Spring 5-2020

Adolescent Mental Health In the Developing World: Three Economic Analyses on Stressors, Coping, and Support

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ADOLESCENT MENTAL HEALTH IN THE DEVELOPING WORLD: THREE ECONOMIC ANALYSES ON STRESSORS, COPING, AND SUPPORT

by

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DISSERTATION

Submitted in Partial Fulfillment of the
Requirements for the Degree of

Doctor of Philosophy
Economics

The University of New Mexico
Albuquerque, New Mexico

May, 2020

DEDICATION

This dissertation is dedicated to today's adolescents – may you soon have holistic physical, emotional, and mental health which allows you to be the economic foundation of a successful world.

ACKNOWLEGEMENT

I would first like to acknowledge and thank my advisor, Dr. Alok K. Bohara, for his willingness to take-on mentoring and guiding me throughout the entirety of my time in the Economics graduate program, despite the fact that I came into the program with no formal training in the topic. The completion of this dissertation would also not have been possible without his openness to my interdisciplinary questions and approaches. He has worked within my goals and his own in the aims for a successful dissertation and my success both in the program and long-term.

Dr. Bohara's patience in dealing with the long-distance constraints faced during the majority of this work, along with the support and assistance of the entire administrative staff of the UNM Department of Economics, is also immeasurable. Of additional particular note is Dr. Jennifer Thacher, who was integral to facilitating the beginning of this long-distance process.

Research-wise, I acknowledge the help provided by the collaborators, Lumbini Center for Sustainability (LCS), and their research and survey team (Ms. Swati Thapa, Mr. Dharma KC, Prakash Rayamajhi, Anup Poudel, Sharada Pathak and the PNMF and PNC college staff and several field supervisors, enumerators, and data coders), and the cooperation of the various schools which provided the interview sites and organized the participants for the data used in Chapters 2 and 4 of this dissertation. Christine Glidden, founder of Women2Be, is also acknowledged for her generous time and cooperation and for providing the hygiene kits for the work presented in Chapter 4. Furthermore, the aid of the Nepal Study Center (NSC) at the University of New Mexico in coordination and arrangement of these studies is also acknowledged.

I also would like to acknowledge Dr. Brady Horn for his support in guiding me on how to walk the line between traditional humanities-based writing and the type of writing more customary among economics-based writing. Dr. Horn was also essential to the publication of my first peer-reviewed journal article, and deserve recognition of such. His service on my dissertation committee, along with Dr. Richard Santos and Dr. Andrew Rowland, is also greatly valued.

A huge acknowledgement goes to my parents, Dr. Jim H. Degnan, PhD and Rikki L. Quintana, JD, for their help in editing this entire dissertation, and for every brainstorming and breakdown session that they helped me through.

Last but certainly not least, I need to present a huge acknowledgement to my husband, Dr. Nadir Yilmaz, PhD, and my son, Evren, for their unending support of me (financially and emotionally) throughout this immense process. God willing, our family will see the benefits of these tough years for many years to come.

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ABSTRACT

Adolescents are slowly being recognized as a generation, worldwide, that may require different policy approaches to improve staggering statistics on their failing wellbeing, including mental health. By providing the support to allow the next generation to achieve better mental health outcomes, they are going to be more economically successful and the future economic growth of nations can be better assured. In face of such a need, this dissertation approaches the evaluation of a number of key stressors and elements of coping and support. Each chapter produces results which overcome limitations throughout existing literature in terms of the simultaneous consideration of both rigorous econometric-based analyses and strong conceptual frameworks. Each chapter also contains relevant policy implications and recommendations which are believed to hold good promise for improving the relevant adolescent mental health problems addressed in each respective chapter.

Chapter 2 addresses the issue of connections between mobile-based health (mHealth) interventions aimed at improving the wellbeing of adolescent and evidence of negative wellbeing/mental health outcomes. We investigate this using primary data from a large-scale, school-based survey of older adolescents in southwestern Nepal, to assess this tension between mobile/smartphone usage as a true mobile health (mHealth) opportunity in Nepal or as a potential problem, introducing additional deleterious wellbeing effects from over-use. Founded in Basic Psychological Needs Theory (BPNT), robust results of analyses using full structural modeling approaches (and traditional regression-based sensitivity analyses) indicate support for the BPNT framework in explaining statistically significant associations between bullying and wellbeing outcomes, including evidence to support the mediating role of problematic mobile phone use.

Chapter 3 expands consideration of adolescent mental health to across the developing world, where suicide has become a leading cause of all adolescent deaths. Using data from the Global School-based Student Health Survey (GSHS) of six different countries, analysis involves estimation of a reduced-form, simultaneous model incorporating specialized clustering to determine the influence of both positive and negative components of social integration on five different deleterious health outcomes, including three levels of suicidal behavior. Robust results indicate that positive parenting and social exclusion reduce and increase the likelihood of all outcomes, respectively, among both pooled and individual country samples. Such results provide an impetus for pursuing interventions in LMICs, including those aimed at suicide prevention, which focus on social-based, multi-level approaches.

Finally, **Chapter 4**, examines a particularly stressful situation faced by female adolescents in regions such as Nepal. Informed by the Transactional Model of Stress and Coping, this chapter evaluates the roles that cultural and school environments play in appraisals of menstruation as a major life stressor and the impacts of emotional stress on missing school. Using primary survey data from schools in both the Terai and Hill areas of Nepal, conditional mixed-process (CMP) estimation with fixed effects, utilizing multiple index building techniques, including principle component and multiple correspondence analysis were performed. Robust results are found in support of the theoretical framework, showing that strong cultural norms during menstruation increase the probability of girls self-reporting as feeling lonely, while presence of hygiene supporting infrastructure at schools reduces this outcome. Furthermore, there is strong support for the hypothesis that the presence of emotional stress during menstruation increases the likelihood of not only missing school, but for a longer period of time.

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CHAPTER 1
Introduction

The consequences of mental health illnesses are now being better recognized, globally. Those with major depression and schizophrenia have a 40-60% greater chance of dying prematurely than the general population, in part because depression predisposes people to heart disease and diabetes, which both conversely increase the likelihood of depression (negative reinforcing cycle) (WHO, 2013). Economically, the cumulative global impact of mental disorders in terms of lost economic output will be approximately US$16.3 trillion between 2011 and 2030, with half of that among low-and-middle income countries (LMICs) (World Economic Forum, the Harvard School of Public Health, 2011). Furthermore, the cost of illness (COI) for mental health is expected to reach $6 trillion by 2030, double the figure in 2010.

Yet attention to this growing concern is lacking in LMICs, with 76-85% of people with severe mental disorders receiving no treatment in LMICs (vs. 35-50% in high-income countries). Annual spending in LMICs ranges from $0.25-$2/person (World Health Organization, 2015), with 67% of this going to mental hospitals (instead of prevention interventions through community-based services). Additionally, among WHO Member States, 68% have a stand-alone policy/plan for mental health, and only 51% have a stand-alone law (World Health Organization, 2015). Plus, almost half of the world population lives in countries with an average of 1 psychiatrist for 200,000 people (WHO, 2013).

Evidence is also growing that health-related behaviors and conditions that underlie major noncommunicable disease often start or are reinforced during ages 10-20, including data showing that half of all lifetime mental disorders appear to start by age 14 (Kessler et al., 2009). Evidence also shows that depression suffered in adolescence is associated with depression recurrence, high severity of symptoms, migraines, poor self-rated health, and low levels of social support up to ten years later (Naicker et al., 2013; Patton et al., 2014). Even depression symptoms below the level required to be diagnosed with "major depressive disorder" have been found to cause impaired functioning in social and family circles and increased suicide among adolescents (Carrellas et al., 2017). The top cause of YLDs (years lost to disability) for both 10-14 and 15-19 year olds is unipolar depressive disorder (WHO, 2014). Globally, suicide ranks number three among leading causes of death for all adolescents, and yet, only 1/4 of national health policy documents from 109 countries address adolescent mental health. While female adolescent deaths due to complications of pregnancy and childbirth have dropped significantly since 2000, the leading cause of death for 15-19 year olds is still suicide. There is evidence that depression, in girls, rises notably after puberty, and that by the end of adolescence, the one year prevalence rate exceeds 4% (Thapar et al., 2012).

Despite mental health disorders often arising in early adolescence, they still go underreported, particularly in the developing world, due to lack of access to services/treatment and large social stigma attached to mental health issues. Within LMICs, suicide rates average around 15%, but suicide attempts are often not monitored, except in such global surveys as the CDC's Global Student Health Survey (GSHS) (CDC & WHO, n.d.). Regionally, Africa and Southeast Asia (SEA) report the highest levels of adolescent deaths. One-sixth of adolescent deaths among females in SEA is due to suicide. In terms of disability adjusted life years (DALYs), SEA still has the highest rate of self-harm mortality (WHO, 2012).

Further examination of the regional mental health struggles in SEA paint an even darker picture. One-fifth of the world's adolescent population lives in this region, meaning that mental health and substance use disorders in SEA, the second most common cause of mortality among youth aged 15-29, after traffic fatalities, account for more than 6% of the global burden of disease (WHO-SEARO, 2017). Yet, as seen elsewhere in resource poor regions, attention to mental health is quite low. WHOs Mental Health Atlas (2015) reported that in the SEA region 40% of nations have no mental health data compiled in the prior 2 years, and of the 80% of respondents that claim they have a stand-alone mental health policy/plan, only 30% have updated it since 2010. None of the respondents claimed to have a mental health law that is available and fully implemented. Additionally, this region scored the lowest in terms of compliance of mental health legislation with human rights instruments, and the mental health workforce is only 4.8/100,000 population (only WHOs African region is smaller). Thus, it is not surprising to find that LMICs in SEA have the highest rates of suicide across all LMICs globally. Suicides in SEA represented 39.1% of 2012 reported global suicides, despite the region representing only 25.9% of global population (Saxena et al., 2014). The burden is even higher among females, where over 85% of female violent deaths in SEA are due to suicide, compared to 70% for males, with the peak age averaging around only 20 years old.

Nepal represents one of the most heavily suffering regions in SEA, in terms of adolescent mental health burdens, where 13-17 year olds represent 11.8% of the total population (United Nations, 2017). Regionally, Nepal had the highest rate for suicide considerations at 13.7% of the students who responded to the most recent wave of the Nepal GSHS (or an estimated adolescent suicide risk of 25.8/100,000) (WHO-SEARO, 2017). Females outpace males in terms of ideation and attempts, and anxiety disorders have also been found to be more prevalent among rural female populations than male, but existing efforts to provide social support appear to only positively impact the mental health of males (Kohrt & Worthman, 2009). In addition, 51% of students reported being bullied once or more in the last 30 days, with victims of bullying 3-5x more likely to report attempting suicide, 2-4x more likely to smoke, and 2-7x more likely to use alcohol or drugs (WHO-SEARO, 2017). Adolescence is the period during which many adverse outcomes in life arise, due in part to such risky behaviors. Gaining better control over the mental health of adolescents is becoming ever more critical to the future, particularly in LMICs like Nepal.

The importance of mental health awareness, generally, is growing, as evidenced by depression being the focus topic of 2017's World Health Day (WHO, 2017a). Entities such as the mhGAP Forum are leading the effort to achieve the objectives of the WHOs Mental Health Action Plan 2013-2030 (WHO, 2017b), including goals to have 90% of countries update their policies/plans for mental health, have 80% of countries possess at least two functioning national, multisectoral promotion and prevention programs, and reduce the rate of suicide by 10%, all by the year 2020 (WHO, 2013). However, many adolescents who participated in a recent World Health Organization (WHO) (2014) analysis on the status of adolescent health globally recognize that there is more to be done, listing mental health as the most important health issue for their generation and that they would like to see more attention and access to treatment/awareness. Among the 41% of WHO Member States that have over two functioning mental health promotion/prevention programs, only 9% of programs have been aimed at adolescents (World Health Organization, 2015). Adolescents have unique mental health challenges, and will play a pivotal role as drivers of change (WHO, 2016).

Thus, there is a prime opportunity to begin more in-depth analysis of the mental health of adolescents. Biological, cognitive, and psychosocial development processes during adolescence are fairly universal, but the timing and influence of them are individually affected and influenced by social/cultural environments. As of 2014, there were 1.8 billion people between the ages of 10 and 24, meaning that there are more individuals in this age bracket than at any other time in history (Population Fund, 2014). Nine out of ten of those in this age range live in LMICs, where in 17 of those countries, 50% of the population is under 18. By focusing on the developing world in future analyses, researchers can enhance the knowledge base with regard to the nature and impact of such influential factors. WHOs SEA regional director, Dr. Poonam Khetrapal Singh, is quoted as saying, “By addressing mental well-being of adolescents, eventually we have a better adjusted and productive adult workforce (WHO-SEARO, 2017),” and through improving and expanding the evidence base of information, such an outcome is possible.

CHAPTER 2

Diffusion of mHealth Innovations for Nepali Adolescents: An Exploration of Indirect Mental Costs and Cultural Context Considerations Based on Basic Psychological Needs Theory (BPNT)

Introduction

The economic future of the world will depend on the next generation. Current population estimates place 1.2 billion young people across the world under age 18, making up 16% of the world's population, with 90% of these adolescents living in the developing world (UNICEF 2019). The success of this upcoming generation will depend on their wellbeing trajectories. In the developing world, these trajectories are not promising (UN 2011; Patalay and Fitzsimons 2018). One of the hardest hit regions, globally, is South East Asia (SEA). According to work in collaboration between the World Health Organization and the Centers for Disease Control, 20-50% of young people in this region report being bullied and on average, 7.1% are using alcohol, 9.7% are smoking, 8.4% report being lonely most or all of the time, 6.9% report being so anxious they lose sleep, and 6.8%, on average, have admitted to seriously considering suicide within the prior year (WHO-SEARO 2017). Such behavioral and mental health/wellbeing concerns are only exacerbated by governments and healthcare systems which either do not acknowledge the need to address mental health in their populations, fail to address adolescents differently than younger children or adults, or both.

One often quoted possibility to aid in addressing the lack of attention, cost, and availability of healthcare professionals within developing world contexts is through mobile-based health initiatives (or mHealth) (Souraya, Canning, and Farmer 2018; Naslund et al. 2017). Mobile-based initiatives are believed to offer opportunities for achievements such as telepsychiatry opportunities (Luxton et al. 2011) and real-time emotional tracking (Reid et al. 2011; Silk et al. 2011). Such cost-effective approaches may seem especially relevant for use in adolescent populations due to their existing high use of mobile-based technologies (Pew Research Center 2018; E. Oh, Jorm, and Wright 2009; Rideout and Robb 2019). On the other hand, while use of mobile technology is prolific among adolescent populations, there is also evidence of lack of sufficient research to fully account for the effectiveness and potential consequences of pursuing mHealth initiatives, especially among adolescents (Grist, Porter, and Stallard 2017; Hollis et al. 2017; Rankin et al. 2016; Ippoliti and L'Engle 2017).

There is growing evidence of the negative mental health and wellbeing outcomes that can come from overuse/maladaptive uses of mobile/smartphones. In the developed world, cell phone use has been associated with higher anxiety, lower self-esteem, higher stress, more insomnia, and even alexithymia (difficulty in identifying /describing feelings and emotions) (Sohn et al. 2019; Stiglic and Viner 2019). Additionally, researchers have found addictive personality traits among heavy cell-phone users (e.g. high approval motivation and self-monitoring/peer comparison) (Ha et al. 2008; Hong, Chiu, and Huang 2012; Ko et al. 2007; Takao, Takahashi, and Kitamura 2009; Vernon, Modecki, and Barber 2018). Further, extensive cell phone use has been associated with lower life satisfaction, worse interpersonal relationships (including relational aggression), higher depression rates, worse attention-spans, and worse academic performance (Lepp, Barkley, and Karpinski 2014; Samaha and Hawi 2016; Tamura et al. 2017). Researchers often find even higher negative effects of cell phone use on females (Beranuy et al. 2009; Hong, Chiu, and Huang 2012; Pierce 2009; Roser et al. 2016; Sánchez-Martínez and Otero 2009; Walsh et al. 2011).

To date, there has been very limited work in the developing world regarding impacts on mental health and wellbeing from mobile phone/internet access. These initial findings appear consistent with those in developed world contexts. Much of that existing work from the developing world is focused in India, with basic statistics reporting higher anxiety, addiction, and reinforcement of emotionally burdensome gender norms (Davey and Davey 2014; Dixit et al. 2010; Doron 2012; Patel and Puri 2017). There is also qualitative evidence from Nepal of beliefs that access to mobile phones/internet increases adolescent desire for sexual relations, thus stimulating self-directed childhood marriage (Maharjan et al. 2012), a common problem in this region. When synthesized, the implication of existing research on mobile phone and wellbeing outcomes present a very bleak picture for adolescent wellbeing if mobile phones are seen as the "solution" to an already suffering population.

When examined with empirical rigor, though, this outlook may not be so bleak. There is other published work indicating that it is only those adolescents most prone to suffer from behavioral, mental, and emotional struggles who are going to be drawn to overuse mobile phones. Existing empirical work which has sought to untangle the directionality of such relationships is fraught with a lack of clarity. Part of this may stem from a lack of focus on why adolescents may be turning to mobile phones, and any connection that this may have to any eventual over/maladaptive use. Better understanding emerges from incorporating theoretical frameworks from fields such as Positive Psychology and Sociology, while analyzing data with the empirical rigor associated with such fields as Economics. In that vein, this work uses primary data from secondary school students in urban and rural Nepal to assess the connections between life burdens, mobile phone overuse/maladaptive use, and overall wellbeing of adolescents, estimating a full structural model based on the assumptions of the theory of Basic Psychological Needs.

In the following sections, background information to place this research in the context of the study population and prior empirical work on the associations between mobile phones and wellbeing is presented. This is followed by descriptions of the empirical model, including elaboration on the conceptual framework underlying this research, and how our work expands upon it. After detailing the data, variables, estimation strategy, and results of estimation, our final section includes interpretation of our findings, limitations of the work, and concluding thoughts accompanied by policy recommendations and considerations.

Background

Research Context: Nepal

Nepal is not only one of the poorest, but also one of the neediest regions in terms of addressing adolescent wellbeing. In Nepal, 11.8% of the population is estimated to be between 13-17 (WHO-SEARO 2017), and in a large representative survey of high school students, it was found that over 50% of adolescents report being bullied, making this the highest rate in the SEA region (WHO-SEARO 2017). Additional burdens adolescents, and in particular females, face in this country include high levels of gender-based violence and inequity (e.g. domestic violence, menstrual taboos, child marriage), which have damaging mental and physical health consequences (Adhikari et al. 2016; Amin et al. 2014; LaSaine 2015; Maharjan et al. 2012; Oster and Thornton 2011; Rai et al. 2017; WaterAid 2009; Watson and Harper 2016; Ghimire et al. 2015), including links to substance abuse and tobacco use (Karki et al. 2016). Such struggles are only exacerbated by a healthcare treatment system that faces infrastructure and treatment malfunction, with limited access to mental health care. According to the Human Development Report (2016), Nepal only has 2.1 physicians per 10,000 people (the United States has 24.5). Plus, there are high levels of stigma surrounding mental health problems, resulting in such outcomes as high initial use of faith healers instead of psychiatric providers (Luitel et al. 2015).

One of the striking outcomes of the cumulative effect of these burdens in that Nepal has an adolescent suicide rate that is second only to India in the SEA Region. A recent WHO Report (2017) found 14% of surveyed adolescents thought about and planned suicide and 10% actually attempted suicide within the prior 12 months. Another study found over 50% of female suicide deaths, evaluated via psychological autopsies, were committed by those under 25 years old (Hagaman et al. 2017). Such risks also appear to continue on into adulthood. The Human Development Report (2016) reveals that Nepal has one of the top 5 overall rates of suicide for women, globally, and among the top 10 highest rates for men. The need is real for interventions aimed at both reducing the wellbeing-damaging burdens and providing treatment/support for the negative outcomes, particularly among adolescent populations.

Unfortunately, most of the existing research and actual interventions addressing these areas in Nepal has primarily focused on the plight of former child soldiers and conflict-displaced youth (Kamrudin 2009; Luitel et al. 2013; Thapa and Hauff 2005; Tol et al. 2007). Furthermore, the use of mHealth interventions, while growing, is still in its infancy in Nepal. Thus far, they have primarily focused on more standard eHealth uses such as telehealth (dermatology) (Shrestha et al. 2016), real-time tracking/reporting by community health workers (CHWs) (Meyers et al. 2016), and Rapid Convenience Monitoring of unvaccinated children (D. H. Oh et al. 2016). At the same time, cell phone/smartphone adoption is growing rapidly in Nepal. A 2014 study found that between 70-90% of households, depending on region, have mobile phones (Amin et al. 2014). The World Bank (2017) also reports that mobile-cellular telephone subscriptions per 100 people in Nepal jumped from 34.4 to 96.7% between 2010 and 2015, and up to 60% among the lowest-income group. Prior research completed by authors of this work found that among the 58% of surveyed girls who owned cell phones, only 14% report owning just a basic phone (Yilmaz 2017). This implies that when phones are adopted by the younger generation, they are adopting smartphones, which carry the highest potential benefits, while also potentially placing youth at the greatest risk of additional poor wellbeing consequences from overuse/maladaptive use.

Prior Literature on Mobile Phones & Negative Wellbeing

With the growth in development, innovation, and adoption of mobile phone technology, in particular smartphones, there is also a growth in research surrounding the consequences of its overuse. There is an established literature examining the associations between cell phone (over)use and certain health and mental health outcomes. Along with findings supporting that high mobile phone use is linked with lost sleep (Elhai et al. 2017; Reid Chassiakos et al. 2016; Tamura et al. 2017; Vernon, Modecki, and Barber 2018; Thomée, Härenstam, and Hagberg 2011), there is consistent evidence of anxiety, stress, and depression being higher among heavy mobile phone users (J.-H. Kim, Seo, and David 2015; van Deursen et al. 2015; Billieux, Van der Linden, and Rochat 2008; Hong, Chiu, and Huang 2012; Lu et al. 2014; Lemola et al. 2015; Gao et al. 2018; Seo et al. 2016; Harwood et al. 2014). The empirical limitation in analyses of this type is that direction of causality has yet to be well established.

While there is work that has focused on theoretical explanations of the motivation for mobile phone use, such work is not supported with empirical validation. Billieax (2008) posits that problematic mobile phone use (PMPU) can develop out of three potential paths: Excessive Reassurance, Impulsive-Antisocial, and Extraversion. The first pathway claims that PMPU is driven by a necessity to maintain relationships and obtain reassurance. The Impulsive-Antisocial pathway would say PMPU is driven by poor impulse control resulting in deregulated use (much like gambling). The Extraversion pathway towards PMPU is driven by strong and constant desire to communicate and establish new relationships, and can be linked to a strong need for stimulation and high sensitivity to rewards. This model would be consistent with initially anxious or depressed people engaging in extensive mobile phone usage to meet various needs. However, among empirical researchers, the general assumption is that cell phone use is the predecessor of negative mental health/wellbeing.

Three key studies have used longitudinal approaches in trying to determine the direction of this relationship. Lu (2014) found that text messaging dependency is temporally stable, based on surveying new/freshman university students in Japan at a 5-month interval using the three subscales (Emotional Reaction, Excessive Use, and Relationship Maintenance) of the Self-Perception of Text-Messaging Dependency Scale. Cluster analysis found that excessive users had high excessive use scores, but dependent users had high emotional reaction and relationship maintenance scores. Further, dependent users were found to have higher depression and anxiety. The authors, however, did not compare the depression/anxiety outcomes at time 1 to those at time 2.

Other researchers have had a cleaner examination of causality, through a one-year long study of young adults (20-23) in Sweden (Thomée, Härenstam, and Hagberg 2011). In examining the relationship between phone use and stress, depression symptoms and sleep disturbances, researchers calculated prevalence ratios for both cross-sectional and prospective associations using a Cox proportional hazard model. Cross-sectionally, they found results consistent with prior literature that there were strong associations between high use of phones and the three outcome variables. Prospectively, by excluding those surveyed who had negative mental health symptoms at baseline, researchers found that high phone use was associated with sleep disturbances (men) and depression (men and women). However, phone use data was only collected at baseline, leaving it unclear if such patterns changed at the follow-up.

The final study of interest which most cleanly examines the causality issue is work based on three years of data from the Korean Children and Youth Panel Survey (2011-2013). This study explored the stability and direction of changes in cell phone overuse (i.e. addiction) and depression symptoms across time for adolescents (Jun 2016). The authors used autoregressive cross-lagged modeling to test hypotheses that earlier age depression positively affects addiction later on, and that earlier age addiction positively affects depression later on. The results supported these hypotheses, indicating increasing severity of both addiction and depression symptoms over time, as well as evidence of bi-directionality.

Such bi-directionality is supported in other work. A study by Ko (2009) found through a two-year follow-up study that existing depression symptoms were significant predictors of later Internet addiction among Taiwanese high-school students, based on Cox proportional hazard regressions. Additionally, laboratory experiments in the United States have shown that mere separation of research participants from smartphones increases their anxiety (Cheever et al. 2014) and increases blood pressure/heart rate (Clayton, Leshner, and Almond 2015).

Thus, there is some pathway by which cell phone use is affecting mental health/wellbeing. It appears, however, that the interaction is likely cyclical: problem smartphone use drives poor wellbeing, and these ills drive further problematic use (or vice versa) (van den Eijnden et al. 2008; Yen et al. 2012).

Such a conclusion is consistent with work looking at loneliness and internet compulsion/addiction, based on path models. That study determined that individuals who were lonely or did not have good social skills developed strong compulsive internet use behavior, and this behavior led to further negative impacts on life (J. Kim, LaRose, and Peng 2009).

The bi-directional "Internet Paradox" (van den Eijnden et al. 2008) found with traditional internet-access mediums is spilling over into mobile phone use as smartphones penetrate society. The rich are getting richer (or in this case, the depressed are getting more depressed, due to their over-use of mobile phones).

To summarize existing literature, the work examining cell phone (over)use and negative mental health/wellbeing outcomes is almost entirely correlational (and based in the developed world), with authors often acknowledging their lack of ability to speak to causation. Longitudinal work seems to best support a bi-directional relationship. Those with mental health struggles are drawn to overuse of mobile phones, while those who use mobile phones extensively appear to develop more negative mental health outcomes (sometimes irrespective of their initial mental health state).

The authors of this work set out to examine the tension between mobile phone/smart phone usage as a true mHealth opportunity in Nepal and its potential for introducing deleterious effects on wellbeing from over-use of mobile phones. This work seeks to bring the literature forward with respect to further clarity about the relationships between mobile phone use and wellbeing, as well as motivational elements that partially explain the findings already seen. Further, given that the research into this wellbeing-cell phone relation is primarily found in disciplines outside of Economics, we seek to bring it front and center to that discipline. The impacts of technology on health deserve to be analyzed with the empirical rigor associated with Economics, given that the impacts of health on micro and macro-level economic problems is becoming ever more apparent. Therefore, by using robust empirical techniques we are able to provide additional validity to the conclusions and policy recommendations we make.

The Model: Framework, Specification, & Hypotheses

Conceptual Framework

Determination of what motivates behavior is among the most central of all social science questions. Within sociology, the fulfillment of personal goals and needs based on social contexts has often served as the jumping-off point to answer this question. Within the study of Self-Determination Theory (SDT), there is a sub-theory called Basic Psychological Needs Theory (BPNT), which claims that satisfaction and/or frustration of the three needs of autonomy, competence, and relatedness serve as strong motivating factors in many behavioral relationships (R. Ryan M. and Deci 2000), many of which have wellbeing outcomes (Zhang et al. 2018; Gui, Kono, and Walker 2019).

As shown in Figure 2.1, low need satisfaction over time can result in costs, but this deterioration process will be exacerbated when needs are actively "frustrated" (or thwarted). When needs are frustrated, there are two consequences. Firstly, there are the immediate costs of reduced well-being. Secondly, chronic need-thwarting can result in development of coping strategies which include searching for "Need Substitutes" and compensatory behaviors. However, most evidence from literature indicates that coping strategies may ultimately be short-lived in producing feelings of need satisfaction, and can lead to (or include) further negative outcomes such as anxiety and substance abuse.

[FIGURE 2.1]

We believe the relationship between problematic mobile phone use and wellbeing outcomes may follow this theoretical pathway, as shown in Figure 2.2. The social/cultural context adolescents face will include both protective and adverse environments and pressures which either meet or frustrate the set of three basic needs. When needs are frustrated, BPNT would indicate the potential for adolescents to seek out remedies to alleviate their sense of loss. We postulate that mobile phones may be seen as such a tool. Human action can be driven to fulfill certain needs, and addictive tendencies/compulsive behaviors can develop when such needs become strong and frequent (Robinson and Berridge 2003). Use of technology that (attempts) to fulfill psychological voids may be more prone to addiction (Masur et al. 2014; Young, Yue, and Ying 2011), which has its own associated links to poor mental health and wellbeing outcomes. Thus, if mobile phones are a medium through which the types of coping strategies BPNT mentions are facilitated, then they have the potential to exacerbate existing states of negative wellbeing. This correlates with existing literature in terms of the negative wellbeing impacts of intense mobile phone use.

[FIGURE 2.2]

Empirical Specification

In accordance with the framework and pathways indicated above, the empirical specification used to measure such relationships is as follows:

$$A_i = \alpha_0 + \alpha_1 PMPU_i + \alpha_2 B_i + \alpha_3 AP_i^* + \alpha_4 FE_i^* + \alpha_5 SS_i^* + \alpha_6 X_{1i} + \alpha_7 X_{2i} + \alpha_8 X_{3i} + u_{1i} \tag{1}$$

$$G_i = \beta_0 + \beta_1 PMPU_i + \beta_2 B_i + \beta_3 AP_i^* + \beta_4 FE_i^* + \beta_5 SS_i^* + \beta_6 X_{1i} + \beta_7 X_{2i} + \beta_8 X_{3i} + u_{2i} \tag{2}$$

$$PMPU_i = \lambda_0 + \lambda_1 B_i + \lambda_2 AP_i^* + \lambda_3 FE_i^* + \lambda_4 SS_i^* + \lambda_5 PC_i + \lambda_6 PC2_i + \lambda_7 FPMPU_i + \lambda_8 X_{1i} + \lambda_9 X_{2i} + \lambda_{10} X_{3i} + u_{3i} \tag{3}$$

Here, the variables A_i and G_i represent two wellbeing outcome measures for individual i, namely those of anxiety and grit[1], respectively. $PMPU_i$ is a measure of mobile phone overuse/maladaptive use, and B_i represents our key need-thwarting factor of bullying experiences. The remaining socio-cultural environmental pressures we consider/control for are academic pressure (AP_i^*), family environment (FE_i^*), and social

[1] Anxiety is a measure of feelings of worry, nervousness, or unease, typically about an imminent event or something with an uncertain outcome., and is a typical measure of negative wellbeing, which hinders a multitude of long-term successes (Knapp et al. 2016; 2011; Snell et al. 2013). Grit, on the other hand, is a measure of perseverance and passion for achieving long-term goals, which serves as a useful measure of positive wellbeing potential and ability to succeed in life. Grittier people have been shown to have greater educational attainment/ achievement, entrepreneurial potential and earnings (Beyhan 2016; Mendolia and Walker 2014; Gerhards and Gravert 2015; Mooradian et al. 2016; B. A. Mueller, Wolfe, and Syed 2017; Butz et al. 2018; Wolfe and Patel 2016).

support (SS_i^*), all latent (i.e. unobservable, or not directly measurable) constructs. In equation (3), PC_i is the monetary cost of individual i's mobile phone, with $PC2_i$ its square. Friend's problematic mobile phone use is represented by $FPMPU_i$. Demographic controls for being female, age, and coming from a rural area are accounted for by X_{1i}-X_{3i}, respectively. White noise error terms for each equation are denoted by u_i with the appropriate equation referenced in subscript.

Hypotheses

The presence and intensity of bullying, often found within the school environment, can be staggering and have dramatic impacts on mental/physical health (Patton et al. 2008; Rudatsikira et al. 2007; Abdirahman et al. 2012; Lila C. Fleming and Jacobsen 2009; L. C. Fleming and Jacobsen 2010; McKinnon et al. 2016; Shapka et al. 2018). Such outcomes have previously been analyzed through a lens of need satisfaction. Tian (2016) examined the mediating role of basic psychological need satisfaction in the relationship between school-related support and subjective well-being at school among Chinese adolescents, and found partial mediation of the three needs in relation to teacher support and full mediation for classmate support's impact on subjective wellbeing.

Orkibi and Ronen's (2017) work with Israeli adolescents found that both boys and girls with high self-control skills perceive themselves as having greater need satisfaction in school and that this leads to higher school-related subjective wellbeing (e.g. satisfaction and affective states). Expanding the analysis to consider impacts within sports/athletics fields, Bartholomew (2011) determined that need satisfaction was predicted by perceptions of autonomy support from a coach, while need thwarting was predicted by a controlling coach. Need satisfaction, in turn, predicted vitality and positive affect (sport participation), while need thwarting predicted maladaptive outcomes including depression, negative affect, and physical symptoms including associations with elevated levels of secretory immunoglobin A, a hormone triggered during acute psychological stress. Given such evidence, we formally hypothesize:

Hypothesis #1: *Those adolescents who experience more bullying will have worse wellbeing outcomes – higher anxiety (A) and lower grit (G).*

There is also a growing literature examining the associations between need satisfaction and digital technology use, given that people's intrinsic motivation for sustained engagement in any media entertainment will be a function of the need satisfaction it affords. In analyzing the relationship between symptoms of internet gaming disorder (IGD) and basic need satisfaction in-game and in real life, researchers determined that satisfaction and frustration of basic psychological needs in real-life and in video games reliably predicts IGD and well-being (Allen and Anderson 2018). Similar research using hierarchical regression modeling found that need satisfaction in real-life was associated with lower levels of IGD, and high levels of need satisfaction in-game was associated with higher levels of IGD (Bender and Gentile 2019). Further, these same researchers found basic need satisfaction in life in general did not moderate the effects of need satisfaction in-game on IGD symptoms.

Beyond gaming, one study has brought BPNT into the realm of mobile phones through investigating the motivational, personality and psychological needs background of problematic Tinder dating app users (Orosz et al. 2018). This study used structural equation modeling (SEM) to determine that relatedness frustration was the strongest predictor of a self-esteem enhancement motivation for Tinder use, which in turn, was the strongest predictor of problematic Tinder use.

Beyond this Tinder study, empirical examination of mobile phones and how their use is related to BPNT is almost non-existent. However, qualitative work such as that done in South Africa by Lamont (2017) has shown that the needs cell-phones meet such as personal safety, sense of control, managing daily routines, and staying connected with love ones are consistent with the propositions of BPNT. Further, there are arguments for the need satisfying potentials of entertainment media (accessible via mobile phones), which would be likely to draw adolescents to their use (Sheldon, Abad, and Hinsch 2011; Calvo and Peters 2014; Reinecke and Oliver 2017). Drawing from this research, we formally hypothesize that:

Hypothesis #2: *Those adolescents who experience more bullying (B) will have more problematic mobile phone use (PMPU).*

The evidence base from literature would seem to indicate support for the idea that those adolescents with a higher need thwarting socio-cultural environment, such as would be expected under intense bullying pressures, would have poorer negative wellbeing outcomes. Additionally, they would be expected to also have more problematic use of digital technology such as mobile phones, given evidence that dependency in adolescents is associated with psychological need frustration (Vandenkerckhove et al. 2019), and stress is a predisposing factor for smartphone addiction (K.-S. Cho and Lee 2017; H. Cho, Kim, and Park 2017). Similarly, there is evidence that university-level students who have unsolved life problems appear to be drawn to excessive smartphone use (Shen and Wang 2019). Prior literature has brought up a “needs-as-motive” hypothesis among young adults, wherein the trio of needs not only sustains wellbeing, but also motivates remedial behavior when missing (Sheldon and Gunz 2009; Machell, Goodman, and Kashdan 2015). However, maladaptive use of the mobile phones would be expected to exacerbate poor wellbeing outcomes, given strong evidence that coping strategies may ultimately be short-lived in producing feelings of need satisfaction, and lead to (or include) further negative outcomes such as anxiety and substance abuse (R. Ryan M. and Deci 2000; Deci and Vansteenkiste 2004; Rigby and Ryan 2017). Formally, this would imply:

Hypothesis #3: *There will be a significant indirect effect of bullying (B) on wellbeing outcomes (A and G), acting through problematic mobile phone use (PMPU).*

Finally, with the use of two measures of wellbeing, namely anxiety (*A*) and grit (*G*), it is also important to establish any potential relationship to be had between them. Within the small literature which has previously linked the two measures of anxiety and grit, the associated relationship has been consistently negative (Sharkey et al. 2018; Tuckwiller and Dardick 2018; Jin and Kim 2017; Jiang et al. 2019). Such findings have been indicated within the developing world context of SEA, as well, (Musumari et al. 2018; Lan, Ma, and Radin 2019; Datu, Valdez, and King 2016), despite the limited wellbeing research within developing world contexts. Given such findings, we formally hypothesize:

Hypothesis #4: *There will be a negative correlation between the wellbeing outcomes of anxiety (A) and grit (G).*

Data & Variables

Data

Data for this survey comes from a self-report survey administered to adolescents in secondary schools in the urban city of Siddharthanagar and surrounding areas of Pulpa, Gulma, and Argankhachi, in southwestern Nepal. This relatively large city has four other cities within one or two hours of driving distance (Butwal and Tansen in the north, Dang in the west, Chitwan in the east), and it is also a gateway city to an important tourist destination, Lumbini, the birthplace of Buddha and a world heritage site. The area boasts two medical schools, one eye hospital, one agriculture college, an engineering college, one science college, and several two- to four-year colleges, allowing access to older adolescent populations (over age 15). Consequently, this area provides a reasonable picture of an active urban area (outside Kathmandu) where technology development is expected to be relatively high, meaning mobile phone and particularly smartphone, ownership rates would be expected to be relatively high. The easy access to rural localities nearby offered additional opportunities to compare research outcomes across urban and rural areas, where the geographic diversity in the region contributes to trapping of local cultures within areas as small as 20 miles across.

Implementation of the survey was done through the support of adult enumerators. Enumerators were selected through personal interviews and were given training to ensure that all the enumerators were uniform in their understanding of the questions and in their language while communicating with students. While enumerators were allowed to answer questions if adolescents had concerns regarding any elements of the survey, as per the protocol, adolescents completed the survey in an “exam-style” set-up so that there was physical space between survey participants. We did not want participants to converse or interact with one another while completing the survey.

The survey administered was designed at the Nepal Study Center (Department of Economics, UNM) in English and was later translated into Nepali by the enumerators, following approval from the institutional review board (IRB) of the University of New Mexico, USA. A thorough literature review on the issues relevant to this study, including adolescent mental health, mobile phone correlates with mental health, adolescent development, mobile phone penetration, and mobile-based health interventions was conducted before drafting of the questionnaire. An exploratory assessment was conducted through a focus group survey of 66 individuals from multiple stakeholder groups relevant to the research (adolescents, mothers, health professionals, and school administrators) in Rupandehi district prior to this study. Information about the state of mental health knowledge/awareness, current mobile phone practices/uses of mobile phones, and insight into those cultural/developmental burdens seen as most detrimental to the wellbeing of adolescents in the region was used to inform the development of this survey. While the total number of adolescents surveyed included both mobile phone owners and non-owners, the aim of this work required we limit our estimation sample for this research to those respondents who said yes to owning a phone. This resulted in a full estimable sample size of 539 adolescents.

Key Variables

To capture two facets of wellbeing, we used two previously validated survey instruments to capture anxiety and grit levels. Anxiety (*A)* is measured based on a modified version of the Beck Anxiety Inventory (Beck et al. 1988), which assesses the extent of certain anxiety-related symptoms such as dizziness, numbness, and breathing difficulties over the last few weeks. Previous validation within a Nepali context (B.A. Kohrt et al. 2003) indicate this instrument has a specificity and sensitivity around 0.90 (actual negatives and actual positives, respectively). Based on the recommendations from that validation, we adjusted the inclusion of certain symptoms from the original instrument to be more culturally relevant and sensitive, resulting in a final (continuous) measure composed of the sum of seventeen, 4-point scale items, where a higher score indicates poorer wellbeing. Summary statistics of this and all other variables can be found in Table 2.1.

[TABLE 2.1]

To measure grit (*G),* we used the Duckworth Grit Scale (A. Duckworth 2016), which assesses one's level of passion and perseverance towards maintaining a long-term goal (internal consistency around 0.80). While not a traditional measure of positive wellbeing, there is evidence which supports the use of grit as a proxy for positive wellbeing (Wong et al. 2018; Salles, Cohen, and Mueller 2014; Sharkey et al. 2018; Kannangara et al. 2018), including among adolescent/young adult populations (Vainio and Daukantaitė 2016; Hill, Burrow, and Bronk 2016). The sum of ten, 5-point Likert-scale items is divided by five to obtain the final (continuous) measure used in estimation, where a higher score indicates more grit.

Operationalization of problematic mobile phone use was accomplished through the use of Bianchi and Phillip's (2005) Problematic Mobile Phone Use survey. This 27 item, 5-point Likert-scale instrument assesses dimensions of problematic phone use. It has been validated in terms of internal reliability (0.93) and validity in capturing the addictive tendencies associated with maladaptive use. The final (continuous) measure used in estimation is the sum of the 27 items, where a higher score is indicative of more (problematic) use by the respondent of his/her mobile phone.

To allow for proper identification of our empirical model, we also include the use of three variables which are believed to influence respondent's PMPU, but would not influence the wellbeing outcomes directly. In traditional econometric approaches, these would be deemed the "instrumental variables". Phone cost (*PC)* is the cost of the respondent's mobile phone in thousands of Nepali rupees (NR), ascertained from an opened ended question. *PC2* is simply the square of this measure. Friend's problematic mobile phone use *(FPMPU)* is a modified version of Bianchi and Phillips' (2005) survey instrument, rephrasing six of the survey questions to reflect respondent's perceptions of their closest friend's interactions with his/her mobile phone. Summation of these six, 5-point Likert-scale questions produces the continuous measure used in estimation.

Prior statistics from international data in Nepal found that around 51% of adolescents have been bullied within the prior month (WHO/CDC 2015), making this one of the most important adverse pressures Nepali youth face. Thus, we chose bullying as the key representative of a need thwarting environment. This variable (*B)* is the summation of three binary indicators for having been bullied in the prior month outside of school, inside of school, and having been physically hurt by someone at school. Framing and use of these measures is consistent with large-scale national and international work examining adolescent life to determine overall wellbeing (e.g., WHO/CDC 2015; Inchley et al. 2016).

