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## *Poverty, depression, and anxiety: Causal evidence and mechanisms*

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# Poverty, Depression, and Anxiety: Causal Evidence and Mechanisms<sup>\*</sup>

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## Abstract

Why are people living in poverty disproportionately affected by mental illness? We review the interdisciplinary evidence of the bi-directional causal relationship between poverty and common mental illnesses – depression and anxiety – and the underlying mechanisms. Research shows that mental illness reduces employment and therefore income and that psychological interventions generate economic gains. Similarly, negative economic shocks cause mental illness, and anti-poverty programs, such as cash transfers, improve mental health. A crucial step toward the design of effective policies is to better understand the mechanisms underlying these causal effects.

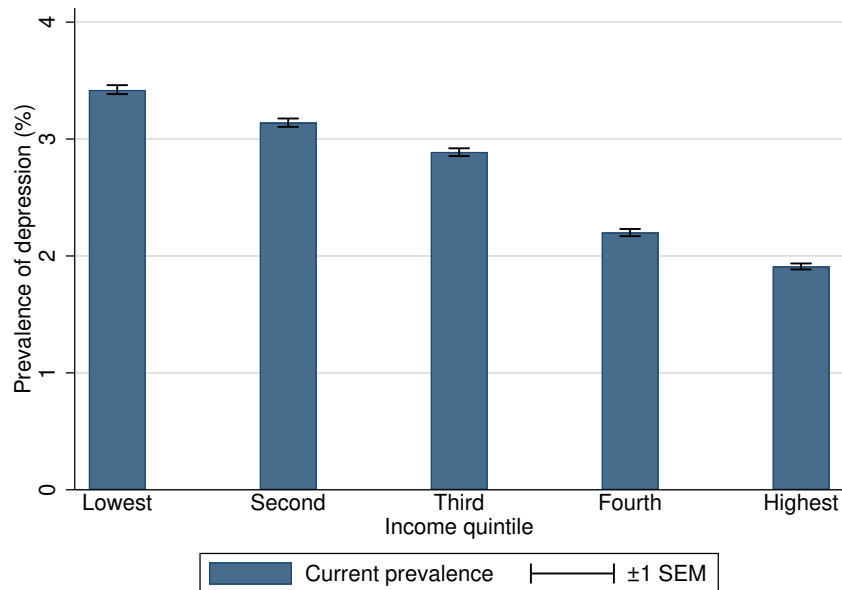
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# 1 Introduction

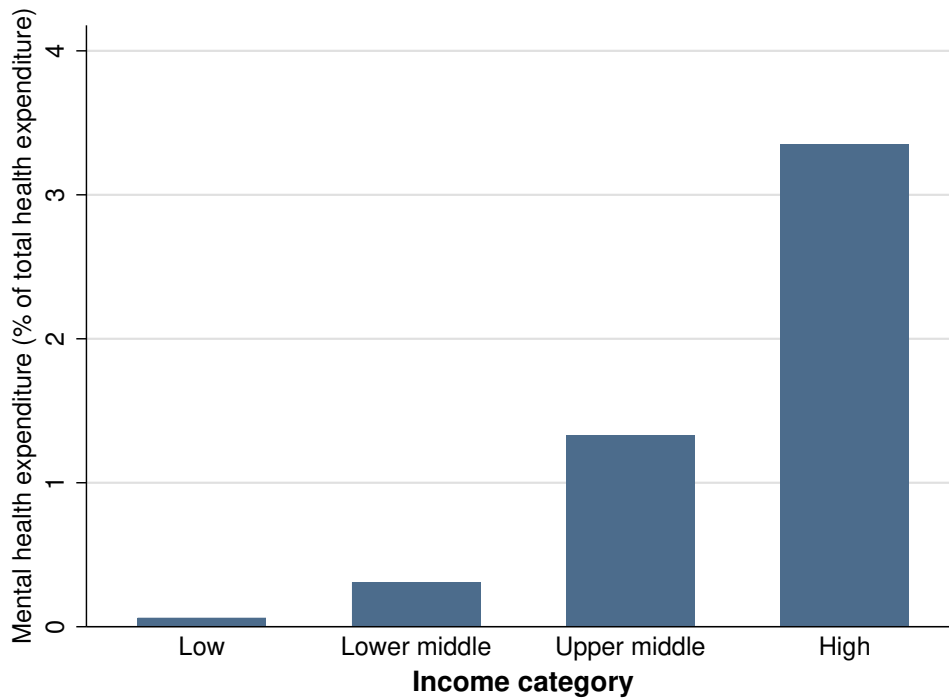
Depression and anxiety are the most common mental illnesses: 3 to 4% of the world’s population suffers from each at any given time, and they are together responsible for 8% of years lived with disability globally (James et al., 2018). Contrary to widely-held preconceptions from the 20th century, these are not ‘diseases of affluence’ (Desjarlais, 1995; Murray et al., 1996). Within a given location, those living in poverty are at least as likely to suffer as the rich. By some measures the poor are substantially more likely to experience mental ill-health than the affluent. Rates of depression, anxiety, and suicide correlate negatively with income (Sareen et al., 2011; Lund et al., 2010; Iemmi et al., 2016; Banks et al., 2018) and employment (Lund et al., 2010; Frasquilho et al., 2016). Those with the lowest incomes in a community suffer 1.5 to 3 times more frequently from depression, anxiety and other common mental illnesses than those with the highest incomes (Lund et al., 2010). For instance, in India, 3.4% of those in the lowest income quintile have experienced depression in the past two weeks, compared to 1.9% of those in the highest quintile (Figure 1).



**Figure 1: Prevalence of depression by income quintile in India.** The average percentage of people in each income quintile in India who have had depression within the past two weeks (‘current’ prevalence). Error bars show  $\pm 1$  standard error of the mean (SEM). These numbers come from Arvind et al. (2019), an analysis of the Indian National Mental Health Survey, 2015-16.

In this review, we shall explore the evidence for the bi-directional causal relationship between poverty and mental health, and its underlying mechanisms. Poverty is also correlated with poor physical health (Cutler et al., 2008; Bleakley, 2010), but the relationship between mental illness and poverty has been overlooked and is worth emphasizing. Mental health has historically not been considered a priority by economists and policymakers, and until recently mental healthcare had not been evaluated as an anti-poverty tool. Mental health services are under-resourced relative to physical health systems. On average, countries spend

1.7% of their health budgets on mental health, even though 14% of years lived with disability globally are known to be caused by depression, anxiety and other mental illnesses (James et al., 2018). Low- and middle-income countries spend an even smaller share of already small health budgets on mental health (Figure 2). Despite the existence of cost-effective treatments, such low investments in mental health have contributed to treatment gaps of over 80% globally for common mental illnesses, much larger than for major physical health conditions (Chisholm et al., 2016; Patel et al., 2009; Wang et al., 2007; Kohn et al., 2004). Mental and physical health are tightly connected: when mental health problems co-exist with physical health problems, health outcomes, disability and costs tend to be much worse (Scott et al., 2016; Vamos et al., 2009; Shen et al., 2008). However, unlike most physical health conditions, mental disorders may directly distort economic decision-making in ways that perpetuate poverty, by directly affecting cognitive function, preferences, and beliefs.



**Figure 2: Mental health expenditure by country income category.** The average percentage of overall health budgets spent on mental health across countries in each of the four income categories used by the World Bank. Percent spent on mental health comes from the authors’ own calculations, using data on overall mental health spending from the WHO Mental Health Atlas 2017, accessible at [https://www.who.int/mental\\_health/evidence/atlas/profiles-2017/en/](https://www.who.int/mental_health/evidence/atlas/profiles-2017/en/), with data on total overall health spending from the WHO’s Global Health Expenditure Database, accessible at <https://apps.who.int/nha/database>.

What are the causal links between poverty and mental illness? Can economic policies improve psychological well-being? Can psychological interventions reduce poverty? Any attempt to understand this relationship must acknowledge the complexity and multi-dimensional nature of both mental health and poverty. Mental health in the broadest possible sense has been defined as “a state of well-being in which the individual realizes his or her

own abilities, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to his or her community” (World Health Organization and Others, 2005). This definition includes both happiness or life satisfaction, which also correlate positively with income (Haushofer and Fehr, 2014), and symptoms associated with anxiety and mood disorders, such as depression. The two are clearly related: depression and anxiety are strong determinants of happiness (Layard et al., 2012), and ultimately mental health and even mental illnesses such as depression and anxiety exist along a continuum.

We focus on the causal evidence linking poverty with depressive and anxiety disorders, the most common mental illnesses, which we refer to here using the more general terms ‘mental health’ and ‘mental illness’. Box 1 provides definitions of these illnesses and a brief primer on their measurement. While other more serious mental illnesses, such as schizophrenia, are also correlated with poverty and may have powerful effects on economic outcomes, we do not discuss them here (Lund et al., 2014).

**Box 1: Definition and Measurement of Depression and Anxiety**

Depression, by which we refer here to Major Depressive Disorder, is a constellation of symptoms including changes in psychomotor function, weight loss, oversleeping or undersleeping, decreased appetite, fatigue, difficulty concentrating, extreme feelings of guilt or worthlessness, and suicidal thoughts. According to the American Psychiatric Association’s Diagnostic and Statistical Manual of Mental Disorders (DSM-5), diagnosis of depression requires a set of these symptoms to be present over a two-week period.

Anxiety, by which we refer here to Generalized Anxiety Disorder, is characterized in the DSM-5 by long-lasting and excessive fear and worries over at least a six-month period, with three or more of the following symptoms: restlessness, fatigue, concentration problems, irritability, muscle tension and problems with sleep. Other definitions require the presence of at least one physical symptom such as heart palpitations, difficulty breathing, nausea or abdominal distress, dizziness and numbness.

Measuring depression and anxiety in large population samples is feasible using non-specialist surveyors or even via self-administration of questionnaires. Reliable short-form diagnostic tools can predict professional diagnosis with rates of false positives and false negatives of 10 to 20%, and have been validated in low-income countries (Patel et al., 2008; Kroenke and Spitzer, 2002; Spitzer et al., 2006). Widely used tools include the Generalized Anxiety Disorder 7-item (GAD-7) scale for anxiety or the Patient Health Questionnaire (PHQ-9) for depression, or the Self-Reporting Questionnaire 20-Item (SRQ-20) scale for any common mental illness. These scales typically ask respondents how much they experienced symptoms of depression or anxiety (such as sadness, lack of concentration, or poor sleep) in the past few weeks. The PHQ-9 and GAD-7 ask one question for each of the symptoms which are used to define major depressive disorder and generalized anxiety disorder, respectively. In practice, depression and anxiety are correlated, as evidenced by the fact that they share some symptoms.

The Center for Epidemiologic Studies Depression Scale (CES-D) is a popular measure among studies of the effect of economic interventions or shocks on mental health. Several studies also use custom indices of psychological well-being, typically an average of a life satisfaction scale, a ‘stress index’, and some measure of worry or anxiety. In practice, such indices often measure several of the same symptoms as the PHQ-9 and GAD-7.

Some national surveys already include short-form screening tools, such as the U.K. Longitudinal Household Panel Survey and the South Africa National Income Dynamics Study.

Like mental health, poverty is multidimensional. We examine causal links between mental illness and important economic dimensions of poverty, particularly income and unemployment. We also touch upon other dimensions of poverty, including a lack of capabilities resulting from low education and physical health, as well as relative poverty and associated low social status. Due to a relative scarcity of studies, we focus less on the relationship between mental health and the consumption of goods and services, which is a more direct economic measure of poverty. The existing evidence on this relationship is contentious, but

the cross-sectional correlation of mental illness with consumption appears to be weaker than that between mental health and income (Tampubolon and Hanandita, 2014; Banks et al., 2018; Das et al., 2009). Income is more volatile than consumption in the short run. The stronger correlation of mental health with income suggests that mental health may be more affected by short-run changes to economic status than long-run or permanent changes.

