Social disadvantage and mental health: A developing country perspective

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Abstract

Studies from the United States document important racial gaps in health. In developing societies, research on social disadvantage and health is more limited. Mental health, in particular, is poorly understood relative to its disease burden. Our study contributes the first population-level analysis of mental health disparities in India, where the two marginalized groups that we study constitute a population larger than that of the United States. Applying two complementary empirical strategies to data on 10,125 adults interviewed by the WHO SAGE, we document and decompose gaps in mental health between the dominant social group (higher caste Hindus) and two marginalized social groups (Scheduled Castes and Muslims). We find that differences in socioeconomic status cannot fully explain the large disparities in mental health that we document, for either marginalized group. Our results highlight the need for policies that move beyond redistribution to reduce violence and discrimination. [145 words]

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Social disadvantage and mental health: A developing country perspective

Documenting and understanding differences in health among people from different social groups is a central pursuit for medical sociologists. Researchers studying the United States have generated a large literature that quantifies differences in physical and mental health outcomes by racial and ethnic group. This literature also investigates the mechanisms that generate health disparities and points to policy responses (Kessler and Neighbors, 1986; Link and Phelan, 1995; Warner and Hayward, 2006; Williams and Sternthal, 2010; Williams, 2012). Researchers studying developing countries have shed light on racial and ethnic health disparities these contexts as well, particularly in mortality (Wood and Lovell, 1992; Burgard, 2002; Burgard and Treiman, 2006).

Mental health, in contrast, is widely recognized to be under-researched relative to its disease burden in developing societies (Kessler and Bromet, 2013; Demyttenaere et al., 2004). Where population-level data do permit researchers to investigate the magnitude and nature of mental health disparities in new contexts, such as in Jackson et al. (2010)'s study of psychological distress in South Africa, gaps in mental health between advantaged and marginalized groups have been large.

We investigate population-level disparities in mental health among adults from different caste and religious groups in India, a large and highly stratified developing country. Although prior research has shown that caste and religion play an important role in many other health outcomes, including infant mortality (Guillot and Allendorf, 2010; Spears and Geruso, forthcoming), child height (Coffey et al., 2017), and the use of health services (Baru et al., 2010), no study has investigated population disparities in mental health by social group in India.

In particular, we document and analyze gaps in mental health between higher caste

Hindus, the dominant social group, and Scheduled Caste Hindus (sometimes called "untouchables" or *Dalits*), a marginalized social group who comprise about 17% of India's population. We also study gaps in mental health between higher caste Hindus and Muslims, a religious minority who constitute about 14% of the population. We ask: Are there disparities in mental health between Muslims and higher Caste Hindus, and between Scheduled Castes and higher Caste Hindus? What is the magnitude of these disparities? And, to what extent can they be explained by disparities in socioeconomic status?

Examining these disparities is important for several reasons. First, it allows us to test insights from medical sociology and social epidemiology in a new, developing country context with well-defined social boundaries and a high burden of material disadvantage. Second, from a global population health perspective, the marginalized groups that we study, Scheduled Castes and Muslims, number 201 million and 172 million respectively. Together, they constitute a population greater than that of the United States. Therefore, studying mental health in these large populations furthers our understanding of the global burden of mental illness and the global burden of disease (Whiteford et al., 2013). Finally, documenting these disparities in mental health contributes to an ongoing conversation about the extent and consequences of social disadvantage and discrimination in India.

We use data from the World Health Organisation's Study of Global Ageing and Adult Health (SAGE) conducted in 6 large Indian states in 2007-08. The WHO's SAGE is representative of the adult population in these states, and collected information on mental health outcomes, social group, and socioeconomic status. Because prior research has pointed to the difficulties of translating and verifying measures of mental health disorders in developing countries (Axinn et al., 2013), we use broad, simple indicators of mental health: how happy a person reports herself to be; what she thinks of her overall quality of life; the extent to which she has problems with feeling sad, low, or depressed; and the extent to which she has problems with worry or anxiety. These questions are common to most scales of subjective well-being and mental health.

To preview some of our results, our descriptive analysis shows that compared to higher caste Hindus, Muslims are three times as likely to say that they have a bad or very bad quality of life, and almost four times as likely to say that they are unhappy or very unhappy. Scheduled Caste respondents are twice as likely to report having bad or very bad quality of life and being unhappy or very unhappy compared to higher caste Hindus.

Because prior research on mental health often finds that richer, better educated people have better mental health (Link and Phelan, 1995; Keyes, 2002), and because India's Scheduled Castes and Muslims are materially disadvantaged as well as socially disadvantaged, we further estimate mental health gaps net of socioeconomic differences. We use two different empirical strategies, with different strengths. First, we use a non-parametric reweighting decomposition to create counterfactual distributions of mental health outcomes among Scheduled Castes and Muslims. These distributions show what the distribution of mental health outcomes among marginalized groups would be if they had the same distribution of education outcomes and asset wealth as higher caste Hindus. An advantage of this approach is that, unlike regression, which matches only on the means of observable characteristics, the reweighting decomposition matches on the entire distribution of education, asset wealth, and their interaction. Our second approach, ordered logit regression, is a parametric one, which facilitates statistical inference. The results of both empirical strategies allow us to draw the same robust conclusion: even after accounting for differences in educational attainment and asset wealth, Muslims and Scheduled Castes have importantly worse mental health outcomes than higher caste Hindus.

In the section that follows, we present a conceptual framework and background to contextualize our approach and findings. We then present our data and approach, followed by our results. We conclude with a discussion of why these findings are important. In short, most efforts by the Indian government to address social disadvantage focus on directing resources to marginalized social groups; either in the form of affirmative action in universities and government jobs, or in the form prioritizing marginalized groups for government transfers, such as houses, loans, or village infrastructure. These policies and programs, while valuable for the people who benefit from them, do little to address the underlying environment of discrimination that perpetuates inequality across the life-course, including disparities in health. Responses to health disparities should combine resource distribution to marginalized groups with stronger stances against violence and broader efforts to address discrimination.

CONCEPTUAL FRAMEWORK & BACKGROUND

This research builds on a literature which documents and interprets health disparities among people from advantaged and marginalized social groups, and especially on those analyses which consider the extent to which health disparities can be explained by differences in economic status and education (Williams et al., 2010; Geruso, 2012; Do et al., 2012). Before presenting our analysis of mental health disparities in India, we briefly present a conceptual framework, largely developed by researchers studying racial disparities in the United States, that helps us interpret our results.

There is considerable evidence that educational attainment and economic resources affect health (Elo and Preston, 1996; Warner and Hayward, 2006; Story and Carpiano, 2017). These relationships often motivate researchers interested in understanding health disparities to control for differences in economic status and education in their analyses. Disparities that remain after controlling for socioeconomic variables provide evidence that discrimination, whether structural, such as forms of discrimination related to the organization of health care or to neighborhood segregation, or interpersonal, such as violence or unfair treatment, also contributes to health disparities. In the case of mental health in particular, a large literature points to the stress generated by exposure to discrimination as an important reason for differences in mental health outcomes among people from different social groups (Noh et al., 1999; Williams et al., 1997; Mossakowski, 2003).

Two observations about this framework are particularly relevant to our analysis. The first is that the causality between socioeconomic variables and health can run in both directions: poor health can also cause low socioeconomic status (Deaton, 2003). To the extent that this is true, decomposition analyses like ours, which investigate how much of gaps in health can be explained by gaps in economic status and education, will provide an upper bound on the explanatory power of the socioeconomic variables included in the model (Geruso, 2012). Of course, to the extent that socioeconomic variables included in the analysis do not capture everything that is relevant about a person's socioeconomic status that is relevant for her health, the decomposition will underestimate the extent to which economic status and education explain health disparities. The second observation that we wish to highlight is that, as Hummer (1996) and others have pointed out, even if differences in socioeconomic status do explain a particular racial or ethnic gap in health, this does not mean that discrimination is not an ultimate cause of the disparity: discrimination can cause differences in economic and educational outcomes, as well (Pager, Bonikowski and Western, 2009; Gaddis, 2014). Nevertheless, from the perspective of a researcher or policy maker who seeks to understand whether redistribution of educational and economic resources can close health gaps, the finding that differences in socioeconomic status cannot entirely explain health disparities suggests the need for addressing the broader social environment as well as unequal material conditions.

Social disadvantage, socioeconomic status, and mental health

The literature on racial disparities in mental health provides relevant background for studies of how other forms of social disadvantage, such as caste and religion, contribute to mental health outcomes. The findings in this literature are nuanced (Earl, Williams and Anglade, 2011): although studies have found lower rates of psychiatric disorders among Black Americans (Breslau et al., 2006), they report worse life satisfaction and less happiness than whites (Hughes and Thomas, 1998).

Table 1 summarizes the contributions of several studies in this literature. Like ours, many of these studies document associations between social group and mental health net of socioeconomic status.[1] For example, Hughes and Thomas (1998) find that differences in life satisfaction and happiness between black and white Americans remain even after controlling for socioeconomic differences. However, Frerichs, Aneshensel and Clark (1981) find that differences in depression are not statistically significant net of socioeconomic variables. Jackson et al. (2010), who study South Africa, find that socioeconomic differences do not entirely explain differences in distress between blacks and whites. Kessler and Neighbors (1986) analyze community studies and find that race and socioeconomic status interact to predict psychological distress. There is also considerable evidence that experiencing or perceiving discrimination triggers stress responses and contributes to poor mental health (Williams et al., 1997; Myer et al., 2008).[2]

Social inequality in India

There are many forms of social inequality that may shape mental health in India; this study focuses on two major divisions – caste and religion. Caste, a system of social stratification with endogamous marriage and hereditary social status, divides Indians into a large number of groups and sub-groups, each occupying varying levels of ritual purity, privilege, and social status (Vaid, 2014). The lowest castes, which were considered "untouchable" because interaction with them was considered polluting, are together classified as the Scheduled Castes (SCs) by the Indian constitution. Scheduled Castes, who describe themselves as *Dalit* or "oppressed," comprise about 17% of the Indian population (Office of the Registrar General, 2011) and qualify for affirmative action in politics, government jobs, and university admissions. If India's 200 million SCs formed a separate country, they would be the 5th largest country in the world, with a population slightly larger than Brazil's.