While bullying is clearly indicated as a potential problem among Nepali youth (WHO/CDC 2015), we also acknowledge the existence of other socio-cultural environments in adolescent lives which are likely to also influence wellbeing outcomes. Adolescent health is strongly affected by social factors (Viner et al. 2012). Negative interactions/influences from family have been shown to increase the likelihood of risky behaviors (Donovan 2004; Repetti, Taylor, and Seeman 2002; Williams et al. 2000; Bauman, Carver, and Gleiter 2001; Kretman et al. 2009; Overbeek et al. 2003) and poor mental health/ impaired development (Wang and Sheikh-Khalil 2014; Hasumi et al. 2012; Barber et al. 2005; Soenens and Vansteenkiste 2010; Chhabra and Sodhi 2012). Additionally, pressure from the school environment has the potential to greatly influence adolescent mental health, given that it represents such a large portion of an adolescent's time (assuming that they are enrolled in school and have not already dropped-out) (Miller, Esposito-Smythers, and Leichtweis 2015; Winfree and Jiang 2010; Deb, Strodl, and Sun 2015). Furthermore, there is also strong evidence that there can be buffering of stressful situations from strong social support (Cohen and Wills 1985; Miller, Esposito-Smythers, and Leichtweis 2015; Christian and Stoney 2006; Berkman and Glass 2000; McFarlane, Bellissimo, and Norman 1995; Brandon A. Kohrt and Worthman 2009). We control for these elements with three latent variables representing social support *(SS*)*, pressures within the family environment *(FE*)*, and pressures related to the academic environment *(AP*)*, such as achievement and competition. Six related variables are used to measure *SS**, and four each for the other two latent variables. Survey framing and consideration of such issues is again supported by international surveys/work examining adolescent wellbeing (such as Amin et al. 2014; Kann et al. 2018). Additional details on these constructs and all other variables can be found in Table 2.2, and descriptive statistics according to gender-grouping are presented in Appendix 1.

[TABLE 2.2]

Estimation Strategy

While a reduced form system of equations may be a natural way to illustrate the model and causal channels laid out in equations (1)-(3) above, doing so will likely mask the underlying channels and complexities that are central to our narrative. The presence of three latent structures which play important controlling roles in our structural model requires a different estimation strategy which allows for the flexibility to appropriately account for the measurement error associated with these constructs. SEM was thus chosen as the primary estimation strategy for this work. As a methodology for representing, estimating, and testing a network of relationships between variables (Hoyle 1995), SEM is often used to assess topics such as health issues, family/peer dynamics, self-efficacy, depression, and psychotherapy because of its highly flexible nature (such as, MacCallum and Austin 2000; Curran, Stice, and Chassin 1997; Duncan et al. 1997).

Through maximum likelihood estimation, with iterative computation, SEM allows us to combine measurement models, which involve the relationships between observed (i.e. exogenous) measurements and latent, or unobserved variables, with path analysis models that relate variables to their causal factors. This stems from the unique assumption with SEM that we can actually model the measurement error (as opposed to the traditional statistical approach of assuming no error). SEM also eliminates problems with multicollinearity, because multiple measures are required to describe a latent construct. Use of multiple indicators for one latent construct also reduces the random error which attenuates regression coefficients towards zero. Further, each unobserved variable is set to represent a distinct latent construct. Finally, use of SEM allows one to specify the appropriate variance-covariance structure for the system of equations based on prior knowledge and assumptions. This is not trivial, given that in SEM you analyze the variance-covariance matrix of the observed variables (not the raw data). One can also incorporate into the model allowances for (or constraining to zero) covariances between specific variables. In straight forward terms, the goal in SEM is to summarize this variance-covariance matrix and compare the estimated/implied variance-covariance matrix from the proposed structural model to the observed matrix from the data to explain as much of the variance as possible (Kline 2016).

With these capabilities in mind, our structural model is enhanced with the addition of three additional sets of equations which make up the measurement model to represent our three latent variables. Within each equation, j is the number of measurement variables associated with each latent construct.

$$AP_{ji} = \Theta_0 + \Theta_{j1} AP_i^* + u_{4j} \qquad \forall j = 1, \dots, 4 \qquad (4)$$

$$FE_{ji} = \Upsilon_0 + \Upsilon_{j1} FE_i^* + u_{5j} \qquad \forall j = 1, \dots, 4 \qquad (5)$$

$$SS_{ji} = \delta_0 + \delta_{j1} SS_i^* + u_{6j} \qquad \forall j = 1, \dots, 6 \qquad (6)$$

With the entire system of equations now specified, we undertook two estimation methods within a SEM framework: linear probability and generalized linear approaches. The key difference between these two approaches, as pertains to our work, is the treatment of the measurement components for our latent constructs. Likert-scale survey items are often treated as interval; however, it is often more accurate to treat them as ordinal[2]. Given this, we chose to use two methods in analyzing our model, since a generalized linear approach can be used under scenarios where the estimation involves non-continuous variables which cannot be estimated under the typical assumptions of linear regression (e.g. binary, ordinal, multinomial) (Kline 2016; Hoyle 1995) [3]. Under both approaches, however, we assume block-independence between the structural (equations (1)-(3)) and the measurement (equations (4)-(6)) systems. Additionally, we note that the parameter estimate of the respective latent variable's impact on the first measured indicator for each latent variable (e.g. SS_{1i}, FE_{1i}, AP_{1i}) is normalized to 1 so that the magnitude of the latent constructs can be pegged against that measure.[4]

With the potential for simultaneity between *PMPU* and the wellbeing outcomes (particularly *A)* as implied by literature, and in the absence of over-identification testing typically associated with traditional regression techniques, we explored the strength of the model by adjusting the assumptions made with regard to covariances between key observed variables. Under both approaches, we used three different covariance and model specification structures for the exogenous/observed variables, results of which are presented in Tables 2.3 and 2.4. Our full model only specified covariances be estimated between *A* and *G, PMPU* and *A,* and *PMPU* and *G,* with no demographic controls

[2] The difference from an answer of "Strongly Agree" to "Agree" (coded as 1 and 2) is not treated as equivalent to that of between "Agree" and "Neutral" (coded as 2 and 3) in an intuitive sense under an ordinal treatment.

[3] Through SEM based on a generalized linear model, the estimation is essentially a generalization of nonlinear least squares, where the likelihood is derived under the assumption that each observed variable is independent and identically distributed (*iid*) across the estimation sample and observed variables are also assumed to be independent of each other. These assumptions are conditional on the latent variables and observed exogenous variables. This is opposed to estimation with a linear probability treatment of the observed measures, where the likelihood is derived based on the means, variances, and covariances of the observed exogenous variables (not conditional upon). Additionally, estimation based on the generalized linear model removes any assumptions of normality of the observed exogenous variables, and instead uses a link function such as logit for distributional families such as ordinal or Bernoulli.

[4] This is a standard practice within SEM to allow for a standardized solution, and to get a usable metric on which to measure a latent variable (Hoyle 1995; Kline 2011).

included in the equation for *PMPU.* The second structure constrained the covariance between *PMPU* and *A* and *SS** and *FE** to be zero, while maintaining no demographic controls in the equation for *PMPU*. The third model allowed for demographic controls in the *PMPU* equation. Goodness of fit diagnostics are reported for those results estimated under linear probability assumptions. (See Appendix 2 for details on the methods and formulas for these tests.)

We determined the best fit model between the three based on lowest Akaike's Information Criteria (AIC), and the remainder of analyses were performed based on this choice, for each estimation method. Assessment of the construct validity of the measurement models was performed (see Appendix 2 for details). Additionally, given a key goal of this research was to assess the strength of the BPNT framework as it applies to the association between need thwarting, mobile phone use, and wellbeing, we also undertook estimation of indirect and total effects for the various pressure points (most notably for bullying *(B))*, results of which are presented in Tables 2.5 and 2.6.

Various sensitivity analyses were performed to test the strength of our findings, including the use of traditional econometric techniques which are often conventionally employed to manage various forms of endogeneity including measurement error and simultaneity. Detailed information on such approaches and their results can be found in Appendix 3. Further, order and rank conditions of our model were examined to ensure econometric identification, and are found in Appendix 4.

Result

Basic Statistics

Summary statistics of all variables used in estimation of our structural model are presented in Table 2.1. The study sample had an average age of 17.6, with 51% of them being female. Among the sample, 48% came from rural secondary schools. The average cost of mobile phones was 19.35 (thousand) Nepali rupees (NR).

With a range in values from 0 to 48, the mean score on the measure of anxiety (*A)* was 13.38. According to previous validation of the Beck Anxiety Inventory, a cutoff of around 13-14 was deemed appropriate in a Nepali context to indicate a level of at least mild to moderate anxiety (B.A. Kohrt et al. 2003). Results indicated at least mild levels of anxiety, on average, in the study sample[5]. Our measure of positive wellbeing, grit *(G)*, showed an average score of 3.26 with a range of 1.8 to 5 (the instrument has a range of 1 to 5). The average measure of problematic mobile phone use (*PMPU)*, was 86.65 on a scale that ranges from 27 to 135, indicating more than half of the population have indicators of addictive mobile phone use placing them above the midline of the scale. The measure of friend's problematic use (*FPMPU)* had an average score of 20.09, with a possible range of 9-30, indicating respondents perceive on average, even higher levels of problematic use among their closest friend than when responding to assessments of their own use.

As it pertains to the variables used to measure the three latent constructs, there is support for our choice to account for such protective/adverse factors in adolescents' lives. There are overall very high indications of pressure in the academic environment to

[5] Note that use of this survey instrument was not meant to diagnose generalized anxiety disorder, but rather to serve as an indicator of overall experience of anxiety-related symptoms – indicative of negatively oriented emotional and mental wellbeing.

perform well in school, along with perceptions of the environment as being highly controlling and competitive (average scores around 4 on a 1/5 agreement scale). There is also a measurable presence of violence and strict oversight within the family/cultural environment, as indicated by average scores between 2.5 and 3.5 on a 1/5 agreement scale. With regard to social support measures, more than a quarter of those adolescents in the sample do not have someone from whom they could borrow money from or stay with in times of trouble. Further, more than one-third of the sample claim they have no one to confide in about violence or to deal with harassing situations, and less than half of the adolescents surveyed have a place to meet same sex friends or are a member of a social club/youth group.

Estimation Results

In Table 2.3 are the results of estimating our full structural model with the latent variables measured according to linear probability estimation, with diagnostic tests of fit indicated in the bottom portion of the table. Across all models, the fit statistics meet standard criterion for assessing goodness of fit (Kline 2016; Fornell and Larcker 1981), with the exception of the chi-square statistics[6] (see Appendix 2 for further details on methods and interpretation). Parameter results of this estimation approach show a statistically significant effect of *PMPU* on both wellbeing outcomes. Higher *PMPU* scores indicate lower grit (*G)* and higher anxiety (*A)* measures. Bullying (*B*) has a statistically significant impact on wellbeing measures, with the direction of association mirroring that of *PMPU.* When covariances between the wellbeing measures and *PMPU*

[6] Chi-square statistics are notoriously not rejected in SEM research, when data sets contain large (over 200) observations.

were both measured, there was no statistically significant effect with anxiety, but there is a positive covariance with grit. Additionally, there is a statistically significant, negative, covariance between the two wellbeing measures, across all models.

As it pertains to the other socio-cultural environmental measures, academic pressure (*AP*)* appears to have a positive significant effect on *G* and *PMPU,* but no effect on *A.* A pressured family environment (*FE*)* appears to have a statistically significant positive effect on *PMPU,* only. Our measures of estimated covariance indicate significant positive associations between the latent variables representing the family and academic environments, and between the academic environment and social support.

All three measures used to allow for identification of the model (the "instruments") and used to explain *PMPU,* are statistically significant. Phone cost (*PC)* and friend's problematic phone use (*FPMPU)* have a positive effect on respondent's *PMPU* measure, and the square of phone cost (*PC2)* a negative association.[7] While results do not indicate any significant effects of demographic controls on *PMPU,* females (*X1)* are predicted to have lower grit and higher anxiety. Rural adolescents (*X3)* appear to have lower scores on our measure of anxiety, as well.

The results found through structural equation modeling based on generalized linear modeling map similarly to those results presented above and are presented in Table 2.4. Again, *PMPU* is shown to have a statistically significant effect on wellbeing outcomes, having a positive relationship with respect to anxiety and negative with respect to grit. Similarly, bullying is shown to have a negative association with grit and positive

[7] The positive association of *PC* and the negative association of *PC2*, indicates diminishing marginal effects of phone cost on problematic phone use (e.g, the marginal increase in PMPU score for an increase in phone cost of 1,000 NR, will get smaller as the cost continues to rise).

with anxiety. Under this estimation approach, we see significant positive effects of bullying on *PMPU*, along with those previously seen from the latent pressures in the academic and family environments. Females and rural adolescent continue to be indicated to have positive and negative effects, respectively, on anxiety, with no significant effects on grit. Older adolescents, are also seen to have higher anxiety measures under this second structural equation modeling approach. The measures used for identification and the referenced key covariances from above continue to be statistically significant as before.

Based on AIC values, the results presented in column (3) of both Tables 2.3 and 2.4, indicate the best fit between the three model structures. Thus, all subsequent analyses were based on this approach. As previously indicated, full assessment of a structural model also requires assessment of the validity of the constructs used in the measurement model portion of the full model. Average variance extracted (AVE) and construct reliability (CR) values for our model (reference Appendix 2 for details on these measures) are all above the 0.7 level indicated for good convergent validity (Kline 2016), under both estimation approaches. To assess discriminant validity, the AVE value should be larger than the squared correlations between two constructs, to reduce any lingering multicollinearity issues (Kline 2016). For our model, this does not appear to be the case, regardless of estimation approach. Thus, the measurement model was deemed to have divergent validity, as well.

[TABLE 2.3]

[TABLE 2.4]

Mediation analysis entails disaggregating the indirect and direct effects of the mediation pathway depicted in Panel C of Tables 2.5 and 2.6. Based on this pathway, the indirect effect of a treatment variable on a wellbeing outcome can be calculated as the product of the parameter estimates A and B, while the direct effect is determined by C. To get the total effect, these two measures are summed. As visualized in the full structural model (approach number three) depicted in Figure 2.3, the treatment variables analyzed are those seven variables which have the potential to exhibit an indirect effect (e.g. they have a pathway which passes through *PMPU*).

[TABLE 2.5]

[TABLE 2.6]

Looking at Panels A and B in Tables 2.5 and 2.6, one can see that with regard to the key variable representing a need thwarting context, *B*, there are consistently significant direct and total effects on both wellbeing outcome measures, regardless of estimation approach. Additionally, there are consistently significant direct and total effects of being female on anxiety. Interpretation of indirect and mediation effects is slightly different between the two estimation approaches. So, for the sake of brevity, we will detail the results from generalized linear modeling, given our belief that the assumptions underlying the measurement model with this approach may more accurately reflect the underlying processes and relationships our structural model attempts to capture, based on the data generating processes.

Referring to Table 2.6, one can see significant indirect effects of bullying, academic pressure, and family environment on both measures of wellbeing. This implies that there is a statistically significant impact on the wellbeing measures, which passes through the mediating variable of *PMPU*. The family environment only has a significant indirect effect (indicative of full mediation), whereas bullying has significant indirect and direct effects, indicating only partial mediation. As it pertains to impacts on grit, academic pressures appear to only be partially mediated, given significant indirect and direct effects. Interpretation of the mediation effects of *PMPU* on the relationship between academic pressures and anxiety is less clear. We offer some further interpretation of these results in the closing section of this work. Overall, there are no mediation effects of problematic phone use on the relationships between demographic controls and wellbeing outcome measures.

[FIGURE 2.3]

Discussion, Policy Implications & Conclusions

It is imperative that government and policy makers focus on ways to improve the wellbeing of adolescents, given the current negative trajectories we are seeing worldwide, and particularly in developing world nations such as Nepal. There is a growing interest in using mobile-based (e.g. mHealth) interventions to combat such issues as high suicide and bullying rates (WHO-SEARO 2017). While use of mobile technology is believed to be high among adolescent populations, existing literature which focuses on mHealth has primarily focused on the potential cost and reach benefits such approaches may offer. However, the importance of also acknowledging potential downsides is also beginning to be recognized.

There is growing evidence from developed-world contexts of the negative mental health and wellbeing outcomes that appear to come from overuse of mobile/smartphones (Vernon, Modecki, and Barber 2018; CommonSense 2016; Dubicka and Theodosiou

2020). Such findings are also being confirmed with initial studies of such issues in developing world contexts. However, clarity of the directionality of these relationships within the “dark side” of technology are proving hard to determine (Elhai et al. 2017; Orben and Przybylski 2019). The small number of rigorous empirical examinations on these topics primarily neglect any underlying motivational framework to answer why adolescents are turning to their mobile phones. Or, if a motivational framework is emphasized, there is lack of strong statistical analyses to ensure validity of the theories postulated.

Thus, the overarching purpose of this study was to evaluate the presence and associations of PMPU in Nepali adolescents, using a strong analytic approach, framed by a well-supported conceptual theory. By incorporating assessment of both a positive and negative wellbeing outcome, we have attempted to capture a more holistic vision of the relationships underlying the connections between need thwarting contexts, PMPU, and wellbeing. We capture two measures of the potential for life success that adolescents may have, based on the downward trajectory chronic anxiety can provide, versus the upward trajectory of grit. Using a full structural modeling approach, which accounts for the measurement error in socio-cultural environmental latent constructs and the covariance between key variables, we have been able to produce robust results which provide new insights and directions for future research into these topics.

While we acknowledge that asserting causality using a SEM approach will trigger some level of debate (R. O. Mueller 1999), the flexibility and usefulness of it as a tool to assess the accuracy of complicated (causal) relationships postulated in literature should not be undercut. As a consequence of this research, we have expanded mHealth literature by looking at the potential downsides of phone use which may come up as negative externalities to mHealth initiatives. In addition, by framing our analysis according to BPNT, we are able to capture motivational factors which may trigger turning to phones in the first place, and have moved beyond analyses based solely on personality traits (Takao, Takahashi, and Kitamura 2009; Ha et al. 2008; Ko et al. 2007; Hong, Chiu, and Huang 2012)[8]. By applying this theory within the context of this work, we have also moved the literature on needs satisfaction forward, by applying it to technology use outside of video games/dating apps. Further, we have expanded the application of the framework beyond the classroom and academic functioning. We have also directly addressed simultaneity concerns in both our main modeling framework through our accounting for covariances, and in our detailed sensitivity analyses using multiple econometric techniques and testing.

Key results from our work indicate support for all four of our initial hypotheses. Those adolescents scoring higher on our measure of bullying are seen to exhibit higher levels of anxiety symptomology and lower on indicators of grit (H1). Those adolescent who report more bullying are seen to also have higher indicators for problematic mobile phone use (H2). Beyond our hypotheses, literature which emphasizes the large portion of adolescents' time endowment spent at school (Miller, Esposito-Smythers, and Leichtweis 2015; Winfree and Jiang 2010; Deb, Strodl, and Sun 2015) allows for the significant direct effects of academic pressure on wellbeing outcomes to make sense. Similarly, the

[8] Unlike typical personality traits such as neuroticisms or introversion, grit, as measured and intended in this work, has been viewed and confirmed as a learned characteristic, which develops over time and can be affected by life experiences (Gillion 2017; Hoeschler, Balestra, and Backes-Gellner 2018), much like anxiety has traditionally been recognized as situation/environmentally triggered/dependent (American Psychiatric Association and American Psychiatric Association 2013).

significant direct effects we see for females having higher anxiety measures is in congruence with existing research which indicates that negative mental health outcomes are often found to be more common among female (versus male) adolescent populations (Kuehner 2003; Naninck, Lucassen, and Bakker 2011; Chaplin, Gillham, and Seligman 2009; Fletcher 2009).

Significant indirect effects of bullying on wellbeing outcomes, mediated by our measure of PMPU, provide support for H3, and are the strongest indicators in support of BPNT being an appropriate framework through which to view the PMPU-wellbeing relationship. The additional significant indirect effects for pressure from the family environment and academic environment on wellbeing, mediated by PMPU, further provide support for the role that need thwarting contexts play in reducing overall wellbeing. These findings appear to be in line with researchers who have pushed forward a "need-density" hypothesis, wherein those who have less basic needs met, may also be less able to autonomously regulate activities and make congruent decisions that match their aims and values (Di Domenico et al. 2012; R. M. Ryan, Deci, and Vansteenkiste 2016). Therefore, they can be more vulnerable to technology overuse and a vicious cycle can continue wherein seeking need fulfillment may ultimately further need frustration. This can been seen in how online communication has been found to actually engender less social support/intimacy, leading to increased feelings of social isolation and detachment (Cummings, Butler, and Kraut 2002).

With regard to our final hypothesis (H4), we found statistically significant covariance between our two outcomes measures, supporting this hypothesis. When calculated out[9], these two measures are shown to have a negative correlation of -0.09. This means that these two wellbeing measures move in opposite directions, in conjunction with one another. This outcome supports our use of a full structural equation modelling approach which accounts for this interconnectedness. The ability to account for covariances between *PMPU* and the two wellbeing outcomes has allowed us to realize a key insight into the lack of a significant covariance (i.e. simultaneous relationship) between anxiety and PMPU. This finding appears contrary to much of the literature examining problematic phone use and mental health, which has pushed for understanding the relationship as bi-directional (Elhai et al. 2017; Billieux, Van der Linden, and Rochat 2008). However, Pivetta, et al. (2019) using a path analysis framework, also did not find evidence of pre-existing psychopathology exerting a significant influence on average smartphone user's behavior. The stability of our finding is confirmed in our sensitivity analyses (see Appendix 3), where econometric tests for statistical exogeneity between our measures of problematic mobile phone use and anxiety are not rejected.

Intriguingly, there are unexpected significant covariances (and concerns for endogeneity) indicated between problematic phone use and our measure of grit. Such a relationship has not been found or analyzed in prior literature examining well-being and mobile phones. Prior evidence of grit's influence on other maladaptive behaviors such as substance use (Guerrero et al. 2016; Griffin et al. 2016) and video game addiction (Borzikowsky and Bernhardt 2018) has been indicated in literature, but there is also literature which found no such associations (Maddi et al. 2013; Bessey 2018). The

[9] Recall that the correlation between two variables, X and Y, $(\rho_{XY}) = \frac{cov(X,Y)}{\sqrt{Var(X)}\sqrt{Var(Y)}}$

evidence supporting the important role that grit plays in the healthy development and success of individuals, and particularly adolescents is growing (A. L. Duckworth et al. 2007; Eskreis-Winkler et al. 2014). The connections between technology use and grit may offer a new and unique direction in which future research in these areas could focus.

In study of our mediation effects (see Tables 2.5 and 2.6), there are instances in which indirect and/or direct effects are statistically significant, while total effects are not. It has been shown that it is possible to have such a situation, and this can be explained by the presence of several mediating paths that cancel each other out (Hayes 2009). This would be viewed as competitive mediation, as compared to complementary mediation where indirect and direct effects both exist and move in the same direction, or indirect-only mediation (Memon et al. 2018; Zhao, Lynch Jr, and Chen 2010). Should further exploration of each adolescent pressure/environmental factor accounted for in our model be pursued, such work may entail further breaking down analyses of such pathways.

Future work may also benefit from further exploration of additional unexpected outcomes in this study, including the lack of significance of our measure for social support (*SS**). While not part of our research hypotheses, the findings of complete lack of significance in our main estimation models for this variable is contrary to what is found in typical regression approaches to the system of equations we estimate (see Appendix 3), and what would be expected from literature (Aker et al. 2017; Berkman and Glass 2000). Initial speculation for this outcome revolves around the possibility that this was a latent construct. AVE and CR values are the lowest for social support (see Appendix 2), which may indicate that the strength of our measures for this construct are weaker than those used for the other socio-cultural environmental latent pressures accounted for in our model.

Additional limitations to our work include that while many studies listed previously have looked at impacts of smartphone use on adolescents' sleeping problems, we did not specifically measure this or focus on it, although there are references to sleep troubles within the PMPU survey instrument we used. We also could have used a different set of explanatory "instrumental variables" to ensure identification within our equation for *PMPU.* Previous authors who have used instrumental variable techniques similar to those used in our sensitivity analyses have captured phone use (not necessarily problematic use phone) with measures of Wi-Fi capabilities, phone download volume, and 4G streaming capabilities (Baert et al. 2018; L. Chen et al. 2016). The limitations in internet coverage in the developing world and length limitations in our survey to avoid survey fatigue meant that we were limited in our ability to capture information about adolescents. However, future empirical work could consider capturing such measures if additional survey development on this topic were to be pursued. In any future survey development on these topics, it might also be useful to consider inclusion of a a specific need thwarting/need satisfaction scale (Beiwen Chen et al. 2015) to delineate differences in the three needs of autonomy, relatedness, and competence and their unique roles in the relationships indicated by our model.

By incorporating key specific factors of life adolescents face which can satisfy/thwart needs in this study, and viewing need thwarting through a more all-encompassing lens, as others have done (Orkibi and Ronen 2017; Allen and Anderson 2018; Conzo et al. 2016), we are able to gain insights into ways that future interventions can be focused. Additionally, results of this study are confirmation of the universality of needs (Rodríguez-Meirinhos et al. 2019; Yu, Levesque-Bristol, and Maeda 2018), and additional confirmation that BPNT applies across cultures. This implies that the best way to focus any health/wellbeing interventions aimed at Nepali adolescents would be to seek out ways to improve their perceptions that their needs for autonomy, relatedness, and competence are being met.

Our results support literature's findings of poorer wellbeing outcomes from maladaptive/problematic use of mobile phones. Consequently, care must taken if mHealth interventions are the path that policymakers choose, given that many mental health apps have not been properly vetted/tested (Seko et al. 2014; Oppenheim 2019). If such interventions are deployed in conjunction with, or subsequent to, non-technology based interventions which focus on meeting the three basic needs, such concerns may be dampened. If adolescents no longer see mobile phones as a compensatory means by which to fulfill their unmet or thwarted needs in life, then the prevalence of problematic phone use may go down, and any negative wellbeing outcomes from that maladaptive use would also fall.

Work in the developed world has focused on the roles of in-school health systems and counselors as a potential front-line approach to negative wellbeing outcomes (Committee on School Health 2004; Lear 2007; Jennings, Pearson, and Harris 2000; Brown, Dahlbeck, and Sparkman-Barnes 2006). However, in many developing world contexts, there is not even a school nurse, let alone a mental/emotional counselor. Among our sample, 62.4% report that there is a school counselor at their school, while 85.2% claim that they would like one present with whom they could discuss their worries/concerns. So, a first step in non-technology-based interventions would be to try to raise the perceived importance of having health professionals on staff at schools, and reducing the stigma that surrounds discussions of poor mental health/wellbeing. In the absence of financial support for such initiatives, there is still the option of mobile-based applications.

Some mHealth interventions/approaches have shown promise to aid in combating the wellbeing concerns of adolescents around the world. A variety of studies show both passive and active entertainment media, including social media, can provide challenges, choices, and relational elements potentially conducive to competence, autonomy, and relatedness satisfactions (Calvo and Peters 2014), which if properly focused could hold promise. Now apps such as the "Woebot" (Karlan and Joe Bankman, n.d.) and the "Youper" (Muzaffar 2019) are being deployed which, unlike traditional mHealth apps that might lead you through a mind-calming exercise or simply provide resources, utilize an AI chatbot which chats with you like a friend, asking questions and assessing your responses (again, like a friend). This type of application genuinely may fulfill such needs as relatedness and autonomy.

Within the cultural context of our study, however, there are additional considerations which will need to be accounted for in endeavors to pursue mHealth apps/interventions. While we found no difference by gender in terms of its predictive power on *PMPU*[10], we did find a significant difference in terms of existing anxiety, indicating that females may need extra attention. Therefore, it may be useful to create gender-targeted interventions (Baifeng Chen et al. 2017). In a Nepali context, females

[10] Findings contrary to those found by researchers such as (Pierce 2009; Roser et al. 2016; Beranuy et al. 2009).

face several unique need thwarting contexts including strong pressures for early marriage (Adhikari et al. 2016; Maharjan et al. 2012), and menstrual taboos (LaSaine 2015; Fatusi and Hindin 2010; Ssewanyana and Bitanihirwe 2017) which prevent attendance at school/social functions. Furthermore, it is not uncommon for adolescents to be sharing their phone with one or more other individuals. Consequently, privacy concerns may be a real barrier to full adoption/success of mobile-based interventions. Within our study, over 30% of adolescents report that they are not the only user of their phone. Close to 32% of the adolescents surveyed say that they worry about their privacy, which makes sense given that 53% of them report that others take and go through their phones without permission.

Overall, though, investing in health systems and looking at minimizing the treatment gap is forecast to produce economic returns of 2.3 to 3.0 to 1 by 2030, indicating a long-term gain of $2.3-3.00 for every $1 invested in prevention and treatment (Chisholm et al. 2016). Such figures are based on not only reduction in long-term healthcare costs, but also increased economic productivity of healthier individuals contributing to society. In less than ten years, today's adolescents populations will be those contributors to society. The "unhappiness" Inverted-U curve is real and ubiquitous across the world (Blanchflower 2020a; 2020b), and if adolescents are already struggling, they are only going to get that much worse down the road. By finding ways to improve their positive wellbeing, now, there are enormous gains to be had long-term. Our work has shown that while PMPU does indeed appear to be a culprit of some of the negative wellbeing outcomes seen in a developing-world context such as Nepal, this connection can also be partially explained by the preexisting need thwarting contexts that these adolescent face. Contexts that drive them to phones in an attempt to meet their needs. Finding ways to meet those needs, whether through carefully targeted mHealth apps or non-technology-based approaches, may be a critical step towards having a next generation of world leaders who surpass the current in their levels of personal, emotional, and financial success.

Tables & Figures

Table 2.1: Summary Statistics of Variables

VARIABLES	DESCRIPTION	Mean	Standard Deviation	Min/Max
OUTCOME VARIABLES				
Anxiety (A)	Validated instrument[1] addressing various symptoms of anxiety, calculated as the sum of 17 Likert-scored questions (0-3 points). Higher score indicates more symptoms of anxiety	13.38	7.97	0/48
Grit Score (G)	Validated instrument[2] which captures elements of passion and persistence in life, calculated as the sum of ten, 5-point Likert scale items, divided by 5; Higher score indicates more Grit	3.26	0.49	1.8/5
EXPLANATORY VARIABLES				
<u>Key Explanatory Variables</u>				
Problematic Mobile Phone Use (PMPU)	Validated instrument[3] addressing indicators of addictive tendencies towards mobile phone use, calculated as the sum of 27 5-point Likert scale items, where a higher score indicates more problematic usage	86.65	21.07	27/135
Bullying (B)	Sum of three binary indicators related to bullying pressures	0.361	0.713	0/3
	Physically Hurt Prior Year	0.138	-	0/1
	Bullied at School	0.107	-	0/1
	Bullied Outside School	0.116	-	0/1
<u>Socio-Cultural Environmental Pressures Controlled For</u>				
Academic Pressures (AP)*	Latent construct measured by four, 5-point Likert questions detailing pressures from the school environment (1=Strongly Disagree, 5=Strongly Agree)			
	Worry About Exam Scores	4.01	1.30	1/5
	Teachers Too Controlling	3.67	1.39	1/5
	School Competitive	3.85	1.29	1/5
	School Success is Life Success	4.12	1.28	1/5

Table 2.1: Summary Statistics of Variables (cont.)

Family Environment (FE)*	Latent construct measured by four, 5-point Likert questions detailing violence and control in the home (1=Strongly Disagree, 5=Strongly Agree)			
	Parents Check Phone	3.17	1.62	1/5
	Physically Hurt in Home	2.54	1.57	1/5
	Punished for Bad Grades	2.64	1.62	1/5
	Women Tolerate Violence	2.62	1.63	1/5
Social Support (SS)*	Latent construct measured by six binary indicators for having someone or somewhere to go to deal with a series of financial or social issues			
	Borrow Money	0.73	-	0/1
	Stay With	0.70	-	0/1
	Confide in About Violence	0.64	-	0/1
	Help with Harassment Situation	0.64	-	0/1
	Place Meet Same Sex Friends	0.44	-	0/1
	Member of Club/Youth Group	0.41		
<u>Instruments</u> (For PMPU)				
Phone Cost (PC)	Cost of mobile phone in Nepali Rupees divided by 1,000.	19.35	16.43	0.2/110
Phone Cost Sq. (PC2)	*Phone Cost* squared	643.62	1469.37	0.04/12100
Friend's PMPU (FPMPU)	Reworking of validated instrument[3] addressing indicators of closest friend's addictive tendencies towards mobile phone use, calculated as the sum of six 5-point Likert scale items, where a higher score indicates more problematic usage	20.09	5.62	6/30
ADDITIONAL CONTROLS				
Age (X1)	Age of adolescent in years	17.6	1.18	15/25
Female (X2)	=1 if adolescent is female, 0 otherwise	0.51	-	0/1
Rural (X3)	=1 if adolescent is from a rural high-school, 0 otherwise	0.48	-	0/1

Source:Sustainable Development Action Lab, Nepal Study Center (University of New Mexico).
Data Sites: Palpa, Gulmi, Argankhachi, & Siddarthnagar, Nepal.
[1](Beck, 1988) & (Kohrt, 2003) [2](Duckworth, 2016) [3] (Bianchi & Phillips, 2005)

Table 2.2: Additional Details on Variables

VARIABLES	DESCRIPTION
OUTCOME VARIABLES	
Anxiety	Beck Anxiety Inventory (BAI)[1], a validated survey instrument, where symptoms evaluated include numbness/tingling, feeling hot, leg wobbliness, inability to relax, fear of the worst, dizzy/lightheaded, heart pounding/racing, unsteady, terrified/afraid, nervous, choking, hands trembling, shakiness, breathing difficulty, fear of dying, & being scared, where 0= No Experience of Symptom & 3= Severe Experience of Symptom over the last few days
Grit Score	Duckworth Grit Scale[2,] a validated survey instrument, which queries agreement with statements such as "I often set a goal but later chose to pursue a different one." and "My interests change from year to year.", where 1= Strongly Agree & 5= Strongly Disagree, along with statements such as "Setbacks don't discourage me. I don't give up easily." and " I have overcome setbacks to conquer an important challenge.", where 1=Strongly Disagree & 5= Strongly Agree
<u>Key Explanatory Variables</u>	
Problematic Mobile Phone Use (PMPU)	Validated survey instrument[3] which asks agreement on statements such as "I can never spend enough time on my phone", "I have tried to hide from others how much time I spend on my mobile phone", & " I have frequent dreams about the mobile phone", where 1= Strongly Disagree & 5=Strongly Agree
Bullying	Summation index composed of "Yes" answers to questions on being physically hurt within the prior year, being bullied in school the prior month, & being bullied outside of school the prior month.
<u>Socio-Cultural Environmental Pressures Controlled For</u>	
Academic Pressures	Latent variable measured through indicators capturing agreement with statements regarding experiences over the last month of being worried a lot about exam scores, having teachers that are too controlling, a school environment that is extremely competitive, & belief that success in school will determine life success , where 1= Strongly Agree & 5= Strongly Disagree
Family Environment	Latent variable measured through indicators capturing agreement with statements regarding experiences over the last month of parents checking the contents of respondent's mobile phone, having been physically hurt in his/her household, have been punished by parents for bad grades/exam scores & that women should tolerate violence in order to keep familial harmony , where 1= Strongly Agree & 5= Strongly Disagree

Table 2.2: Additional Details on Variables (cont.)

Social Support	Latent variable measured through binary indicators to having someone outside family to borrow money from, stay with in case of a problem, confide in about violence, assist if someone is harassing respondent, a place to meet same sex friends, & membership in a social/cultural club or youth group.
Instruments (For Potentially Endogenous PMPU)	
Phone Cost	Open-ended query on the cost of mobile phone in Nepali Rupees (divided by 1,000)
Friend's PMPU	Reworked instrument asks agreement on statements such as "My close friends are on their mobile phone when they should be doing other things, and it causes problems.", "My close friends try to hide from others how much time they spend on the mobile phone.", & "You complain about your friends' use of the mobile phone." where 1= Strongly Disagree & 5=Strongly Agree

Source: Sustainable Development Action Lab, Nepal Study Center (University of New Mexico).
[1](Beck, 1988) & (Kort, 2003) [2](Duckworth, 2016) [3](Biancchi & Philips, 2005)

Table 2.3: Results of Linear Probability Estimation for Structural Model of Adolescent Life Influences on Wellbeing

	(1) Full Model			**(2) Constraining Non-Sig. Co-variances to Zero**			**(3) Constraining Non-Sig. Co-variances to Zero & Control Variables in PMPU Eq.**		
VARIABLES	Grit	Anxiety	PMPU Score	Grit	Anxiety	PMPU Score	Grit	Anxiety	PMPU Score
PMPU	**-0.012*** **	**0.077***		**-0.012*** **	**0.088*** **		**-0.013*** **	**0.088*** **	
	(0.003)	**(0.043)**		**(0.003)**	**(0.020)**		**(0.003)**	**(0.021)**	
B	**-0.070*** *	**1.506*** **	0.669	**-0.070*** *	**1.488*** **	0.668	**-0.069*** *	**1.493*** **	0.903
	(0.030)	**(0.477)**	(1.027)	**0.030**	**(0.471)**	(1.027)	**(0.030)**	**(0.472)**	(1.026)
*AP**	**0.177*** *	0.233	**4.681*** *	**0.178*** *	0.095	**4.642***	**0.194*** *	0.152	**7.162*** **
	(0.077)	(1.241)	**(2.372)**	**0.078**	(1.131)	**(2.378)**	**(0.083)**	(1.142)	**(2.594)**
*FE**	-0.106	0.298	**9.244*** **	-0.102	0.094	**9.284*** **	-0.104	0.060	**7.894*** **
	(0.073)	(1.144)	**(2.575)**	0.073	(1.010)	**(2.596)**	(0.072)	(0.994)	**(2.528)**
*SS**	0.281	-3.416	-0.285	0.273	-3.401	0.256	0.283	-3.441	2.073
	(0.176)	(2.762)	(5.489)	0.175	(2.745)	(5.439)	(0.177)	(2.756)	(5.923)
PC			**0.368*** **			**0.363*** **			**0.298*** **
			(0.122)			**(0.122)**			**(0.123)**
PC2			**-0.003*** *			**-0.003*** *			**-0.003*** *
			(0.001)			**(0.001)**			**(0.001)**
FPMPU			**1.693*** **			**1.695*** **			**1.601*** **
			(0.159)			**(0.159)**			**(0.165)**
X1	**-0.070***	**3.121*** **		**-0.075***	**3.136*** **		**-0.089*** *	**3.125*** **	-2.234
	(0.0297)	**(0.704)**		**0.043**	**(0.702)**		**(0.045)**	**(0.705)**	(1.525)
X2	0.010	0.424		0.010	0.417		0.005	0.416	-0.739
	(0.017)	(0.273)		0.017	(0.273)		(0.017)	(0.273)	(0.593)
X3	0.072	**-1.561*** *		0.073	**-1.532*** *		0.051	**-1.547*** *	**-3.855*** *
	(0.047)	**(0.744)**		0.047	**(0.755)**		(0.051)	**(0.759)**	**(1.663)**
Constant	**4.19*** **	-2.116	**48.06*** **	**4.194*** **	-2.975	**48.085*** **	**4.327*** **	-2.937	**66.765*** **
	(0.374)	(6.105)	**(3.651)**	**0.373**	(5.317)	**(3.652)**	**(0.419)**	(5.370)	**(11.280)**
Cov(Acad-Fam)		**0.114*** **			**0.111*** **			**0.114*** **	
Cov(Acad-SS)		**0.025*** **			**0.024*** **			**0.024*** **	
Cov(Fam-SS)		0.007			Constrained to Zero			Constrained to Zero	
Cov(BAI-Grit)		**-0.337*** *			**-0.353*** *			**-0.355*** *	

Table 2.3: Results of Linear Probability Estimation for Structural Model of Adolescent Life Influences on Wellbeing (cont.)

Cov(BAI-PMPU)	3.121	Constrained to Zero	Constrained to Zero
Cov(Grit-PMPU)	**1.257***	**1.281***	**1.296***
N	539	539	539
ln(L)	-23330.248	-23330.723	-23326.214
AIC	46856.497	46853.446	46850.428
DIAGNOSTIC TESTS			
χ^2_{ms}(dof,)	356.228(191); p> χ^2 =0	357.177(193); p> χ^2 =0	348.16 (190); p> χ^2 =0
CFI	0.883	0.884	0.888
RMSEA	0.041	0.040	0.040
SRMR	0.047	0.048	0.047
CD	0.959	0.959	0.959

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

AIC= Akaike information criterion ; CFI = Comparative Fit Index; RMSEA = Root Mean Square Error of Approximation; SRMR= Standardized Root Mean Square Residual; CD = Coefficient of Determination; χ^2_{ms} = Chi-Sq. Test of the Likelihood Ratio Between the Specified and Saturated Model

Table 2.4: Results of Generalized Linear Estimation for Structural Model of Adolescent Life Influences on Wellbeing

	(1) Full Model			(2) Constraining Non-Sig. Covariances to 0			(3) Constraining Non-Sig. Covariances to 0 & Control Variables in PMPU Eq.		
VARIABLES	Grit	Anxiety	PMPU Score	Grit	Anxiety	PMPU Score	Grit	Anxiety	PMPU Score
PMPU	-0.013***	0.099***		-0.013***	0.097***		-0.013***	0.097***	
	(0.002)	(0.030)		(0.002)	(0.015)		(0.002)	(0.014)	
B	-0.088***	1.892***	1.390**	-0.088***	1.898***	1.390**	-0.089***	1.896***	1.243**
	(0.025)	(0.329)	(0.688)	(0.025)	(0.290)	(0.688)	(0.025)	(0.291)	(0.629)
*AP**	0.111**	-.403	1.519	0.111**	-0.393	1.518	0.115**	-0.379	2.391**
	(0.050)	(0.421)	(1.074)	(0.050)	(0.392)	(1.074)	(0.049)	(0.382)	(1.089)
*FE**	-0.072	0.399	6.794***	-0.072	0.408	6.804***	-0.075	0.399	6.269**
	(0.050)	(0.504)	(2.506)	(0.050)	(0.506)	(2.488)	(0.050)	(0.502)	(2.477)
*SS**	0.022	-.383	-0.215	0.022	-0.380	-0.191	0.022	-0.382	-0.154
	(0.030)	(0.317)	(0.879)	(0.030)	(0.318)	(0.887)	(0.030)	(0.317)	(0.861)
PC			0.270***			0.271***			0.276***
			(0.093)			(0.091)			(0.098)
PC2			-0.003**			-0.003**			-0.003**
			(0.001)			(0.001)			(0.001)
FPMPU			1.888***			1.888***			1.844***
			(0.174)			(0.174)			(0.185)
X1	-0.066	3.021***		-0.066	3.018***		-0.077	3.017***	-1.866
	(0.053)	(0.789)		(0.053)	(0.782)		(0.055)	(0.782)	(2.021)
X2	0.007	0.503**		0.007	0.505**		0.004	0.504**	-0.481
	(0.016)	(0.223)		(0.016)	(0.228)		(0.016)	(0.228)	(0.491)
X3	0.116**	-1.219**		0.116**	-1.220**		0.102*	-1.222**	-2.217
	(0.054)	(0.505)		(0.054)	(0.500)		(0.053)	(0.500)	(1.692)
Constant	4.263***	-5.819	44.519***	4.262***	-5.698	44.509***	4.336***	-5.715	56.011***
	(0.369)	(5.614)	(3.546)	(0.370)	(4.913)	(3.552)	(0.372)	(4.906)	(8.479)
Cov(Acad-Fam)		0.265**			0.262**			0.268**	
Cov(Acad-SS)		0.323**			0.317***			0.320***	
Cov(Fam-SS)		0.019			Constrained to Zero			Constrained to Zero	

TABLE 2.4: Results of Generalized Linear Estimation for Structural Model of Adolescent Life Influences on Wellbeing (cont.)

