Heat, Economic Stress, and Mental Health: Evidence from Indonesia*

Jingyao Wei[†] Simon Taye[‡] Damien de Walque[§]
Heather Schofield[¶] Hao Wang[‖]

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Abstract

The potential for heat to harm mental health is well-known, but inconsistent across populations. We explore a potential source of heterogeneity in this effect that may drive these conflicting results: underlying economic stress. We draw on panel data from Indonesia and capture three types of economic shocks: income losses driven by international price changes for palm oil, sudden and large fuel cost increases, and job loss. In the general population we find no association between temperature and depressive symptoms — captured via the CES-D scale — and are able to rule out even small harmful effects. But, for those experiencing a negative economic shock, we find robust negative impacts of heat ranging from 0.044 to 0.09 SD per degree Celsius. As climate change increases both the frequency of extreme heat and the prevalence of economic shocks, our findings suggest the psychological toll of a warming climate will be concentrated among the most economically vulnerable.

*The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the World Bank, its Executive Directors, or the countries they represent.

[†]NHH (jingyao.wei@nhh.no)

[‡]Yale University (simon.taye@yale.edu)

[§]World Bank, Development Research Group (ddewalque@worldbank.org)

[¶]Cornell University. (hws44@cornell.edu) Corresponding author. Sage Hall 375, Ithaca, NY 14850.

[‖]University of California, Davis (hwa@ucdavis.edu)

1 Introduction

Roughly 1 in 20 adults suffer from depression around the globe (World Health Organization, 2025). In low- and middle-income countries (LMICs), many individuals remain undiagnosed and therefore untreated (Lund et al., 2010). The costs of this high burden of disease from depression are large both in terms of welfare and income. Depression is the leading cause of years lived with disability (YLDs) and productivity losses and other costs usually far exceed health care costs (World Health Organization, 2022). Poor mental health, especially depression and anxiety, is also associated with worse cognition, and those cognitive deficits spill into learning and productivity (Awadalla et al., 2024; de Oliveira et al., 2022; Rock et al., 2014).

While there are many drivers of poor mental health, heat is a rising concern. There are many potential links between heat and poor mental health via biological channels such as the effect of heat stress on cortisol (Lõhmus, 2018; McMorris et al., 2006), sleep quality (Christodoulou et al., 2024; Hou et al., 2023; Hua et al., 2023; Mullins and White, 2019; Srivastava and Mullins, 2025), behavioral channels such as social withdrawal (Wang and Fang, 2025), and economic channels such as reduced income (Barve et al., 2021; Carleton, 2017; Pailler and Tsaneva, 2018) and warming temperatures around the globe may exacerbate such connections. However, existing evidence on this link to date is mixed.

Multiple sources document a clear relationship between heat and extreme forms of poor mental health, in particular, suicide and hospitalizations related to mental health (Burke et al., 2018; Carleton, 2017; Hansen et al., 2008; Mullins and White, 2019; Nori-Sarma et al., 2022; Page et al., 2007). However, while associations are generally negative, the relationship between heat and less extreme forms of poor mental health remains more mixed with results that can vary with the temperature measure used and across sub-populations (e.g., Fritz (2026); Hua et al. (2023); Pailler and Tsaneva (2018). For example, Hua et al. (2023) find that less educated (junior high or below) and rural populations experience significant reductions in mental health with higher temperatures while more educated populations and urban residents see no change in mental health at higher temperatures.

These disparate results raise the question of why such heterogeneity exists. In this paper, we test one potential source of heterogeneity that is consistent with much of the variation observed – underlying economic stress. Both the medical and public health literatures suggest that the effects of stressors may interact in important ways. For example, the allostatic load literature highlights that as stressors accumulate, the bur-

den can compound (McEwen, 1998; McEwen and Stellar, 1993). Similarly, the stress-sensitization literature suggests that the effects of multiple stressors concurrently may be super-additive (Hammen, 2005; Hammen et al., 2000). This idea is consistent with earlier results such as fairly consistent large impacts on extreme events such as suicides and hospitalizations as well as effects on vulnerable populations such as farmers – for whom heat is both directly stressful and economically impactful via yields (Carleton, 2017).

In order to test whether heat's impact on mental health is exacerbated by economic stress, we draw on data from Indonesia — the Indonesia Family Life Survey (IFLS), a panel dataset with approximately 30,000 individuals. Because the measure of depression, the ten-item CES-D, asks about symptoms over the past week, we measure heat as mean temperature over the seven days ending on the interview date, matched to each respondent's sub-district from satellite reanalysis data. We leverage three disparate economic shocks: 1) a large decline in the price of palm oil between the 4th and 5th wave of the survey, economically stressing palm farmers, 2) a large increase in the price of fuel, economically stressing urban vehicle owners, and 3) recent job loss.

In more detail, the palm-oil price shock is identified from time variation in world markets that passes through to the incomes of palm-farming households. We leverage a triple-difference approach comparing the heat–depression slope of exposed households against non-exposed households in the same district and against the same households in the unshocked wave. The fuel-subsidy cut of November 2014 is identified differently: from the timing of interviews around an abrupt, unanticipated national policy change. We draw on urban vehicle ownership in the wave prior to the shock to avoid endogeneity in the measure of exposure. We then compare respondent's response to additional heat among the "exposed" households (with higher fuel expenditures) that were interviewed just before and just after the cut, within a single survey wave. Recent job loss is identified from cross-sectional contrasts between individuals who lost their job and remain out of work and those who are currently employed, within a district-by-date cell.[1]

Although the economic stressors we study are not themselves randomly assigned, our effect of interest is not the effect of the particular stressor, but its interaction with heat. Identification therefore does not require that palm-price exposure, fuel-cost exposure, or job loss be exogenous. Rather, it requires that conditional on controls

[1]We are unable to leverage the panel structure of the data for this approach due to a very small number of transitions into and out of unemployment.

and fixed effects, interview-week temperature is as good as random. Because these strategies draw on cross-wave commodity-price movements, within-wave policy timing, and individual-level labor-market shocks respectively — variation operating at different levels, over different horizons, and through different economic channels — the diverse strategies make a single omitted confound unlikely.

We find that heat is essentially unrelated to depression in the full sample. A one-degree increase in seven-day mean temperature is associated with a 0.001 standard-deviation change in the CES-D score, and the interview-day mean and maximum yield similarly negligible coefficients of 0.006 and 0.004; none is statistically distinguishable from zero (Table 2). These are precisely estimated nulls—the standard errors are small enough to rule out average effects larger than roughly 0.018 standard deviations per degree Celsius. With one exception in which we observe an *improvement* in mental health with higher 7-day wetbulb temperatures, the null result is insensitive to how heat is measured leveraging common variations found in the literature (i.e. time span, inclusion of humidity, focus on high temperatures).

However, this null effect on average masks strong heterogeneity by economic circumstances. When we interact heat with each of our three stressors, the interaction is positive (indicating greater depression), statistically significant, and economically large in every case, even as the heat main effect remains close to zero (Table 3). Among palm-farming households exposed to the price collapse, a one-degree increase in seven-day mean temperature raises depressive symptoms by 0.08 standard deviations relative to unexposed households; among urban vehicle-owning households after the fuel-subsidy cut the differential is 0.044 standard deviations, and among the recently job-displaced it is 0.053 standard deviations. In other words, the same temperature variation that has no impact on average is meaningfully harmful for those simultaneously experiencing an economic shock and heat stress. Notably, this pattern holds across all three stressors irrespective of the differences in their source, timing, and the population impacted and without a direct effect of heat on economic circumstances. The interactions are, if anything, somewhat larger when heat is measured by wet-bulb temperature, indicating that the result is not an artifact of the dry-bulb specification choice.

The interaction is robust across a range of specifications such as the inclusion of individual fixed effects and alternative definitions of who is considered to be a palm farmer in the palm farmer analysis. Also supporting the identification, we see strong evidence of a dose-response relationship among palm farmers on two dimensions. First, for the palm shock we replace the binary shocked-wave indicator with the magnitude of

the price decline each household actually faced, computed from the gap between world palm prices in its interview month and the corresponding month of the prior wave. Heat interacted with this continuous price drop enters positively and significantly (Table 3, column 3), indicating that households facing larger income shocks show larger heat penalties. This result suggests that any confound would need the also track a similar path, a much higher bar to clear given the volatile price path (Figure A.2). Second, we exploit the likely intensity of exposure within palm-farming households: self-employed smallholders, whose incomes move most directly with the farmgate price, show a heat interaction of 0.073 standard deviations, an effect that is about 10% larger, though not significantly different than for other palm-region agricultural households whose incomes are more insulated (Table A.4). In addition, the fuel cut analysis shows clear and distinct heterogeneity among those with an offsetting positive economic shock: those receiving a cash transfer that offsets the effect of the fuel price increase see no additional impact of heat while those impacted by the price shock without the additional transfer see large declines in mental health.

The findings in the growing literature linking temperature to mental health are inconsistent. The most robust evidence demonstrates effects at the extreme tail of the distribution: higher temperatures raise suicide rates and hospitalizations, a relationship documented across varying settings and identification strategies (Burke et al., 2018; Carleton, 2017). For less extreme self-reported measures of mental health the picture is less clear. Previous work has found that heat can meaningfully worsens mental well-being (Hou et al., 2023; Obradovich et al., 2018; Xue et al., 2019). Yet, studies which examine sub-populations often find striking heterogeneity, with null effects for many groups, particularly those who are more advantaged (Hua et al., 2023; Pailler and Tsaneva, 2018; Zhang et al., 2023).[2] We contribute to reconciling these results by demonstrating that the effects of heat may be differential depending on the underlying economic stress in the population. We show that in the general population in Indonesia, heat has no detectable effect on depressive symptoms—a precisely estimated null across many temperature measures. But, for individuals simultaneously experiencing an economic shock, the same temperature variation produces large and robust increases in depression symptoms regardless of the source of the shock. By identifying economic stress as a moderating channel, we offer a unifying explanation for the conflicting evidence: heat appears to harm mental health where it compounds economic strain, which

[2]Previous research also demonstrates that this relationship can also be sensitive to the precise measure of temperature used (Fritz, 2026). We examine multiple measures of temperature to address this concern.

is most prevalent in the populations and settings where prior work has detected effects.