With a population of over 170 million, Muslims are India's largest minority religious group; 14% of the Indian population is Muslim. India has the third largest population of Muslims in the world, after Indonesia and Pakistan. Indian Muslims face economic and social discrimination, and often have human development outcomes similar to those among Scheduled Castes, with fewer legal protections (Sachar and Prime Minister's High Level Committee, 2006). Compared to the Scheduled Castes, there are fewer government affirmative action programs for Muslims.[3] Muslims in India have frequently suffered violence (Varshney, 2002), and the rise of right-wing Hindu political parties has further marginalized Muslims (Wilkinson, 2006).

Comparative sociologists, starting from Marx and Weber, have noted similarities between caste and religious stratification in India, and other ascribed systems of stratification, such as race.[4] The caste school of race relations in American sociology described racial relations in segregated settings, particularly in the US South, as a caste system (Warner, 1936; Dollard, 1998). The school came under criticism from prominent black sociologists, such as Oliver Cox and Franklin Frazier (Cox, 1942, 1945; Frazier, 1947), for its implication that race relations are unchanging.[5] There are important differences between these systems of social stratification, however. Whereas racial boundaries are typically considered to be based on phenotypic differences, caste differences are typically considered to be based on occupational segregation and rules of social interaction governed by rules about purity and pollution (Ambedkar, 1937; Vaid, 2014).

Although caste and religion are social group identities distinct from class, many studies document the role of social disadvantage in reinforcing economic disparities in India (Deshpande, 2017; Borooah, 2005), in shaping education and schooling achievement (Dreze and Kingdon, 2001; Desai and Kulkarni, 2008), and in shaping employment outcomes (Thorat and Neuman, 2012; Aggarwal et al., 2015). Several experiments help establish a role for discrimination against marginalized social groups in determining these differences. For example, Hanna and Linden (2012) find that the same exams are scored between 0.3 to 0.8 standard deviations lower when they are given to randomly assigned evaluators with a lower caste name than when they are given to evaluators with higher caste names. Similarly, Thorat and Attewell (2007) use correspondence study methods to find that the same resumés are less likely to be called for job interviews when they carry Scheduled Castes and Muslims names than when they carry higher caste Hindu names. These discriminatory practices likely adversely affect the mental health of SCs and Muslims over and above the effects they have on economic and educational status.

Mental health in India

Prior research on the prevalence and nature of poor mental health in India is sparse, and tends to draw on specialized data or community samples, rather than on population level data. For example, the World Mental Health Surveys were conducted in Pondicherry, a relatively advantaged union territory in south India. Bromet et al. (2011) find that patterns of mental health in Pondicherry broadly match patterns found in other countries.

A very limited number of studies point to links between social disadvantage and mental health in India. Mathias et al. (2015) find higher levels of depression among people from lower castes in Dehradun district of Uttarkhand, a state in north India. Spears (2016) uses data from a survey conducted in villages in 13 districts of North India to document that Scheduled Castes report lower life satisfaction than people from other castes. To our knowledge, only one study investigates the effect of discrimination on mental health in India using population-level data: Ram, Strohschein and Gaur (2014) find that young women's experience of gender discrimination at home was associated with worse mental health, while the same discriminatory household behaviors were associated with better mental health for young men.

There is growing awareness among researchers of the importance of integrating the study of social inequality with the study of mental health in India. Several autobiographies and short stories by Scheduled Caste and Muslim authors explore links between experiences of marginalization, discrimination, and violence, and mental health (Hasan and Asaduddin, 2000; Valmiki and Mukherjee, 2008; Pawar and Pinto, 2015). After the suicides of students from marginalized social groups in Indian universities, many journalistic accounts have focused on the mental health impacts of discrimination in India's elite universities (Jeelani, 2012; Mondal, 2016). The recognition of these links has also been present in accounts of caste and religious violence (Balagopal, 1991; Mander, 2015). Recently, psychiatrist Sushrut Jadhav, and anthropologists David Mosse and Ned Dostaler have pointed out that "caste, mediated by gender and class among other things, affects millions of people and yet we know little about the mechanisms or experiences of social suffering involved" (Jadhav et al., 2016) [p. 2]. Our research brings the tools of population health to advancing this understanding.

DATA & APPROACH

Data

We analyze the World Health Organization's SAGE (Survey of Global AGEing and Adult Health) data collected in India in 2007-08. SAGE surveys adult health, with a focus on older adults, and is unique among large-scale population surveys in India because it asks questions about mental health as well as about physical health. SAGE is representative of the adult population aged above 18 in six states: Assam, Karnataka, Maharashtra, Rajasthan, Uttar Pradesh, and West Bengal. These states were selected from among Indian states with populations of more than five million based on their geographic region and level of economic and human development (World Health Organization, 2013). They are home to almost half of India's 1.2 billion people (Office of the Registrar General, 2011).

SAGE used a multi-stage process to select respondents in each state. In rural areas, a stratified random sample of villages was selected based on village population size. 28 households were selected from each village. In urban areas, a stratified random sample of city wards was selected based on ward population size. Within selected wards, researchers further selected two census enumeration blocks, from which 33 households were selected. In both urban and rural areas, respondents were chosen from within households using a household roster and a Kish grid (World Health Organization, 2013).

SAGE collected detailed demographic data for each respondent, including sex, age, caste, and religion. It also collected information on whether respondents belonged to one of the Scheduled Tribes recognized by the Indian government's affirmative action programs. Scheduled Tribes, also called *adivasis*, primarily live in central and eastern India. With the exception of Assam, which has the smallest overall population of any of the states studied, SAGE was not conducted in places with a substantial Scheduled Tribe population. Consequently, only a small proportion of the overall SAGE sample identify as Scheduled Tribe. Due to the small sample size, we do not include people from Scheduled Tribes in our analysis. However, when future data collection efforts permit it, it will be useful for researchers to investigate mental health disparities between Scheduled Tribes and other groups. Like Scheduled Castes and Muslims, Scheduled Tribes are marginalized and often discriminated against (Xaxa, 2008).

We note that SAGE's demographic data do not distinguish among the three broad subgroups within higher caste Hindus – Other Backward Classes (OBCs), Forward castes, and Brahmins. These three subgroups are hierarchically ranked in the order that they are listed here, with Brahmins having the highest social rank. The average educational and economic outcomes for these groups match their social ranking. The fact that we cannot distinguish among these groups is a limitation of the SAGE data because, although OBCs have not been as marginalized as Scheduled Castes, Scheduled Tribes, and Muslims, they have historically faced caste-based discrimination. As a result, affirmative action programs were expanded to include OBCs in the late 1990s. If we were able to remove OBCs from the group "higher caste Hindus," we would be able to document mental health gaps between marginalized groups and socially-privileged groups which would almost certainly be larger than the disparities between these marginalized groups and the group of higher caste Hindus that SAGE allows us to identify. Therefore, the magnitudes of the disparities that we document should be considered conservative.

Mental health outcomes. We use responses to four general, simply-worded questions about mental health as our outcomes of interest. SAGE asked respondents the following questions:

- "How would you rate your overall quality of life? Very good, good, moderate, bad, or very bad?"
- "Taking all things together, how would you say you are these days? Are you very unhappy, unhappy, neither happy nor unhappy, happy, or very happy?"
- "Overall in the last 30 days, how much of a problem did you have with feeling sad, low or depressed? None, mild, moderate, severe, or extreme?"
- "Overall in the last 30 days, how much of a problem did you have with worry or anxiety? None, mild, moderate, severe, or extreme?"

These questions are common to most subjective well-being scales and mental health screening tools (Diener et al., 1999).

Table 2 shows the proportion of people in each social group who gave one of the worst two responses for each of these mental health questions. Among the three social groups we study, 8% of respondents reported having a bad or very bad quality of life and 8% reported being unhappy or very unhappy. About 6% reported experiencing severe or extreme sadness or depression in the last one month, while 12% said that they experienced severe or extreme anxiety. We use the weights provided by SAGE to make the estimates in table 2 representative of the population of the 6 states in the sample.

For all four mental health outcomes, Scheduled Caste and Muslim respondents had worse mental health than higher caste Hindu respondents. We note that mental health disparities are larger for the questions about overall quality of life and about happiness, which may be less stigmatizing and use words that are easier to understand than questions about depression and anxiety. While 5% of higher caste Hindus reported bad or very bad quality of life, 12% of Schedule Caste respondents and 17% of Muslim respondents reported having bad or very bad overall quality of life. Similarly, 5% higher caste Hindu respondents reported being unhappy or very unhappy, but 11% of Scheduled Caste respondents and 19% of Muslim respondents reported being unhappy or very unhappy. Thus for both outcomes, Scheduled Caste respondents were twice as likely to have poor mental health outcomes, and Muslim respondents were three times as likely to have poor mental health outcomes than higher caste Hindu respondents. 6% of higher caste Hindu respondents, 7% of Scheduled Caste respondents, and 8% of Muslim respondents reported being severely or extremely depressed in the last month. 11% of higher caste Hindu respondents, 13% of Scheduled Caste respondents, and 16% of Muslim respondents reported facing severe or extreme anxiety in the last month.