Cov(BAI-Grit)	**-0.297*** **	**-0.293*** **	**-0.295*** **
Cov(BAI-PMPU)	-0.582	Constrained to Zero	Constrained to Zero
Cov(Grit-PMPU)	**1.533*** **	**1.530*** **	**1.502*** **
N	539	539	539
ln(L)	-11643.04	-11643.1	-11592.51
AIC	23314.08	23314.2	23211.02

Standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$; [1]Measurement Model based on ologit estimation. [2]Measurement Model based on logit estimation.
AIC= Akaike information criterion

Table 2.5: Mediation Analysis for Linear Probability Estimation of Structural Model of Adolescent Life Influences on Wellbeing

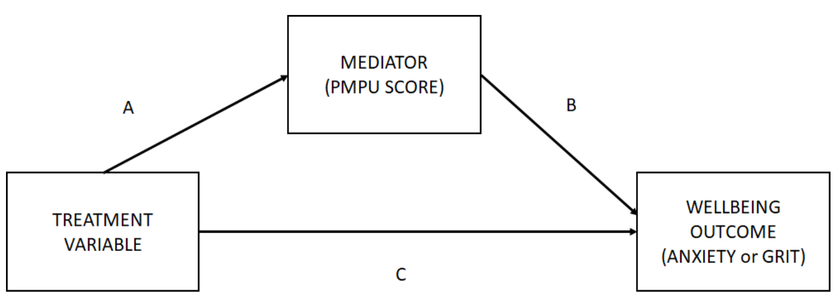
PANEL A: ANXIETY
Mediator Variable: PMPU Score

TREATMENT VARIABLE	Indirect Effect (IE)	Direct Effect (DE)	Total Effect (TE)
B	0.079	**1.493*** **	**1.572*** **
	(0.092)	**(0.472)**	**(0.479)**
*AP**	**0.631** **	0.152	0.783
	(0.269)	(1.142)	(1.123)
*FE**	**0.695*** **	0.060	0.847
	(0.279)	(0.994)	(1.103)
*SS**	0.182	-3.441	-3.259
	(0.526)	(2.756)	(2.802)
X1	-0.197	**3.125*** **	**2.928*** **
	(0.163)	**(0.705)**	**(0.713)**
X2	-0.065	0.416	0.351
	(0.054)	(0.273)	(0.278)
X3	**-0.339** **	**-1.547** **	**-1.887** **
	(0.168)	**(0.759)**	**(0.761)**

PANEL B: GRIT
Mediator Variable = PMPU Score

TREATMENT VARIABLE	Indirect Effect (IE)	Direct Effect (DE)	Total Effect (TE)
B	-0.011	**-0.069** **	**-0.080*** **
	(0.013)	**(0.030)**	**(0.029)**
*AP**	**-0.091** **	**0.194** **	0.103
	(0.040)	**(0.083)**	(0.072)
*FE**	**-0.100** **	-0.104	0.094
	(0.039)	(0.072)	(0.082)
*SS**	-0.026	0.283	0.257
	(0.075)	(0.177)	(0.177)
X1	0.028	**-0.089** **	-0.060
	(0.021)	**(0.045)**	(0.044)
X2	0.009	0.005	0.015
	(0.008)	(0.017)	(0.017)
X3	**0.049** **	0.051	0.055
	(0.024)	(0.051)	(0.056)

PANEL C: MEDIATION PATHWAY DIAGRAM



Standard errors (obtained by the delta method) in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 2.6: Mediation Analysis for Generalized Linear Estimation of Structural Model of Adolescent Life Influences on Wellbeing

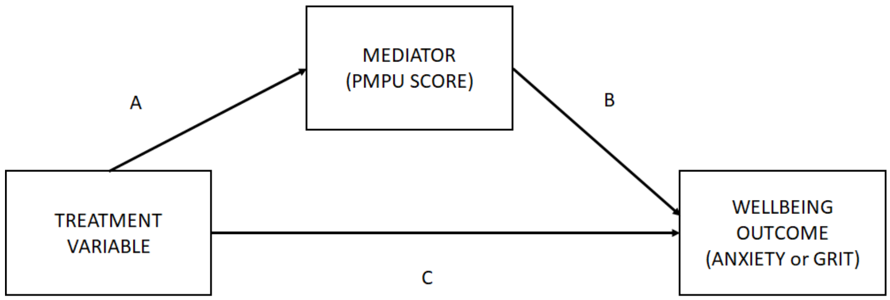
PANEL A: ANXIETY
Mediator Variable: PMPU Score

TREATMENT VARIABLE	Indirect Effect (IE)	Direct Effect (DE)	Total Effect (TE)
B	**0.121***	**1.896*****	**2.018*****
	(0.068)	**(0.291)**	**(0.302)**
*AP**	**0.233****	-0.379	-0.146
	(0.110)	(0.382)	(0.392)
*FE**	**0.611*****	0.399	0.232
	(0.216)	(0.502)	(0.455)
*SS**	-0.015	-0.382	-0.397
	(0.084)	(0.317)	(0.312)
X1	-0.182	**3.017*****	**2.835*****
	(0.209)	**(0.782)**	**(0.866)**
X2	-0.047	**0.504****	**0.457****
	(0.052)	**((0.228)**	**(0.218)**
X3	-0.216	**-1.222****	**-1.438*****
	(0.152)	**(0.500)**	**(0.515)**

PANEL B: GRIT
Mediator Variable = PMPU Score

TREATMENT VARIABLE	Indirect Effect (IE)	Direct Effect (DE)	Total Effect (TE)
B	**-0.016***	**-0.089*****	**-0.105*****
	(0.009)	**(0.025)**	**(0.020)**
*AP**	**-0.031***	**0.115****	**0.084***
	(0.016)	**(0.049)**	**(0.047)**
*FE**	**-0.080****	-0.075	0.035
	(0.033)	(0.050)	(0.042)
*SS**	0.002	0.022	0.024
	(0.011)	(0.030)	(0.034)
X1	0.024	-0.077	-0.054
	(0.028)	(0.055)	(0.056)
X2	0.006	0.004	0.010
	(0.006)	(0.016)	(0.017)
X3	0.028	**0.102***	**0.112***
	(0.019)	**(0.053)**	**(0.059)**

PANEL C: MEDIATION PATHWAY DIAGRAM



Standard errors (obtained by the delta method) in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Figure 2.1: Framework of Basic Psychological Needs Theory (BPNT)

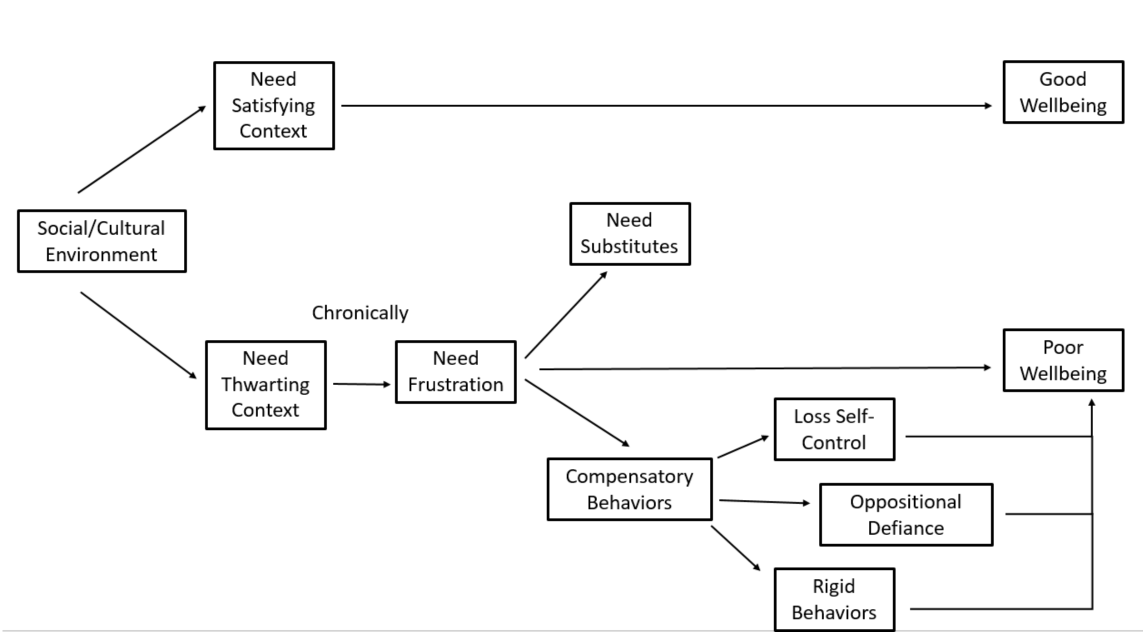


Figure 2.2: Research Application of BPNT Framework

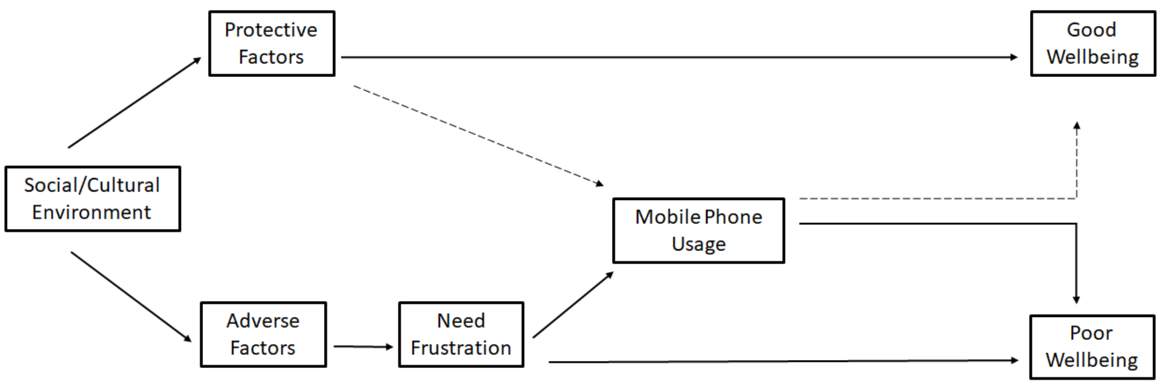
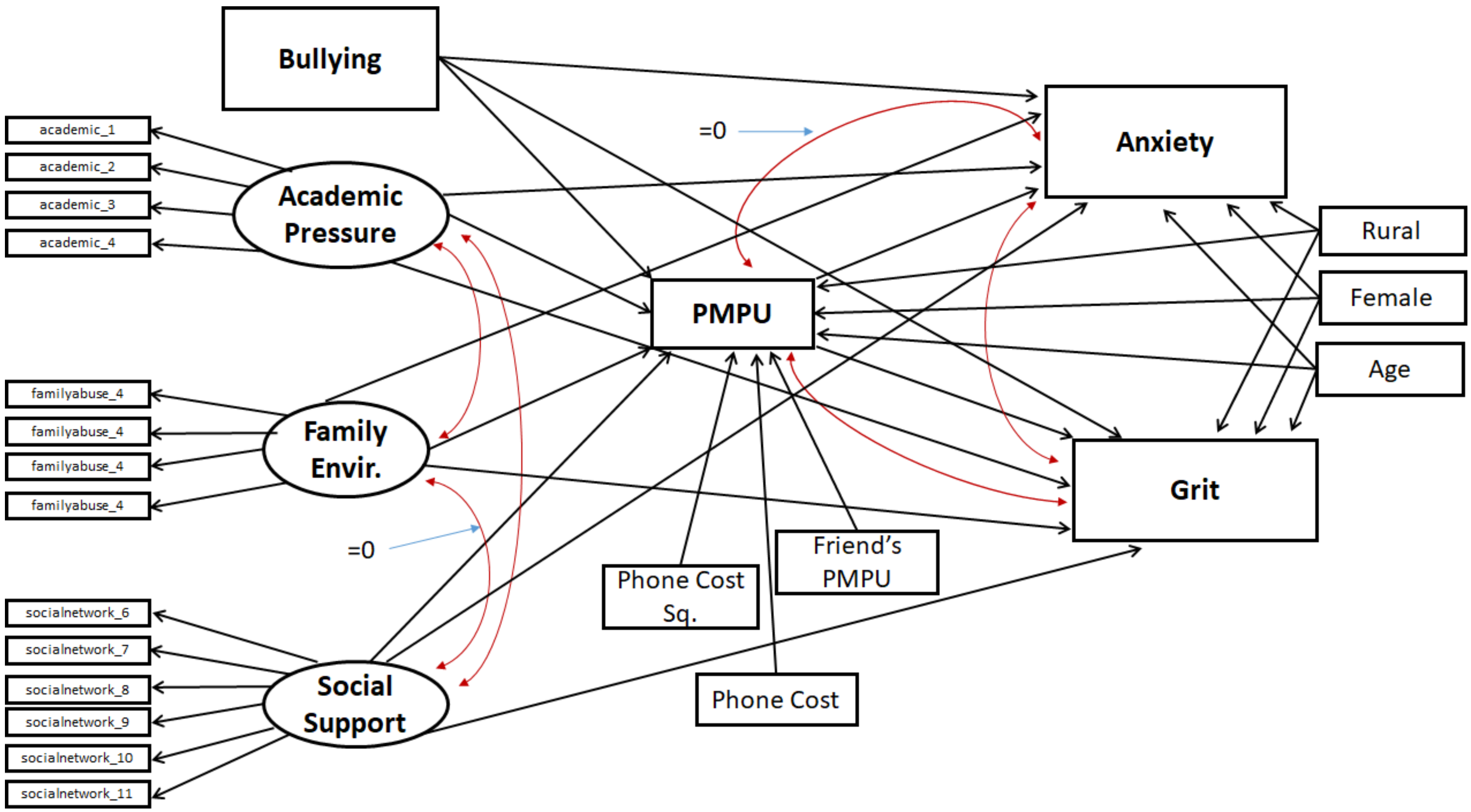


Figure 2.3: Final Structural Model



CHAPTER 3

A Step Back from the Edge: Empirical Modeling of the Role of Social Integration on Suicide & Deleterious Health Outcomes Across the World's Adolescents

Introduction

Across the globe, there is growing recognition of the poor mental health of adolescents (Petroni, Patel, and Patton 2015; Wasserman, Cheng, and Jiang 2005). An ultimate measure of failing mental health is suicide. More than 800,000 people died by suicide in 2016, making it the second leading cause of death among those aged 15-29 (World Health Organization 2018). Particularly hard hit are low-and-middle income countries (LMICs) throughout the developing world, in which 79% of suicides in 2016 occurred (World Health Organization 2018). Eight out of the ten countries with the highest-suicide rates are regarded as LMICs (Iemmi et al. 2016). In a survey of 40 different LMICs, it was found that 82.5% of countries exceeded a 10% suicide attempt rate, with a 12-month prevalence of suicide attempts at 17.4% among adolescents (Liu, Huang, and Liu 2018). These rates are higher than the prevalence reported in most studies of developed countries (Miron et al. 2019; Kann et al. 2018), and have been confirmed by multiple researchers (McKinnon et al. 2016; Page et al. 2013; Jordans et al. 2018). Life stressors and underlying mental illness which contribute to suicide are also linked to outcomes which drain society such as teenage pregnancy and marital instability (Kessler et al. 1997; Overbeek et al. 2003). Such outcomes are themselves associated with low educational attainment, poor work productivity, and lower wages, resulting in lower economic growth potential for a nation.

Partially to blame for this adolescent mental health predicament is the lack of good government funding for support programs in most developing world countries.

According to the most recent World Health Atlas published by the World Health Organization (WHO) (2017), the median number of mental health beds per 100,000 people in the population is <7 in LMICs, compared to 50 beds in high-income countries (HICs). These large disparities are even more apparent for child/adolescent services and social support with less than 0.2/100,000 in LMICs compared to >1.5 in HICs. Per capita government mental health expenditure (US$) is $1.05 in LMICs and $2.62 in Upper-Middle Income Countries (UMICs), compared to $80.24 in HICs, with more than 80% of public health expenditure allocated to mental health being applied to mental hospitals. As a consequence, more than 40% of countries in Africa and South East Asia have populations where people must pay out of pocket for mental health services. To top it off, 20-24% of member states in the Americas, Africa, and South East Asia have had no mental health data compiled in the last two years, making it hard to impress upon policymakers the dire need for more funding (World Health Organization 2017).

Lack of information on the economic benefits of health promotion and disease prevention strategies/interventions is also a big barrier to getting support from policymakers. A key question policymakers must consider is the cost of inaction. One U.S.-based study found total lifetime costs of suicidal events to be $59 billion, with $5 billion for nonfatal attempts (Shepard et al. 2016). Costs for non-fatal attempts on the healthcare system alone can be 10 times greater than a completed suicide, and 17% of survivors are permanently disabled, restricting their ability to be productive long-term (T. R. Miller 1995). McDaid’s (2016) summary of existing costing studies across the developed world indicates that the mean costs of suicide vary from between $0.4-4.3

million/event, based on direct[11], indirect (productivity loss)[12], and intangible (stigma)[13] costs. Direct costs are the smallest fraction of total costs surrounding suicidal behavior, while the greatest are lost opportunities to contribute to the economic output of a nation and the burden placed on society to handle a loss of life (Sinclair et al. 2011; D. McDaid and Kennelly 2009; Cox and Miller 1999). These latter costs are particularly high for younger populations where failed suicide attempts are likely to contribute to school absences and reduced productivity while there (Greenberg et al. 1993; Conti and Burton 1994; Slap, Goodman, and Huang 2001).

In Taiwan, productivity costs associated with total potential years of life lost in 2007 were estimated to be $1.95 billion (Law, Yip, and Chen 2011) and in Japan, lifetime lost earnings were calculated at $1.63 billion (Sado et al. 2011). In Brazil, indirect costs accounted for about 10% of total mean costs per patient of nonfatal suicides, at a cost of $7,200 (Sgobin, 2015). These costs were found to not be statistically different from the costs from treating patients with acute coronary syndrome. So just pre-discharge, the cost of non-fatal suicide treatment was equivalent to doubling the number of acute coronary incidences. Costs of mental health care in Pakistan had a calculated economic burden in 2006 equivalent to 250,483 million (PKR), or 4,264.27 million US$, with medical care costs and productivity losses contributing 37% and 58.97% of the economic burden,

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[11] Medical and related costs of completed suicides (including emergency services and use of potentially life-saving interventions), healthcare system costs of failed attempts (including follow-up physical and psychological rehabilitation), police investigations, disruption of transportation systems (depending on method), funeral costs.

[12] Absence from paid/voluntary work, education or home responsibilities; lost economic contributions of family members having to care/grieving.

[13] Often measured via willingness-to-pay (WTP) for say avoiding death or serious injury as the result of an unanticipated accident (Mcdaid, Knapp, and Raja 2008) or being the victim of homicide.

respectively (Malik and Khan 2016). Overall, though, there are few usable cost estimates for poor mental health or suicide, particularly outside the developed world. Indirect and especially, intangible costs, would be expected to be quite high in LMICs, and policy makers should recognize this reality.

The best hope for reducing such financial burdens is to devote more attention to prevention and support, so that the problems at the treatment end are less pressing. Economic literature has shown that the socioeconomic correlates with suicide may differ according to age (Andrés 2005) and models built and supported by evidence from one data set may not fit with a different set. Similarly, the results from developed countries may not hold for developing world adolescents. The dearth of available evidence relating to suicide (and mental health) in low-income countries is noted as a major concern for understanding such issues in the majority world (Boahen-Boaten, White, and O'Connor 2017). Consequently, analyzing the antecedents, mitigation, and protective factors of suicide and associated deleterious health behaviors among developing-world youth needs to be better studied, including through better systematic tracking to better determine the most vulnerable populations (Marmot et al. 2008; WHO Commission on Social Determinants of Health and World Health Organization 2008). Furthermore, there is a need for more rigorous empirical techniques and an expanded scope of theoretical frameworks being used to motivate such studies. This study aims to fill such voids, by implementing a strong empirical analysis, coupled with a conceptual framework that to this point has been overlooked or ignored in Economics literature.

The next section of this paper provides a brief literature review of the topics relevant to this study, including emphasis on the major gaps this study fills. Methodology sections follow, with details on the conceptual framework, empirical model, and data/variables details. Results of analysis are found in the sixth section, and this work concludes with a section of discussion and policy implications.

Background

Research on Mental Health & Suicide in LMICs

As indicated, it is difficult to access information and data on mental health and suicide statistics in the developing world. There is high underreporting of suicidal behavior in LMICs because of a lack of national systematic reporting, high stigma, and religious/cultural/legal sanctions. The lack of information on non-fatal suicidal behavior also hinders development of effective intervention strategies. What evidence does exist, however, indicates that there are consistencies across countries in terms of risk profiles. Females, being younger, having existing mental illness, lower education, and lower economic status all represent factors which indicate an individual is more likely to suffer from mental health problems (Jordans et al. 2018).

Lower economic status (e.g. poverty) is one of the most commonly evaluated factors in research looking at mental health in LMICs. In their systematic review, Iemmi et al. (2016) determined that more than half of studies using either individual or country-level indicators showed positive associations between poverty and suicide, but with multivariate analysis, such effects were attenuated. This would indicate that the relationship between poverty and suicide appears to be complex, much as it would be with general mental health. This strand of literature has often lacked attention to perceptions of poverty. It may be that these individuals' perceptions (which are socially-formed) are what play such a vital deterministic role.

In a systematic review focusing on South and Southeast Asia, Knipe et al. (2015) found consistent evidence that lower socio-economic status (usually measured by education) increased associative risk with suicide/attempting suicide, but their findings were not always consistent between and within countries. The greatest and most consistent association found was with subjective measures of financial circumstances. While important, such results are almost exclusively based on studies among adult populations. The impacts of income and long-run implication of education are likely less relevant when examining adolescent populations and seeking ways to improve their short-term health/behavior.

Available Data & Prior Analyses

Work using the Global School-based Student Health Survey (GSHS) has offered the most promise into understanding adolescent mental health and deleterious health behaviors, including suicide, in the developing world. GSHS includes specific questions on considering (and often planning and attempting) suicide. Multiple studies using data from this international surveying system have found bullying to be a prominent factor in teens' lives (such as Fleming and Jacobsen 2009; Due and Holstein 2008). In other published work using GSHS, poor mental health and suicide have been correlated with bullying (Rudatsikira et al. 2007) and other potential risk factors such as substance use and parental understanding (Abdirahman et al. 2012; Mahfoud et al. 2011; Brown 2009).

Most of the work published using GSHS data, however, is focused on only one or two countries, and is quite lacking in empirical rigor. Across the board, studies fail to consider simultaneity of various factors and only evaluate one level of suicidal behavior (most often consideration). Furthermore, most studies reduce many explanatory factors to binary, single entries, reducing the explanatory power of their estimation models. In addition, most of these studies possess no underlying framework to motivate their study. Such limitations are highlighted in Iemma et al's (2016) review, which points out the a-theoretic manner of many LMIC poverty-suicide studies and the lack of attention to social/cultural elements[14].

Among published research which does incorporate somewhat more empirical rigor and expands analyses to include multiple countries, there are still aspects which could be improved. Using GSHS data, Liu et al. (2018) used multilevel logistic regression to evaluate 40 different LMICs. They determined that having close friends and parental support showed significant protective factors for suicide attempts, but they also found no association between the prevalence of suicide and a country's per capita GDP. However, there are concerns over endogeneity because some of the explanatory variables that they used could be seen as a health outcome in of themselves, creating simultaneity concerns. Furthermore, they did not frame their findings or conclusions with any underlying conceptual explanatory framework as to what causes suicide (consistent with most other adolescent suicide/mental health research in LMICs). McKinnon et al. (2016) examined suicidal ideation and ideation with a plan across 32 LMICs using GSHS data, and found strong associations between suicide consideration/planning with bullying, loneliness, and limited parental support using a random-effects meta-analysis with multivariable logistic regression to get risk ratios. However, their parenting measure was based on a single question, they clustered at the school-level, and again, had no

[14] King and Merchant (2008) pointed out these same arguments among suicidal studies in the developed world.

underlying framework to drive their choices of explanatory variables. Such work could be improved through more empirically rigorous approaches.

Suicide's Treatment in Economics Literature

Economics can be considered among the most quantitatively rigorous of research fields. However, when it comes to analysis of suicide (and associated deleterious health outcomes), there are very few applied studies and the majority of published work has remained focused on determinants related to income, unemployment and divorce (J. Chen et al. 2012). Until the end of the 20th century, the primary manner in which economists dealt with suicide was as a rational choice based on income (Hamermesh and Soss 1974), given evidence that suicide rates appear to fall with rising incomes and rise with unemployment rates, creating a rather viscous cycle. This fundamental utility maximization-based approach indicates that a rational individual would choose death when the value of future income streams is costlier than death, given the need to maintain oneself and keep one's family supported at an acceptable level[15].

Marcotte (2003) reformulated the standard utility maximizing problem traditionally used in Economics literature to view the suicide decision as more consciously strategic. That work focused on the idea of suicide based on an imbalance of needs/means, where the attempt can be seen as a signal or cry out for more help, because there is some level of expectation that additional income/attention/medical care is there and just not offered. This theory posits that the expectation of increased utility through

[15] The elements of unemployment and human capital/education have been incorporated into this framework thanks to Koo and Cox (2008), as they saw it applied to Japan.

income and health maintenance costs/aid, post-attempt, means an individual chooses to attempt suicide.

Other work in the literature has also examined the impacts of divorce and its interplay with unemployment (Daly, Wilson, and Johnson 2013; Kposowa 2001; Blakely, Collings, and Atkinson 2003; Halicioglu and Andres 2010; Botha 2012), along with some “real-options”[16] approaches (Dixit and Pindyck 1994; Miao and Wang 2011). Overall, though, these works are premised on the primary role that income plays to motivate/determine suicide.

While such findings offer one explanation for suicide in more financially-stable countries, the assumptions underlying these existing models/studies may not be appropriate when applied to developing world populations. Hammeremech and Soss’s (1974) work was based on the developed world in the 1960’s, and Marcotte’s (2003) on the U.S. in the 1990’s. Further, the financial instability in many LMICs may indicate less applicability of arguments based on a theoretical cry for help. LMICs do not have strong health-care systems (Dupas 2011; Das, Hammer, and Leonard 2008), so there would not be a strong expectation of possible additional health-based investment to be gained from a suicide attempt. Another criticism of the traditional approaches to explain suicide in Economics literature is that many suicidal individuals have underlying mental health disorders, meaning that they cannot act “rationally”. Furthermore, there may be underlying views/preferences for the disutility of suicide depending on the legality and

[16] Founded in principles of investment, where the prospect of a better tomorrow can convince serious contemplators to delay acting on suicide attempts.

religious views of the act (D. McDaid and Kennelly 2009), which are usually not considered.

Another limitation of existing Economics-based work on suicide, is its primary focus on adult populations. The income-based arguments on which most of the literature is based, may not hold as much traction for explaining suicide in adolescent populations. A large survey study found that the biggest income effects on suicide have been found among older samples/age-brackets (J. Chen et al. 2012). Despite such concerns, researchers who have ventured to look at suicides among adolescents have remained in the income arena. Mathur and Freeman (2002) presented a model of household production and consumption where parents optimize their time away from time-intensive commodities like adolescent's well-being towards market work, with less time-intensive consumption commodities[17]. Under this model, reallocation of time results in mixed effects on adolescents' mental health, where higher money income can overall improve family wellbeing, but time lost with children can increase mental health issues and increase risks of suicide. They used state panel regressions of adolescent suicide rates in the U.S. and found results consistent with their model, indicating that parental income generation may impact adolescent mental health. Tekin and Markowitz (2008) used data from the National Longitudinal Study of Adolescent Health (Addhealth) in the U.S. and found that both suicidal thoughts and attempts decrease the likelihood that young adults (ages 18-26) engage in productive work or schooling, by 3 to 12%. Here, again, schooling has implications for long-term employment and income potentialities.

[17] Modeling in-line with Becker's (1974; 1965) work.

In light of a continued focus on income-based studies and the lack of progress in reducing the mental health burden adolescents face across the world, there is a burgeoning seed of thought in Economics-circles about the need to look beyond income-driven theories (S. O. Becker and Woessmann 2018; Pecchenino 2015). Our study seeks to further expand the conversation outside income-based explanations and the applicability of suicide theories among developing world adolescents by leveraging the knowledge gathered from other disciplines to help explain suicide (and associated deleterious health outcomes). Although structural factors (national wealth, income inequality, and education access) are strong predictors of adolescent health, adolescent health is also strongly affected by social factors, including family and peers (Viner et al. 2012; Berkman and Glass 2000). Development literature has long indicated the importance of social interactions, where research has concluded that maintenance of strong relationships with parents while concurrently having an independent network of close friends and community is needed for normal socioemotional growth (Steinberg 2001; 1990; 2001). It not surprising to find literature outside Economics which has also found positive associations between peer and parental support and suicide (King and Merchant 2008; Sun, Hui, and Watkins 2006). This study explores the social-correlates with deleterious health behaviors, using a strong sociological theory as our conceptual framework, and performing analysis with the rigor associated with the field of Economics.

The Model: Framework, Specification, & Hypotheses

Conceptual Framework

A theoretical framework appreciated by sociologists to be a good explanation for suicide and other deleterious health outcomes/behaviors is social integration theory (Berkman and Glass 2000). This theory stems from the field of research begun by Emile Durkheim (1897), and later reinvigorated by John Cassel (1976) and Sidney Cobb (1976), who were social epidemiologists who combined insights on attachment theory, social network analysis, and stress. Durkheim specifically tackled the issue of suicide, and posited that this ultimate example of individual health choice/behavior is instigated by social dynamics. He explained how "social facts" can be used to explain the changing patterns of aggregate tendencies towards suicide. Durkheim found however, that the rates of suicide appeared to remain unchanged over time within a country, even as the population and its individual people changed. He argued that attachment (the extent to which an individual retains ties with the members of society) and regulation (the extent to which he/she is held in the fabric of society by its values, beliefs, and norms) bond an individual to society. Thus, he theorized that the level of social integration within a society was going to be a major predictor of an individual's choice to commit suicide.

Beyond its applications to suicide, researchers elsewhere have also found evidence of the importance of social ties and networks on health behaviors and outcomes. Throughout the 1970's and 80's, there were a number of studies showing that lack of social ties or networks predicted mortality from almost every cause of death, meaning the effects are not specific to any one disease process (Berkman 1995; J. S. House 1981; J. House, Landis, and Umberson 1988; Blazer 1982; Cassel 1976). Such work found that people who are socially isolated/disconnected from others have a 2-5x higher risk of dying from all causes compared to those with strong ties to family, friends, and community. Other researchers, when studying human behaviors from a life course approach, have taken into consideration those members of a person's cohort who surround her/him and how the members of a cohort provide support to one another, reciprocally, over time (Kahn and Antonucci 1980; T. C. Antonucci and Akiyama 1987; Toni C. Antonucci and Akiyama 1987). Further social network analysis researchers' work is posited on the idea that the structural arrangement of social institutions shapes the resources available to an individual (social capital) and hence their eventual behavioral and emotional responses (e.g. coping, etc.), with the result that the network does not have to be limited by blood or geographical boundaries.

Given these various lines of research, Berkman and Glass (2000) formalized a holistic social integration framework seen in Figure 3.1. This framework embeds social networks into a larger social/cultural context with upstream forces conditioning network structure, and then the networks (and their structure) providing the opportunities for downstream mechanisms to occur, which impact health through certain pathways. Mechanisms include social capital, companionship, social support, social influence, social engagement/attachment, access to resources and goods, and social undermining, where social support is often divided into the subtypes of emotional, instrumental, appraisal and informational (J. S. House 1981; Heaney and Israel 2015). Pathways through which the impacts of these mechanisms can be realizes are through health-behavioral pathways, psychological pathways, and physiologic pathways.

[FIGURE 3.1]

These downstream components of the model are where our work focuses, namely through analyses influenced by the mechanisms and pathways of the social integration model/theory. The mechanism of social support and its different forms, as laid out by the theory, can be offered by parents, one of the most important sources of potential support for adolescents. Parental support can take many forms: love/caring/understanding; help/aid with access to resources; decision-making help/feedback; and advice/info for particular needs. Given that it is often hard to disentangle the various forms of social support from one another, we use a composite measure of positive parenting to encapsulate these various support types.

The mechanisms of social engagement, influence, and person-to-person contact we bring into our analysis through the use of social exclusion. Exclusion is related to social undermining wherein others express negative affect/criticism which can hinder one's goal attainment. In the presence of social exclusion, there is going to be a noted absence of each of these mechanism of social integration/interaction, including constraining of functional mental health behaviors/reactions, norms regarding help-seeking/adherence, and handling/coping effects.

The pathways-component of the conceptual framework gives rise to a number of potential means by which to measure social integration's influence. Although there are three distinct pathways given in the model, there is nothing preventing them from working simultaneously. Thus, in our choice of health outcome variables, we sought to capture all three pathways through examining suicidal actions/thoughts, drug use, and mental stress**.** Visual representation of how our empirical estimation is framed by the model is seen in Figure 3.2.

[FIGURE 3.2]

Empirical Specification

As previously indicated, we sought to examine the impacts of social integration and exclusion on adolescents' deleterious health behavior outcomes, including those of suicidal behavior in this study, and apply it to a cross-national context. Below is the empirical estimation equation that we used in that regard:

$$HealthOut_i = \beta_1 PosParent_i + \beta_2 SocExcl_i + \beta_3 X_i + \gamma_i + u_i$$

$HealthOut_i$ is the vector of outcome variables measured and includes considered suicide, planned suicide, attempted suicide, mental stress and using drugs. *$PosParent_i$* is an index representative of trust and engagement associated with positive parenting. *$SocExcl_i$* is an index representing elements of social exclusion. *X_i* is a demographic vector containing age and gender. Finally, there are country fixed-effects *(γ_i)* and a white noise error term *(u_i)*.

Hypotheses

As the social integration theory/model and existing literature would imply, we predict the following hypotheses as they pertain to the explanatory variables of positive parenting, social exclusion, and gender:

Hypothesis #1: *Positive parenting ($PosParent_i$) will decrease the likelihood of adolescents engaging in/experiencing deleterious health outcomes ($HealthOut_i$).*

Life-course models of the social determinants of health (SDH) point to supportive parenting as a crucial element in life-long health (Marmot et al. 2008; Repetti, Taylor, and Seeman 2002). Engaging parenting behaviors have been shown to predict positive outcomes across cultures (Barber et al. 2005; Neff 2003; Chandler et al. 2003; Q. Wang, Pomerantz, and Chen 2007; Siziya, Muula, and Rudatsikira 2007; B. Chen et al. 2016), where evidence indicates that in countries with greater family connections, adolescents face fewer behavioral and mental health problems (especially girls) (Viner et al. 2012). Parental monitoring has been shown to protect against peer violence and risk taking (Catalano and Hawkins 1996; Bonanno and Hymel 2010) and aid in increasing self-confidence (Baumrind, 1991). Warmth and monitoring appear to deter problem behavior by enhancing parental knowledge of adolescents' activities, whereabouts, and associates (Fletcher, Steinberg, and Williams-Wheeler 2004; Abar, Jackson, and Wood 2014). On the flip side, parents who model risky behaviors such as smoking (Bauman, 2001), drinking (Donovan, 2004), sexual promiscuity (Crosby et al. 2003), and violence (Kretman, 2009) have been shown to have children more likely to experience poor emotional wellbeing and engage in such risky behaviors (e.g. "violence begets more violence") (Bradford et al. 2003), including suicide (Wagner 1997; Chhabra and Sodhi 2012). The literature abounds with evidence that autonomy-supporting and monitoring parenting styles are associated with higher levels of positive, and lower levels of negative, health-related behaviors (Lohaus, Vierhaus, and Ball 2008; Steinberg 2001; Williams et al. 2000; Yap et al. 2014). Consequently, we predict that adolescent reporting of positive parenting behaviors/interactions will be reflected in lower likelihoods of deleterious health outcomes.

Hypothesis #2: *Social exclusion ($SocExcl_i$) will increase the likelihood of adolescents engaging in/experiencing deleterious health outcomes ($HealthOut_i$).*

Research has also shown that social networks, via multiple pathways, influence cognitive and emotional states, particularly through social influence (Berkman and Syme 1979; Holahan and Moos 1987; Holahan et al. 1995; 1997; Oxman et al. 1992; Vilhjalmsson 1993; McAvay, Seeman, and Rodin 1996; Wolf et al. 1991). There is also increasing evidence that negative interpersonal interactions, in particular, are strongly related to such factors as negative mood (Fleishman et al. 2000), stress (J. S. House 1987), depression (Cranford 2004), risky-health behaviors (Oetzel et al. 2007), and disease susceptibility (Cohen 1997). Longitudinal work with Canadian 10^{th} graders found that social self-efficacy (SSE) is strongly associated with peer support and that this has as an indirect effect on reducing depression tendencies (McFarlane, Bellissimo, and Norman 1995). Social networks may also have direct effects on health outcomes by influencing a series of physiological pathways largely related to stress (e.g. different hormonal responses, impacting immune and cardiovascular systems) (S. J Suomi 1997; Stephen J. Suomi 1991; Francis et al. 1996). There is evidence among stroke survivors that lack of social support can induce negative responses including suicidal thoughts (Kishi, Kosier, and Robinson 1996). Work comparing the suicidal tendencies of Jewish versus Arab Israelis indicated much higher suicide rates for Arab-Israelis, which may be a reflection of their more socially-marginalized identity (Harel-Fisch et al. 2012). Not having support available and being shut-out from social interaction is the crux of the social integration theory. We would therefore expect that suicide, mental stress, and drug use likelihoods are all going to increase with less social interface.

Hypothesis #3*: Females will be more likely to display suicidal tendencies and mental stress than males.*

Literature has well documented the role that gender may play in tendencies to display symptoms of poor mental health. While not directly influenced by the social integration theory previously laid out, there are multiple examples from both developed and developing world sources of females exhibiting higher likelihoods of experiencing mental depression and anxiety. The evidence also points to higher rates of suicidal tendencies among adolescent females than males (Gao et al. 2010; Patton et al. 2008; Jordans et al. 2018; Niraula et al. 2013; Luitel et al. 2013; Thapa and Hauff 2005; OECD 2017). In developing world countries, such tendencies may actually be higher, given the gender biases and violence perpetrated on women within cultures with more patriarchal norms. Females in such cultures may feel even more isolated and prone to suffer deleterious health outcomes. However, these same gender norms may limit females' ability to access such substances as drugs, so we cannot a priori hypothesize about whether or not females would be more driven/able to use drugs than their male counterparts.

Data & Variables

Data

The data used for this study comes from the Global School-based Student Health Survey (GSHS). This is a standardized survey instrument created in collaboration among the WHO, United Nations' UNICEF, UNESCO, and UNAIDS, with technical assistance from the U.S. Center for Disease Control (CDC) (CDC and WHO, n.d.). This survey uses a standardized scientific sample selection process, common school-based methodology, and core questionnaire modules. There are also expanded question modules and country-specific questions which form a self-administered questionnaire that 13-17-year-old students can be expected to complete in one regular class period.

The purpose of this survey is to provide data on a multitude of issues surrounding adolescent life to enable countries to develop priorities, establish programs, and advocate for resources aimed at enabling proper development of youth. The consistency across the main modules of the survey also enables international agencies (and researchers) the ability to make comparisons across countries regarding the prevalence of health behaviors and protective/risk factors, including topics such alcohol use, drug use, and mental health. Multiple waves of this survey have been administered in many countries, with representatives from more than 120 countries trained and 94 countries having completed a GSHS by 2013.

Our study uses data from the publically available core-modules of six developing world countries, using the most recently published data available from the CDC: Indonesia (2015), Bangladesh (2014), Costa Rica (2009), Peru (2010), Namibia (2013), and Morocco (2010). None of these countries was marred by war or significant civil strife during the 10 years prior to the administration of the survey. We feel these countries offer a reasonable cross-section of key regions of the developing world. In Table 3.1 we present some comparative statistics regarding international standards by which each country can be measured, as well as comparison to three major developed world nations (e.g. United States, United Kingdom, and Canada) to better place these nations along the entire international spectrum.

[TABLE 3.1]

Key Variables

Each of the deleterious health outcome variables is a binary variable, where suicide consideration and planning come straight from the survey. For suicide attempts, we took the survey question of how many times in the last 12 months the individual attempted suicide and created an indicator if this answer was larger than zero. A positive indicator for drug use was formed from an answer greater than zero for the age of first drug use. Mental stress reflects a positive indicator for either having felt lonely and/or having had trouble sleeping due to intense worrying over the last 12 months. Each of these mental health indicators is itself a binary variable formulated from an answer of "sometimes" or "most times" on a 5-point Likert scale.

The first key explanatory variable of positive parenting (*PosParent*), is the sum of four questions, each with a 5-point Likert scale, addressing two positive and two negative components of how adolescents interpret their parents' awareness and oversight of their behavior. These elements include parents going through adolescent's possessions, knowing where adolescent goes, understanding worries, and checking homework. The first two variables (going through possessions and not knowing where adolescent goes) were recoded so that a score of 5 reflects an answer of "Never" and a score of 1 an answer of “Always”. In this manner, the higher the score on the parenting index, the more positive parenting input the adolescent has perceived.

The second major explanatory variable, social exclusion (*SocExcl*), is a summation index of two binary indicators of forms of social isolation/exclusion: bullying and having no close friends. The indicator for being bullied was formulated based on giving an answer greater than zero to a query of how many times the respondent was bullied in the last month. Similarly, the indicator for having no close friends was an answer of zero on a question asking the number of close friends. The interpretation of all analysis variables are summarized in Table 3.2, and key descriptive statistics across the study sample can be found in Table 3.3 (available in the appendix are these descriptive statistics according to gender-grouping).

[TABLE 3.2]

[TABLE 3.3]

Estimation Strategy

Given the assumed correlation between the five deleterious health outcome variables, we used multivariate probit estimation to estimate a reduced form multi-equation system, where all five outcome equations are estimated simultaneously. We incorporated a unique weighting and clustering scheme in this estimation to account for the various complications of working with and pooling cross-country samples. Clustering was done through a “Grand-Clustering” approach wherein we created clusters based on country, stratum, and primary sampling unit (psu). For the unique weighting structure, we created a “modified-weight” based on within-country design effects in the manner of Skinner and Mason (2012). With this approach, one takes the mean survey weight value from within each country, and each individual observation's survey weight given from data is divided (i.e. weighted) by the mean weight from their respective country. This approach is focused on overcoming the biases inherent from the common finding that sample sizes in cross-national surveys often vary much less than population sizes, meaning that sampling fractions can be quite different. Results of this multi-equation system are presented in Table 3.4. Tables 3.5 and 3.6 report a summary of the key hypotheses in raw coefficient and marginal effects form, respectively. The full coefficient results tables for each country, estimated individually using robust standard errors and the survey weights provided with the data, are found in the appendix of this work. (Formulation of both the GSHS weights and further information about the problems and potential solutions to survey weighting and combining datasets can also be found in the Appendix.)