Our second contribution is to use multiple and varied identification strategies to causally identify economic stress as a moderator of the heat–mental-health relationship. Prior literature that connects heat to mental health through an economic channel has typically inferred that channel indirectly from the timing of heat within the agricultural season or comparisons of more vs. less advantaged populations (e.g., Carleton (2017); Pailler and Tsaneva (2018)). These designs are suggestive but cannot fully separate the economic mechanism from many other factors that covary with season or socio-economic status. We exploit multiple sources of direct, plausibly exogenous variation in economic stress whose identifying variation differs and where we observe dose-response relationships to isolate and identify this channel as well as demonstrate robustness to the broader impact of economic stress generally rather than one specific driver.

Finally, although mental illness is a leading source of disability worldwide, and the burden is disproportionately borne in low- and middle-income countries where much of it goes undiagnosed and untreated (Lund et al., 2010; World Health Organization, 2022) the temperature–mental-health literature is dominated by high-income settings. And within this context, the focus has remained on administrative outcomes such as suicides, hospitalizations, emergency-department visits that capture only the most severe cases and only those who reach care. We provide evidence on broad based mental health as well as heterogeneous effects in a low-income setting, where the burden is heaviest and the existing temperature evidence is thinnest. By using a validated, self-reported depression scale fielded in a large, representative panel of a major developing country, we capture sub-clinical mental-health responses that administrative data often overlook and do so where the gap between disease burden and measured outcomes is largest. This setting also speaks to a first-order policy concern: developing-country populations are both more exposed to rising temperatures and less equipped with the technological adaptations, such as air conditioning, that might buffer the effect.

The remainder of the paper proceeds as follows. Section 2 describes the data sources used in the study and relevant variation. Section 3 lays out the empirical approach and describes the economic shocks that we leverage to examine heterogeneity. Section 4 describes the results and discusses robustness and dose-response effects. Section 5 concludes.

2 Data

The empirical analysis combines three data sources: (i) individual-level survey data on depression symptoms and economic exposure from the Indonesia Family Life Survey (IFLS), (ii) daily satellite-derived weather data matched to each respondent's Kecamatan (sub-district) of residence on the interview date and preceding days, and (iii) monthly world-market palm-oil prices from the World Bank Pink Sheet. We describe each in turn below.

2.1 IFLS individual-level data and the CES-D outcome

The IFLS is a longitudinal household survey representative of 83 % of the Indonesian population and contains over 30,000 individuals. It is conducted by RAND in collaboration with local Indonesian and international institutions. We use the two most recent waves, IFLS-4 (fielded July 2007 to August 2008) and IFLS-5 (fielded September 2014 to September 2015). We restrict the analysis to these waves because they are the only waves which contain data on our primary outcome of interest: the 10-item short form of the Center for Epidemiologic Studies Depression Scale (CES-D). The CES-D is a self-reported questionnaire designed to measure a wide range of symptoms associated with depression.[3]. This scale has been widely validated in Indonesia and in other samples (Andresen et al., 1994; Priyadi, 2023; Radloff, 1977; Tran et al., 2019). Additionally, the IFLS includes demographic data, consumption measures, and variables related to the economic shocks described below.

2.2 Temperature data

To capture heat, we use daily kecamatan (sub-district) level surface temperature from the ERA5-Land reanalysis dataset generated by the Copernicus Climate Change Service (C3S) and provided by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Copernicus Climate Change Service, 2022; Gorelick et al., 2017; Muñoz Sabater, 2019). The climate data are available at a 9-km resolution but are

[3]Responses are recorded on a four-point frequency scale. The IFLS data originally codes the responses on a 1-4 scale, but we rescale to the more standard 0-3 coding in the literature where 0 (rarely, $<$ 1 day in the past week) through 3 (most of the time, 5–7 days) for comparability. In addition, the two waves administer the question differently. IFLS-4 asks each item in two steps: a first yes/no question on whether the respondent experienced the symptom at all in the past week, followed by the frequency question only for those who answered "yes". IFLS-5 instead asks the frequency directly, with "rarely" as the lowest option. We harmonise the two waves by assigning a frequency of 0 (equivalent to the IFLS-5 "rarely" response) to IFLS-4 items answered "no" at the first step, and using the reported frequency for items answered "yes".

aggregated to the kecamatan level based on administrative boundaries.[4] Each respondent is matched to the ERA5-Land temperature values in their kecamatan for the appropriate time period. Because the CES-D-10 asks about symptoms experienced "during the past week," our baseline heat measure is the mean daily temperature over the seven days ending on the interview date, aligning the exposure window with the outcome's recall window. However, we also examine robustness to measures for the day of the interview alone. This data also provides information on relative humidity which is used to generate wet-bulb temperature measures as an alternative heat specification.[5]

As can be seen in Figure 1, Panel A, temperature in Indonesia during the IFLS is warm but not excessively hot, with a 24-hour daily mean of 24.83°C. Seasonal variation in more limited in Indonesia than in many countries (Figure 1, Panel B). Regressions include month-year fixed effects, allowing us to exploit idiosyncratic short term changes in temperature. Temperatures increase slightly on average between waves 4 and 5, though with variation across particular months.

2.3 World palm-oil prices

We obtain monthly world palm-oil prices from the World Bank Commodity Price Data (World Bank, 2026). The price of palm-oil declines heavily between the two waves: averaged over each fielding window, it falls from USD 1,096/MT during IFLS-4 (July 2007–August 2008) to USD 701/MT during IFLS-5 (September 2014–September 2015), a 36% decline on average though with considerable variation (Figure A.2).

2.4 Economic stressors

Economic stress can take many forms. To understand the robustness of the relationship between economic stress and how heat shapes mental health, we study three diverse sources of economic stress: the collapse in palm-oil prices between survey waves, a November 2014 fuel-subsidy cut, and experiencing a recent job loss and remaining unemployed. The first two stressors arise from plausibly exogenous price movements that hit identifiable groups of households. Recent job loss, by contrast, is at least partly

[4] Administrative boundaries were sourced from version 4.1 of the Database of Global Administrative Areas (GADM, 2022) For the ∼3% of households whose kecamatan code is missing from GADM, we use the kabupaten-mean temperature to avoid dropping those observations.

[5] Wet-bulb temperature is computed from dry-bulb temperature T (in °C) and relative humidity RH (in %) using the Stull (2011) approximation, $T_w = T\arctan\left[0.151977\,(\mathrm{RH}+8.313659)^{\frac{1}{2}}\right] + \arctan(T+\mathrm{RH}) - \arctan(\mathrm{RH}-1.676331) + 0.00391838\,\mathrm{RH}^{\frac{3}{2}}\arctan(0.023101\,\mathrm{RH}) - 4.686035$, valid for $\mathrm{RH}\in[5,99]\%$ and $T\in[-20,50]$°C at standard sea-level pressure.

endogenous to the individual, so we treat it as a more suggestive source of variation.

Palm-oil price shock. Indonesia is the world's largest palm-oil producer and exports most of its output. Given the reliance on exporting, world-price movements pass through to local farmgate prices and palm-farming households' incomes. Indeed, a large literature shows that this price-driven variation in palm returns materially shapes rural household welfare in Indonesia: as prices increase consumption, living standards, and nutrition improve and poverty is reduced at the household, village, and district levels (Edwards, 2026; Euler et al., 2017; Gatto et al., 2017; Qaim et al., 2020; Santika et al., 2019).

We exploit the cross-wave collapse in palm-oil prices documented in Figure A.2 as an income shock to palm-farming households. PalmFarmerHH_i equals one if any adult in respondent i's household reports a primary job in agriculture and the household resides in a palm-producing province.[6] The shock variable is defined as $\text{PalmShock}_{it} = \text{PalmFarmerHH}_i \times \mathbf{1}\{\text{IFLS5}\}$, where $\mathbf{1}\{\text{IFLS5}\}$ is set to zero in IFLS-4 and one in IFLS-5.

We use the household-level rather than the individual-level palm-farmer indicator to capture within-household income spillovers: when a palm-farming member's income collapses, non-farming adults in the same household are also exposed through shared consumption and intra-household transfers. The household definition matches the unit at which the income shock is felt as well as roughly doubling the at-risk sample relative to the individual measure, increasing statistical power. As a robustness check, we replace the binary IFLS-5 indicator with a continuous measure of the price drop based on precise interview timing—the gap between the palm-oil price in a household's IFLS-5 interview month and that in the corresponding IFLS-4 interview month. This approach exploits the "treatment intensity" — the magnitude of the price decline each household actually faced rather than wave membership alone. Additionally, we address the potential for selection into or out of palm farming by examining including a specification with individual fixed effects as well as testing robustness to the definition of a palm farmer household across waves.

The November 2014 fuel-subsidy cut. On 18 November 2014, President Joko Widodo implemented a sudden 30% increase in subsidized gasoline and diesel prices,

[6]The IFLS occupation category covers agriculture, forestry, fishing, and hunting; we restrict to households residing in a palm-producing province to isolate likely palm-related work because no data on the crop being farmed is available. Palm producing provinces include BPS codes 11–19 in Sumatra; 21 in Riau Islands; 61–64 in Kalimantan

removing a long-standing fuel subsidy that had cost the Indonesian government roughly Rp 211 trillion (USD 18 billion) in 2014. The cut took immediate effect and was unanticipated by households. We exploit it as an exogenous shock to transport costs and identify the most exposed households as urban households that own a vehicle.[7] Vehicle ownership is taken from wave 4 to prevent endogenous reactions to the fuel-price change from contaminating it. Because the government paired the cut with cash-transfer programs (PKH and BLT) designed to offset its impact on lower-income households, we additionally test for heterogeneity within urban vehicle owners according to whether the household received such a transfer; the effect should be attenuated for transfer recipients if it operates through the economic burden of higher fuel costs.