Independent variables. Table 2 also reports summary statistics for the independent variables we use in our analysis. Higher caste Hindus, Scheduled Castes and Muslims have similar age and sex profiles: the average age is about 41 years and about 49% of respondents are female.

Income data is typically hard to collect in developing countries; asset wealth is a more reliable indicator of economic status (Filmer and Pritchett, 2001). We therefore use asset wealth as our primary indicator of economic status. SAGE asked respondents whether or not their household owns each of 17 assets: a chair; a table; a car; a motorcyle; a bicycle; a bullock cart; livestock; a clock; a bucket; a cot, a bed, or mattress; a refrigerator; a fixed line telephone; a mobile phone; a radio; a tape recorder, or cd player; and sewing machine. We created five asset ownership categories (0-4, 5-6, 7-8, 9-10, more than 10) based roughly on quintiles of asset ownership among all the respondents in our sample. Similarly, we created five educational attainment categories (no education, 1-5 years, 6-8 years, 9-12 years, more than 12 years) based, roughly, on quintiles of educational attainment. The results in figure 3 use these two variables as measures of socioeconomic status.

In addition to asset wealth and educational attainment, the results presented in table 3 also control for the log of monthly household expenditure per capita, which is an estimate based on a respondent's answer to the question: "In general, what is your household's average overall monthly spending?" The summary statistics in table 2 show, as many other studies do, that Scheduled Castes and Muslims are poorer and have less education than higher caste Hindus.

Figures A1 and A2 in the online Appendix provide summary statistics for mental health outcomes by social group and by age and sex. The age pattern of mental health outcomes shown in Figure A1 is similar to the age pattern found in studies of mental health elsewhere in the world (Kessler and Bromet, 2013). Specifically, older people have worse mental health, on average, than younger people. Figure A2 shows that, within the social groups that we study, there are not statistically significant differences between men's and women's mental health outcomes.

Approach

We ask: can the gaps in mental health outcomes between Scheduled Castes and higher caste Hindus, and between Muslims and higher caste Hindus, be explained by differences in their socioeconomic status? In order to answer these questions, we use two complementary empirical strategies. We first use a non-parametric reweighting decomposition to generate counterfactual distributions of mental health outcomes among Scheduled Castes and Muslims. These distributions tell us what the mental health outcomes of the two marginalized groups would look like if they had the same distribution of educational attainment and asset wealth as higher caste Hindus. An advantage of this approach is that it matches on the full distribution of SES variables, not just the means, as a regression would. It flexibly allows any non-parametric interaction between educational attainment and asset wealth. Second, we use parametric ordered logit regression to show that after controlling for SES differences, Scheduled Castes and Muslims have worse mental health. The advantage of this regression analysis over the non-parametric reweighting approach is that there are standard inference procedures that allow us to test the statistical significance of our results.

Non-parametric reweighting decomposition. The reweighting decomposition that we use to create counterfactual distributions of mental health outcomes for Scheduled Castes and Muslims is similar to the one used by DiNardo, Fortin and Lemieux (1996) in their study of changes in the wage distribution in the United States. It has been used in health disparities research as well (Geruso, 2012; Coffey et al., 2017). The reweighting function that we use to produce the counterfactual distributions in figure 3 is defined as

$$\Psi(\mathbf{x}) = \frac{f(\mathbf{x}|g=1)}{f(\mathbf{x}|g=0)}, \tag{1}$$

where $\mathbf{x}$ is a single set of indicators for the intersections of the 5 educational attainment categories and 5 asset ownership categories described in table 2. Reweighting is therefore done over 25 education by asset ownership bins. The function $f(x|g)$ is the empirical probability mass function for bin x among the higher caste Hindu population ($g=1$) or the Scheduled Caste or Muslim population ($g=0$). In other words, $f(x|g)$ is the fraction of the population group g sample in education by asset bin x, computed using survey sampling weights. The reweighting function $\Psi(\mathbf{x})$ is multiplied by the sampling weight of each Scheduled Caste or Muslim observation, so that a counterfactual distribution can be computed for a counterfactual Scheduled Caste or Muslim population that has educational attainment and asset ownership to match that of higher caste Hindus.

Therefore, the counterfactual reweighted distribution of mental health outcomes m is

$$\tilde{m} = \frac{\Sigma_i \Psi(\mathbf{x_i}) w_i m_i}{\Sigma_i \Psi(\mathbf{x_i}) w_i}, \tag{2}$$

where m_i is the mental health outcome of person i; x_i is the education by asset bin of person i; and w_i is the survey sampling weight of person i.

To provide some intuition for what the reweighting does, we note that because Muslims and Scheduled Castes have less education and fewer assets than higher caste Hindus, the reweighted distribution puts more weight on the mental health outcomes of more educated and wealthier Muslim and Scheduled Caste respondents than it does on the mental health outcomes of less educated and poorer respondents. The extent to which mental health outcomes in the counterfactual distributions improve relative to the unadjusted distributions can be interpreted as the extent to which mental health outcomes among Muslims and Scheduled Castes can be explained by their socioeconomic disadvantage relative to higher caste Hindus.

It is important to note that the non-parametric nature of this approach limits the number of SES variables that can be adjusted for: if the sample is partitioned into many bins, computing reweighted mental health outcomes for Scheduled Castes and Muslims would require dropping some of the higher caste Hindu respondents from the sample. This is because the denominator in equation 1 would be zero if there are higher caste Hindus who have no counterparts in the marginalized group. However, when we reweight over the 25 educational attainment $\times$ asset wealth bins, we do not need to drop any higher caste Hindu respondents from the sample. In the ordered logit regression approach, which we describe below, we control for household expenditure per capita as well as for asset wealth.

Parametric ordered logit regression. Each of the outcome variables we study is measured using five ordered categories (for example: very unhappy, unhappy, neither happy nor unhappy, happy, or very happy). We model the ordered, discrete mental health outcome using a linear ordered logit regression model. In this literature, ordered logit models have previously been used to study other disparities in ordered health outcomes, including disparities in self-reported health by sex and martial status (Gorman and Read, 2006; Zheng and Thomas, 2013).

In this model, a latent variable m^* is assumed to be a linear function of the independent variables, with an error term with a logistic distribution. The ordered outcome *categories* correspond to *cutpoints* in the continuous distribution of m^* that are unobservable parameters fit by maximum likelihood (Rodríguez, 2007).

We write the linear model for m^* as

$$\begin{aligned} m^*_{ij} = &\beta_1 Muslim_{ij} + \beta_2 Scheduled\,Caste_{ij} + \\ &\beta_3 female_{ij} + \alpha^{age}_{ij} + E_{ij}\theta + A_{ij}\lambda + \\ &\beta_4 log(expenditure)_{ij} + \beta_5 log(expenditure)^2_{ij} + \varepsilon_{ij}, \end{aligned} \tag{3}$$

where ε_{ij} has a logistic distribution and the ordered logit link function additionally includes four cut-points for the five levels of the outcome variable. Subscripts i index respondents and subscripts j index survey primary sampling units, which are villages or urban census enumeration blocks. The coefficients of interest are β_1, on $Muslim_{ij}$, and β_2, on $Scheduled\,Caste_{ij}$. In table 3, we add controls in stages to see whether, in controlled specifications, the gap in mental health decreases, comparing Scheduled Castes and higher caste Hindus, and comparing Muslims and higher caste Hindus. $female_{ij}$ is an indicator for whether person i is female; α^{age}_{ij} is a set of dummy variables for the age of the respondent, in years; E_{ij} is a set of five indicators for educational attainment; A_{ij} is a set of five indicators for asset wealth; $log(expenditure)_{ij}$ and $log(expenditure)^2_{ij}$ are controls for log monthly household expenditure and log monthly household expenditure squared.

One disadvantage of the ordered logit approach is that it constrains the covariates to have the same linear effect latent on mental health at each cut point. For example, if the question is, "Taking all things together, how would you say you are these days? Are you very unhappy, unhappy, neither happy nor unhappy, happy, or very happy?," and if the exponentiated coefficient on $Scheduled\,Caste_{ij}$ is 2, that implies that Scheduled Castes have twice the odds of reporting both of being very unhappy relative to higher caste Hindus and of being unhappy or very unhappy relative to higher caste Hindus.[6]

The ordered logit has two main advantages over the non-parametric reweighting decomposition described above. First, it is possible to include a much larger number of control variables. Second, unlike the reweighting decomposition, inference here is straightforward: we can determine whether Muslims and Scheduled Castes have statistically significantly different mental health outcomes after controlling for relevant demographic and socioeconomic variables.

RESULTS

Descriptive results

Cumulative distributions of mental health outcomes. Figure 1 shows cumulative distributions of the four mental health variables that we study. The panel at left (panel a) compares Muslims and higher caste Hindus; the panel at right (panel b) compares Scheduled Castes and higher caste Hindus. These cumulative distributions show that higher caste Hindus are more likely to report better mental health responses and less likely to report worse mental health responses. Differences between higher caste Hindus and marginalized groups exist across all categories of the responses; they are not driven by differential responses in just one category among the five possible responses.

Figure 1 also reports p-values and z-statistics for non-parametric Mann-Whitney-Wilcoxon rank-sum tests that compare the distribution of each mental health outcome among the marginalized group to that of higher caste Hindus. The p-values, which are all less than 0.001, allow us to reject the null hypotheses that the distributions of mental health outcomes among marginalized groups and higher caste Hindus are the same.