We discuss evidence on poverty alleviation programs and mental health treatments obtained from randomized-controlled trials (RCTs). These generate variation in individuals' poverty and mental health status, respectively, that is entirely by chance and therefore uncorrelated with all other shared risk factors. Such studies allow us to isolate evidence of causal relationships. We also discuss studies of 'natural experiments' in which naturally-occurring variation in economic circumstances or mental health is argued to be 'as good as random'. Examples range from financial windfalls, such as lottery wins — where lottery winners may be thought of as a treatment group and lottery losers as a control group — to weather shocks that affect some farmers' incomes more than others'.

## 2 The Causal Impact of Poverty on Mental Ill-Health

Job loss and income declines are drivers of poverty, and often precede episodes of mental illness (Olesen et al., 2013; Alloush, 2018). Evidence from natural experiments confirms that this relationship is causal. For instance, reduced agricultural output and income due to extreme rainfall caused increased rates of depression and suicide in rural parts of Indonesia (Christian et al., 2019) (Box 2). Similarly, job losses due to plant closures in Austria were associated with higher subsequent antidepressant use and mental health-related hospitalization (Kuhn et al., 2009). Areas in the USA more exposed to trade liberalization with China saw reduced income and employment for some groups of workers and increased mortality through drug overdoses among those same groups (Pierce and Schott, 2016). Whether job loss worsens mental health beyond the impacts of the associated loss of income is unclear, but both mechanisms are argued to play a role in the phenomenon of 'deaths of despair' (Case and Deaton, 2020).

Conversely, income or wealth increases can improve mental health. For example, Native American tribes that opened casinos have seen substantial rises in income and reductions in anxiety relative to those that did not (Wolfe et al., 2012). Some studies have shown that lottery winners enjoy better mental health compared to those who win less or play but don't win (Apouey and Clark, 2015). However, when fully controlling for the number and frequency of lottery tickets bought, winnings have small or no impacts on mental health (Cesarini et al., 2016; Lindqvist et al., 2018).

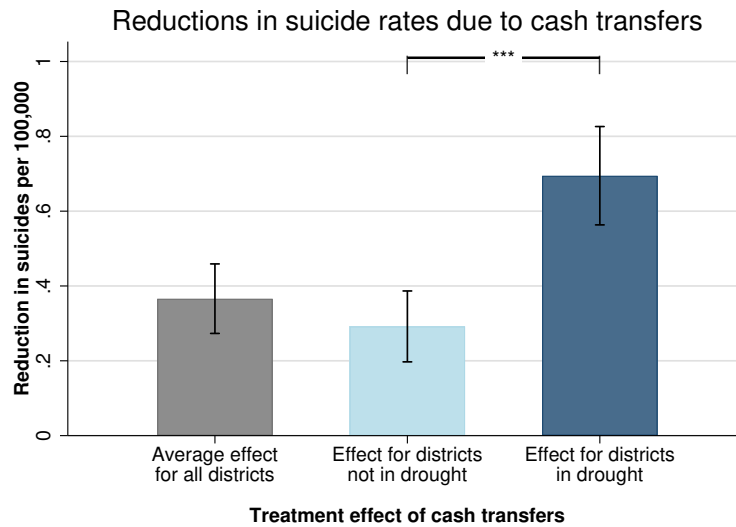
The most compelling causal evidence that poverty causes mental illness comes from randomized-controlled trials (RCTs) that evaluate *anti-poverty* programs. Several studies evaluating cash transfer and broader anti-poverty programs have found significant positive impacts on mental health, including over long time horizons, after the effects of any initial celebratory reactions among recipients have worn off. Figure 4 reports a meta-analysis of

## Box 2: Cash Transfers, Rainfall Shocks, and Suicides

Christian, Hensel and Roth (2019) examined how income shocks affect suicide rates and depression in Indonesia. They use two natural experiments: the staggered roll-out across sub-districts of a conditional cash transfer program and annual and spatial variation in rainfall that affects farmers' incomes. They measure depression using a 10-question CES-D scale which is included in the Indonesian Family Life Survey. They also use the incidence of suicides, as measured by the reports of village leaders in census surveys.

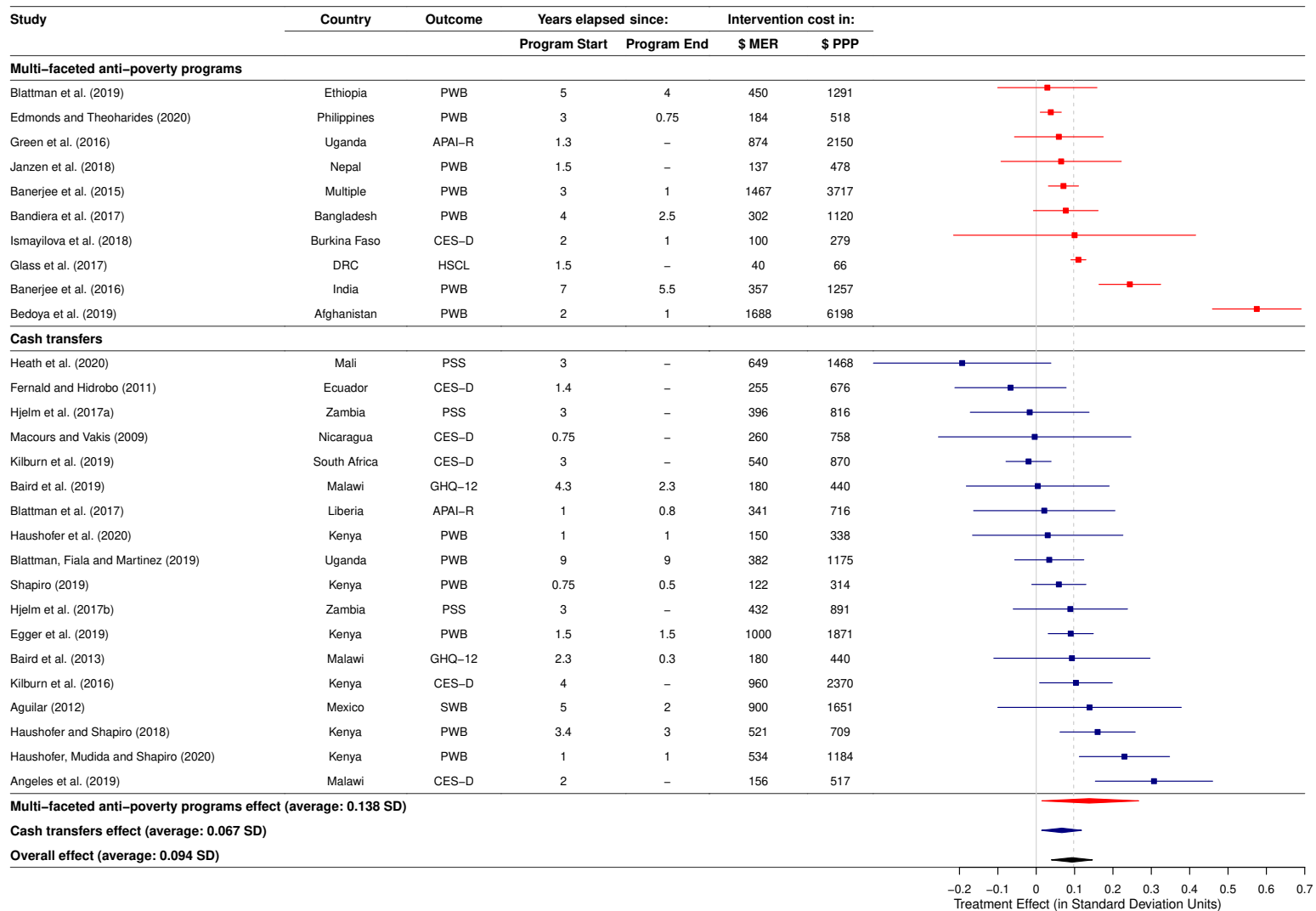
Sub-districts which received the cash transfer program in the first wave of roll-out saw an 18% drop in suicides ( $p < 0.01$ ) relative to those that received it later, even though both sets of districts had similar trends in suicide before the program's start. Meanwhile, rural sub-districts that experienced excess rainfall that increased crop yields between census years saw decreases in depression and suicides relative to sub-districts experiencing drought. The cash transfer had its largest effects on suicide in districts undergoing droughts, suggesting that policy can play a role in mitigating the mental health effects of economic shocks (Figure 3).

Since suicide was only measured at the sub-district level in this study, it is not possible to fully disentangle the direct effects of the cash transfers on recipients from spillover effects to others in the village. This highlights the need for better routine data collection on mental health outcomes alongside economic variables.



**Figure 3: Cash transfers, suicide rates, and droughts.** The estimated effect of the cash transfer roll-out on district suicide rates, for all districts and separately by whether or not they were experiencing a drought (bottom 20% of the rainfall distribution) when the cash transfers reached them. Error bars show  $\pm 1$  SEM. Stars denote a significant difference between effects. \*\*\*:  $p < 0.01$ ; \*\*:  $p < 0.05$ ; \*:  $p < 0.1$ .

these studies. For instance, cash transfers to Kenyan households worth \$400 to \$1,500 at purchasing power parity (i.e., about 3 to 12 months of household income) increased consumption and happiness while reducing depression, stress, and worries (Haushofer and Shapiro, 2016, 2018). Scores on a depression scale were 0.12 standard deviations (SD, closely related to Cohen's  $d$ ) lower 4 months after completion and 0.16 SD lower after almost three years, with larger transfers causing substantially larger effects.



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**Figure 4: The impacts of anti-poverty programs on mental health.** This figure plots the estimated treatment effects of RCTs evaluating anti-poverty programs in low- or middle-income countries on indices of mental health (see appendix for a list of the papers included in this meta-analysis). Positive treatment effects imply better mental health. ‘Cash Transfers’ refers to studies of unconditional cash transfers to low-income households, with the exception of Baird et al. (2013) and Kilburn et al. (2019) who examined conditional cash transfer programs. ‘Multi-Faceted Anti-Poverty Programs’ refers to interventions that aimed to lift people out of poverty by providing a range of elements, typically including asset transfers, skills training, cash support, and access to savings and healthcare opportunities. Treatment effects are expressed in standard deviation units (SD). If multiple follow-up measures were available, this figure shows the final measure. The outcomes vary across studies and include screening instruments to detect common mental illnesses (GHQ-12) and symptoms of depression (CES-D, APAI-R), indices of psychological well-being (PWB), and a perceived stress scale (PSS). ‘Intervention cost’ refers to the total cost of implementing the intervention, when this is available. When implementation costs are unavailable (as with most of the cash transfer studies) it refers to the total undiscounted value of the transfer. ‘MER’ stands for Market Exchange Rates and ‘PPP’ stands for Purchasing Power Parity (which adjusts exchange rates to reflect the true cost of living). A missing value of years elapsed since program end means the transfer was still ongoing when outcomes were measured. A complete description of the methodology of this analysis and details on each of the studies is provided in the supplementary materials.



Similarly, multi-faceted anti-poverty programs beyond cash transfers yield mental health benefits. A recent large-scale randomized evaluation of a “graduation program” in six countries that provided extremely poor participants with a mix of assets, intensive training, temporary cash support, savings incentives, and help to access healthcare, found increases in consumption and assets three years later. The program also improved an index of psychological well-being by 0.1 SD, which was driven by an increase in happiness and a decrease in mental distress (Banerjee et al., 2015). Programs in other settings with similar approaches have found similar effects (Bandiera et al., 2017; Bedoya et al., 2019). Longer-run effects of such programs, when measured, appear to be even larger for both economic outcomes and mental health. In India, for example, an index of psychological well-being was 0.24 SD higher in the treatment group seven years after the completion of a graduation program (Banerjee et al., 2016).