The shock variable is defined as $\text{FuelShock}_{it} = \text{UrbanVehicle}_i \times \mathbf{1}\{\text{interview date}_i \geq 18 \text{ Nov } 2014\}$, equal to one for urban vehicle-owning households interviewed on or after the cut. Because the cut occurred midway through IFLS-5 fielding and IFLS-4 fielding ended years earlier, identification for this stressor draws on the IFLS-5 sub-sample only, within which 73.6% of respondents were interviewed post-cut. Both time fixed effects and UrbanVehicle_i are included separately in the regression, so that the interaction identifies the heat amplification of the fuel shock rather than a level difference between vehicle-owning and other households. Alongside the cut, the government rolled out compensating cash transfers to low-income households through the *Program Keluarga Harapan* (PKH) and *Bantuan Langsung Tunai* (BLT) programs, which offset part of the higher fuel costs for recipients. Because these transfers cushioned the income loss, households receiving these transfers were only partially exposed to the shock. As a further robustness check, we examine heterogeneity among urban vehicle owners by whether the household received a transfer, defining the "no cash transfer" group as those with no PKH/BLT receipt and no BLT card in IFLS-5.

Recent job loss. The IFLS captures whether each respondent lost a job in the past five years, and if so, when the most recent job loss occured. To capture a shock, we code $\text{JobLoss}_i = 1$ if the respondent's most recent termination occurred within the last six months *and* they remain unemployed — defined as not having done paid work in the past week. We examine alternative windows for job loss (3 months, 1 year, 3 years, and 5 years) for robustness, while requiring that the individual remain without work

[7] In IFLS, a vehicle includes a car, motorbike, bicycle, or boat. The variable does not indicate which type of vehicle is owned resulting in some misclassification of households which may potentially bias our estimates down. We focus on urban households because ownership of motorized vehicles is more common in cities, while bicycles are more common in rural areas.

in the past week for all definitions. Requiring current non-employment ensures the indicator captures respondents currently experiencing the income loss from the recent shock, rather than those who have already returned to work or those who have entered the long-term unemployed and may have adjusted in other ways.

Economic stress. The sources of economic stress chosen for this analysis vary widely. Each design, taken alone could have potential confounds: the palm-price triple-difference rests on the assumption that nothing else differentially shifted palm-farming households' heat sensitivity across the seven-year gap between waves; the fuel subsidy-cut design requires that the pre/post comparison captures the price change rather than other seasonal factors; and the job-loss contrast could in principle reflect the steeper heat sensitivity of certain types of workers who are more prone to job loss rather than economic stress per se. Crucially however, these threats are not shared. A seasonal confound in the fuel design has no analogue in the cross-wave palm comparison; selection into palm farming is addressed directly through multiple definitions of palm farming households and has no bearing on the within-wave fuel timing; differential heat exposure across occupations which could also be correlated with job loss is addressed directly by comparing similar workers with industry fixed effects. Examining these shocks collectively hence both provides additional support for the causal nature of the relationship and for the robustness of the results across different types of economic stress.

2.5 Sample construction and summary statistics

Our analysis sample comprises all adults aged 15+ in IFLS-4 and IFLS-5 with non-missing values on the CES-D outcome, ERA5-Land temperature for the interview week, demographic controls, and the relevant stressor exposure. We additionally drop kecamatans with only one observation in the resulting sample, which would be perfectly absorbed by the kecamatan fixed effects we include, yielding the pooled sample of $n = 58{,}906$ individuals used in our main pooled-specification analyses; the IFLS-5-only sub-sample relevant for the fuel-cut analysis is $n = 20{,}038$. Table 1 reports summary statistics for this pooled sample.

Depressive symptoms are well above global averages, but in line with or somewhat lower than other middle-income countries: the mean CES-D-10 score is 5.3 on the 0–30 scale, and 15.6% of adults score at or above the conventional cut-off of 10 that indicates probable depression (World Health Organization, 2025). Temperatures are warm, but not exceptionally hot: the seven-day mean temperature, our baseline heat measure,

averages 25.0°C (SD 1.8), almost identical to the single-day mean (25.0°C) and the 30-day mean (25.0°C), while the seven-day mean wet-bulb temperature averages 22.9°C. The standard deviations are small and fall as the averaging window widens (from 1.87 for the daily measure to 1.82 over seven days and 1.78 over thirty), confirming that our identifying variation comes from modest, high-frequency fluctuations around a stable local climate rather than large seasonal swings.

Exposure to each stressor is concentrated in a minority of the sample. Recent job loss is rare, affecting 0.8% of adults; palm-farmer households make up 12.2% and urban vehicle-owning households 35.6%. The pooled sample contains 60,419 adults, 29,006 from IFLS-4 and 31,413 from IFLS-5. They span 2,014 kecamatans within 303 kabupatens; we include kecamatan fixed effects and cluster standard errors at the kabupaten level to be more conservative in accounting for any economic or spatial spillovers.

Consistent with being a middle-income country, monthly employment earnings per household are $179 and monthly food expenditures at the household level are $111 (2010 USD).

3 Empirical Strategy

This section sets out how we estimate the effect of heat on depressive symptoms and test whether it depends on economic stress. We first estimate the average effect of heat across the full sample, relating depressive symptoms to temperature in the week prior to the interview, controlling for location and calendar month. We then ask whether this effect is concentrated among adults under economic stress, interacting heat with three distinct sources of stress: the collapse in palm-oil prices between survey waves, the November 2014 fuel-subsidy cut, and recent job loss. The two steps rely on different sources of identifying variation, which we describe alongside each specification below.

3.1 The average effect of heat

To capture the effect of temperature on depressive symptoms on average in the population we estimate:[8]

$$\text{CES-D}_{ict} = \alpha + \beta_H \, \bar{T}^{7}_{ct} + \gamma' \mathbf{X}_{it} + \mu_m + \theta_c + \varepsilon_{ict}, \tag{1}$$

[8]Only adults are asked to respond to the CES-D portion of the questionnaire. Hence, these estimates apply only to adult populations in Indonesia.

where i indexes the respondent, c the kecamatan (sub-district) of residence, t the interview date, and m the calendar month-year.[9] The dependent variable CES-D$_{ict}$ is the 10-item CES-D score, standardized within wave, so all coefficients are interpretable in standard deviations of within-wave CES-D.

The primary heat regressor $\bar{T}^7_{ct}$ is the mean of ERA5-Land daily mean temperature over the seven days ending on the interview date in kecamatan c. We measure heat at the kecamatan level because it is the finest administrative unit at which we can match respondents to the climate grid. In our primary specification, we use a seven-day window rather than the single interview-day temperature to align the exposure window with the recall window of the outcome: the CES-D-10 asks how frequently each symptom was experienced "during the past week," so the climatic exposure plausibly relevant to those symptoms is cumulative heat over the same week. We focus on temperature rather than wet-bulb both for ease of interpretation and to parallel the majority of the literature to date. However, to assess whether the average effect of heat is robust to how heat is defined, we estimate Equation (1) with a range of alternative measures including variation extreme heat measures and whether the measure captures humidity (wet-bulb).

The fixed effects in Equation (1) absorb several potential confounders. The kecamatan (sub-district) fixed effects θ_c remove time-invariant local characteristics such as average climate, infrastructure, ethnic composition, and labor-market structure. The calendar-month-year fixed effects μ_m absorb Indonesia-wide seasonal patterns such as the rainy season or common temporal shocks as well as any differences in survey instrumentation between IFLS-4 and IFLS-5. $\mathbf{X}_{it}$ is the vector of basic demographic controls (age, years of education, gender, religion, martial status and ethnicity). The identifying variation that remains for β_H is therefore within-kecamatan, within-calendar-month-year deviation in $\bar{T}^7_{ct}$, a high-frequency and plausibly exogenous component reflecting week-to-week weather fluctuation within a kecamatan across interview dates. We cluster inference at the coarser kabupaten level to account for any geographic spillovers.[10]

[9] Note that the month-year fixed effects negate the need for a wave fixed effect, which would be co-linear.

[10] On spatial grounds, the determinants of CES-D (weather realizations, local economic and labor-market conditions, prices, and public services) are shared across the respondents and kecamatans of a kabupaten, so ε_{ict} is unlikely to be independent within it. On treatment-assignment grounds, our regressors vary no more finely than the kecamatan-date cells that the kabupaten nests, so the cluster must be at least this coarse. For the price-shock specifications the treatment additionally varies over time across waves, which could equally motivate clustering on time; we cluster on kabupaten because it captures the dominant, spatial source of within-cluster dependence and is the conservative choice.

3.2 Heterogeneity by economic stress

We now ask whether this average effect is amplified for adults under acute economic stress. To build intuition, we begin with our simplest specification which augments Equation 1 with an economic shock variable and the interaction between that shock and heat. This specification applies to the job loss shock directly, but will be broadened to a triple-difference in Equation 3 below for the price shock specifications.

Our baseline regression for stressor S is:

$$\text{CES-D}_{ict} = \alpha + \beta_H \bar{T}^7_{ct} + \beta_S S_{it} + \beta_{HS} (\bar{T}^7_{ct} \times S_{it}) + \gamma' \mathbf{X}_{it} + \mu_m + \theta_c + \varepsilon_{ict}, \quad (2)$$

where S_{it} is a binary variables which captures whether an individual i is impacted by the economic stressor at time t (i.e, a job loss in the past six months and current unemployment). This variable is interacted with $\bar{T}^7_{ct}$, which captures the average temperature in the past 7 days. All other variables and clustering are as described in Equation 1 above. The key parameter of interest is β_{HS}, the heat $\times$ stressor interaction. A positive β_{HS} indicates that higher temperatures raise depressive symptoms more for individuals exposed to the stressor than for those who are not.

The job-loss main effect, S_{it} absorbs level differences in depressive symptoms for the recently unemployed, but not differences in how they respond to heat. Hence, any characteristic that both differs across the two groups and modifies the mapping from heat to reported depression is a threat. This concern is discussed in more detail in Section 3.4 below.