Muslims and Scheduled Caste respondents are far more likely to report having worse mental health outcomes: Muslims were more than three times as likely to say that they have a bad quality of life compared to higher castes, while Scheduled Castes were more than twice as likely to say that they had a bad quality of life. Disparities in reported happiness were also large. Scheduled Castes and Muslims were also more likely to report worse outcomes for depression and anxiety as well. Although disparities in depression and anxiety were smaller than disparities for quality of life and for happiness, all of the distributions we compare are nevertheless statistically significantly different.

Mental health disparities by socioeconomic status. Figure 2 shows differences in mental health outcomes by social group at different levels of socioeconomic status. The graphs in this figure plot the fraction of respondents who report the two worst mental health outcomes for each question: bad or very bad quality of life; being unhappy or very unhappy; severe or extreme problems with depression; and severe or extreme problems with worry or anxiety. The panel at left (panel a) plots this fraction against the number of assets owned; the panel at right (panel b) plots this fraction against years of education.

Figure 2 shows that for all social groups, respondents with more assets or more education are less likely to experience poor mental health outcomes. It also suggests that for quality of life and for happiness, differences in education and wealth by social group do not account for differences in the dichotomized measures of mental health. However, differences in socioeconomic status appear to be able to account for differences in this dichotomized measured of depression. Below, we use ordered logit regression to test the statistical significance of relationships between group membership and mental health outcomes as described by five response categories, holding socioeconomic variables constant.

Non-parametric reweighting decomposition results

Figure 3 plots cumulative distributions of mental health outcomes that are reweighted using the non-parametric approach described above. Figure 3 also plots the original CDFs from Figure 1 for comparison. The reweighted CDFs represent counterfactual distributions of mental health outcomes that answer the question: what would the mental health outcomes of Muslims (or Scheduled Castes) look like if they had the same distribution of assets and educational attainment as higher caste Hindus?

The reweighted distributions are closer to the distributions of mental health outcomes among higher caste Hindus than the unweighted distributions, but for most outcomes, there is nevertheless still a mental health gap. The exception is sadness/depression among Scheduled Castes, which appears to be entirely explained by differences in assets and educational attainment.

Parametric ordered logit results

Table 3 reports proportional odds from the ordered logit regressions of our four mental health outcomes on social group membership and control variables. In each panel, model 1 shows proportional odds of reporting worse mental health responses for Muslims, Scheduled Caste respondents, and women, with age fixed effects. The age fixed effects allow a non-linear relationship between mental health and the age of the respondent. Models 2 to 4 additionally control for socioeconomic variables: model 2 adds controls for education categories, model 3 adds controls for asset categories, and model 4 adds controls for log expenditure and log expenditure squared.

All models use clustered standard errors to account for the survey design. The models also use survey weights provided by the WHO SAGE. Keeping space constraints in mind, the table does not report coefficients and standard errors for control variables except for the sex of the respondent. Coefficients for all of the control variables are shown in the online Appendix, in Tables A1 to A4.

Model 1, which has only demographic controls for age fixed effects and for sex, finds that Muslims have more than twice the proportional odds of reporting worse overall quality of life and less happiness compared to higher caste Hindus. With controls for differences in education, the associations between being Muslim and having worse quality of life, and between being Muslim and happiness reduce in magnitude. After controlling for education, Muslims are twice as likely to report worse outcomes. Additional controls for assets reduce the magnitude of the relationship somewhat, but controlling for expenditure does not. The strength of the relationship between Muslim and having worse quality of life or being less happy remains statistically significant throughout, with p-values less than 0.001.

For problems with feeling sad, low or depressed, and for problems with worry or anxiety, Muslims have about 1.5 times the proportional odds of reporting worse outcomes than higher caste Hindus, even after controlling for SES controls. The magnitude of the association drops from 1.7 times for depression and 1.9 times for anxiety to about 1.5 times and 1.6 times respectively as SES controls are introduced.

For Scheduled Castes, relative to higher caste Hindus, the proportional odds of reporting worse mental health outcomes reduce from 1.9 to 1.4 for overall quality of life, from 1.8 to 1.4 for happiness, from 1.4 to 1.15 for feeling depressed, and from 1.5 to 1.24 for feeling anxious when SES controls are introduced. As the results of the non-parametric reweighting suggested, the association between being Scheduled Caste and having depression is not statistically significant after controlling for socioeconomic status.

Tables A5 and A6 in the Appendix report results of a robustness check with a slightly fuller model: the regressions in Tables A5 and A6 take the same form as in Table 3, except that we add interactions between social group and asset category, and interactions between social group and educational attainment category. We find no evidence that social group interacts with socioeconomic status to predict mental health outcomes in this ordered logit framework.

DISCUSSION

Our research provides the first population-level evidence that Scheduled Castes and Muslims have worse mental health outcomes than higher caste Hindus, even after accounting for the fact that these groups have less education and own fewer assets. The paper's main conclusions are most simply depicted in Figure 3: we find that only about half of the gaps in overall quality of life and in happiness between dominant and marginalized groups in India can be explained by adjusting for differences in asset ownership and educational attainment. These socioeconomic variables explain the depression gap between higher caste Hindus and SCs, but not the depression gap between higher caste Hindus and Muslims.[7] These results cohere with the findings on race, socioeconomic status, and mental health summarized in Table 1: as several studies suggest, material disadvantage rarely provides a full explanation for why socially disadvantaged groups have worse mental health outcomes.

Researchers require additional data to better understand the mechanisms and processes that generate the gaps that we document. The study of mental health disparities in the United States has benefited data sets which provide information not only on mental health outcomes, social group membership, and socioeconomic status, but also on experiences of discrimination, perceptions of discrimination, the extent to which discrimination is internalized by people from oppressed groups, stressors, experiences of violence or trauma, sources of social support, childhood health, childhood socioeconomic status, neighborhood-level variables, and, more recently, even mental-health related biomarkers. Because understanding of social disadvantage and health may be usefully informed by considering multiple life course frameworks and the ways in which health may be transmitted across generations (Colen, 2011; Goosby and Heidbrink, 2013), some studies of mental health in developed countries have even used longitudinal data that allow researchers to control for individual, unobserved variables and to better understand how mental health problems develop over time.

If we are to learn exactly how caste and religion shape mental health outcomes in India, these variables will need to be added to existing health surveys and new surveys will need to be fielded. There are many challenges to collecting this kind of data in India. Perhaps understandably, considering India's high rates of mortality and burden of infectious disease, the government and international organizations have traditionally collected data only on physical health.

Yet, as awareness grows about the global burden of poor mental health, we hope that future health surveys will ask about mental health as well as physical health. We also hope that new tools for measuring discrimination will be developed to complement new mental health data. With the exception of a few studies which document how discrimination against Scheduled Castes is practiced (Shah et al., 2006; Jodhka, 2002), there are few quantitative measures of experiences of discrimination by marginalized groups.

Despite these data limitations, our results nevertheless point to the incompleteness of government efforts to address the consequences of social disadvantage. First, it is important to note that there are not federally-sponsored programs to reduce economic, educational, or health disparities between Hindus and Muslims. Rather than being assisted by the state, Muslims in India are all too often the victims of politically motivated violence (Wilkinson, 2006; Ghassem-Fachandi, 2012). The state arguably does more to promote the interests of Scheduled Castes. Affirmative action in the form of caste-based quotas for political office, higher education, and government jobs is written into the Indian constitution, and is relatively widely implemented. Government development programs also often make Scheduled Caste priority beneficiaries; for example, in many states, a proportion of annual government budgetary allocations are specially marked for Scheduled Castes under the Scheduled Caste Sub-plan.

But our results suggest that merely redistributing wealth, and even helping Scheduled Castes or Muslims get more education, will not close gaps in mental health. Discrimination against Scheduled Castes is still widespread – even though a set of discriminatory practices known collectively as "untouchability" have been criminalized since the 1950s, these laws go unenforced. Surveys suggest that a large fraction of people still openly admit to engaging in these forms of discrimination (Thorat and Joshi, 2015; Coffey et al., forthcoming). To our knowledge, the extent to which people from dominant social groups admit to discrimination against Muslims has not been similarly quantified, although such estimates would certainly be valuable.

We hope that these results will contribute to broader efforts to draw attention to the need for more research and more comprehensive policies to address social inequality in India. Further study of the relationships among discrimination, prejudice, and mental health in the context of social inequality and material disadvantage in India would inform social policy in India and, by testing external validity, theories of health and social inequality everywhere.

Notes

[1]This is because numerous studies find that poorer, less educated people have worse mental health than richer, better educated people (Hamilton et al., 1990; Link and Phelan, 1995; Keyes, 2002). Further literature documents that poorer and less educated people are exposed to more stress and have less social support (Turner et al., 1995; Turner and Lloyd, 1999; Aneshensel, 2009). We note that correlations between mental health and socioeconomic status may also reflect the consequences of poor mental health for a person's employment or productivity (Bartel and Taubman, 1986; Frank and Gertler, 1991).

[2]Williams et al. (2003) and Kessler et al. (1999) provide informative reviews of the literature on this topic.

[3]A small number of states have affirmative action programs for Muslims.

[4]Marx described India as "a country not only divided between Mahommedan and Hindoo, but between...caste and caste" (Marx et al., 2007), while Weber described caste as a "closed status group" (Weber, 2000). Immerwahr (2007) describes a history of exchange between scholars and activists of race and of caste.

[5]We note that despite the fact that a person cannot change his/her caste, the caste system is nevertheless a dynamic system of social stratification because castes often negotiate and renegotiate their positions within local hierarchies (Srinivas, 1952; Weber, 2000).

