucci & Bennett, 2024; Blattman et al., 2017; Haushofer, Mudida, & Shapiro, 2020). Bi-directional effects were also found in two observational panel studies, using a dynamic GMM approach with bi-annual South African data (Alloush, 2024) and a cross-lagged model with annual Australian data (Olesen et al., 2013), respectively.

Economic field experiments and mental health interventions, while valuable, face inherent limitations in studying the poverty-mental health dynamics. First, these studies typically focus on *gains* rather than losses, creating a significant gap in our understanding in the presence of loss aversion, i.e. if income drops trigger greater psychological distress than equivalent income gains bring satisfaction (Kahneman & Tversky, 1979). While behavioral games can, to some extent, introduce losses during the experiment, this may not compare to the real-life worries about providing for one's family in the face of financial hardship. Second, existing studies often rely on externally imposed interventions, overlooking the endowment effect, whereby individuals assign greater value to assets or income they already possess compared to those they have not yet acquired (Kahneman et al., 1991). Income generated via established routines through personal effort may carry different psychological weight than external transfers, which are often viewed as supplementary and temporary, and may not trigger the same level of ownership. While observational studies examine losses to habitual earnings, they typically capture one-time natural events rather than the continuous dynamic evolution of poverty and mental health over time or measure outcomes at infrequent intervals. As a result, they may miss the interplay of short-term changes that unfold in between survey waves.

This paper addresses these gaps by examining the bi-directional relationship between poverty and mental health in the context of naturally occurring, short-term fluctuations in income and depression. The analysis is based on high-frequency data from 669 low-income adults in rural Kenya, collected through weekly financial diaries and monthly mental health assessments over 17 months from 2019 until 2021. These data are complemented with a baseline survey, the weekly recording of household-level idiosyncratic shocks, and a daily COVID-19 stringency index. The combination of granular data with detailed shock measures enables us to provide novel insights into the real-life temporal dynamics of the income-depression relationship, advancing our understanding beyond what is possible with traditional cross-sectional or low-frequency panel studies.

We use a Generalized Methods of Moments (GMM) dynamic panel estimator to examine how income levels and depressive symptoms move together in the short-term, and whether their relationship is strong enough to create a poverty trap. We investigate how these dynamics vary by gender and wealth, and explore their correlation with household-level idiosyncratic shocks and nationwide COVID-19 restrictions.

Our analysis reveals three key findings. First, we find a significant unidirectional relationship from income to depression, but not vice versa. A unit increase in log-transformed average weekly income is associated with a 0.128-point decrease in contemporaneous depression scores, measured with the 10-item Center for Epidemiologic Studies Depression Scale (CES-D). Conversely, short-term changes in depressive symptoms do not significantly predict subsequent levels of income. In other words, our findings do not support the existence of a poverty trap in the short-term.

Second, the analysis of household-level shocks shows that deaths in the family, as well as illnesses and injuries, are significantly associated with heightened depression scores but not with individual income, suggestive of compensating labor activities. Job loss is a significant determinant of weekly income, but not of depression in the same wave. The COVID-19 stringency measures have a strong impact on both outcomes. When restrictions are tightened, the level of depressive symptoms increases. Income first increases as well, potentially capturing an immediate strategic response in anticipation of the lockdown consequences, and significantly decreases in the weeks thereafter.

Third, a decomposition of the CES-D scale reveals that income fluctuations show the strongest correlations with cognition-related symptoms of depression. A unit increase in log-transformed income is associated with a 0.187-point reduction in sleep problems and a 0.036-point decrease in concentration difficulties. These patterns suggest that income affects mental well-being through different channels of depression; primarily via cognitive bandwidth-related domains rather than emotional channels (Schilbach et al., 2016).

These results have important implications for both policy and theory. The unidirectional nature of the short-term relationship - flowing from income to depression, but not vice versa - challenges the psychological poverty trap hypothesis, which requires significant bi-directional effects. This temporal asymmetry implies that improvements in mental health may not immediately translate into economic returns. Instead, programs that boost income could yield substantial mental health benefits, particularly through improved sleep and concentration. The role of household-level as well as covariate shocks further highlights the importance of social protection mechanisms for households in low-income, high-risk settings.

This paper contributes to two strands of literature. First, we advance research on the causal feedback loops between poverty and mental health in two key ways: First, by examining naturally occurring income fluctuations, both positive and negative, enriched by an analysis of recurring individual-specific and community-wide shocks. This complements existing experimental and observational evidence that shows mixed results on bi-directionality (Alloush, 2024; Angelucci & Bennett, 2024; Blattman et al., 2017; Bossuroy et al., 2022; Haushofer, Mudida, & Shapiro, 2020; Olesen et al., 2013; Orkin et al., 2023). Our second contribution is methodological, introducing a novel approach using high-frequency measurements that capture poverty-mental health dynamics at monthly intervals over a one-and-a-half-year period, rather than the infrequent measurements common in previous studies. This focus on short-term dynamics is particularly important as experimental evidence suggests that short-term and long-term effects may differ substantially (Angelucci & Bennett, 2024; Blattman et al., 2017). Such temporal granularity is especially relevant in low-resource settings, where individuals regularly experience unpredictable income changes due to seasonal work, agricultural weather dependence, informal employment, and uninsured risk.

Second, our exploratory decomposition analysis adds to the literature that investigates the different underlying mechanisms linking poverty with sleep quality. While sleep problems are common, they are particularly prevalent among those living in poverty (Dean et al., 2017). Our analysis reveals that the short-term, repeated association between income and depression runs primarily via self-reported sleep quality. This confirms earlier findings (Patel et al., 2010) and provides additional descriptive insights into the pathway from poverty to impaired cognitive function and economic decision-making (Schilbach et al., 2016).

The next section explains the conceptual framework. Section 3 provides the methodology, section 4 presents the empirical results, and section 5 concludes the paper.

# 2 Conceptual Framework

The psychological poverty trap hypothesis extends the classical economic theory of poverty traps. In the traditional framework, poverty traps are characterized by an S-shaped relationship between current and future income, as in Figure 1. This captures a feedback loop, in which a scarcity of (financial, human, social, mental) resources prevents people from making the investments needed to improve their future well-being, reinforcing their disadvantage (Banerjee & Duflo, 2011; Bowels et al., 2006). The S-curve creates distinct zones of economic mobility: In segment $A$, below the unstable equilibrium point $E$, dynamics push households toward a lower stable equilibrium representing persistent poverty, while above this threshold, in segment $B$, households tend to move toward a higher stable equilibrium of relative prosperity.

The potential role of psychological factors in generating such a trap emerges from a feedback mechanism between economic circumstances and mental states. Early work by Mani et al. (2013), Mullainathan and Shafir (2013), and Shah et al. (2012) highlights how scarcity—including income scarcity—can deplete cognitive bandwidth, impairing decision-making and perpetuating poverty. Haushofer and Fehr (2014) formalizes this idea, proposing that poverty might affect economic decision-making and preferences through psychological channels. Haushofer (2019) further develops this framework by formally modeling and testing a specific mechanism through which this feedback loop could operate, with two distinct channels where current income affects mental health, and mental health in turn affects subsequent income.

$$MentalHealth_{i,t} = g(Income_{i,t})$$
$$Income_{i,t+1} = f(MentalHealth_{i,t})$$

For a psychological poverty trap to exist, the combined effect of these two channels

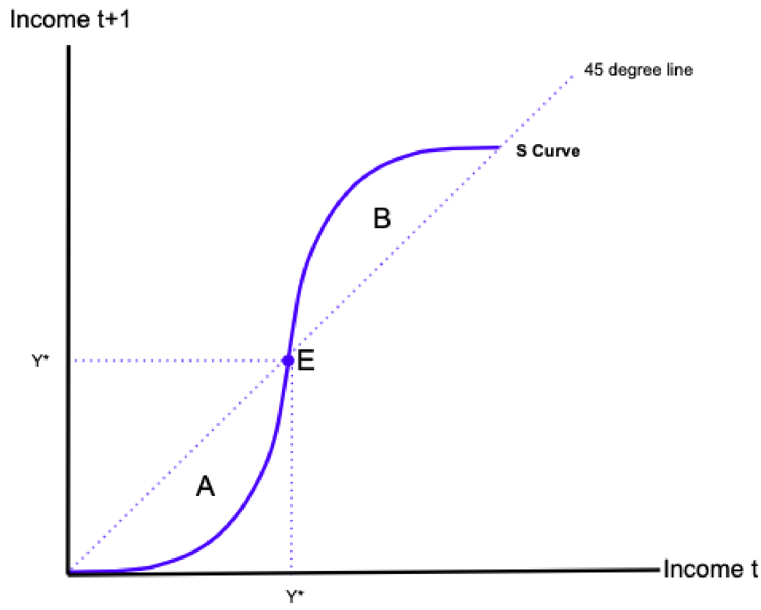



**Figure 1:** The S-shape curve and Poverty Trap

*Note:* This figure illustrates the non-linear relationship between current (t) and future (t+1) income. The curve intersects the 45-degree line at equilibrium point E with income level $Y^*$. Area A demonstrates the case where there is a poverty trap for those below income level $Y^*$ at equilibrium point E, while area B shows the region of potential income growth.

–represented by the slope of the income-mapping in Figure 1 between current and future income $Income_{i,t+1} = f(g(Income_{i,t}))$ which runs through psychological wellbeing – must exceed unity at some point. This condition creates the potential for multiple equilibria characteristic of poverty traps.

This study examines whether the bidirectional relationship between income and psychological well-being exists in the context of short-term changes. If such bidirectional effects are present, we will estimate their elasticities to compare with findings from longer-term studies.

# 3 Methodology

## 3.1 Study Setting

Kenya is classified as a lower-middle-income country. The average annual GDP growth rate was 4.8% in 2022, well above the Sub-Saharan Africa average of 3.6% (World Bank, 2023). Although the Kenyan economy has a leading position in Sub-Saharan Africa, poverty rates remain high with 39.8% of the Kenyan population living below the national poverty line (Kenya National Bureau of Statistics, 2024). Poverty is more pronounced in rural areas, such as our study counties Kakamega

(29.8%) and Kisumu (31.5%), compared to the capital Nairobi (15.8%).

Mental health problems are pervasive in Kenya. An estimated quarter of the Kenyan population experiences psychological problems at some point during their lives (World Bank, 2017). However, resources allocated to mental health care in Kenya are limited and professionals are scarce (Bukusi, 2015). Currently, there are approximately 115 psychiatrists practicing in the country (0.22 per 100,000 inhabitants), with the majority concentrated in Nairobi (World Health Organization, 2021). Outside of Nairobi, the ratio is 0.1 psychiatrists per 100,000 inhabitants (Meyer & Ndetei, 2016). These are complemented by 12 psychologists and 0.9 mental health nurses per 100,000 inhabitants in total (World Health Organization, 2021). Therefore, the Kenyan context is well-suited to examine the relationship between income and mental health in a setting marked by economic growth, persistent poverty, and limited mental health resources.

## 3.2 Data

### 3.2.1 Study sample

The data utilized in this study originates from the Financial and Health Diaries Study (Janssens & Pradhan, 2023), which aimed to assess the country's Universal Health Coverage policy in Kisumu and evaluate a mobile phone-based health insurance program, called i-PUSH (Innovative Partnership for Universal Sustainable Healthcare), in Kakamega. Consistent with the i-PUSH eligibility criteria, the study sample in both counties consisted of households with at least one woman of reproductive age (aged 18-49 years) who was either pregnant or living with a child below age 4 at baseline. The sampling methodology was based on a two-stage clustered randomized approach. First, 32 villages were chosen at random from six health facilities (two in Kisumu and four in Kakamega) that were empaneled in the National Health Insurance Fund (NHIF) at baseline. All were rural, low-income villages. Subsequently, within each village, ten to fifteen households were randomly selected from a list of all eligible households according to the sampling criteria. The planned sample consisted hence of 360 households. The actual number of households interviewed at baseline in 2019 was 371 (105 in Kisumu and 266 in Kakamega). To ensure a sufficiently powered RCT, Kakamega households that did not to have a national ID-card (a prerequisite for enrolment in NHIF) or that migrated before the roll-out of the i-PUSH program in June 2020 were replaced with other households from the sampling list and administered a shortened version of the baseline.[1] We keep all households with baseline information and at least four months of diaries data in our sample.[2] The final sample size is 364 households (95 in Kisumu and 269 in Kakagema).

[1] Both replaced and replacement households were statistically similar to the rest of the sample in Kakamega, suggesting that selection bias was limited (Janssens et al., 2021).

[2] Not applying this exclusion criterion yields similar results (See Columns 2 and 4 in Table A1).

Within these households, all economically active adults were invited to participate in weekly interviews, for a total of 669 respondents. Young adults still in school or college were excluded as respondents, as well as old-age people who were no longer engaged in economic transactions themselves or adults who were physically or cognitively unable to respond.

Through the i-PUSH program, a random half of the selected households in Kakamega were offered a full subsidy to enroll in NHIF for one year from June 2020 onwards (Groot et al., 2023). In our analyses, treated households are included but we test for the sensitivity of our results to their exclusion.

#### 3.2.2 Data collection

Data collection took place from October 2019 until June 2021. It consisted of three household surveys, weekly financial and health diaries, and monthly modules on specific topics. The baseline survey, collected in October-November 2019, provided comprehensive household and individual data on demographic, socio-economic, and general health and insurance characteristics. The second survey was collected in November-December 2020, representing the endline for the Kisumu sample and midline for the Kakamega sample. The third survey was collected only in Kakamega as endline in June 2021.

The collection of the weekly diaries started after the baseline in December 2019. As many respondents were unavailable during the festive season, the sample includes diary data from January 2020 onward. Data collection continued until the respective endlines, covering 12 and 17 months, respectively, in Kisumu and Kakamega. Each week, every diaries respondent was interviewed individually and in private. The financial diaries collected detailed information on all outgoing and incoming financial transactions in the past 7 days, including expenditures; income from salaries, casual labour or own business; loans, gifts, and remittances given or received; and savings withdrawn or deposited. The health dairies collected information on all health events in the past 7 days, including symptoms, health provider consultations, health expenditures, and foregone care. Adults responded to the health diaries for themselves as well as for under-age children and any adult household members who were absent during that week's interview. Important advantages of weekly health data are the significant reduction in recall bias and the increased reporting of minor but frequent illnesses (Das et al., 2012). It also enhances the reporting of sensitive events, e.g. related to pregnancy or mental health, as the built-up rapport with the interviewer increases trust (Geng et al., 2018). The weekly interviews ended with a qualitative recording of major events that had happened to the household that week, including job loss, livestock events, illness, births, marriage, or deaths. Finally, monthly modules collected information on mental well-being and depression, as well on pregnancy and childbirth.

In March 2020, data collection shifted from face-to-face interviews to phone-based interviews due to the COVID-19 social distancing guidelines. The majority of households owned a phone at baseline (79%). Within two to three weeks after the onset of the pandemic, households who did not have a phone received a basic feature phone to facilitate the interviews.[3]

### 3.2.3 Variables

Our two primary outcomes of interest are depression and personal income. Depression is measured with the 10-item Center for Epidemiologic Studies Depression Scale (CES-D). This psychological tool measures depression symptoms in non-clinical settings and has been validated in the Kenyan context (Kilburn et al., 2018). The survey items ask questions about sleep quality, happiness, hope, loss of motivation, loneliness, depressed feelings, concentration, and fear experienced in the past seven days (Figure A1). Answers are scaled from 0 to 3, where 0 indicates "never" and 3 refers to "most of the time or all of the time". The total CES-D score is calculated as the sum of all items after required reverse coding (range 0-30). High scores indicate more severe depressive symptoms, with a 0-1 depression cut-off at a total score of 10. It should be noted that the CES-D does not provide a clinical diagnosis, and hence scores of 10 or above should be interpreted as 'indicative of depression'. Cronbach's Alpha (scale reliability coefficient) is 0.77 for the CES-D total depression score, above the rule of thumb of 0.70. CES-D items were included as questions in the monthly mental health module. Depression data were collected from all adult respondents on a monthly basis.

While the aggregate CES-D score provides an overall assessment of depression, the scale can be decomposed into distinct factors. Following Radloff (1977), the original 20-item CES-D comprises four main components: depressed affect, positive affect, somatic and retarded activity, and interpersonal. The short 10-item version of the CES-D focuses on three subscales: depressed affect (feelings of depression/stress, loneliness, fearfulness), positive affect (happiness, hopefulness), and somatic and retarded activity (sleep quality, concentrating, effort, getting going, feeling bothered). This factor structure aligns with Schilbach et al. (2016)'s framework suggesting that depression among the poor manifests through distinct channels. Specifically, symptoms such as sleep deprivation and concentration difficulties (cf. the somatic factor) directly affect cognitive bandwidth and may be more responsive to short-term economic circumstances. Other symptoms, particularly those related to a depressed or positive affect, like feelings of hopelessness, loneliness (helplessness), and sadness, are thought to represent broader psychological states that extend beyond cognitive function and have a different relationship with financial states. Given these theoretical distinctions, we examine the relationship between income changes and the sub-questions of the CES-D to investigate

[3] After an initial drop in response rates following the first lockdown, response rates picked up again within one month. Non-response in these first few weeks was not systematically related to household characteristics other than baseline phone ownership (Janssens et al., 2021).

whether income fluctuations differentially interact with somatic symptoms versus emotional manifestations.