Next, we generalize this specification slightly for the specific construction of the price shocks. Where the stressor is a single indicator, as with recent job loss, it enters Equation (2) directly. The palm and fuel stressors, however, are by construction themselves interactions, $S_{it} = G_i \times P_t$, of a group indicator G_i (a palm-farmer or a household with high fuel expenditures) and a shocked-period indicator P_t (IFLS-5 for palm, post-subsidy-cut for fuel), since each exposed group is defined by being impacted by a price change that we identify from a before/after comparison. Substituting this construction into Equation (2) and including the required main and double interaction terms turns β_{HS} into a triple difference specification:

$$\begin{aligned} \text{CES-D}_{ict} = \alpha &+ \beta_H \bar{T}^7_{ct} + \beta_G G_i + \beta_S (G_i \times P_t) \\ &+ \lambda_1 (\bar{T}^7_{ct} \times G_i) + \lambda_2 (\bar{T}^7_{ct} \times P_t) + \beta_{HS} (\bar{T}^7_{ct} \times G_i \times P_t) \\ &+ \gamma' \mathbf{X}_{it} + \mu_m + \theta_c + \varepsilon_{ict}, \end{aligned} \quad (3)$$

where β_{HS} remains the coefficient of interest. Relative to the general form in Equation (2), Equation (3) makes the constituent lower-order terms explicit: the group main effect G_i and the two two-way interactions with heat, $\bar{T}^7_{ct} \times G_i$ and $\bar{T}^7_{ct} \times P_t$. The period main effect P_t is absorbed by the month-year fixed effects. Including the two-way interactions with heat ensures that β_{HS} is identified only from the differential change in the exposed group's heat slope, net of any stable difference in that group's heat sensitivity (λ_1) and any shift in the heat slope common to all households across the period (λ_2). The group main effect β_G absorbs the cross-sectional level difference between exposed and unexposed households, so that β_{HS} captures heat amplification rather than a baseline gap. Given the large number of interaction terms, we report only direct effects of heat and the coefficient of interest, shock*heat, in all tables.

These constructions give each stressor its own source of identifying variation. For palm, β_{HS} draws on the differential change in heat sensitivity across survey waves among palm-farming households, relative to the same change among non-palm-farming households in the same kecamatan. The fuel-subsidy interaction is identified within IFLS-5 from the differential change in heat sensitivity before vs after 18 November 2014 among urban vehicle owning households, relative to the same before/after change among non-vehicle owning households, where the measure of vehicle ownership is taken from the prior survey wave to avoid endogeneity. The job-loss interaction varies across individuals within a kecamatan-by-date cell, generating cross-sectional contrast in exposure to acute labor-market stress. In all three cases, identification of β_{HS} does not require the stressor itself to be randomly assigned. Rather, it requires, that conditional on the controls and fixed effects, unobserved heterogeneity in how heat impacts depression is uncorrelated with exposure to the stressor — in other words, whatever distinguishes the stressor-exposed from the unexposed does not itself alter the heat-depression relationship.

3.3 Construction of the stressor variables

The three stressors are constructed as described in Section 2 and summarized below:

Palm price shock. $\text{PalmShock}_{it} = \text{PalmFarmerHH}_i \times \mathbf{1}\{\text{IFLS5}\}$, equal to one for palm-farmer households interviewed in IFLS-5—the wave during which the world palm price had collapsed by 36% relative to the IFLS-4 level—and zero otherwise. PalmFarmerHH_i equals one if any adult in the household reported a primary job in agriculture during

wave 4 and the household resided in a palm-producing province.[11]

Fuel price shock. $\text{FuelShock}_{it} = \text{UrbanVehicle}_i \times \mathbf{1}\{\text{interview date}_i \geq 18 \text{ Nov } 2014\}$, a binary indicator equal to one for urban households that own a vehicle and were interviewed on or after the 18 November 2014 fuel-subsidy cut. The measure of ownership is taken from wave 4 data because households may re-optimize in response to higher fuel prices — e.g., sell vehicles — making wave 5 measures endogenous. Identified within IFLS-5 only, the specification for columns (4) and (5) of Table 3 restricts to IFLS-5 data with the exception of the construction of the ownership variable.

Job loss. A binary indicator equal to one for adults whose most recent job termination occurred within the past six months (0 to 180 days before interview) *and* who did no paid work in the past week. We use a six-month window to capture acute, recent labour-market stress; we report robustness to alternative recall windows (3 months to 5 years) in Table A.3.

3.4 Identifying assumptions and threats to identification

Because our coefficient of interest β_{HS} is an interaction, identification requires that, conditional on the controls and fixed effects, unobserved heterogeneity in how heat impacts depression is uncorrelated with exposure to the stressor. Below, we spell out what this means for each stressor, the main threats to this identifying assumption, and how we address those threats for each approach. The palm-price and fuel-subsidy designs rest on plausibly exogenous price movements and provide our most credible variation; the job-loss design is more suggestive, for reasons we make explicit below.

Palm-price shock. Our estimate comes from a triple-difference. The specification includes main effects for time (month-year), heat, and palm farming, all three two-way interactions, and the triple interaction of palm farming, the shocked wave (IFLS-5), and heat. Identification of β_{HS} therefore asks whether the heat–depression relationship is differential between IFLS-4 to IFLS-5 for palm-farming households relative to other households.

The central threat to identification is that, because the price collapse spans the whole of IFLS-5, the shock indicator and the corresponding month-year indicators are the same time variable. Identification thus requires that nothing else differentially

[11] We also examine robustness the wave in which the household's agricultural status is determined.

changed the palm-farmer heat–depression relationship between 2007 and 2014 except the price decline. Any palm-specific, 2014-timed, heat-interacting change would violate this, for instance selection into or out of palm farming, divergent adaptation to heat over the seven-year gap, or the November 2014 fuel-subsidy reform if palm-farming costs were differentially fuel-exposed.

We address this in three ways. First, we replace the binary shocked-wave indicator with the continuous size of the price decline implied by each household's interview timing. With this adjustment, identification comes from the magnitude of the price drop household actually faced rather than from wave membership alone; a generic 2014 confound would not track the price path to produce these results, a much higher bar to clear. Second, we examine robustness to multiple definitions of palm farming households (palm farmer in wave 4, palm farmer in wave 5, or palm farmer in both waves) as well as estimate a panel version of the specification with individual fixed effects. Finally, we exploit variation within palm-farming households, comparing self-employed smallholders, whose incomes move most directly with the farmgate price, against other palm-region agricultural households to determine whether household that were more directly impacted have larger elasticities.

Fuel-subsidy cut. This design uses the timing of interviews relative to the 18 November 2014 fuel-price increase and is identified within IFLS-5 alone, which avoids the cross-wave comparison the palm farmer design relies on. The triple interaction asks whether the heat–depression relationship shifted for urban vehicle-owning households after the cut, relative to other households over the same window.

Identification requires that, conditional on controls, nothing else correlated with interview date differentially affected vehicle owners' response to heat except the fuel-price increase. A confounder would have to be timed with the cut, specific to urban vehicle owners, and interacting with heat. The most plausible candidate is seasonality: the pre/post split is also a calendar split, so if vehicle owners' heat response varies by season and the post period differs in temperature, the interaction could capture a seasonal rather than a price effect. A second concern is enumeration sequencing, since non-random fielding across regions could let the post indicator proxy for geography, which itself correlates with vehicle ownership.

We address these potential concerns in three ways. First, we include calendar-month-year fixed effects, so that identification also comes from within-period, week-to-week weather variation rather than the pre/post seasonal shift; we include kabupaten

fixed effects and verify that vehicle ownership and demographics are balanced on either side of the cut;[12] and we use the government's compensating cash transfers (PKH and BLT) as a sharpening device. Because cash transfer recipients were more insulated from the higher fuel costs, we are able to examine heterogeneity among vehicle owners who are more or less impacted by the policy. Any other end-2014 shocks that hit all households would load on the post main effect rather than on the triple interaction, unless they were themselves specific to vehicle owners and interacted with heat.

Recent job loss. For job loss we pool both waves and include main effects for recent job loss and heat together with their interaction. The heat main effect is well identified, since CES-D and employment status are both past-week measures and interview-week weather is plausibly as good as random conditional on location and season. The interaction, however, is a cross-sectional slope contrast: it asks whether the CES-D–heat gradient is steeper for the recently unemployed than for the employed.

Identification therefore requires that, absent the economic stress of job loss, the two groups would share the same CES-D–heat slope. The job-loss main effect absorbs level differences in who the unemployed are, but not differences in how they respond to heat. Any characteristic that both differs across the two groups and modifies the mapping from heat to reported depression may confound the relationship. Outdoor, manual, and casual workers, for example, are both more likely to have lost work and more physically exposed to heat, which would steepen their heat slope for reasons unrelated to economic stress.

We probe this by adding occupation- and sector-by-heat interactions, which identify the job-loss interaction from variation within occupation, comparing employed and recently unemployed workers doing similar work. The interaction survives these controls. Even so, because job loss may be endogenous to the individual, we treat this design as more suggestive than the palm-price and fuel-subsidy designs, and read it as corroborating rather than independently establishing the main result.

Given the construction of the shock variables, across all three stressors the headline parameter remains β_{HS}.

[12] As seen in Table A.1, demographics are well balanced with the exception that those interviewed post subsidy skew slightly younger.

4 Results

This section presents our main results: ambient temperature has a precisely estimated null effect on mental health in the population as a whole, but it meaningfully worsens mental health for individuals already under economic stress. We first establish this average null and show that it is generally insensitive to how heat is measured; we then document the heterogeneous response by economic stress and show that it holds consistently across all three sources of economic stress we study.

4.1 Heat does not impact self-reported depression in the overall population

We begin by estimating the average effect of heat on depressive symptoms in the full sample, before allowing for any interaction with economic stress. Table 2 reports the heat coefficient from Equation (1), where the outcome is the within-wave z-standardized CES-D score and each column uses a different measure of heat. Columns 1 to 3 draw on the last week's mean, number of days above 30°C, and mean wet-bulb temperature (which combines heat and humidity), respectively. Columns 4 to 6 use day-of temperature measures including the interview-day mean, interview-day maximum, and interview-day mean wet-bulb temperature, respectively.