Hence, across a wide range of populations and study designs, positive economic shocks to individuals are shown to improve mental health, whereas negative economic shocks undermine mental health. This robust evidence, on the effects of changes in economic circumstances, indicates that poverty does cause mental illness. However, with two exceptions (Lindqvist et al., 2018; Banerjee et al., 2016), the above studies consider the consequences of changes in economic status for a few years at most. An important question is whether these short-run effects can persist or grow over time. For instance, some of the causal mechanisms we discuss below could take decades to manifest. On the other hand, there may be a hedonic adaptation effect in which mental health eventually adapts to the change in circumstances, so that even permanent increases in one’s income level have a limited long-run effect. Of course, it could also be that the positive economic shocks are themselves undone by future negative shocks, causing mental health to revert to initial levels or even worsening. Ongoing long-run evaluations of cash-transfer programs are expected to provide evidence on this question (Banerjee et al., 2019).

## 2.1 Mechanisms for Poverty Causing Mental Ill-Health

How does poverty cause mental illness? We discuss several plausible causal mechanisms and the limited evidence for each. The worries and uncertainty that come with living in poverty seem to be an important driver of mental illness, as do the effects of poverty on childhood development and one’s living environment. We have more limited causal evidence for other plausible channels, including worsening of physical health caused by poverty, increased exposure to violence or crime, and the effects of low relative social status and social isolation. Understanding which of these mechanisms are important may have implications for policy choices. For instance, if worries and uncertainty play a major role, then providing health and unemployment insurance may be crucial, while if early-life conditions are the key drivers, then cash transfers to parents of young children could be the most appropriate policy response.

***Worries and uncertainty.*** The anticipation of economic shocks, not just their occurrence, may cause mental illness. People living in poverty face substantial uncertainty and income volatility, and juggle what are, in effect, complex financial portfolios, often without

access to formal insurance (Collins et al., 2009). Sustained long-run exposure to stress from managing this volatility may threaten mental health (Staufenbiel et al., 2013). Consistent with this hypothesis, a large-scale randomized experiment among low-income individuals in Oregon found that receiving largely free health insurance worth \$550-\$750 per year reduced rates of depression by about a quarter within a few months (Finkelstein et al., 2012). This effect did not appear to be explained by increased mental healthcare or changes in physical health. While the increase in recipients' effective income may have played a role, it represented a much smaller relative increase than the cash transfer programs described above, and yet generated a similar effect size on depression. Further suggestive evidence for uncertainty as a mechanism comes from the small or zero effect of wealth shocks on mental health in countries with generous and comprehensive systems of social insurance, such as Sweden (Cesarini et al., 2016; Lindqvist et al., 2018).

***Environmental factors.*** Those living in poverty are generally more exposed to environmental irritants such as pollution, temperature extremes, and challenging sleep environments (Dean et al., 2018). Many of these factors have been linked directly to mental illness. Days with extreme heat see worse self-reported mental health and increased rates of self-harm and suicide (Ding et al., 2015; Williams et al., 2016). Similarly, sleep deprivation is widespread among the urban poor in developing countries (Bessone et al., 2020), and sleep is thought to be a mechanism affecting mental health (Harvey, 2011; Grubb and Lauritzen, 2019). Some evidence exists that clinical interventions to improve sleep reduce depression (Bessone et al., 2020; Manber et al., 2008). Exposure to air pollution is associated with living in poverty, and may influence mental health through multiple channels, by restriction of physical activity or directly due to neurotoxicity (Jia et al., 2018). Changes in air pollution in China have been associated with changes in mental health (Xue et al., 2019). In the US, randomly selected low-income households that were paid to move to more affluent neighborhoods saw reductions in depression and anxiety despite little effect on income (Ludwig et al., 2012). However, it is not clear whether environmental factors or other features of high-income neighborhoods generated this effect.

***Physical health.*** Lower income is robustly associated with worse physical health (Cutler et al., 2008). Poverty increases exposure to the environmental factors described above, and often also implies lower access to health care, which increases the burden of acute and chronic health conditions. Worse physical health may impact mental health through various channels. Chronic pain, worries about health and mortality, the financial costs of illness, and reduced physical activity may all worsen mental health. It is therefore unsurprising that physical ill-health often co-occurs with depressive and anxiety disorders (Scott et al., 2016). However, only limited causal evidence exists of poverty impacting mental health via changes in physical health. Many of the randomized interventions described in the previous section had no detectable effect on physical health even as they reduced mental illness (Haushofer and Shapiro, 2016; Egger et al., 2019; Banerjee et al., 2015). However, changes in physical well-being may manifest over a longer timeframe, which may not be captured by these short-run studies.

***Early-life conditions.*** Exposure to poverty early in life can threaten mental health in

later years. Such effects can be generated in utero, by exposing pregnant women to malnutrition or stress. For instance, the death of a mother’s relative during pregnancy (compared to after childbirth) predicts depression and anxiety among her grown children later in life (Persson and Rossin-Slater, 2018). Poverty may also disproportionately expose children to adverse shocks while their brains are highly plastic. Such shocks can profoundly impact brain development, cognitive ability, and mental health in adolescence and adulthood (Noble et al., 2015; Blair and Raver, 2016). Economic stresses around the time of birth also have long-term mental health costs: in Ghana, a decrease in crop prices by 1 SD at an individual’s time of birth was found to increase incidence of anxiety or depression in adulthood by 50%, associating with maternal nutrition, breastfeeding duration, vaccination rates and improved adult health (Adhvaryu et al., 2019). These results imply that programs that provide financial support for households with pregnant women or young children may have high long-run mental health and economic returns.

***Trauma, violence and crime.*** Living in poverty disproportionately exposes individuals to crime, including violent offenses (Sharkey et al., 2016). People living in poverty are also more likely to suffer traumatic events such as the early deaths of loved ones (Marmot, 2005). Likewise, within the household, women and children in poor households are disproportionately affected by intimate partner violence (Cunradi et al., 2000). The relationship between poverty and experiencing violence itself may be causal: cash transfers to households reduce intimate partner violence (Haushofer et al., 2019). In turn, both exposure to violence within the household and exposure to violent crime in general predict depression and other mental illnesses (Goodman et al., 2009; Cornaglia et al., 2014). Causal evidence on the effect of reductions in crime and violence on mental illness is needed to shed further light on this mechanism.

***Social status, shame, and isolation.*** Relative poverty, i.e., consumption or income relative to others in one’s society, may play a role in the relationship between poverty and mental illness through the resulting social status and interpersonal comparisons. In an interesting natural experiment, Norwegian tax records were posted online in 2001, making citizens’ income easily searchable. Using survey data from 1985-2013, a study showed that the gap in happiness and life-satisfaction between the rich and poor within Norway increased sharply once relative income became easily visible (Perez-Truglia, 2019). While similar causal evidence is lacking for mental illness, it is plausible that diminished social status resulting from poverty causes or exacerbates depression and anxiety. Frequent marginalization of people living in poverty may also result in social isolation and loneliness (Walker and Bantebya-Kyomuhendo, 2014), which in turn are correlated with depression (Cacioppo et al., 2006).

### 3 The Causal Impact of Mental Ill-Health on Poverty

Mental illness predicts worse labor market outcomes later in life. Following a diagnosis of depression or anxiety, employment rates and incomes have been estimated to fall by as much as half, relative to the non-depressed or non-anxious (Hakulinen et al., 2019; Mojtabai et al., 2015). Beyond such comparisons, which may be driven in part by unknown factors such as

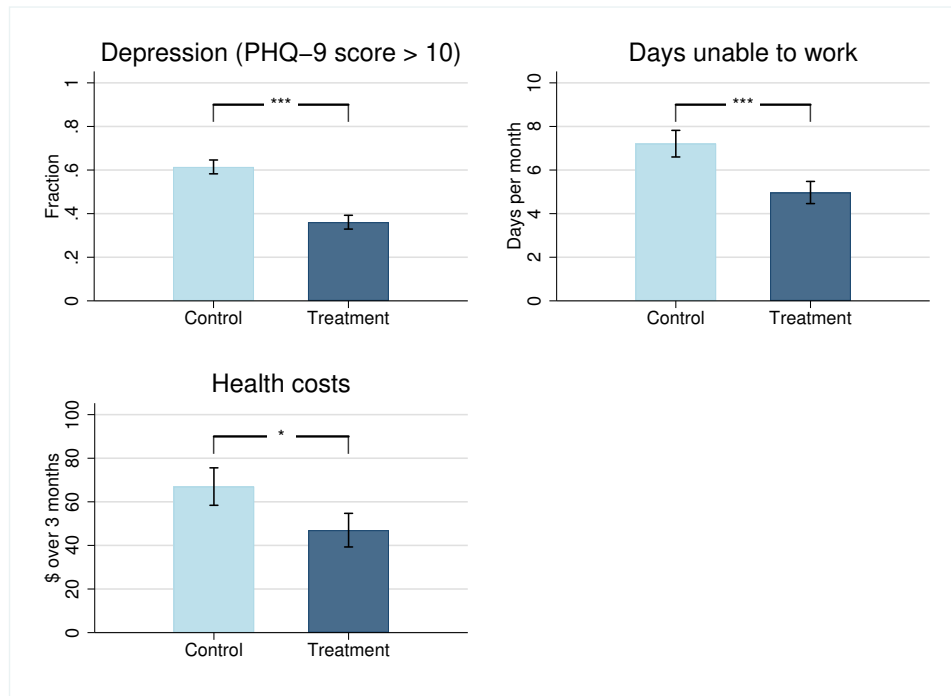
physical health, there is little evidence from natural experiments linking depression or anxiety to incomes. A study showed that the approval of lithium for treatment of bipolar disorder reduced the earnings penalty associated with bipolar illness by a third in Denmark, from 38 to 26 percent, with larger effects in the lower half of the earnings distribution (Biasi et al., 2019). Studying similar natural experiments for depression and anxiety would be valuable.

**Box 3: An Example of a Psychotherapy Intervention With Positive Economic Effects**

Patel et al. (2017) conducted an RCT of a brief behavioral activation therapy (BA) program, administered by non-specialist counsellors in a sample of 495 depressed adults in Goa, India. Compared to a control group which received enhanced usual care, treated patients were over 60% more likely to be in remission three months later (64% versus 39%), as measured by a PHQ-9 score (see Box 1) below 10, and maintained these gains after 12 months.

Those patients also reported being able to work 2.3 more days per month on average ( $p=0.004$ ) and reduced health costs, excluding intervention costs, of \$20 per month ( $p=0.07$ ) (Figure 5). For comparison, a month’s wages for a low-skilled worker in the study context was around \$415. Given an average intervention cost of \$66 per patient, in economic terms the intervention was highly cost-effective and may have paid for itself within a few months. After 12 months, the fall in treated patients’ health costs alone had already significantly outpaced the cost of intervention, although the difference in days worked was no longer significant (Weobong et al., 2017).

Other evaluations of inexpensive psychotherapies implemented by non-specialist counsellors in low-income settings have found similarly large effects on mental health (Singla et al., 2017). More evidence on the effect of such psychological interventions on broader economic outcomes would be highly valuable. For instance, future trials could be linked to administrative or standardized survey data on wages, earnings, and consumption.



**Figure 5: Impacts of behavioral activation on depression, labor supply, and health costs.** The mean values for the treatment and control groups of depression (measured by a PHQ-9 score greater than 10), days unable to work, and health costs (excluding the intervention cost) at 3 months. Error bars denote  $\pm 1$  SEM. Stars above the bars denote a significant difference between treatment and control after adjusting for covariates. \*\*\*:  $p < 0.01$ ; \*\*:  $p < 0.05$ ; \*:  $p < 0.1$ .