[6]We note that, because odds are ratios of probabilities, a uniform effect on odds could have different effects on probabilities that are low, moderate or high.

[7]The results for anxiety depend on the comparison group (SC or Muslim) and on modeling choices.

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Table 1: Prior findings on social disadvantage and mental health

study	**data**	**mental health outcomes**	**conclusion about social disadvantage and mental health**
Frerichs, Aneshensel and Clark (1981)	Los Angeles Depression Study	CES-D score	race was not a significant predictor of depression after controlling for SES, demographics
Jackson et al. (2010)	South African Stress and Health Study	non-specific distress; anger, hostility	socioeconomic disadvantage & social stressors explain differences in non-specific distress between blacks & whites
Kessler and Neighbors (1986)	8 epidemiological studies from the United States	depression; somatization	racial differences in mental health are particularly pronounced for low SES people
Breslau et al. (2006)	National Comorbidity Survey Replication	psychiatric disorders measured by the DSM-IV	blacks had lower risk of common psychiatric disorders than whites
Hughes and Thomas (1998)	General Social Survey	life satisfaction; happiness	blacks report lower quality of life than whites; disparities not explained by SES differences
Williams et al. (1997)	Detroit Area Study	psychological well-being; distress	blacks report worse psychological well-being; this is partially explained by experiences of discrimination
Myer et al. (2008)	South African Stress and Health Study	psychological distress	blacks report more psychological distress than whites; this can be explained by SES differences & by experiences of racial discrimination

Table 2: Summary statistics by social group

	Higher Caste Hindu		Scheduled Caste		Muslim		Total	
	mean	s.e.	mean	s.e.	mean	s.e.	mean	s.e.
mental health outcomes								
bad or very bad quality of life	0.05	(0.005)	0.12	(0.015)	0.17	(0.025)	0.08	(0.006)
unhappy or very unhappy	0.05	(0.005)	0.11	(0.015)	0.19	(0.029)	0.08	(0.007)
severe or extreme depression	0.06	(0.006)	0.07	(0.009)	0.08	(0.013)	0.06	(0.005)
severe or extreme anxiety	0.11	(0.009)	0.13	(0.016)	0.16	(0.002)	0.12	(0.008)
predictor variables								
mean age	41.7	(0.357)	39.8	(0.472)	41.0	(0.940)	41.2	(0.304)
female	0.49	(0.010)	0.47	(0.020)	0.47	(0.215)	0.49	(0.007)
mean # of assets (out of 16)	7.8	(0.139)	6.0	(0.175)	6.2	(0.224)	7.2	(0.117)
asset wealth categories								
0-4 assets	0.16	--	0.32	--	0.28	--	0.21	--
5 or 6 assets	0.22	--	0.29	--	0.29	--	0.24	--
7 or 8 assets	0.21	--	0.19	--	0.24	--	0.21	--
9 or 10 assets	0.18	--	0.13	--	0.10	--	0.16	--
more than 10 assets	0.23	--	0.07	--	0.08	--	0.18	--
mean years of education	6.6	(0.205)	4.5	(0.304)	4.0	(0.403)	5.7	(0.176)
years of education categories								
no education	0.29	--	0.45	--	0.47	--	0.35	--
1 to 5	0.16	--	0.17	--	0.20	--	0.17	--
6 to 8	0.14	--	0.14	--	0.14	--	0.14	--
9 to 12	0.26	--	0.15	--	0.13	--	0.22	--
more than 12	0.15	--	0.08	--	0.05	--	0.12	--
mean log expenditure	8.0	(0.031)	7.7	(0.038)	7.9	(0.042)	7.9	(0.257)
n	6,832		1,951		1,342		10,125	

Source: WHO SAGE 2007-08.
Note: Totals excludes others and Scheduled Tribes. Standard Errors, clustered at the primary sampling unit level, in parantheses.

Table 3: Ordered logit regression results show statistically significantly worse mental health among Muslims and Scheduled Castes.

	overall quality of life from 1 "very good" to 5 "very bad"			
	(1)	(2)	(3)	(4)
Muslim	2.437***	2.024***	1.816***	1.850***
	(0.398)	(0.311)	(0.273)	(0.278)
Scheduled Caste	1.916***	1.643***	1.425**	1.418**
	(0.221)	(0.185)	(0.157)	(0.156)
Female	0.955	0.713***	0.832+	0.831+
	(0.0896)	(0.0716)	(0.0854)	(0.0849)
age fixed effects	X	X	X	X
education categories		X	X	X
asset categories			X	X
log expenditure				X
log expenditure squared				X
n	10,125	10,125	10,125	10,125

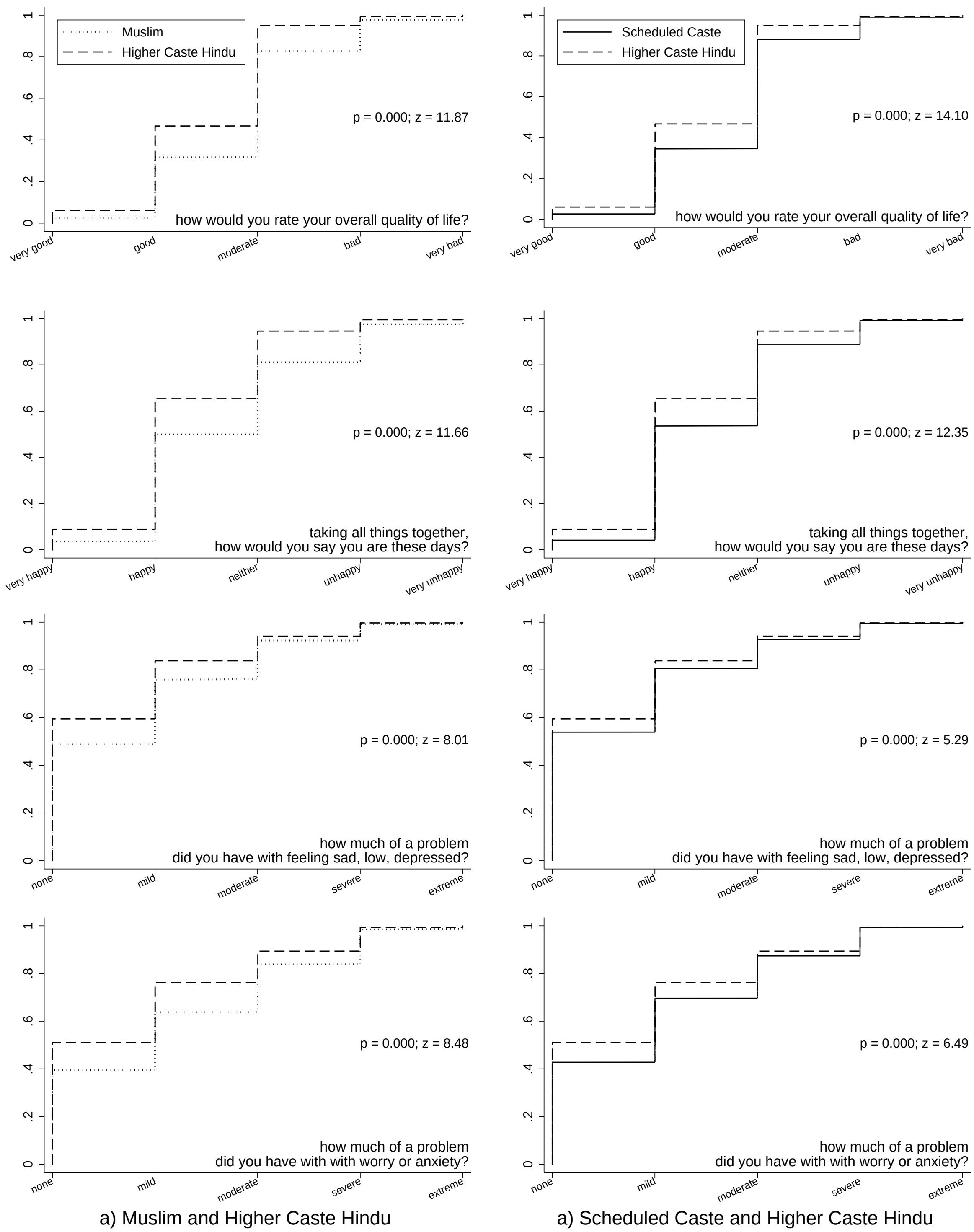
	happiness from 1 "very happy" to 5 "very unhappy"			
	(1)	(2)	(3)	(4)
Muslim	2.492***	2.125***	1.966***	2.016***
	(0.341)	(0.286)	(0.254)	(0.263)
Scheduled Caste	1.777***	1.547***	1.373***	1.373***
	(0.173)	(0.145)	(0.126)	(0.126)
Female	0.801*	0.627***	0.703***	0.703***
	(0.0741)	(0.0643)	(0.0738)	(0.0738)
age fixed effects	X	X	X	X
education categories		X	X	X
asset categories			X	X
log expenditure				X
log expenditure squared				X
n	10,125	10,125	10,125	10,125

	problems with feeling sad, low, or depressed from 1 "none" to 5 "extreme"			
	(1)	(2)	(3)	(4)
Muslim	1.683***	1.513***	1.422**	1.452**
	(0.211)	(0.185)	(0.169)	(0.175)
Scheduled Caste	1.380**	1.257*	1.149	1.146
	(0.135)	(0.123)	(0.116)	(0.116)
Female	1.847***	1.611***	1.783***	1.787***
	(0.164)	(0.155)	(0.178)	(0.178)
age fixed effects	X	X	X	X
education categories		X	X	X
asset categories			X	X
log expenditure				X
log expenditure squared				X
n	10,125	10,125	10,125	10,125

	problems with worry or anxiety from 1 "none" to 5 "extreme"			
	(1)	(2)	(3)	(4)
Muslim	1.870***	1.653***	1.557***	1.571***
	(0.257)	(0.224)	(0.207)	(0.210)
Scheduled Caste	1.485***	1.346**	1.239*	1.236*
	(0.157)	(0.139)	(0.130)	(0.130)
Female	2.030***	1.751***	1.920***	1.921***
	(0.197)	(0.184)	(0.203)	(0.203)
age fixed effects	X	X	X	X
education categories		X	X	X
asset categories			X	X
log expenditure				X
log expenditure squared				X
n	10,125	10,125	10,125	10,125