Across the temperature-based measures, heat is unrelated to depressive symptoms in 5 of the 6 specifications. In our preferred specification, drawing on the mean temperature in the past week, a 1°C increase in the 7-day mean temperature is associated with a 0.001 standard-deviation change in CES-D (column 1). The interview-day mean, maximum, and wetbulb temperatures yield similarly small coefficients of 0.006, 0.004, and 0.009 (columns 4, 5, and 6); none is statistically distinguishable from zero. The count of recent days above 30°C has a small, negative, and insignificant coefficient of -0.004 (column 2). These are precisely estimated nulls: the standard errors are small enough to rule out average effects larger than roughly 0.015 standard deviations per degree, so the absence of a detectable effect does not simply reflect a lack of statistical power.

The one exception to this finding is the 7-day mean wet-bulb temperature, which enters negatively and is marginally significant (column 3, -0.027, $p < 0.10$), implying *fewer* symptoms of depression at higher humid heat. Given the other precisely estimated null effects, we do not interpret this as a robust protective effect. It may be noise among the multiple specifications we test and marginal significance, though it may also reflect

residual seasonality in humidity that the month and year fixed effects do not fully absorb.

Taken together, Table 2 shows that ambient heat has no robust association with depression in the general population, and that this null is generally insensitive to a number of different proxies for heat. This average null is the central motivation for the analysis that follows. Rather than concluding that heat is irrelevant to mental health, we ask whether its effect is concentrated among individuals already under acute economic stress, for whom a given rise in temperature may be far more consequential.

4.2 Heat increases depression among those under economic stress

Table 3 details how temperature affects depression among individuals under economic stress, using the three economic stressors described earlier. The top panel displays results using (dry bulb) temperature, while the bottom panel displays the results using wet bulb temperature. Columns 1 to 3 examine three different specifications for the palm farmer shock: interacting the palm farmer household variable with heat, using the panel version of the data with individual fixed effects, and using the continuous price decrease, respectively. For the fuel shock, column 4 reports the overall effect for urban vehicle owners, our proxy for exposure to higher fuel prices, while columns 5 and 6 examine its heterogeneity by whether the household received a government cash transfer.[13] Column 7 examines the job loss shock.

As in Table 2, the direct effect of temperature remains small and statistically insignificant. However, the coefficients on the interaction terms between temperature and the economic stressor, denoted by "differential impact of heat," are positive for every specification except among the cash-transfer recipients, reflecting greater depression with more exposure to heat while under economic stress. Setting aside the less-economically stressed cash-transfer recipients (column 6), ten of the remaining twelve coefficients across both panels are statistically significant at the 5% level, with the remaining two are significant at the 10% level. The cash-transfer recipients are the exception by design: among urban vehicle owners, the differential effect is present for households that received no compensating transfer (column 5) but absent for those that did (column 6), consistent with the response operating through the economic burden of the price increase. While the magnitudes of the interaction terms drawing on continuous variables are more difficult to interpret, the coefficients with binary indicators and mean

[13] Because Indonesia paired the subsidy cut with transfer programs intended to offset it, contrasting recipients with non-recipients tests whether the transfers buffered the effect.

temperature range from 0.044 SD to 0.090 SD per degree Celsius (0.067 SD to 0.094 SD for wet-bulb temperature). These effects are relatively large given the temperature ranges typically experienced and when compared to the effects of interventions targeting mental health. For example, the 10th percentile coolest week has a mean temperature that is 4.5 degrees cooler than the 90th percentile warmest week. This implies that an economically stressed respondent would report a CES-D score that is 0.20 to 0.41 SD larger when responding in the warm week than the cool one. These effects are equivalent to 30% to 100% of the effect of direct interventions to reduce depression such as cognitive behavioral therapy or pharmacotherapy among disadvantaged populations (Angelucci and Bennett, 2024; Baranov et al., 2020).

In short, our results in Table 3 represent robust and consistent evidence that while higher temperatures do not directly affect the likelihood of depression symptoms in non-economically stressed populations, temperature differentially impairs the mental health of individuals under economic stress and that the effects are meaningful in magnitude.

4.3 Robustness checks

Having shown that heat amplifies depressive symptoms among economically stressed groups, we now examine the robustness of this finding and the channels behind it. We first verify that the result is not an artifact of our heat measure being correlated with who is surveyed, nor of how we define the stressed groups. We then turn to mechanisms, confirming that each stressor genuinely worsens household economic conditions and asking how the effect maps onto households' income exposure, the symptoms it affects, and sleep.

In Table A.1 we examine how our main regressors relate to basic demographic characteristics. Column 1 reports the means of the age, gender, education, and marital-status variables in the sample. Column 2 shows that temperature is not significantly associated with any of these factors, supporting our assumption that interview-week heat is as good as randomly assigned when considering Equation 1. Recent unemployment is correlated with a number of demographic characteristics. Women, the more educated, and single individuals are more likely to have recently lost their job (column 3). This does open the door to potential confounding in the cross-sectional identification. We control for these variables (along with industry) to minimize these effects, but recognize this may not fully address unobservable confounding. Vehicle owners after the subsidy cut are slightly younger (column 4) which we control for, but all other demographics are well balanced suggesting that the interview timing is indeed

quasi-random.[14]

In Table A.2 we conduct robustness checks on sample composition for the specification using membership in a palm-farmer household as the source of economic stress. Column 1 uses the same sample definition and reproduces the results in Table 3. In Column 2, we restrict the sample to individuals who were in palm-farmer households in both waves of the IFLS, excluding people who either quit or entered palm farming between the two waves. In Column 3, we include all palm farmers in IFLS-5, irrespective of their status in IFLS-4. The results are highly consistent across the three sample definitions, with coefficients ranging from 0.078 to 0.080 SD, reinforcing the robustness of the findings.

In addition, in Table A.4 we ask whether the palm result is concentrated among the households whose incomes track the palm price most directly, by splitting palm farmers into self-employed smallholders and wage workers. The effect is not confined to a single type of palm household; both are exposed to the price collapse, though through different routes. Self-employed smallholders may bear it most directly, since their income comes from selling their crop at the farmgate price, whereas wage workers are exposed indirectly, as a falling palm price depresses labour demand and wages across the local palm economy. The differential impact of heat is positive, significant, and of similar magnitude in both groups, though about 10% larger for the self-employed: 0.073 for self-employed smallholders (Column 2) and 0.067 for wage workers (Column 3). That the two groups respond comparably, despite their different routes of exposure, is consistent with the response operating through the broader economic hit to palm incomes rather than some feature specific to one type of household. We treat the comparison as suggestive, since the two estimates are statistically indistinguishable and the distinction between smallholders and wage workers is not randomly assigned.

In Table A.3 we test the sensitivity of the heat $\times$ job-loss interaction to the recall window used to define a recent job loss. Each column re-estimates the specification with a different window, from three months (Column 1) to five years (Column 6), which raises the number of respondents coded as having lost a job from 246 to 1,757. The interaction is concentrated among recent losses: it is positive throughout and statistically significant at the six- and nine-month windows (0.053 and 0.062 in Columns 2 and 3, respectively), then attenuates steadily toward zero, becoming small and insignificant once the window

[14]We do not compare the demographics of palm farmers in wave 4 versus wave 5 — our identifying variation in that shock — because the default specification uses one's location and farming status in wave 4 to define the shock. Hence, the groups are the same. We do, however, compare robustness across this definition of being a palm-farming household below.

reaches a year or more (Columns 4–6). The three-month estimate is comparable in magnitude but imprecise, reflecting the small number of very recent job-losers (246). This pattern is consistent with the stress of a relatively recent job loss, rather than longer-standing non-employment to which individuals may adjust or alter household arrangements, heightening vulnerability to heat.

4.4 Confirmation of impact of economic stressors

Beyond examining the robustness of the results, it is important to confirm that each stressor actually moves household economic conditions, the channel through which heat is presumed to amplify depressive symptoms.

Table A.1 displays clear evidence of the impact of the reduction in the fuel subsidy: urban vehicle owners measured post subsidy have a statistically significant increase of \$4.59 (25%) in transportation expenditures. This corresponds closely to the 30% increase in fuel costs after the subsidy reduction.[15]

To confirm the impact of the palm shock and unemployment, Table A.5 reports the effect of each of these stressors on household income, estimated without any temperature interaction. The palm oil price shock (Columns 1) and job loss (Column 2) sharply reduce household labor income: the palm-price shock reduces monthly income by about USD 54 and a recent job loss by about USD 50, equal to roughly 30% and 28% of the USD 179 mean, and both are significant at the 1% level.

In short, all three shocks show clear impacts on household budgets for the impacted households.

4.5 CES-D sub-scale decomposition

In Table A.6 we ask which symptoms drive the heat × stressor effect, decomposing the CES-D into the three sub-scales of Radloff (1977): somatic and activity-related symptoms (Panel A), depressed affect (Panel B), and positive affect (Panel C, reverse-coded so that higher values denote worse mental health). Each sub-scale is individually normalized within wave and then Equation 2 and Equation 3 are re-estimated across the three stressor specifications.

The differential impact of heat is concentrated in the somatic and activity-related symptoms, where it is positive and significant for the palm shocks (Columns 1–3), urban vehicle owners (Column 4), and job loss (Column 7), with the cash-transfer recipients

[15] The remaining 5% gap is likely accounted for by behavioral changes in response to the price shock such as taking fewer trips or changing transportation modes.

again being the exception (Column 6). It also appears in depressed affect, though more narrowly: significant for the palm shocks (Columns 1–3) and for the unbuffered urban vehicle owners (Column 5), but not for job loss. By contrast, no stressor produces a significant adverse effect on positive affect (Panel C). The heat-under-stress response therefore appears to operate mainly through somatic and depressed-affect symptoms, such as restless sleep, poor concentration, low energy, and low mood, rather than through a loss of positive affect.

4.6 Exploring sleep disruption as a mechanism

Heat is often argued to harm mental health by disrupting sleep. In Tables A.7 and A.8 we provide suggestive evidence on whether this channel is operative in this context. We begin by following Equation 1 to examine the overall effect of heat on sleep in the population, regressing sleep duration on each of our heat measures with the same controls and fixed effects. In the population broadly and across all six temperature measures, the estimates are small and statistically insignificant, suggesting heat has no detectable effect on how long people sleep in this context across the broader population.