The personal income variable is constructed based on the sum of weekly reported business income (revenue), income from employment (salary), income from farming (crop sales), casual labour (e.g. cleaning, laundry, hawking), and other sources of income, such as the sale of livestock. This variable is transformed into a weekly average per month by averaging income over all reported weeks in that month. As result, it is non-missing if the individual was present in at least one week per month. In weeks where individuals recorded other financial transactions but had missing income data, we impute their income as zero, in line with the design of the data entry program. For robustness, we also present results without this zero imputation in Table A15. Average weekly household income is calculated as the average of the total personal weekly incomes of all household members, including the individual. The average weekly income of other household members is calculated as the average of total personal weekly incomes within the household, excluding the individual. If a household member is absent in a particular week, both household income measures are coded as missing that week. Weekly average incomes exceeding the 99.9th percentile of the distribution are replaced with the 99.9th percentile to reduce outliers' influence.

Our income variables are log-transformed following Chen and Roth (2024)'s approach of explicitly calibrating the relative weights placed on extensive and intensive margins. Their method differs from conventional approaches like log(1+Y) or inverse hyperbolic sine transformations, which implicitly weigh the extensive margin (transitions from zero to positive values) and the intensive margin (percentage changes in positive values) through their functional form. Instead, their approach requires taking an explicit stance on these relative weights, providing greater transparency in the treatment of zero values. Accordingly, the income variables are standardized such that a value of one corresponds to the minimum non-zero income observed in the dataset (2.5 Kenyan Shillings (KES) for personal income, 5 KES for other household members, and 7.14 KES for household income). Subsequently, all zero incomes are set equal to the natural logarithm of the scaled smallest positive income value in the dataset (ln(1)). This adjustment eliminates the extensive margin change between 0 and the minimum income (ymin).

In the heterogeneity analyses, we examine two key baseline characteristics: gender and wealth status. Gender is important to consider given documented differences in mental health patterns between men and women, as well as cultural expectations about household financial responsibilities. Wealth status helps us understand whether households' initial economic position affects their resilience to financial challenges, particularly relevant in our low-resource setting. The wealth index is calculated using principal component analyses (PCA) of household dwelling assets following DHS recommendations, with households below and above median classified as low and high wealth, respectively.

In additional analyses, leveraging our unique weekly data collection, we identify household-specific idiosyncratic shocks through detailed enumerator notes and weekly health diaries, categorizing them into four broad types on a monthly basis: job loss/unemployment, health problems, death in the family, and pregnancy/birth.

To account for community-level covariate shocks, we use the variation in COVID-19 restrictions that overlapped with our data collection period. We employ the COVID-19 Stringency Index, a composite measure incorporating nine policy dimensions: school closures; workplace closures; cancellation of public events; restrictions on public gatherings; closures of public transport; stay-at-home requirements; public information campaigns; restrictions on internal movements; and international travel controls (Mathieu et al., 2020). This daily index, ranging from 0 to 100 (with 100 being the most stringent), is averaged within waves to provide a comprehensive measure of the intensity of external restrictions faced by households in our sample. In the analysis, we focus on the COVID-19 Stringency Index rather than case or death counts of COVID-19, as it provides a clear signal of pandemic severity in environments where reliable case data was not readily accessible. Aksunger et al. (2023) demonstrate that, although mental health outcomes were influenced by both policy stringency and COVID-19 cases, the psychological impact of the stringency policies was substantially more pronounced - with effect sizes roughly triple those observed for case numbers. This heightened impact of policy measures stems most likely from the immediate socioeconomic consequences of restrictions on daily life.

## 3.3 Statistical Methods

Drawing on the psychological poverty trap hypothesis, we examine the relationship between depression and income through a dynamic panel model: economic conditions affect psychological well-being, while mental health status influences subsequent economic outcomes. We specify a system of simultaneous equations that captures these dynamic feedback loops while accommodating for unobserved individual heterogeneity and temporal interdependencies.

We model depression dynamics as follows:

$$\begin{aligned} Depression_{i,t} = &\beta_1 Depression_{i,t-1} + \beta_2 Depression_{i,t-2} \\ &+ \beta_3 Ln(Avg\_Income)_{i,t} + \beta_4 Ln(Avg\_Income)_{i,t-1} \\ &+ \beta_t + \eta_i + \epsilon_{i,t} \end{aligned} \tag{1}$$

where $Depression_{i,t}$ represents the CES-D depression score for individual $i$ at wave $t$. The model incorporates two autoregressive terms ($Depression_{i,t-1}$, $Depression_{i,t-2}$), contemporaneous and lagged logarithmic average weekly personal income ($Ln(Avg\_Income)_{i,t}$,

$Ln(Avg\_Income)_{i,t-1}$), time fixed effects ($\beta_t$), individual fixed effects ($\eta_i$), and Windmeijer-corrected robust standard errors ($\epsilon_{i,t}$).[4]

To capture the reverse channel, we specify the income dynamics equation as follows:

$$\begin{aligned} Ln(Avg\_Income)_{i,t} =& \gamma_1 Ln(Avg\_Income)_{i,t-1} + \gamma_2 Ln(Avg\_Income)_{i,t-2} \\ & + \gamma_3 Depression_{i,t-1} + \gamma_4 Depression_{i,t-2} \\ & + \gamma_t + \alpha_i + \mu_{i,t} \end{aligned} \tag{2}$$

where $\gamma_t$ and $\alpha_i$ capture time and individual fixed effects, respectively, and $\mu_{it}$ represents the Windmeijer-corrected robust error term.

We employ a two-step Generalized Method of Moments (GMM) panel estimator, which enhances estimation efficiency and test power compared to a one-step estimation. The Windmeijer correction is implemented to address potential downward bias in the standard errors of the two-step GMM estimator, providing heteroskedastic-consistent estimates of the variance-covariance matrix (Windmeijer, 2005).

Figure 2 illustrates the dynamic feedback structure between depression and income, where both contemporaneous and lagged effects operate alongside autoregressive processes.

To examine parameter heterogeneity across demographic and socioeconomic dimensions in Equation 1 and Equation 2, we further estimate interaction models of the form:

$$\begin{aligned} Depression_{i,t} =& \sum_{k=1}^{2} (\beta_k + \lambda_k H_i) Depression_{i,t-k} \\ & + \sum_{k=0}^{1} (\beta_{k+3} + \lambda_{k+3} H_i) Ln(Avg\_Income)_{i,t-k} \\ & + \beta_t + \eta_i + \epsilon_{i,t} \end{aligned} \tag{3}$$

where $H_i$ represents indicator variables for gender and baseline wealth status. An equivalent specification is applied to estimate the income equation Equation 2.

To investigate the role of exogenous disturbances in this dynamic system, we augment equations Equation 1 and Equation 2 with both idiosyncratic and covariate shock measures:

[4] To test for robustness, we also estimate the models with additional lags (Table A2, Table A3).

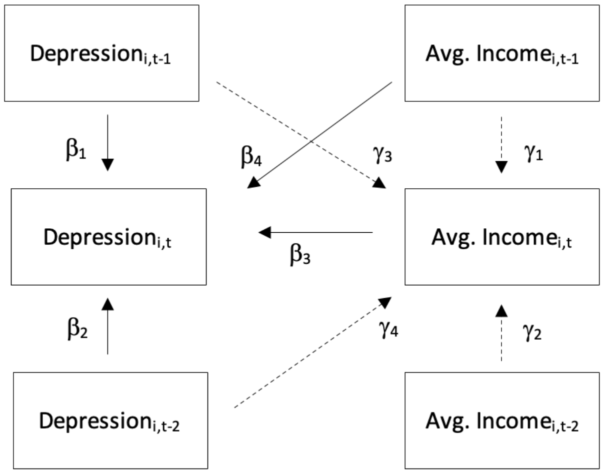



**Figure 2:** Simplified estimation model

*Note:* This figure illustrates the simplified estimation model showing the relationships between depression and average income across time periods. The solid arrows represent the main specification of Equation 1, and the dashed arrows indicate the specification of Equation 2. Subscript $t$ denotes the current period, while $t-1$ and $t-2$ represent the previous two periods.

$$\begin{aligned} Depression_{i,t} =& \beta_1 Depression_{i,t-1} + \beta_2 Depression_{i,t-2} \\ & + \beta_3 Ln(Avg\_Income)_{i,t} + \beta_4 Ln(Avg\_Income)_{i,t-1} \\ & + \sum_{k=1}^{K} \theta_k S_{i,t}^h \\ & + \beta_t + \eta_i + \epsilon_{i,t} \end{aligned} \tag{4}$$

$$\begin{aligned} Depression_{i,t} =& \beta_1 Depression_{i,t-1} + \beta_2 Depression_{i,t-2} \\ & + \beta_3 Ln(Avg\_Income)_{i,t} + \beta_4 Ln(Avg\_Income)_{i,t-1} \\ & + \phi S_t^c \\ & + \beta_t + \eta_i + \epsilon_{i,t} \end{aligned} \tag{5}$$

where $S_{i,t}^h$ represents a vector of $K$ household-level shock indicators (job loss/unemployment, health problems, death in the family, and pregnancy/birth) and $S_t^c$ captures community-level COVID-19 stringency measures. The coefficients $\theta_k$ and $\phi$ measure the associations between these events and our outcomes of interest. An analogous specification is estimated for the income equation Equation 2.

While several panel estimators exist, the GMM dynamic panel estimator offers three distinct advantages: it accounts for fixed individual effects, handles independent variables that are not strictly exogenous, and accommodates a dynamic dependent variable that depends on its past values (Roodman, 2009). These features are crucial given the complex temporal relationship between income and mental health that we aim to model.

First, unobserved heterogeneity in our panel data model means that time-invariant individual characteristics affect both income and depression but cannot be directly measured. This violates the strict exogeneity assumption: $E[\epsilon_i|X_{i1}, ...X_{iT}, \eta_i] = 0$ as these unobserved factors correlate with our independent variables, making traditional estimation methods biased and inconsistent. While both fixed effect and random effect panel data models can address unobserved heterogeneity, GMM provides additional advantages in handling our second challenge.

The second challenge stems from the potential reverse causality between income and depression, where depression in the current period may affect future income and vice versa. This feedback loop violates strict exogeneity through the condition: $E[\epsilon_{it}|X_{it+1}] \neq 0$ as current shocks to one variable affect future values of the other. The GMM estimator addresses this by allowing for sequential (weak) exogeneity instead of requiring strict exogeneity (Leszczensky & Wolbring, 2022). Under sequential exogeneity, independent variables may be predetermined —current errors can correlate with future values of independent variables, but not with their current or past values— enabling the use of lagged values as valid instruments. Fixed and random effect estimators do not provide consistent estimates in the presence of reverse causality.

The presence of autoregressive terms in our specifications introduces a third violation of strict exogeneity, known as the dynamic panel bias or Nickell bias. In both the depression and income equations, the lagged dependent variables are mechanically correlated with the fixed effects ($\eta_i$, $\alpha_i$) in their respective error terms ($E[y_{i,t-1}\epsilon_{it}] \neq 0$). This correlation emerges because the same individual effects that influenced past realizations of the dependent variable also affect its current value.

Moreover, in our system of equations, the lagged dependent variables are necessarily correlated with other regressors ($X$), as past realizations of each dependent variable appear as regressors in the other equation (Leszczensky & Wolbring, 2022). This cross-equation dependency compounds the dynamic panel bias, resulting in biased estimates not only for the autoregressive parameters but also for the coefficients of other independent variables. The GMM estimator addresses these complex endogeneity issues by instrumenting the differenced lagged variables with their past levels, following Arellano and Bond (1991).

To estimate our model equations, we employ the Forward Orthogonal Deviation GMM (FOD-GMM) method (Arellano & Bover, 1995), one of three main GMM transformations. See Appendix section A1 for a more detailed comparison of the three GMM transformations and the application of the FOD-GMM to our data. All estimations are implemented using Stata version 18.0 with the `xtdpdgmm` package (Kripfganz, 2019).

### 3.4 Response rates and attrition

Of the initial baseline participants in 2019, 55 (8.2%) left between the baseline and endline survey. Apart from the replacement of entire households in Kakamega for programming reasons, individual attrition rates were generally modest: 9 individuals from Kisumu left between the baseline and second survey (which was the endline for Kisumu). From the replenished sample in Kakamega, an additional 13 participants departed between the second and the third survey.

In total, the main analysis sample includes 669 adults who responded to the baseline survey as well as the monthly mental health modules and the weekly financial diaries. The maximum number of mental health waves that could potentially be observed was 12 for Kisumu and 17 for Kakamega respondents, with a lower maximum for individuals from replacement households. We define an individual's participation window by the months between their first and last observation on the mental health module. Missing values in these participation windows comprise 11.4% of non-imputed income observations, 3.6% of income observations, and 11.5% of depression score observations. This suggests high response rates during active participation periods.

To formally test for non-random attrition, we use the variable addition test by Verbeek and Nijman (1992), following the guidelines provided by Jones et al. (2012). This entails adding the number of waves that an individual is present in the panel into the specifications that are estimated based on the unbalanced panel. These tests do not show signs of selection bias (See Columns 2 and 4 in Table A4).

## 4 Results

### 4.1 Descriptive statistics

Table 1 Panel A presents the descriptive statistics at baseline of the 669 respondents in the analysis sample. On average, respondents are 32.3 years old, 61% are female, and among them, 86% are pregnant or have a child below age 4. 71% of respondents are married, and 74% live in Kakamega county, with the remaining 26% in Kisumu county. Respondents have completed on average 9.2 years of education, corresponding to incomplete secondary education in Kenya. Almost two-thirds (61%) of the diaries respondents were employed at baseline, reporting an average monthly income of 4,626 Kenyan Shilling (KES) – approximately 30% of the minimum wage in Kenya (15,120 KES).

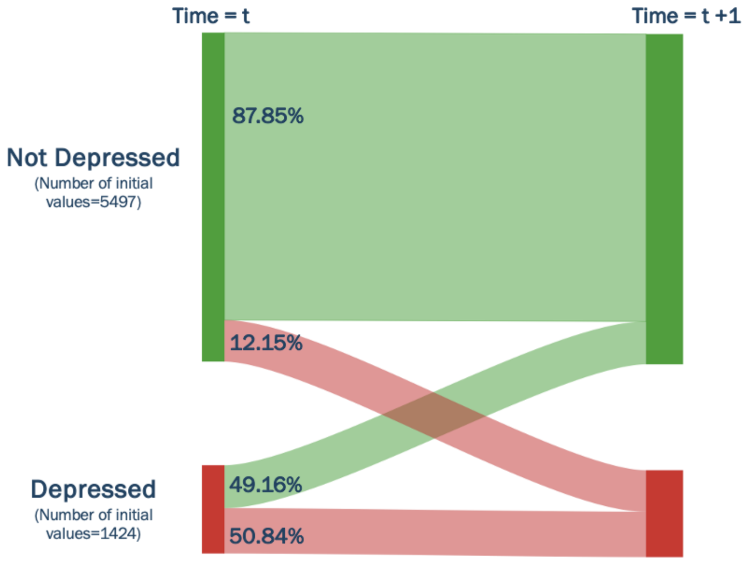



**Figure 3: Transition probabilities of depression diagnosis**

*Notes:* This figure shows the pooled transition probabilities of depression states (depressed and not depressed) between consecutive waves in the sample. The calculation is based on the `xttrans` command in Stata. The figure is created by SankeyMATIC.

The baseline depression score, measured using the CES-D scale (0-30) with higher scores indicating more severe symptoms, averages 8.42. In addition, 36% of the population report a CES-D score $\geq 10$, which is the screening cut-off for depression. This is well above the Kenyan average of 25% (World Bank, 2017). Disaggregating by gender, the prevalence of depression is more pronounced among women, reaching 39%, compared to 29% among men. Additionally, women exhibit a higher average depression score of 8.77, while men have an average score of 7.74.

Approximately 70% of the sample experienced an indication of depression at least once during the study period based on a CES-D cut-off score of 10. For readability, we will refer to this state as 'depressed' in the rest of the paper, acknowledging that the CES-D does not provide a formal, clinical diagnosis. For those ever depressed, depression recurred in 30% of their monthly observations. Figure 3 shows the transition probabilities in and out of depression based on the cut-off score: 87.85% of the non-depressed individuals in the data remain non-depressed in the next wave; the remaining 12.15% become depressed. Depressed individuals are about as likely to remain in a state of depression in the next wave (50.84%) as to get out of it (49.16%).