This estimation strategy allows for non-zero covariance between all equations. By allowing for this covariance structure we are also overcoming the concerns some may have regarding the endogeneity between some (or all) of these outcome variables, should one try to estimate only the outcomes of, say, suicide. By removing this endogeneity concern, it is no longer necessary to try and account for the issue with methods such as instrumental variables in a circumstance where the data available to us offer few feasible instruments. Further, we believe that all five outcome variables are important representatives of the myriad of health and behavior outcomes from social integration being positively applied or hampered. Additionally, the pooling of the data offers greater statistical power to the estimation and a more accurate picture of the influence of these social measures on adolescent health outcomes, across cultural and national boundaries.

To provide checks of our assumptions and the robustness of our findings, the following steps were taken. We performed likelihood ratio tests of independence between the five equations, in both the main pooled estimation sample and for each individual country's sample. Results of these are reported at the bottom of each coefficient table. Further, we tested for the significance of using the country dummies in the pooled data (e.g. a Structural Break Test). We also re-performed estimation of the entire analysis with a redefined version of the mental stress variable, wherein we replaced the binary indicators for loneliness and troubling sleeping with an ordinal indicator formulated from the quartiles of the summation of the two, 5-point Likert scale, variables. This reformulation required conditional mixed process estimation to allow for the mixed methods. Summary coefficient results of this analysis are found in the Appendix. The final robustness check involved the estimation of a three-equation system where suicidal behaviors are represented by one indicator variable for either considering or planning or attempting suicide, along with the binary indicators for mental stress and drug use. These results are not reported, but available upon request.

Results

Basic Statistics

As shown in Table 3.3, over the entire sample, 9.9%, 10%, and 8.7% of adolescents reported considering, planning, and attempting suicide in the year prior to being surveyed, respectively. Figure 3.3 combines these numbers to depict an overall suicide tendency rate for each country, which represents the (weighted) percent of adolescents who either considered, planned, or attempted suicide the year prior to being surveyed. Namibia, by far, had the highest rates of suicidal tendency at 33.7%, followed by Peru at 24.9%. Indonesia and Bangladesh have the lowest overall rates of suicidal tendency at 8 and 11%, respectively. Figure 3.4 depicts the intensity of this suicidal desire by presenting the average number of suicide attempts (within 1 year) among those adolescents who admitted to attempting suicide, by country. The range in average number of attempts is 1.59 (Bangladesh) to 2.21 (Indonesia).

[FIGURE 3.3]

[FIGURE 3.4]

Overall, 5.6% of adolescents reported having used drugs and 43.2% reported having had mental stress. The highest rates of drug use are in Costa Rica (18.8%) and Namibia (17.2%), with rates of drug use under 6% in the remaining countries. Mental stress appears highest in Namibia (59.9%) and lowest in Costa Rica (27.3%). The average age of the whole sample is 14.4 years old and 49.9% of the overall sample is female. Only Bangladesh has a study sample where there is uneven gender distribution in respondents, with 35.1% being female.

In terms of explanatory variables, Table 3.3 depicts the statistics for the component variables which make up the indices used in estimation for both positive parenting (*PosParent*) and social exclusion (*SocExcl*). With a range of 1-5 for each of the four positive parenting component variables, the overall mean scores are 3.12, 3.04, 3.13 and 4.06, where a higher score indicates perceptions of more positive parenting behaviors. Going through adolescents' possessions without their permission is the least common practice across all countries. Adolescents from Morocco and Peru exhibit the lowest scores on positive parenting components, most noticeably reporting lower rates of parents that understand respondent's worries and problems and who actually know where the adolescent goes during his/her free time.

Only about 5.6% of the overall sample report having no close friends. However, in Costa Rica, 22.7% of respondents claim that they have zero close friends, and 11.7% of Namibian adolescents report the same. In terms of bullying, the other major component of our measure of social exclusion, 25.9% of the overall sample report being bullied at least once in the last 30 days. The lowest rate of reported bullying is in Morocco (16.2%) and the highest is in Peru (46.9%). Figure 3.5 depicts the spread of bullying incidence rates for all countries in visual form, where the label above each bar indicates the average number of times bullying occurred for those adolescents who were bullied in each country. Adolescents bullied in Namibia were bullied at the highest average of 3.13 times within the 30 days prior to surveying.

[FIGURE 3.5]

Estimation Results

Table 3.4 presents the full estimation results for our main (pooled) model. Across the top are the five outcome variables, each of which was estimated using the same set of explanatory variables. Note that with the fixed-effects, Indonesia serves as our base category, given that adolescents from that country overall exhibited the lowest rates of suicidal behaviors (see Table 3.3). There is strong significance across all key explanatory variables. Positive parenting has a negative impact on the likelihoods of all suicidal behavior measures, as well as, for the likelihood of experiencing mental stress and using drugs. Alternatively, our measure of social exclusion indicates a positive association with the likelihoods of all deleterious health outcomes. Being female increases the likelihood of reporting mental stress and considering and planning suicide, but the likelihood of using drugs is significantly lower among females. As shown at the bottom of the table, all intra-equation correlations are significant, and the χ^2 value for the test of independence is high and significant, indicating a rejection of a null hypothesis that the equations are independent.

[TABLE 3.4]

As mentioned, while the key focus in this study is to examine the pooled model, there may be benefits to also comparing the estimations on each country individually. Table 3.5 repeats the key explanatory coefficients from estimation on the pooled sample (Column 1), followed by the results from each country run on its own. The significance of a negative effect of positive parenting and a positive effect of social exclusion on all deleterious health outcomes remains fairly consistent, even when analyzing each country individually. The importance of gender on likelihoods for each respective outcome are less consistent across country and dependent on outcome.

[TABLE 3.5]

Given that the coefficients from probit estimation are hard to directly interpret, we have also reproduced the same layout as Table 3.5, in Table 3.6, where the (average) marginal effects are presented. Again, Column 1 shows the marginal effects from the pooled sample, and the remaining six columns are the marginal effects for each country's individual sample. Our estimation results indicate that our measure of positive parenting reduces the likelihood of all deleterious health outcomes by less than 1% for a unit change in the index, with the highest impact being 1.1% (Mental Stress). On the other hand, social exclusion appears to increase the likelihood of the suicidal measures by a range of 6.4-7.8%, increase the likelihood of drug use by 3.1% and increase the likelihood of reported mental stress measures by 15.4% for a unit change in the index. Being female has the greatest impact on reported mental stress, increasing the likelihood by 10.9%. The range of positive effects on suicidal measures from being female range from 0.9% to 4.1%, and the negative impact on likelihood of drug use is -5.1%. The magnitude of impacts when examining each country individually are similar to those from the pooled sample, where the greatest impacts are seen from social exclusion on increasing the likelihoods of reported mental stress or attempting suicide.

[TABLE 3.6]

Discussion, Policy Implications & Conclusions

There is growing awareness and concern about suicide rates, globally, particularly among adolescents. Suicide has become a leading cause of all adolescent deaths, second only to transportation related incidents. Associated with suicide are other deleterious mental and behavioral health outcomes, which are also beginning to come to the forefront in the minds of policy-makers and researchers alike. Awareness and research into such topics has been neglected among LMICs due to lack of accurate data, stigma, and poor healthcare reporting systems. Existing published work primarily focuses on prevalence rates and basic correlational associations, lacking a strong empirical framework. While Economics literature has primarily relegated suicide into a box of utility-maximization (e.g. rational) based decisions, there is another theoretical motivation behind suicide postulated and supported by Durkeim related to social integration theory, which may be more relevant to both LMICs and adolescents.

Leveraging the knowledge gained from social integration research, we used data from the Global School-based Student Health Survey (GSHS) of six different countries, covering adolescents from major regions of the world to examine the influence of both positive and negative components of social integration on five different deleterious health outcomes, including three levels of suicide behavior. Estimation of a reduced-form, simultaneous model incorporating specialized clustering to account for the sampling design and cross-cultural components of our data set produced robust results indicating that positive parenting has the potential to reduce the likelihood of all five deleterious health outcomes, while social exclusion increases these likelihoods, among both pooled and individual country samples. Such findings support our initial research hypotheses and bring enhanced empirical rigor to developing world examinations of deleterious health behaviors and continues to broaden the focus of existing Economics-based literature on suicide.

Our results provide support for the choice to approach deleterious health outcomes from a more socially-focused perspective, in-line with a small, but growing, interest from (Economics) researchers to look outside income-focused explanations for such behaviors. Pecchenino (2015), in his development of a despair-oriented theoretical model to explain suicide, emphasized the need to recognize how a situation such as despair can be viewed as an individual's repositioning from societal approval to disapproval and from a place inside to a place outside society. Becker and Woessmann's (2018) economically-framed examination of the association between Protestantism and suicidal risk examined the competing theories of theological and sociologic-driven mechanisms. They found support for the sociological-based argument based on social cohesion (e.g. higher attendance at church). Other work actually examining whether it is the social approach or the neoclassical, utility maximization, approach from Economics which drives suicide, has found statistically significant support for the social support argument in both an Italian (Detotto and Sterzi 2011) and Japanese (Yamamura 2010) setting. However, these studies were based on adult populations, and neither examined the contrast of social exclusion and positive engagement and trust (e.g. positive parenting).

Findings from sociology literature have shown the relevance of parental variables beyond that postulated by Mathur and Freeman (2002), who focused on allocation of time and income-generating consequences. Stack (2000), who reviewed hundreds of studies, determined that there was a strong connection between both divorce and migration and suicide. Further, Cutler (2001) found that an increasing proportion of youth living with divorced parents was one of the strongest predictors of rising suicide among youth in the developed world. Both divorce and migration would place adolescents in a situation with less social cohesion and support from their parents, which social integration theory would predict would lead to poorer mental health and behavioral outcomes. Literature from both developing and developed-world context supports such predictions with poorer emotional/ physical health and academic functioning among youth where one or both parents are absent (Amato 2005; Capron, Thérond, and Duyme 2007; Gao et al. 2010; Shi et al., n.d.; Gray et al. 2013; Patton et al. 2014). This gives additional credence to our underlying framework.

One of the completed studies closest to our work is that by Kim (2016) which used multi-level modeling to examine the roles of parenting and peer networks on youth suicides, using GSHS data. That study, however, only examined suicide, running each outcome variable separately, without accounting for other deleterious health outcomes. Furthermore, that study was performed only using data from China. Our analysis showed the importance of running our reduced-form model simultaneously, and that the impacts of parental involvement and social exclusion are both relevant to multiple deleterious health behaviors. We have thus been able to expand such findings to find that they hold across countries which represent a wide cross-section of the developing world.

Empirically, our study also expands the literature through its empirical approach, including the use of a unique clustering measure and more descriptive variable definitions. In addition, we used individual-level suicidal tendencies, in line with what Tekin and Markowirz (2008) and Marcotte (2003) did, and not just suicide counts. Reflective of successful suicide attempts, suicidal count data are based on death records and in developing countries, accurate reporting of suicide deaths may be doubly inaccurate due to stigma and poor overall reporting systems. Suicidal tendency may be more reflective of the overall health "outcome" of suicidal tendency because of what it reflects in terms of seeing no way out and seeing no sources of support (Daly, Wilson, and Johnson 2013).

Our results, thus, indicate a need to focus on improving the social outlook of adolescents in the developing world. One key element of social exclusion is bullying. Our data indicates the rate of bullying is non-negligible among adolescents (Figure 3.5), with the highest rates in Namibia and Peru, where over 40% of adolescent report being bullied in the last 30 days. Such high rates are consistent with prevalence rates found across the world, including Due and Holstein's (2008) summation of 66 countries worth of GSHS data indicating an average of 37.4% of adolescents being bullied. These findings reiterate the necessity for attention to combat bullying, given growing evidence of the long-term neuro-biologic consequences and correlates between peer victimization and various deleterious health outcomes (Quinlan et al. 2018).

Potential solutions may be related to turning bullying on its head, and offering adolescent peers activities which incentivize and facilitate supportive interactions. Having social interactions with others has been shown to alter the trajectories of psychological distress during adolescence. Such findings are exemplified in how those individuals who are extraverted have shown lower levels of depressive symptoms over time (Lien, Hu, and Chen 2016). There is also existing evidence that peer-based interventions hold promise for such outcomes as suicide reduction, and can be cost-effective. One good long-term study and economic evaluation of a multi-level suicide prevention intervention among young (15-19 years old) American Indians in New Mexico (USA), which incorporated peer training, post intervention outreach, community education programs, and suicide-risk screening was shown to save $1.7 million due to a decrease in suicide rates from 59/1000 to 7-10/1000, with cost per QALY[18] saved of $419 (Zaloshnja et al. 2003). Modeling based on data from Florida university students showed that a peer support program to prevent suicide would generate benefits 5.35 greater than the costs, as compared to a general education intervention which only generated 2.92-times greater benefits (De Castro et al. 2004).

There are potential benefits of considering interventions aimed at reducing bullying and/or increasing participation in community/youth groups, given the results that

[18] Quality-Adjusted Life Years

social exclusion appears to have larger effects on deleterious health outcomes than does positive parenting. However, we do not disregard the importance of educating parents about the positive effects trust and engaging approaches to parenting have on reducing negative mental health and risky behavior outcomes. There is also evidence that at times, parental involvement may be more important than peers in inducing positive changes (Kim 2016; A. B. Miller, Esposito-Smythers, and Leichtweis 2015).

Appropriate forms of parental-based interventions could be informed by awareness of the importance between negative versus positive interactions. There is evidence that negative parental interactions are actually more impactful/hurtful than mere absence of positive interactions (Patton et al. 2008). Such findings are mirrored in those from an Australian study using matched parent and adolescent panel data, where researchers found that the negative emotional and physical health impacts from having a single parent were transmitted through increased work-family conflict (Dockery, Li, and Kendall 2016). That study also found that such negative outcomes were exacerbated when that parent had low job control. This finding is in congruence with other research indicating that the perceptions adolescents have of how they are parented (e.g. controlling, autonomy-supporting, etc.) are often a reflection of how well the parents' needs are being met/ fulfilled[19].

Parents who experience high levels of psychological need frustration are more likely to use psychological control and in turn, to promote a feeling of need frustration in their adolescents. On the other hand, parents who experienced high levels of psychological needs satisfaction tend to exert more autonomy support, and in turn,

[19] For an in-depth discussion of psychological need fulfillment (BPNT) see works such as Deci & Ryan (1995), Deci & Vansteenkiste (2004), and Allen & Anderson (2018).

adolescents tend to perceive higher level of needs satisfaction, with associated better mental and physical health (Costa et al. 2019; Mabbe et al. 2018). As a consequence, researchers believe that a negative cycle can persist. Soenens et al. (2008) conclude from their work with Belgian teens that parents of less well-adjusted teens may be more prone to resort to psychological control, which in turn may lead to increases in adolescents' susceptibility to depression, findings supported by Pettit et al. (2001).

In a cross-cultural study of the roles of social support and adolescent mental health, Cheng et al. (2014) determined that elevated perceptions of having a caring female adult in the home and feeling connected to their neighborhoods were positively associated with adolescents' levels of hope across the sites and negatively associated with depression and post-traumatic stress symptoms. Authors of that study particularly recommended strengthening the support between female caretakers and their adolescents at home. In another study, researchers found that income transfers improved parental relationships among American Indians in the United States, attributable to reduced parental stress (Akee et al. 2018). The greatest improvements in emotional and behavioral health were found among those adolescents with the lowest initial endowment. Thus, one potential intervention avenue which holds promise would be to find ways to increase parents feelings of more support in their own relationships/life. This would increase their perceptions of self-competence and autonomy, which would result in being able to offer more positive parenting interaction with their adolescents.

As it pertains to our results, Figure 3.6 displays the distribution of positive parenting across the three regions of Africa, Central/South America, and Central Asia/Middle East. As one can see, females across the board display a higher density of positive parenting interactions than do males. This is more obvious in Central Asia/Middle East, where perhaps girls are more strongly associated with (and expected to remain at) home, allowing them to have more time to interact with their parents. In such a context, it may be important to focus interventions aimed at adolescent males that incorporate a parental focus. This would allow the opportunity for adolescent males to have improved perceptions of their parental interactions and gain the health outcome benefits our study would indicate flow from positive parental relations. Similarly, the significance of our gender identifier which indicates that females are at a higher risk of both mental stress and suicide-related behavior may suggest the need to develop intervention policies which maintain consideration of the differential risks each gender has for certain deleterious health behaviors/outcomes.

[FIGURE 3.6]

While determination of targets for specific interventions will require further research, there are some key elements to keep in mind. Thoits (1995; 2011) believes that effective provision of support is likely going to come from people who are socially similar and experiencing similar stressors/situations, regardless of gender or culture, which for adolescents would be their peers. Also, perceptions of support (rather than objective behaviors themselves) are most strongly linked to recipients' health and wellbeing (Wethington and Kessler 1986; Winfree and Jiang 2010; King and Merchant 2008; Dunkel-Schetter and Bennett 1990; Opperman et al. 2015). So, future work may need to identify and track factors that influence whether behaviors are perceived as supportive. There is also evidence that there is not a dose-response curve in the relationship between social relationships and health (J. S. House 2001). Rather, very low levels of social integration are most deleterious with higher levels being less advantageous once some sort of threshold level is reached (e.g. diminishing marginal returns). Even just one strong intimate relationship has been found to be an important predictor of good health (Michael et al. 1999).

Keeping these considerations in mind, overall policy and intervention changes which are likely to be impactful in reduced deleterious health outcomes among developing world adolescents will need to be multi-faceted. It will be important to combine interventions targeted at improving awareness/support for the general public (e.g. peers and parents), and different ones to ensure key front-line professionals are better aware of the risks of poor mental health and the methods that can be used to prevent its decline (David McDaid 2016). It is also important to remember that infrastructure-based interventions are very expensive, and government-spenders will want to see policies which have effective returns on investment. In that way, a focus on social-based policies may be more appealing, given that there are efficiency gains to be made from shifting from treatment to promotion/prevention (Knapp, McDaid, and Parsonage 2011). If entire communities can be brought together to support one another, including through being on the lookout for triggers of poor mental health and behaviors, the success of interventions will be greater. There needs to be buy-in at the family, school, and community-health workers level, as they have all been associated with successful interventions (Chan et al. 2013; M.-T. Wang and Sheikh-Khalil 2014; Marmot et al. 2008; Sigfusdottir et al. 2010).

While results of this study are robust, we do acknowledge several limitations which future work could seek to remedy. There is the potential of measurement error in our measures of deleterious health behaviors. In Bangladesh, suicide is known to be illegal (Arafat 2017), and while the legal status of suicide in the other countries used in this sample are unknown, given the high level of stigma surrounding suicide, it is quite possible that there was underreporting of suicidal behaviors among the samples. It is possible that a more accurately measured, and related, deleterious behavior would be self-harm, which adolescents may be more willing to acknowledge than suicide (Iemmi et al. 2016; WHO 2014) . The data source we used, however, did not contain such measures. It also did not offer any information about the forms/methods of attempted suicide, which could have a big impact on the types of infrastructure-related interventions governments might consider (David McDaid 2016).

We also did not incorporate a measure of social capital, such as social program funding, which other suicide and mental health researchers have done (Detotto and Sterzi 2011; Ho 2016; Ko et al. 2018; D. L. Miller et al. 2006). However, attention to social capital reflects a more macro-based form of analysis, and our focus in this study was to remain at the micro-level (recall Figures 3.1 and 3.2). Looking at the broader culture through a social capital lens, however, may shed additional light on the differences we see cross-culturally (Lester and Yang 1991), should a similar study be conducted in the future. Future work may also benefit from consideration of additional macro-level elements which can better capture and account for overall cultural and socioeconomic perceptions/standards. Berkman and Glass (2000) posit in their overall conceptual framework that such elements are relevant considerations in more fully understanding social integration theory.

Another potential unaccounted for element is recent shocks or traumatic events which may have a financial or emotional component which previously increased the risks of deleterious health outcomes among our analysis sample (such as in Gedela 2008; Kaur, Dhaliwal, and Singh 2011). However, in our choice of sample countries, we are not aware of any striking shocks which could cause a severe bias. The most striking source of potential bias we do acknowledge stems from longitudinal research which shows distressed adolescents view parents as becoming increasingly controlling (Barber et al. 2005; Soenens et al. 2008; Q. Wang, Pomerantz, and Chen 2007). Already upset kids report their parents as more controlling/intrusive and will already be themselves more prone to commit suicide and experience/engage in other deleterious health behaviors. This same mechanism may be at play in how they report their experiences of social exclusion. Unfortunately, we are unable to delve into some of the mechanisms explaining our findings as deeply as some may desire to offer more nuanced policy guidance, given the limitations of using secondary data.

Psychology literature has often used more in-depth survey instruments which may capture more nuanced aspects of which parental support or social exclusion/inclusion elements matter most (A. B. Miller, Esposito-Smythers, and Leichtweis 2015; Winfree and Jiang 2010). However, such literature has again bypassed LMICs. Use of the GSHS data set also means that we are unable to account for students who have dropped out of school. UNESCO (UIS 2018) estimates that one in five children, adolescents and youth are out of school. Such populations could be expected to have a greater prevalence of deleterious health behaviors if school support matters more than close-friend support (A. B. Miller, Esposito-Smythers, and Leichtweis 2015). Alternatively, should adolescents not in school have less exposure to bullying, perhaps they suffer less. The lack of information in our data about the source of bullying means that we are unable to tease out such impacts. Overall, though, we felt that the GSHS data source offered us the best ability to analyze our key research questions, and apply it cross-culturally using standardized measures.

As a closing caution, the ability to offer more monitoring and support of adolescents may be limited in nations where the need to earn income and improve physical health are perceived as greater priorities for policy makers (Repetti, Taylor, and Seeman 2002). Furthermore, the likelihood that an individual will seek help is dependent on the probability that the support will remove the target problems with certainty (Yaniv 2001; J. Chen et al. 2012), Thus, there needs to be effective support/treatment and increasing public awareness of problems. Additional income only goes so far in improving health. While it does matter, there are other ways which help to reduce multiple negative health outcomes (i.e. suicide, mental stress, and drug use) (O'Connor and Pirkis 2016). In our study we focused on the social domain and returned to a focus on Durkeim's thesis surrounding social integration and its impacts on not only suicide but health in general. We have expanded existing literature to include LMICs and used rigorous analytic techniques to offer some guidance to begin to answer House's (1981) key question of "Who should provide what, to whom (and when)?"

Part of the reason social connectedness is so important is that these ties give meaning to a person's life by virtue of enabling for fuller/more complete participation in life and connection/commitment to community. Participation and membership in community, itself, can enhance health above and beyond the "take" that having a strong social network can allow. Social integration allows for life to have a sense of coherence, meaningfulness, and interdependence (Berkman and Glass 2000; Rook 1990). Having a more developmentally stable and healthier adolescent population is going to enhance the economic potential of a country. Economic growth is particularly important for poor countries, as it gives the opportunity to provide resources to invest in further improvements to the lives of a nation's population (Marmot et al. 2008). Adolescents that are able to develop holistically and be empowered offer the greatest potential to their nations and economies as the next generation to lead this world to a better place.

Tables & Figures

Table 3.1: Country Comparisons

	Indonesia	Bangladesh	Costa Rica	Peru	Morocco	Namibia	U.S.	U.K.	Canada
Population[1]	258.4 mil	154.5 mil	4.52 mil	29 mil	32.3 mil	2.2 mil	309 mil	62.8 mil	34 mil
Region[1]	East Asia & Pacific	South Asia	Latin America & Caribbean	Latin America & Caribbean	Middle East & North Africa	Sub-Saharan Africa	North America	Europe & Central Asia	North American
Income Level[1]	Lower Middle Income	Lower Middle Income	Upper Middle Income	Upper Middle Income	Lower Middle Income	Upper Middle Income	High Income	High Income	High Income
GDP (Current US$)[1]	$860.9 bil	$172.89 bil	$30.56 bil	$147.5 bil	$93.2 bil	$12.7 bil	$15 tril	$2.5 tril	$1.6 tril
Poverty Headcount[1,4]	15.70%	19.60%	1.50%	5.50%	1%	22.60%	1%	0.2%	0.2%
Life Expectancy[1]	69	71.8	78.6	73.7	74	62	78.5	80.4	81.2
Expected Years of School[1]	12.3	11	12.5	12.7	10.6	8.9	13.9	13.3	13.7
Human Capital Index (HCI)[1]	0.5	0.5	0.6	0.6	0.5	0.4	0.8	0.8	--
Human Development Index (HDI)[2]	0.694	0.608	0.794	0.75	0.667	0.647	0.924	0.922	0.926
Ineq. Adjusted HDI[2]	0.563	0.462	0.651	0.606	--	0.422	0.797	0.835	0.852
HDI Rank[2]	116	136	63	89	123	129	13	14	12
Physicians /1,000[3]	0.38	0.53	1.15	1.27	0.73	2.7 beds	2.59	2.81	2.61

Table 3.1: Country Comparisons (cont.)

Current Health Expenditure[3,5]	3.30%	2.60%	8.10%	5.30%	5.50%	8.90%	16.8%	9

[1] World Bank. “World Development Indicators.” DataBank, 2018. https://databank.worldbank.org/source/world-development-indicators.
[2] UNDP, United Nations Development Programme. “Human Development Indicators.” Human Development Reports, 2018. http://hdr.undp.org/en/countries/profiles.
[3] CIA, Central Intelligence Agency. “The World Factbook,” 2018. https://www.cia.gov/library/publications/resources/the-world-factbook/.
[4] 2010 Poverty Headcount at $1.90/day 2011 Purchasing Power Parity (PPP)
[5] The share of spending on health in country relative to the size of its economy (final consumption) in 2015.
*World Bank statistics reflect the rankings and figures from year of GSHS survey; For developed world countries, year is 2010.

Table 3.2: Description of Variables

VARIABLES	DESCRIPTION
OUTCOME VARIABLES	
Considered Suicide	=1 if adolescent reports Yes to considering suicide in last 12 months, 0 otherwise
Table 3.2: Description of Variables	
Planned Suicide	=1 if adolescent reports Yes to planning suicide in last 12 months, 0 otherwise
Attempted Suicide	=1 if adolescent has attempted suicide in last 12 months, 0 otherwise
Mental Stress	Sum of binary indicators for feeling lonely and worrying so much individual has trouble sleeping most of the time or sometimes, over last 12 months
Used Drugs	=1 if adolescent has used drugs, 0 otherwise
EXPLANATORY VARIABLES	
Positive Parenting	Sum of 5-point Likert scales for frequency with which parents go through possessions without permission and don't know where kids go after school over last 30 days (1=Always, 5=Never), and frequency with which parents understand problems and worries and check on homework being done over last 30 days (1=Never, 5=Always)
Social Exclusion	Sum of binary indicators for having zero close friends and for reporting having been bullied in last 30 days
Female	=1 if female, 0 male
ADDITIONAL CONTROLS	
Age	Age of adolescent
Country	
Indonesia (BASE)	=1 if adolescent from Indonesia, 0 otherwise
Bangladesh	=1 if adolescent from Bangladesh, 0 otherwise
Namibia	=1 if adolescent from Namibia, 0 otherwise
Morocco	=1 if adolescent from Morocco, 0 otherwise
Peru	=1 if adolescent from Peru, 0 otherwise
Costa Rica	=1 if adolescent from Costa Rica, 0 otherwise

Table 3.3: Descriptive Statistics Across Countries

VARIABLES	TOTAL SAMPLE	INDONESIA	BANGLADESH	NAMIBIA	MOROCCO	PERU	COSTA RICA
PERCENT OF TOTAL SAMPLE	100%	41.7%	11.7%	14.7%	10%	11.2%	10.7%
OUTCOME							
Considered Suicide	0.099	0.047	0.046	0.179	0.150	0.197	0.102
Planned Suicide	0.100	0.050	0.066	0.228	0.133	0.150	0.067
Attempted Suicide	0.087	0.027	0.052	0.215	0.115	0.164	0.075
Mental Stress	0.432	0.430	0.428	0.599	0.394	0.407	0.273
Used Drugs	0.056	0.014	0.021	0.172	0.057	0.050	0.188
EXPLANATORY							
Positive Parenting[1]							
Check Homework	3.12	3.14	3.42	2.99	3.19	3.21	2.70
	(1.44)	(1.36)	(1.32)	(1.53)	(1.62)	(1.34)	(1.57)
Understand Worries	3.04	3.05	3.34	3.14	2.44	2.96	3.20
	(1.43)	(1.39)	(1.28)	(1.42)	(1.54)	(1.35)	(1.53)
Know Where Really Go	3.13	3.23	3.17	2.91	2.91	2.95	3.40
	(1.433)	(1.36)	(1.39)	(1.39)	(1.68)	(1.39)	(1.51)
Don't Go Through Stuff	4.06	3.85	4.55	3.84	4.18	4.25	4.35
	(1.21)	(1.26)	(0.89)	(1.33)	(1.28)	(1.02)	(1.01)
Social Exclusion							
Zero Close Friends	0.056	0.025	0.079	0.117	0.078	0.048	0.227
Bullied	0.259	0.195	0.238	0.416	0.162	0.469	0.391
Female	0.547	0.563	0.606	0.535	0.489	0.522	0.563
ADDITIONAL CONTROLS							
Age	14.4	14.0	14.2	16.0	14.0	14.4	14.3
	(1.59)	(1.61)	(0.98)	(1.78)	(1.29)	(1.04)	(1.08)

*Weighted using population survey weights for each respective country; total sample statistics are weighted wherein each observation's weight is scaled in relation to the mean probability weight in the respective country of residence. Table 3.3: Descriptive Statistics Across Countries

*Mean values reported, with standard deviations in parentheses for non-binary variables. Mean of binary variables represents percentages.

[1]Range is 1-5 for each component question, higher value is associated with more positive parenting.

Table 3.4: Multivariate Probit Results

	DEPENDENT VARIABLES				
EXPLANATORY VARIABLES	Consider Suicide	Plan Suicide	Attempt Suicide	Mental Stress	Drug Use
Positive Parenting	-0.050***	-0.041***	-0.047***	-0.030***	-0.068***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.006)
Social Exclusion	0.425***	0.387***	0.529***	0.422***	0.297***
	(0.028)	(0.025)	(0.027)	(0.025)	(0.036)
Age	0.037***	0.014	0.002	0.119***	0.092***
	(0.011)	(0.011)	(0.010)	(0.009)	(0.018)
Female	0.251***	0.128***	0.066*	0.299***	-0.493***
	(0.029)	(0.029)	(0.028)	(0.022)	(0.037)
Bangladesh	0.057	0.174*	0.327***	0.027	0.061
	(0.076)	(0.079)	(0.073)	(0.057)	(0.137)
Namibia	0.581***	0.774***	0.998***	0.057	0.954***
	(0.055)	(0.063)	(0.072)	(0.055)	(0.081)
Morocco	0.633***	0.534***	0.726***	-0.09	0.468***
	(0.057)	(0.053)	(0.058)	(0.050)	(0.110)
Costa Rica	0.369***	0.103*	0.447***	-0.485***	0.854***
	(0.053)	(0.046)	(0.049)	(0.043)	(0.093)
Peru	0.654***	0.429***	0.750***	-0.231***	0.370***
	(0.057)	(0.053)	(0.051)	(0.042)	(0.107)
Constant	-1.789***	-1.464***	-1.497***	-1.700***	-2.426***
	(0.174)	(0.175)	(0.176)	(0.142)	(0.319)
Rho (ρ) 1-2			0.788***		
			(0.011)		
Rho (ρ) 1-3			0.723***		
			(0.012)		
Rho (ρ) 1-4			0.23***		
			(0.017)		
Rho (ρ) 1-5			0.276***		
			(0.025)		
Rho (ρ) 2-3			0.75***		
			(0.011)		
Rho (ρ) 2-4			0.184***		
			(0.017)		
Rho (ρ) 2-5			0.239***		
			(0.024)		
Rho (ρ) 3-4			0.178***		
			(0.019)		
Rho (ρ) 3-5			0.312***		
			(0.028)		
Rho (ρ) 4-5			0.115***		
			(0.019)		

Table 3.4: Multivariate Probit Results (cont.)

N	24217
ln(L)	-37301
χ^2 (Null Model)	3080.8
χ^2 ($\rho_{ij}=0, \forall$ i,j)	10585.56
AIC	74721.7
BIC	75207.4

*** p<0.01, ** p<0.05, * p<0.1; Weighted using intercountry design-weighting; SE clustered at the grouping of Country-Stratum-PSU ("Grand-Clustering")

Table 3.5: Summary Hypotheses Table

	ALL	*INDONESIA*	*BANGLADESH*	*NAMIBIA*	*MORROCCO*	*PERU*	*COSTA RICA*
PANEL A: CONSIDERED SUICIDE							
Positive Parenting	-0.050***	-0.058***	-0.043*	-0.018*	-0.041***	-0.070***	-0.085***
	(0.005)	(0.009)	(0.018)	(0.008)	(0.008)	(0.009)	(0.010)
Social Exclusion	0.425***	0.576***	0.486***	0.217***	0.489***	0.433***	0.384***
	(0.028)	(0.045)	(0.109)	(0.041)	(0.058)	(0.054)	(0.070)
Female	0.251***	0.241***	0.234*	0.04	0.289***	0.595***	0.391***
	(0.029)	(0.047)	(0.114)	(0.049)	(0.062)	(0.061)	(0.075)
PANEL B: PLANNED SUICIDE							
Positive Parenting	-0.041***	-0.056***	-0.058***	0.009	-0.037***	-0.069***	-0.074***
	(0.005)	(0.009)	(0.018)	(0.007)	(0.009)	(0.009)	(0.011)
Social Exclusion	0.387***	0.429***	0.443***	0.330***	0.353***	0.407***	0.275***
	(0.025)	(0.045)	(0.098)	(0.038)	(0.061)	(0.056)	(0.075)
Female	0.128***	0.067	0.053	-0.039	0.158*	0.524***	0.315***
	(0.029)	(0.047)	(0.103)	(0.046)	(0.064)	(0.063)	(0.079)
PANEL C: ATTEMPTED SUICIDE							
Positive Parenting	-0.047***	-0.049***	-0.082***	-0.007	-0.033***	-0.076***	-0.074***
	(0.005)	(0.011)	(0.018)	(0.007)	(0.009)	(0.010)	(0.011)
Social Exclusion	0.529***	0.743***	0.545***	0.414***	0.532***	0.460***	0.403***
	(0.027)	(0.051)	(0.093)	(0.038)	(0.059)	(0.055)	(0.077)
Female	0.066*	0.002	-0.018	-0.101*	0.12	0.388***	0.315***
	(0.028)	(0.055)	(0.106)	(0.046)	(0.064)	(0.061)	(0.081)

Table 3.5: Summary Hypotheses Table (cont.)

PANEL D: MENTAL STRESS							
Positive Parenting	-0.030***	-0.015**	-0.017	-0.036***	-0.022**	-0.048***	-0.064***
	(0.003)	(0.005)	(0.011)	(0.007)	(0.007)	(0.008)	(0.008)
Social Exclusion	0.422***	0.537***	0.395***	0.209***	0.418***	0.469***	0.467***
	(0.025)	(0.033)	(0.069)	(0.037)	(0.055)	(0.048)	(0.060)
Female	0.299***	0.297***	0.062	0.217***	0.449***	0.394***	0.418***
	(0.022)	(0.029)	(0.063)	(0.044)	(0.053)	(0.052)	(0.058)
PANEL E: DRUG USE							
Positive Parenting	-0.068***	-0.114***	-0.046	-0.042***	-0.048***	-0.067***	-0.091***
	(0.006)	(0.012)	(0.030)	(0.008)	(0.013)	(0.014)	(0.011)
Social Exclusion	0.297***	0.629***	0.542***	0.119**	0.349***	0.213**	0.115
	(0.036)	(0.063)	(0.146)	(0.046)	(0.081)	(0.080)	(0.077)
Female	-0.493***	-0.550***	-0.540**	-0.363***	-0.729***	-0.486***	-0.524***
	(0.037)	(0.081)	(0.206)	(0.054)	(0.109)	(0.091)	(0.080)

*** p<0.01, ** p<0.05, * p<0.1

- Individual country models run using survey probability weighting; Total sample - each observation's weight is scaled by mean probability weight in the respective country.
- Standard errors in parentheses - clustered at a grand clustering level identifying each unique Country-Strata-PSU pairing under full sample estimation
- For estimation with all countries, country fixed effects included

Table 3.6: Summary Hypotheses Table (Marginal Effects)

	ALL	*INDONESIA*	*BANGLADESH*	*NAMIBIA*	*MORROCCO*	*PERU*	*COSTA RICA*
PANEL A: CONSIDERED SUICIDE							
Positive Parenting	-0.0082***	-0.0057***	-0.0041***	-0.0049**	-0.0092***	-0.018***	-0.014***
	(0.0007)	(0.0009)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Social Exclusion	0.069***	0.057***	0.046***	0.058***	0.11***	0.109***	0.063***
	(0.005)	(0.005)	(0.011)	(0.011)	(0.013)	(0.013)	(0.012)
Female	0.041***	0.024***	0.022**	0.011	0.065***	0.15***	0.064***
	(0.002)	(0.005)	(0.010)	(0.013)	(0.014)	(0.014)	(0.012)
PANEL B: PLANNED SUICIDE							
Positive Parenting	-0.0068***	-0.0060***	-0.0074***	0.0028	-0.0081***	-0.015***	- 0.0092***
	(0.0008)	(0.0009)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Social Exclusion	0.064***	0.046***	0.056***	0.101***	0.077***	0.088***	0.034***
	(0.004)	(0.005)	(0.012)	(0.011)	(0.013)	(0.012)	(0.009)
Female	0.021***	0.0072	0.0068	-0.012	0.034**	0.113***	0.039***
	(0.002)	(0.148)	(0.013)	(0.014)	(0.014)	(0.013)	(0.010)
PANEL C: ATTEMPTED SUICIDE							
Positive Parenting	-0.0069***	-0.0033***	-0.0088***	-0.0020	-0.067***	-0.018***	-0.010***
	(0.0008)	(0.0007)	(0.002)	(0.002)	(0.019)	(0.002)	(0.002)
Social Exclusion	0.078***	0.049***	0.059***	0.123***	0.106***	0.107***	0.055***
	(0.004)	(0.004)	(0.010)	(0.011)	(0.012)	(0.013)	(0.011)
Female	0.0098**	0.00014	-0.0019	-0.030**	0.024*	0.090***	0.043***
	(0.004)	(0.004)	(0.012)	(0.014)	(0.013)	(0.014)	(0.011)

Table 3.6: Summary Hypotheses Table (Marginal Effects) (cont.)