Because the effect may only apply to those who are economically stressed, we also estimate Equations 2 and 3 with sleep as an outcome measure for the job loss and unemployment shocks. Because the sample is restricted to IFLS-5, the only wave that records sleep timing, we are unable to examine the differential effect of heat on palm farmers, which relies on cross-wave identification.[16] Among the economically stressed, the evidence is more suggestive. For urban vehicle owners, heat significantly reduces sleep duration, by about five minutes (Column 1), consistent with sleep disruption operating as a channel for this group. For the recently unemployed, by contrast, the interaction is small and statistically insignificant (Column 2). Sleep disruption may therefore contribute to the response, at least among the fuel-stressed, though its modest magnitude (about five minutes) suggests it is not the dominant channel; however, we also cannot rule out effects on sleep quality, which the duration measure does not capture.

5 Conclusion

Climate change has and will continue to increase the frequency of extreme heat as well as the occurrence of economic shocks associated with it. In this paper, we investigate how

[16] IFLS-4 carries just a one-month recall of difficulty sleeping.

higher temperatures affect mental health, in particular depressive symptoms measured by the CES-D scale. Using two waves of the Indonesia Family Life Survey, a survey representative of 83% of one of the largest countries in the developing world, we find a precisely estimated null effect of temperature on depressive symptoms in the overall population across a wide range of temperature measures. However, we find a large and statistically significant negative effect of heat on mental health for people exposed to economic shocks. This analysis includes three wide-ranging economic shocks: a drop in the price of palm oil affecting palm farmers, a fuel price increase caused by a sudden elimination of a fuel subsidy, and recent job losses. Among individuals exposed to these economic shocks, our results indicate that heat increases self-reported depression symptoms between 0.044 and 0.090 SD per degree Celsius.

One potential limitation of our analysis is that the economic stressors we investigate are not randomly assigned. However, we are not interested in the direct effect of the specific economic stressor, but rather in its interaction with temperature. Identification thus requires only that, conditional on controls and fixed effects, interview-week temperature is uncorrelated with the portion of a stressor's effect on mental health that operates through heat. The palm-price and fuel-subsidy designs rest on plausibly exogenous price movements and provide our most credible variation; the job-loss design is more suggestive.

Further, these strategies draw on very different sources of variation: cross-wave commodity-price movements, within-wave policy timing, and individual-level labor-market shocks respectively. A single omitted variable confounding our results is therefore unlikely. The fact that the robustness and range of our results is consistent across the three very different sources of economic stress reinforces the strength and robustness of the findings.

These results indicate that heat's mental health costs are not uniformly distributed in the population: individuals who are economically stressed are significantly more prone to report higher levels of depression with greater heat. This pattern supports suggestive notes in prior work in which an economic channel was been inferred only indirectly. For example, in Carleton (2017), heat is associated with elevated suicide rates among Indian farmers through heat-driven crop losses — but because heat there is simultaneously the stressor and the cause of the economic shock, it is difficult to separate an economic channel from other correlates of rural, agricultural life. Hua et al. (2023) document a related pattern of larger heat effects among less-educated populations, though without directly testing an economic mechanism. Because the

shocks we study are not themselves caused by heat, our design isolates economic stress as a moderator of the heat–mental-health relationship independent of its source, offering more direct evidence for a channel.

Future research could extend this framework to other potentially compounding stressors, such as social isolation or bereavement, as well as to other low- and middle-income settings facing both rising economic volatility and rising heat exposure. Our results also speak, suggestively, to policy design: in our data, government cash transfers (PKH and BLT) partially offset the fuel-subsidy shock for recipient households, dampening the effects of heat on depression. This suggests that policies cushioning households from economic shocks may be an underappreciated lever for mitigating the psychological toll of a warming climate, particularly where the capacity to adapt to heat itself is most limited.

Main Tables

Table 1: Summary statistics

Variable	Mean	SD
A. Mental-health outcome		
CES-D raw score	5.283	4.385
Depressed	0.155	0.362
B. Temperature exposure and variation		
Daily mean temperature	25.009	1.857
7-day mean temperature	25.006	1.815
30-day mean temperature	25.022	1.778
7-day mean wet-bulb	22.936	1.524
C. Stressors		
Job loss	0.008	0.087
Palm Farmers	0.121	0.326
Urban Vehicle Owners	0.357	0.479
D. Economic outcomes		
Monthly Work Income (2010 USD)	178.57	177.54
Monthly Nonfood Expenditure (2010 USD)	134.83	134.42
Monthly Food Expenditure (2010 USD)	110.74	71.32
Kabupaten clusters		303
Kecamatan fixed-effect units		2,010
Observations		59,146
IFLS4		28,662
IFLS5		30,484

Notes: The table reports means and standard deviations for the sample of respondents in the IFLS4 and IFLS5 with a complete 10-item CES-D score (our outcome variable of interest) and demographic controls. The CES-D score sums ten item-frequency responses on a 0–30 scale; Depressed equals one for scores of 10 or above. Temperature and wet-bulb measures are in degrees Celsius; the 7- and 30-day measures are rolling means ending on the interview date. Job loss equals one when the respondent lost a job within 6 months before the interview and remained unemployed. Palm Farmers and Urban Vehicle Owners are IFLS4 household characteristics carried forward across waves: the former identifies households with an agricultural worker in a palm-producing province, and the latter identifies vehicle-owning households in urban areas. Monetary outcomes are winsorized at the 95th percentile. Kabupaten and Kecamatan are geographic units used for clustering and fixed effects, respectively. Kabupaten's are the second level of administrative in Indonesia, under provinces, and Kecamatan's are the third level of administrative units.

Table 2: Effects of Heat on Mental Health

	CES-D z-score					
	7-day mean Temperature	>30 °C days in past week	7-day mean Wet-bulb	Daily mean Temperature	Daily max Temperature	Daily mean Wet-bulb
	(1)	(2)	(3)	(4)	(5)	(6)
Heat	0.001	-0.004	-0.027*	0.006	0.004	0.009
	(0.012)	(0.006)	(0.015)	(0.009)	(0.006)	(0.010)
Kecamatan	x	x	x	x	x	x
Month-Year	x	x	x	x	x	x
Observations	58,906	58,906	58,906	58,906	58,906	58,906
R^2	0.084	0.084	0.085	0.084	0.084	0.084

Notes: This table reports the average effect of heat on depressive symptoms in the full sample, prior to any interaction with economic stress for the sample of respondents in the IFLS4 and IFLS5 with a complete 10-item CES-D score (our outcome variable of interest) and demographic controls. The dependent variable is the respondent's 10-item CES-D score, standardized within IFLS wave; higher values indicate worse mental health. Each column reports a separate OLS regression using the heat measure named in the column heading. Column 1 reports the change in the CES-D z-score associated with a one-degree Celsius increase in the 7-day mean temperature experienced over the past week. Column 2 reports the change associated with each additional day where the maximum temperature exceeds 30 °C in the past week. Columns 3–6 report the change in the CES-D z-score associated with a one-degree increase in the 7-day mean wet-bulb, daily mean, daily max, and daily wet-bulb temperatures, respectively. All specifications control for age, sex, years of education, indicators for married and widowed status, and indicators for religion and ethnicity, and include Kecamatan and calendar-month-year fixed effects. The sample pools respondents from IFLS4 and IFLS5 with complete CES-D and and demographic controls. Standard errors, clustered by Kabupaten, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

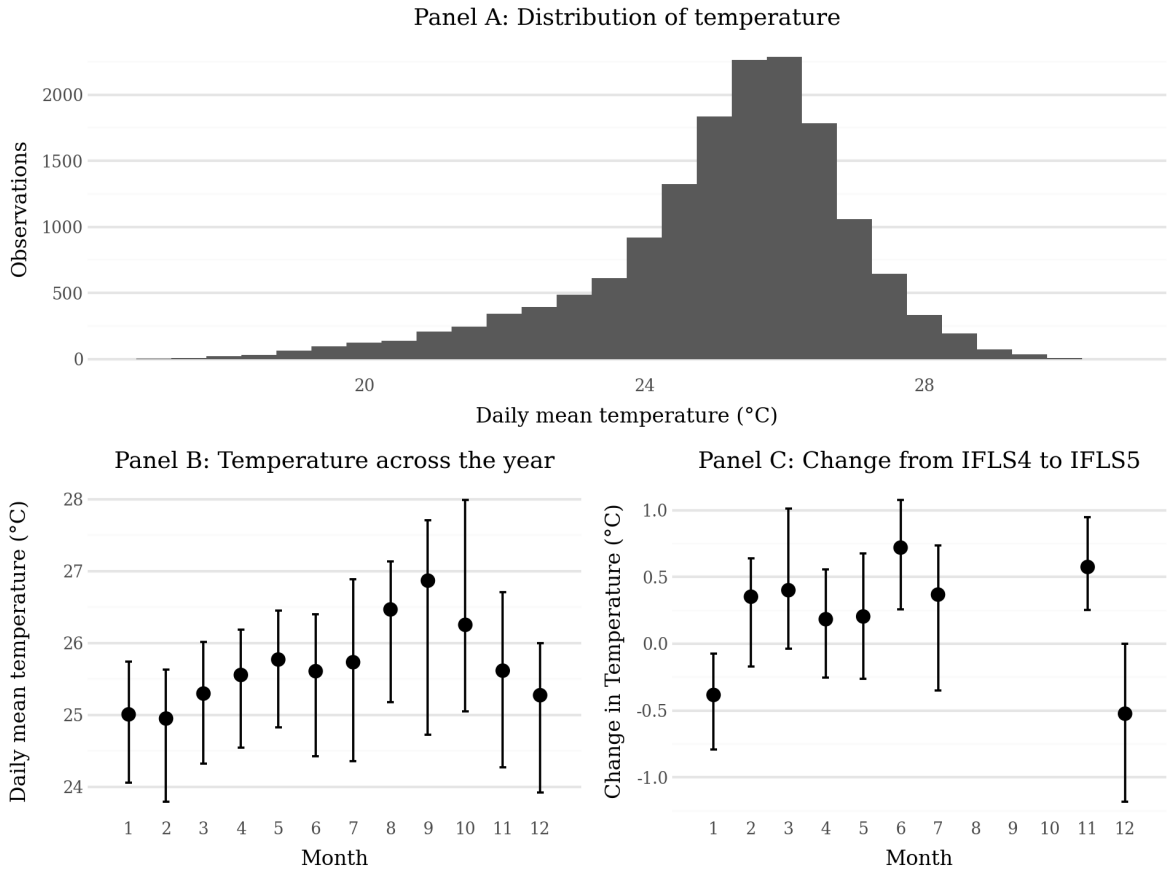
Table 3: Impacts of Heat on those under Economic Stress