Table 1 Panel B shows the monthly outcome variables. The average weekly income (calculated based on the weekly financial diaries within a month) is 1,200.86 KES for respondents, which is in line with reported last months' earnings in the baseline

**Table 1:** Descriptive statistics of the sample

| **Panel A: Baseline Variables** | Mean | Std. Dev. | Min | Max | n | N |
|---|---|---|---|---|---|---|
| Age | 32.33 | 10.39 | 18 | 77 | 669 | . |
| Female | .61 | .49 | 0 | 1 | 669 | . |
| Female pregnant or with child <4 y.o[1] | .86 | .35 | 0 | 1 | 405 | . |
| Married | .71 | .46 | 0 | 1 | 665 | . |
| Kakamega region (omitted: Kisumu) | .74 | .44 | 0 | 1 | 669 | . |
| Years of education | 9.22 | 2.71 | 0 | 16 | 605 | . |
| Employed | .61 | .49 | 0 | 1 | 644 | . |
| Earning last month (KES)[2] | 4625.64 | 6874.76 | 0 | 70000 | 250 | . |
| Baseline depression score (CES-D) | 8.42 | 5.59 | 0 | 26 | 513 | . |
| Baseline depression indicator (CES-D≥10) | .36 | .48 | 0 | 1 | 513 | . |
| **Panel B: Outcomes** | Mean | Std. Dev. | Min | Max | n | N |
| Average weekly income | 1200.86 | 3087.22 | 0 | 48600 | 669 | 8074 |
| Average weekly income of other hh members | 1443.96 | 4050.99 | 0 | 50240 | 294 | 2789 |
| Average weekly income of hh | 2641.52 | 5845.21 | 0 | 68140 | 324 | 3142 |
| Depression score (CES-D) | 6.11 | 4.9 | 0 | 30 | 669 | 8065 |
| Depression indicator (CES-D≥10) | .20 | .4 | 0 | 1 | 669 | 8065 |
| **Panel C: Household Shocks** | Mean | Std. Dev. | Min | Max | n | N |
| Job Loss/Unemployment | .0138 | .12 | 0 | 1 | 669 | 9059 |
| Health Issues/Illness | .4126 | .49 | 0 | 1 | 669 | 9065 |
| Death in Family | .0139 | .12 | 0 | 1 | 669 | 9059 |
| Pregnancy/Childbirth | .0519 | .22 | 0 | 1 | 669 | 9061 |

[1] Conditional on begin a female.

[2] Conditional on employed status at the baseline.

*Note:* Descriptive statistics are calculated for the full analysis sample of n=669 unique individuals and 17 monthly waves (totaling N=9113 monthly observations taking into account each individual's participation window – running from their first to their last monthly observation). Panel A reports baseline characteristics measured in October-November 2019. Years of education measures completed schooling years. Income is reported in Kenyan Shillings (KES). Depression score is measured using the CES-D scale (0-30), with higher scores indicating more severe symptoms. Depression indication is a binary variable equal to 1 if the CES-D score $\geq$ 10. The depression module was not asked in the shortened baseline for replacement households, hence the lower number of observations. Panel B shows outcomes measured over a maximum of 17 months (Jan 2020-May 2021). Income variables represent weekly averages in a wave. N $<$ 9113 indicates missing variables within individual windows of participation. Panel C presents the share of weeks in which households experienced specific shocks, identified through interview notes and health diaries. The construction of variables is discussed in Section 3.2.3.

survey. It is 1,443.96 KES for other household members (conditional on there being other diaries respondents in the household), and 2,641.52 KES for the total household. The average depression score over the entire study period is 6.11 – below the average at baseline – and 20% of all monthly depression measurements were above the cut-off score of 10 as can be seen in Panel A and Panel B of Figure 4.

Figure 4 shows the histograms of the baseline and monthly depression scores and the log of average weekly incomes over the entire period. As is clear from the Panel C, the average weekly income is bi-modal with a peak at zero income in 17% of waves and its log normally distributed in the other weeks.

In a similar vein, the heat maps in Figure A2 show a bi-modal joint distribution of the log of average weekly income and depression. This suggests the presence of two distinct groups of individuals: those with low income who tend to cluster at the lower end of the depression scores, and those with higher, fluctuating incomes and more variability in the depression measures. The lower average depression score among low-income individuals appears counterintuitive. Further disaggregation by gender, baseline employment status, and baseline type of work, i.e. casual versus non-casual work, (Rows 2, 3, and 4) reveals that this combination is primarily driven by female casual laborers and unemployed individuals. In the robustness section, we will check the sensitivity of our results to the exclusion of these non-regular income earners.

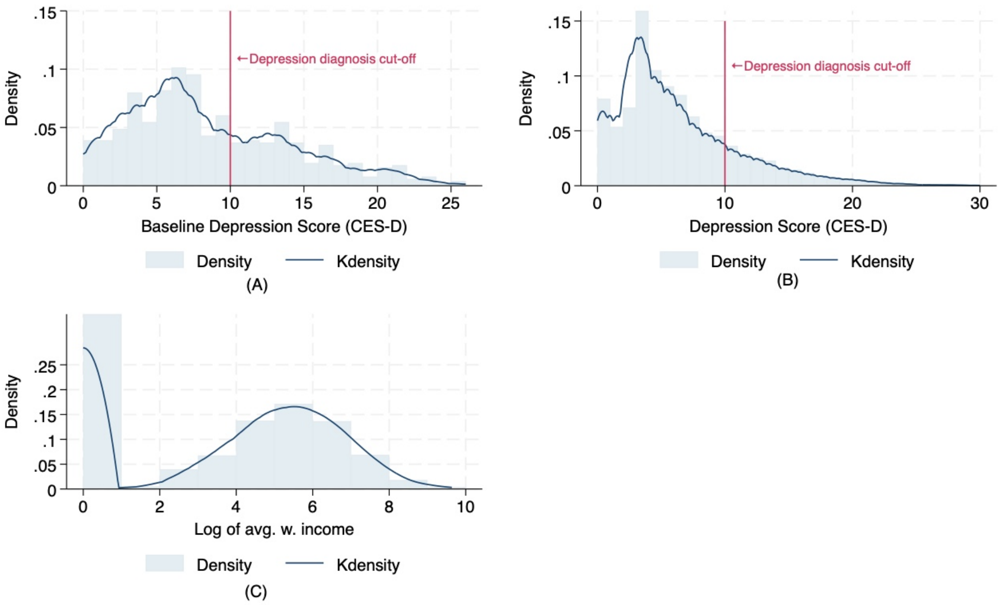
Panel C of Table 1 summarizes the shocks that were experienced by households in each wave, as recorded in the weekly interview notes and health diaries. Throughout the study period, job loss/unemployment was reported in 1.3% of the waves. The most frequent shocks were health-related: in 41.3% of waves, households faced health issues or illness. Death in the family and pregnancy or childbirth were reported in 1.4% and 5.1% of waves, respectively.

## 4.2 Main dynamic results

Our main analysis is presented in Table 2, with Columns 1 and 2 showing the estimates of Equation 1 and Equation 2, respectively. Column 1 shows that depression scores exhibit significant persistence over time - a one-point increase in the previous month's depression score is associated with a 0.097-point rise in the current month's score. Nevertheless, while statistically significant, the relatively small magnitude of the coefficient is suggestive of considerable month-to-month variation in mental health states. Further lags are not significant.

Looking at the contemporaneous relationship between income and depression in Column 1, we find that one-unit increase in the log-transformed average weekly income is associated with a 0.128 point decrease in depression scores. Thus, in line with the hypothesis, individuals experience fewer symptoms of depression if they earn a higher average weekly income in the four weeks prior to the depression

**Figure 4: Histogram of depression scores and log of weekly avg. income**




*Notes:* This figure shows the distribution of depression scores and weekly income. Panels A and B display depression scores at baseline and throughout the study period, with a vertical line indicating the depression indication cutoff of 10. Panel C shows the distribution of log average weekly income. All panels include a density plot and kernel density estimates.

measurement. The lagged weekly income coefficient is not statistically significant. This indicates that controlling for recent income levels, current depressive symptoms are not associated with income levels in the month before.

Column 2 examines the reverse relationship between income as a dependent variable and depression as an explanatory variable. Here, too, we find significant persistence in the outcome variable - an approximate percentage (log point)[5] increase in the previous month's income is associated with a 0.24% increase in current income, with an additional 0.11% increase from income two waves ago. Lagged depression does not predict subsequent income levels. Both depression coefficients have a positive sign but are very small in magnitude and statistically insignificant. That is, our high-frequency data do not support the hypothesis that depression is correlated with a reduction in income in the short-term.

Both equations pass the necessary specification tests for GMM estimation. The Arellano-Bond tests indicate the presence of first-order serial correlation but reject second-order serial correlation across all specifications, confirming that our models are dynamically complete. Additionally, the Hansen J test fails to reject the null hypothesis of valid overidentifying restrictions, supporting the validity of our instrument set. Lastly, the Kleibergen-Paap underidentification test also rejects the null hypothesis that the instruments lack sufficient relevance for model identification. These test results are reported at the bottom of each results table and consistently validate the key assumptions underlying our GMM estimations.

In sum, we find a unidirectional dynamic relationship from income to depression but not vice versa. This finding challenges the existence of a psychological poverty trap in the short term, as such a trap would require significant effects in both directions to create a self-reinforcing cycle.

The above analysis considered individuals in isolation. However, households often serve as primary units of informal insurance through income pooling and resource sharing (Baland & Ziparo, 2018). This is particularly relevant in Kenya where extended family networks and intra-household transfers play a crucial role in consumption smoothing and risk mitigation (Robinson, 2012). What matters for mental health, may be the income of the entire household, rather than one's own income. We therefore extend our analysis to account for informal insurance mechanisms within households in Table A5. Column 1 replicates the main specification from Equation 1, Column 2 incorporates other household members' income alongside one's own income, while Column 3 examines the effect of total household income. This reduces sample sizes substantially because observations drop out as soon as one household member is absent, resulting in imprecise estimates with large standard errors. Although the direction of the effects of others' income remains consistent with our main findings, the results suggest that it is primarily one's

[5] Throughout the remainder of the text, we use "percentage (%)" to refer to approximate percentage (log point) changes for improved readability.

**Table 2:** Dynamic panel estimates of depression-income relationship

| | (1)<br>Y= Depression<br>X= (Lagged) Avg. Income | (2)<br>Y= Avg. Income<br>X= Lagged Depression |
|---|---|---|
| L.Depression score | 0.097*** | 0.002 |
| | (0.027) | (0.012) |
| L2.Depression score | 0.033 | 0.009 |
| | (0.026) | (0.010) |
| Log of avg. weekly income | -0.128** | |
| | (0.056) | |
| L.Log of avg. weekly income | 0.023 | 0.247*** |
| | (0.044) | (0.034) |
| L2.Log of avg. weekly income | | 0.114*** |
| | | (0.026) |
| Time Dummies | Yes | Yes |
| Number of individuals | 660 | 663 |
| Observations | 5,901 | 6,145 |
| # of coefficients (K) | 19 | 19 |
| # of instruments (L) | 26 | 26 |
| Serial correlation test<br>Arellano-Bond first order (m1) | 0.00 | 0.00 |
| Serial correlation test<br>Arellano-Bond second order (m2) | 0.35 | 0.48 |
| Overidentification test (Hansen J (2,2)) | 0.88 | 0.58 |
| Overidentification test (Hansen J (2,3)) | 0.88 | 0.58 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 |

*Notes:* This table reports the FOD-GMM dynamic panel estimation results of the relationship between depression and income, including time fixed effects. Depression is measured using the 10-item CES-D scale, with range 0-30, where higher scores indicate more severe depressive symptoms. Income is measured as the log-transformation of average weekly incomes per month. Windmeijer-corrected robust standard errors are shown in parentheses. Statistical significance is indicated at the $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$ levels.

own income that matters for mental well-being. A potential explanation could lie in the often gendered norms around financial responsibilities within households. Even if spouses help each other financially, this may not take away worries about the contribution respondents are expected to make to specific household expenditures. Alternatively, it may reflect that not all spouses are equally supportive financially in times of need. In Column 4, we investigate whether accounting for informal transfers *between* households affects the relationship between income and depression by examining disposable income including inter-household gifts and remittances. The results suggest that disposable income does not have a significant relationship with depression, indicating that the mental health benefits of income may be primarily driven by earned income rather than transfers. Following the train of thought above, gifts and remittances may be received precisely when respondents are worried about not being able to make ends meet. Although they alleviate financial concerns, they may create their own challenges in terms of social obligations.

In parallel, we examine how different household income measures affect future income generation in Table A6. The persistence in income remains robust when controlling for other household members' income (Column 2). Interestingly, we find that other household members' income has no significant effect on personal income generation, suggesting limited income substitution within households. Column 3 examines persistence in total household income but fails to pass coherence tests for instrument validity. The coefficients on lagged depression scores remain consistently insignificant across all specifications, further supporting our finding that depression does not create significant feedback effects on future income.

## 4.3 Heterogeneity

We examine potential heterogeneous effects across different subgroups. First, we investigate heterogeneity by gender and baseline wealth status. The results show that the impact of income on depression does not vary significantly by gender or baseline wealth (Table A7). The interaction terms across both specifications are statistically insignificant (Columns 2 and 3).

Although we find a significant interaction between lagged depression and male gender when estimating average weekly income (Table A8 Column 2), weak instrument validity in this specification suggests these results should be interpreted cautiously. Meanwhile, the interaction between depression and baseline wealth status remains small in size and insignificant, indicating that the relationship between depression and future income does not systematically differ across wealth groups.

Second, we split the observations into deciles based on individuals' average depression level over the entire study period and their baseline wealth, respectively, as shown in Figure A3 and Figure A4). The results in Figure A3 Panels A and B show that the impact of contemporaneous and lagged income on depression scores is similar for individuals in different depression severity deciles. Although the coefficients on contemporaneous income are smaller in magnitude for subgroups in low deciles (representing individuals with minimal depression symptoms throughout the study) compared to high deciles (i.e. individuals with consistently severe depression symptoms) —suggesting that some individuals are mentally more affected by income fluctuations than others— the difference is statistically insignificant. Similarly, the effects of the first and second lags of depression on income remain consistently stable around zero when estimated separately for different baseline wealth deciles, rather than using the single median cutoff (Figure A4 Panels C and D).

## 4.4 Role of Household and Community-Level Shocks

Our high-frequency data collection allows us to identify both idiosyncratic household-level shocks and broader community-level events that might confound the relationship between mental health and income at the wave level.

The analysis of idiosyncratic household-level shocks in Table 3 reveals strong associations between life events and mental health (Column 1) but shows limited correlations with income (Column 2). Specifically, deaths in the family are associated with a 1.77 point increase in the depression score, while the occurrence of an illness, injury, or other health issue in the household is associated with a 0.45 points increase in the depression score. Although job loss/unemployment has a positive coefficient in the estimation of depression, it is not statistically significant. The coefficient on pregnancy and childbirth is negative but small and insignificant as well.[6] In contrast, when examining these same life events' relationship with income in Column 2, job loss is correlated with approximately a 39% decrease in log-transformed average weekly income (calculated as (exp(-0.488)-1)*100 = -38.6%). Death and pregnancy or childbirth are also negatively related to weekly income, but not significantly so. The coefficient on health issues is negligible, potentially indicating a counteracting effect of reduced incomes for ill adults with increased income of adults who increase working hours to cope with medical expenses (Geng et al., 2018). These findings highlight how fluctuations in real-life events can have a direct and short-term bearing on mental well-being and income-generating capacity, which may be missed in traditional panel surveys with infrequent measurements.

Rather than looking at idiosyncratic shocks, Table 4 investigates the covariate impact of the COVID-19 pandemic. Incorporating the monthly COVID-19 stringency measures into our analysis in Table 4 reveals subtle changes in both income

[6] We also measured business decline/closure, family conflicts/separation, and legal issues such as court warrants and arrests, but these variables did not pass the Kleibergen-Paap underidentification test and were hence excluded.

**Table 3:** Dynamic panel estimates controlling for household shocks

| | (1)<br>Y= Depression<br>X= (Lagged) Income | (2)<br>Y= Avg. Income<br>X= Lagged Depression |
|---|---|---|
| L.Depression score | 0.103*** | -0.003 |
| | (0.026) | (0.011) |
| L2.Depression score | 0.040* | 0.008 |
| | (0.024) | (0.009) |
| Log of avg. weekly income | -0.112* | |
| | (0.058) | |
| L.Log of avg. weekly income | 0.029 | 0.236*** |
| | (0.045) | (0.033) |
| L2.Log of avg. weekly income | | 0.109*** |
| | | (0.026) |
| Job Loss/Unemployment | 0.136 | -0.488* |
| | (0.510) | (0.250) |
| Health Issues/Illness | 0.445*** | 0.009 |
| | (0.136) | (0.062) |
| Death in Family | 1.767** | -0.197 |
| | (0.751) | (0.301) |
| Pregnancy/Childbirth | -0.064 | -0.188 |
| | (0.399) | (0.163) |
| Time Dummies | Yes | Yes |
| Number of individuals | 660 | 663 |
| Observations | 5,901 | 6,138 |
| # of coefficients (K) | 23 | 23 |
| # of instruments (L) | 52 | 46 |
| Serial correlation test<br>Arellano-Bond first order (m1) | 0.00 | 0.00 |
| Serial correlation test<br>Arellano-Bond second order (m2) | 0.46 | 0.55 |
| Overidentification test (Hansen J (2,2)) | 0.73 | 0.40 |
| Overidentification test (Hansen J (2,3)) | 0.73 | 0.41 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 |

*Notes:* This table reports the FOD-GMM dynamic panel estimation results of the relationship between depression and income, also controlling for household idiosyncratic shocks. Time fixed effects are included. Depression is measured using the 10-item CES-D scale, with range 0-30, where higher scores indicate more severe depressive symptoms. Income is measured as the log-transformation of average weekly incomes per month. Household shocks are dummy variables based on occurrences reported in enumerator notes and weekly health diaries. Windmeijer-corrected robust standard errors are shown in parentheses. Statistical significance is indicated at the $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$ levels.

and depression dynamics. In Column 1 the persistence in depression scores (measured by the coefficient on lagged depression) increases to 0.101 while maintaining significance at the 1% level. Current COVID-19 stringency shows a strong, positive association with depression (0.199 points), while the negative correlation of current income on depression (-0.106) becomes slightly smaller than in models without COVID controls (-0.128). The impact of COVID-19 stringency on income dynamics reveals an interesting temporal pattern. A unit increase in stringency is associated with a 36% increase in log-transformed average weekly income (calculated as (exp(0.306)-1)*100 = 35.8%), while lagged stringency correlates with a 25.8% decrease in log-transformed average weekly income (calculated as (exp(-0.298)-1)*100 = -25.8%). This pattern likely reflects how households in rural Kenya responded to containment measures. The findings suggest that while households could temporarily adapt to and prepare for the restrictions, sustained containment measures ultimately undermined their income-generating capacity. That is, the immediate defensive responses masked deeper structural impacts that emerged over time. Overall, these findings suggest that while household-specific shocks primarily affect mental health, broader population-wide conditions significantly influence both psychological and economic outcomes.