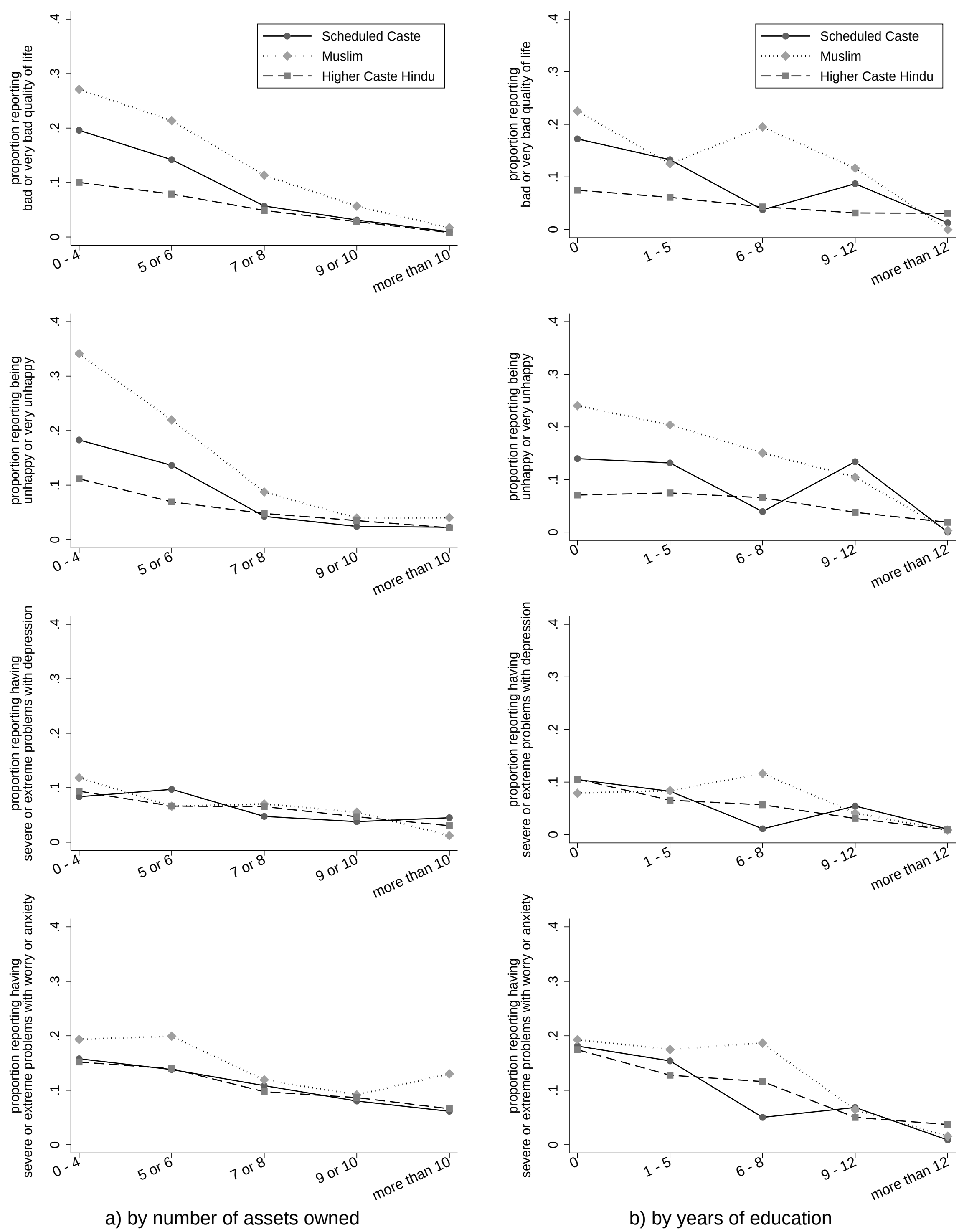
Note: Exponentiated coefficients. Standard errors clustered at the level of the primary sampling unit in parentheses. + p<.1, * p<.05, ** p<.01, *** p<.001. All regressions are weighed using national individual weights. An X indicates that the model controls for the variable in the row.
Source: SAGE 2007-08.

Figure 1: CDFs show that Muslims and Scheduled Castes have worse mental health than higher caste Hindus



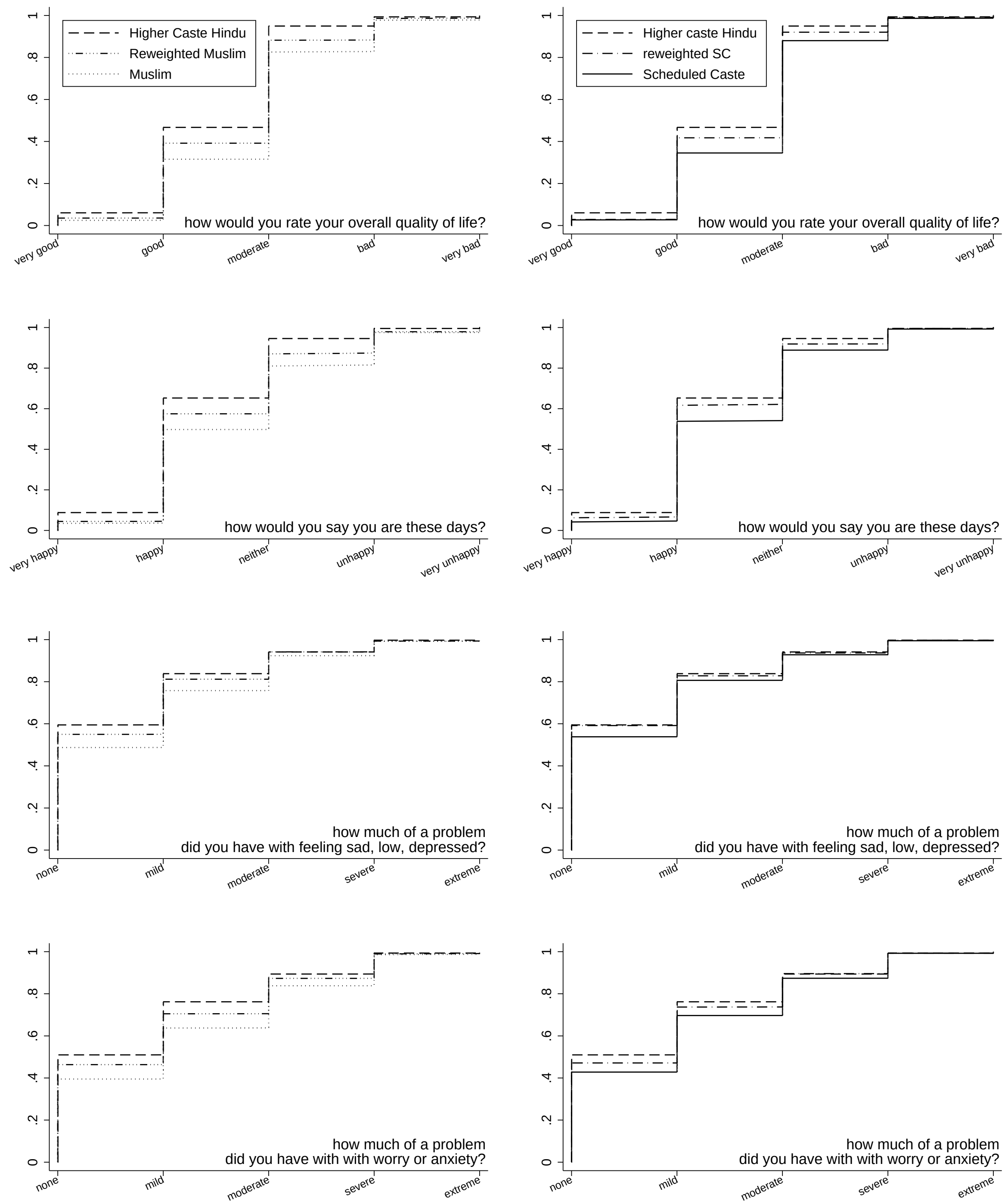
Source: WHO SAGE 2007-08.

Figure 2: Mental health outcomes are often worse for Muslims and Scheduled Caste even at the same level of asset wealth or education



Source: WHO SAGE 2007-08.

Figure 3: Reweighted CDFs show that mental health gaps exist even after accounting for socioeconomic differences between social groups



a) Muslim and Higher Caste Hindu

b) Scheduled Caste and Higher Caste

Source: WHO SAGE 2007-08.

SUPPLEMENTARY APPENDIX

Appendix tables.

Appendix tables A1 to A4 show the full models, including coefficients and clustered standard errors for all variables included in models presented in Table 3. Table A1 shows these models for the measure of quality of life, Table A2 for happiness, Table A3 for sadness or depression, and Table A4 for worry or anxiety. As in Table 3, the first model does not includes only age-fixed effects, model 2 includes controls for education, model 3 adds controls for assets, and model 4 adds control for log of expenditure and log of expenditure squared. Both higher years of education and higher asset wealth are associated with better mental health outcomes.