	CES-D z-score						
	Palm Shock	Palm Shock Panel	Palm Shock Price Drop	Urban Vehicle Owners	Urban Vehicle Owners No Cash Transfer	Urban Vehicle Owners Cash Transfer	Job Loss
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
7-day mean Temperature							
Differential Impact of Heat	0.080***	0.090***	0.026***	0.044*	0.067**	-0.060	0.053*
	(0.019)	(0.031)	(0.007)	(0.025)	(0.026)	(0.038)	(0.029)
Heat	0.006	0.026	0.007	0.029	0.028	0.018	0.001
	(0.015)	(0.026)	(0.015)	(0.027)	(0.026)	(0.028)	(0.012)
7-day mean Wet-bulb							
Differential Impact of Heat	0.090***	0.094***	0.029***	0.072**	0.077**	-0.018	0.067**
	(0.020)	(0.032)	(0.008)	(0.035)	(0.033)	(0.050)	(0.033)
Heat	-0.026	-0.008	-0.030	0.013	0.012	0.001	-0.027*
	(0.018)	(0.032)	(0.019)	(0.039)	(0.037)	(0.038)	(0.015)
Kecamatan	x	x	x	x	x	x	x
Month-Year	x	x	x	x	x	x	x
Individual	-	x	-	-	-	-	-
Observations	48,824	40,012	41,152	20,038	20,038	20,038	58,906
Stressed Group Proportion	0.121	0.121	0.322	0.350	0.281	0.069	0.008

Notes: The table reports how economic stress changes the effect of heat on depressive symptoms. The outcome is the 10-item standardized CES-D depression score. In Column 1-6, "Differential Impact of Heat" is the coefficient on the three way interaction (heat × shocked-group × shocked-period). In Column 7 it is the coefficient on the two-way interaction (heat × shocked-group) as there is no indicator for the shocked period (heat × shocked-group). In all columns, "Heat" is the slope for the heat: in the top panel, heat is the 7-day mean temperature; in the bottom panel, it is the 7-day mean wet-bulb temperature. Column headers indicate the shock definition. Columns: palm-price shock = palm-farmer household from IFLS4 × $\mathbf{1}\{\text{IFLS5}\}$, by wave triple-difference (1), the same with individual fixed effects (2), and using the decline in price observed by palm farmers between interview dates for the fourth and fifth wave (3); the November 2014 fuel-subsidy cut interacted with: urban vehicle ownership in the fourth wave (4), split into owners who did not receive a cash transfer (5), and those who did (6) identified within IFLS5; and recent job loss, within six months and still out of work (7). For the palm and fuel columns the reported interaction is a triple difference; its constituent main and two-way terms are included but not shown. Included fixed effects are indicated in the footer. All columns include controls for age, years of education, gender, religion, martial status and ethnicity. The sample in Column 1 is restricted to households with complete 10-item CES-D score, demographic controls, and observed palm farmer status in wave 4. Column 2 further restricts the sample to individuals observed in both waves. Column 3 has the same restrictions as column 1 and additionally restricts to households observed in both waves. Column 4-6 is restricted to complete observations in IFLS5 for whom urban and vehicle ownership status is observed in wave 4. Column 7 includes all observations with a complete 10-item CES-D score, demographic controls, and employment status. Standard errors clustered at the Kabupaten level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Main Figures

Figure 1: Distribution of Temperature



Notes: The figure describes interview-day temperature variation in the IFLS analysis sample. Panel A plots the distribution of daily mean temperature. Panel B reports the median (points) and interquartile range (vertical bars), of mean temperature by calendar month. Panel C reports the median and interquartile range of the within-Kecamatan, within-calendar-month change in temperature from IFLS4 to IFLS5 (IFLS5 IFLS4). Temperature is the ERA5-Land daily mean at the interview date, matched at the Kecamatan level.

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Appendix Tables

Table A.1: Balance Table

		Regressor		
	Mean (SD)	Temperature	Job Loss	Vehicle Owners Post Subsidy
	(1)	(2)	(3)	(4)
Age	36.917	-0.089	-9.813	-3.564**
	(15.245)	(0.136)	(0.545)	(1.373)
Female	0.529	-0.001	0.097***	-0.031
	(0.499)	(0.003)	(0.024)	(0.030)
Years of education	8.596	-0.003	1.355***	0.607*
	(4.378)	(0.038)	(0.154)	(0.350)
Married	0.709	-0.001	-0.191***	-0.051
	(0.454)	(0.005)	(0.023)	(0.033)
Widowed	0.054	0.001	-0.035***	0.002
	(0.226)	(0.002)	(0.007)	(0.023)
Cash-transfer recipient	0.258	-0.002	0.055***	-0.055
	(0.438)	(0.006)	(0.021)	(0.058)
Work Income (2010 USD)	178.571	-2.272	-45.038***	42.542
	(177.536)	(2.689)	(6.804)	(33.365)
Transport Expenditure (2010 USD)	18.302	0.193	-1.334*	3.628
	(17.562)	(0.246)	(0.731)	(2.294)
Observations	59,146	58,906	58,906	6,900

Notes: This table assesses the balance of our key regressors, testing whether the heat measure and the stressor exposures are systematically related to respondents' demographic and economic characteristics. Column 1 reports means, with standard deviations in parentheses, for the analysis sample; binary-variable means are proportions. Columns 2–4 report coefficients from separate regressions of each row variable on the indicated regressor. Temperature is the Kecamatan-level seven-day mean ending on the interview date, measured in degrees Celsius. Job Loss indicates a job loss within the preceding 6 months. Column 1-3 restrict the sample to observations with complete 10-item CES-D score and demographic controls. Column 4 regresses each characteristic on an indicator for interviews conducted on or after the November 18, 2014 fuel-subsidy cut, restricting the sample to IFLS5 respondents from urban vehicle-owning households in IFLS4. All regressions include month-year and Kecamatan fixed effects. Standard errors, clustered by Kabupaten, are in parentheses. Work income and transport expenditure are winsorized at the 95th percentile. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: Palm Farmer Robustness Checks

	CES-D z-score		
	Main Definition	Both IFLS4&5	IFLS5
	(1)	(2)	(3)
Differential Impact of Heat	0.080***	0.080***	0.081***
	(0.019)	(0.021)	(0.018)
Heat	0.006	0.009	0.002
	(0.015)	(0.015)	(0.015)
Kecamatan	x	x	x
Month-Year	x	x	x
Observations	48,824	40,480	50,564
R^2	0.089	0.094	0.092

Notes: The table checks whether the palm-price-shock result is robust to how the palm-farmer sample is defined. The outcome is the 10-item standardized CES-D depression score. Heat is the 7-day mean temperature. "Differential Impact of Heat" is the coefficient on the three way interaction (heat × palm-farmer × shocked-period). Column 1 uses the baseline palm-farmer definition and reproduces the main result; Column 2 restricts to households that are palm farmers in both waves, excluding those that enter or exit palm farming; Column 3 includes all IFLS5 palm farmers regardless of their IFLS4 status. The constituent main and two-way terms of the triple difference are included but not shown. "Heat" is the 7-day mean temperature at the Kecamatan level. All columns include Kecamatan and month-year fixed effects; standard errors clustered at the Kabupaten (district) level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3: Job Loss Window

	CES-D z-score					
	3 months	6 months	9 months	12 months	3 years	5 yr
	(1)	(2)	(3)	(4)	(5)	(6)
Job Loss × Heat	0.039	0.053*	0.062**	0.018	0.012	-0.002
	(0.038)	(0.029)	(0.026)	(0.026)	(0.016)	(0.016)
Kecamatan	x	x	x	x	x	x
Month-Year	x	x	x	x	x	x
People with job loss	240	450	595	746	1400	1725
Observations	58,906	58,906	58,906	58,906	58,906	58,906
R^2	0.085	0.085	0.085	0.085	0.085	0.085

Notes: The table reports the robustness of the heat × job-loss interaction to the recall window used to define a recent job loss. The outcome is the standardized 10-item CES-D depression score, and heat is the 7-day mean temperature. "Job Loss × Heat" is the interaction of heat with the job-loss indicator (the coefficient of interest). The job-loss indicator equals one if the respondent's most recent job termination occurred within the window heading the column (from 3 months to 5 years) *and* the respondent did no paid work in the past week; each column re-estimates the specification with a different window. "People with job loss" is the number of respondents coded as having lost a job under that window. All columns include Kecamatan and month-year fixed effects as well as demographic controls (age, education, gender, martial status, religion and ethnicity). Standard errors clustered at the Kabupaten (district) level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4: Heat amplification of depression among palm smallholders vs other palm households

	CES-D z-score		
	Palm Farmers	Palm Farmer Self-Employed	Palm Farmer Wage
	(1)	(2)	(3)
Differential Impact of Heat	0.080***	0.073***	0.065**
	(0.019)	(0.022)	(0.029)
Heat	0.006	0.005	-0.002
	(0.015)	(0.014)	(0.015)
Kecamatan	x	x	x
Month-Year	x	x	x
Palm Farmer Count	5947	3640	2307
Observations	48,824	48,824	48,824
R^2	0.089	0.089	0.089