## 4.5 Decomposition of Depression Effects

Unlike our main model specifications, the depression decomposition analysis examines individual CES-D components as separate outcome variables. To maintain consistency in diagnostics tests, we adapt our model specification accordingly based on The Akaike Information Criterion (AIC). To account for multiple hypothesis testing, we calculate False Discovery Rate q-values following Benjamini and Yekutieli (2001), implemented through Stata's `qqvalue` package (Newson, 2010).

Table 5 and Table 6 reveal distinct patterns in how income levels correlate with different aspects of depression. The strongest associations with income are found for symptoms related to cognitive bandwidth. Sleep deprivation exhibits the most pronounced relationship, with a unit increase in log-transformed average weekly income associated with a 0.187-point reduction in sleep problems (q-value=0.039). Similarly, concentration difficulties show a robust association, decreasing by 0.036 points with each percent increase in income (q-value=0.023). We do not find strong evidence that emotional indicators of depression are associated with income. The coefficient on weekly income in the estimation of feelings of sadness becomes insignificant when correcting for multiple hypothesis testing (q-value=0.35).

These decomposition results suggest that the negative relationship between income and the overall depression score is primarily driven by cognitive-related symptoms, particularly sleep quality and concentration. The stronger correlations for bandwidth-related symptoms compared to emotional symptoms align with Schilbach et al. (2016)'s framework, suggesting that different depression mani-

**Table 4:** Dynamic panel estimates including COVID-19 Stringency

| | Y= Depression<br>X= (Lagged) Avg. Income | Y= Avg. Income<br>X=Lagged Depression |
|---|---|---|
| L.Depression score | 0.101*** | 0.008 |
| | (0.027) | (0.010) |
| L2.Depression score | 0.036 | 0.011 |
| | (0.025) | (0.009) |
| Log of avg. weekly income | -0.106** | |
| | (0.052) | |
| L.Log of avg. weekly income | 0.034 | 0.282*** |
| | (0.043) | (0.030) |
| L2.Log of avg. weekly income | | 0.143*** |
| | | (0.025) |
| Covid Stringency Index | 0.199** | 0.306*** |
| | (0.081) | (0.040) |
| L.Covid Stringency Index | -0.132 | -0.298*** |
| | (0.083) | (0.041) |
| Time Dummies | Yes | Yes |
| Number of individuals | 660 | 663 |
| Observations | 5,901 | 6,145 |
| # of coefficients (K) | 19 | 19 |
| # of instruments (L) | 32 | 32 |
| Serial correlation test<br>Arellano-Bond first order (m1) | 0.00 | 0.00 |
| Serial correlation test<br>Arellano-Bond second order (m2) | 0.39 | 0.16 |
| Overidentification test (Hansen J (2,2)) | 0.82 | 0.15 |
| Overidentification test (Hansen J (2,3)) | 0.83 | 0.18 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 |

*Notes:* This table reports the FOD-GMM dynamic panel estimation results of the relationship between depression and income, also controlling for COVID-19 Stringency Index. Time fixed effects are included. Depression is measured using the 10-item CES-D scale, with range 0-30, where higher scores indicate more severe depressive symptoms. Income is measured as the log-transformation of average weekly incomes per month. COVID Stringency Index is a composite measure incorporating strictness of nine policy dimensions, ranging from 0 to 100 (with 100 being most stringent), is averaged over the waves. Windmeijer-corrected robust standard errors are shown in parentheses. Statistical significance is indicated at the $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$ levels.

festations may operate through distinct channels - some directly affecting cognitive capacity and others working through broader psychological mechanisms.

Examining the reverse relationship in Table A9 and Table A10, we find that none of the correlations between the separate symptoms of depression and subsequent income remain significant after correcting for multiple hypothesis testing. While sleep problems and problems with "getting going" initially show a significant association with income, their q-values are 0.55 and 0.35, respectively. These findings again indicate that while income levels have robust effects on specific depression symptoms, particularly those related to cognitive bandwidth, depression's disaggregated symptoms do not impact future income.

**Table 5:** Dynamic panel estimates with bandwidth related decomposition of the depression score

| | (1)<br>Y=Sleep<br>X= (Lagged) Income | (2)<br>Y=Concentration<br>X= (Lagged) Income | (3)<br>Y=Effort<br>X= (Lagged) Income | (4)<br>Y=Getting Going<br>X= (Lagged) Income | (5)<br>Y=Bothered<br>X= (Lagged) Income |
|---|---|---|---|---|---|
| Log of avg. weekly income | -0.187*** | -0.036*** | 0.014 | -0.010 | 0.099 |
| | (0.067) | (0.012) | (0.018) | (0.010) | (0.072) |
| L.Log of avg. weekly income | 0.018 | -0.005 | 0.010 | 0.010 | -0.017 |
| | (0.016) | (0.009) | (0.013) | (0.007) | (0.016) |
| L.Having problems in sleep | 0.055** | | | | |
| | (0.023) | | | | |
| L2.Having problems in sleep | 0.018 | | | | |
| | (0.021) | | | | |
| L.Having problems in concentration | | 0.057** | | | |
| | | (0.024) | | | |
| L2.Having problems in concentration | | 0.030 | | | |
| | | (0.022) | | | |
| L.Feeling that everything you did was an effort | | | 0.155*** | | |
| | | | (0.032) | | |
| L2.Feeling that everything you did was an effort | | | 0.084*** | | |
| | | | (0.026) | | |
| L3.Feeling that everything you did was an effort | | | 0.107*** | | |
| | | | (0.023) | | |
| L.Feeling could not get going | | | | 0.105*** | |
| | | | | (0.028) | |
| L2.Feeling could not get going | | | | 0.051* | |
| | | | | (0.026) | |
| L.Feeling bothered by things | | | | | 0.121*** |
| | | | | | (0.027) |
| L2.Feeling bothered by things | | | | | 0.041* |
| | | | | | (0.023) |
| FDR correction passed (Log of avg. weekly income) | Yes | Yes | N/A | N/A | N/A |
| q-value (Log of avg. weekly income) | [0.039] | [0.023] | - | - | - |
| Time Dummies | Yes | Yes | Yes | Yes | Yes |
| Number of individuals | 660 | 660 | 637 | 660 | 660 |
| Observations | 5,901 | 5,901 | 5,097 | 5,901 | 5,901 |
| # of coefficients (K) | 19 | 19 | 19 | 19 | 19 |
| # of instruments (L) | 25 | 22 | 25 | 26 | 25 |
| Serial correlation test (Arellano-Bond first order (m1)) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Serial correlation test (Arellano-Bond second order (m2)) | 0.29 | 0.16 | 0.63 | 0.10 | 0.72 |
| Overidentification test (Hansen J (2,2)) | 0.65 | 0.85 | 0.23 | 0.71 | 0.99 |
| Overidentification test (Hansen J (2,3)) | 0.64 | 0.85 | 0.23 | 0.71 | 0.99 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

*Notes:* This table reports the FOD-GMM dynamic panel estimation results of the relationship between depression and income by using cognitive bandwidth domain related sub-items of depression scale (CES-D 10). Time fixed effects are included. Depression sub-items are questions of the 10-item CES-D scale, with range 0-3, where higher scores indicate more severe depressive symptoms. Income is measured as the log-transformation of average weekly incomes per month. Windmeijer-corrected robust standard errors are shown in parentheses. All the results are subjected to Benjamini and Yekutieli (2001) correction and the table reports if significant average income coefficients pass the FDR correction criteria (q-values in square brackets). Statistical significance is indicated at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ levels.

**Table 6:** Dynamic panel estimates with emotions related decomposition of the depression score

| | (1) Y=Sadness X= (Lagged) Income | (2) Y=Hopelessness X= (Lagged) Income | (3) Y=Loneliness X= (Lagged) Income | (4) Y=Stress X= (Lagged) Income | (5) Y=Fearfulness X= (Lagged) Income |
|---|---|---|---|---|---|
| Log of avg. weekly income | -0.021** | -0.011 | -0.009 | -0.020 | -0.012 |
| | (0.010) | (0.011) | (0.010) | (0.013) | (0.010) |
| L.Log of avg. weekly income | 0.004 | 0.003 | -0.001 | 0.004 | 0.010 |
| | (0.008) | (0.008) | (0.007) | (0.009) | (0.008) |
| L.Feeling sad | 0.040 | | | | |
| | (0.025) | | | | |
| L2.Feeling sad | -0.005 | | | | |
| | (0.022) | | | | |
| L.Feeling hopeless | | 0.050** | | | |
| | | (0.025) | | | |
| L2.Feeling hopeless | | 0.009 | | | |
| | | (0.021) | | | |
| L.Feeling lonely | | | 0.125*** | | |
| | | | (0.026) | | |
| L2.Feeling lonely | | | 0.027 | | |
| | | | (0.023) | | |
| L.Feeling depressed/stressed | | | | 0.062** | |
| | | | | (0.026) | |
| L2.Feeling depressed/stressed | | | | 0.007 | |
| | | | | (0.022) | |
| L.Feeling fearful | | | | | 0.039 |
| | | | | | (0.029) |
| L2.Feeling fearful | | | | | 0.021 |
| | | | | | (0.025) |
| FDR correction passed (Log of avg. weekly income) | No | N/A | N/A | N/A | N/A |
| q-value (Log of avg. weekly income) | [0.350] | - | - | - | - |
| Time Dummies | Yes | Yes | Yes | Yes | Yes |
| Number of individuals | 660 | 660 | 660 | 660 | 660 |
| Observations | 5,901 | 5,901 | 5,901 | 5,901 | 5,901 |
| # of coefficients (K) | 19 | 19 | 19 | 19 | 19 |
| # of instruments (L) | 26 | 26 | 26 | 26 | 26 |
| Serial correlation test (Arellano-Bond first order (m1)) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Serial correlation test (Arellano-Bond second order (m2)) | 0.57 | 0.73 | 0.42 | 0.31 | 0.76 |
| Overidentification test (Hansen J (2,2)) | 0.85 | 0.41 | 0.22 | 0.24 | 0.58 |
| Overidentification test (Hansen J (2,3)) | 0.85 | 0.41 | 0.24 | 0.24 | 0.58 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

*Notes:* This table reports the FOD-GMM dynamic panel estimation results of the relationship between depression and income by using emotional domain related sub-items of depression scale (CES-D 10). Time fixed effects are included. Depression sub-items are questions of the 10-item CES-D scale, with range 0-3, where higher scores indicate more severe depressive symptoms. Income is measured as the log-transformation of average weekly incomes per month. Windmeijer-corrected robust standard errors are shown in parentheses. All the results are subjected to Benjamini and Yekutieli (2001) correction and the table reports if significant average income coefficients pass the FDR correction criteria (q-values in square brackets). Statistical significance is indicated at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ levels.

## 4.6 Robustness checks

We conduct several robustness checks to assess our instrumental variables strategy, the number of included lags, and the missing variables imputation. First, we examine the sensitivity of our results to the number of available instruments in Table A11 and Table A12. While our preferred specification uses instruments with up to 5 lags, we test alternative specifications with 3, 4, and 6 lags. AIC mostly indicates that our preferred specification outperforms these alternatives, while our main findings remain qualitatively unchanged across these different instrument sets.

Next, we test the robustness of our results to different classifications of the instrument set in Table A13 and Table A14. While our main analysis treats income as predetermined based on the theoretical considerations explained in the Methods section and section A1, we examine how results change when income is instead classified as strictly exogenous or fully endogenous. Most coefficients remain stable across these alternative classifications. The only notable change occurs when current income is classified as endogenous and thus excluded from the instrument set, causing its coefficient to become statistically insignificant in the depression equation Equation 1 (Table A13 Column 3). However, both the AIC and incremental Hansen test support our original classification of income as predetermined - the incremental Hansen test fails to reject the validity of using current income as an instrument (p=0.86), while the lower AIC indicates a better model fit with this specification.

We also examine the sensitivity of our results to including additional lags of both dependent and independent variables. In Table A2, adding a third lag of depression scores and income to the depression equation does not substantially alter our main findings. The third lag of depression itself is not statistically significant, suggesting that our baseline specification with two lags adequately captures the temporal dynamics of depression. Similarly, in Table A3, including third lags in the income equation reinforces our main conclusions. The AIC values suggest that adding these additional lags does not improve model fit, supporting our more parsimonious baseline specification with two lags.

Fourth, we examine the robustness of our results to different treatments of missing income data. Our preferred specification imputes missing income as zero when individuals report other financial transactions in the same week, which helps preserve sample size and improves precision. This is in line with how the data entry program was designed. Table A15 compares this approach with a specification using only non-imputed income data. In the non-imputed specification (Column 2), the main income effect on depression reduces in size and becomes less precise, but the specification tests show evidence of second-order serial correlation (p=0.08), suggesting potential dynamic misspecification. To address this, Column 3 adds a third lag of depression and income, which yields results similar to our baseline specification while restoring the model's dynamic completeness. The estimates of the income regressions are highly comparable in the imputed and non-imputed specifications, but the non-imputed specification fails to pass Hansen's overidentification tests (Column 5). The consistency of results across specifications suggests that our income imputation strategy while improving precision and sample size, does not substantially alter our main conclusions about the depression-income relationship.

The inclusion of individuals with limited income during the study period could create a spurious income-depression relationship. We therefore also test whether our main results are sensitive to the exclusion of respondents who generate very little income throughout the study period in Table A16 and Table A17, in line with the heat maps in Figure A2. To identify respondents who rarely earn income, we apply two criteria. First, we exclude female respondents who indicate to be casual laborers at baseline and who report zero income for more than half of their entries in the weekly financial diaries. Second, we remove (male and female) individuals who are not employed at baseline and who report zero income in more than 50% of the waves. We also conduct robustness checks using alternative thresholds (70% and 90%) for zero-income reporting. In total, these criteria led to the exclusion of 163, 128, and 70 individuals from our analysis, respectively. As shown in Table A16 and Table A17, the different thresholds for the exclusion of irregular earners do not yield significant changes in the overall results.

Finally, we rerun our analyses, excluding post-intervention data from treated individuals in Kakamega to investigate whether our results are affected by the impact of health insurance on a subset of respondents. Groot et al. (2023) find that the mobile insurance program significantly reduces healthcare expenditures for enrolled households. To the extent that the relation between income and depression partly runs through the occurrence of health shocks, the program may have changed treated individuals' responsiveness to income fluctuations. Table A18 shows that the exclusion of post-treatment observations does not yield significant qualitative changes in the overall results, but it doubles the effect of income on depression. This suggests that being insured against health shocks may reduce the negative impacts of low income on depressive symptoms. Since the program was randomly assigned, and the availability of NHIF in the study region is a common background feature for all, we have opted to keep all respondents in the study sample and maintain the sample size.

# 5 Discussion

This paper investigates the reciprocal relationship between income fluctuations and mental health, a prerequisite for the poverty trap hypothesis to hold. While existing studies provide causal evidence of the poverty-mental health feedback loop, little attention has been paid to short-term dynamics, especially those driven by naturally occurring shocks rather than external interventions. The high-frequency data on 669 low-income adults of our study offer unique insights into the complex relationship between income and mental health in a real-life, non-experimental setting.

We find that weekly income strongly predicts depressive symptoms, but not vice versa. These findings challenge prevailing theories about psychological poverty traps, at least in the short-term. The lack of a feedback loop from depression to subsequent income indicates that the psychological burden of poverty may not immediately translate into reduced economic productivity, even if such effects emerge over longer timeframes, as found in Alloush (2024).

A recent review by Haushofer and Salicath (2023) documented bi-directional effects based primarily on randomized interventions. Our observational data suggest these dynamics may operate differently in real-life settings where households face volatile earnings, with sufficient income in some weeks but also weeks with hardly any income at all. Rather than reflecting the impact of (repeated) windfall gains, we capture the effect of households' daily financial struggles.