PANEL D: MENTAL STRESS								
	Positive Parenting	-0.011***	-0.0054***	-0.0067	-0.013***	-0.0081***	-0.0175***	-0.019***
		(0.001)	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)
	Social Exclusion	0.154***	0.200***	0.152***	0.078***	0.152***	0.170***	0.142***
		(0.009)	(0.012)	(0.025)	(0.014)	(0.019)	(0.017)	(0.017)
	Female	0.109***	0.110***	0.024	0.080***	0.163***	0.143***	0.127***
		(0.008)	(0.011)	(0.024)	(0.016)	(0.018)	(0.018)	(0.017)
PANEL E: DRUG USE								
	Positive Parenting	-0.007***	-0.0050***	-0.0024	-0.010***	-0.0054***	-0.0069***	-0.015***
		(0.0007)	(0.0006)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
	Social Exclusion	0.031***	0.027***	0.028***	0.030***	0.039***	0.022***	0.019
		(0.004)	(0.003)	(0.008)	(0.011)	(0.009)	(0.008)	(0.012)
	Female	-0.051***	-0.024***	-0.028**	-0.090***	-0.082***	-0.050***	-0.084***
		(0.004)	(0.004)	(0.012)	(0.013)	(0.013)	(0.010)	(0.013)

*** p<0.01, ** p<0.05, * p<0.1

- Individual country models run using survey probability weighting; Total sample - each observation's weight is scaled by mean probability weight in the respective country.
- Standard errors (Delta-Method) in parentheses - clustered at a grand clustering level identifying each unique Country-Strata-PSU pairing under full sample estimation
- For estimation with all countries, country fixed effects included

Figure 3.1: A Social Integration Model

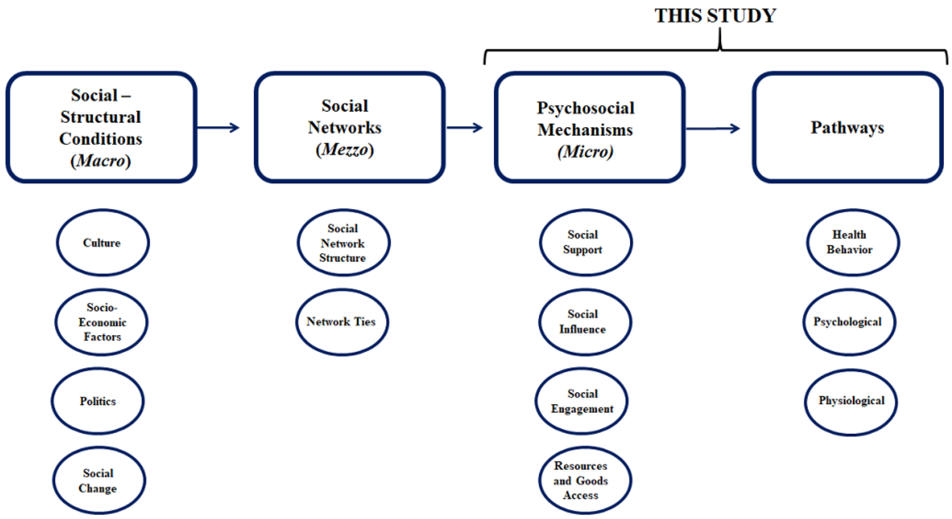


Figure 3.2: Framework & Study

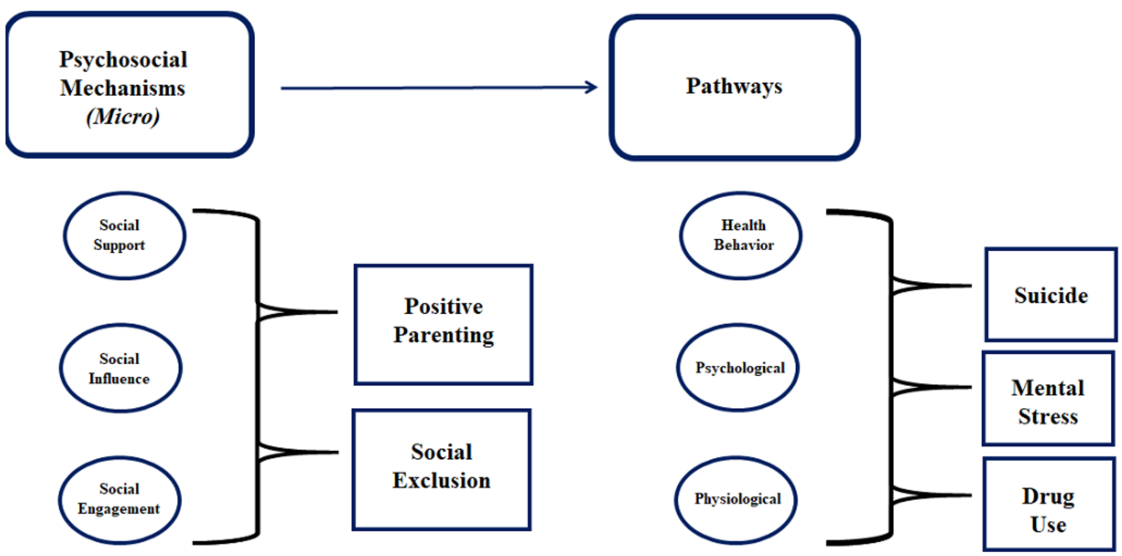


Figure 3.3: Suicidal Tendency

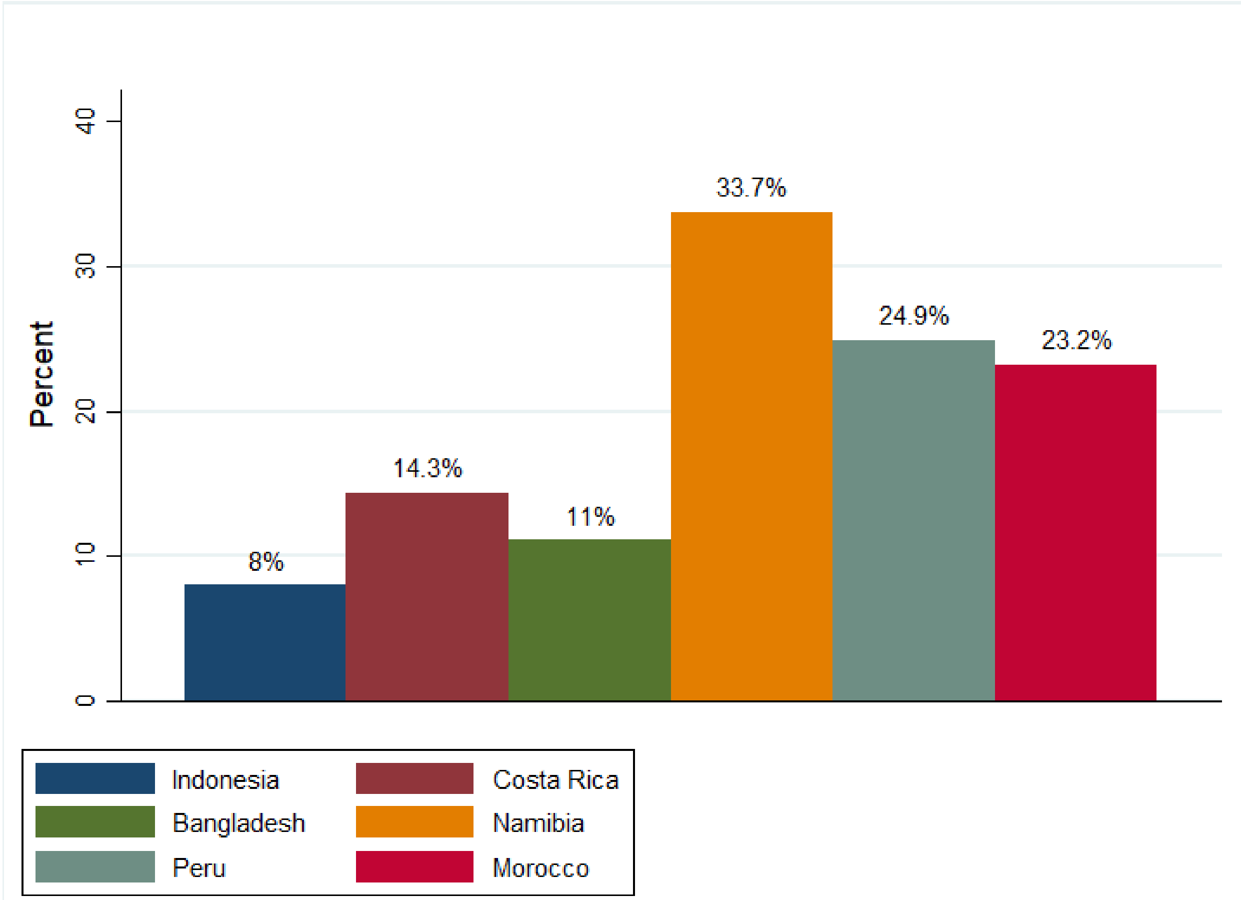


Figure 3.4: Suicide Intensity

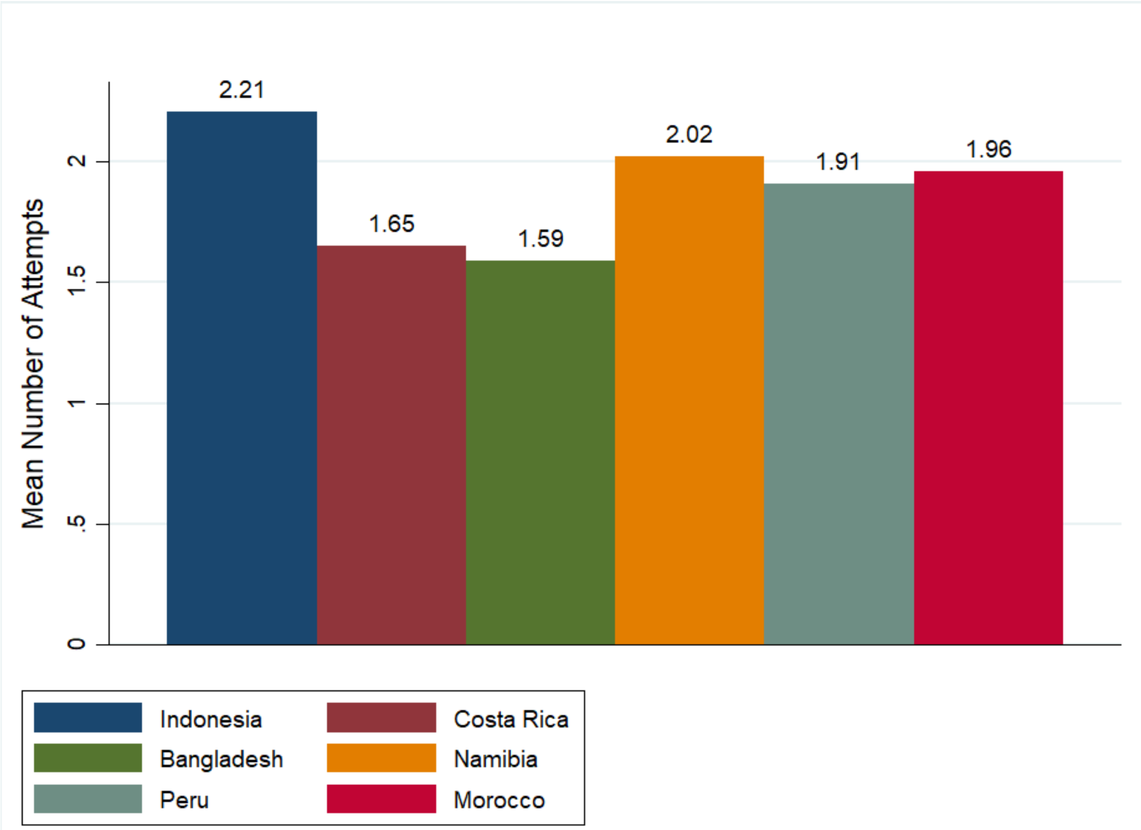


Figure 3.5: Bullying Incidence

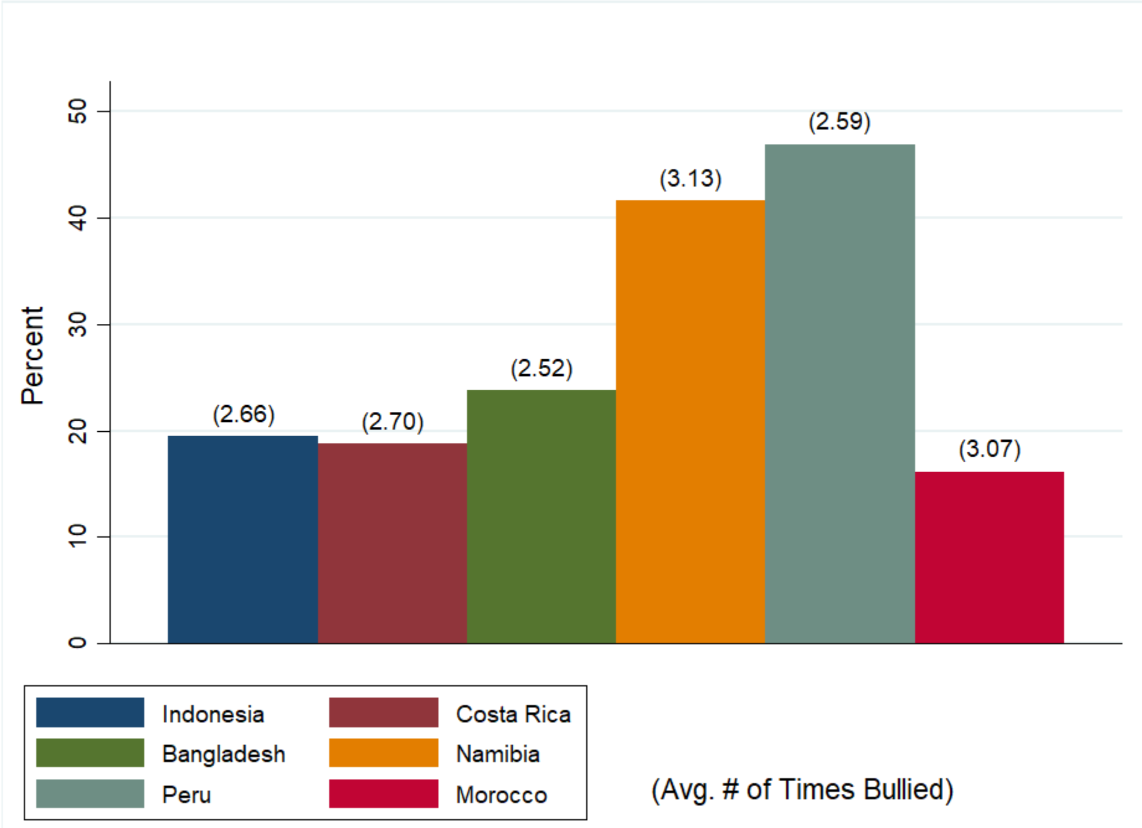
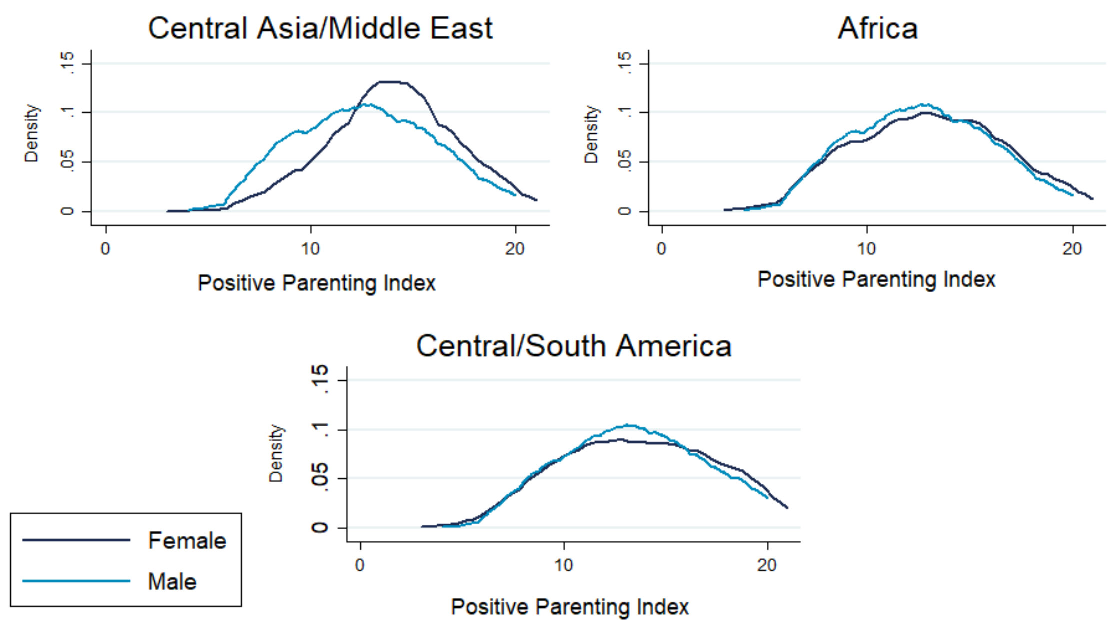


Figure 3.6: Positive Parenting by Region



CHAPTER 4

The Stressor in Adolescence of Menstruation: Coping Strategies, Emotional Stress & Impacts on School Absences

Introduction

Research on water, sanitation, and hygiene (WASH) in developing nations includes a burgeoning focus on menstrual hygiene management (MHM) (Sommer and Sahin 2013). The confusion and surprise many females face when confronted with the onset of menses is often attributed to lack of knowledge (Sharma et al. 2013; WaterAid 2009; Sommer et al. 2012; Adhikari et al. 2007) and proper facilities (Crofts and Fisher 2012; Sommer 2010; BRIDGE 2015; Ndlovu and Bhala 2015). Such outcomes are exacerbated by the many cultural taboos/stigmas still currently associated with menstruation in many developing countries (LaSaine 2015; Fatusi and Hindin 2010; Ssewanyana and Bitanihirwe 2017). Thus, there is a call for policy to improve the quality and availability of sanitation and hygiene options to facilitate greater health among females, given that there is a link between reproductive tract infections (RTI's) and poor menstrual hygiene (Anand, Singh, and Unisa 2015; Ranabhat et al. 2015).

There are also social and behavioral consequences to consider, including missed opportunities at school. The World Health Organization (WHO) emphasizes the need to focus on better school facilities, as parents may see the lack of facilities as a reason for keeping girls home. An accumulation of missed schools days may ultimately lead to girls dropping out of school altogether (BRIDGE 2015; WHO 2014; Sinha 2011; Auemaneekul, Bhandari, and Kerdmongkol 2013). This trend opens the door for such practices as child brides and female genital mutilation – practices that international initiatives such as the Millennium and Sustainable Development Goals (WHO 2000; 2015) seek to eradicate. In addition, by keeping girls in school, their long-term educational and thus earning potentials are higher. A higher earning population translates to an overall better economic standing for the nation. Progress towards these goals will be enhanced through strong empirical evidence which justifies further research and presents potential policy approaches.

In countries like Nepal, the cultural taboos females face during menstruation can be severe, adding an additional hurdle to proper MHM in the region. Of particular concern is the practice known as *Chhaupadi*, wherein females are made to live in separate huts while menstruating due to superstitions surrounding the impurity of blood. While this practice was officially banned in 2005 by the Nepali government, one still finds it practiced, especially rurally (Katz 2014). Girls still face the likelihood of such reproductive health problems as abnormal discharge, itching, pain/foul smelling menstruation, and burning urination (e.g. UTI) from improper care during isolation times (Ranabhat et al. 2015). Furthermore, multiple incidents of death associated with menstrual isolation have been documented, even among "enlightened" women who are literate and engaged in helping women improve their reproductive health (Gettleman 2018).

Work, both in Nepal and globally, focused on MHM is based primarily on qualitative studies, typically capturing information on lack of knowledge, specific interventions, and attendance rates (Fatusi and Hindin 2010). Little work has been published with a focus on the emotional impacts on girls during menstruation, while also incorporating quantitative statistical methods. By implementing simultaneous estimation of a system of two equations, using multiple estimation techniques, and our use of the Transactional Model of Stress and Coping as a foundational conceptual framework, the current work seeks to add to existing literature by incorporating the emotional elements of managing menstruation into existing findings regarding missing school.

This paper is organized with section two presenting some background information on relevant strands of literature. This is followed by the conceptual and empirical frameworks and data descriptions. Results, discussion, and conclusions close, with mention of certain key policy implications.

Background

Quantitative work in MHM has primarily focused on the impacts of infrastructure or education-based interventions. Randomized control trials (RCT) in India have found that in-school training on various topics can lead to improvements in health behaviors including daily genital hygiene and changing pads 3x per day (Kapadia-Kundu et al. 2014), as well as improving menstrual health knowledge (Bhudhagaonkar and Shinde 2014). Adukai (2017) used a difference-in-difference empirical model to find that toilet construction increased enrollment of adolescent girls at school, particularly when sex-specific toilets were provided, allowing for gender disparities of school attendance to decrease.

In Nepal researchers determined that random provision of sanitary supplies caused no change in school absenteeism (Oster and Thornton 2009; 2011), running contrary to expected outcomes based on the breadth of research indicating that school-aged girls do not see school as a source of support or information during menstruation. In contrast, other controlled studies which investigated interventions of pads and/or education have produced very promising results in terms of increased school attendance (Montgomery et al. 2012; Freeman et al. 2011). Correlations and multivariate analyses have shown evidence of the additional importance of the home environment in determining better hygiene and school attendance (Grant, Lloyd, and Mensch 2013; Sudeshna and Aparajita 2012; Tegegne and Sisay 2014).

While this strand of more quantitative research analyzing MHM is growing, one should note a gap in its attention to the cognitive experiences during menstruation. So far, attention to cognitive components often only appears in quantitative studies as a single question revealing such elements as shame/fear or lack of confidence (McMahon et al. 2011a). There are studies indicating improvement in psychological factors (e.g. depression/stress) from hygiene education interventions (Haque et al. 2014), but lacking strong empirical analysis. Theory-based literature is stronger, where one finds studies discussing the emotional content surrounding menstrual shame which reinforces gender inequalities (Jewitt and Ryley 2014), and the role of objectification theory in emphasizing how females adopt the sexualization of women that society creates and internalize it, leading to views of menstruation as "bad" (Grose and Grabe 2014; Fredrickson and Roberts 1997).

Researchers involved in the global discussion of MHM think that now is the time for determination of which factors will best enhance females' experience during menstruation, noting lack of guidance, facilities, and materials to educate girls and communities, in general, about MHM (Sommer et al. 2016). The lack of quantitative evidence looking at the extent of challenges (including mental hurdles) and effectiveness of MHM interventions is coupled with a lack of focus on increasing self-esteem. There is also continued attention, globally, on improving awareness of the mental health issues women face, including building evidence on the prevalence and causes of mental health problems, along with mediating and protective factors (Trivedi, Mishra, and Kendurkar 2007). If we can begin to tackle all of these elements simultaneously, this field of research will have much more impact and greater gains can be made to ensure that young girls can remain in school and become economically productive members of society.

The Model: Framework, Specification & Hypotheses

Conceptional Framework

Stress has been known to contribute to illness both through direct physiological effects (e.g. hormone fluctuations, flight-or-fight responses (Cannon and Cannon 1967)) and indirect effects via maladaptive health behaviors. However, the ways individuals have for coping with stress in their lives can be important influencers on their ultimate psychological and physical health outcomes. Reactions can promote or hinder healthful practices and influence the motivation to practice habits that promote health/wellbeing, including motivations/abilities to attend school.

One modeling framework which has been developed to help explain such behavior surrounding stressful life events is the Transactional Model of Stress and Coping (R.S. Lazarus 1966; Richard S. Lazarus and Cohen 1977), which positions stressful life events as person-environment interactions. Under this framework, the impact of an external stressor is mediated by a person's appraisal of the stressor itself and the psychological, social, and cultural resources at her disposal to aid in dealing with the stressor. When a stressor is appraised as having a major impact on a person's goals/concerns (high relevance), that person is likely to experience greater anxiety and situation-specific distress (Smith and Lazarus 1993). Such distress is exacerbated if appraisal also shows a lack of resources/controllability, in essence, a lack of self-efficacy (Bandura 1997; Taylor et al. 1992; Kok et al. 2007).

[FIGURE 4.1]

As shown in Panel A of Figure 4.1, the success of coping efforts, based on environmental appraisals, is often measured through specific health behaviors, functional status, or emotional well-being. Menstruation for adolescent Nepali females has been shown to limit their ability to access school (Auemaneekul, Bhandari, and Kerdmongkol 2013) and other social/cultural events (Katz 2014). However, a stronger answer as to why is needed, and that is where this model serves as a useful guide. As shown in Panel B of Figure 4.1, our work applies this model by evaluating appraisals of cultural and school environments to deal with menstruation, a major life stressor. Coping efforts (e.g. emotional outcomes) which come out of such appraisals, we believe, may have additional impacts on such behavioral outcomes as missing school.

Empirical Specification

Given the hypothesized pathway presented above and informed by the Transactional Model of Stress and Coping, we believe that in the face of menstruation, the perceptions young women have of their supporting environments will influence how well they cope. The success of such coping can be captured in measures of emotional stress, which we believe in turn will impact their abilities/willingness to attend school. To represent this system, set out below are the two empirical equations for estimating our key outcomes of emotional stress and school absences:

$$Em_i^* = \alpha_1 Env_i + \alpha_2 X_i + u_{1i} \qquad (1)$$

$$Sch_i^* = \beta_1 Em_i + \beta_2 X_i + u_{2i} \qquad (2)$$

Em_i^* and Sch_i^* are two latent variables (qualitative) representing Emotional Stress and School Absences. Env_i is a column vector of three environmental variables {*SchEnv*, *CommEnv*, *FamEnv*}. *SchEnv* is an index that represents perceptions of the school environment, both physical infrastructure and presence of hygiene informative health education. *CommEnv* and *FamEnv* are indices representative of perceptions of the community cultural and family cultural environments, respectively. The vector X_i contains socioeconomic and demographic controls including age, caste, and school-level fixed effects. In this two-equation model, we can allow for non-zero covariance, cov $(u_{1i}, u_{2i}) \neq 0$, to enable simultaneity between the emotion and the schooling outcome equations.

Hypotheses

Recall that appraisal of a stressful event involves perceptions of supportive elements to effectively cope. When females face menstruation, they perceive whether there is supporting infrastructure (e.g. hygiene materials) and/or cultural support/knowledge to aid in coping. Findings from the WHO (WHO 2014) show that parents fear sending their girls to school, and girls have also reported that they fear judgement from others (McMahon et al. 2011b), for not having underwear or leaking. The presence of the right infrastructure would likely greatly reduce such fears, and allow them to face/cope with their menstruation. Having hygiene management materials at school would likely increase perceptions of controllability and bolster self-efficacy, leading to more effective coping strategies. Thus, our first hypothesis is:

Hypothesis # 1*: The presence of infrastructure and education to support hygiene in schools (SchEnv$_i$) will help adolescent females to feel less emotional stress (Em_i^*) during menstruation.*

Evidence has also shown that social support can be a "stress-buffer" (Cohen and Wills 1985; Christian and Stoney 2006), and this importance grows with stressor intensity. Having a confidant can affect perceptions of both personal risk/severity and bolster beliefs about self-efficacy (Cohen and McKay 1984). Perceptions of lack of social support can remove any potential buffering benefits. The practices of isolating menstruating females (Katz 2014; Pokharel and Gurung 2017; Ranabhat et al. 2015), as well as the noted lack of knowledge about menstruation in Nepal (WaterAid 2009; Sommer et al. 2012; Adhikari et al. 2007), appears reminiscent of avoidance and denial strategies to dealing with a stressor, which are generally seen as maladaptive approaches (Carver et al. 1993; Schwartz et al. 1995).

There is also evidence that when key social supports actively discourage the disclosure of feelings about a stressor, this can increase avoidant coping, ultimately leading to adverse psychosocial outcomes (Cordova et al. 2001; Zakowski et al. 2004). In cultures with a strong subordination of women, women are often found to be at a greater risk of developing depression and a number of other mental disorders (Douki et al. 2007; Lee et al. 2009; Yaacob et al. 2009). In Nepal, the culture of "self-silencing" where women sacrifice for the common good, while seeking to maintain harmonious relations with their own and husband's family, has been critiqued by younger women. Clinically depressed women often describe feelings of isolated disconnection within their family (Jack and Ali 2010). Thus, strong gender-focused cultural limitations surrounding stressful life events have previously been shown to lead to lower mental wellbeing, consistent with our conceptual framework, and leads to our second hypothesis:

Hypothesis #2: *Strong cultural norms which restrict adolescent girls' mobility and freedom during menstruation ($CommEnv_i$, $FamEnv_i$) will lead them to experience more emotional stress (Em_i^*).*

One potential manifestation of avoidant coping, linked to poor stress-buffering from social support, may be for females to skip school to avoid potential judgments from other people and stressors in that environment. Better coping practices from improved school infrastructure/environment and better social support we expect would be reflected in better emotional wellbeing outcomes. This in turn is likely to reduce emotional barriers, allowing girls to more easily attend school during menstruation. Thus, our final hypothesis is as follows:

Hypothesis #3: *Presence of emotional stress (Em_i^*) during menstruation will increase the likelihood of girls missing school (Sch_i^*) during menstruation.*

Data and Variables

Data

This study makes use of primary survey data collected by the Pratiman-Neema Memorial Foundation (PNMF). Women2Be, a non-profit organization, provided female hygiene packets, in the style of those put together by Days for Girls, to Nepali females in May 2016 and December 2017. Along with providing these reusable kits, good for up to three years, educational information about female health and hygiene was provided and a survey was administered to females at schools in the central Terai (plains) area near the southern border with India (2016) and Purkot, in the central hills area of Nepal (2017).[20]

Survey questions were asked regarding basic demographic information (i.e. age, religion, caste, family possession of cement home/land), along with information on current knowledge and practices regarding menstrual hygiene (i.e. genital cleaning, hand washing, pain treatments). In addition, of importance for this study, the survey also included information on current school infrastructure (i.e. presence of trash bins, emergency menstrual hygiene kits, and soap for washing hands) and on cultural restrictions women face in their home environment during menstruation (i.e. separate sleeping quarters, not allowed in kitchen, etc.). Key to this work was the inclusion of a question evaluating whether the girls felt sad or lonely during their menstruation period and assessments of whether or not the respondents have had to miss school due to their menstruation (along with a range of how many days were missed the previous month).

Key Variables

The dependent variable from Equation 1, Emotional Stress (Em_i^*) , is a binary (1/0) indicator of whether the respondent reports feeling sad and lonely during menstruation[21]. We have two means by which to represent the dependent variable from Equation 2, School Absences (Sch_i^*). In our first specification (Specification A) school absences is measured as a binary (1/0) indicator of having missed school due to

[20]Informed consent was sought in administration of the survey and was approved by local authorities. Parents and teachers were present at this event and representatives of the Pratiman-Neema College were on hand to ensure that the study was carried out in a manner consistent with the ethical standards of the Declaration of Helsinki.
[21] Survey Question: "Do you feel lonely and sad during your menstruation cycle?"

menstruation[22]. The second representation (Specification B) is an ordinal variable with three-levels for numbers of days missed the prior month (zero, 1-2 days, and 3 or more)[23].

Our key explanatory variables from the column vector Env_i in Equation 1 represent the appraisals of respondents' environments. The variable representative of perceptions of school support is based on questions pertaining to the perceived presence/absence of certain key hygiene facilities/infrastructure at school[24]. Those variables capturing the cultural environment in which girls live at home assess both more family-based elements (e.g. forced isolation, ability to meet with family)[25] and more community-based elements (e.g. permission to enter worship room, cultural functions, and kitchen)[26]. Entering each of these questions individually into our empirical regressions would eat up too much power, and would not be very useful in explaining the variance. Thus, we built an index for the various environmental perceptions via principle component analysis (PCA)[27], with confirmation of our findings using multiple correspondence analysis (MCA)[28].

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[22] Survey Question: "Have you missed your school due to your menstruation?"

[23] Survey Question: "How many days in the last month have you missed school due to your menstruation?"

[24] Survey Questions: "Do you get sanitation supplies in school in case you need it in emergency?; Do you have a separate toilet for girls where you can change your menstruation materials?; Do you get soap/ liquid lotion to wash your hand after you change your menstruation material in school?; Do you have a proper disposable bin where you can dispose your menstruation materials in school?; Do you get to learn within school curriculum about recommended hygiene practices that you should follow and some guidelines about menstruation cycle?"

[25] Survey Questions: "Do you stay in a separate house during menstruation?; Are you allowed to meet with your family and friends like every other normal day during your menstruation cycle?"

[26] Survey Questions: "Are you allowed to enter prayer room during your menstruation cycle?; Have you participated in cultural functions during menstruation; Are you allowed in the kitchen during your menstruation cycle?"

[27] PCA is a standard statistical technique for data reduction. The leading eigenvectors from the eigen decomposition of the correlation matrix of the variables is used to describe a series of uncorrelated linear combinations of the variables which contain most of the explanatory variance. The goal is to find unit-length linear combinations, where the first principle component has the maximal overall variance, and each additional principle component has the maximal variance among all unit length linear combination that are uncorrelated to the first component (Rencher and Christensen 2012). Elaboration on more advanced approaches with using PCA can be found in the Appendix.

[28] MCA is a generalization of correspondence analysis (CA), where the latter's aim is to develop simple indices that show relations between the rows and columns of a contingency table of categorical variables. MCA can also be viewed as a generalization of PCA, where the variables to be analyzed are categorical (i.e. binary) not continuous. MCA analyzes the inter-individual variability (or how similar individuals fall into sets of categories), trying to extract which dimensions (i.e. categories) separate extremely different individuals from average individuals. Additionally, there is

PCA of the sample revealed only one primary component met the standard criteria of the Kaiser Rule (Rabe-Hesketh and Everitt 2004) [29] for factor retention within those variables capturing information about the school environment[30]. The first principle component is heavily loaded[31] on “hard” infrastructure elements such as soap, bins, and hygiene kits. While the second component for the school environment is just shy of the Kaiser Rule, it is most heavily loaded with the key “softer” support element of knowledge from hygiene education curriculum. We only included the former (first) principle component, and this is our School Environment ($SchEnv_i$) variable. This choice was supported by results from MCA, where analysis of the school environment only produced one dimension[32], explaining 90.4% of the variance and was more heavily influenced by the “harder” infrastructure.

PCA analysis in relation to the cultural environment indicated that this series of variables was best represented by two separate variables, based on the criteria described above. One index is heavily loaded with more external/community factors such as restrictions on worship and cultural participation, which we have labeled the Community Environment ($CommEnv_i$). The second principle component is loaded heavily on the more internal components of having the ability to meet family and being forced into

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assessment of the links between variables, and which categories of one variable are connected to categories of another (Abdi and Valentin 2007). Elaboration on more advanced approaches with using MCA can be found in the Appendix.

[29] This is an informal rule that one should only use those principle components with eigenvalues greater than one (i.e. variances greater than average).

[30] We also used screeplots to confirm that we only gave attention to components whose eigenvalues fell “above” a distinct elbow in a plot of eigenvalues against their rank.

[31] Factor loadings are the correlations between the original variables used in the PCA and the components computed from the analysis, and these can be used to determine which components to include to summarize the raw data with little loss of information.

[32] The dimensions that MCA gives are akin to the principle components of PCA and inertia, the key explanatory element of this type of analysis, based on sequential searching for axes, where each axis must maximize the inertia and be orthogonal to all previous ones, and are thus akin to the eigenvalues (e.g. how much variance is explained) (Abdi and Valentin 2007).

isolation during menstruation, leading us to label this variable as the Family Environment ($FamEnv_i$). Again, these choices based on PCA were confirmed with MCA, where we found a split in dimensions where external behaviors appeared together in the first dimension (83.6% of variance explained) and internal behaviors were in the second dimension.

In terms of control variables, Age is included, beyond just as a control for grade, as it would be expected that age of females may greatly impact their abilities to both physically and emotionally manage menstruation. Their coping efforts may have become more fully honed the longer they have had to manage menstruation (Alcalá-Herrera and Marván 2014), and perceptions of support may shift. Descriptive summary statistics of all key and control variables can be found in Table 4.1.

[TABLE 4.1]

Estimation Strategies

Single Equation Estimation

The first stage of empirical estimation was through separate regressions of each outcome equation, to serve as a form of baseline analysis. Given that our outcomes of interest are latent variables, probit estimation was used for single equation estimation of Equation 1 and for Specification A (e.g. binary outcome variable) of Equation 2. Ordered probit was the estimation technique for estimating Specification B (e.g. ordinal outcome variable) of Equation 2, as a single equation.

Estimates presented in this paper used school fixed effects and caste dummies (with the highest caste, Brahman-Chhetri, as the base category). Additional control variables considered included dummies for current hygiene product use (base as old rags/cloths), marriage status, and a wealth index. Presentation of model fitting for these single equations are found in the Appendix. Table 4.2 presents the results from a summary of best-fit estimates based on separate equation analysis.

Due to the possibility of a sort of self-selection into the survey, in that these girls are not a random nor necessarily representative sample of all teenage girls in Nepal, we also ran our single equation estimations using bootstrapped errors. Additional attempts at robustness checking included running the most preferred estimations with an expanded sample to include older females (ages 21-44) who were also surveyed at the time, and likely represent teachers at the schools. Additionally, due to the fact that close to 83.3% of those surveyed reported having a teacher to talk to about problems during menstruation, we also checked our estimations (in all specifications) with inclusion of this variable (additional dummy).

Simultaneous Estimation of Emotional Stress & School Absences

Results of single equation probit/ordered probit results could be biased due to unobserved characteristics that determine both emotional stress and school attendance, which would result in endogeneity concerns from correlation between the error terms of the two outcome equations (Greene 2012). While instrumental variables (IV) is a common technique for dealing with such concerns, binary choice models are almost exclusively estimated via maximum likelihood estimation (MLE). MLE is not about any form of least squares being used to estimate parameters, but rather, estimation is of the likelihood of getting the data one did based on parameter estimates.

Specification A: Binary-Binary Dependent Variables

Analyzing Equation 1 and Equation 2, where both outcomes (Em_i^*, Sch_i^*) are represented by binary indicators, we used bivariate probit estimation. Bivariate probit, based on MLE of the joint density of two outcomes, is the standard estimation technique when dealing with such a simultaneous estimation structure. This approach allows for full information, where one can consider non-zero covariance between the two estimation equations. We present an estimate with only fixed-effects (Model 1) and a second where we also include caste dummies (Model 2), found in Table 4.3. We have also proceeded to present the marginal effects of these estimates in Table 4.4, given that there is limited meaningful interpretation of the raw coefficients from probit estimates.

Specification B: Binary-Ordinal Dependent Variables

In this study, we have the unique opportunity to also represent our school absence variable with an ordinal-structure, and so this specification involved simultaneous estimation of Equation 1 with its binary emotional stress (Em_i^*) outcome and Specification B of Equation 2 with its ordinal representation of school absences (Sch_i^*). With two separate coding structures for the two outcome variables, we would not be able to use bivariate probit to estimate our simultaneous equation system. Therefore, we implemented conditioned mixed-process modeling (CMP)[33].

[33] CMP Modeling is based on the premise that because the normal distribution has a natural multidimensional generalization, models can be combined into equation systems where errors share the multivariate normal distribution. All models allowed with CMP are built on generalized linear models and the Gaussian distribution, where MLE assumes normally distributed errors. Observation-level likelihood is a ratio of two integrals over certain regions of the joint distribution, where each region of integration is the Cartesian product of line segments, rays, and lines; however, this ratio reduces to only the numerator if there is no truncation (as is the case with this study). Thus, one is capable of estimating a system such as a bivariate probit, where both outcomes are binary (latent) variables, or one can estimate a "mixed"-model system with one binary outcome and one ordinal, and allow for non-zero covariance between the error terms (Roodman 2011).

We repeated the same pattern of analysis and presentation for this version of joint estimation of our two latent outcome equations. Table 4.5 presents the results from an estimation with only fixed-effects (Model 1) and from a version which includes caste dummies (Model 2). Marginal effects of these estimates are presented in Table 4.6, to enable more meaningful interpretation of results.

Results

Basic Statistics

The average age of females in our sample was 16.6 years old, with girls ranging from 12 to 20 among a sample size of 281 females. In terms of products used during menstruation, 22.8% use old rags/clothes, 66.9% use disposable pads, and 10.3% reusable products. In total, 60.1% of women claimed that they experience extreme pain during their menses, and yet, only 13.3% report using a hot pack, 21.4% report using pain medicine, and 21.3% report going to a doctor to deal with their menstruation discomfort. In terms of general hygiene practices, 89.5% of women report washing hygiene supplies with just soap, with only 8.7% using some form of antiseptic. Almost all girls report that they wash their hands after changing hygiene products, but less wash their hands prior. Additionally, there is not universal practice of changing pads at a recommended 4-5-hour interval. Overall, it appears that these girls, on average, practice some key hygiene behaviors, but presence of proper infrastructure is likely important to maintaining these healthy behaviors.

As mentioned, one of the biggest concerns of improper MHM is the consequence of lost days of school, which may lead to a whole host of other hindrances to girls' eventual success. Of all girls sampled, 42.1% reported knowing someone who had to drop out of school due to menstrual problems and 10% missed school due to having to cover some of the chores for their mothers, during her menses cycle. Overall, when asked how hard it was for them to manage work and/or school during menses, 68.4% of those surveyed claimed it was hard or very hard. So, in the face of 32.7% reporting that they miss school due to menstruation, and 48% of our sample reporting that they experience emotional stress during menstruation (represented as sadness and loneliness in our estimation), there is still a need for improvement in how menstruation is dealt with among these Nepalese female students.

Single Equation Estimation Results

We ran three single equation estimations using probit for Equation 1 and Specification A (e.g. binary outcome variable) of Equation 2, and then ordered probit for Specification B (e.g. ordinal outcome variable) of Equation 2, under various control situations (see Appendix). Table 4.2 presents a summary of the best-fit of each single equation estimate based on the minimum Akaike information criterion (AIC)[34].

[TABLE 4.2]

In column 1 of Table 4.2 are the results from estimating the impacts of environmental assessments of support (Env_i) on emotional stress (Em_i^*). The perceptions of the school environment (*SchEnv*$_i$) appear to be significant (-0.299, *t=-3.15*), indicating that more menstruation supporting infrastructure at school reduces the likelihood of a girl reporting feeling sad/lonely during menstruation. Column 2 (Table 4.2) reports the impacts of emotional stress (Em_i^*) during menstruation on missing school

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[34] Akaike information criterion (AIC) is a common model comparison calculation statistics which deals with the trade-off between the goodness of fit of the model and the simplicity of the model (Akaike 1974). The lowest AIC figure among a set of potential models is deemed the most useful model.

(Sch_i^*), showing a significant positive effect (0.58, *z=3.42*). Significant results are also found for the impact of emotional stress (Em_i^*) on days of school missed (Sch_i^*) in Column 3 (0.341, *z=2.12*). In both cases, the presence of emotional stress increases the likelihood of the outcome variable. This indicates that having emotional stress during menstruation increases the chances of also missing school during menstruation, and that having emotional stress during menstruation has a positive association with missing more days of school during the last month.

Simultaneous Estimation Results

Specification A: Binary-Binary Dependent Variables

With concerns over the endogeneity of emotional stress in our school absence equation, we undertook estimation of the two outcome equations simultaneously, allowing for covariance in their error structures. Presented in Table 4.3 are the parameter estimates from bivariate probit estimation of the equation system, where Sch_i^* is binary (Specification A).

[TABLE 4.3]

Under this approach, we find significance under two different specifications (including caste dummies and not) for all three variables representing perceptions of environmental support, with cultural environment (*CommEnv_i*, *FamEnv_i*) increasing the likelihood of feeling sad/lonely (Em_i^*) (0.146, *z=2.57;* 0.148*, z=2.54,* respectively*)* and the school environment (*SchEnv_i*) decreasing this likelihood during menstruation (-0.25, *z=-3.05*). Rho (ρ), representative of the associations between the two equations, very strongly indicates a correlation (*z=-5.95*) between the errors of the two equations, supporting the choice to simultaneously estimate them. As shown in Table 4.4, the average marginal effects of such results indicate that perceptions of supporting infrastructure at school reduce the likelihood of emotional stress by 8.1-9.2% (*z=-3.19*). When examining marginal effects, there is a statistically significant impact of perceptions of strong restrictions in both the family and community environments, estimated to increase the likelihood of emotional stress by around 5% (*z=2.63*).

[TABLE 4.4]

With regard to the second outcome equation, we see strong significant results of the impact of emotional stress (Em_i^*) on school absences (Sch_i^*) during menstruation. Table 4.3 shows that there is a strong positive association between presence of emotional stress and missing school (regardless of controlling for caste) (1.82, *z=15.1*). The marginal effects of these associations, found in Table 4.4, indicate that the likelihood of missing school increases 47.4-48.9% (z=*36.7*) if the respondent also reports feeling sad/lonely during menstruation.

Specification B: Binary-Ordinal Dependent Variables

Results of simultaneous estimation of Equation 1 and Specification B (e.g. ordinal outcome) of Equation 2 are found in Tables 4.5 and 4.6. The parameter estimates of environmental support perceptions under this estimation indicate that perceptions of menstruation supporting infrastructure at school ($SchEnv_i$) reduce the likelihood of emotional stress (Em_i^*)(-0.226, *z=-3.08)*, while restrictions in the family environment ($FamEnv_i$) increase this likelihood (0.15, *z=2.45)*. These findings are robust to the inclusion of caste controls.

[TABLE 4.5]

Marginal effects (Table 4.6) indicate that perceptions of more support for menstruation at school reduces the likelihood of reporting emotional stress by 7.7-8.4% (z=-*3.18*), while stronger family controls increase this likelihood by around 5.7% (z=*2.5*).

Parameter estimates with our ordinal representation of school absences due to menstruation, indicate a positive association between the presence of emotional stress (Em_i^*) and missing more days of school (Sch_i^*) due to menstruation in the last month (1.67, *z=11.76*). Again, this strong significance is unaffected by inclusion of caste dummies. Table 4.6's presentation of marginal effects reveals this association to be stronger for more reported days missed. While presence of emotional stress increases the chances of missing 1-2 days by 14.2-15.1% (*z=3.51*), it increases the chances of missing 3 or more days by 31% (*z=5.18*). While counterintuitive, the negative marginal effect of emotional stress on the first-level outcome of days missed indicates that the presence of emotional stress during menstruation reduces the likelihood of missing zero days of school by 45-46% (*z=-19.26*), consistent with the marginal effects found in Table 4.4. Rho again indicates a strong correlation between the equations, supporting the choice to simultaneously estimate them.

[TABLE 4.6]

Robustness Checks

Robustness checks mentioned previously, wherein we checked single equation estimates with bootstrapped errors showed no change in sign and minimal loss in significance. Inclusion of a dummy for perceived presence of a teacher with whom the girl could share her problems/concerns during menstruation also did not impact significance/sign, nor add any additional useful explanatory power to the preferred estimations, in either the single or simultaneously estimated approaches. Examination of impacts on our results from including a larger estimation sample of women (likely teachers) aged up to 44 produced no change in sign or significance of our key results. Nor did it change any of our overarching conclusions. Results of these analyses are available upon request.

Results Summary

To aid in summarizing the results of this research, Table 4.7 presents a summary table indicating the strength of our findings based on estimation technique and interpretation of results based on our initial research hypotheses. Levels of significance correspond to the results from the best-fit estimate (e.g. raw coefficients) for the single equation (baseline) analysis. Model 1 for both bivariate probit and CMP analysis refers to the marginal effects found under an analysis without caste controls, while Model 2 refers to the corresponding marginal effects under an estimation scenario with caste controls. Across all estimation approaches there is strong support for both our first and third hypotheses, and modest support for our second hypothesis, giving credence to our conclusions detailed below.