There is, however, a substantial body of experiments showing a causal effect of treating mental illness on employment. A meta-analysis aggregating results across 31 RCTs in developing countries showed a positive average effect of various interventions to treat mental illness on labor supply Lund et al. (2019). Among these interventions, pharmacological and psychological treatments had similar positive effects on labor supply (0.1 to 0.15 SD), while combining both types of treatments had even larger effects (0.34 SD). For instance, a cheap and scalable cognitive behavioral therapy (CBT) administered in India reduced depression by 25 percentage points compared to the control group, and in turn increased reported days of work by 2.3 days per month (Box 3). While these studies do not directly show that treating mental illness reduces poverty rates, higher labor supply and earnings naturally reduce the likelihood of living in poverty. Whether treating mental illness has larger long-run effects on consumption per unit cost than the cash transfers described above is unknown (Lund et al., 2019).

### 3.1 Mechanisms for Mental Ill-Health Causing Poverty

*Cognitive function.* Like any illness, depression and anxiety may have economic effects because they directly reduce individuals’ ability to work. Unlike most physical conditions, however, depression and anxiety also directly affect the way people think. Poverty itself can influence cognitive function by capturing attention and taxing mental bandwidth (Mani et al., 2013; Kaur et al., 2019). Mental illness may have similar effects, by capturing attention, causing excessive rumination, and distorting people’s memories and beliefs about their abilities (Gotlib and Joormann, 2010). Such cognitive impacts could alter a range of economic decisions and outcomes, from finding jobs to saving to education, and by exacerbating ‘behavioral biases’ that economists increasingly recognize as important (Kremer et al., 2019). For instance, depressed individuals might avoid making active choices and may stick with ‘default options’, may have decreased sensitivity to incentives due to anhedonia or may have difficulty choosing among several options. Understanding the importance of this mechanism relative to more ‘direct’ economic effects through disability or health expenditures is crucial for correctly measuring the economic burden of mental illness and designing economic policy for those whose mental health is compromised.

*Beliefs.* Beliefs about one’s own and others’ abilities, circumstances, and actions are central to economic decision-making. Mental illness may distort such beliefs in various ways. Depression is associated with more negative beliefs about oneself and the external world (Beck, 1967; de Quidt and Haushofer, 2016). Depressed individuals are more likely to remember negative stimuli and have trouble disengaging from negative information once it grabs their attention (Gotlib and Joormann, 2010). As such, while healthy individuals tend to protect overly optimistic beliefs about themselves by ignoring negative information (Eil and Rao, 2011), correlational evidence suggests that the depressed update their beliefs more pessimistically (Korn et al., 2014). Anxiety, meanwhile, is associated with greater selective attention towards threatening stimuli (Armstrong and Olatunji, 2012), which could lead to overestimation of risks and thus reduced risk-taking. Such evidence is consistent with mental illness causing pessimistic beliefs, pessimistic beliefs causing mental illness, or both. Causal evidence on how treating depression or anxiety affects beliefs would help disentangle these

potential explanations.

***Preferences.*** Mental illness may affect economic preferences, such as the extent to which people are willing to defer gratification (time preferences), tolerate risk for higher expected rewards (risk preferences), or split rewards between themselves and others (social preferences). For instance, depression may diminish a person’s patience and altruism. Similarly, anxiety disorders may reduce people’s willingness to take on even modest levels of potentially profitable risk. Such impacts could in turn change a variety of economic behaviors, such as labor supply decisions, savings and investment choices, consumption behavior, and the take-up of social programs. The limited evidence on correlations between mental illness and economic preferences is mixed (Bayer et al., 2018; Cobb-Clark et al., 2019).

***Labor supply and productivity.*** Depression and anxiety often affect individuals in the prime of their economic lives, and can be highly recurrent (Kessler et al., 2007). The depressed beliefs and distorted preferences described above may reduce motivation and labor supply. In addition, depression can have a direct effect on productivity, e.g. through increased fatigue and lack of concentration. Depressed individuals may therefore work fewer and shorter days and produce less per hour (Mall et al., 2015). Depressed workers might also be more easily discouraged during their job search, or when facing setbacks at work. As described above, substantial causal evidence exists that treating mental illnesses increases employment (Lund et al., 2019). However, there is little evidence on whether this happens through higher at-work productivity, greater job search intensity, changed beliefs, or other mechanisms.

***Stigma.*** Mentally ill individuals contend with substantial social stigma and negative stereotyping (Pescosolido et al., 2013). This may result in discrimination in employment (Sharac et al., 2010), which could lower wages and limit employment opportunities relative to equally productive mentally-healthy workers. On top of this, those living with a mental illness are excluded from disability benefit schemes in many low-income countries (Saxena et al., 2006). More generally, others’ reluctance to interact socially with mentally ill people (Pescosolido et al., 2013) may exclude them from social networks which provide economic opportunities. Stigma may also affect the formation and dissolution of households in ways that disadvantage the mentally ill (Lauber and Rössler, 2007). Depression and anxiety may come with a ‘discount’ on the marriage market, causing mentally ill individuals to form households with less well-off partners, increasing the chances of living in poverty.

***Health expenditures.*** Mental illnesses may deepen poverty through its impacts on health and health expenditures. Globally, people living in poverty usually pay most of their health costs out of pocket (Duflo and Banerjee, 2007). 150 million people globally are estimated to have catastrophic health expenditures each year, defined as health care payments totaling over 40 percent of a household’s non-subsistence expenditures (Xu et al., 2007). Costs associated with treating mental illness rarely account for large shares of individuals’ budgets, as most affected individuals remain untreated. However, depression and anxiety frequently co-occur with other health conditions (Scott et al., 2016), and such comorbidity with depression is associated with substantially higher health expenditures for a range of

health conditions (Vamos et al., 2009; Shen et al., 2008). Indeed, treating depression has been found to reduce overall health care costs (Weobong et al., 2017).

***Women’s empowerment.*** The burden of mental illness falls disproportionately on women (James et al., 2018). A large-scale (N=903) RCT evaluating cognitive behavioral therapy intervention for depressed pregnant women in Pakistan found a 17-percent reduction in depression rates compared with a control group seven years after the intervention (Baranov et al., 2017). Reduced depression among these women was accompanied by increased economic empowerment by 0.29 SD as measured by increased control over household and personal expenditures. Such impacts may have implications for women’s consumption and relative poverty within the household.

***Intergenerational effects.*** Improving a parent’s mental health can benefit the next generation. In the above study in Pakistan, women who had received the intervention sent their children to better schools and had more learning materials in their homes. Similarly, other RCTs found that treating mothers’ depression improves their interaction with their children, and their children’s mental health (Cuijpers et al., 2015). While little direct evidence shows that such interventions lead to improved educational outcomes or earnings, there is reason to believe they may. A significant body of work from other contexts shows that early-childhood investments have large effects on children’s income as adults (Heckman and Mosso, 2014).

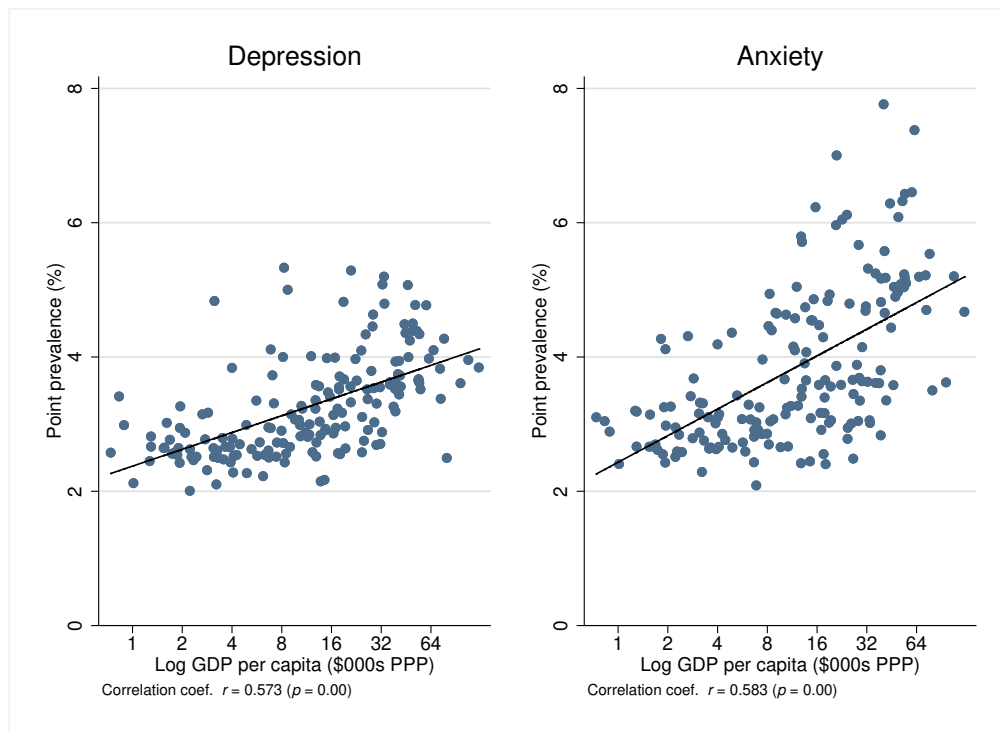
***Human capital accumulation.*** The onset of common mental illnesses often coincides with secondary and tertiary education and the early stages of an adult’s work career (Kessler et al., 2007). Mental illness may therefore cause long-run economic hardship by reducing school and college completion rates, worsening early-career job placements, and hindering skill acquisition (Patton et al., 2016). This suggests the possibility of particularly high economic returns from improving mental health among adolescents and young adults. While longitudinal studies show a substantial correlation between mental illness among students and subsequent educational outcomes, there is little experimental evidence to date that treating depression or anxiety among adolescents leads to improved educational outcomes (Prinz et al., 2018).

## 4 Outlook

Having discussed some of the mechanisms influencing the relationship between poverty and mental health, we can speculate more broadly on how the relationship between poverty and mental illness may evolve, what this means for policy, and what directions might be fruitful for research.

***Aggregate economic conditions.*** Economic growth and other ongoing global trends are unlikely to improve mental health by themselves. Higher income causes better mental health at the individual level, yet on average the prevalence of mental illness is not lower in rich countries. To the contrary, existing evidence shows a higher prevalence of common

mental illness in richer countries (Figure 6) (Dückers et al., 2019). This cross-country difference cannot be interpreted causally, and concerns remain about differences in methodology, diagnosis, or reporting across contexts (Brhlikova et al., 2011). However, one way to reconcile the contrasting within-country and cross-country relationships is the possibility that relative, rather than absolute, poverty is the more relevant cause of mental illness. Risk factors, including inequality and relative poverty, or the stresses of urban environments, may deteriorate rather than improve as whole economies expand. Within-country inequality has increased in many countries in recent decades, despite significant reductions in extreme poverty and global inequality (Milanovic, 2016). Complacency about mental health among the poor is therefore not warranted even in the presence of aggregate economic growth. For instance, the burden of disease due to mental and neurological disorders in India and China increased by 61 and 28 percent respectively between 1990 and 2013, despite impressive economic growth (Charlson et al., 2016).



**Figure 6: Prevalence of common mental illnesses by country.** For each country, the percentage of the population estimated to have a depressive disorder (left panel) or anxiety disorder (right panel) is shown at a given point in time against that country’s log GDP per capita. Each scatter point represents one country. The line shown is an Ordinary Least Squares regression line of country prevalence rates on a constant and log GDP per capita. Prevalence rate data come from the *Global Burden of Disease Study, 2017*, accessible at: <http://ghdx.healthdata.org/gbd-results-tool>. GDP per capita data are for 2017, measured in constant 2011 international \$, and come from the World Bank’s *World Development Indicators* dataset, accessible at: <https://databank.worldbank.org/source/world-development-indicators/>.