We also observe significant associations between various life events and mental health. Deaths in the family have the strongest association with elevated depression symptoms, followed by severe illnesses and injuries. In addition to the emotional burden of mortality and morbidity, this might reflect the need to pay for sizeable (funeral and medical) expenditures. Indeed, excluding the (random) subset of individuals who were enrolled in health insurance from June 2020 onward, increases the effect of income on depression. This suggests that being insured soothes the financial risk due to illness and increases peace of mind, in line with Haushofer, Chemin, et al. (2020). Pregnancy and childbirth, although associated with a high risk of maternal mental health disorders in the region (De Sanctis et al., 2024), do not have a significant impact on mental well-being. This might be due to a counterbalancing effect of the joy of parenthood. Part of the effect may also be picked up directly by the income variable, as reduced income-generating capacity and poverty are important determinants of maternal depression (Dieteren et al., 2024).

The inclusion of COVID-19 containment measures in the analyses shows how the pandemic and its economic consequences influenced the depression-income relationship. The more stringent the lockdown measures, the more pronounced were depressive symptoms. Interestingly, the immediate behavioral response to tightened measures was to increase income. Still, prolonged measures ultimately weakened households' ability to generate income. When accounting for COVID-19 stringency, the negative association between income and depression weakens. This suggests that the pandemic-related economic conditions partially explain the effect of income on depression, extending recent work by Aksunger et al. (2023).

The decomposition of depression symptoms suggests that income fluctuations may have stronger associations with cognitive than emotional manifestations of depression in our setting. Income correlates most strongly with sleep quality and concentration difficulties, providing some support for Schilbach et al. (2016)'s conceptual framework that differentiates bandwidth-related and emotional domains of depression.

Our study has some limitations. First, we rely on a single screening tool (the CES-D scale) to measure depressive symptoms, which gives an indication of depression but not a clinical diagnosis, and which may not capture all relevant aspects of mental health. Second, while examining longer-term relationships between income and mental health would be valuable, this requires using fewer time periods, significantly reducing our observation set given the unbalanced nature of our panel data. This would limit the statistical power needed for GMM estimation.

Our results have direct policy implications. The unidirectional nature of the income-depression relationship suggests that breaking poverty traps may require sustained economic support rather than short-term psychological interventions. This aligns with recent observations by De Schutter (2024) advocating for structural economic approaches to mental health. In addition, the role of aggregate economic conditions suggests that macroeconomic stability can have important mental health spillovers. Indeed, prioritizing rapid aid distribution through social protection programs during crises could help prevent mental health deterioration. Lastly, if poverty reduces mental bandwidth, poverty reduction programs may generate substantial spillovers on other domains of life. In resource-constrained settings, like rural Kenya, where mental health services are limited, economic interventions may serve as an indirect but effective approach to improving psychological well-being.

### Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Claude AI and ChatGPT to improve readability. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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# Appendix

## A1 Application of the GMM Panel Data Estimator

### A1.1 Choice of GMM Transformation

To estimate our model equations, we employ the Forward Orthogonal Deviation GMM (FOD-GMM) method (Arellano & Bover, 1995), one of three possible GMM transformations. While Arellano and Bover (1995) demonstrate that the GMM estimator is theoretically invariant to the chosen transformation when all available instruments are used, in practical terms the choice matters. The FOD-GMM is preferred for our analyses because it produces smaller bias in case of a large number of time periods (Hayakawa, 2009) and it preserves more observations (Kripfganz, 2019).

The three main GMM transformations operate as follows:

1. System GMM (sys-GMM), developed by Blundell and Bond (1998), uses first differences of instrument variables and assumes they are uncorrelated with fixed effects.

2. Difference GMM (diff-GMM), introduced by Arellano and Bond (1991), removes unobserved heterogeneity through first differencing.

3. Forward Orthogonal Deviation GMM (FOD-GMM), proposed by Arellano and Bover (1995), eliminates time-invariant variables by subtracting the average of subsequent observations from the regression equation.

We select FOD-GMM for our analysis based on three key considerations. First, sys-GMM is unsuitable as potential correlation between $Y_{it-1}$ and $\eta_i, \alpha_i$ would violate the weak exogeneity assumption, leading to inconsistent results. Second, compared to diff-GMM, FOD transformation produces smaller bias, particularly with larger time periods ($T \approx 15$) as demonstrated in Monte-Carlo experiments (Hayakawa, 2009). Third, FOD transformation preserves more observations than first differencing in unbalanced panels (Kripfganz, 2019). Given these advantages and our dataset's characteristics (17 time periods in unbalanced form), FOD-GMM emerges as the most appropriate choice.

To remove the individual fixed effects in Equation 1 and Equation 2 while preserving sample information in our unbalanced panel, we implement the FOD transformation as follows:

$$
\begin{aligned}
\tilde{\Delta}_t Depression_{i,t} =& \beta_1 \tilde{\Delta}_t Depression_{i,t-1} + \beta_2 \tilde{\Delta}_t Depression_{i,t-2} \\
&+ \beta_3 \tilde{\Delta}_t Ln(Avg\_Income)_{i,t} + \beta_4 \tilde{\Delta}_t Ln(Avg\_Income)_{i,t-1} \\
&+ \tilde{\Delta}_t \epsilon_{i,t}
\end{aligned} \tag{6}
$$

$$
\begin{aligned}
\tilde{\Delta}_t Ln(Avg\_Income)_{i,t} =& \gamma_1 \tilde{\Delta}_t Ln(Avg\_Income)_{i,t-1} + \gamma_2 \tilde{\Delta}_t Ln(Avg\_Income)_{i,t-2} \\
&+ \gamma_3 \tilde{\Delta}_t Depression_{i,t-1} + \gamma_4 \tilde{\Delta}_t Depression_{i,t-2} \\
&+ \tilde{\Delta}_t \mu_{i,t}
\end{aligned} \tag{7}
$$

where $\tilde{\Delta}_t$ represents the forward orthogonal deviation operator, which transforms each observation by subtracting the mean of all future observations in the sample and applying a scale factor to maintain homoskedasticity (Kripfganz, 2019):

$$
\tilde{\Delta}_t \epsilon_{i,t} = \sqrt{\frac{T-t+1}{T-t}} (\epsilon_{i,t} - \frac{1}{T-t+1} \sum_{s=0}^{T-t} \epsilon_{i,t+s}) \tag{8}
$$

where $T$ represents the total number of time periods, and $t$ denotes the current time period. This transformation removes individual-specific effects by subtracting the mean of the current and all remaining future observations for that individual and applies a scaling factor $\sqrt{\frac{T-t+1}{T-t}}$ to preserve homoskedasticity of the transformed errors. The transformation maintains orthogonality while minimizing data loss compared to first-differencing methods.

## A1.2 Model Identification and Validation

The validity of our FOD-GMM estimation relies on two key identifying assumptions. First, the regressor must be independent of the transformed error terms $\tilde{\Delta}_t \epsilon_{it}$ and $\tilde{\Delta}_t \mu_{it}$ to serve as valid instruments where $\tilde{\Delta}_t \epsilon_{it} = \epsilon_{it} - \overline{(\epsilon_{it} + \epsilon_{it+1} ... + \epsilon_{iT})}$ and $\tilde{\Delta}_t \mu_{it} = \mu_{it} - \overline{(\mu_{it} + \mu_{it+1} ... + \mu_{iT})}$. Second, there should be no serial correlation in $\epsilon_{it}$ $(E[\epsilon_{it}\epsilon_{is}] \neq 0, t \neq s)$ and $\mu_{it}$.

The first assumption depends on the classification of the regressor (strictly exogenous, predetermined, endogenous), which defines the available instrument set based on the following moment conditions:

- For strictly exogenous regressors:

$$
E[\mathbf{x}_{i,t-s} \tilde{\Delta}_t \epsilon_{it}] = 0 \text{ for } t - s = 0, 1, ..., T
$$

- For predetermined regressors:

$$E[\mathbf{x}_{i,t-s}\tilde{\Delta}_t\epsilon_{it}] = 0 \text{ for } s = 0, 1, ..., t$$

- For endogenous regressors and lagged dependent variables:

$$E[\mathbf{x}_{i,t-s}\tilde{\Delta}_t\epsilon_{it}] = 0 \text{ for } s = 1, 2, ..., t$$

Both predetermined and endogenous regressors use past realizations as instrumental variables. The main difference lies in the assumed contemporaneous correlation with the error term, which affects whether we can use the contemporaneous value of the variable as additional instrument. We classify the lagged regressors ($Ln(Avg\_Income)_{i,t-1}$, $Depression_{i,t-1}$ and $Depression_{i,t-2}$) as well as $Ln(Avg\_Income)_{i,t}$ as predetermined, assuming that $E[x_{it}\tilde{\Delta}_t\epsilon_{it}] = 0$. To see this, note that, in Equation 2, current $Ln(Avg\_Income)_{i,t}$ is defined as determined by previous depression states and independent from contemporaneous or future realizations of depression, in line with the theoretical framework. Consequently, $Ln(Avg\_Income)_{i,t}$ remains orthogonal to the transformed error $\tilde{\Delta}_t\epsilon_{it} = \epsilon_{it} - \overline{(\epsilon_{it} + \epsilon_{it+1} ... + \epsilon_{iT})}$ in Equation 1, in line with the predetermined moment conditions. This classification is supported by statistical evidence, including the incremental Hansen J test, which confirms that our specifications are consistent with the data, and the Akaike Information Criteria, which supports the appropriateness of treating these variables as predetermined.

We classify all other control variables —including household-level shocks, COVID-19 stringency measures, and gender and wealth interactions with income and depression— as predetermined variables as well.

The second assumption is crucial as its violation, often arising from measurement error, can lead to inconsistent findings in poverty trap identification (Antman & McKenzie, 2007). Following Kiviet (2020)'s guidelines for p-value thresholds ($p < 0.05$ for first-order and $p > 0.10$ for second-order), we employ the Arellano-Bond test with a null hypothesis of no serial correlation. For all reported models, the test results reject serial correlation for order 1 but not for order 2 and higher, confirming no autocorrelation in $\epsilon_{it}$ and $\mu_{it}$ and indicating dynamically complete models.

Our empirical specification, including the classification of variables as strictly exogenous, predetermined or endogenous, is guided by both Kiviet (2020)'s methodological framework and the theoretical model of the psychological poverty trap. The coherence tests and moment selection criteria inform our choice of five lagged variables as instruments. We evaluate this selection using the Arellano-Bond serial correlation test, Hansen overidentification test, Kleibergen-Paap underidentification test, and moment selection criteria based on the Akaike Information Criteria (AIC), with significance thresholds in line with Kiviet's recommendations. To enhance finite-sample properties, we implement instrument reduction through collapsing, as suggested by Kiviet (2020). The specification includes appropriate time dummies and their corresponding instruments through the teffects option.

## Figure A1: CES-D questionnaire

### Module 13 MENTAL HEALTH

RESPONDENT: ALL DIARY RESPONDENTS [18 YEARS AND OLDER, FINANCIALLY ACTIVE, PHYSICALLY ABLE]

#### A. Mental Health

***Now I am going to read to you a series of statements about how often you have certain feelings. If you uncomfortable, let me know***

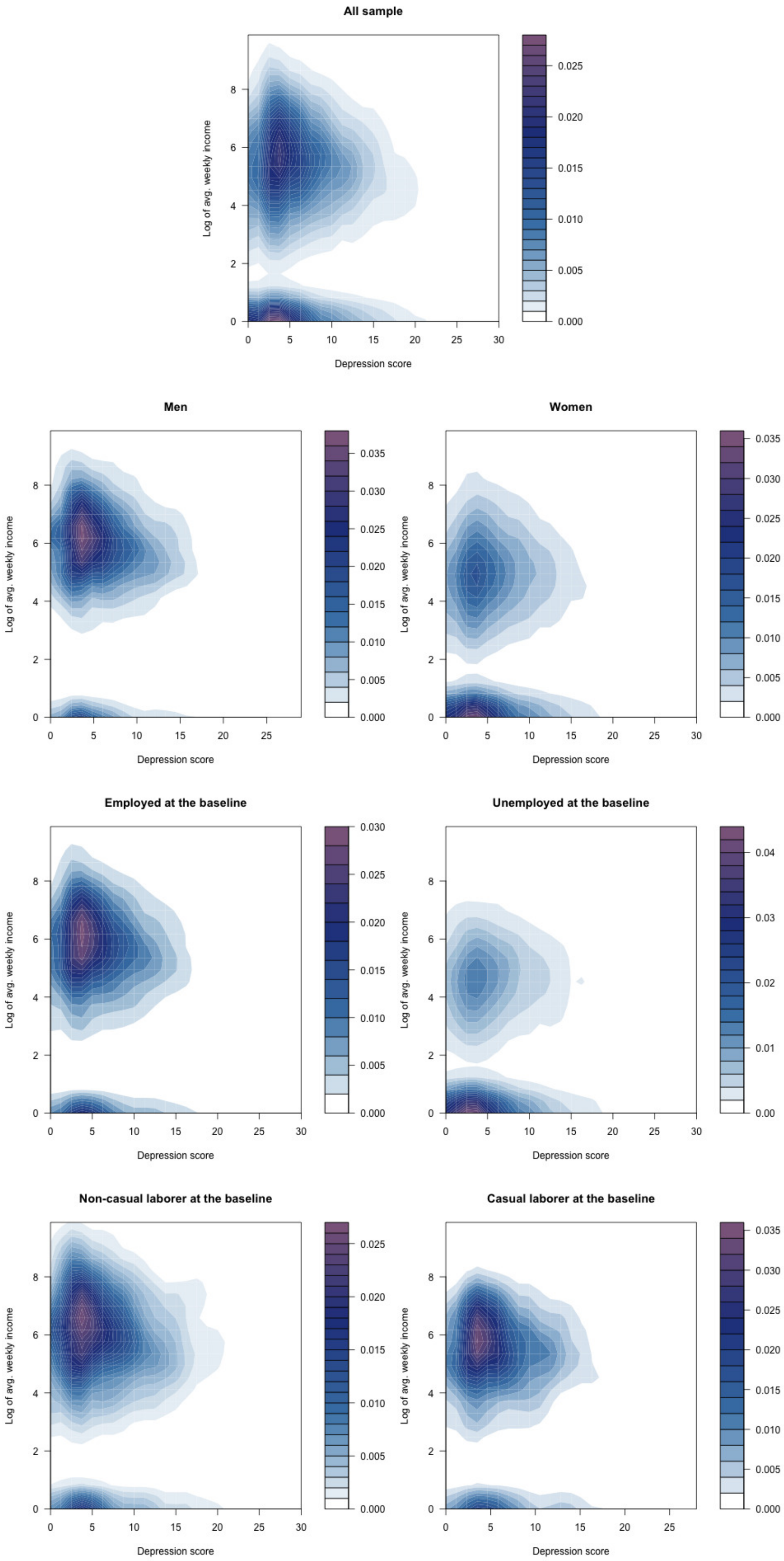
**[ENUMERATOR] CHECK FOR PRESENCE OF OTHERS BEFORE CONTINUING. ENSURE PRIVACY. MOVE TO SECLUDED OR PRIVATE PLACE IF NECESSARY**

***Over the last 7 days …***

| | | |
|---|---|---|
| (13.01) Did you sleep well? | NEVER | 1 |
| | A LITTLE OF THE TIME (1 - 2 DAYS DURING THE PAST WEEK) | 2 |
| | A MODERATE AMOUNT OF TIME (3 - 4 DAYS DURING THE PAST WEEK) | 3 |
| | MOST OR ALL OF THE TIME (5 - 7 DAYS DURING THE PAST WEEK) | 4 |
| (13.02) Were you happy | NEVER | 1 |
| | A LITTLE OF THE TIME (1 - 2 DAYS DURING THE PAST WEEK) | 2 |
| | A MODERATE AMOUNT OF TIME (3 - 4 DAYS DURING THE PAST WEEK) | 3 |
| | MOST OR ALL OF THE TIME (5 - 7 DAYS DURING THE PAST WEEK) | 4 |
| (13.03) Did you have trouble concentrating? | NEVER | 1 |
| | A LITTLE OF THE TIME (1 - 2 DAYS DURING THE PAST WEEK) | 2 |
| | A MODERATE AMOUNT OF TIME (3 - 4 DAYS DURING THE PAST WEEK) | 3 |
| | MOST OR ALL OF THE TIME (5 - 7 DAYS DURING THE PAST WEEK) | 4 |
| (13.04) Do you feel hopeful about the future? | NEVER | 1 |
| | A LITTLE OF THE TIME (1 - 2 DAYS DURING THE PAST WEEK) | 2 |
| | A MODERATE AMOUNT OF TIME (3 - 4 DAYS DURING THE PAST WEEK) | 3 |
| | MOST OR ALL OF THE TIME (5 - 7 DAYS DURING THE PAST WEEK) | 4 |
| (13.05) Did you feel that everything you did was an effort? | NEVER | 1 |
| | A LITTLE OF THE TIME (1 - 2 DAYS DURING THE PAST WEEK) | 2 |
| | A MODERATE AMOUNT OF TIME (3 - 4 DAYS DURING THE PAST WEEK) | 3 |
| | MOST OR ALL OF THE TIME (5 - 7 DAYS DURING THE PAST WEEK) | 4 |
| (13.06) Did you feel lonely? | NEVER | 1 |
| | A LITTLE OF THE TIME (1 - 2 DAYS DURING THE PAST WEEK) | 2 |
| | A MODERATE AMOUNT OF TIME (3 - 4 DAYS DURING THE PAST WEEK) | 3 |
| | MOST OR ALL OF THE TIME (5 - 7 DAYS DURING THE PAST WEEK) | 4 |
| (13.07) Did you feel depressed/STRESSED? | NEVER | 1 |
| | A LITTLE OF THE TIME (1 - 2 DAYS DURING THE PAST WEEK) | 2 |
| | A MODERATE AMOUNT OF TIME (3 - 4 DAYS DURING THE PAST WEEK) | 3 |
| | MOST OR ALL OF THE TIME (5 - 7 DAYS DURING THE PAST WEEK) | 4 |
| (13.08) Did you feel that you could not 'get going'? | NEVER | 1 |
| | A LITTLE OF THE TIME (1 - 2 DAYS DURING THE PAST WEEK) | 2 |
| | A MODERATE AMOUNT OF TIME (3 - 4 DAYS DURING THE PAST WEEK) | 3 |
| | MOST OR ALL OF THE TIME (5 - 7 DAYS DURING THE PAST WEEK) | 4 |
| (13.09) Were you bothered by things that don't usually bother you? | NEVER | 1 |
| | A LITTLE OF THE TIME (1 - 2 DAYS DURING THE PAST WEEK) | 2 |
| | A MODERATE AMOUNT OF TIME (3 - 4 DAYS DURING THE PAST WEEK) | 3 |
| | MOST OR ALL OF THE TIME (5 - 7 DAYS DURING THE PAST WEEK) | 4 |
| (13.10) Did you feel fearful? | NEVER | 1 |
| | A LITTLE OF THE TIME (1 - 2 DAYS DURING THE PAST WEEK) | 2 |
| | A MODERATE AMOUNT OF TIME (3 - 4 DAYS DURING THE PAST WEEK) | 3 |
| | MOST OR ALL OF THE TIME (5 - 7 DAYS DURING THE PAST WEEK) | 4 |