[TABLE 4.7]

Discussion, Policy Implications & Conclusions

As MHM becomes a more important WASH initiative in the developing world, there is a greater call for strong empirical and quantitative analysis. Appealing to the Transactional Model of Stress and Coping framework, we examined the impact on Nepali females of coping efforts on self-reported psychological wellbeing during menstruation and the associated impacts on school attendance. Results of several estimation techniques shows that the cultural environment girls face increases their probability of emotional stress (e.g. feeling sad/lonely), while the presence of school infrastructure to support menstrual hygiene reduces this probability. In turn, the presence of emotional stress increases the likelihood of missing school during menstruation, and appears to have stronger effects on missing more days. These findings provide support for all three of our initial study hypotheses.

Literature provides evidence that knowledge is powerful in changing behavior, including self-efficacy (Chandra-Mouli and Patel 2017), and can be done through schools (Adukia 2017; Montgomery et al. 2012; Dupas 2011). Given that cultural norms or taboos are very hard to change with policy and our strongest results refer to the mitigating power of school infrastructure (Hypothesis #1), the implication is that focus in future MHM initiatives would be to aim policy at schools to provide better support for young women. With greater perceptions of support, girls would then have better coping skills, resulting in improvements to their psychological well-being, which can have further additional benefits on improved attendance rates, in line with indications from qualitative work of what adolescent girls themselves desire (such as (Sommer 2010). However, such initiatives must be carried out with a wide range of considerations, allowing for comprehensive support, as evidence has shown that unidirectional and sole-medium interventions are often ineffective (Garg, Goyal, and Gupta 2012; Dolan et al. 2014; Montgomery et al. 2016). This work may point to part of that ineffectiveness from interventions aimed solely at providing more MHM supplies - there may be lack of consideration of the emotional toll that menstruation has on girls.

In Nepal, there has been prior work aimed at determining the best means by which to improve health-supporting infrastructure, but with little to show for it. In 2010, Nepal launched its National Adolescent Sexual and Reproductive Health Programme, which was aimed at merging health and reproductive education with other health services, at centers separate from schools (WHO 2017). The decision to focus outside of the school environment was due to a feeling that there was still a need to better empower teachers with the right training and information. The impact of this program has thus far not been evaluated and many young people still don't know where to acquire the services of the program. Workers in the program nevertheless admit that students are desirous of evidence-based information to counter misconceptions about health related issues. Given this situation, our results provide some additional evidence of benefits to be gained from continuing to focus on improving infrastructure (particularly at schools), including improvements to hygiene education.

Of additional consideration is Snel and Shordt's (2005) argument that children can be change makers. Not only do initiatives to improve school learning environments allow students to be healthier, but they also allow for dissemination of hygiene information which can be taken home and shared with other family members. By targeting younger school-aged females, efforts may be able to affect behavior beyond the classroom environment. There is preliminary evidence of this phenomena from Jamkhed, India, showing that older generations of women are beginning to indicate desires for their own daughters to be less influenced by superstitions (Kirsten 2015).

We do acknowledge several important limitations of our study. One of the most obvious is that all of our variables are self-reported. Self-perceived notions of loneliness and presence/absence of the various environmental support system variables, which form the indices, may differ slightly across individuals and cultures. While we acknowledge that these answers are perceptions of individuals, it is these perceptions which form the basis for the conceptual framework which underlies this study. It is each person's perceptions of the supporting environment available to aid in coping with a major life stressor which determines how well they ultimately cope. We also have not included certain extensions to the Transactional Model of Stress and Coping which have been used by others, including coping styles, optimism, overall positive psychology, or accounting for individuals as being "information seekers" versus "blunters" (Glanz, Rimer, and Viswanath 2015).

There is also some research on emotions and behaviors during menstruation which might indicate a slight bias of our findings. A meta-analysis of menstrual cycle effects on mental health outcomes, due to hormonal fluctuations, found that there is a greater risk of suicide deaths/attempts and greater risk of psychiatric admissions during menstruation (Jang and Elfenbein 2018). Researchers have also found that self-esteem was lowest and paranoid thinking highest in the para-menstrual period (3 days before and after menstrual flow) as compared to mid-cycle (Brock, Rowse, and Slade 2016). However, these findings are based on data collected in the developed world and may not be as relevant to our sample. While it would be comforting to be able to account for these elements which might bias the data, our data does not include the menstrual cycle stage of girls at the time of surveying. Furthermore, our emotional stress outcome variable specifically speaks to loneliness during menstruation, and not just sadness. Finally, it is reasonable to assume that not every girl would be at the peak hormonal period when surveyed, meaning analysis of averages is likely to wash-out some of this potential bias. Nevertheless, future work could try to better account for the timing of the menstrual cycle, and more clearly specify a psychological outcome based on diagnostic criteria of the psychological state being measured (e.g. depression, sadness, anxiety, loneliness).

In terms of analytic limitations, some may express concern over our choice of "instruments", e.g. our environmental variables which we have set to explain emotional stress, but not missing school. Examination of the single equation and joint estimation analyses show consistent significance of the school environmental variable and at least one of the cultural environmental variables to explain emotional stress, indicating that we have an acceptable set. Further, a likelihood ratio test on the instruments from a simple probit estimation of stress on the instruments (and controls) shows a test statistic over 10, which in a linear probability model would be considered supportive of a decent set of instruments. It is also important to note that the results reported in the body of this paper, while reflecting the best-fit estimates based on AIC, do not represent spurious occurrences of statistical significance. Examination of model fitting (found in the Appendix) shows that there is continued significance for the key variables of interest. An analysis based on single-equations should be viewed as baseline results. Simultaneous estimations revealed the importance of jointly estimating these two equations (e.g. significance of the correlation coefficient, ρ). The implications and conclusions drawn in our study are based on these latter analyses, which better represent the dynamics at play in this study.

Regardless of the noted potential limitations, we are very intrigued by the results captured across three schools in markedly different regions of Nepal. Furthermore, when examining how difficult life is during menstruation, based on the type of hygiene product they currently use, our data indicates that those girls who use reusable products show a lower rate of reporting life as being hard or very hard to manage (see Figure 4.2). Greater insight into the viability of this particular hygiene kit may be an interesting avenue for future work.

[FIGURE 4.2]

Finally, as older women and those girls who have already dropped out may not be able to benefit directly from policies aimed at improving school infrastructure, future research could benefit from further examination of means to help them combat their loneliness and improve their coping skills, likely through more focus on improving social support. Perhaps such changes may be possible through the aforementioned link of children as change makers. The goal is that all women can find their light in the dark and become more powerful and productive people, with the coping skills to overcome any stressor that they may face. By improving the emotional state of young women, the goal would be to get them back in school so that they can become more useful and influential in the future growth of their society.

Tables & Figures

Table 4.1: Descriptive Statistics of Variables

VARIABLES	DESCRIPTION	MEAN	S.D.	MIN/MAX
OUTCOME VARIABLES				
Emotional Stress	=1 if female self-reports as feeling sad or lonely during menstruation, 0 otherwise	0.480	-	0/1
Missed School	=1 if female self-reports missing school due to menstruation, 0 otherwise	0.327	-	0/1
Days Miss School	=1 if missed 0 days of school last month due to menstruation, 2 if missed 1-2 days, 3 if missed 3+	1.331	(0.554)	1/3
EXPLANATORY VARIABLES				
School Environment	Index based on PCA of (1/0) self-reported yes answers to existence of sanitation supplies, separate toilet, soap, disposal bin, & hygiene education at school	-	-	-
Community Cultural Environment	Index based on PCA heavily loaded with (1/0) self-reported yes answers to not being able to enter prayer room, participate in cultural functions, or be allowed in kitchen during menstruation	-	-	-
Family Cultural Environment	Index based on PCA heavily loaded with (1/0) self-reported yes answers to not being able to stay in same house & not meet family during menstruation	-	-	-
Age	Age of female	16.6	(1.96)	12/20
ADDITIONAL CONTROLS				
PNMHI	=1 if attending PNMHI School, 0 otherwise	0.196	-	0/1
Paklihawa	=1 if attending Paklihawa School, 0 otherwise	0.317	-	0/1
Purkot	=1 if attending school in Purkot, 0 otherwise (Base Category)	0.488		

Table 4.1: Descriptive Statistics of Variables (cont.)

Hygiene Product Use				
Old Clothes	=1 if female currently using old clothes during menstruation, 0 otherwise	0.228	-	0/1
Reusable	=1 if female currently using reusable hygiene product during menstruation, 0 otherwise	0.103	-	0/1
Disposable	=1 if female currently using disposable hygiene product during menstruation, 0 otherwise	0.669	-	0/1
Caste				
Brahman Chhetri	=1 if female belongs to Brahman-Chhetri caste, 0 otherwise (Base Category)	0.470	-	0/1
Dalit	=1 if female belongs to Dalit caste, 0 otherwise	0.114	-	0/1
Madhesi	=1 if female belongs to Madhesi caste, 0 otherwise	0.164	-	0/1
Other	=1 if female belongs to other castes, 0 otherwise	0.231	-	0/1
Wealth Index	Sum of binary (1/0) self-reported yes answers to self or family owning land & cement home	1.38	(0.568)	0/2
Married	=1 if female is married, 0 otherwise	0.036	-	0/1

Table 4.2: Single Equation Estimation of Menstruation Related Emotional Stress & School Absence[1]

VARIABLES	(1) Emotional Stress[2] (Probit)	(2) Missed School[3] (Probit)	(3) Days Missed[4] (Oprobit)
Community Environment	0.116		
	(0.070)		
Family Environment	0.128		
	(0.075)		
School Environment	-0.299**		
	(0.095)		
Emotional Stress		0.580***	0.341*
		(0.170)	(0.161)
Age	1.096	-0.997	-0.958
	(0.614)	(0.619)	(0.557)
Age Sq.	-0.035	0.031	0.028
	(0.019)	(0.019)	(0.017)
Constant/Cut Point 1	-8.7	7.055	-7.132
	(5.042)	(5.052)	(4.651)
Cut Point 2			-5.924
			(4.659)
Fixed Effects[5]	Yes	Yes	Yes
Caste[6]	Yes	Yes	No
N	281	281	281
ln(L)	-180	-159	-192
χ^2	29	32.9	25.5
AIC	381	336.4	398.3
BIC	421	369.2	423.7

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[1] Each Model Based on Lowest AIC from Estimation Fitting for Respective Equation (See Appendix)
[2] Dependent Variable is Binary Indicator of Whether Girl Feels Sad/Lonely During Menstruation
[3] Dependent Variable is Binary Indicator of Whether Girl Misses School Due to Menstruation
[4] Dependent Variable is Ordinal Indication of # Missed Days of School (1=None, 2=1-2days, 3=3+ days)
[5] School-level Fixed Effects (Purkot as Base Category)
[6] Brahman-Chhetri (highest caste) as Base Category

Table 4.3: Bivariate Probit Estimation of Menstruation Related Emotional Stress & School Absence[1]

Explanatory Variables	MODEL 1 Emotional Stress	MODEL 1 Missing School	MODEL 2 Emotional Stress	MODEL 2 Missing School
Community Environment	0.158**		0.146*	
	(0.056)		(0.057)	
Family Environment	0.160**		0.148*	
	(0.061)		(0.058)	
School Environment	-0.221**		-0.252**	
	(0.083)		(0.083)	
Emotional Stress		1.737***		1.818***
		(0.183)		(0.120)
Age	1.191*	-1.017	1.372*	-0.957
	(0.600)	(0.568)	(0.606)	(0.571)
Age Sq.	-0.038*	0.032	-0.044*	0.03
	(0.019)	(0.018)	(0.019)	(0.018)
Constant	-9.463	6.651	-10.697*	6.092
	(4.868)	(4.559)	(4.892)	(4.582)
Rho (ρ)	-0.917***		-1***	
	(0.176)		(2.20e-11)	
Fixed Effects[1]	Yes	Yes	Yes	Yes
Caste[2]	No	No	Yes	Yes
N	281		281	
ln(L)	-341		-333	
AIC	713		706.6	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[1] School-level Fixed Effects (Purkot as Base Category)

[2] Brahman-Chhetri (highest caste) as Base Category

Table 4.4: Marginal Effects of Bivariate Probit Estimation of Menstruation Related Emotional Stress & School Absence

	MODEL 1		MODEL 2	
	Emotional Stress	Missing School[1]	Emotional Stress	Missing School[1]
Community Environment	0.0586**		0.053**	
	(0.022)		(0.020)	
Family Environment	0.0592**		0.0537*	
	(0.022)		(0.020)	
School Environment	-0.0819**		-0.0916***	
	(0.030)		(0.0287)	
Emotional Stress		0.474***		0.489***
		(0.026)		(0.013)
Fixed Effects[2]	Yes	Yes	Yes	Yes
Caste[3]	No	No	Yes	Yes

Delta Method standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[1] Dependent Variable is Binary Indicator (1/0) if Missing School During Menstruation
[2] School-level Fixed Effects (Purkot as Base Category)
[3] Brahman-Chhetri (highest caste) as Base Category

Table 4.5: Conditioned Mixed Process (CMP) Estimation of Menstruation Related Emotional Stress & School Absence

Explanatory Variables	MODEL 1 Emotional Stress	MODEL 1 Days Missed[1]	MODEL 2 Emotional Stress	MODEL 2 Days Missed[1]
Community Environment	0.085		0.08	
	(0.069)		(0.070)	
Family Environment	0.153*		0.152*	
	(0.061)		(0.062)	
School Environment	-0.206**		-0.226**	
	(0.069)		(0.074)	
Emotional Stress		1.630***		1.671***
		(0.131)		(0.142)
Age	1.274*	-0.938	1.325*	-1.001
	(0.585)	(0.567)	(0.597)	(0.585)
Age Sq.	-0.040*	0.028	-0.042*	0.031
	(0.018)	(0.017)	(0.018)	(0.018)
Constant/Cut 1	-10.157*	-6.195	-10.488*	-6.537
	(4.818)	(4.681)	(4.898)	(4.802)
Cut 2		-5.32		-5.636
		(4.670)		(4.789)
Rho (ρ)	-0.905***		-0.899***	
	(0.064)		(0.073)	
Fixed Effects[2]	Yes	Yes	Yes	Yes
Caste[3]	No	No	Yes	Yes
N	281		281	
ln(L)	-369.56		-364.24	
AIC	771.12		772.49	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[1] Dependent Variable is Ordinal Indication of # Missed Days of School (1=None, 2=1-2 days, 3=3+ days)
[2] School-level Fixed Effects (Purkot as Base Category)
[3] Brahman-Chhetri (highest caste) as Base Category

Table 4.6: Marginal Effects of Conditioned Mixed Process (CMP) Estimation of Menstruation Related Emotional Stress & School Absence

	MODEL 1			MODEL 2		
Effect on No. Days Miss School[1]	0 Days	1-2 Days	3+ Days	0 Days	1-2 Days	3+ Days
Emotional Stress	-0.454***	0.142***	0.312***	-0.465***	0.151***	0.314***
	(0.021)	(0.039)	(0.054)	(0.024)	(0.043)	(0.061)
Effects on Emotional Stress						
School Environment	-0.0771**			-0.0836***		
	(0.025)			(0.026)		
Family Environment	0.0574*			0.0563*		
	(0.022)			(0.023)		
Community Environment	0.0317			0.0297		
	(0.026)			(0.026)		
Fixed Effects[2]	Yes	Yes	Yes	Yes	Yes	Yes
Caste[3]	No	No	No	Yes	Yes	Yes

Delta Method standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[1] Dependent Variable is Ordinal Indication of # Missed Days of School (1=None, 2=1-2 days, 3=3+ days)
[1] School-level Fixed Effects (Purkot as Base Category)
[1] Brahman-Chhetri (highest caste) as Base Category

Table 4.7: Summary of Results' Significance & Hypothesis Support Based on Estimation Technique

HYPOTHESIS	Single Equations	Bi-probit (Binary-Binary)		CMP (Binary-Ordinal)		REMARKS
	BEST FIT MODEL	MODEL 1	MODEL 2	MODEL 1	MODEL 2	
***H1**: School Infrastructure Decreases Emotional Stress*	-**	-**	-***	-**	-***	Presence of greater hygiene supporting infrastructure will decrease probability females report menstruation related emotional stress
***H2:** Cultural Norms Increase Emotional Stress*		+** (Comm.) +** (Family)	+** (Comm.) +* (Family)	+* (Family)	+* (Family)	Presence of greater cultural restrictions/norms increases probability females report menstruation related emotional stress
***H3:** Emotional Stress Increases Missing School*	+*** (Binary) +* (Ordinal)	+***	+***	-*** (0 Days) +*** (1-2 Days) +*** (3+ Days)	-*** (0 Days) +*** (1-2 Days) +*** (3+ Days)	Presence of menstruation related emotional stress increases likelihood girls miss school and the number of days missed during menstruation

Figure 4.1: Conceptual Framework

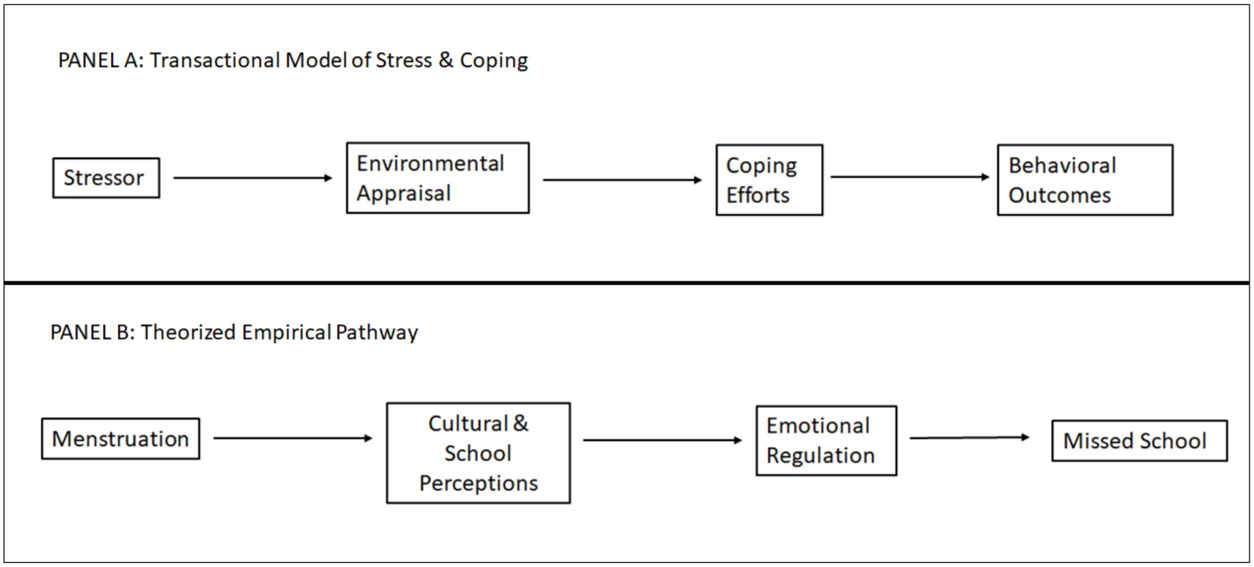
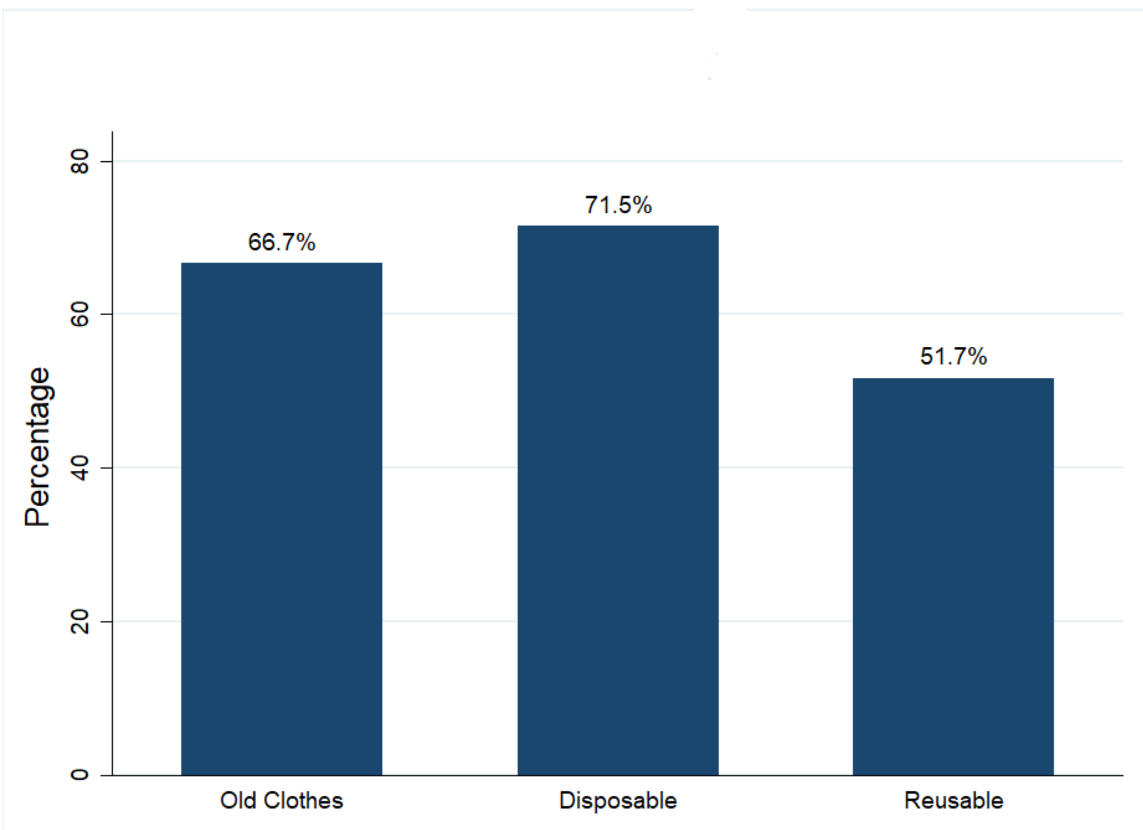


Figure 4.2: Life Seen as Hard/Very Hard During Menses (By Hygiene Product Use Type)



APPENDIX

Chapter 2

1. **Descriptive Statistics by Gender**
2. **Methods & Formulas for SEM Model Assessment**
3. **Sensitivity Analyses**
4. **Model Identification**

Appendix One: Descriptive Statistics by Gender

VARIABLES	FEMALES		MALES		Min/Max
	Mean	Standard Deviation	Mean	Standard Deviation	
OUTCOME VARIABLES					
Anxiety (A)	14.51	7.97	12.24	7.91	0/48
Grit Score (G)	3.27	0.50	3.26	0.50	1.8/5
KEY EXPLANATORY VARIABLES					
Problematic Mobile Phone Use (PMPU)	83.95	20.55	89.21	21.40	27/135
Bullying (B)	0.34	0.68	0.37	0.73	0/3
Physically Hurt Prior Year	0.099	-	0.164	-	0/1
Bullied at School	0.112	-	0.101	-	0/1
Bullied Outside School	0.128	-	0.104	-	0/1
SOCIO-CULTURAL ENVIRONMENTAL FACTORS					
Academic Pressures (AP)*					
Worry About Exam Scores	4.10	1.27	3.97	1.33	1/5
Teachers Too Controlling	3.63	1.43	3.72	1.34	1/5
School Competitive	3.99	1.21	3.74	1.34	1/5
School Success is Life Success	4.28	1.17	4.01	1.35	1/5
Family Environment (FE)*					
Parents Check Phone	3.29	1.62	3.07	1.62	1/5
Physically Hurt in Home	2.40	1.56	2.68	1.58	1/5
Punished for Bad Grades	2.59	1.66	2.69	1.58	1/5
Women Tolerate Violence	2.50	1.66	2.72	1.61	1/5
Social Support (SS)*					
Borrow Money	0.734	-	0.732	-	0/1
Stay With	0.694	-	0.718	-	0/1
Confide in About Violence	0.618	-	0.678	-	0/1
Help with Harassment Situation	0.648	-	0.658	-	0/1
Place Meet Same Sex Friends	0.418	-	0.487	-	0/1
Member of Club/Youth Group	0..355	-	0.480	-	
INSTRUMENTS (FOR *PMPU*)					
Phone Cost (PC)	18.27	15.37	19.86	16.25	0.2/110
Phone Cost Sq. (PC2)	569.06	1431.13	656.63	1315.51	0.04/12100
Friend's PMPU (FPMPU)	19.42	5.71	20.76	5.47	6/30
ADDITIONAL CONTROLS					
Age (X1)	17.41	1.12	17.78	1.23	15/25
Rural (X3)	0.576	-	0.403	-	0/1

Appendix Two: Methods and Formulas for SEM Assessment

Central to any complete research using structural equation modeling (SEM) is assessment of the full model based on a number of diagnostic tests. There are two primary steps to model analysis, namely assessment of the measurement model (e.g. the constructs and their validity), and then assessment of the overall model's goodness of fit. The intuitive methods and formulas for the tests presented in this work are presented below.

Measurement Model Assessments

For full assessment of a construct's validity, Campbell and Fiske (1959) propose addressing convergent validity and discriminant validity. These two assessments are also what is traditionally performed under confirmatory factor analysis (CFA) (Jöreskog 1969). Determination of the validity of constructs based on these methods is primarily evaluated according to the criterions set by Fornell and Larker (1981).

Convergent validity is the degree of confidence that a latent trait is well measured by its indicators. The first step in determination of convergence validity is to examine if the coefficients on the latent indicators (e.g., the factor loadings of the observed variables on their latent constructs) are greater than 0.7 (Farrell and Rudd 2009). Those indicators with a lower factor loading are typically removed from the measurement model. Following this base-level step, the standard measures of assessment are average variance extracted (AVE) and construct reliability (CR). AVE measures the level of variance captured by a construct versus the level due to measurement error, while CR is a measure of reliability akin to the Chronbach Alpha (Cronbach 1951) typically used with psychometric tests. With K_j as the number of indicators of construct ξ_j, λ_{jk} as factor loadings, and Θ_{jk} the error variance of the kth indicator ($k = 1, ..., K_j$) of constuct ξj, below are the formulas for the calculation of these measures:

$$AVE\xi_j = \frac{\sum_{k=1}^{K_j} {\lambda_{jk}}^2}{\left(\sum_{k=1}^{K_j} {\lambda_{jk}}^2\right) + \theta_{jk}}$$

$$CR_{c\xi j} = \frac{\left(\sum_{k=1}^{K_j} \lambda_{jk}\right)^2}{\left(\sum_{k=1}^{K_j} \lambda_{jk}\right)^2 + \theta_{jk}}$$

Where:

$$\theta_{jk} = \sum_{k=1}^{K_j} 1 - {\lambda_{jk}}^2$$

Construct Reliability (CR), Average Variance Extracted (AVE), & Squared Correlations for Latent Constructs

PANEL A: LINEAR PROBABILITY ESTIMATION			
	SS*	***AP****	***FE****
CR	0.997	1.078	1.216
SS*	0.983		
AP*	0.058	1.398	
FE*	0	0.158	3.044
PANEL B: GENERALIZED LINEAR ESTIMATION			
	SS*	***AP****	***FE****
CR	0.968	1.128	1.297
SS*	0.840		
AP*	0.075	1.749	
FE*	0	0.169	5.678

AVE values are shaded in grey for each latent construct.
SS=Social Support*; AP = Academic Pressure*; FE = Family Environ.*

While convergent validity is associated with each latent construct individually, discriminant validity is a measure focused on the differences between construct. It is a measure of the degree to which measures of different traits are unrelated. Essentially, that the different constructs are indeed capturing different elements. Confirmation of discriminant validity is determined based on a comparison between AVE values and the respective squared correlations between constructs in a model. Levels of the square root of the AVE for each construct should be greater than the correlation involving the constructs. If AVE is smaller than the squared correlations between two constructs, multicollinearity issues are likely (Kline 2016). For our model, this does not appear to be the case (See Table), regardless of estimation approach. Thus, the measurement model was deemed to have divergent validity.

Goodness of Fit Measures

While construct validity assesses the measurement model portion of a full structural model, to determine the appropriateness of the overall model, it is usually considered appropriate to compute overall goodness of fit measures. Most measures of goodness of fit will rely on comparison of the log-likelihood value from the specified (e.g. research and hypothesis-proposed) model and what are known as the *baseline (*or *independent)* and *saturated* model. The saturated model perfectly reproduces all of the variances, covariances, and means of the observed variables, and it allows for all possible covariances to exist. Put another way, the saturated model is an exactly identified model in which the number of free parameters exactly equals the number of known values. The saturated model has the best fit possible because it perfectly reproduces all of the variances, covariances, and means, and hence this is why it serves as the standard for comparison with the models one estimates. This is the least restrictive of all models. The baseline model, on the other hand, involves estimation of the means and variances of all observed variables plus the covariances of all observed exogenous variables (e.g. those observed variables with no arrows coming "in"). This means that only the exogenous variables are considered as correlated. The baseline model is thus the most restrictive model.

Chi-Square Statistics

There are two Chi-squared statistics based on log-likelihood ratio tests which are often reported by standard structural equation modeling software: one comparing the saturated log-likelihood (L_s) to the baseline model's log-likelihood (L_b), and the other comparing L_s to the specified model's log-likelihood (L_m). With p representing the number of endogenous (e.g. determined within the structural model), and q the number of exogenous (e.g. external to the model), degrees of freedom for each model and the appropriate test statistics are as follows:

$$\mathrm{df}_s = \binom{p+q+1}{2} + p + q$$

$$\mathrm{df}_b = \begin{cases} 2q, & \text{if } p = 0 \\ 2p + q + \binom{q+1}{2}, & \text{if } p > 0 \end{cases}$$

$$\chi^2_{bs} = 2(\log L_s - \log L_b), \text{ with } \mathrm{df}_{bs}=\mathrm{df}_s-\mathrm{df}_b$$

$$\chi^2_{ms} = 2\{\log L_s - \log L(\hat{\theta})\}, \text{ with } df_{ms}=df_s-df_m$$

For these tests, unlike most Chi-Squared tests used in regression analyses, the optimal outcome would be to not reject the statistic. These tests are measuring how closely the specified model's variance-covariance matrix maps onto that of the saturated model. The closer the values are together, the better the model fit, and the smaller the Chi-squared value. Despite this goal, there are a number of reasons why it is often difficult to not reject the value in real-world applications. With a large sample size, the Chi-square values will be inflated (statistically significant), which might erroneously imply a poor data-to-model fit (Lomax and Schumacker 2004). For models with about 75 to 200 cases, the chi square test is generally a reasonable measure of fit. But, for models with more cases (400 or more), the chi square is almost always statistically significant. Chi-square is also affected by the size of the correlations in the model: the larger the correlations, the poorer the fit (Carmines and McIver 1981). While some researchers have recommended the use of a relative chi-square equal to the chi-square value divided by the degrees of freedom (Carmines and McIver 1981; Marsh and Hocevar 1985; Byrne 1991), others indicate that use of this ratio provided a no better measure of the fit of the overall model (Wheaton 1987). Due to this lack of agreement among researchers, much more attention is paid to more "descriptive" measures of model overall fit.

Standardized Root Mean Square Residual (SRMR)

SRMR is a measure of the average difference between the observed and model-implied correlations (Hancock and Mueller 2013), and does not require calculation of the log-likelihood ratios associated with Chi-square statistics. This is simply the square root of the differences between actual variances and covariances and variances and covariances generated assuming the model is true (e.g., the estimated variances and covariances). The formula for this measure is shown below. The value of this measure will be close to 0 when a model fits well, as such, Hu and Bentler (1999) suggest a value at 0.08 or below to meet good-fit criteria. With k being the number of observed variables in a model, r_{ij} as the standardized covariance residual, and G the number of groups (1 in our case):

$$\text{SRMR} = \left\{\frac{2\sum_{i=1}^{k}\sum_{j\leq i} r_{ij}^2}{k(k+1)G}\right\}^{1/2}$$

And,

$$r_{ij} = \frac{s_{ij}}{\sqrt{s_{ii}s_{jj}}} - \frac{\hat{\sigma}_{ij}}{\sqrt{\hat{\sigma}_{ii}\hat{\sigma}_{jj}}}$$

<u>Coefficient of Determination (CD)</u>

Also not based on log-likelihood values, the CD is based on the difference of the determinant of the var-cov matrix of the error variables $(\widehat{\Psi})$ divided by the determinant of the var-cov matrix of all variables $(\hat{\Sigma})$. This is the measure akin to R^2, and assesses the amount of overall variance explained by the model. Its formula is below:

$$\text{CD} = 1 - \frac{\det(\widehat{\Psi})}{\det(\hat{\Sigma})}$$

Root Mean Square Error of Approximation (RMSEA)

RMSEA is a measure composed of differences between the Chi-square value of the log-likelihood ratio between the specified and saturated models, along with the associated degrees of freedom (Brown and Cudeck 1993), which avoids issues of sample size. It compares the current model with the saturated one, under a null hypothesis that the model fits. Its formula can be seen below. RMSEA values seen as indicating good model fit range from 0.01 (MacCallum, Browne, and Sugawara 1996) to 0.06 (Hu and Bentler 1999).

$$\text{RMSEA} = \left\{\frac{(\chi^2_{ms} - \text{df}_{ms})G}{N\text{df}_{ms}}\right\}^{1/2}$$

Comparative Fit Index (CFI)

The CFI is a relative fit index, which compares the current/specified model to the baseline model, as described previously, using the appropriate Chi-square and degrees of freedom as shown below (Bentler 1990). This is a measure of the proportionate improvement in fit of the specified model over the baseline. Having a CFI close to 1 indicates a very good fit, > 0.9 or close to 0.95 indicates good fit, and by convention, CFI should be equal to or greater than .90 to accept the model (Hoyle and Panter 1995).

$$\text{CFI} = 1 - \left[\frac{(\chi^2_{ms} - \text{df}_{ms})}{max\{(\chi^2_{bs} - \text{df}_{bs}), (\chi^2_{ms} - \text{df}_{ms})\}}\right]$$

Akaike's Information Criterion

Another form of relative fit is AIC. AIC is a common model comparison calculation statistics which deals with the trade-off between the goodness of fit of the model and the simplicity of the model (Akaike 1974). The lowest AIC figure among a set of potential models is deemed the most useful model. Its formula is as follows:

$$\text{AIC}= - 2\text{log}L(\hat{\theta}) + 2\text{df}_m$$

Appendix Three: Sensitivity Analyses

To facilitate in determining the robustness of the findings from our main structural modelling estimation, which incorporated the ability to account for measurement error in certain latent measures of key adolescent-life pressure points, several sensitivity analyses were performed. These additional estimation approaches do not allow one to account for the measurement error of the latent constructs. Each of the three constructs were operationalized through summing the values of the respective indicators detailed in Table 2.2. Due to collinearity issues, the use of the demographic control *X3* (e.g. rural binary indicator), was also removed in these analyses.

The first sensitivity analysis was a baseline estimation of ordinary least squares (OLS), which would ignore any potential endogeneity to be found between our key technology variable (*PMPU)* and either of the wellbeing outcome variables. As seen in columns one and five of Table A1, there is a statistically significant positive (negative) impact of *PMPU* on anxiety (grit), with impacts of bullying mirroring these results in terms of sign and significance. Females are indicated, just as with structural equation modeling (SEM), to have a higher likelihood of exhibiting more anxiety symptoms. Our measure of academic pressure in this context only has a significant (positive) association with grit, while social support is shown to have a statistically significant negative effect on anxiety. This latter outcome is the major departure from the results found through SEM. We address speculation as to this outcome in the main text of this work. There is indication from literature of potential (econometric) endogeneity between the key technology/mediating variable, *PMPU,* and the two wellbeing outcomes, as referenced in the body of this work. This required that we also attempt a number of instrumental variable estimation methods under this regression-oriented estimation framework testing the sensitivity of our results. Determination of the best instruments required initial exploration of studies examining similar outcome and explanatory variables.

Using the National Longitudinal Study of Adolescent Health (AddHealth) database, researchers examining the impact of suicidal thoughts/attempts on likelihood of engaging in school used the suicidal behavior of friends as an instrument to account for reverse causality concerns (Tekin and Markowitz 2008). As applied to this work, such an approach would be based on the assumption that the perception of friends' use/overuse of cell phones impacts one's own use/overuse of mobile phones, but does not impact wellbeing outcomes directly. Similarly, prices have also been a common instrument used in economic studies investigating substance abuse (Fang, Ali, and Rizzo 2009; Amialchuk, Bornukova, and Ali 2018; French and Popovici 2011). Thus, we can capture the prices of cell phone, based on the assumption that the cost of a phone will impact its use/overuse, but will not directly affect wellbeing outcomes such as anxiety and grit.

Using the above instruments, estimations were undertaken using traditional two-stage least squares (2SLS) and with two-step feasible generalized method of moment (GMM2) estimation. The latter estimator is more efficient relative to 2SLS due to the use of an optimal weighting matrix and relaxation of the *iid* assumption (Hayashi 2000). Results are shown in Table A1, columns (2)–(3) and (6)-(7) as they pertain to the outcomes of anxiety and grit, respectively. Results in terms of sign and significance from these IV techniques are consistent with those found from OLS, where the only departure from the SEM results is the significant negative impact of our measure of social support on anxiety. Compared to those estimates from OLS, these coefficient estimates are of similar magnitude to those found with OLS, which would provide support for an argument that simultaneity between anxiety and problematic phone use is not a concern. In contrast, the OLS coefficient for *PMPU*'s effect on grit is attenuated towards zero in comparison to the IV estimates, supporting an argument that there is potential bias caused from endogeneity for this estimation equation. Such conclusions match with the results found via our SEM approaches that the covariances between *PMPU* and *A* are insignificant, while those between *PMPU* and *G* are significant. These conclusions are also supported by the test statistics reported at the bottom of Table A1.

Appropriate application of instrument variable techniques requires determination of both the satisfaction of the exclusion restriction and strength of the relevance condition. With respect to the strength of our instrumental variables (i.e. their predictive power concerning overuse/problematic use of mobile phones), we conduct F-tests of their joint significance in the first stage of the 2SLS regressions. We also report the Sargan/Hansen J over-identification test. With respect to the exogeneity of our instrumental variables, we present the Hausman test statistic. One can see that the Hausman tests for exogeneity of PMPU are not rejected in the case where anxiety is the outcome variable, while they are rejected with marginal significance (at the 90% level) in the case where grit is the outcome variable. Regardless of outcome variable, however, the Sargan/Hansen J statistics are not rejected, supporting the null hypothesis that the instruments are valid (or more appropriately, that the exclusion restriction is met), should *PMPU* be deemed as leading to an endogeneity problem. Additionally, the strength of our set of instruments is supported by F-tests in the first stage equation being larger than 10 (Greene 2003).

The final (limited information) technique undertaken was to re-estimate our 2SLS models, with an IV technique that has been developed which does not require using any external instruments. This Lewbel technique (2012) has been used in examinations of smoking and subjective wellbeing (happiness and depression), along with work examining the interplay of alcohol consumption and depression (Awaworyi Churchill and Farrell 2017a; 2017b). The premise is to internally generate instruments in an approach similar to 2SLS, when external instruments are unavailable or weak. Even in the presence of potentially strong instruments, the use of the Lewbel technique is believed to increase the strength of the estimation with truly exogenous instruments. One constructs internal instruments from the residuals of auxiliary equations that are multiplied by included exogenous variables in their mean-centered form. Identification with this approach stems from heteroskedastic covariance restrictions. As shown in the final columns ((4) and (8)) of Table A1, the results of including these additional instruments are unchanged from those found with the prior two IV techniques.

Given that limited information methods such as 2SLS and GMM2 do not properly account for the (potential) correlation between the two wellbeing outcomes themselves, we also undertook the full-information estimation technique of three-stage least squares (3SLS), results of which can be found in Table A2. To mirror the approach used in our main structural modeling analyses, we present two versions of the estimation: one where we include demographic controls in the equation for *PMPU*, and one where we do not (first column). Results here again indicate the same sign and significance for all key variables. Across the board, the magnitude of parameter estimates are smaller than those found with IV or SEM techniques. Additionally, the strength of a significant positive effect of social support on anxiety is smaller.

In total, these sensitivity analyses we believe provide good support for the findings of our structural equation estimation results. They reemphasize the importance of monitoring problematic mobile phone use and bullying to avoid deleterious wellbeing outcomes. Further, they provide empirical support for the BPNT framework and the role that need thwarting contexts play in reducing overall wellbeing.