*Climate change.* The more frequent occurrence of extreme heat due to climate change is anticipated to exacerbate mental illness directly (Masson-Delmotte, 2018; Trang et al., 2016). The increased frequency of weather-related disasters, such as floods and hurricanes, poses a



threat to mental health through greater exposure to trauma (Berry et al., 2018). Climate change also threatens mental health through its negative economic consequences, which are likely to be more pronounced in low-income countries (Masson-Delmotte, 2018). Extreme temperatures during the agricultural growing season that damage crops and thus economic well-being have been reported to increase suicides in agricultural regions in India (Carleton, 2017). Predicted increases in water scarcity and droughts are also likely to worsen economic and in turn psychological well-being. Climate change is also expected to lead to increased violence and political conflict over the next century through increased pressure on resources, such as productive land and, possibly, psychological effects of heat on aggression (Burke et al., 2015). This combination of economic and political consequences of climate change may increase the flow of refugees and economic migrants, with concomitant challenges to mental health (McMichael et al., 2012).

***Technological change and globalization.*** For many of those living in poverty across the world, technological change and globalization offer enormous economic opportunities; however, both phenomena produce winners and losers. The costs to losers, especially low-wage workers in high- and middle-income countries who lose jobs as a result of changes in patterns of trade or automation, can be long-lasting and substantial (Autor et al., 2016), resulting in significantly worse mental health (Kuhn et al., 2009; Pierce and Schott, 2016). While most economic research on these topics focuses on rich countries, there is an urgent need to understand the mental-health effects of these economic changes in poorer countries.

Offering social insurance and welfare, skills training, and job transition programs, including psychotherapies for workers exposed to the harmful effects of technological change and globalization will be important to protect mental health. One example is the ongoing Building Bridges and Bonds evaluation, which provides a tailored cognitive behavioral therapy intervention to unemployed (formerly incarcerated) men in the United States, in conjunction with traditional job-seeking services, in an attempt to increase employment and wages.

***Pandemics.*** Public-health crises such as the ongoing COVID-19 pandemic tend to disproportionately affect those living in poverty (Adams-Prassl et al., 2020). They may worsen mental health on average, and particularly among the poor. First, income and employment losses as a result of morbidity can be large, which in turn can reduce mental health through the mechanisms described above. In addition, the exposure to trauma, increased worries and uncertainty, and worse physical health will tend to impair mental health, in turn reducing income and employment. On the other hand, ongoing progress in reducing the burden of other diseases which disproportionately affect the poor, such as cholera and diarrhoeal infections, tuberculosis, malaria and other insect-borne diseases, will provide a countervailing force likely to improve mental health among the poor. The COVID-19 pandemic has the potential to set back progress in reducing the enormous burden of these diseases.

***Social media.*** The spread of mobile phones and the internet opens up new opportunities for poverty alleviation (Suri and Jack, 2016) and novel ways to deliver mental health care. However, some of these technologies may pose new threats to mental health. While more causal evidence is needed, some studies have found that depression is correlated with internet

addiction and with the intensity of use of social media among young adults and adolescents (Ha et al., 2007; Lin et al., 2016). Recent randomized interventions show that deactivating social media accounts for four weeks led to 0.1 SD reductions in depression and anxiety scores (Allcott et al., 2019; Mosquera et al., 2019). Increased access to the internet and social media among the global poor, while presenting enormously valuable benefits, may therefore also pose some threat to mental health among the poor (World Bank Group, 2016).

## 4.1 Implications for Research and Policy

Since mental health and poverty are intimately linked, interdisciplinary collaborations between mental-health researchers and social scientists studying poverty are essential (Box 4). Evaluations of economic interventions should carefully measure impacts on mental health, and vice versa. An example of such work is Bhat et al. (2019), wherein a team of psychiatrists and economists followed up on psychotherapy clinical trials in India and deployed the tools of behavioral economics and psychiatry to study long-run effects of psychotherapy on mental health, economic well-being, and decision-making.

***Policy tools.*** There is a strong economic case for investing in the mental health of people in poverty. A recent meta-analysis showed that mental health interventions in low- and middle-income countries, including psychotherapy and pharmacotherapy, had similar or larger effects on employment than economic interventions such as cash transfers, job training programs, and multi-faceted anti-poverty programs (Lund et al., 2011). Yet, they were an order of magnitude less expensive to deliver. Such treatments could therefore be the most cost-effective anti-poverty intervention, at least among the subset of people who are mentally ill. However, we know little about how to optimally combine, dose, sequence, and target economic and mental health interventions. For instance, combining psychological and economic interventions might lead to treatment effects that are greater than the sum of their parts. In particular, improved mental health could increase the economic returns of receiving cash or asset transfers by improving decision-making and productivity.

Recently, innovative studies have compared the effects of providing psychotherapy, cash support, or both among low-income populations. An RCT measured the effect of eight weeks of cognitive behavioral therapy and/or \$200 in cash support to a thousand criminally-engaged men in Liberia (Blattman et al., 2017). While the psychotherapy targeted antisocial behavior rather than mental illness per se, the study found that the combination of cash transfer and psychotherapy improved an index of self-regard and mental health by 0.2 SD a year later ( $p=0.024$ ), accompanied by a modest reduction in depression and psychological distress ( $-0.11$  SD,  $p=0.24$ ). The combined treatment not only reduced antisocial behavior but also increased patience and self-control, while neither cash nor therapy alone had detectable effects. However, none of the treatments apparently influenced consumption or income a year later. More studies along these lines would be valuable.

***Treatment gaps.*** In poor countries, the fraction of individuals diagnosed with depression and anxiety who do not receive treatment often exceeds 90 percent (Chisholm et al., 2016; Patel et al., 2009; Wang et al., 2007; Kohn et al., 2004). Such treatment gaps likely

result from a combination of poor supply and low demand for mental health services.

***Increasing supply.*** Resources for mental health care are extremely limited in low-income countries (Figure 7) and people living in poverty often lack access to basic mental health care (Thirunavukarasu and Thirunavukarasu, 2010). For instance, some estimates suggest that India has only 3,900 psychiatrists for over 1.3 billion people, while 13 psychiatrists serve Zimbabwe’s 14 million people (World Health Organization, 2018). However, cost-effective and scalable strategies for treating mental illness in low-resource settings do exist. Evidence from multiple countries shows that ‘psychosocial’ treatments, such as manualized talk therapies can be highly effective at low cost, even when delivered by non-specialist community health workers (Singla et al., 2017; Patel et al., 2011). An even more pared-down—but still effective—approach is the ‘friendship benches’ of Zimbabwe, where non-specialist health workers (popularly known as ‘community grandmothers’) provide problem-solving therapy with components of behavior activation to patients (Chibanda et al., 2016).

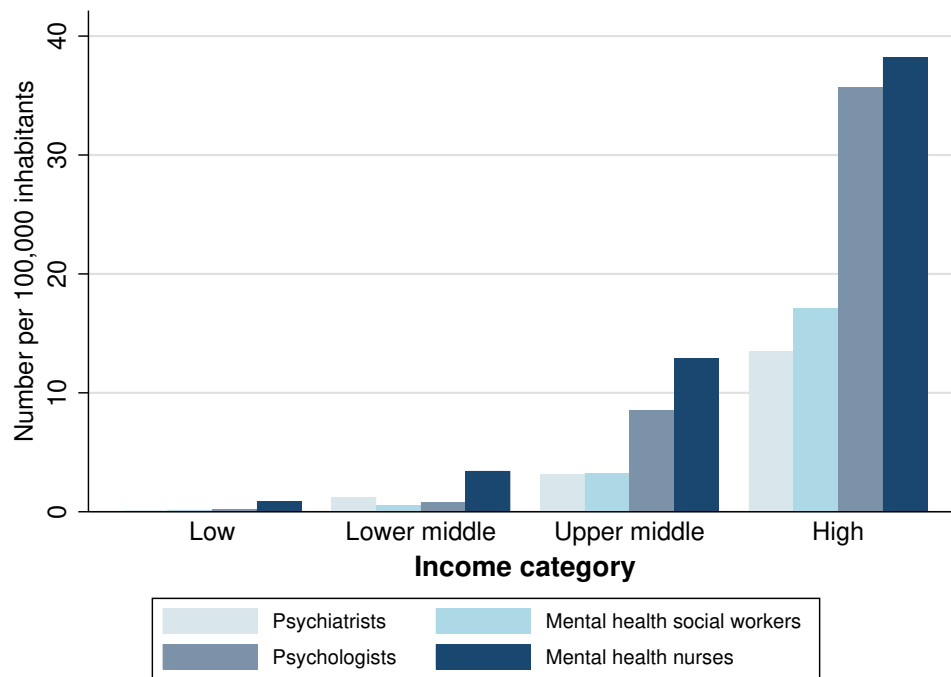
Reliance on in-person training and supervision of the community health workers by experts is a major barrier to scaling these approaches. The EMPOWER initiative seeks to address these structural barriers through the deployment of digital platforms to enable front-line workers to learn, deliver, and master evidence-based brief psychological treatments for mental health problems, using innovative practices such as coach-supported learning and peer-supervised quality assurance, all delivered through digital tools (Waters, 2020). EMPOWER will roll out the brief behavioral activation treatment developed and evaluated in India and Nepal (Box 3) to community health workers in India and the US from 2021 onwards.

***Stimulating demand.*** Even in settings with affordable and effective mental health services, many people do not seek or adhere to treatment (Patel et al., 2016). People often lack mental health literacy and may not possess basic information about mental health conditions and their risk factors, symptoms, and potential treatment options (Jorm, 2000). Stigma and shame can further depress demand for mental health services. But there are examples of successful community-based programs that increase mental-health literacy and boost the share of mentally-ill individuals who seek treatment; for example, the VISHRAM initiative, rolled out in 30 villages in rural India, deployed ‘change agents’, typically persons already playing leadership roles in the villages, to engage the community in conversations around mental health and illness, using a range of contextually appropriate strategies such as group discussions; the program led to a six-fold increase in help-seeking by persons with depression in just 18 months (Shidhaye et al., 2017). A priority for future work should be the evaluation of such programs at scale, as well as testing approaches that bundle mental health treatments with other unstigmatized services, subsidizing or even rewarding the take-up of treatment, or using remote technologies such as app-based therapy that are less likely to expose individuals to stigma.

***Poverty traps.*** A classic idea in development economics is the existence of a ‘poverty trap’ (Dasgupta and Ray, 1986). This is the idea that, below a certain threshold level of wealth, people are not able to earn and save their way out of poverty. They remain trapped in poverty precisely due to the deprivations associated with poverty, and not because of any

intrinsic lack of ability. Such poverty traps could exist for many reasons. For instance, the very poor may not be able to afford enough food to be productive at work. Recent evaluations of multi-faceted anti-poverty programs have provided some evidence for the existence of such poverty traps (Bandiera et al., 2017; Banerjee et al., 2016). However, the underlying mechanisms are unclear. The evidence of a bi-directional causal relationship between poverty and mental health presented in this review suggests that mental health could be a key mechanism: there could be *psychological* poverty traps. Some of those living in poverty may be ensnared in a vicious cycle of poverty and mental illness (Lund et al., 2010). If this is the case, a one-time economic or psychological intervention of sufficient magnitude might ‘push’ people into a state of sustainably higher income and better mental health.

***Conclusion.*** The causal relationship between poverty and mental health we have described could not be more pertinent than in the ongoing pandemic, which has already adversely affected both these outcomes. Given the surge of ‘deaths of despair’ in the United States in the wake of the Great Recession of 2008 (Case and Deaton, 2020), we have grave concerns about the mental-health implications of the economic recession confronting the world. The pandemic has disproportionately affected the poor and may have lasting adverse impacts on their economic and mental well-being. A massive investment in mental health was long overdue even before the pandemic, and has become critically urgent now. Beyond more money, this is also an important opportunity to invest wisely in lower-cost innovations which provide quality care to low-income and disadvantaged communities, and to integrate economic interventions with mental health care to reduce historic disparities in both wealth and mental health.