Table A5 and A6 show interactions with assets and years of education, respectively. Each of these tables includes all the four mental health outcomes. In general, the interactions show that association of higher asset wealth or years of education with mental health is not significantly different for Muslims or Scheduled Caste respondents.

Appendix figures.

Figure A1 shows age patterns for dichotomous mental health outcomes for the three social groups. Age-misreporting and heaping is an important concern for data collection efforts in developing countries, and age-misreporting is likely to be higher among Scheduled Castes and Muslims, given that they are poorer and less-educated. Another concern is selection and mortality, especially above ages sixty. Still, these graphs show a pattern well-known to mental health researchers, that with age, mental health tends to worsen. Overall, Muslims and Scheduled Caste Hindus have worse mental health outcomes when compared to higher Caste Hindus at most ages.

Figure A2 shows these mental health outcomes by sex and social group. Muslim women are more likely to report having low quality of life or not being happy, but the difference between Muslim women and men is not significant. On questions that are more difficult to understand, such as those relating to depression and anxiety, men are more likely to say that they have worse outcomes, which may partly be because of a greater understanding of these questions.

Table A1: Quality of life: Ordered logit regression results from Table 3 displaying coefficients on control variables.

	overall quality of life			
	(1)	(2)	(3)	(4)
Muslim	2.437***	2.024***	1.816***	1.850***
	(0.398)	(0.311)	(0.273)	(0.278)
Scheduled Caste	1.916***	1.643***	1.425**	1.418**
	(0.221)	(0.185)	(0.157)	(0.156)
Female	0.955	0.713***	0.832+	0.831+
	(0.0896)	(0.0716)	(0.0854)	(0.0849)
no education (reference)				
1 - 5 years of education		0.736*	0.849	0.843
		(0.0898)	(0.103)	(0.102)
6 - 8 years of education		0.613***	0.790*	0.790*
		(0.0679)	(0.0919)	(0.0924)
9 - 12 years of education		0.459***	0.742*	0.750*
		(0.0611)	(0.101)	(0.102)
more than 12 years of education		0.260***	0.552**	0.569**
		(0.0448)	(0.0996)	(0.104)
0 - 4 assets (reference)				
5 or 6 assets			0.728**	0.763*
			(0.0796)	(0.0840)
7 or 8 assets			0.539***	0.581***
			(0.0612)	(0.0681)
9 or 10 assets			0.345***	0.388***
			(0.0450)	(0.0515)
more than 10 assets			0.230***	0.276***
			(0.0298)	(0.0382)
log of expenditure				1.025
				(0.485)
log of expenditure squared				0.989
				(0.0284)
n	10,125	10,125	10,125	10,125

Note: Exponentiated coefficients. Standard errors clustered at the level of the primary sampling unit in parentheses. + p<.1, * p<.05, ** p<.01, *** p<.001. All regressions are weighed using national individual weights.
Source: WHO SAGE 2007-08.

Table A2: Happiness: Ordered logit regression results from Table 3 displaying coefficients on control variables.

	happiness			
	(1)	(2)	(3)	(4)
Muslim	2.492***	2.125***	1.966***	2.016***
	(0.341)	(0.286)	(0.254)	(0.263)
Scheduled Caste	1.777***	1.547***	1.373***	1.373***
	(0.173)	(0.145)	(0.126)	(0.126)
Female	0.801*	0.627***	0.703***	0.703***
	(0.0741)	(0.0643)	(0.0738)	(0.0738)
no education (reference)				
1 - 5 years of education		0.976	1.111	1.104
		(0.116)	(0.132)	(0.130)
6 - 8 years of education		0.660**	0.825	0.823
		(0.0855)	(0.111)	(0.111)
9 - 12 years of education		0.582***	0.888	0.895
		(0.0753)	(0.119)	(0.120)
more than 12 years of education		0.249***	0.460***	0.469***
		(0.0462)	(0.0835)	(0.0857)
0 - 4 assets (reference)				
5 or 6 assets			0.688***	0.734**
			(0.0766)	(0.0849)
7 or 8 assets			0.544***	0.595***
			(0.0608)	(0.0701)
9 or 10 assets			0.343***	0.391***
			(0.0488)	(0.0600)
more than 10 assets			0.307***	0.368***
			(0.0451)	(0.0586)
log of expenditure				0.505
				(0.271)
log of expenditure squared				1.034
				(0.0343)
n	10,125	10,125	10,125	10,125

Note: Exponentiated coefficients. Standard errors clustered at the level of the primary sampling unit in parentheses. + p<.1, * p<.05, ** p<.01, *** p<.001. All regressions are weighed using national individual weights.
Source: SAGE 2007-08.

Table A3: Sadness or depression: Ordered logit regression results from Table 3 displaying coefficients on control variables.

	problems with feeling sad, low, or depressed			
	(1)	(2)	(3)	(4)
Muslim	1.683***	1.513***	1.422**	1.452**
	(0.211)	(0.185)	(0.169)	(0.175)
Scheduled Caste	1.380**	1.257*	1.149	1.146
	(0.135)	(0.123)	(0.116)	(0.116)
Female	1.847***	1.611***	1.783***	1.787***
	(0.164)	(0.155)	(0.178)	(0.178)
no education (reference)				
1 - 5 years of education		0.916	1.000	0.994
		(0.0961)	(0.107)	(0.106)
6 - 8 years of education		0.791*	0.920	0.918
		(0.0853)	(0.104)	(0.104)
9 - 12 years of education		0.730*	0.960	0.969
		(0.0893)	(0.123)	(0.123)
more than 12 years of education		0.421***	0.655*	0.674*
		(0.0766)	(0.124)	(0.129)
0 - 4 assets (reference)				
5 or 6 assets			0.800*	0.843+
			(0.0798)	(0.0863)
7 or 8 assets			0.738**	0.801+
			(0.0820)	(0.0920)
9 or 10 assets			0.528***	0.601***
			(0.0690)	(0.0889)
more than 10 assets			0.435***	0.529***
			(0.0548)	(0.0808)
log of expenditure				0.950
				(0.688)
log of expenditure squared				0.993
				(0.0457)
n	10,125	10,125	10,125	10,125

Note: Exponentiated coefficients. Standard errors clustered at the level of the primary sampling unit in parentheses. + p<.1, * p<.05, ** p<.01, *** p<.001. All regressions are weighed using national individual weights.
Source: SAGE 2007-08.

Table A4: Worry or anxiety: Ordered logit regression results from Table 3 displaying coefficients on control variables.

	problems with worry or anxiety			
	(1)	(2)	(3)	(4)
Muslim	1.870***	1.653***	1.557***	1.571***
	(0.257)	(0.224)	(0.207)	(0.210)
Scheduled Caste	1.485***	1.346**	1.239*	1.236*
	(0.157)	(0.139)	(0.130)	(0.130)
Female	2.030***	1.751***	1.920***	1.921***
	(0.197)	(0.184)	(0.203)	(0.203)
no education (reference)				
1 - 5 years of education		0.984	1.066	1.063
		(0.104)	(0.113)	(0.112)
6 - 8 years of education		0.749*	0.866	0.866
		(0.0899)	(0.108)	(0.108)
9 - 12 years of education		0.678***	0.882	0.886
		(0.0760)	(0.103)	(0.103)
more than 12 years of education		0.429***	0.652*	0.663*
		(0.0723)	(0.115)	(0.118)
0 - 4 assets (reference)				
5 or 6 assets			0.940	0.962
			(0.0962)	(0.0991)
7 or 8 assets			0.707**	0.735**
			(0.0768)	(0.0846)
9 or 10 assets			0.505***	0.537***
			(0.0601)	(0.0719)
more than 10 assets			0.510***	0.562***
			(0.0691)	(0.0829)
log of expenditure				1.088
				(0.744)
log of expenditure squared				0.990
				(0.0436)
n	10,125	10,125	10,125	10,125

Note: Exponentiated coefficients. Standard errors clustered at the level of the primary sampling unit in parentheses. + p<.1, * p<.05, ** p<.01, *** p<.001. All regressions are weighed using national individual weights. Source: SAGE 2007-08.