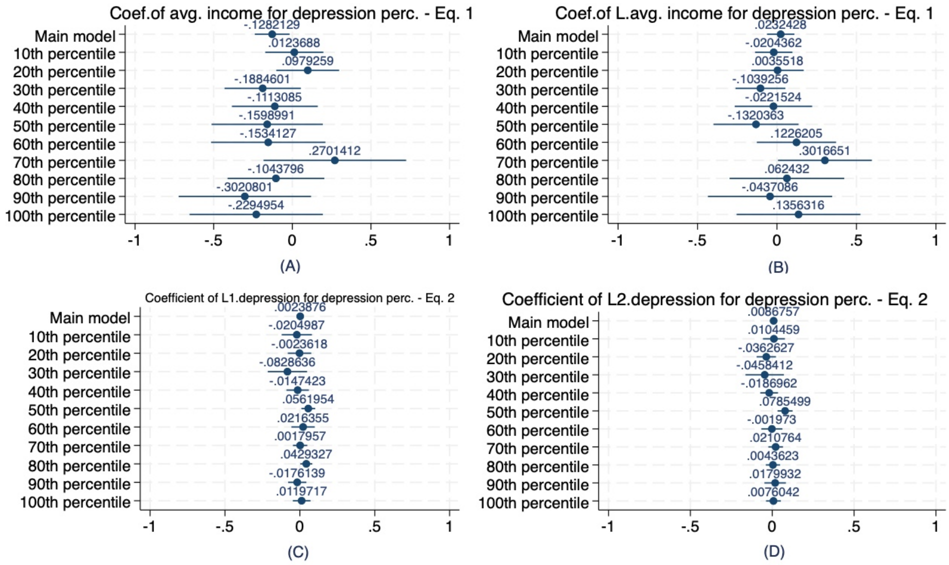
**Note:** This figure shows the sub-questions from the CES-D 10-item depression scale.

**Figure A2: Bivariate density of monthly depression score and log of average weekly income on heat maps**



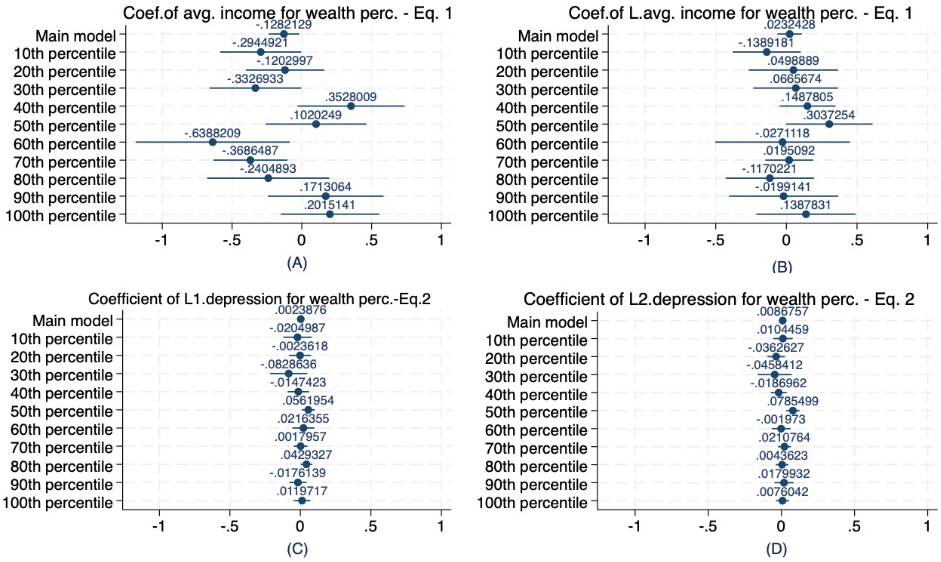

*Notes:* This figure shows the joint density of monthly depression score (CES-D) on x-axis and log of average weekly income on y-axis by gender, employment status, and occupation at the baseline in the sample. Figure is created by using `filled.contour` command in R.

**Figure A3: Comparison of coefficients of interest based on mean depression percentiles**




*Notes:* The graph illustrates coefficient estimates derived from the subgroup analysis categorized by mean depression score percentiles. The 10th percentile represents the regression results for a sub-group of individuals who either do not exhibit depression symptoms or show very mild symptoms, while the 100th percentile represents individuals who experience severe depression throughout the study period and have high depression mean. Panel A displays coefficients for average income and Panel B for lagged average income from Equation 1. Panels C and D show coefficients for first and second lags of depression respectively from Equation 2

**Figure A4: Comparison of coefficients of interest based on wealth percentiles**




*Notes:* The graph illustrates coefficient estimates derived from the subgroup analysis categorized by wealth index percentiles. The 10th percentile represents the regression results for a sub-group of individuals who are poorest proportion of the sample, while the 100th percentile represents individuals who are richest proportion. Panel A displays coefficients for average income and Panel B for lagged average income from Equation 1. Panels C and D show coefficients for first and second lags of depression respectively from Equation 2.

**Table A1:** Dynamic panel estimates without exclusion on number of missings

| | Y= Depression<br>X= Avg. Income<br>Exclude if less than 4 waves | Y= Depression<br>X= Avg. Income<br>No exclusion | Y= Avg. Income<br>X=Depression<br>Exclude if less than 4 waves | Y= Avg. Income<br>X=Depression<br>No exclusion |
|---|---|---|---|---|
| L.Depression score | 0.096*** | 0.095*** | 0.002 | 0.005 |
| | (0.027) | (0.027) | (0.012) | (0.012) |
| L2.Depression score | 0.033 | 0.033 | 0.009 | 0.011 |
| | (0.026) | (0.026) | (0.010) | (0.010) |
| Log of avg. weekly income | -0.128** | -0.131** | | |
| | (0.056) | (0.056) | | |
| L.Log of avg. weekly income | 0.023 | 0.021 | 0.247*** | 0.256*** |
| | (0.044) | (0.044) | (0.034) | (0.034) |
| L2.Log of avg. weekly income | | | 0.114*** | 0.120*** |
| | | | (0.026) | (0.026) |
| Time Dummies | Yes | Yes | Yes | Yes |
| Number of individuals | 660 | 672 | 663 | 679 |
| Observations | 5,901 | 5,920 | 6,145 | 6,169 |
| # of coefficients (K) | 19 | 19 | 19 | 19 |
| # of instruments (L) | 26 | 26 | 26 | 26 |
| Serial correlation test (Arellano-Bond first order (m1)) | 0.00 | 0.00 | 0.00 | 0.00 |
| Serial correlation test (Arellano-Bond second order (m2)) | 0.35 | 0.36 | 0.48 | 0.40 |
| Overidentification test (Hansen J (2,2)) | 0.87 | 0.89 | 0.57 | 0.56 |
| Overidentification test (Hansen J (2,3)) | 0.87 | 0.89 | 0.57 | 0.56 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 | 0.00 | 0.00 |

*Notes:* This table reports robustness checks for the FOD-GMM dynamic panel estimation results of the relationship between depression and income by not applying any exclusion criteria based on non-missing number of reported outcome measures. Time fixed effects are included. Depression is measured using the 10-item CES-D scale, with range 0-30, where higher scores indicate more severe depressive symptoms. Income is measured as the log-transformation of average weekly incomes per month. Windmeijer-corrected robust standard errors are shown in parentheses. Statistical significance is indicated at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ levels.

**Table A2:** Dynamic panel estimates controlling third lags as regressor

| | (1)<br>Y= Depression<br>X= Avg. Income | (2)<br>Y= Depression<br>X=Avg. Income<br>+Third lags |
|---|---|---|
| L.Depression score | 0.097*** | 0.100*** |
| | (0.027) | (0.033) |
| L2.Depression score | 0.033 | 0.051* |
| | (0.026) | (0.030) |
| L3.Depression score | | 0.018 |
| | | (0.022) |
| Log of avg. weekly income | -0.128** | -0.178** |
| | (0.056) | (0.070) |
| L.Log of avg. weekly income | 0.023 | 0.011 |
| | (0.044) | (0.053) |
| L2.Log of avg. weekly income | | -0.016 |
| | | (0.047) |
| Time Dummies | Yes | Yes |
| Number of individuals | 660 | 637 |
| Observations | 5,901 | 5,074 |
| # of coefficients (K) | 19 | 20 |
| # of instruments (L) | 26 | 25 |
| Serial correlation test (Arellano-Bond first order (m1)) | 0.00 | 0.00 |
| Serial correlation test (Arellano-Bond second order (m2)) | 0.35 | 0.31 |
| Overidentification test (Hansen J (2,2)) | 0.88 | 1.00 |
| Overidentification test (Hansen J (2,3)) | 0.88 | 1.00 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 |
| Akaike information criterion (AIC) | -10.94 | -9.61 |

*Notes:* This table reports robustness checks for the FOD-GMM dynamic panel estimation results of the relationship between depression and income by including a third lag of depression and income as regressors. Time fixed effects are included. Depression is measured using the 10-item CES-D scale, with range 0-30, where higher scores indicate more severe depressive symptoms. Income is measured as the log-transformation of average weekly incomes per month. Windmeijer-corrected robust standard errors are shown in parentheses. Statistical significance is indicated at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ levels.

**Table A3:** Dynamic panel estimates controlling third lags as regressor

| | (1)<br>Y= Avg. Income<br>X= Depression | (2)<br>Y=Avg. Income<br>X= Depression<br>+Third lags |
|---|---|---|
| L.Log of avg. weekly income | 0.247*** | 0.260*** |
| | (0.034) | (0.039) |
| L2.Log of avg. weekly income | 0.114*** | 0.111*** |
| | (0.026) | (0.028) |
| L3.Log of avg. weekly income | | 0.030 |
| | | (0.025) |
| L.Depression score | 0.002 | 0.012 |
| | (0.012) | (0.014) |
| L2.Depression score | 0.009 | 0.009 |
| | (0.010) | (0.012) |
| L3.Depression score | | -0.002 |
| | | (0.010) |
| Time Dummies | Yes | Yes |
| Number of individuals | 663 | 650 |
| Observations | 6,145 | 5,243 |
| # of coefficients (K) | 19 | 20 |
| # of instruments (L) | 26 | 25 |
| Serial correlation test (Arellano-Bond first order (m1)) | 0.00 | 0.00 |
| Serial correlation test (Arellano-Bond second order (m2)) | 0.48 | 0.33 |
| Overidentification test (Hansen J (2,2)) | 0.58 | 0.60 |
| Overidentification test (Hansen J (2,3)) | 0.58 | 0.60 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 |
| Akaike information criterion (AIC) | -8.35 | -6.34 |

*Notes:* This table reports robustness checks for the FOD-GMM dynamic panel estimation results of the relationship between depression and income by including a third lag of depression and income as regressors. Time fixed effects are included. Depression is measured using the 10-item CES-D scale, with range 0-30, where higher scores indicate more severe depressive symptoms. Income is measured as the log-transformation of average weekly incomes per month. Windmeijer-corrected robust standard errors are shown in parentheses. Statistical significance is indicated at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ levels.

**Table A4:** Dynamic panel estimates with non-random attrition tests

| | (1)<br>Y= Depression<br>X= Avg. Income | (2)<br>Y= Depression<br>X=+Number of waves | (3)<br>Y= Avg. Income<br>X=Depression | (4)<br>Y= Avg. Income<br>X=+Number of waves |
|---|---|---|---|---|
| L.Depression score | 0.096*** | 0.091*** | 0.002 | 0.003 |
| | (0.027) | (0.031) | (0.012) | (0.016) |
| L2.Depression score | 0.033 | 0.030 | 0.009 | 0.009 |
| | (0.026) | (0.027) | (0.010) | (0.012) |
| Log of avg. weekly income | -0.128** | -0.135** | | |
| | (0.056) | (0.060) | | |
| L.Log of avg. weekly income | 0.023 | 0.018 | 0.247*** | 0.248*** |
| | (0.044) | (0.046) | (0.034) | (0.042) |
| L2.Log of avg. weekly income | | | 0.114*** | 0.114*** |
| | | | (0.026) | (0.032) |
| Number of waves present | | -0.102 | | 0.005 |
| | | (0.303) | | (0.155) |
| Time Dummies | Yes | Yes | Yes | Yes |
| Number of individuals | 660 | 660 | 663 | 663 |
| Observations | 5,901 | 5,901 | 6,145 | 6,145 |
| # of coefficients (K) | 19 | 20 | 19 | 20 |
| # of instruments (L) | 26 | 26 | 26 | 26 |
| Serial correlation test (Arellano-Bond first order (m1)) | 0.00 | 0.00 | 0.00 | 0.00 |
| Serial correlation test (Arellano-Bond second order (m2)) | 0.35 | 0.33 | 0.48 | 0.49 |
| Overidentification test (Hansen J (2,2)) | 0.87 | 0.81 | 0.57 | 0.46 |
| Overidentification test (Hansen J (2,3)) | 0.87 | 0.81 | 0.57 | 0.46 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 | 0.00 | 0.00 |

*Notes:* This table reports non-random attrition bias checks for the FOD-GMM dynamic panel estimation results of the relationship between depression and income by including number of waves present as independent variable. Time fixed effects are included. Depression is measured using the 10-item CES-D scale, with range 0-30, where higher scores indicate more severe depressive symptoms. Income is measured as the log-transformation of average weekly incomes per month. Windmeijer-corrected robust standard errors are shown in parentheses. Statistical significance is indicated at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ levels.

**Table A5:** Dynamic panel estimates including other household members' income

| | (1) Y= Depression X= Avg. Income | (2) Y= Depression X=+ other hh | (3) Y= Depression X= HH total income | (4) Y= Depression X= Disposable income |
|---|---|---|---|---|
| L.Depression score | 0.097*** | 0.034 | 0.062 | 0.099*** |
| | (0.027) | (0.044) | (0.042) | (0.027) |
| L2.Depression score | 0.033 | 0.039 | 0.043 | 0.035 |
| | (0.026) | (0.042) | (0.039) | (0.026) |
| Log of avg. weekly income | -0.128** | -0.083 | | |
| | (0.056) | (0.114) | | |
| L.Log of avg. weekly income | 0.023 | 0.022 | | |
| | (0.044) | (0.072) | | |
| Log of avg. weekly income (Other hh members) | | -0.037 | | |
| | | (0.135) | | |
| L.Log of avg. weekly income (Other hh members) | | 0.059 | | |
| | | (0.097) | | |
| Log of avg. weekly income (Household total) | | | -0.029 | |
| | | | (0.154) | |
| L.Log of avg. weekly income (Household total) | | | 0.199* | |
| | | | (0.104) | |
| Log of avg. weekly disposable income (income + gifts/remittances) | | | | -0.063 |
| | | | | (0.070) |
| L.Log of avg. weekly disposable income (income + gifts/remittances) | | | | 0.041 |
| | | | | (0.051) |
| Time Dummies | Yes | Yes | Yes | Yes |
| Number of individuals | 660 | 476 | 506 | 660 |
| Observations | 5,901 | 2,872 | 3,156 | 5,901 |
| # of coefficients (K) | 19 | 21 | 19 | 19 |
| # of instruments (L) | 26 | 32 | 26 | 26 |
| Serial correlation test (Arellano-Bond first order (m1)) | 0.00 | 0.00 | 0.00 | 0.00 |
| Serial correlation test (Arellano-Bond second order (m2)) | 0.35 | 0.32 | 0.58 | 0.40 |
| Overidentification test (Hansen J (2,2)) | 0.88 | 0.68 | 0.98 | 0.70 |
| Overidentification test (Hansen J (2,3)) | 0.88 | 0.68 | 0.98 | 0.70 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 | 0.00 | 0.00 |

*Notes:* This table reports the FOD-GMM dynamic panel estimation results of the relationship between depression and income, also controlling for other household members' income and gifts/remittances received. Time fixed effects are included. Depression is measured using the 10-item CES-D scale, with range 0-30, where higher scores indicate more severe depressive symptoms. Income variables is measured as the log-transformation of average weekly incomes per month. Other household members' income represents the mean of total personal weekly incomes within the household, excluding the respondent. Household average income comprises the mean of all household members' total personal weekly incomes, including the respondent. Disposable income incorporates gifts and remittances to personal income. Windmeijer-corrected robust standard errors are shown in parentheses. Statistical significance is indicated at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ levels.