**Figure 7: Availability of Mental Health Workers across Countries.** The mean numbers of psychiatrists, social workers, psychologists and nurses working in the mental health sector (per 100,000 people) are shown for countries in each of the four income categories used by the World Bank. Data on mental health workers comes from the WHO’s Global Health Observatory, accessible at <http://apps.who.int/gho/data/node.main.MHHR?lang=en>, and is for the most recent year available (which ranges from 2013-2017).

#### **Box 4: Priorities for Future Research on Poverty and Common Mental Illnesses**

1. Measurement of mental health in economic surveys to estimate:
  - The comparative impacts of diverse economic interventions, such as insurance, social safety, and employment support, relative to cash transfers
  - The longer-run effects of anti-poverty programs
  - The effects of absolute versus relative poverty
  - The effect of technological change and globalization on high and low-wage workers
  - The impact of the looming global economic recession resulting from Covid-19
2. Measurement of economic outcomes in intervention studies for depression and anxiety, including:
  - Income, labor supply, productivity and profits from self-employment
  - Economic preferences and beliefs; investment and savings behaviors
  - Household expenditures and consumption, including within-household allocation of resources
3. Evaluations of interventions to reduce stigma and to boost demand for mental health care, including:
  - Diverse mental health literacy approaches, from mass-media campaigns to grass-root awareness building
  - Subsidies and incentives for seeking and engaging with mental health care
  - The effects of interventions on marginalized and under-served communities
4. Evaluating technologies to increase the coverage of effective psychotherapies, including:
  - Text, phone or video-delivery
  - Digital approaches to training, supervision, and quality assurance for front-line providers
  - AI bot-based and other guided self-help approaches, adapted to different languages and cultural contexts
5. Evaluating interventions to interrupt the intergenerational transmission of poverty and mental illness, for example through:
  - School mental health promotion programs, measuring effects also on educational attainment, labor supply, productivity, and earnings
  - Treating parental mental illness, measuring effects on children's cognitive and educational outcomes

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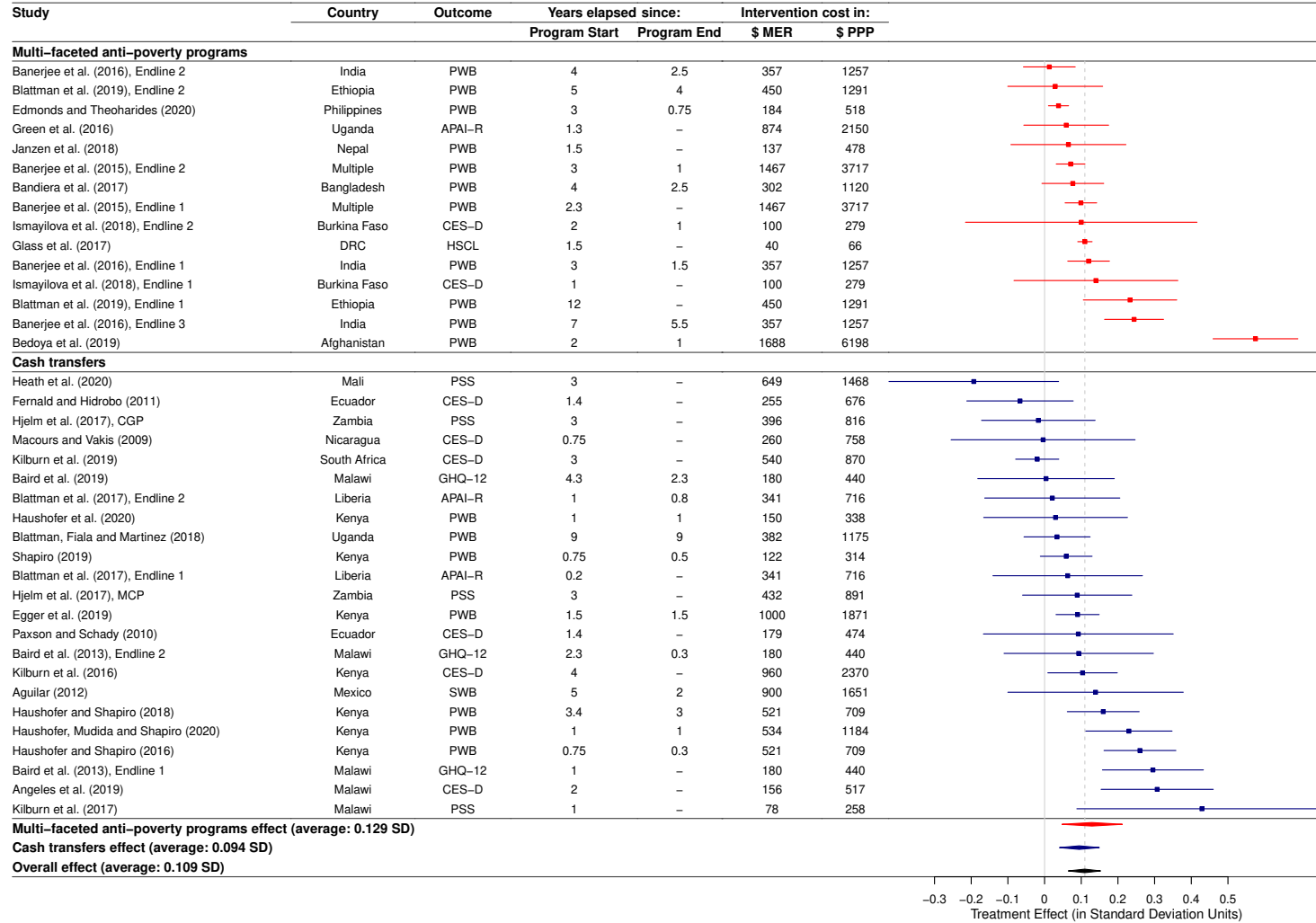
**yi Lin, Liu, Jaime E Sidani, Ariel Shensa, Ana Radovic, Elizabeth Miller, Jason B Colditz, Beth L Hoffman, Leila M Giles, and Brian A Primack**, “ASSOCIATION BETWEEN SOCIAL MEDIA USE AND DEPRESSION AMONG U.S. YOUNG ADULTS: Research Article: Social Media and Depression,” *Depress. Anxiety*, April 2016, *33* (4), 323–331.

## A Meta-Analysis of the impact of poverty alleviation programs on mental health

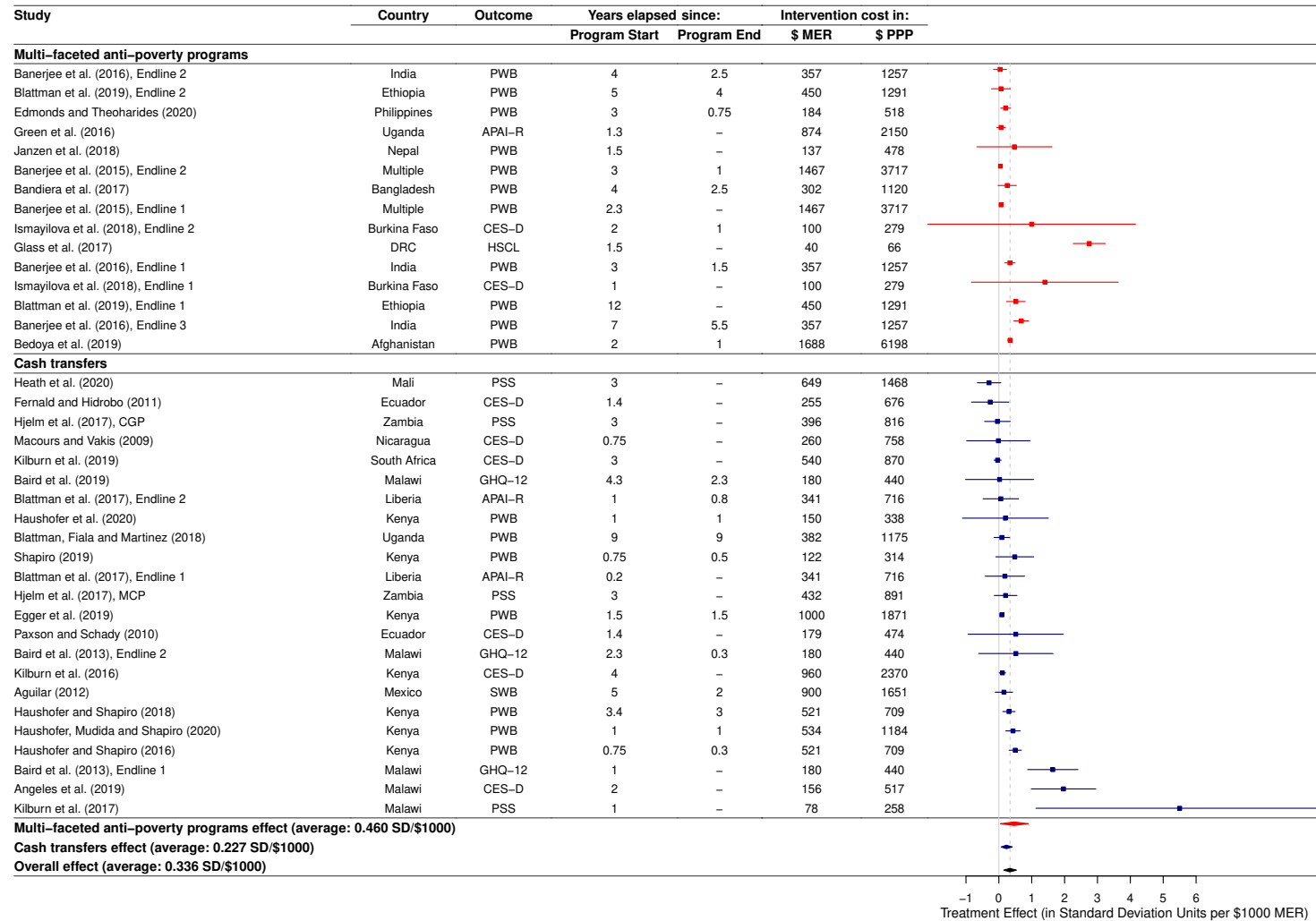
We focused our review on experimental studies that examined the impact of two types of poverty alleviation programs across low- or middle-income countries and measured a mental health outcome. Specifically, we identified RCTs that studied the impact of unconditional cash transfers or multi-faceted anti-poverty programs on mental health outcomes: depression, anxiety, stress, a mental health index, and/or a psychological well-being index. We employed JSTOR, Google, and Google Scholar and used combinations of the keywords: “cash transfer”, “poverty alleviation”, “anti-poverty programs”, and “graduation programs”, with “mental health”, “depression”, “anxiety”, “psychological well-being”, “stress”, “randomized”, and “RCTs”. We reviewed the literature cited in each of the studies that met our criteria to identify additional studies. We also reviewed the studies cited in various review papers and reports (Evans and Popova, 2014; Sulaiman et al., 2016; Roelen et al., 2020; Bastagli et al., 2016; Hashemi and De Montesquiou, 2011; Sulaiman et al., 2016). We identified 30 studies that met our criteria. We briefly describe each of these below.

We conducted a meta-analysis using a Bayesian random effects model that was implemented using R’s *baggr* Rubin (1981) model with normal priors (0,0.1) on the hyper-standard deviation. The bottom panel of Figure 4 in the main text shows the estimated posterior treatment effects using this model, separately by type of transfer and overall. Where multiple studies evaluated the same intervention, or a study featured multiple follow-up surveys, to avoid double-counting we included only the treatment effect which was measured most recently (i.e., the longest-run effect). The overall impact of anti-poverty programs was 0.094 SD (95% CI: 0.040, 0.147). An Egger test of funnel plot symmetry (162) failed to reject the null hypothesis of no publication bias ( $p = 0.96$ ).