TABLE 2.A1: IV Results for Adolescent Life Influences on Health Outcomes of Anxiety & Grit

	Anxiety				Grit			
VARIABLES	OLS	2SLS	GMM2	Lewbel[4]	OLS	2SLS	GMM2	Lewbel[4]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PMPU[1]	0.0946***	0.0929***	0.1000***	0.0925***	-0.00895***	-0.0135***	-0.0139***	-0.0134***
	(0.0118)	(0.0277)	(0.0252)	(0.0285)	(0.00135)	(0.00195)	(0.00178)	(0.00176)
B	1.918***	1.977***	1.772***	1.978***	-0.109***	-0.0918***	-0.0717***	-0.0921***
	(0.180)	(0.338)	(0.305)	(0.339)	(0.0209)	(0.0261)	(0.0189)	(0.0268)
*AP**	0.0282	0.0320	-0.0237	0.0326	0.0133**	0.0223***	0.0260***	0.0222**
	(0.0744)	(0.0804)	(0.0723)	(0.0765)	(0.00608)	(0.00850)	(0.00773)	(0.00799)
*FE**	0.0520	0.0226	0.0431	0.0231	-0.00983*	-0.00224	-0.00451	-0.00236
	(0.0626)	(0.0629)	(0.0615)	(0.0718)	(0.00462)	(0.00477)	(0.00392)	(0.00453)
*SS**	-0.486***	-0.398***	-0.317**	-0.398**	0.0200	0.0276*	0.0181	0.0276
	(0.125)	(0.143)	(0.129)	(0.150)	(0.0190)	(0.0153)	(0.0124)	(0.0163)
Age	0.497*	0.588***	0.497***	0.589**	-0.00835	-0.00342	-0.00765	-0.00348
	(0.240)	(0.220)	(0.112)	(0.230)	(0.0150)	(0.0157)	(0.0150)	(0.0163)
Female	2.509***	2.660***	2.330***	2.658***	-0.0352	-0.0585	-0.0405	-0.0581
	(0.743)	(0.735)	(0.617)	(0.759)	(0.0444)	(0.0437)	(0.0403)	(0.0465)
Constant	-4.886	-6.637	-5.118	-6.622	4.076***	4.141***	4.258***	4.138***
	(5.326)	(5.571)	(3.190)	(5.851)	(0.261)	(0.264)	(0.242)	(0.282)
N	527	485	485	485	500	459	459	459
R^2	0.143	0.152	0.150	0.152	0.203	0.164	0.154	0.165
AIC	3619.81	3304.13	3305.10	3304.14	633.07	596.28	601.63	595.68
BIC	3653.95	3337.60	3338.57	3337.61	666.79	629.32	634.67	628.71
F-Value First Stage		39.46	39.46			42.87	42.87	
Sargan/Hansen J[2]		2.761	2.761			1.380	1.380	
(p-value)		(0.251)	(0.251)			(0.502)	(0.502)	
Hausman[3]		0.104	0.104			3.750	3.750	
(p-value)		(0.747)	(0.747)			(0.053)	(0.053)	

Standard Errors Clustered at the School-Grade Level; *** p<0.01, ** p<0.05, * p<0.1
[1]Instrumented with PhoneCost, PhoneCostSQ, FriendsPMPU
[2] H0: Instruments Are Valid
[3] H0: Endog. Var Are Actually Exog.
[4] Instruments used are those generated internally from the data & external instruments, where use of clustered SE's doesn't allow for appropriate testing of endogeneity or overID

TABLE 2.A2: 3SLS Results for Adolescent Life Influences on Health Outcomes of Anxiety & Grit

	No Demographic Controls			With Demographic Controls		
VARIABLES	Grit	Anxiety	PMPU Score	Grit	Anxiety	PMPU Score
PMPU	-0.0122***	0.0895***		-0.0122***	0.0894***	
	(0.00206)	(0.0334)		(0.00206)	(0.0334)	
B	-0.0853***	1.542***	1.225	-0.0852***	1.542***	1.246
	(0.0286)	(0.464)	(0.977)	(0.0286)	(0.464)	(0.975)
*AP**	0.0203***	0.0102	0.752***	0.0205***	0.0105	0.797***
	(0.00697)	(0.113)	(0.223)	(0.00697)	(0.113)	(0.224)
*FA**	-0.00518	0.0180	0.723***	-0.00517	0.0180	0.720***
	(0.00547)	(0.0886)	(0.170)	(0.00547)	(0.0886)	(0.170)
*SS**	0.0312**	-0.415*	0.229	0.0308**	-0.415*	0.150
	(0.0132)	(0.214)	(0.455)	(0.0132)	(0.214)	(0.456)
PC			0.392***			0.381***
			(0.119)			(0.119)
PC2			-0.00350**			-0.00337**
			(0.00137)			(0.00136)
FPMPU			1.897***			1.887***
			(0.137)			(0.139)
Age	0.00122	0.546**		-0.000983	0.544**	-0.459
	(0.0164)	(0.269)		(0.0166)	(0.269)	(0.579)
Female	-0.0504	2.945***		-0.0616	2.932***	-2.321*
	(0.0408)	(0.671)		(0.0414)	(0.671)	(1.407)
Constant	3.993***	-4.881	22.57***	4.038***	-4.832	31.75***
	(0.315)	(5.157)	(4.173)	(0.318)	(5.158)	(10.80)
N	522	522	522	522	522	522
R^2	0.176	0.133	0.437	0.176	0.133	0.440
AIC (Overall)		8595.99			8596.93	
BIC (Overall)		8698.18			8707.63	

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

Appendix Four: Model Identification

Within literature which has applied structural equation modeling (SEM), the matter of proper identification of the model is paramount. An unidentified model indicates that at least one parameter is not unique, with a consequence that results may be misleading. Within SEM literature, identification in relation to a measurement model is often defined as having more equations to explain the different latent constructs than the number of latent constructs in the model (Hancock and Mueller 2013), and a path model is deemed identified if it is recursive . Such definitions can equivalently (Kline 2016; Hoyle 1995) be explained by the necessary and sufficient conditions for identification of order and rank.

To meet the order condition (necessary) in a model of M simultaneous equation, the number of predetermined (or exogenous) variables from the whole system that are excluded from a particular equation must be equal to or greater than the number of endogenous (e.g, determined within the model) variables, minus one (Gujarati 2009). This means that each equation must meet the following inequality: $K-k \geq m-1$, where K is the number of exogenous variables in the system, k is the number of exogenous variables in the equation of focus, and m is the number of endogenous variables in the equation of focus. By assuming block independence between each of the three measurement components and also between them and the path portion of our full structural model, we can evaluate each set of equations (or block) separately. Equation 1 (Anxiety outcome) is overidentified. Equation 2 (Grit outcome) is overidentified. Finally, Equation 3 (PMPU outcome) is exactly identified. As it pertains to each individual block representing a latent construct, every equation in a measurement model will be exactly identified. Many researchers would refer to the measurement models as equivalent to factor analysis, where each latent variable captures the extent to which the respective indicators for each of the three latent variables (Social Support*, Academic Pressure*, Family Environ.*) move together.

While the order condition is necessary for model identification, rank is both necessary and sufficient. To satisfy this condition for a model of M simultaneous equations, each equation can be determined as identified if one or more coefficients exist for variables not included in the equation of focus, but included in other equations in the system (Gujarati 2009). By way of a step-wise process, below are the various matrices which display this scenario for our model:

Step-1: List all variables represented in the system of equations and below this, place each equation on one row indicated with a series of ones and zeroes the presence or absence of that variable in the specified equation.

	Grit	Anxiety	PMPU	Bully	AP	FE	SS	PC	PC2	FPMPU	Age	Female	Rural
Eq. 1	1	0	1	1	1	1	1	0	0	0	1	1	1
Eq. 2	0	1	1	1	1	1	1	0	0	0	1	1	1
Eq. 3	0	0	1	1	1	1	1	1	1	1	1	1	1

*AP = Academic Pressure**; *FE = Family Environ.**; *SS= Social Support**; *FPMPU= Friend's PMPU*

Step 2: To check the rank condition for equation *i*, take the columns corresponding to 0 in the i^{th} row, exclude the row for equation *i*, and write out the presence/absence of the remaining variables for the other equations in the system.

Step 3: Determine if there are any rows/columns that have all zeroes. As shown below, none of the equations in our structural system exhibit such a pattern.

Equation 1:

	Anxiety	PC	PC2	FPMPU
Eq. 2	1	0	0	0
Eq. 3	0	1	1	1

Equation 2:

	Grit	PC	PC2	FPMPU
Eq. 1	1	0	0	0
Eq. 3	0	1	1	1

Equation 3:

	Grit	Anxiety
Eq. 1	1	0
Eq. 2	0	1

APPENDIX

Chapter 3

1. **Individual Country Estimation Results**
2. **Descriptive Statistics By Gender**
3. **Weighting**

Appendix One: Individual Country Estimation Results

TABLE 3.A1: Multivariate Probit Results (Indonesia)

EXPLANATORY VARIABLES	DEPENDENT VARIABLES				
	Consider Suicide	Plan Suicide	Attempt Suicide	Mental Stress	Drug Use
Positive Parenting	-0.058***	-0.056***	-0.049***	-0.015**	-0.114***
	(0.009)	(0.009)	(0.011)	(0.005)	(0.012)
Social Exclusion	0.576***	0.429***	0.743***	0.537***	0.629***
	(0.045)	(0.045)	(0.051)	(0.033)	(0.063)
Age	0.065***	0.009	-0.013	0.138***	-0.036
	(0.014)	(0.014)	(0.017)	(0.009)	(0.026)
Female	0.241***	0.067	0.002	0.297***	-0.550***
	(0.047)	(0.047)	(0.055)	(0.029)	(0.081)
Constant	-2.128***	-1.176***	-1.333***	-2.186***	-0.188
	(0.227)	(0.222)	(0.271)	(0.146)	(0.405)
Rho (ρ) 1-2			0.822***		
			(0.016)		
Rho (ρ) 1-3			0.69***		
			(0.027)		
Rho (ρ) 1-4			0.248***		
			(0.029)		
Rho (ρ) 1-5			0.405***		
			(0.051)		
Rho (ρ) 2-3			0.715***		
			(0.025)		
Rho (ρ) 2-4			0.171***		
			(0.028)		
Rho (ρ) 2-5			0.335***		
			(0.060)		
Rho (ρ) 3-4			0.107**		
			(0.035)		
Rho (ρ) 3-5			0.536***		
			(0.047)		
Rho (ρ) 4-5			0.026		
			(0.047)		
N			9939		
ln(L)			-12689467		
χ^2 (Null Model)			1117.7		
χ^2 ($\rho_{ij}=0, \forall$ i,j)			1949184		
AIC			25379004.4		
BIC			25379256.5		

*** p<0.01, ** p<0.05, * p<0.1

- Weighted using survey-provided probability weightings
- Robust SE in parentheses

TABLE 3.A2: Multivariate Probit Results (Bangladesh)

EXPLANATORY VARIABLES	DEPENDENT VARIABLES				
	Consider Suicide	Plan Suicide	Attempt Suicide	Mental Stress	Drug Use
Positive Parenting	-0.043*	-0.058***	-0.082***	-0.017	-0.046
	(0.018)	(0.018)	(0.018)	(0.011)	(0.030)
Social Exclusion	0.486***	0.443***	0.545***	0.395***	0.542***
	(0.109)	(0.098)	(0.093)	(0.069)	(0.146)
Age	0.073	-0.057	-0.095	-0.015	0.026
	(0.059)	(0.053)	(0.056)	(0.035)	(0.088)
Female	0.234*	0.053	-0.018	0.062	-0.540**
	(0.114)	(0.103)	(0.106)	(0.063)	(0.206)
Constant	-2.399**	-0.063	0.654	0.135	-1.859
	(0.929)	(0.785)	(0.818)	(0.529)	(1.386)
Rho (ρ) 1-2			0.735***		
			(0.055)		
Rho (ρ) 1-3			0.595***		
			(0.070)		
Rho (ρ) 1-4			0.082		
			(0.074)		
Rho (ρ) 1-5			0.237		
			(0.144)		
Rho (ρ) 2-3			0.721***		
			(0.052)		
Rho (ρ) 2-4			0.128		
			(0.070)		
Rho (ρ) 2-5			0.141		
			(0.128)		
Rho (ρ) 3-4			0.026		
			(0.072)		
Rho (ρ) 3-5			0.121		
			(0.124)		
Rho (ρ) 4-5			0.128		
			(0.113)		
N			2764		
ln(L)			-6139518		
χ^2 (Null Model)			167.8		
χ^2 ($\rho_{ij}=0, \forall$ i,j)			752972		
AIC			12279105.8		
BIC			12279313.1		

*** p<0.01, ** p<0.05, * p<0.1

- Weighted using survey-provided probability weightings
- Robust SE in parentheses

TABLE 3.A3: Multivariate Probit Results (Namibia)

EXPLANATORY VARIABLES	DEPENDENT VARIABLES				
	Consider Suicide	Plan Suicide	Attempt Suicide	Mental Stress	Drug Use
Positive Parenting	-0.018*	0.009	-0.007	-0.036***	-0.042***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)
Social Exclusion	0.217***	0.330***	0.414***	0.209***	0.119**
	(0.041)	(0.038)	(0.038)	(0.037)	(0.046)
Age	-0.007	0.006	0.003	0.109***	0.112***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.016)
Female	0.04	-0.039	-0.101*	0.217***	-0.363***
	(0.049)	(0.046)	(0.046)	(0.044)	(0.054)
Constant	-0.679**	-1.082***	-0.875***	-1.244***	-2.095***
	(0.245)	(0.241)	(0.238)	(0.232)	(0.286)
Rho (ρ) 1-2			0.712***		
			(0.019)		
Rho (ρ) 1-3			0.661***		
			(0.021)		
Rho (ρ) 1-4			0.166***		
			(0.031)		
Rho (ρ) 1-5			0.176***		
			(0.037)		
Rho (ρ) 2-3			0.771***		
			(0.016)		
Rho (ρ) 2-4			0.159***		
			(0.028)		
Rho (ρ) 2-5			0.186***		
			(0.034)		
Rho (ρ) 3-4			0.154***		
			(0.029)		
Rho (ρ) 3-5			0.191***		
			(0.035)		
Rho (ρ) 4-5			0.096**		
			(0.034)		
N			3787		
ln(L)			-458343		
χ^2 (Null Model)			439.5		
χ^2 (ρ_{ij}=0, ∀ i,j)			96735		
AIC			916755.9		
BIC			916974.2		

*** p<0.01, ** p<0.05, * p<0.1

- Weighted using survey-provided probability weightings
- Robust SE in parentheses

TABLE 3.A4: Multivariate Probit Results (Morocco)

EXPLANATORY VARIABLES	DEPENDENT VARIABLES				
	Consider Suicide	Plan Suicide	Attempt Suicide	Mental Stress	Drug Use
Positive Parenting	-0.041***	-0.037***	-0.033***	-0.022**	-0.048***
	(0.008)	(0.009)	(0.009)	(0.007)	(0.013)
Social Exclusion	0.489***	0.353***	0.532***	0.418***	0.349***
	(0.058)	(0.061)	(0.059)	(0.055)	(0.081)
Age	0.122***	0.083**	0.076**	0.154***	0.222***
	(0.025)	(0.025)	(0.025)	(0.021)	(0.037)
Female	0.289***	0.158*	0.12	0.449***	-0.729***
	(0.062)	(0.064)	(0.064)	(0.053)	(0.109)
Constant	-2.505***	-1.957***	-2.013***	-2.434***	-4.010***
	(0.383)	(0.387)	(0.379)	(0.321)	(0.565)
Rho (ρ) 1-2			0.742***		
			(0.024)		
Rho (ρ) 1-3			0.762***		
			(0.024)		
Rho (ρ) 1-4			0.247***		
			(0.037)		
Rho (ρ) 1-5			0.439***		
			(0.053)		
Rho (ρ) 2-3			0.609***		
			(0.032)		
Rho (ρ) 2-4			0.167***		
			(0.039)		
Rho (ρ) 2-5			0.29***		
			(0.059)		
Rho (ρ) 3-4			0.234***		
			(0.039)		
Rho (ρ) 3-5			0.484***		
			(0.052)		
Rho (ρ) 4-5			0.147**		
			(0.056)		
N			2598		
ln(L)			-1775094		
χ^2 (Null Model)			416.1		
χ^2 ($\rho_{ij}=0, \forall$ i,j)			23777931		
AIC			3550258		
BIC			3550463		

*** p<0.01, ** p<0.05, * p<0.1

- Weighted using survey-provided probability weightings
- Robust SE in parentheses

TABLE 3.A5: Multivariate Probit Results (Peru)

EXPLANATORY VARIABLES	DEPENDENT VARIABLES				
	Consider Suicide	Plan Suicide	Attempt Suicide	Mental Stress	Drug Use
Positive Parenting	-0.070***	-0.069***	-0.076***	-0.048***	-0.067***
	(0.009)	(0.009)	(0.010)	(0.008)	(0.014)
Social Exclusion	0.433***	0.407***	0.460***	0.469***	0.213**
	(0.054)	(0.056)	(0.055)	(0.048)	(0.080)
Age	0.007	0.011	-0.005	0.061*	0.140**
	(0.029)	(0.029)	(0.029)	(0.025)	(0.043)
Female	0.595***	0.524***	0.388***	0.394***	-0.486***
	(0.061)	(0.063)	(0.061)	(0.052)	(0.091)
Constant	-0.637	-0.845	-0.389	-0.922*	-2.725***
	(0.437)	(0.439)	(0.440)	(0.381)	(0.646)
Rho (ρ) 1-2			0.878***		
			(0.014)		
Rho (ρ) 1-3			0.822***		
			(0.018)		
Rho (ρ) 1-4			0.313***		
			(0.035)		
Rho (ρ) 1-5			0.269***		
			(0.059)		
Rho (ρ) 2-3			0.83***		
			(0.018)		
Rho (ρ) 2-4			0.28***		
			(0.037)		
Rho (ρ) 2-5			0.312***		
			(0.058)		
Rho (ρ) 3-4			0.273***		
			(0.037)		
Rho (ρ) 3-5			0.332***		
			(0.057)		
Rho (ρ) 4-5			0.155**		
			(0.055)		
N			2654		
ln(L)			-1958315		
χ^2 (Null Model)			477.4		
χ^2 (ρ_{ij}=0, ∀ i,j)			715717.8		
AIC			3916701		
BIC			3916907		

*** p<0.01, ** p<0.05, * p<0.1

- Weighted using survey-provided probability weightings
- Robust SE in parentheses

TABLE 3.A6: Multivariate Probit Results (Costa Rica)

EXPLANATORY VARIABLES	DEPENDENT VARIABLES				
	Consider Suicide	Plan Suicide	Attempt Suicide	Mental Stress	Drug Use
Positive Parenting	-0.085***	-0.074***	-0.074***	-0.064***	-0.091***
	(0.010)	(0.011)	(0.011)	(0.008)	(0.011)
Social Exclusion	0.384***	0.275***	0.403***	0.467***	0.115
	(0.070)	(0.075)	(0.077)	(0.060)	(0.077)
Age	0.033	0.037	-0.003	0.132***	0.266***
	(0.036)	(0.037)	(0.038)	(0.027)	(0.036)
Female	0.391***	0.315***	0.315***	0.418***	-0.524***
	(0.075)	(0.079)	(0.081)	(0.058)	(0.080)
Constant	-0.986	-1.328*	-0.726	-1.997***	-3.755***
	(0.552)	(0.564)	(0.581)	(0.418)	(0.558)
Rho (ρ) 1-2			0.818***		
			(0.026)		
Rho (ρ) 1-3			0.748***		
			(0.032)		
Rho (ρ) 1-4			0.264***		
			(0.046)		
Rho (ρ) 1-5			0.229***		
			(0.059)		
Rho (ρ) 2-3			0.76***		
			(0.031)		
Rho (ρ) 2-4			0.224***		
			(0.050)		
Rho (ρ) 2-5			0.202**		
			(0.064)		
Rho (ρ) 3-4			0.246***		
			(0.050)		
Rho (ρ) 3-5			0.193**		
			(0.061)		
Rho (ρ) 4-5			0.198***		
			(0.049)		
N			2475		
ln(L)			-310017		
χ^2 (Null Model)			502.5		
χ^2 ($\rho_{ij}=0, \forall$ i,j)			64281.56		
AIC			620104.6		
BIC			620308.1		

*** p<0.01, ** p<0.05, * p<0.1

- Weighted using survey-provided probability weightings
- Robust SE in parentheses

TABLE 3.A7: Summary Hypotheses Table (Mental Stress as Ordinal)

		ALL	INDONESIA	BANGLADESH	NAMIBIA	MORROCCO	PERU	COSTA RICA
PANEL A: CONSIDERED SUICIDE								
	Positive Parenting	-0.050***	-0.058***	-0.043*	-0.018*	-0.042***	-0.069***	-0.085***
		(0.005)	(0.009)	(0.018)	(0.008)	(0.008)	(0.009)	(0.010)
	Social Exclusion	0.424***	0.579***	0.478***	0.217***	0.494***	0.430***	0.387***
		(0.028)	(0.045)	(0.107)	(0.041)	(0.058)	(0.054)	(0.070)
	Female	0.250***	0.251***	0.229*	0.041	0.281***	0.585***	0.390***
		(0.029)	(0.047)	(0.115)	(0.049)	(0.062)	(0.060)	(0.074)
PANEL B: PLANNED SUICIDE								
	Positive Parenting	-0.041***	-0.056***	-0.058**	0.009	-0.038***	-0.068***	-0.074***
		(0.005)	(0.009)	(0.018)	(0.007)	(0.009)	(0.009)	(0.011)
	Social Exclusion	0.385***	0.429***	0.435***	0.329***	0.355***	0.405***	0.279***
		(0.025)	(0.045)	(0.098)	(0.038)	(0.061)	(0.057)	(0.075)
	Female	0.128***	0.07	0.048	-0.038	0.156*	0.515***	0.314***
		(0.029)	(0.047)	(0.103)	(0.046)	(0.064)	(0.063)	(0.079)
PANEL C: ATTEMPTED SUICIDE								
	Positive Parenting	-0.047***	-0.049***	-0.082***	-0.007	-0.034***	-0.076***	-0.075***
		(0.005)	(0.011)	(0.019)	(0.007)	(0.009)	(0.010)	(0.011)
	Social Exclusion	0.528***	0.742***	0.540***	0.413***	0.535***	0.459***	0.407***
		(0.027)	(0.051)	(0.092)	(0.038)	(0.059)	(0.056)	(0.077)
	Female	0.065*	0.003	-0.022	-0.100*	0.114	0.382***	0.313***
		(0.028)	(0.055)	(0.106)	(0.046)	(0.064)	(0.061)	(0.081)

TABLE 3.A7: Summary Hypotheses Table (Mental Stress as Ordinal) (cont.)

PANEL D: MENTAL STRESS							
Positive Parenting	-0.038***	-0.026***	-0.019	-0.035***	-0.021***	-0.049***	-0.080***
	(0.003)	(0.004)	(0.010)	(0.006)	(0.006)	(0.008)	(0.006)
Social Exclusion	0.462***	0.592***	0.370***	0.263***	0.499***	0.574***	0.560***
	(0.022)	(0.028)	(0.064)	(0.032)	(0.047)	(0.045)	(0.052)
Female	0.342***	0.346***	0.031	0.265***	0.400***	0.499***	0.543***
	(0.019)	(0.025)	(0.054)	(0.038)	(0.045)	(0.048)	(0.047)
PANEL E: DRUG USE							
Positive Parenting	-0.068***	-0.116***	-0.047	-0.042***	-0.048***	-0.067***	-0.091***
	(0.006)	(0.012)	(0.030)	(0.008)	(0.013)	(0.014)	(0.011)
Social Exclusion	0.295***	0.628***	0.527***	0.119**	0.352***	0.212**	0.114
	(0.036)	(0.063)	(0.143)	(0.046)	(0.081)	(0.081)	(0.077)
Female	-0.495***	-0.550***	-0.540**	-0.363***	-0.736***	-0.486***	-0.524***
	(0.037)	(0.081)	(0.206)	(0.055)	(0.110)	(0.091)	(0.080)

*** p<0.01, ** p<0.05, * p<0.1

- Individual country models run using survey probability weighting; Total sample - each observation's weight is scaled by mean probability weight in the respective country.
- Standard errors in parentheses - clustered at a grand clustering level identifying each unique Country-Strata-PSU pairing under full sample estimation
- For estimation with all countries, country fixed effects included

Appendix Two: Descriptive Statistics by Gender

VARIABLES	TOTAL SAMPLE		INDONESIA		BANGLADESH		NAMIBIA		MOROCCO		PERU		COSTA RICA	
	F	M	F	M	F	M	F	M	F	M	F	M	F	M
PERCENT OF GROUP	54.7%	45.3%	56.3%	43.7%	60.6%	39.4%	53.5%	46.5%	48.9%	51.1%	52.2%	47.8%	52%	48%
OUTCOME														
Considered Suicide	0.122	0.077	0.056	0.037	0.055	0.041	0.186	0.170	0.185	0.120	0.274	0.118	0.134	0.070
Planned Suicide	0.112	0.087	0.053	0.047	0.067	0.066	0.226	0.230	0.151	0.118	0.209	0.090	0.087	0.047
Attempted Suicide	0.097	0.077	0.028	0.025	0.051	0.053	0.205	0.228	0.134	0.098	0.216	0.112	0.099	0.051
Mental Stress	0.482	0.382	0.472	0.383	0.437	0.422	0.635	0.557	0.473	0.327	0.478	0.334	0.337	0.407
Used Drugs	0.035	0.077	0.006	0.023	0.006	0.029	0.128	0.224	0.019	0.089	0.029	0.072	0.060	0.148
EXPLANATORY														
Positive Parenting[1]														
Check Homework	3.12 (1.43)	3.12 (1.45)	3.16 (1.32)	3.13 (1.39)	3.48 (1.32)	3.39 (1.32)	2.96 (1.52)	3.02 (1.54)	3.29 (1.62)	3.10 (1.61)	3.24 (1.36)	3.17 (1.32)	2.63 (1.55)	2.77 (1.58)
Understand Worries	3.13 (1.42)	2.96 (1.43)	3.17 (1.34)	2.92 (1.42)	3.55 (1.23)	3.22 (1.28)	3.15 (1.42)	3.13 (1.42)	2.51 (1.58)	2.39 (1.51)	3.02 (1.37)	2.90 (1.33)	3.22 (1.53)	3.18 (1.52)
Know Where Really Go	3.28 (1.42)	2.98 (1.43)	3.47 (1.31)	2.96 (1.37)	3.34 (1.39)	3.07 (1.38)	2.94 (1.38)	2.89 (1.38)	2.96 (1.72)	2.88 (1.64)	3.04 (1.39)	2.85 (1.38)	3.48 (1.51)	3.32 (1.51)
Don't Go Through Stuff	4.05 (1.22)	4.07 (1.21)	3.86 (1.24)	3.83 (1.27)	4.59 (0.88)	4.52 (0.89)	3.84 (1.32)	3.84 (1.33)	4.26 (1.24)	4.11 (1.30)	4.22 (1.05)	4.27 (0.99)	4.34 (1.03)	4.36 (0.99)
Social Exclusion														
Zero Close Friends	0.058	0.053	0.020	0.029	0.114	0.060	0.123	0.111	0.097	0.063	0.047	0.050	0.055	0.054
Bullied	0.251	0.267	0.169	0.224	0.172	0.273	0.424	0.406	0.185	0.142	0.487	0.451	0.193	0.386
ADDITIONAL CONTROLS														
Age	14.31 (1.62)	14.45 (1.56)	13.93 (1.61)	14.06 (1.59)	13.98 (0.94)	14.24 (0.98)	15.80 (1.81)	16.13 (1.73)	13.73 (1.27)	14.18 (1.27)	14.39 (1.03)	14.41 (1.05)	14.27 (1.06)	14.34 (1.09)

*Weighted using population survey weights for each respective country; total sample statistics are weighted using within-country design effects

*Mean values reported, with standard deviations in parentheses for non-binary variables. Mean of binary variables represents percentages.[1]Range is 1-5 for each component question, higher value is associated with more positive parenting.

Appendix Three: Weighting

SAMPLE WEIGHTING FORMULA USED FOR GSHS DATA

$$W = W_1 * W_2 * f_1 * f_2 * f_3 * f_4$$

With:

W_1 = the inverse of the probability of selecting the school

W_2 = the inverse of the probability of selecting the classroom within the school

f_1 = a school-level non response adjustment factor calculated by school size (small, medium, large) category

f_2 = a class-level non response adjustment factor calculated for each school

f_3 = a student-level non response adjustment factor calculated by class

f_4 = a post stratification adjustment factor calculated by grade

REVIEW OF SURVEY WEIGHTING & COMBINING DATASETS

Survey weighting is an important element to consider when working with survey data. The manner in which large national/international cross-sectional surveys are conducted most often involves complex sample designs. Most complex survey/sample designs constitute levels of stratification, multi-stage sampling, and unequal sampling rates. “Design-based” weights are generally calculated as the inverse of the selection probability for selected observational units, given that observations are usually selected through a random process, but with different probabilities of selection (StataCorp. LP 2013). The “survey” weights published with large-scale survey data are often adjusted to account for non-response, post-stratification to agree with known marginal totals, and/or trimmed to limit the unequal weighting effects of large weights which occur due to unforeseen sampling/field data collection issues (Chrony and Abeyasekera 2005). (Such adjustments are seen in the above formulation for the GSHS survey weighting published with the data used for this study.) Weights are needed when conducting analysis to thus, compensate for unequal sampling rates and to make adjustments for non-responses. Recognition of the stratification (e.g. strata) and clustering (e.g. primary sampling units (PSUs)) within a survey enables broader generalization of findings.

Ultimately, most large-scale surveys have end-goals of producing estimates of population totals, means, or correlational effects. Failure to incorporate survey design weights will often lead to biased findings from analysis techniques such as regressions. While the structure of the design (e.g. numbers of PSU and strata) do not directly influence first-order estimates such as means, totals, ratios, or model coefficients, second-order statistics (e.g. variance estimates) are affected. Thus, the standard errors of coefficients and the ability to properly run hypothesis tests are dependent on recognition of the survey design structure (Chrony and Abeyasekera 2005). Put another way, while the proper use of weights (e.g. probability weights) enables appropriate point estimation, it is accounting for clustering/stratification which enables standard errors to not be deflated (StataCorp. LP 2013).

In STATA, the code to account for these three survey design variables is:

//svyset, clear
svyset psu [pweight=weight], strata(stratum)//

Subsequently, estimation and analysis on the survey data in question (based on the weighting, strata, and PSU defined) can be accomplished when preceded by the <<*svy:*>> code. One should note, though, that robust standard errors are not an option with the survey-based family of commands.

//svy: regress y x1 x2 x3//

Some research may require, however, the combination of different surveys to run their analyses. Most surveys are aimed at collecting information from a few specific domains of life. Thus, combining surveys which possess different information can allow a researcher to “fill-in-the-blanks” and gain a broader picture of the relationships under investigation. Furthermore, the larger sample sizes achieved through pooling data can improve the precision and lower sampling error of estimates. By expanding a sample/analysis to include multiple groups, one is also able to avoid producing misleading results and conclusions arising from concentration on only one population or subset of a particular population (Schenker and Parsons 2011). However, when combining multiple survey datasets, one needs to remember that the data may stem from surveys with differing survey designs. Therefore, consideration must be made as to how to account for the survey weights under such a context.

There is the option to simply drop the survey weights and use models which allow regression coefficients between groups (if using data from multiple groups/populations) to be different through such means as separate regressions for each group or interaction terms. Such approaches would, however, inherently assume equal variances or the same interpretation of findings across each group. Given evidence of cultural biases in how people respond to the same questions, this type of approach towards an analysis aimed at uncovering more general phenomena would be inappropriate. Other solutions where weights are retained may be preferable.

There are a few approaches based on an idea of doing very little modification, but they are reliant on some strong assumptions. One can simply retain the survey weights and design elements already in place for each observation, based on the survey from which they originated. This approach, though, would require that each dataset being used was weighted towards a proper total count and did not overstate the importance of any one individual record relative to another dataset (Jonathan 2013). This approach would not be an appropriate choice if one is trying to combine data from two different populations. However, if the data was a repeated cross-section/panel of the same population, this approach of retaining the original weights would likely be sufficient (Samuels 2014). Similarly, if analyzing panel data, one can choose to rely on the weights from the year/wave of data on which the primary analysis is focused. For example, if analyzing time trends where the focus in on the final wave, it is this final wave's weights which should be used.

//svyset, clear
svyset psu [pweight=weight_wave3], strata(stratum)//

Or, if analyzing trends from wave one to three, it is the first wave's weights which should be used in the programming.

//svyset, clear
svyset psu [pweight=weight_wave1], strata(stratum)//

In cases where the datasets being joined do not reflect the same population, or necessarily the same survey design/weights, additional modification may be called for. One approach is composite estimation, where weights are adjusted by a factor reflective of the relative sample size of each group to the total pooled sample size. This approach allows the weights to now correspond to those obtained from deriving pooled weights based on inverses of selection probabilities of units being in either/any sample (Chu, Brick, and Kalton 1999). This approach is in essence "weighting" the initial survey weights.

```
//svyset, clear
gen group1=1
gen group2=1
gen pop1= sum(group1)
gen pop2= sum(group2)
gen alpha_null=pop1/(pop1+pop2)
gen adj_weight=alpha_null*weight if group1==1
replace adj_weight=(1-alpha_null)*weight if group2==1
svyset psu [pweight=adj_weight], strata(stratum)//
```

In a similar vein, one can pool/union the data and recalculate the weights on the new entire dataset, but this requires the assumption that there are similar reasons across the datasets for non-response (Samuels 2014), and requires an underlying understanding of how the initial survey weights were calculated (including post-stratification, trimming, etc.).

Another major means by which to adjust survey weights and how they are incorporated into analysis is to create "super-variables". This approach can be to manipulate all the probability weights to account for equally-sized datasets. Such a scenario would be where one has five waves/groups of data collected from samples with equal size, but different weights. In this case, every probability weight would be weighted with equal importance (e.g. 1/5 in the above example) and this would serve as the new probability weight to be considered in survey-based statistical analysis (Jonathan 2013).

```
//
svyset, clear
gen adj_weight=(1/5)*weight
svyset psu [pweight=adj_weight], strata(stratum)//
```

If analysis samples, however, are not of equal size, then it is the stratification component of survey design which must become "super". One incorporates the group delineation (ex: country or year) into the strata definition, so that strata and group are tied together to represent the strata for the pooled data set, while the original probability weights themselves remain unchanged (Samuels 2014).

```
//An example where country is the delineating factor between datasets:
svyset, clear
gen super_strata = group (strata country)
svyset psu [pweight=adj_weight], strata(super_strata)//
```

In work looking at cross-national analysis, there has also been evidence of success in modifying survey weights to account for unequal probabilities of selection, by computing within-country design effects and using these as the modified weights (Skinner and Mason 2012). The issue of concern is focused on overcoming the biases inherent from the common finding that sample sizes in cross-national surveys often vary much less than population sizes, meaning that sampling fractions can be quite different. To overcome this, researchers have shown greatest success in reducing standard errors through dividing each observation's design weight by the mean weight for the region/country surveyed. The work where this technique was introduced did not, however, have consistent access to design elements such as strata or psu, and as a consequence, results of incorporating these elements are unknown and only the (modified) probability weights were used. (Recall, that standard errors may be understated without proper stratification and clustering considerations).

```
//svyset, clear
gen mean_weight_country1 = mean weight if Country==1
gen mean_weight_country2 = mean weight if Country==2  // etc.
gen modified_weight = weight/ mean_weight_country1 if Country==1
replace modified_weight = weight/ mean_weight_country2 if Country==2 //etc.
regress y x1 x2 x3 [pweight=modified_weight], robust //
```

APPENDIX

Chapter 4

1. **Model Fitting**
2. **Data Reduction**

Appendix One: Model Fitting

Table 4.A1: Model Selection of Equation 1 – Environmental Impacts on Emotional Health (Binary Outcome)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Community Cultural Environ.	0.108	0.135	0.116	0.137*	0.152*	0.114	0.131
	(0.067)	(0.069)	(0.070)	(0.069)	(0.070)	(0.070)	(0.071)
Family Cultural Environ.	0.112	0.11	0.128	0.104	0.104	0.12	0.123
	(0.076)	(0.074)	(0.075)	(0.077)	(0.076)	(0.078)	(0.077)
School Support Environ.	-0.123*	-0.254**	-0.299**	-0.188**	-0.273**	-0.206**	-0.312**
	(0.061)	(0.093)	(0.095)	(0.068)	(0.094)	(0.071)	(0.096)
Age	0.837	1.083	1.096	0.828	0.992	0.829	1.074
	(0.574)	(0.614)	(0.614)	(0.587)	(0.624)	(0.608)	(0.622)
Age Sq.	-0.025	-0.034	-0.035	-0.024	-0.031	-0.025	-0.034
	(0.018)	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)	(0.019)
Constant	-7.006	-8.665	-8.7	-7.543	-8.402	-7.197	-8.795
	(4.639)	(5.059)	(5.042)	(4.763)	(5.121)	(4.961)	(5.093)
Fixed Effects[1]	No	Yes	Yes	No	Yes	No	Yes
Caste[2]	No	No	Yes	No	No	Yes	Yes
Control[3]	No	No	No	Yes	Yes	Yes	Yes
N	281	281	281	281	281	281	281
ln (L)	-186	-183	-180	-182	-181	-179	-178
χ^2	17.6	22.8	29	23.9	27.9	31.4	32.8
AIC	383.1	382.1	381	384.1	385.1	384.2	385
BIC	404.9	411.3	421	420.4	428.7	431.5	439.6

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[1] School-level Fixed Effects (Purkot as Base Category)
[2] Brahman-Chhetri (highest caste) as Base Category
[3] Includes dummies for current hygiene product use type (old rags/cloths as base category), marriage dummy, wealth index indicator for cement home and owning land

Table 4.A2: Model Selection of Equation 2, Specification A – Emotional Stress Impact on Missing School (Binary Outcome)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Emotional Stress	0.490**	0.548***	0.580***	0.515**	0.577***	0.525**	0.598***
	(0.161)	(0.166)	(0.170)	(0.163)	(0.168)	(0.167)	(0.172)
Age	-						
	1.526**	-0.976	-0.997	-1.406*	-0.905	-1.526*	-0.974
	(0.553)	(0.596)	(0.619)	(0.558)	(0.603)	(0.596)	(0.631)
Age Sq.	0.049**	0.03	0.031	0.045**	0.027	0.049**	0.03
	(0.017)	(0.018)	(0.019)	(0.017)	(0.019)	(0.018)	(0.020)
Constant	11.068*	6.972	7.055	9.547*	6.48	10.532*	6.852
	(4.426)	(4.856)	(5.052)	(4.511)	(4.861)	(4.824)	(5.089)
Fixed Effects[1]	No	Yes	Yes	No	Yes	No	Yes
Caste[2]	No	No	Yes	No	No	Yes	Yes
Control[3]	No	No	No	Yes	Yes	Yes	Yes
N	281	281	281	281	281	281	281
ln (L)	-169	-163	-159	-165	-160	-163	-156
χ^2	16.1	28.8	32.9	25.1	36.6	29.2	41
AIC	346	337.1	336.4	345.6	339.1	347.3	338.5
BIC	360.5	358.9	369.2	374.7	375.4	387.4	385.8

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[1] School-level Fixed Effects (Purkot as Base Category)

[2] Brahman-Chhetri (highest caste) as Base Category

[3] Includes dummies for current hygiene product use type (old rags/cloths as base category), marriage dummy, wealth index indicator for cement home and owning land

Table 4.A3: Model Selection of Equation 2, Specification B – Emotional Stress Impact on Days of Missed School (Ordinal Outcome)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Emotional Stress	0.305	0.341*	0.400*	0.330*	0.381*	0.373*	0.432**
	(0.156)	(0.161)	(0.166)	(0.157)	(0.162)	(0.163)	(0.166)
Age	-1.386**	-0.958	-1.037	-1.318*	-0.912	-1.440*	-1.052
	(0.523)	(0.557)	(0.579)	(0.540)	(0.570)	(0.559)	(0.593)
Age Sq.	0.043**	0.028	0.031	0.041*	0.026	0.045**	0.031
	(0.016)	(0.017)	(0.017)	(0.016)	(0.017)	(0.017)	(0.018)
Cut Point 1	-10.141*	-7.132	-7.587	-9.184*	-6.93	-9.895*	-7.693
	(4.283)	(4.651)	(4.829)	(4.463)	(4.723)	(4.596)	(4.899)
Cut Point 2	-8.961*	-5.924	-6.36	-7.972	-5.689	-8.67	-6.434
	(4.282)	(4.659)	(4.835)	(4.464)	(4.728)	(4.598)	(4.903)
Fixed Effects[1]	No	Yes	Yes	No	Yes	No	Yes
Caste[2]	No	No	Yes	No	No	Yes	Yes
Control[3]	No	No	No	Yes	Yes	Yes	Yes
N	281	281	281	281	281	281	281
ln (L)	-198	-192	-189	-194	-188	-191	-186
χ^2	11.3	25.5	30.6	21.2	38.1	24	43.3
AIC	405.2	398.3	398.9	405.1	398.5	407	399.5
BIC	423.4	423.7	435.3	437.9	438.5	450.6	450.4

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[1] School-level Fixed Effects (Purkot as Base Category)
[2] Brahman-Chhetri (highest caste) as Base Category
[3] Includes dummies for current hygiene product use type (old rags/cloths as base category), marriage dummy, wealth index indicator for cement home and owning land

Appendix Two: Data Reduction Techniques

<u>Principle Component Analysis:</u>

One of the most commonly used statistical techniques for data reduction is principle component analysis (PCA). With this approach, the leading eigenvectors from the eigen decomposition of the correlation matrix of the variables the researcher seeks to reduce are used to describe a series of uncorrelated linear combinations of the variables which contain most of the explanatory variance. The goal is to find unit-length linear combinations, where the first principle component has the maximal overall variance, and each additional principle component has the maximal variance among all unit length linear combination that are uncorrelated to the first component (Rencher and Christensen 2012). Earlier components contain more information than latter ones, and all principle components and scores are orthogonal to one another.

Of particular interest when using PCA is the ability to derive useful indices to include in empirical analysis based on the factor loadings of each principle component. Factor loadings are the correlations between the original variables used in the PCA and the components computed from the analysis. These correlations/loadings, along with the eigenvalues associated with the components can be used to determine which components best summarize the raw data with little loss of information. It is a common practice to only retain/use factors, based on the Kaiser Rule (Rabe-Hesketh and Everitt 2004). This informal rule indicates that one should only use those principle components with eigenvalues greater than one (i.e. variances greater than average). It is also common to examine the screeplots of PCA to visualize which components have eigenvalues which fall "above" a distinct elbow in a plot of eigenvalues against their rank (Fabrigar et al.

1999). Work by Gavish and Donoho (2014) has also produced a procedure whereby one estimates the noise (e.g. σ) in a dataset and throws away/ignores all components whose singular values are below a specific threshold, given by the equation $\tau = \lambda(\beta) * \sqrt{n}\sigma$, where $\beta = m/n$, with m= number of parameters and n = number of observations. Within their published work is a table of appropriate λ values based on β. Once a decision is made as to which principle components to retain, the factor loadings of those components can be used as factor weights in order to produce weighted estimates of the standardized data being summarized for each observation. This process produces the sought after indices researchers often desire for data reduction and increased power in their empirical estimations.

Following production of such indices, researchers then have multiple means by which to assess the effectiveness of the PCA generated and estimated indices in representing the data, as well as means by which to interpret the meaning of the components (and their loadings). The Kaiser-Mayer-Okin (KMO) measure of sampling adequacy compares correlations and partial correlations between variables. If the calculated partial correlations are high in comparison to the correlations, the KMO measure will be small (close to zero), which indicates that there is too little in common between the set of variables to actually warrant use of PCA (Kaiser 1974; Cerny and Kaiser 1977). Inspection of squared multiple correlations (SMC), or the regression R^2-values of each variable run on all other variables in the PCA, can also be used to identify variables which cannot be well explained by other variables. Recall that PCA is about forming linear combinations of variables, so a series of variables that are not well associated or explained by others will not lead to useful PCA components which can well represent the data. Sometimes, these post-estimation tests may indicate that the data is well associated and PCA is appropriate, but the components and their loadings do not form easily interpretable results. In this case, it is often common to perform rotation of the components.

Rotation following PCA is a way to make interpretation of factor loadings on principle components more interpretable. However, this process does destroy some of the properties associated with principle components. Most notably, the first rotated component no longer has the maximal variance of all components. Despite this, the overall variance explained by the rotated components still remains equivalent to what was explained by the original (un-rotated) principle components. The two main approaches to rotation are orthogonal and oblique, where the former is often preferred, as it maintains the orthogonality of the components. With orthogonal rotation, the only thing that has changed from the rotation process is that the explanation is distributed differently among the chosen number of rotated components. With two rotated components, the original components are related to the rotated ones via the following factor rotation matrix and equations:

$$\begin{matrix} Z1 & Z2 \\ -Z2 & Z1 \end{matrix}$$

$$PCA1_{Rotated} = Z1*PCA1_{Unrotated} - Z2*PCA2_{Unrotated}$$
$$PCA2_{Rotated} = Z2*PCA1_{Unrotated} + Z1*PCA2_{Unrotated}$$

The most commonly used method of orthogonal rotation is Varimax rotation, wherein rotation of the components occurs to maximize the sum over the columns of the within-in column variances (i.e., the goal is to maximize the variance of the squared loadings within factors (Kaiser 1958)). The visual consequence of such a rotation is that a plot of the loadings of principle component one by principle component two is turned by 45-degrees, and the goal would be to see one group of variables close to one axis and another to the other axis, allowing for more discernable distinction in what the two principle components may represent in their reduced form. However, if the goal in using PCA is to produce some sort of general factor contributing to all variables, a better rotation is Quartimax rotation, wherein rows-wise simplicity is the aim (while still maintaining the goal to maximize the variance in squared loadings).