Notes: The table examines whether the palm-shock result is concentrated among self-employed smallholders. The outcome is the standardized 10-item CES-D depression score, and heat is the 7-day mean temperature. "Differential Impact of Heat" is the heat × palm-shock triple interaction (the coefficient of interest) and "Heat" is the heat slope for non-palm households. The palm shock is palm-farmer household × $\mathbf{1}\{\text{IFLS5}\}$ throughout, with the palm-farmer group varying by column: all palm-farmer households (column 1), self-employed palm farmers (column 2), and wage-earning palm farmers (column 3). Self-employment status is measured in IFLS4 to avoid endogeneity; "Palm Farmer Count" reports the number of palm-farmer respondents in each group. The constituent main and two-way terms of the triple difference are included but not shown. All columns include Kecamatan and month-year fixed effects and demographic controls (age, gender, education, martial status, religion and ethnicity.). Standard errors clustered at the Kabupaten (district) level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Direct economic channel: each stressor moves household economic conditions

	Work Income (2010 USD)	
	Palm Shock	Job Loss
	(1)	(2)
Shock effect	-54.227***	-50.287***
	(8.348)	(6.747)
Kecamatan	x	x
Month-Year	x	x
DV mean	178.57	178.57
Observations	44,383	50,418
R^2	0.281	0.278

Notes: The table reports the direct effect of each economic stressor on household economic outcomes. The coefficient shown ("Shock effect") is the average effect of the stressor on monthly household work income (2010 USD, winsorized at the 95th percentile). In Column 1, The palm shock is palm-farmer household $\times \mathbf{1}\{\text{IFLS5}\}$. Column 2 reports the effect of a recent job loss (within six months, still out of work). Both columns include Kecamatan and month-year fixed effects and demographic controls (age, gender, education, marital status, religion and ethnicity). Column 1 restricts the sample to observations where palm farmer status is observed in wave, demographic controls are complete, and income is observed. Column 2 restricts the sample to observations where employment status, demographic controls, and work income is observed. Standard errors clustered at the Kabupaten (district) level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: Heat × stressor by CES-D sub-scale (Radloff factor decomposition)

	CES-D z-score						
	Palm Shock	Palm Shock Panel	Palm Shock Price Drop	Urban Vehicle Owners	Urban Vehicle Owners No Cash Transfer	Urban Vehicle Owners Cash Transfer	Job Loss
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Somatic / activity-related CES-D factor							
Differential Impact of Heat	0.063***	0.076**	0.021***	0.056**	0.070***	-0.031	0.056**
	(0.017)	(0.034)	(0.007)	(0.027)	(0.027)	(0.039)	(0.028)
Heat	0.009	0.024	0.009	0.020	0.020	0.010	0.003
	(0.016)	(0.028)	(0.017)	(0.027)	(0.026)	(0.027)	(0.013)
Depressed-affect CES-D factor							
Differential Impact of Heat	0.056***	0.057**	0.017**	0.031	0.061**	-0.068**	0.009
	(0.019)	(0.026)	(0.007)	(0.023)	(0.024)	(0.034)	(0.029)
Heat	0.007	0.031	0.012	0.004	0.008	-0.003	0.000
	(0.013)	(0.025)	(0.014)	(0.025)	(0.024)	(0.025)	(0.011)
Positive-affect CES-D factor							
Differential Impact of Heat	0.026	0.029	0.009	-0.016	-0.009	-0.036	0.026
	(0.025)	(0.033)	(0.008)	(0.024)	(0.022)	(0.034)	(0.025)
Heat	0.001	0.007	-0.000	0.040*	0.034	0.035	0.000
	(0.017)	(0.030)	(0.017)	(0.022)	(0.021)	(0.021)	(0.014)
Kecamatan	x	x	x	x	x	x	x
Month-Year	x	x	x	x	x	x	x
Individual	-	x	-	-	-	-	-
Observations	48,824	40,012	41,152	20,038	20,038	20,038	58,906
Stressed Group Proportion	0.121	0.121	0.322	0.350	0.281	0.069	0.008

Notes: The table decomposes the heat × stressor interaction across the three CES-D sub-scales of Radloff (1977) to examine which symptom dimensions drive the result. The outcome in each panel is the sub-scale z-score, standardized within wave. The somatic and activity-related panel (top) sums five items: bothered by things, trouble concentrating, everything an effort, restless sleep, and could not get going. The depressed-affect panel (middle) sums three items: felt depressed, fearful, and lonely. The positive-affect panel (bottom) sums two items — hopeful and happy — reverse-coded so that higher values indicate worse mental health across all panels. Within each panel, "Differential Impact of Heat" is the heat × stressor interaction (the coefficient of interest) and "Heat" is the heat slope for the unexposed group. Heat is the 7-day mean temperature at the Kecamatan level. Stressor definitions, column structure and sample restrictions, are identical to Table 3. All columns include Kecamatan and month-year fixed effects and demographic controls (age, gender, education, marital status, religion and ethnicity); and column 2 adds individual fixed effects. Standard errors clustered at the kabupaten (district) level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Heat doesn't impact sleep in the Indonesian population

	Sleep duration (hours)					
	7-day mean Temperature	>30 °C days in past week	7-day mean Wet-bulb	Daily mean Temperature	Daily max Temperature	Daily mean Wet-bulb
	(1)	(2)	(3)	(4)	(5)	(6)
Heat	-0.019	0.014	0.017	-0.022	0.004	0.004
	(0.029)	(0.012)	(0.031)	(0.018)	(0.011)	(0.025)
Kecamatan	x	x	x	x	x	x
Month-Year	x	x	x	x	x	x
Observations	28,978	28,978	28,978	28,978	28,978	28,978
R^2	0.158	0.158	0.158	0.158	0.158	0.158

Notes: This table examines whether heat affects sleep duration, a commonly proposed channel through which temperature might harm mental health. The dependent variable is sleep duration in hours, defined as wake time minus bedtime on the previous night; durations > 16 hours are dropped. Each column reports a separate OLS regression using the heat measure named in the column heading. Temperature and wet-bulb coefficients represent the change in sleep hours associated with a one-degree Celsius increase; the hot-day coefficient (column 2) represents one additional day with maximum temperature above 30 °C during the seven-day window. Seven-day measures include the interview date and the preceding six days. All specifications control for age, sex, years of education, and indicators for married and widowed status, and include kecamatan and month-year fixed effects. The sample is restricted to IFLS5, the only wave that records sleep timing. Standard errors, clustered by kabupaten, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Mixed impact of heat on sleep hours among the economically stressed

	Sleep Hours	
	Urban Vehicle Owners	Job Loss
	(1)	(2)
Differential Impact of Heat	-0.084*	0.074
	(0.043)	(0.070)
Heat	-0.001	-0.019
	(0.046)	(0.029)
Kecamatan	x	x
Month-Year	x	x
Observations	19,206	28,978
Stressed Group Proportion	0.350	0.008

Notes: This table examines whether heat affects sleep duration for those under economic stress. The dependent variable is sleep duration in hours, defined as wake time minus bedtime on the previous night; durations > 16 hours are dropped. Column 1 reports the impact of temperature on the sleep duration of urban vehicle owners after the fuel subsidy cut; Column 2 reports the impact on those who recently lost their job. "Differential Impact of Heat" is the coefficient on the three way interaction for Column 1 (heat $\times$ shocked-group $\times$ shocked-period) and the two way interaction (heat $\times$ shocked-group) for Column 2. Both specifications control for age, sex, years of education, marital status, religion, ethnicity and include kecamatan and month-year fixed effects. The sample is restricted to IFLS5, the only wave that records sleep timing. Furthermore, Column 1 is restricted to observations for whom urban ahd vehicle ownership status in wave 4 is observed; Column 2 is restricted to observations for whom employment status is observed. Standard errors, clustered by kabupaten, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

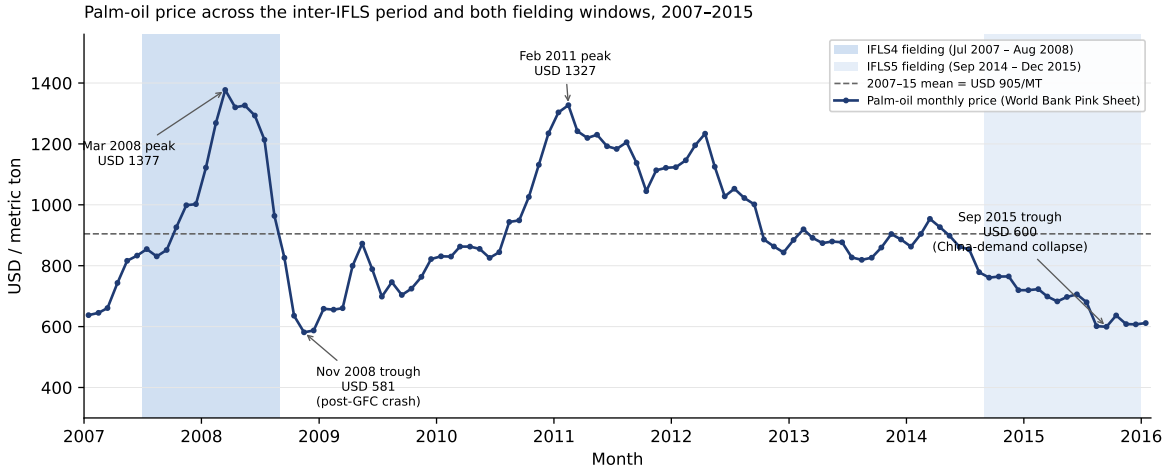
Appendix Figures

Figure A.1: IFLS spatial coverage across the analysis sample



Notes: This figure shows the geographic distribution of the analysis sample across Indonesian kabupaten (districts). Each kabupaten polygon is shaded by the number of adults in the pooled IFLS4 + IFLS5 analysis sample who reside there, using the bins shown in the legend. Provinces in the IFLS sampling frame are outlined in dark green.

Figure A.2: World palm-oil price across both IFLS fielding windows, 2007–2015



Notes: This figure plots the world price of palm oil across the inter-IFLS period and both survey fielding windows. The solid line is the World Bank Pink Sheet monthly palm-oil price (USD per metric ton), 2007–2015. The two shaded bands mark the IFLS4 (July 2007–August 2008) and IFLS5 (September 2014–December 2015) fielding windows. The dashed horizontal line is the 2007–2015 sample mean(USD 905/MT). Notable peaks and troughs are labeled with their month and price.