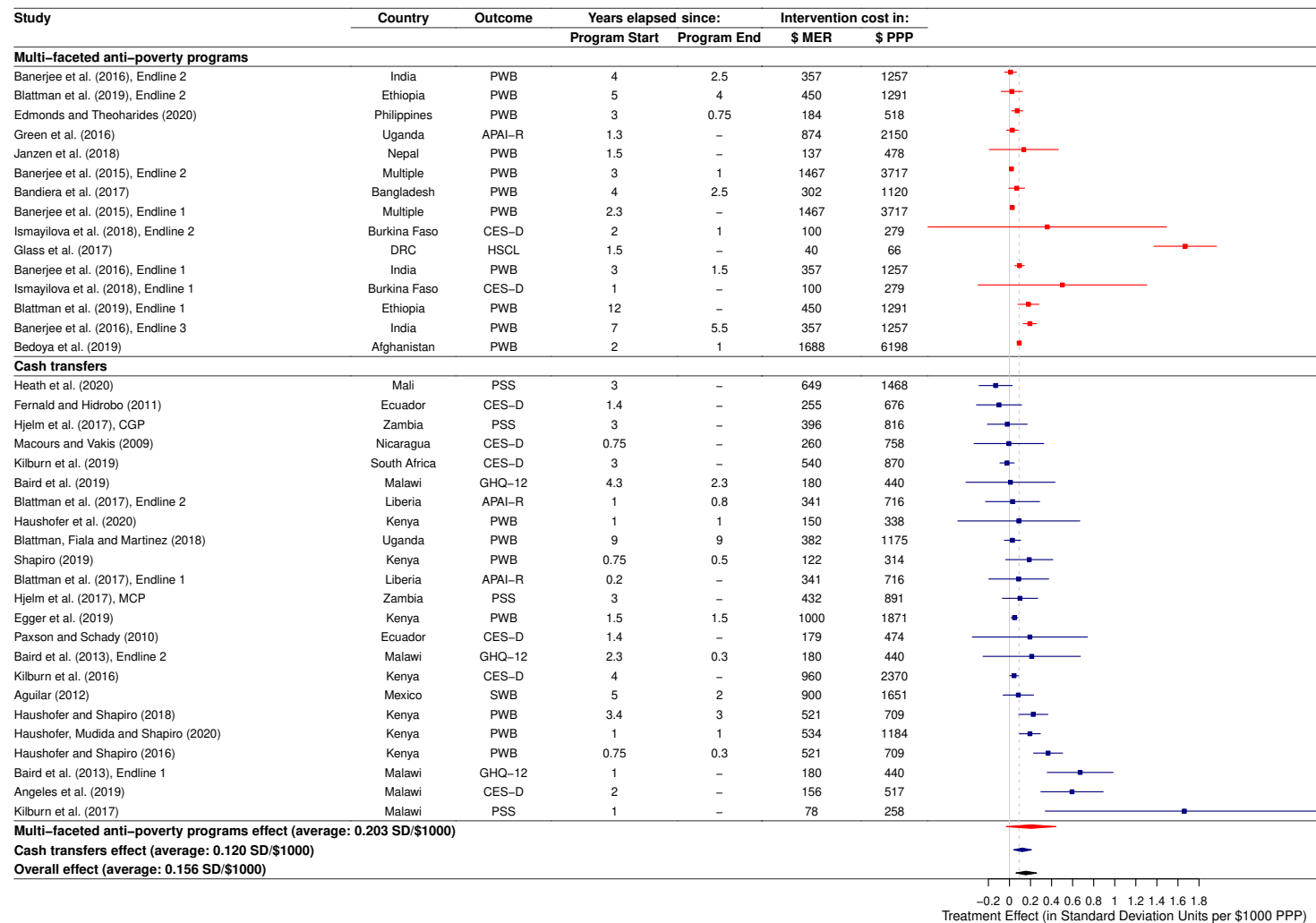
Figure A1 below reproduces Figure 4 but with all available follow-up measures from all studies included (thus double-counting some interventions). The overall impact of anti-poverty programs when measured this way was 0.109 SD (95% CI: 0.065, 0.153).



**Figure A1: The impacts of anti-poverty programs on mental health.** This is an augmented version of Figure 4 which reports results from all follow-up surveys (endlines) and all studies that fit our criteria, rather than reporting only the longest-run treatment effect per intervention as in Figure 4 (Haushofer and Shapiro, 2016; Paxson and Schady, 2010; Haushofer et al., 2020). All terms and abbreviations, etc., used in this figure are the same as in Figure 4.



**Figure A2: The impacts of anti-poverty programs on mental health, per dollar spent (at market exchange rates).** This is the same as Figure A1 except that the treatment effects are divided by the intervention cost at market exchange rates (MER).



**Figure A3: The impacts of anti-poverty programs on mental health, per dollar spent (at purchasing power parity).** This is the same as Figure A1 except that the treatment effects are divided by the intervention cost at purchasing power parity (PPP).



## A.1 Multi-Faceted Anti-Poverty Programs

1. **Blattman et al. (2019a)**. This study compared the impact of an industrial job offer to young, mostly female job seekers in Ethiopia with the impact of a package consisting of a cash grant (worth about \$300) and five days of microenterprise training. The number reported in this meta-analysis is the effect of the cash grant and training package on a mental health and subjective well-being index, which includes measures of depression and generalized anxiety symptoms.

The total operating cost of the cash grant and training package was \$450 MER.

2. **Green et al. (2016)**. This study examines the impact of a poverty alleviation program, *Women's Income Generating Support (WINGS)*, on economic security and symptoms of depression of vulnerable women in Northern Uganda. The program consisted of: (i) business skills training, (ii) an individual start-up grant worth \$150, and (iii) home visits to provide advice and encouragement to use the grant. The follow-up survey was conducted 1.3 years after the intervention was rolled out. They used APAI-R, a locally developed short survey instrument to measure symptoms of depression.

The average cost of the program per household was \$2,150 PPP Blattman et al. (2015), and includes individual start-up grant, targeting and disbursement, supervisory visits, training (business and group dynamics), and other costs.

3. **Banerjee et al. (2015)**. This study examines the results from six RCTs that study the impact of a transfer package including: a productive asset (one time transfer), consumption support, technical skills training, high-frequency home visits, savings, and some health education. This was conducted across six different countries: Ethiopia, Ghana, Honduras, India, Pakistan, and Peru. The key outcome measures include consumption, assets, food security, finance, time use, income, physical health, mental health, political involvement, and women's decision-making. Two follow-up surveys were conducted: 2 years after the intervention (endline 1), and 3 years after the intervention (endline 2). The psychological well-being index was measured as an average of self-reported happiness, a stress index, and an indicator for having experienced anxiety lasting more than 30 days in the past year.

The average cost of the program per household, across the six programs, was \$3,717 PPP (Table 4), and includes direct transfer costs (asset cost and food stipend), supervision costs, and indirect costs.

4. **Bandiera et al. (2017)**. This study evaluates an anti-poverty program in Bangladesh that transferred a productive asset (livestock) and skills training to poor women, who mostly engage in seasonal casual labor. The intervention was randomized across 21,000 households (6,700 ultra-poor) in 1,309 villages. The key outcome measures include labor supply and earnings of women, consumption, household, financial assets, and mental health. The follow-up survey was conducted 4 years after the intervention was started. The psychological well-being index was measured as an average of self-reported happiness and an indicator for having experienced anxiety lasting more than 30 days in the past year.

The average cost of the program per household was \$1,120 PPP (Table 9 in Bandiera et al. (2017)).

5. **Banerjee et al. (2016).** This study examines the long-run impact of an anti-poverty program, Bandhan’s “*Targeting the Hard Core Poor program*”, in West Bengal, India. The beneficiaries of the program receive a productive asset, consumption support, technical skills training, general life skills coaching, savings, and some health education. The follow-up surveys were conducted at various stages: 1.5 years after the intervention (endline 1), 3 years after the intervention (endline 2), and 7 years after the intervention (endline 3). The psychological well-being index was measured as an average of self-reported happiness, stress index, and an indicator for having experienced anxiety lasting more than 30 days in the past year.

The average cost of the program per household was \$1,257 PPP, and includes direct transfer costs (asset cost and food stipend), supervision costs, and indirect costs. This was estimated from Table 4 in Banerjee et al. (2015).

6. **Bedoya et al. (2019).** This study examines the impact of a graduation program (TUP package) — consisting of a transfer of a productive asset, monthly cash transfer, basic training, health subsidy, and mentoring visits — in the Balkh region in Afghanistan. They conducted a household-level randomization of 1,219 households in 80 villages, where 491 households received the TUP package. The key outcome measures include consumption, assets, financial inclusion index, psychological well-being index, women’s empowerment index, and time spent working. The program lasted for 12 months and the follow-up surveys were conducted 1 year after the program was completed. The psychological well-being index was measured as a weighted average of scores on the CES-D, the happiness and life satisfaction questions from the World Values Survey (WVS), Cohen’s stress scale, and the log cortisol levels obtained from saliva samples.

The average cost of the program per household was \$6,198 PPP (Table 9 in Bedoya et al. (2019)), and includes direct transfer costs (asset cost, food stipend, and health voucher), supervision costs, and indirect costs.

7. **Janzen et al. (2018).** This study examines the short-run impact of an anti-poverty program, *Heifer International’s (HI) Smallholders in Livestock Value Chain* program in Nepal. The beneficiaries of this program receive a package that includes: group formation, livestock, technical skills training, and value-based training. The follow-up survey was conducted 1.5 years after the intervention. The psychological well-being index includes measures for depression, life satisfaction, self-esteem, and worry.

The average cost of the program per household was \$137 MER, and includes direct transfer costs and indirect costs.

8. **Ismayilova et al. (2018).** This study examines the impact of a graduation program (TUP package) — consisting of savings group formation and training, livelihood training and planning, seed capital grants and one-on-one mentoring, and family counseling on child’s mental health — in Burkina Faso. The follow-up surveys were conducted at

various stages: 1 year after the intervention (endline 1), and 2 years after the intervention (endline 2). CES-D was used to measure psychological well-being.

The average cost of the program per household was \$279 PPP.

9. **Edmonds and Theoharides (2020)**. This study examines the impact of an anti-poverty program, *KASAMA* in the Philippines, on child labor elimination. The beneficiaries of the program receive a productive asset, and training related to operating a business and child labor. The follow-up survey was conducted 3 years after the intervention was rolled out. The child well-being index includes depression, child life satisfaction, enumerator assessment of social behavior, and caregiver assessment of child’s strengths and difficulties.

The average cost of the program per household was \$518 PPP.

10. **Glass et al. (2017)**. This study examines the impact of a livestock transfer program, *PPF*, on economic, health, and women’s empowerment in the Democratic Republic of Congo. The beneficiaries of the program receive a livestock productive asset. The follow-up survey was conducted 1.5 years after the intervention. They measured depression and anxiety using the Hopkins Symptoms Checklist (HSCL).

Implementation cost data was not available for this program; instead, we use the estimated average value of livestock transferred per participant, calculated from table 2 (\$66 PPP).

## A.2 Cash Transfers

1. **Hjelm et al. (2017)**. This study uses secondary data to examine the impact of two unconditional cash transfer programs: (i) *Zambia Child Grant Program* (CGP) that targets households with a child under the age of five, and (ii) *Zambia Multiple Category Cash Transfer Program* (MCP) that targets households under different categories.

In the figures, Hjelm et al. (2017a) is the estimated treatment effect of CGP, and Hjelm et al. (2017b) is the effect of MCP.

These programs were conducted by the Zambian Government. CGP was randomized across 90 communities and across households within treated communities, for a total sample size of 2,515 households. MCP was randomized across 92 communities and across households within treated communities, for a total sample size of 3,078 households. Follow-up surveys were conducted 3 years after the intervention was rolled out. The key outcome measures include stress, consumption, food security, and non-productive assets. Stress was measured using the negatively worded items from Cohen’s perceived stress scale (PSS); in brief, this asks respondents how often they have felt upset, stressed, or that difficulties were out of control in the past 4 weeks.