Table A5: Ordered logit regressions do not find evidence that social group interacts with asset wealth to predict mental health.

	quality of life	happiness	depression	anxiety
Muslim	2.699***	2.851***	1.424+	1.642*
	(0.676)	(0.711)	(0.304)	(0.379)
Scheduled Caste	1.792**	1.497*	0.914	1.093
	(0.344)	(0.265)	(0.135)	(0.183)
Female	0.941	0.776**	1.870***	2.052***
	(0.0908)	(0.0745)	(0.172)	(0.203)
0 - 4 assets (reference)				
5 or 6 assets	0.777+	0.682**	0.635**	0.818
	(0.108)	(0.0950)	(0.0883)	(0.122)
7 or 8 assets	0.568***	0.568***	0.672**	0.656**
	(0.0783)	(0.0876)	(0.0970)	(0.0901)
9 or 10 assets	0.348***	0.319***	0.484***	0.447***
	(0.0564)	(0.0583)	(0.0756)	(0.0675)
more than 10 assets	0.211***	0.274***	0.361***	0.423***
	(0.0323)	(0.0506)	(0.0528)	(0.0610)
5 or 6 assets X Muslim	0.808	0.853	1.411	1.241
	(0.295)	(0.342)	(0.395)	(0.390)
7 or 8 assets X Muslim	0.535	0.514+	0.915	0.725
	(0.211)	(0.179)	(0.301)	(0.262)
9 or 10 assets X Muslim	0.709	0.730	0.502	1.108
	(0.279)	(0.257)	(0.219)	(0.361)
more than 10 assets X Muslim	0.400+	0.390**	0.930	0.764
	(0.187)	(0.142)	(0.285)	(0.269)
5 or 6 assets X Scheduled Caste	0.783	1.063	1.801**	1.349
	(0.213)	(0.265)	(0.385)	(0.301)
7 or 8 assets X Scheduled Caste	0.867	0.938	1.263	1.300
	(0.218)	(0.247)	(0.306)	(0.335)
9 or 10 assets X Scheduled Caste	0.591*	0.827	1.147	0.930
	(0.153)	(0.223)	(0.310)	(0.252)
more than 10 assets X Scheduled Caste	0.971	0.650	1.151	1.193
	(0.433)	(0.265)	(0.567)	(0.573)
n	10,125	10,125	10,125	10,125

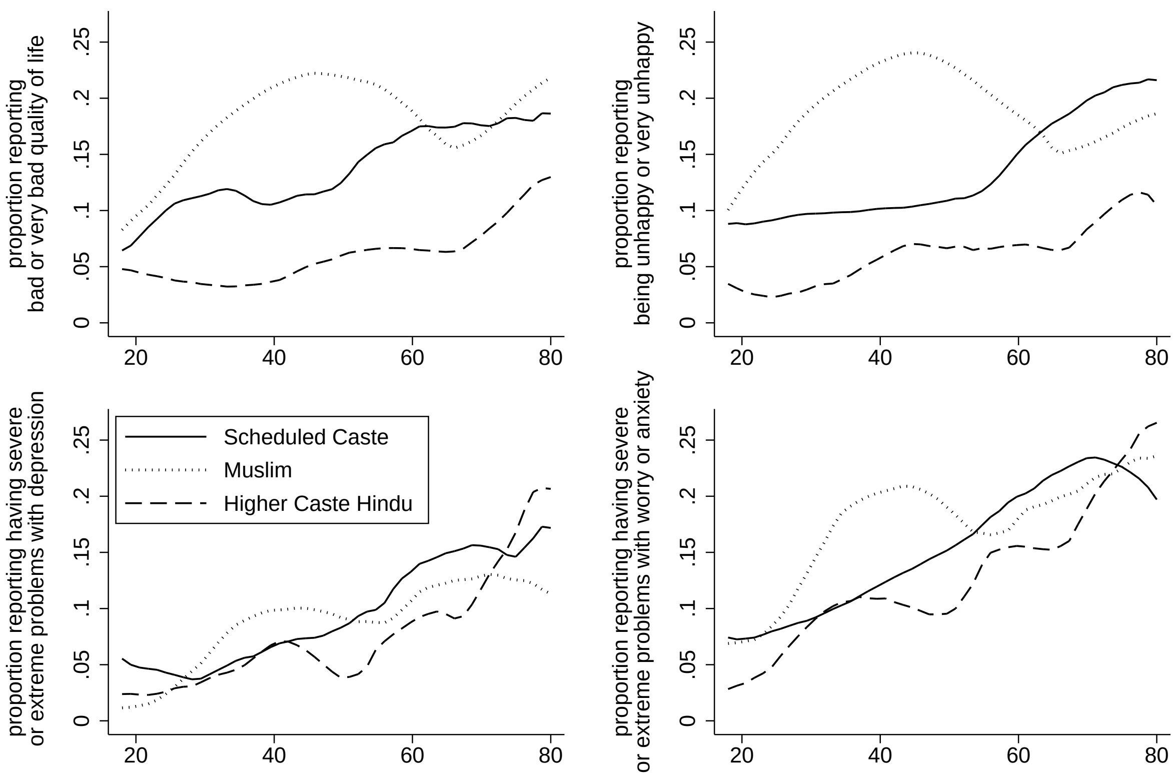
Note: Exponentiated coefficients. Standard errors clustered at the level of the primary sampling unit in parentheses. + p<.1, * p<.05, ** p<.01, *** p<.001. All regressions are weighed using national individual weights.
Source: SAGE 2007-08.

Table A6: Ordered logit regressions do not find evidence that social group interacts with education to predict mental health.

	quality of life	happiness	depression	anxiety
Muslim	2.086**	2.086***	1.507*	3.809***
	(0.526)	(0.458)	(0.240)	(1.339)
Scheduled Caste	1.922***	1.739***	1.186	1.676+
	(0.274)	(0.205)	(0.173)	(0.458)
Female	0.712***	0.628***	1.759***	0.932
	(0.0720)	(0.0643)	(0.185)	(0.0914)
no education (reference)				
1 - 5 years of education	0.742*	0.962	0.881	0.840
	(0.0927)	(0.135)	(0.118)	(0.119)
6 - 8 years of education	0.668***	0.727*	0.773+	0.748+
	(0.0761)	(0.106)	(0.104)	(0.113)
9 - 12 years of education	0.471***	0.579***	0.722*	0.621***
	(0.0606)	(0.0805)	(0.0983)	(0.0811)
more than 12 years of education	0.298***	0.282***	0.448***	0.426***
	(0.0521)	(0.0580)	(0.0875)	(0.0780)
1 - 5 years of education X Muslim	0.903	1.087	1.384	1.557
	(0.281)	(0.354)	(0.359)	(0.422)
6 - 8 years of education X Muslim	1.061	1.033	1.537	0.967
	(0.431)	(0.430)	(0.530)	(0.385)
9 - 12 years of education X Muslim	1.431	1.261	1.017	1.025
	(0.581)	(0.469)	(0.368)	(0.293)
more than 12 years of education X Muslim	0.443*	0.614	0.894	0.905
	(0.173)	(0.241)	(0.366)	(0.438)
1 - 5 years of education X Scheduled Caste	1.074	1.035	0.928	1.430
	(0.252)	(0.248)	(0.214)	(0.325)
6 - 8 years of education X Scheduled Caste	0.650+	0.624+	0.826	0.973
	(0.150)	(0.169)	(0.227)	(0.282)
9 - 12 years of education X Scheduled Caste	0.748	0.969	1.042	1.530+
	(0.225)	(0.273)	(0.278)	(0.390)
more than 12 years X Scheduled Caste	0.599	0.543+	0.596	0.921
	(0.222)	(0.173)	(0.292)	(0.441)
n	10,125	10,125	10,125	10,125

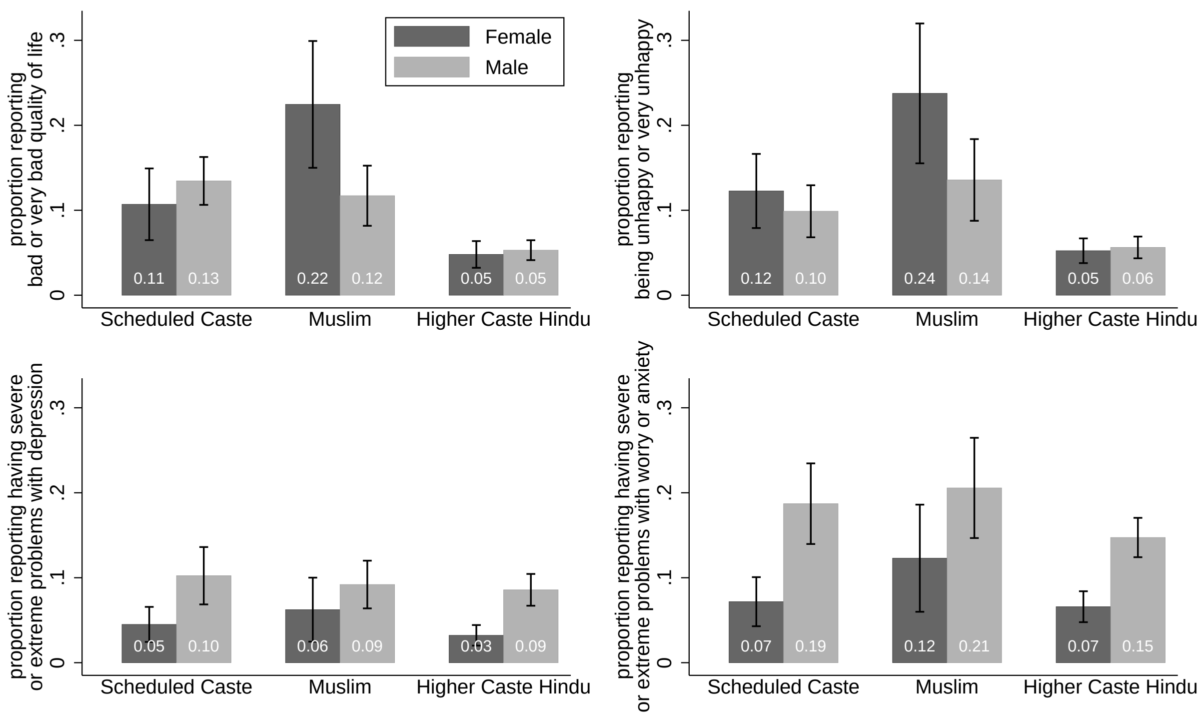
Note: Exponentiated coefficients. Standard errors clustered at the level of the primary sampling unit in parentheses. + p<.1, * p<.05, ** p<.01, *** p<.001. All regressions are weighed using national individual weights.
Source: SAGE 2007-08.

Figure A1: Local polynomial regressions of mental health outcomes by age and social group.



Source: WHO SAGE 2007-08.

Figure A2: Mental health outcomes by sex and social group.



Source: WHO SAGE 2007-08.