**Table A6:** Dynamic panel estimates including other household members' income

| | (1)<br>Y= Avg. Income<br>X= Depression | (2)<br>Y= Avg. Income<br>X=+ other hh | (3)<br>Y=HH total income<br>X= Depression |
|---|---|---|---|
| L.Log of avg. weekly income | 0.247*** | 0.168*** | |
| | (0.034) | (0.061) | |
| L2.Log of avg. weekly income | 0.114*** | 0.097** | |
| | (0.026) | (0.047) | |
| L.Depression score | 0.002 | -0.003 | 0.011 |
| | (0.012) | (0.022) | (0.014) |
| L2.Depression score | 0.009 | 0.013 | 0.023* |
| | (0.010) | (0.016) | (0.013) |
| L.Log of avg. weekly income (Other hh members) | | -0.086 | |
| | | (0.073) | |
| L2.Log of avg. weekly income (Other hh members) | | -0.070 | |
| | | (0.048) | |
| L.Log of avg. weekly income (Household total) | | | 0.254*** |
| | | | (0.068) |
| L2.Log of avg. weekly income (Household total) | | | 0.144*** |
| | | | (0.056) |
| Time Dummies | Yes | Yes | Yes |
| Number of individuals | 663 | 450 | 453 |
| Observations | 6,145 | 2,832 | 2,989 |
| # of coefficients (K) | 19 | 21 | 19 |
| # of instruments (L) | 26 | 32 | 26 |
| Serial correlation test (Arellano-Bond first order (m1)) | 0.00 | 0.00 | 0.00 |
| Serial correlation test (Arellano-Bond second order (m2)) | 0.48 | 0.34 | 0.95 |
| Overidentification test (Hansen J (2,2)) | 0.58 | 0.73 | 0.00 |
| Overidentification test (Hansen J (2,3)) | 0.58 | 0.73 | 0.00 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 | 0.00 |

*Notes:* This table reports the FOD-GMM dynamic panel estimation results of the relationship between depression and income, also controlling for other household members' income. Time fixed effects are included. Depression is measured using the 10-item CES-D scale, with range 0-30, where higher scores indicate more severe depressive symptoms. Income variables is measured as the log-transformation of average weekly incomes per month. Other household members' income represents the mean of total personal weekly incomes within the household, excluding the respondent. Household average income comprises the mean of all household members' total personal weekly incomes, including the respondent. Windmeijer-corrected robust standard errors are shown in parentheses. Standard errors are shown in parentheses. Statistical significance is indicated at the $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$ levels.

**Table A7:** Dynamic panel estimates by controlling heterogeneity interactions

| | (1)<br>Y= Depression<br>X= Avg. Income | (2)<br>Y= Depression<br>X=Avg. Income<br>*Male | (3)<br>Y= Depression<br>X= Avg. Income<br>*Wealth |
|---|---|---|---|
| L.Depression score | 0.097***<br>(0.027) | -0.034<br>(0.096) | 0.071<br>(0.043) |
| L2.Depression score | 0.034<br>(0.026) | 0.030<br>(0.035) | 0.015<br>(0.035) |
| Log of avg. weekly income | -0.128**<br>(0.056) | -0.138**<br>(0.068) | -0.201**<br>(0.093) |
| L.Log of avg. weekly income | 0.024<br>(0.044) | -0.011<br>(0.056) | -0.001<br>(0.074) |
| Male*L.Depression score | | 0.375<br>(0.275) | |
| Male*L2.Depression score | | -0.016<br>(0.053) | |
| Male*Log of avg. weekly income | | -0.050<br>(0.119) | |
| Male*L.Log of avg. weekly income | | 0.057<br>(0.105) | |
| Low wealth*L.Depression score | | | 0.017<br>(0.056) |
| Low wealth*L2.Depression score | | | -0.003<br>(0.050) |
| Low wealth*Log of avg. weekly income | | | 0.176<br>(0.121) |
| Low wealth*L.Log of avg. weekly income | | | 0.040<br>(0.098) |
| Time Dummies | Yes | Yes | Yes |
| Number of individuals | 660 | 660 | 574 |
| Observations | 5,901 | 5,901 | 5,436 |
| # of coefficients (K) | 19 | 23 | 23 |
| # of instruments (L) | 26 | 39 | 40 |
| Serial correlation test<br>(Arellano-Bond first order (m1)) | 0.00 | 0.00 | 0.00 |
| Serial correlation test<br>(Arellano-Bond second order (m2)) | 0.36 | 0.42 | 0.20 |
| Overidentification test (Hansen J (2,2)) | 0.88 | 0.65 | 0.37 |
| Overidentification test (Hansen J (2,3)) | 0.88 | 0.65 | 0.36 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 | 0.00 |

*Notes:* This table reports heterogeneity analysis for the FOD-GMM dynamic panel estimation results of the relationship between depression and income by including gender and wealth status interactions. Time fixed effects are included. Depression is measured using the 10-item CES-D scale, with range 0-30, where higher scores indicate more severe depressive symptoms. Income is measured as the log-transformation of average weekly incomes per month. Gender is a dummy variable with male and female categories. The wealth status is a dummy variable with with low and high wealth status based on median wealth index. Windmeijer-corrected robust standard errors are shown in parentheses. Statistical significance is indicated at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ levels.

**Table A8:** Dynamic panel estimates by controlling heterogeneity interactions

| | (1) Y= Avg. Income X= Depression | (2) Y=Avg. Income X= Depression *Male | (3) Y= Avg. Income X= Depression *Wealth |
|---|---|---|---|
| L.Log of avg. weekly income | 0.247*** | 0.342*** | 0.216*** |
| | (0.034) | (0.121) | (0.058) |
| L2.Log of avg. weekly income | 0.114*** | 0.068* | 0.060 |
| | (0.026) | (0.036) | (0.047) |
| L.Depression score | 0.002 | -0.003 | 0.008 |
| | (0.012) | (0.018) | (0.019) |
| L2.Depression score | 0.009 | -0.009 | 0.006 |
| | (0.010) | (0.014) | (0.016) |
| Male*L.Log of avg. weekly income | | -0.278 | |
| | | (0.300) | |
| Male*L2.Log of avg. weekly income | | 0.110 | |
| | | (0.086) | |
| Male*L.Depression score | | 0.023 | |
| | | (0.027) | |
| Male*L2.Depression score | | 0.050** | |
| | | (0.021) | |
| Low wealth*L.Log of avg. weekly income | | | 0.034 |
| | | | (0.066) |
| Low wealth*L2.Log of avg. weekly income | | | 0.072 |
| | | | (0.052) |
| Low wealth*L.Depression score | | | -0.017 |
| | | | (0.023) |
| Low wealth*L2.Depression score | | | -0.002 |
| | | | (0.020) |
| Time Dummies | Yes | Yes | Yes |
| Number of individuals | 663 | 663 | 577 |
| Observations | 6,145 | 6,145 | 5,669 |
| # of coefficients (K) | 19 | 23 | 23 |
| # of instruments (L) | 26 | 39 | 40 |
| Serial correlation test (Arellano-Bond first order (m1)) | 0.00 | 0.00 | 0.00 |
| Serial correlation test (Arellano-Bond second order (m2)) | 0.48 | 0.93 | 0.69 |
| Overidentification test (Hansen J (2,2)) | 0.58 | 0.16 | 0.48 |
| Overidentification test (Hansen J (2,3)) | 0.58 | 0.17 | 0.48 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 | 0.00 |

*Notes:* This table reports heterogeneity analysis for the FOD-GMM dynamic panel estimation results of the relationship between depression and income by including gender and wealth status interactions. Time fixed effects are included. Depression is measured using the 10-item CES-D scale, with range 0-30, where higher scores indicate more severe depressive symptoms. Income is measured as the log-transformation of average weekly incomes per month. Gender is a dummy variable with male and female categories. The wealth status is a dummy variable with with low and high wealth status based on median wealth index. Windmeijer-corrected robust standard errors are shown in parentheses. Statistical significance is indicated at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ levels.

**Table A9:** Dynamic panel estimates with bandwidth related decomposition of the depression score

| | (1)<br>Y=Avg. Income<br>X=Sleep deprivation | (2)<br>Y=Avg. Income<br>X=Concentration | (3)<br>Y=Avg. Income<br>X=Effort | (4)<br>Y=Avg. Income<br>X=Getting Going | (5)<br>Y=Avg. Income<br>X=Bothered |
|---|---|---|---|---|---|
| L.Log of avg. weekly income | 0.236*** | 0.221*** | 0.252*** | 0.233*** | 0.231*** |
| | (0.036) | (0.035) | (0.034) | (0.035) | (0.035) |
| L2.Log of avg. weekly income | 0.108*** | 0.092*** | 0.114*** | 0.103*** | 0.100*** |
| | (0.028) | (0.026) | (0.026) | (0.027) | (0.027) |
| L.Having problems in sleep | -0.013 | | | | |
| | (0.051) | | | | |
| L2.Having problems in sleep | 0.081* | | | | |
| | (0.047) | | | | |
| L.Having problems in concentration | | -0.036 | | | |
| | | (0.045) | | | |
| L2.Having problems in concentration | | -0.059 | | | |
| | | (0.044) | | | |
| L.Feeling that everything you did was an effort | | | -0.003 | | |
| | | | (0.045) | | |
| L2.Feeling that everything you did was an effort | | | 0.007 | | |
| | | | (0.036) | | |
| L.Feeling could not get going | | | | -0.103* | |
| | | | | (0.054) | |
| L2.Feeling could not get going | | | | 0.064 | |
| | | | | (0.049) | |
| L.Feeling bothered by things | | | | | 0.004 |
| | | | | | (0.054) |
| L2.Feeling bothered by things | | | | | 0.017 |
| | | | | | (0.045) |
| FDR correction passed (Log of avg. weekly income) | No | N/A | N/A | No | N/A |
| q-value (Log of avg. weekly income) | [0.551] | - | - | [0.353] | - |
| Time Dummies | Yes | Yes | Yes | Yes | Yes |
| Number of individuals | 663 | 663 | 663 | 663 | 663 |
| Observations | 6,145 | 6,145 | 6,145 | 6,145 | 6,145 |
| # of coefficients (K) | 19 | 19 | 19 | 19 | 19 |
| # of instruments (L) | 26 | 26 | 26 | 26 | 26 |
| Serial correlation test (Arellano-Bond first order (m1)) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Serial correlation test (Arellano-Bond second order (m2)) | 0.52 | 0.83 | 0.51 | 0.69 | 0.70 |
| Overidentification test (Hansen J (2,2)) | 0.41 | 0.87 | 0.34 | 0.70 | 0.88 |
| Overidentification test (Hansen J (2,3)) | 0.41 | 0.87 | 0.34 | 0.70 | 0.88 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

*Notes:* This table reports the FOD-GMM dynamic panel estimation results of the relationship between depression and income by using cognitive bandwidth domain related sub-items of depression scale (CES-D 10). Time fixed effects are included. Depression sub-items are questions of the 10-item CES-D scale, with range 0-3, where higher scores indicate more severe depressive symptoms. Income is measured as the log-transformation of average weekly incomes per month. Windmeijer-corrected robust standard errors are shown in parentheses. All the results are subjected to Benjamini and Yekutieli (2001) correction and the table reports if significant sub-item coefficients pass the FDR correction criteria (q-values in square brackets). Statistical significance is indicated at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ levels.

**Table A10:** Dynamic panel estimates with emotions related decomposition of the depression score

| | (1)<br>Y=Avg. Income<br>X=Sadness | (2)<br>Y=Avg. Income<br>X=Hopelessness | (3)<br>Y=Avg. Income<br>X=Loneliness | (4)<br>Y=Avg. Income<br>X=Stress | (5)<br>Y=Avg. Income<br>X=Fearfulness |
|---|---|---|---|---|---|
| L.Log of avg. weekly income | 0.240*** | 0.251*** | 0.237*** | 0.246*** | 0.244*** |
| | (0.035) | (0.035) | (0.035) | (0.035) | (0.036) |
| L2.Log of avg. weekly income | 0.107*** | 0.117*** | 0.102*** | 0.115*** | 0.107*** |
| | (0.027) | (0.026) | (0.027) | (0.026) | (0.028) |
| L.Feeling sad | 0.023 | | | | |
| | (0.053) | | | | |
| L2.Feeling sad | 0.023 | | | | |
| | (0.046) | | | | |
| L.Feeling hopeless | | 0.006 | | | |
| | | (0.049) | | | |
| L2.Feeling hopeless | | -0.034 | | | |
| | | (0.041) | | | |
| L.Feeling lonely | | | 0.067 | | |
| | | | (0.054) | | |
| L2.Feeling lonely | | | 0.035 | | |
| | | | (0.053) | | |
| L.Feeling depressed/stressed | | | | 0.008 | |
| | | | | (0.051) | |
| L2.Feeling depressed/stressed | | | | 0.026 | |
| | | | | (0.042) | |
| L.Feeling fearful | | | | | 0.009 |
| | | | | | (0.051) |
| L2.Feeling fearful | | | | | 0.032 |
| | | | | | (0.047) |
| FDR correction passed (Log of avg. weekly income) | N/A | N/A | N/A | N/A | N/A |
| q-value (Log of avg. weekly income) | - | - | - | - | - |
| Time Dummies | Yes | Yes | Yes | Yes | Yes |
| Number of individuals | 663 | 663 | 663 | 663 | 663 |
| Observations | 6,145 | 6,145 | 6,145 | 6,145 | 6,145 |
| # of coefficients (K) | 19 | 19 | 19 | 19 | 19 |
| # of instruments (L) | 26 | 26 | 26 | 26 | 26 |
| Serial correlation test (Arellano-Bond first order (m1)) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Serial correlation test (Arellano-Bond second order (m2)) | 0.60 | 0.41 | 0.75 | 0.43 | 0.63 |
| Overidentification test (Hansen J (2,2)) | 0.78 | 0.22 | 0.80 | 0.34 | 0.22 |
| Overidentification test (Hansen J (2,3)) | 0.78 | 0.22 | 0.80 | 0.34 | 0.22 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

*Notes:* This table reports the FOD-GMM dynamic panel estimation results of the relationship between depression and income by using emotional domain related sub-items of depression scale (CES-D 10). Time fixed effects are included. Depression sub-items are questions of the 10-item CES-D scale, with range 0-3, where higher scores indicate more severe depressive symptoms. Income is measured as the log-transformation of average weekly incomes per month. Windmeijer-corrected robust standard errors are shown in parentheses. All the results are subjected to Benjamini and Yekutieli (2001) correction and the table reports if significant sub-item coefficients pass the FDR correction criteria (q-values in square brackets). Statistical significance is indicated at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ levels.

**Table A11:** Dynamic panel estimates with different number of instruments

| | (1)<br>Y= Depression<br>X= Avg. Income<br>Up to lag 5 | (2)<br>Y= Depression<br>X=Avg. Income<br>Up to lag 3 | (3)<br>Y= Depression<br>X= Avg. Income<br>Up to lag 4 | (4)<br>Y= Depression<br>X=Avg. Income<br>Up to lag 6 |
|---|---|---|---|---|
| L.Depression score | 0.097*** | 0.084*** | 0.094*** | 0.093*** |
| | (0.027) | (0.031) | (0.028) | (0.028) |
| L2.Depression score | 0.033 | 0.027 | 0.032 | 0.029 |
| | (0.026) | (0.027) | (0.026) | (0.027) |
| Log of avg. weekly income | -0.128** | -0.151** | -0.130** | -0.103* |
| | (0.056) | (0.059) | (0.057) | (0.057) |
| L.Log of avg. weekly income | 0.023 | 0.007 | 0.023 | 0.027 |
| | (0.044) | (0.046) | (0.045) | (0.046) |
| Time Dummies | Yes | Yes | Yes | Yes |
| Number of individuals | 660 | 660 | 660 | 660 |
| Observations | 5,901 | 5,901 | 5,901 | 5,901 |
| # of coefficients (K) | 19 | 19 | 19 | 19 |
| # of instruments (L) | 26 | 22 | 24 | 28 |
| Serial correlation test (Arellano-Bond first order (m1)) | 0.00 | 0.00 | 0.00 | 0.00 |
| Serial correlation test (Arellano-Bond second order (m2)) | 0.35 | 0.29 | 0.36 | 0.26 |
| Overidentification test (Hansen J (2,2)) | 0.88 | 0.89 | 0.72 | 0.11 |
| Overidentification test (Hansen J (2,3)) | 0.88 | 0.89 | 0.72 | 0.11 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 | 0.00 | 0.00 |
| Akaike information criterion (AIC) | -10.94 | -5.39 | -7.12 | -3.63 |

*Notes:* This table reports robustness checks for the FOD-GMM dynamic panel estimation results of the relationship between depression and income using different instrument sets. Time fixed effects are included. Depression is measured using the 10-item CES-D scale, with range 0-30, where higher scores indicate more severe depressive symptoms. Income is measured as the log-transformation of average weekly incomes per month. Windmeijer-corrected robust standard errors are shown in parentheses. Statistical significance is indicated at the $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$ levels.