Households included in the CGP and MCP programs received \$11 and \$12 per month respectively for 36 months. The average cash transfer per household under the CGP and MCP program was \$396 MER and \$432 respectively. Cost of implementation data was not available.

2. **Blattman et al. (2017)**. This study examined the effects of a cognitive behavioral therapy (CBT) program cross-randomized with an unconditional cash grant of around \$200. Participants were randomized into four groups, receiving either (i) both the CBT and then the cash grant, (ii) only the CBT, (iii) only the cash grant, or (iv) neither. Key outcome measures included antisocial behavior such as crime and economic performance and preferences. In our meta-analysis we include the effects of the cash grant for those who did *not* receive the CBT intervention (i.e., the comparison between (iii) and (iv)) on an index of depression and mental distress, which asked about depressive symptoms, bad thoughts or feelings, and worry.

The authors report the average size of the cash grant as \$216 and the registration and administration costs for both programs as \$125, at market exchange rates. We conservatively assume that all of the latter costs are fixed and thus estimate the implementation cost of the cash transfer program as  $\$216 + \$125 = \$341$  MER.

3. **Haushofer et al. (2019)**. This study examines the impact of cash transfers and health insurance on 789 informal Kenyan workers. The workers were randomized into three groups: the first received a free health insurance policy, the second an unconditional cash transfer (worth the price of the policy), and the third received no intervention. The key outcome measures include insurance ownership, assets, willingness to pay for insurance, labor mobility, labor productivity, job risk, psychological well-being index, and log cortisol levels. The coverage was for 1 year and follow-up surveys were conducted a year after the completion of the program. The psychological well-being index was measured as self-reported well-being (stress and depression) and log cortisol levels. The average cash transfer per household was \$338 PPP.

4. **Blattman et al. (2019b)**. This study revisited a randomized cash grant program, the *Youth Opportunities Program* (YOP) in Uganda to examine its long-term effects. While applicants had to apply in small groups and submit a business proposal, the grants were unconditional once awarded. About half of 535 eligible groups were randomized to receive the money, which for most was between \$200-\$600 per person. Key outcomes included employment, earnings, and consumption.

Implementation cost data was not available for this program; instead, we use the average grant per participant (\$382 MER)..

5. **Egger et al. (2019)**. This study examines the impact of the GiveDirectly Cash Transfer Program in Kenya, across 653 villages using a two-level randomization. All households in the treatment villages received a one-time cash transfer (\$1000 MER). The key outcome measures include economic activities, asset ownership, psychological well-being, health and nutrition. The follow-up survey was conducted 1.5 years after the intervention was rolled out. The psychological well-being index was measured using depression, happiness, life satisfaction, and stress scales.

The households received transfers in three payments: \$151 PPP for completion of enrollment, and \$860 PPP each in two installments. The average cash transfer per household was \$1871 PPP.

6. **Paxson and Schady (2010)**. This study examines the effect of an Ecuadorian cash transfer program, the *Bono de Desarrollo Humano (BDH)*, which provided unconditional cash transfers averaging \$10.51 per month to eligible mothers. The program was randomized across 77 rural and 41 urban parishes, though the authors only report results from rural parishes. Key outcome measures are cognitive, behavioral, and physical outcomes for children. The paper also reports effects of *BDH* on mothers' mental health as measured by the CES-D depression scale.

As implementation costs were not available, we report a rough estimate of average transfer value: \$10.51/month x 17 months = \$179 MER on average from start to endline.

This study evaluates the same intervention as Fernald and Hidrobo (2011). Both studies evaluated the same intervention at the same follow-up date; we exclude Paxson and Schady from the main meta-analysis in Figure 4 because they report results from a smaller subsample (rural parishes only). (This also explains why the average transfer value is different between these two studies).

7. **Baird et al. (2013)**. This study examines the effects of a cash transfer program — unconditional and conditional cash transfers — in Malawi on mental health among adolescent girls. The key outcome measures include psychological well-being and school attendance. Randomization was conducted at enumerator-area level, and a sample of 3,796 young women was stratified into two groups: baseline school dropouts and baseline schoolgirls. Two follow-up surveys were conducted: 1 year after the intervention was rolled out (endline 1), and 2 years after the intervention was rolled out (endline 2). In both the follow-up surveys, the GHQ-12 instrument was used to measure psychological well-being; in endline 2, MHI-5 (Mental Health Inventory-5) was also used.

The monthly transfer amount varied according to the enumeration area (\$4 to \$10) and the school-age (\$1 to \$5). They also covered the school fees for the girls in secondary school, which amounted to \$60. This program was for a year. The average transfer amount per household was \$180 MER.

8. **Kilburn et al. (2016)**. This study examines the effects of Kenya's Cash Transfer Program for Orphans and Vulnerable Children. The program was randomized across 28 locations, covering 1960 households. Treated households received monthly transfers of \$20. The key outcome measure is an indicator of depressive symptoms using the 10-question CES-D scale. The treatment effect we report in our meta-analysis is derived from the unadjusted means in the treatment and control groups reported in Table 2 of Kilburn et al. (2016). (Note standard errors are not adjusted for clustering).

Implementation cost data was not available; thus, we use the total undiscounted value of the transfer: \$20/month x 48 months = \$960 MER.

9. **Haushofer and Shapiro (2016)**. This study examines the short-term effects of an unconditional transfer program from GiveDirectly in Kenya on poor households. Randomization was conducted at both household and village level, and the authors randomized gender of recipient, timing of transfer, and size of transfer. The key outcome

measures include consumption, assets, financial inclusion index, and psychological well-being index. Follow-up surveys were conducted 9 months after the intervention was rolled out. The psychological well-being index was measured as a weighted average of scores on the CES-D, WVS, Cohen's stress scale, and the log cortisol levels obtained from saliva samples.

The households received transfers in varied magnitudes: \$404 PPP and \$1,525 PPP. The average transfer amount was \$709 PPP.

10. **Haushofer and Shapiro (2018)**. This is a follow-up study to Haushofer and Shapiro (2016), and examines the long-term impacts of transfers on economic and psychological outcomes 3 years after the program by GiveDirectly in Kenya.
11. **Haushofer et al. (2020)**. This study looks at the effects of an unconditional cash transfer program cross-randomized with five weeks of psychotherapy among 5,756 people in rural Kenya. Key outcome measures include consumption, assets and psychological well-being. Their psychological well-being index consists of the GHQ-12, Cohen's perceived stress scale, and the happiness and life satisfaction questions from the WVS. The value of the transfer was \$1,076 PPP (\$485 MER). The authors conservatively assume a cost of delivery of 10% of the transfer value (section 4.4), reasonably given that the transfers are delivered by mobile money, implying a total implementation cost of \$1,184 PPP (\$534 MER).
12. **Angeles et al. (2019)**. This study examines the impact of the Malawi Government's *Social Cash Transfer Program (SCTP)* on youth mental health, with 2782 households across 29 villages. 1678 households across 14 villages received unconditional cash transfers and the recipients were encouraged to invest the money in the human capital of their children and basic needs of the households. The program spanned 2 years and included bi-monthly payments. The follow-up surveys were conducted 2 years after the program was rolled out with the youth of the households (aged 15 to 22 years old during follow-up). CES-D was used to measure psychological well-being. The monthly cash transfer value varied with household size (\$3 to \$7) and composition (\$1 and \$2 per primary and secondary school aged child). The program spanned two years. The average transfer amount per household was \$156 MER. This study evaluates the same intervention as Kilburn et al. (2017).
13. **Kilburn et al. (2019)**. This study examines the impact of *HIV Prevention Trials Network (HPTN) 068*, a conditional cash transfer program in South Africa, on young women's health and behavior. This program was targeted at young women attending high school in rural areas of South Africa. The young girls and their parents received monthly cash transfers conditional on continued school attendance. 2,537 participants were recruited for the study. The follow-up surveys were conducted in various stages until the participant had graduated from school: 1 year after the intervention, 2 years after the intervention, and 3 year after the intervention. The psychological well-being index was measured using CES-D, Hope Scale, and SRPS.

The monthly cash transfer varied with the recipient: \$10 for the young girls and \$20 for the parent or guardian. The average transfer amount per household was \$540 MER.

14. **Heath et al. (2020)**. This study examines the impact of Mali’s *National Cash Transfer Program* on intimate partner violence (IPV) targeting household heads (mostly men) in both polygamous and monogamous households. The cash transfers were accompanied with other health measures, and preventive nutrition packages for children (below 5 years of age) and pregnant women. The key outcomes include IPV and stress levels for men. The stress levels for men were measured using PSS, a standardized stress scale, and Rosenberg’s self-esteem instrument.

As implementation costs were not available, we report a rough estimate of average transfer value: \$18.02/month x 36 months = \$649 MER on average from start to endline.

15. **Baird et al. (2019)**. This is a follow-up study to Baird et al. (2013), and examines the long-term impacts of a cash transfer program — unconditional and conditional cash transfers — on economic and psychological outcomes 4 years after the intervention was rolled out in Malawi.

16. **Aguilar (2012)**. This study examines the medium-term impact of *Progresa*, Mexico’s conditional cash transfer program, on the physical and cognitive development of children. The study uses the outcome from a follow-up survey conducted in 2003 with 2,049 households, conducted 5 years after the intervention was rolled out. An index of depressive symptoms was used to measure psychological well-being.

As implementation costs were not available, we report a rough estimate of average transfer value: \$900 MER on average from start to endline.

17. **Kilburn et al. (2017)**. This study examines the impact of the Malawi Government’s *Social Cash Transfer Program* (SCTP) on child schooling outcomes with 2,782 households across 29 villages. 1,678 households across 14 villages received unconditional cash transfers and the recipients were encouraged to invest the money in the human capital of their children and basic needs of the households. The program spanned for 2 years and included bi-monthly payments. This study uses the first follow-up survey conducted 1 year after the program was rolled out. PSS was used to measure psychological well-being.

The monthly cash transfer value varied with household size (\$3 - \$7) and composition (\$1 and \$2 per primary and secondary school aged child). The program spanned two years, however this study considers the follow-up survey which was conducted a year after the program started. The average transfer amount per household was \$78 MER. This study evaluates the same intervention as Angeles et al. (2019).

18. **Shapiro (2019)**. This study examines the impact of cash transfers and development programs (agricultural extension, subsidized agricultural inputs, and poultry transfers). 1,471 out of 3,008 low-income Kenyans were randomized to receive cash transfers equivalent to the value of the development programs. Their psychological well-being index

consists of the CES-D, GHQ-12, and the happiness and life satisfaction questions from the WVS.

As implementation costs were not available, we report a rough estimate of average transfer value: \$122 MER on average from start to endline.

19. **Macours and Vakis (2009)**. This study examines the effect of an Ecuadorian cash transfer program, the *Atención a Crisis*, which provided cash transfers conditional on children's primary school and health service attendance during the program. The program was randomized across six municipalities with 3000 households. CES-D was used to measure psychological well-being.

As implementation costs were not available, we report a rough estimate of average transfer value: \$260 MER on average from start to endline.

20. **Fernald and Hidrobo (2011)**. This study examines the effect of a Nicaraguan cash transfer program, the *Bono de Desarrollo Humano* (BDH), which provided unconditional cash transfers averaging \$15 per month to eligible mothers. The program was randomized across 77 rural and 41 urban parishes (small administrative units), and the authors report results for both rural and urban parishes. The paper also reports effects of BDH on mothers' mental health as measured by the CES-D depression scale.

As implementation costs were not available, we report a rough estimate of average transfer value: \$15/month x 17 months = \$255 MER on average from start to endline.

This study evaluates the same intervention as Paxson and Schady (2010). Both studies evaluated the same intervention at the same date; we exclude Paxson and Schady from the main meta-analysis in Figure 4 because they report results from a smaller subsample (rural parishes only).