**Table A12:** Dynamic panel estimates with different number of instruments

| | (1)<br>Y= Avg. Income<br>X= Depression<br>Up to lag 5 | (2)<br>Y=Avg. Income<br>X= Depression<br>Up to lag 3 | (3)<br>Y= Avg. Income<br>X= Depression<br>Up to lag 4 | (4)<br>Y= Avg. Income<br>X= Depression<br>Up to lag 6 |
|---|---|---|---|---|
| L.Log of avg. weekly income | 0.247*** | 0.251*** | 0.250*** | 0.246*** |
| | (0.034) | (0.039) | (0.035) | (0.034) |
| L2.Log of avg. weekly income | 0.114*** | 0.116*** | 0.116*** | 0.115*** |
| | (0.026) | (0.029) | (0.027) | (0.026) |
| L.Depression score | 0.002 | 0.003 | 0.003 | 0.001 |
| | (0.012) | (0.012) | (0.012) | (0.012) |
| L2.Depression score | 0.009 | 0.009 | 0.009 | 0.008 |
| | (0.010) | (0.010) | (0.010) | (0.010) |
| Time Dummies | Yes | Yes | Yes | Yes |
| Number of individuals | 663 | 663 | 663 | 663 |
| Observations | 6,145 | 6,145 | 6,145 | 6,145 |
| # of coefficients (K) | 19 | 19 | 19 | 19 |
| # of instruments (L) | 26 | 22 | 24 | 28 |
| Serial correlation test (Arellano-Bond first order (m1)) | 0.00 | 0.00 | 0.00 | 0.00 |
| Serial correlation test (Arellano-Bond second order (m2)) | 0.48 | 0.45 | 0.47 | 0.44 |
| Overidentification test (Hansen J (2,2)) | 0.58 | 0.14 | 0.36 | 0.64 |
| Overidentification test (Hansen J (2,3)) | 0.58 | 0.14 | 0.37 | 0.64 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 | 0.00 | 0.00 |
| Akaike information criterion (AIC) | -8.35 | -0.57 | -4.56 | -11.04 |

*Notes:* This table reports robustness checks for the FOD-GMM dynamic panel estimation results of the relationship between depression and income using different instrument sets. Time fixed effects are included. Depression is measured using the 10-item CES-D scale, with range 0-30, where higher scores indicate more severe depressive symptoms. Income is measured as the log-transformation of average weekly incomes per month. Windmeijer-corrected robust standard errors are shown in parentheses. Statistical significance is indicated at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ levels.

**Table A13:** Dynamic panel estimates with different classification of instruments

| | (1)<br>Y= Depression<br>X= Avg. Income<br>Predetermined | (2)<br>Y= Depression<br>X=Avg. Income<br>Exogenous | (3)<br>Y= Depression<br>X= Avg. Income<br>Endogenous |
|---|---|---|---|
| L.Depression score | 0.097*** | 0.091*** | 0.097*** |
| | (0.027) | (0.028) | (0.027) |
| L2.Depression score | 0.033 | 0.033 | 0.034 |
| | (0.026) | (0.026) | (0.026) |
| Log of avg. weekly income | -0.128** | -0.142*** | -0.065 |
| | (0.056) | (0.036) | (0.363) |
| L.Log of avg. weekly income | 0.023 | 0.033 | 0.011 |
| | (0.044) | (0.035) | (0.080) |
| Time Dummies | Yes | Yes | Yes |
| Number of individuals | 660 | 660 | 660 |
| Observations | 5,901 | 5,901 | 5,901 |
| # of coefficients (K) | 19 | 19 | 19 |
| # of instruments (L) | 26 | 26 | 25 |
| Serial correlation test (Arellano-Bond first order (m1)) | 0.00 | 0.00 | 0.00 |
| Serial correlation test (Arellano-Bond second order (m2)) | 0.35 | 0.38 | 0.33 |
| Overidentification test (Hansen J (2,2)) | 0.88 | 0.82 | 0.81 |
| Overidentification test (Hansen J (2,3)) | 0.88 | 0.82 | 0.80 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 | 0.00 |
| Akaike information criterion (AIC) | -10.94 | -10.33 | -8.97 |
| Incremental Hansen J test | 0.86 | 0.89 | 0.75 |

*Notes:* This table reports robustness checks for the FOD-GMM dynamic panel estimation results of the relationship between depression and income using different instrument classifications. Time fixed effects are included. Depression is measured using the 10-item CES-D scale, with range 0-30, where higher scores indicate more severe depressive symptoms. Income is measured as the log-transformation of average weekly incomes per month. Windmeijer-corrected robust standard errors are shown in parentheses. Statistical significance is indicated at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ levels.

**Table A14:** Dynamic panel estimates with different classification of instruments

| | (1) Y= Avg. Income X= Depression Predetermined | (2) Y=Avg. Income X= Depression Exogenous | (3) Y= Avg. Income X= Depression Endogenous |
|---|---|---|---|
| L.Log of avg. weekly income | 0.247*** | 0.228*** | 0.228*** |
| | (0.034) | (0.034) | (0.043) |
| L2.Log of avg. weekly income | 0.114*** | 0.101*** | 0.119*** |
| | (0.026) | (0.027) | (0.029) |
| L.Depression score | 0.002 | 0.001 | -0.184 |
| | (0.012) | (0.006) | (0.235) |
| L2.Depression score | 0.009 | 0.006 | 0.024 |
| | (0.010) | (0.006) | (0.023) |
| Time Dummies | Yes | Yes | Yes |
| Number of individuals | 663 | 663 | 663 |
| Observations | 6,145 | 6,145 | 6,145 |
| # of coefficients (K) | 19 | 19 | 19 |
| # of instruments (L) | 26 | 26 | 25 |
| Serial correlation test (Arellano-Bond first order (m1)) | 0.00 | 0.00 | 0.00 |
| Serial correlation test (Arellano-Bond second order (m2)) | 0.48 | 0.66 | 0.89 |
| Overidentification test (Hansen J (2,2)) | 0.58 | 0.79 | 0.62 |
| Overidentification test (Hansen J (2,3)) | 0.58 | 0.80 | 0.63 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 | 0.67 |
| Akaike information criterion (AIC) | -8.35 | -10.12 | -7.58 |
| Incremental Hansen J test | 0.37 | 0.96 | 0.49 |

*Notes:* This table reports robustness checks for the FOD-GMM dynamic panel estimation results of the relationship between depression and income using different instrument classifications. Time fixed effects are included. Depression is measured using the 10-item CES-D scale, with range 0-30, where higher scores indicate more severe depressive symptoms. Income is measured as the log-transformation of average weekly incomes per month. Windmeijer-corrected robust standard errors are shown in parentheses. Statistical significance is indicated at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ levels.

**Table A15:** Dynamic panel estimates using non-imputed income

| | (1)<br>Y= Depression<br>X=Avg. income | (2)<br>Y= Depression<br>X=Non-imputed avg. income | (3)<br>Y=Depression<br>X= + L3.Depression | (4)<br>Y=Avg. income<br>X=Depression | (5)<br>Y=Non-imputed avg. income<br>X=Depression |
|---|---|---|---|---|---|
| L.Depression score | 0.096*** | 0.095*** | 0.098*** | 0.002 | -0.006 |
| | (0.027) | (0.029) | (0.036) | (0.012) | (0.019) |
| L2.Depression score | 0.033 | 0.039 | 0.056* | 0.009 | 0.005 |
| | (0.026) | (0.027) | (0.033) | (0.010) | (0.014) |
| L3.Depression score | | | 0.013 | | |
| | | | (0.023) | | |
| Log of avg. weekly income | -0.128** | | | | |
| | (0.056) | | | | |
| L.Log of avg. weekly income | 0.023 | | | 0.247*** | |
| | (0.044) | | | (0.034) | |
| L2.Log of avg. weekly income | | | | 0.114*** | |
| | | | | (0.026) | |
| Non-imputed log of avg. weekly income | | -0.084 | -0.140** | | |
| | | (0.083) | (0.071) | | |
| L.Non-imputed log of avg. weekly income | | 0.045 | 0.020 | | 0.261*** |
| | | (0.064) | (0.057) | | (0.097) |
| L2.Non-imputed log of avg. weekly income | | | | | 0.135* |
| | | | | | (0.071) |
| Time Dummies | Yes | Yes | Yes | Yes | Yes |
| Number of individuals | 660 | 657 | 633 | 663 | 659 |
| Observations | 5,901 | 5,426 | 4,807 | 6,145 | 5,435 |
| # of coefficients (K) | 19 | 19 | 19 | 19 | 19 |
| # of instruments (L) | 26 | 26 | 25 | 26 | 26 |
| Serial correlation test (Arellano-Bond first order (m1)) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Serial correlation test (Arellano-Bond second order (m2)) | 0.35 | 0.08 | 0.37 | 0.48 | 0.36 |
| Overidentification test (Hansen J (2,2)) | 0.87 | 0.80 | 0.94 | 0.57 | 0.00 |
| Overidentification test (Hansen J (2,3)) | 0.87 | 0.80 | 0.94 | 0.57 | 0.00 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

*Notes:* This table reports robustness checks for the FOD-GMM dynamic panel estimation results of the relationship between depression and income by using imputed versus non-imputed income measures. Time fixed effects are included. Depression is measured using the 10-item CES-D scale, with range 0-30, where higher scores indicate more severe depressive symptoms. Income is measured as the log-transformation of average weekly incomes per month. Windmeijer-corrected robust standard errors are shown in parentheses. Statistical significance is indicated at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ levels.

**Table A16:** Dynamic panel estimates excluding non-regular income earners

| | (1)<br>Y= Depression<br>X= Avg. Income<br>No exclusion | (2)<br>Y= Depression<br>X= Avg. Income<br>Share zero=0.9 | (3)<br>Y= Depression<br>X= Avg. Income<br>Share zero=0.7 | (4)<br>Y= Depression<br>X= Avg. Income<br>Share zero=0.5 |
|---|---|---|---|---|
| L.Depression score | 0.096*** | 0.098*** | 0.082*** | 0.079*** |
| | (0.027) | (0.028) | (0.029) | (0.029) |
| L2.Depression score | 0.033 | 0.033 | 0.025 | 0.017 |
| | (0.026) | (0.027) | (0.030) | (0.031) |
| Log of avg. weekly income | -0.128** | -0.127** | -0.149** | -0.160** |
| | (0.056) | (0.056) | (0.059) | (0.062) |
| L.Log of avg. weekly income | 0.023 | 0.021 | 0.022 | 0.029 |
| | (0.044) | (0.044) | (0.046) | (0.047) |
| Time Dummies | Yes | Yes | Yes | Yes |
| Number of individuals | 660 | 590 | 534 | 499 |
| Observations | 5,901 | 5,287 | 4,802 | 4,489 |
| # of coefficients (K) | 19 | 19 | 19 | 19 |
| # of instruments (L) | 26 | 26 | 26 | 26 |
| Serial correlation test (Arellano-Bond first order (m1)) | 0.00 | 0.00 | 0.00 | 0.00 |
| Serial correlation test (Arellano-Bond second order (m2)) | 0.35 | 0.32 | 0.22 | 0.15 |
| Overidentification test (Hansen J (2,2)) | 0.87 | 0.94 | 0.79 | 0.75 |
| Overidentification test (Hansen J (2,3)) | 0.87 | 0.94 | 0.79 | 0.75 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 | 0.00 | 0.00 |

*Notes:* This table reports robustness checks for the FOD-GMM dynamic panel estimation results of the relationship between depression and income by excluding irregular income earners. Time fixed effects are included. Depression is measured using the 10-item CES-D scale, with range 0-30, where higher scores indicate more severe depressive symptoms. Income is measured as the log-transformation of average weekly incomes per month. Columns 2-4 progressively exclude individuals with larger shares of zero income weeks (>0.9, >0.7, >0.5 respectively). Windmeijer-corrected robust standard errors are shown in parentheses. Statistical significance is indicated at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ levels.

**Table A17:** Dynamic panel estimates excluding non-regular income earners

| | (1)<br>Y= Avg. Income<br>X= Depression<br>No exclusion | (2)<br>Y= Avg. Income<br>X= Depression<br>Share zero=0.9 | (3)<br>Y= Avg. Income<br>X= Depression<br>Share zero=0.7 | (4)<br>Y= Avg. Income<br>X= Depression<br>Share zero=0.5 |
|---|---|---|---|---|
| L.Log of avg. weekly income | 0.247*** | 0.253*** | 0.243*** | 0.251*** |
| | (0.034) | (0.034) | (0.035) | (0.037) |
| L2.Log of avg. weekly income | 0.114*** | 0.117*** | 0.110*** | 0.118*** |
| | (0.026) | (0.026) | (0.027) | (0.028) |
| L.Depression score | 0.002 | 0.009 | 0.004 | 0.007 |
| | (0.012) | (0.012) | (0.012) | (0.013) |
| L2.Depression score | 0.009 | 0.014 | 0.010 | 0.013 |
| | (0.010) | (0.010) | (0.011) | (0.011) |
| Time Dummies | Yes | Yes | Yes | Yes |
| Number of individuals | 663 | 593 | 536 | 501 |
| Observations | 6,145 | 5,513 | 5,014 | 4,695 |
| # of coefficients (K) | 19 | 19 | 19 | 19 |
| # of instruments (L) | 26 | 26 | 26 | 26 |
| Serial correlation test (Arellano-Bond first order (m1)) | 0.00 | 0.00 | 0.00 | 0.00 |
| Serial correlation test (Arellano-Bond second order (m2)) | 0.48 | 0.46 | 0.65 | 0.66 |
| Overidentification test (Hansen J (2,2)) | 0.57 | 0.77 | 0.89 | 0.85 |
| Overidentification test (Hansen J (2,3)) | 0.57 | 0.77 | 0.89 | 0.86 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 | 0.00 | 0.00 |

*Notes:* This table reports robustness checks for the FOD-GMM dynamic panel estimation results of the relationship between depression and income by excluding irregular income earners. Time fixed effects are included. Depression is measured using the 10-item CES-D scale, with range 0-30, where higher scores indicate more severe depressive symptoms. Income is measured as the log-transformation of average weekly incomes per month. Columns 2-4 progressively exclude individuals with larger shares of zero income weeks (>0.9, >0.7, >0.5 respectively). Windmeijer-corrected robust standard errors are shown in parentheses. Statistical significance is indicated at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ levels.

**Table A18:** Dynamic panel estimates excluding intervention period

| | (1) Y= Depression X= Avg. Income No exclusion | (2) Y= Depression X= Avg. Income Intervention excluded | (3) Y= Avg. Income X=Depression No exclusion | (4) Y= Avg. Income X=Depression Intervention excluded |
|---|---|---|---|---|
| L.Depression score | 0.096*** | 0.116*** | 0.002 | 0.007 |
| | (0.027) | (0.034) | (0.012) | (0.014) |
| L2.Depression score | 0.033 | 0.043 | 0.009 | 0.001 |
| | (0.026) | (0.027) | (0.010) | (0.012) |
| Log of avg. weekly income | -0.128** | -0.209*** | | |
| | (0.056) | (0.066) | | |
| L.Log of avg. weekly income | 0.023 | -0.013 | 0.247*** | 0.298*** |
| | (0.044) | (0.052) | (0.034) | (0.043) |
| L2.Log of avg. weekly income | | | 0.114*** | 0.112*** |
| | | | (0.026) | (0.033) |
| Time Dummies | Yes | Yes | Yes | Yes |
| Number of individuals | 660 | 552 | 663 | 555 |
| Observations | 5,901 | 4,112 | 6,145 | 4,278 |
| # of coefficients (K) | 19 | 19 | 19 | 19 |
| # of instruments (L) | 26 | 26 | 26 | 26 |
| Serial correlation test (Arellano-Bond first order (m1)) | 0.00 | 0.00 | 0.00 | 0.00 |
| Serial correlation test (Arellano-Bond second order (m2)) | 0.35 | 0.61 | 0.48 | 0.47 |
| Overidentification test (Hansen J (2,2)) | 0.87 | 0.63 | 0.57 | 0.26 |
| Overidentification test (Hansen J (2,3)) | 0.87 | 0.63 | 0.57 | 0.26 |
| Underidentification test (Kleibergen-Paap) | 0.00 | 0.00 | 0.00 | 0.00 |

*Notes:* This table reports robustness checks for the FOD-GMM dynamic panel estimation results of the relationship between depression and income by excluding intervention period. Time fixed effects are included. Depression is measured using the 10-item CES-D scale, with range 0-30, where higher scores indicate more severe depressive symptoms. Income is measured as the log-transformation of average weekly incomes per month. Windmeijer-corrected robust standard errors are shown in parentheses. Statistical significance is indicated at the $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$ levels.