Despite this array of tools to aid in PCA usefulness, there is a strong caution. A key drawback of PCA is that it functions best under the conditions where the variables being analyzed are continuous in nature. When researchers are faced with categorical data, including binary and ordinal coding structures, it is often considered better to reduce the data via other methods.

Multiple Correspondence Analysis:

One option researchers may turn to when trying to reduce a series of categorical variables is multiple correspondence analysis (MCA). MCA is a generalization of correspondence analysis (CA), where the latter's aim is to develop simple indices that show relations between the rows and columns of a contingency table of categorical variables. In this way, MCA can also be viewed as a generalization of PCA, based on categorical variables. MCA analyzes the inter-individual variability (or how similar individuals fall into sets of categories), trying to extract which dimensions (i.e. categories) separate extremely different individuals from average individuals. This process is done by performing CA on a Burt or indicator matrix of the variables, including all of the categories possible within each variable. The Burt table is the symmetric matrix of all two-way cross-tabulations between the categorical variables, and has an analogy to the covariance matrix of continuous variables (Abdi and Valentin 2007).

Inertia is the key explanatory element of this type of analysis. MCA involves the sequential searching for axes, where each axis must maximize the inertia and be orthogonal to all previous ones (similar to PCA). In terms of interpretation, the dimensions that MCA gives are akin to the principle components of PCA, and inertia is akin to the eigenvalues (e.g. how much variance is explained). Inertia reflects the variability of the data because rare categories have high inertia, and inertia of a dimension measures the link between the dimension and all the variables included in the MCA.

MCA is useful, thus, in visualizing the ways in which a series of variables and the associated categories within them compare. One can visualize if there are particular variables wherein the distribution of answers appear to behave differently, and which may represent a different latent component being captured. However, the use of MCA in many empirical analyses and estimations using subsequent regression are less developed.

Alternative Approaches within Principle Component Analysis:

The use of straight PCA is not always considered best when working with anything but continuous data. PCA procedures assume that the correlations used in the correlation matrix are Pearson correlations, which assumes all variables are normally distributed (e.g. quantitative, symmetric and bell-shaped). With ordinal data, this assumption is not necessarily correct, and opens up the potential need for alternative approaches to/within PCA.

One sticking point in the debate over use of PCA for certain forms of categorical data is reflected in the optimal approach to reducing data with coding structures such as Likert-scales. This structure offers answer options such as 3, 5 or 7-point scales running from “Strongly Agree” to “Strongly Disagree”. Some may argue that this reflects a true continuum much like a continuous variable would, and is thus a “close-enough” representation to the continuous nature of the underlying structure researchers are seeking to capture, to justify the use of PCA. However, others would argue that if the underlying structure is not correct (e.g. non-normal), the use of a statistical technique based on it is inappropriate. This is where the use of polychoric correlations may come in.

Polychoric correlations assume variables are ordered measurements of an underlying continuum (nicely reflecting what Liker-scaled survey items are meant to capture) (Drasgow 1986). These types of correlations are performed in software via maximum likelihood, but are easily interpretable in the same manner as Pearson correlations, by measuring the strength and direction of association between two variables on a 1-to-1 scale. Factor analysis (FA) on this polychoric correlation matrix can then be undertaken for data reduction. Unlike PCA where components are calculated as linear combinations of the original variables, FA proceeds where the original variables are defined as linear combinations of the factors (Bartholomew 2008). In this way, while PCA has a goal of accounting for as much of the total variance in the variables as possible, FA’s goal is to explain the covariances/correlations among the variables, and focuses more on allowing one to visualize the constructs that underlie data.

With (linear) PCA, it is also assumed that scaling occurs at a numeric level for variables used in the analysis. Thus, even if the underlying structure of say an ordinal variable is actually some sort of continuum, there is an additional concern that the intervals between consecutive categories cannot be assumed to be equal. Driven by this, a slightly different approach to using PCA with ordinal/categorical data which has arisen is termed nonlinear or categorical PCA and is based on the work by Guttman (1941) and other researchers (Kruskal 1965; Kruskal and Shepard 1974; Shepard 1966; Young, Takane, and de Leeuw 1978). For each variable, every observed value is termed a "category", and nonlinear PCA converts each category into a numeric value using optimal quantification (also called, optimal scaling or optimal scoring). These numeric values are referred to as "category quantifications", and these quantifications for one variable, together, form that variable's "transformation" into a usable numeric representation (e.g. quantitative/continuous data). This optimization process replaces the category labels with category quantifications so that as much as possible of the variance in the quantified variables is accounted for. These category quantifications and their correlations are what are then then fed into the PCA process, whereby the method maximizes the first p eigenvalues of the correlation matrix of the quantified variables, where p is the number of components chosen for analysis. Put another way, the aim is to maximize the VAF (proportion of variance accounted for) in the quantified variables.

The optimal quantification task and PCA model estimating are performed in an iterative algorithm which proceeds until there is convergence to a stationary point where the optimal quantifications of the categories do not change anymore. Thus, in essence, nonlinear PCA performs much in the same way as original PCA, with both methods providing eigenvalues, component loadings, and component scores which can be used in subsequent estimation procedures. Interpretation of factor loadings and component treatment is the same, as are the decisions/procedures for component retention and rotation. However, because of the allowance for nonlinear transformations, the VAF for nonlinear PCA will almost always be higher than linear PCA. Furthermore, the choice of analysis level (by the researcher) influences the extent of this difference. Choice of nominal, ordinal, or numerical analysis level in the optimal quantification process determines what the correlations are based on in the iterative computation of the data. A nominal analysis-level will produce the largest VAF, whereas the VAF from a numerical approach (e.g. standard linear PCA) will be smallest. The benefits of greater variance being explained by principle components has merit in its own right, but there is a caveat to nonlinear PCA's use. In cases in which variables have only slightly nonlinear relationships with each other (as is often the case when only Likert-scales are measured), a nonlinear approach will not add a great deal to linear solutions (Linting et al. 2007).

STATA CODES

[Chapter 2]

```
//CHAPTER 2 MAIN ANALYSIS CODE////////////////////////////////////////////

use Chap2_LabeledData.dta

rename PMPU_Score BAI_Mod GritScore CurrentAge Female ///
	PhoneCost PhoneCostSQ FriendsPMPU  ///
	Bullying_1 Bullying_2 Bullying_3 ///
	FamilyAbuse_1 FamilyAbuse_2 FamilyAbuse_3 FamilyAbuse_4 ///
	AcademicPressure_1 AcademicPressure_2 AcademicPressure_3 AcademicPressure_4 ///
	SocialNetwork_6 SocialNetwork_7 SocialNetwork_8 SocialNetwork_9
	SocialNetwork_10 SocialNetwork_11 ///
	SchoolGradeID Rural CellPhone_Yes ,lower	//Observed

//"OBSERVABLE" BULLYING
gen bullying=bullying_1+bullying_2+bullying_3


//New Protective Factor - Social Network Support
gen socialsupport = socialnetwork_6 + socialnetwork_7 + socialnetwork_8 + ///
	socialnetwork_9 + socialnetwork_10 + socialnetwork_11

//Rescaling Cost
gen phonecostscale=phonecost/1000
gen phonecost2=phonecostscale^2

************************************************************************
//DESCRIPTIVE STATISTICS (TABLE 2.1)

sum bai_mod gritscore pmpu_score bullying bullying_1 bullying_2 bullying_3 ///
	academicpressure_1 academicpressure_2 academicpressure_3 academicpressure_4 ///
	familyabuse_1 familyabuse_2 familyabuse_3 familyabuse_4 ///
	socialnetwork_6 socialnetwork_7 socialnetwork_8 socialnetwork_9 ///
	socialnetwork_10 socialnetwork_11 phonecostscale phonecost2 ///
	friendspmpu currentage female rural if cellphone_yes==1

//DESCRIPTIVE STATISTICS BY GENDER (TABLE 2.A1)

sum bai_mod gritscore pmpu_score bullying bullying_1 bullying_2 bullying_3 ///
	academicpressure_1 academicpressure_2 academicpressure_3 academicpressure_4 ///
	familyabuse_1 familyabuse_2 familyabuse_3 familyabuse_4 ///
	socialnetwork_6 socialnetwork_7 socialnetwork_8 socialnetwork_9 ///
	socialnetwork_10 socialnetwork_11 phonecostscale phonecost2 ///
```

```
        friendspmpu currentage rural if cellphone_yes==1 & female==1

sum bai_mod gritscore pmpu_score bullying bullying_1 bullying_2 bullying_3 ///
        academicpressure_1 academicpressure_2 academicpressure_3 academicpressure_4 ///
        familyabuse_1 familyabuse_2 familyabuse_3 familyabuse_4 ///
        socialnetwork_6 socialnetwork_7 socialnetwork_8 socialnetwork_9 ///
        socialnetwork_10 socialnetwork_11 phonecostscale phonecost2 ///
        friendspmpu currentage rural if cellphone_yes==1 & female==0

*****************************************************************************
//SEM/LINEAR PROBABILITY APPROACHES (TABLE 2.3)

//MODEL 1 - NO COV CONSTRAINTS & NO DEMOGRAPHIC CONTROLS IN PMPU EQ.
sem ///
(SocialSupport->socialnetwork_6 socialnetwork_7 socialnetwork_8 /// measurement
      socialnetwork_9 socialnetwork_10 socialnetwork_11) ///
 (FamilyAbuse -> familyabuse_1 familyabuse_2 familyabuse_3 /// measurement
      familyabuse_4) ///
 (Academic -> academicpressure_1 academicpressure_2 /// measurement
      academicpressure_3 academicpressure_4) ///
 (bai_mod <- pmpu_score SocialSupport /// structural
      Academic FamilyAbuse bullying female currentage rural) ///
 (gritscore <- pmpu_score SocialSupport /// structural
      Academic FamilyAbuse bullying female currentage rural) ///
 (pmpu_score <- Academic  /// structural
      SocialSupport FamilyAbuse bullying ///
      phonecostscale phonecost2 friendspmpu)if cellphone_yes==1 , ///
      cov(e.bai_mod*e.gritscore) ///
      cov(e.gritscore*e.pmpu_score) ///
      cov(e.bai_mod*e.pmpu_score)
estat gof, stats(all)

//MODEL 2 - COV CONSTRAINTS & NO DEMOGRAPHIC CONTROLS IN PMPU EQ.

sem ///
(SocialSupport->socialnetwork_6 socialnetwork_7 socialnetwork_8 /// measurement
      socialnetwork_9 socialnetwork_10 socialnetwork_11) ///
 (FamilyAbuse -> familyabuse_1 familyabuse_2 familyabuse_3 /// measurement
      familyabuse_4) ///
 (Academic -> academicpressure_1 academicpressure_2 /// measurement
      academicpressure_3 academicpressure_4) ///
 (bai_mod <- pmpu_score SocialSupport /// structural
      Academic FamilyAbuse bullying female currentage rural) ///
 (gritscore <- pmpu_score SocialSupport /// structural
      Academic FamilyAbuse bullying female currentage rural) ///
 (pmpu_score <- Academic  /// structural
      SocialSupport FamilyAbuse bullying ///
```

```
	phonecostscale phonecost2 friendspmpu)if cellphone_yes==1 , ///
	cov(e.bai_mod*e.gritscore) ///
	cov(e.gritscore*e.pmpu_score) ///
	cov(e.bai_mod*e.pmpu_score@0) ///
			cov(FamilyAbuse*SocialSupport@0)
estat gof, stats(all)

//MODEL 3 - COV CONSTRAINTS & DEMOGRAPHIC CONTROLS IN PMPU EQ.
sem ///
(SocialSupport->socialnetwork_6 socialnetwork_7 socialnetwork_8 /// measurement
	socialnetwork_9 socialnetwork_10 socialnetwork_11) ///
 (FamilyAbuse -> familyabuse_1 familyabuse_2 familyabuse_3 /// measurement
	familyabuse_4) ///
 (Academic -> academicpressure_1 academicpressure_2 /// measurement
	academicpressure_3 academicpressure_4) ///
 (bai_mod <- pmpu_score SocialSupport /// structural
	Academic FamilyAbuse bullying female currentage rural) ///
 (gritscore <- pmpu_score SocialSupport /// structural
	Academic FamilyAbuse bullying female currentage rural) ///
 (pmpu_score <- Academic  /// structural
	SocialSupport FamilyAbuse bullying ///
	phonecostscale phonecost2 friendspmpu female currentage rural) ///
			if cellphone_yes==1 , ///
	cov(e.bai_mod*e.gritscore) ///
	cov(e.gritscore*e.pmpu_score) ///
	cov(e.bai_mod*e.pmpu_score@0) ///
			cov(FamilyAbuse*SocialSupport@0)
estat gof, stats(all)

*****************************************************************
//INDIRECT & TOTAL EFFECTS FOR MODEL 3 (BEST FIT BASED ON AIC) (TABLE 2.5)

//ANXIETY////////////

//SocialSupport
//Indirect Effect
nlcom _SS_I: _b[bai_mod:pmpu_score]*_b[pmpu_score:SocialSupport]
//Total Effect
nlcom _SS_T: _b[bai_mod:SocialSupport] +
_b[bai_mod:pmpu_score]*_b[pmpu_score:SocialSupport]

//Academic
//Indirect Effect
nlcom _A_I: _b[bai_mod:pmpu_score]*_b[pmpu_score:Academic]
//Total Effect
nlcom _A_T: _b[bai_mod:Academic] + _b[bai_mod:pmpu_score]*_b[pmpu_score:Academic]
```

```
//FamilyAbuse
//Indirect Effect
nlcom _FA_I: _b[bai_mod:pmpu_score]*_b[pmpu_score:FamilyAbuse]
//Total Effect
nlcom _FA_T: _b[bai_mod:Academic] +
_b[bai_mod:pmpu_score]*_b[pmpu_score:FamilyAbuse]


//bullying
//Indirect Effect
nlcom _B_I: _b[bai_mod:pmpu_score]*_b[pmpu_score:bullying]
//Total Effect
nlcom _B_T: _b[bai_mod:bullying] + _b[bai_mod:pmpu_score]*_b[pmpu_score:bullying]

//Age
//Indirect Effect
nlcom _A_I: _b[bai_mod:pmpu_score]*_b[pmpu_score:currentage]
//Total Effect
nlcom _A_T: _b[bai_mod:currentage] + _b[bai_mod:pmpu_score]*_b[pmpu_score:currentage]


//Female
//Indirect Effect
nlcom _FA_I: _b[bai_mod:pmpu_score]*_b[pmpu_score:female]
//Total Effect
nlcom _FA_T: _b[bai_mod:female] + _b[bai_mod:pmpu_score]*_b[pmpu_score:female]


//Rural
//Indirect Effect
nlcom _B_I: _b[bai_mod:pmpu_score]*_b[pmpu_score:rural]
//Total Effect
nlcom _B_T: _b[bai_mod:rural] + _b[bai_mod:pmpu_score]*_b[pmpu_score:rural]

//GRIT////////////

//SocialSupport
//Indirect Effect
nlcom _SS_I: _b[gritscore:pmpu_score]*_b[pmpu_score:SocialSupport]
//Total Effect
nlcom _SS_T: _b[gritscore:SocialSupport] +
_b[gritscore:pmpu_score]*_b[pmpu_score:SocialSupport]

//Academic
//Indirect Effect
nlcom _A_I: _b[gritscore:pmpu_score]*_b[pmpu_score:Academic]
```

```
//Total Effect
nlcom _A_T: _b[gritscore:Academic] + _b[gritscore:pmpu_score]*_b[pmpu_score:Academic]


//FamilyEnv
//Indirect Effect
nlcom _FA_I: _b[gritscore:pmpu_score]*_b[pmpu_score:FamilyAbuse]
//Total Effect
nlcom _FA_T: _b[gritscore:Academic] +
_b[gritscore:pmpu_score]*_b[pmpu_score:FamilyAbuse]


//bullying
//Indirect Effect
nlcom _B_I: _b[gritscore:pmpu_score]*_b[pmpu_score:bullying]
//Total Effect
nlcom _B_T: _b[gritscore:bullying] + _b[gritscore:pmpu_score]*_b[pmpu_score:bullying]

//Age
//Indirect Effect
nlcom _A_I: _b[gritscore:pmpu_score]*_b[pmpu_score:currentage]
//Total Effect
nlcom _A_T: _b[gritscore:currentage] + _b[gritscore:pmpu_score]*_b[pmpu_score:currentage]


//Female
//Indirect Effect
nlcom _FA_I: _b[gritscore:pmpu_score]*_b[pmpu_score:female]
//Total Effect
nlcom _FA_T: _b[gritscore:female] + _b[gritscore:pmpu_score]*_b[pmpu_score:female]


//Rural
//Indirect Effect
nlcom _B_I: _b[gritscore:pmpu_score]*_b[pmpu_score:rural]
//Total Effect
nlcom _B_T: _b[gritscore:rural] + _b[bai_mod:pmpu_score]*_b[gritscore:rural]



*************************************************************************
*************************************************************************
//GSEM/NONLINEAR ESTIMATION APPROACHES (TABLE 2.4)

//MODEL 1 - NO COV CONSTRAINTS & NO DEMOGRAPHIC CONTROLS IN PMPU EQ.
 gsem ///
(SocialSupport->socialnetwork_6 socialnetwork_7 socialnetwork_8 /// measurement
```

```
        socialnetwork_9 socialnetwork_10 socialnetwork_11, logit) ///
 (FamilyAbuse -> familyabuse_1 familyabuse_2 familyabuse_3 /// measurement
        familyabuse_4, ologit) ///
 (Academic -> academicpressure_1 academicpressure_2 /// measurement
        academicpressure_3 academicpressure_4, ologit) ///
 (bai_mod <- pmpu_score SocialSupport /// structural
        Academic FamilyAbuse bullying 1.female currentage 1.rural) ///
 (gritscore <- pmpu_score SocialSupport /// structural
        Academic FamilyAbuse bullying 1.female currentage 1.rural) ///
 (pmpu_score <- Academic  /// structural
        SocialSupport FamilyAbuse bullying ///
        phonecostscale phonecost2 friendspmpu)if cellphone_yes==1 , ///
        vce(cluster schoolgradeid) ///
        cov(e.bai_mod*e.gritscore) ///
        cov(e.gritscore*e.pmpu_score) ///
        cov(e.bai_mod*e.pmpu_score)
estat ic

//MODEL 2- COV CONSTRAINTS & NO DEMOGRAPHIC CONTROLS IN PMPU EQ.
 gsem ///
(SocialSupport->socialnetwork_6 socialnetwork_7 socialnetwork_8 /// measurement
        socialnetwork_9 socialnetwork_10 socialnetwork_11, logit) ///
 (FamilyAbuse -> familyabuse_1 familyabuse_2 familyabuse_3 /// measurement
        familyabuse_4, ologit) ///
 (Academic -> academicpressure_1 academicpressure_2 /// measurement
        academicpressure_3 academicpressure_4, ologit) ///
 (bai_mod <- pmpu_score /*phoneutilization_sum*/ SocialSupport /// structural
        Academic FamilyAbuse bullying 1.female currentage 1.rural) ///
 (gritscore <- pmpu_score /*phoneutilization_sum*/ SocialSupport /// structural
        Academic FamilyAbuse bullying 1.female currentage 1.rural) ///
 (pmpu_score /*phoneutilization_sum*/ <- Academic  /// structural
        SocialSupport FamilyAbuse bullying ///
        phonecostscale phonecost2 friendspmpu)if cellphone_yes==1 , ///
        vce(cluster schoolgradeid) ///
        cov(e.bai_mod*e.gritscore) ///
        cov(e.gritscore*e.pmpu_score) ///
        cov(e.bai_mod*e.pmpu_score@0) ///
                    cov(FamilyAbuse*SocialSupport@0)
estat ic


//MODEL 3 - COV CONSTRAINTS & DEMOGRAPHIC CONTROLS IN PMPU EQ.
gsem ///
(SocialSupport->socialnetwork_6 socialnetwork_7 socialnetwork_8 /// measurement
        socialnetwork_9 socialnetwork_10 socialnetwork_11, logit) ///
 (FamilyAbuse -> familyabuse_1 familyabuse_2 familyabuse_3 /// measurement
        familyabuse_4, ologit) ///
```

```
 (Academic -> academicpressure_1 academicpressure_2 /// measurement
        academicpressure_3 academicpressure_4, ologit) ///
 (bai_mod <- pmpu_score SocialSupport /// structural
        Academic FamilyAbuse bullying 1.female currentage 1.rural) ///
 (gritscore <- pmpu_score SocialSupport /// structural
        Academic FamilyAbuse bullying 1.female currentage 1.rural) ///
 (pmpu_score <- Academic  /// structural
        SocialSupport FamilyAbuse bullying ///
        phonecostscale phonecost2 friendspmpu 1.female currentage 1.rural) ///
                  if cellphone_yes==1 , ///
        vce(cluster schoolgradeid) ///
        cov(e.bai_mod*e.gritscore) ///
        cov(e.gritscore*e.pmpu_score) ///
        cov(e.bai_mod*e.pmpu_score@0) ///
                  cov(FamilyAbuse*SocialSupport@0)
estat ic

*****************************************************************************

//INDIRECT & TOTAL EFFECTS FOR MODEL 3 (BEST FIT BASED ON AIC) (TABLE 2.6)

//ANXIETY////////////

//SocialSupport
//Indirect Effect
nlcom _SS_I: _b[bai_mod:pmpu_score]*_b[pmpu_score:SocialSupport]
//Total Effect
nlcom _SS_T: _b[bai_mod:SocialSupport] +
_b[bai_mod:pmpu_score]*_b[pmpu_score:SocialSupport]

//Academic
//Indirect Effect
nlcom _A_I: _b[bai_mod:pmpu_score]*_b[pmpu_score:Academic]
//Total Effect
nlcom _A_T: _b[bai_mod:Academic] + _b[bai_mod:pmpu_score]*_b[pmpu_score:Academic]


//FamilyAbuse
//Indirect Effect
nlcom _FA_I: _b[bai_mod:pmpu_score]*_b[pmpu_score:FamilyAbuse]
//Total Effect
nlcom _FA_T: _b[bai_mod:Academic] +
_b[bai_mod:pmpu_score]*_b[pmpu_score:FamilyAbuse]


//bullying
//Indirect Effect
```

```
nlcom _B_I: _b[bai_mod:pmpu_score]*_b[pmpu_score:bullying]
//Total Effect
nlcom _B_T: _b[bai_mod:bullying] + _b[bai_mod:pmpu_score]*_b[pmpu_score:bullying]

//Age
//Indirect Effect
nlcom _A_I: _b[bai_mod:pmpu_score]*_b[pmpu_score:currentage]
//Total Effect
nlcom _A_T: _b[bai_mod:currentage] + _b[bai_mod:pmpu_score]*_b[pmpu_score:currentage]


//Female
//Indirect Effect
nlcom _FA_I: _b[bai_mod:pmpu_score]*_b[pmpu_score:1.female]
//Total Effect
nlcom _FA_T: _b[bai_mod:1.female] + _b[bai_mod:pmpu_score]*_b[pmpu_score:1.female]


//Rural
//Indirect Effect
nlcom _B_I: _b[bai_mod:pmpu_score]*_b[pmpu_score:1.rural]
//Total Effect
nlcom _B_T: _b[bai_mod:1.rural] + _b[bai_mod:pmpu_score]*_b[pmpu_score:1.rural]

//GRIT////////////

//SocialSupport
//Indirect Effect
nlcom _SS_I: _b[gritscore:pmpu_score]*_b[pmpu_score:SocialSupport]
//Total Effect
nlcom _SS_T: _b[gritscore:SocialSupport] +
_b[gritscore:pmpu_score]*_b[pmpu_score:SocialSupport]

//Academic
//Indirect Effect
nlcom _A_I: _b[gritscore:pmpu_score]*_b[pmpu_score:Academic]
//Total Effect
nlcom _A_T: _b[gritscore:Academic] + _b[gritscore:pmpu_score]*_b[pmpu_score:Academic]


//FamilyEnv
//Indirect Effect
nlcom _FA_I: _b[gritscore:pmpu_score]*_b[pmpu_score:FamilyAbuse]
//Total Effect
nlcom _FA_T: _b[gritscore:Academic] +
_b[gritscore:pmpu_score]*_b[pmpu_score:FamilyAbuse]
```

```
//bullying
//Indirect Effect
nlcom _B_I: _b[gritscore:pmpu_score]*_b[pmpu_score:bullying]
//Total Effect
nlcom _B_T: _b[gritscore:bullying] + _b[gritscore:pmpu_score]*_b[pmpu_score:bullying]

//Age
//Indirect Effect
nlcom _A_I: _b[gritscore:pmpu_score]*_b[pmpu_score:currentage]
//Total Effect
nlcom _A_T: _b[gritscore:currentage] + _b[gritscore:pmpu_score]*_b[pmpu_score:currentage]


//Female
//Indirect Effect
nlcom _FA_I: _b[gritscore:pmpu_score]*_b[pmpu_score:1.female]
//Total Effect
nlcom _FA_T: _b[gritscore:1.female] + _b[gritscore:pmpu_score]*_b[pmpu_score:1.female]


//Rural
//Indirect Effect
nlcom _B_I: _b[gritscore:pmpu_score]*_b[pmpu_score:1.rural]
//Total Effect
nlcom _B_T: _b[gritscore:1.rural] + _b[bai_mod:pmpu_score]*_b[gritscore:1.rural]

*******************************************************************************
*******************************************************************************
*******************************************************************************

//CHAPTER 2 SENTIVITY ANALYSES USING TRADITIONAL REGRESSION/IV
APPROACHES///////////////////////////////////////////////////////////////////////////////


use Chap2_LabeledData.dta

//"OBSERVABLE" BULLYING
gen bullying=Bullying_1+Bullying_2+Bullying_3


//New Protective Factor - Social Network Support
gen socialsupport = SocialNetwork_6 + SocialNetwork_7 + SocialNetwork_8 + ///
	SocialNetwork_9 + SocialNetwork_10 + SocialNetwork_11

//Rescaling Cost
gen phonecostscale=PhoneCost/1000
```

```
gen phonecost2=phonecostscale^2


/////////////////////////////////////////////////////////////////////////////////////
//TABLE 2.A2

//OLS - Anxiety
reg BAI_Mod  /*GritScore*/ PMPU_Score  ///
  AcademicPressure bullying FamilyAbuse socialsupport ///
  CurrentAge Female if CellPhone_Yes==1, cluster(SchoolGradeID)
 estat ic
 outreg2 using OLS.doc, replace ctitle (OLS-BAI)

//OLS - Grit
reg /*BAI_Mod*/ GritScore PMPU_Score  ///
  AcademicPressure bullying FamilyAbuse socialsupport ///
  /*PeerPressureDrug*/ CurrentAge Female if CellPhone_Yes==1, cluster(SchoolGradeID)
 estat ic
 outreg2 using OLS.doc, append ctitle (OLS-Grit)


*****************************************************************************
//2SLS - Anxiety
ivreg2 ///
 BAI_Mod /*GritScore*/  ///
  AcademicPressure bullying FamilyAbuse socialsupport ///
  CurrentAge Female ///
  (PMPU_Score =  ///
  phonecostscale phonecost2 FriendsPMPU) ///
  if CellPhone_Yes==1, ///
 endog(PMPU_Score) first cluster(SchoolGradeID)

outreg2 using 2SLS.doc, replace ctitle(2SLS - BAI)

ivreg2 ///
 BAI_Mod /*GritScore*/  ///
  AcademicPressure bullying FamilyAbuse socialsupport ///
  CurrentAge Female ///
  (PMPU_Score =  ///
 phonecostscale phonecost2  FriendsPMPU) ///
  if CellPhone_Yes==1, gmm2s ///
 endog(PMPU_Score) first cluster(SchoolGradeID)

outreg2 using 2SLS.doc, append ctitle(GMM - BAI)


//////////////////////////////////////////////////////////////////////////////
```

```
//2SLS- Grit
ivreg2 ///
 /*BAI_Mod*/ GritScore  ///
  AcademicPressure bullying FamilyAbuse socialsupport ///
  CurrentAge Female ///
  (PMPU_Score =  ///
  phonecostscale phonecost2  FriendsPMPU) ///
  if CellPhone_Yes==1, ///
 endog(PMPU_Score) first cluster(SchoolGradeID)

 outreg2 using 2SLS.doc, append ctitle(2SLS - Grit)

 ivreg2 ///
 /*BAI_Mod*/ GritScore  ///
  AcademicPressure bullying FamilyAbuse socialsupport ///
   CurrentAge Female ///
  (PMPU_Score =  ///
 phonecostscale phonecost2  FriendsPMPU) ///
  if CellPhone_Yes==1, gmm2s ///
 endog(PMPU_Score) first cluster(SchoolGradeID)

 outreg2 using 2SLS.doc, append ctitle(GMM - Grit)

 **********************************************************************

 //IV W/ HETEROSKEDASTICITY (LEWBEL)
//ANXIETY
ivreg2h ///
 BAI_Mod /*GritScore*/  ///
  AcademicPressure bullying FamilyAbuse socialsupport ///
  CurrentAge Female ///
  (PMPU =  phonecostscale phonecost2 FriendsPMPU) ///
  if CellPhone_Yes==1, ///
  small first cluster(SchoolGradeID)

  outreg2 using IV_Lewbel.doc, replace ctitle(BAI)

//GRIT
ivreg2h ///
 /*BAI_Mod*/ GritScore  ///
  AcademicPressure bullying FamilyAbuse socialsupport ///
  CurrentAge Female ///
  (PMPU =  ///
 phonecostscale phonecost2 FriendsPMPU) ///
  if CellPhone_Yes==1, ///
  small first cluster(SchoolGradeID)
```

```
 outreg2 using IV_Lewbel.doc, append ctitle(Grit)

**************************************************************************

//TABLE 2.A3

//3SLS (MODEL 1)
 reg3 ///
 (GritScore = PMPU_Score ///
  AcademicPressure bullying FamilyAbuse socialsupport ///
  CurrentAge Female) ///
 (BAI_Mod = PMPU_Score ///
  AcademicPressure bullying socialsupport ///
 FamilyAbuse CurrentAge Female ) ///
 (PMPU_Score = ///
  phonecostscale phonecost2  FriendsPMPU) ///
  ///i.School  ///
  if CellPhone_Yes==1, ireg3 corr(unstructured)

 outreg2 using 3SLS.doc, replace ctitle(3SLS - Model 1)


*********************************************************************************

//3SLS (MODEL 2)
 reg3 ///
 (GritScore = PMPU_Score ///
  AcademicPressure bullying FamilyAbuse socialsupport ///
  CurrentAge Female) ///
 (BAI_Mod = PMPU_Score ///
  AcademicPressure bullying socialsupport ///
 FamilyAbuse CurrentAge Female ) ///
 (PMPU_Score =  ///
  phonecostscale phonecost2 FriendsPMPU  ///
  AcademicPressure bullying FamilyAbuse socialsupport) ///
  ///i.School  ///
  if CellPhone_Yes==1, ireg3 corr(unstructured)

 outreg2 using 3SLS.doc, append ctitle(3SLS - Model 2)
```

[Chapter 3]

```
//CHAPTER 3 MAIN ANALYSIS CODE//////////////////////////////////////////////////////////////////////////////

use Chap3_LabeledData.dta

//EXPLANATORY VARIABLES
//ONLY POSITIVE PARENTING

tab ParentsKnowWhereGo
recode ParentsKnowWhereGo (1=5) (5=1) (2=4) (4=2)
label define ParentsKnowWhereGo3 1 "Never" 2 "Rarely" 3 "Sometimes" 4 "Most Times" 5
"Always"
label values ParentsKnowWhereGo ParentsKnowWhereGo3

tab ParentsGoThruStuff
recode ParentsGoThruStuff (1=5) (5=1) (2=4) (4=2)
label define ParentsGoThruStuff4 1 "Always" 2 "Most Times" 3 "Sometimes" 4 "Rarely" 5
"Never"
label values ParentsGoThruStuff ParentsGoThruStuff4

tab ParentsKnowWhereGo
tab ParentsGoThruStuff
tab ParentsCheckHmwk
tab ParentsUnderstandWorries

gen
ParentalTrustEngage=ParentsKnowWhereGo+ParentsGoThruStuff+ParentsCheckHmwk+Parents
UnderstandWorries
gen PeerIndex=Bullied_Yes+CloseFriends_No

gen MentalHealth=1 if TroubleSleep_Yes==1| Lonely_Yes==1
recode MentalHealth (.=0)

//////////////////////////////////////////////////////////////////////////////
//DESCRIPTIVE STATS (TABLE 3.3)
sort Country

drop if ParentalTrustEngage==.| PeerIndex==.| UsedDrugs_Yes==.| Age==.| ///
     Gender==.| ConsiderSuicide_Yes==.| PlanSuicide_Yes==.| ///
     AttemptSuicide_Yes==.| MentalHealth==.

tab Country

by Country: sum CloseFriends_No Bullied_Yes MentalHealth ///
```

```
    ParentsKnowWhereGo ParentsGoThruStuff ///
    ParentsCheckHmwk ParentsUnderstandWorries ///
    UsedDrugs_Yes ConsiderSuicide_Yes ///
    PlanSuicide_Yes AttemptSuicide_Yes ///
    Age Gender [w=weight]

sum CloseFriends_No Bullied_Yes MentalHealth ///
    ParentsKnowWhereGo ParentsGoThruStuff ///
    ParentsCheckHmwk ParentsUnderstandWorries ///
    UsedDrugs_Yes ConsiderSuicide_Yes ///
    PlanSuicide_Yes AttemptSuicide_Yes ///
    Age Gender [w=modified_weight]


*******************************************************************************
//DESCRIPTIVE STATS BY GENDER (FOR APPENDIX)
sort Country

by Country: sum CloseFriends_No Bullied_Yes MentalHealth ///
    ParentsKnowWhereGo ParentsGoThruStuff ///
    ParentsCheckHmwk ParentsUnderstandWorries ///
    UsedDrugs_Yes ConsiderSuicide_Yes ///
    PlanSuicide_Yes AttemptSuicide_Yes ///
    Age [w=weight] if Gender==1

by Country: sum CloseFriends_No Bullied_Yes MentalHealth ///
    ParentsKnowWhereGo ParentsGoThruStuff ///
    ParentsCheckHmwk ParentsUnderstandWorries ///
    UsedDrugs_Yes ConsiderSuicide_Yes ///
    PlanSuicide_Yes AttemptSuicide_Yes ///
    Age [w=weight] if Gender==0


sum CloseFriends_No Bullied_Yes MentalHealth ///
    ParentsKnowWhereGo ParentsGoThruStuff ///
    ParentsCheckHmwk ParentsUnderstandWorries ///
    UsedDrugs_Yes ConsiderSuicide_Yes ///
    PlanSuicide_Yes AttemptSuicide_Yes ///
    Age [w=modified_weight] if Gender==1

sum CloseFriends_No Bullied_Yes MentalHealth ///
    ParentsKnowWhereGo ParentsGoThruStuff ///
    ParentsCheckHmwk ParentsUnderstandWorries ///
    UsedDrugs_Yes ConsiderSuicide_Yes ///
    PlanSuicide_Yes AttemptSuicide_Yes ///
    Age [w=modified_weight] if Gender==0
```

```
by Country: tab Gender

tab Gender

////////////////////////////////////////////////////////////////////////////////////////////////////////////////
//MULTIVARIATE PROBIT RESULTS (POOLED) (TABLE 3.4)

global xlist3 ParentalTrustEngage PeerIndex Age Gender
global xlist7 ParentalTrustEngage PeerIndex Age Gender CostaRica Bangladesh Namibia Peru
Morocco

cmp setup

cmp (ConsiderSuicide_Yes= $xlist7 ) ///
    (PlanSuicide_Yes= $xlist7 ) ///
    (AttemptSuicide_Yes= $xlist7 ) ///
    (MentalHealth= $xlist7 ) ///
    (UsedDrugs_Yes= $xlist7 ) ///
    [pweight=modified_weight], ///
        indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_probit) ///
        vce(cluster grand_cluster)

estimates store CMP_5Equations_Pooled

estout CMP_5Equations_Pooled using CMP_5Equations_Pooled.html, label cells(b(star fmt(3))
///
    se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
    label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//MARGINAL EFFECTS (FOR TABLE 3.6)
margins, dydx(*) predict(pr) force
margins, dydx(*) predict(pr eq(#2)) force
margins, dydx(*) predict(pr eq(#3)) force
margins, dydx(*) predict(pr eq(#4)) force
margins, dydx(*) predict(pr eq(#5)) force

//LR TEST OF INDEP (FOR TABLE 3.4)
gen M_U_ALL= e(ll)

quietly cmp (ConsiderSuicide_Yes= $xlist3 ) ///
    (PlanSuicide_Yes= $xlist3 ) ///
    (AttemptSuicide_Yes= $xlist3 ) ///
    (MentalHealth= $xlist3 ) ///
    (UsedDrugs_Yes= $xlist3 ) ///
    [pweight=modified_weight], ///
        indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_probit) ///
        vce(cluster grand_cluster) cov(independent)
```

```
gen M_R_ALL= e(ll)

di "chi2(10) = " 2*(M_U_ALL-M_R_ALL)
di "Prob > chi2 = "chi2tail(10, 2*(M_U_ALL-M_R_ALL))

/////////////////////////////////////////////////////////////////////////////////
//INDIVIDUAL COUNTRY ESTIMATES (FULL RESULTS REPORTED IN APPENDIX)
//COEFFICIENTS REPORTED IN TABLE 3.5
//MARGINAL EFFECTS REPORTED IN TABLE 3.6


//Indonesia
cmp (ConsiderSuicide_Yes= $xlist3 ) ///
    (PlanSuicide_Yes= $xlist3 ) ///
    (AttemptSuicide_Yes= $xlist3 ) ///
    (MentalHealth= $xlist3 ) ///
    (UsedDrugs_Yes= $xlist3 ) ///
    [pweight=weight] if Country==1, ///
        indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_probit) ///
        vce(robust)
estat ic
estimate store CMP_5Eq_Indonesia

estout CMP_5Eq_Indonesia using Appendix_5Eq_Indo.html, label cells(b(star fmt(3)) ///
    se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
    label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//MARGINAL EFFECTS
margins, dydx(*) predict(pr) force
margins, dydx(*) predict(pr eq(#2)) force
margins, dydx(*) predict(pr eq(#3)) force
margins, dydx(*) predict(pr eq(#4)) force
margins, dydx(*) predict(pr eq(#5)) force

//LR TEST OF INDEP
gen M_U1= e(ll)

quietly cmp (ConsiderSuicide_Yes= $xlist3 ) ///
    (PlanSuicide_Yes= $xlist3 ) ///
    (AttemptSuicide_Yes= $xlist3 ) ///
    (MentalHealth= $xlist3 ) ///
    (UsedDrugs_Yes= $xlist3 ) ///
    [pweight=weight] if Country==1, ///
        indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_probit) ///
        vce(robust) cov(independent)
gen M_R= e(ll)
```

```
di "chi2(10) = " 2*(M_U1-M_R)
di "Prob > chi2 = "chi2tail(10, 2*(M_U1-M_R))

//////////////////////////////////////////////////////////////////////////////

//Costa Rica
cmp (ConsiderSuicide_Yes= $xlist3 ) ///
    (PlanSuicide_Yes= $xlist3 ) ///
    (AttemptSuicide_Yes= $xlist3 ) ///
    (MentalHealth= $xlist3 ) ///
    (UsedDrugs_Yes= $xlist3 ) ///
    [pweight=weight] if Country==2, ///
        indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_probit) ///
        vce(robust)
estat ic
estimate store CMP_5Eq_CostaRica

estout CMP_5Eq_CostaRica using Appendix_5Eq_CR.html, label cells(b(star fmt(3)) ///
    se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
    label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//MARGINAL EFFECTS
margins, dydx(*) predict(pr) force
margins, dydx(*) predict(pr eq(#2)) force
margins, dydx(*) predict(pr eq(#3)) force
margins, dydx(*) predict(pr eq(#4)) force
margins, dydx(*) predict(pr eq(#5)) force

//LR TEST OF INDEP
drop M_R
gen M_U2= e(ll)

quietly cmp (ConsiderSuicide_Yes= $xlist3 ) ///
    (PlanSuicide_Yes= $xlist3 ) ///
    (AttemptSuicide_Yes= $xlist3 ) ///
    (MentalHealth= $xlist3 ) ///
    (UsedDrugs_Yes= $xlist3 ) ///
    [pweight=weight] if Country==2, ///
        indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_probit) ///
        vce(robust) cov(independent)
gen M_R= e(ll)

di "chi2(10) = " 2*(M_U2-M_R)
di "Prob > chi2 = "chi2tail(10, 2*(M_U2-M_R))

//////////////////////////////////////////////////////////////////////////////
```

```
//Bangladesh
cmp (ConsiderSuicide_Yes= $xlist3 ) ///
      (PlanSuicide_Yes= $xlist3 ) ///
      (AttemptSuicide_Yes= $xlist3 ) ///
      (MentalHealth= $xlist3 ) ///
      (UsedDrugs_Yes= $xlist3 ) ///
      [pweight=weight] if Country==3, ///
            indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_probit) ///
            vce(robust)
estat ic
estimate store CMP_5Eq_Bang

estout CMP_5Eq_Bang using Appendix_5Eq_Bang.html, label cells(b(star fmt(3)) ///
      se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
      label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//MARGINAL EFFECTS
margins, dydx(*) predict(pr) force
margins, dydx(*) predict(pr eq(#2)) force
margins, dydx(*) predict(pr eq(#3)) force
margins, dydx(*) predict(pr eq(#4)) force
margins, dydx(*) predict(pr eq(#5)) force

//LR TEST OF INDEP
drop M_R
gen M_U3= e(ll)

quietly cmp (ConsiderSuicide_Yes= $xlist3 ) ///
      (PlanSuicide_Yes= $xlist3 ) ///
      (AttemptSuicide_Yes= $xlist3 ) ///
      (MentalHealth= $xlist3 ) ///
      (UsedDrugs_Yes= $xlist3 ) ///
      [pweight=weight] if Country==3, ///
            indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_probit) ///
            vce(robust) cov(independent)
gen M_R= e(ll)

di "chi2(10) = " 2*(M_U3-M_R)
di "Prob > chi2 = "chi2tail(10, 2*(M_U3-M_R))

//////////////////////////////////////////////////////////////////////////////

//Namibia
cmp (ConsiderSuicide_Yes= $xlist3 ) ///
      (PlanSuicide_Yes= $xlist3 ) ///
      (AttemptSuicide_Yes= $xlist3 ) ///
      (MentalHealth= $xlist3 ) ///
```

```
    (UsedDrugs_Yes= $xlist3 ) ///
    [pweight=weight] if Country==4, ///
        indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_probit) ///
        vce(robust)
estat ic
estimate store CMP_5Eq_Namibia

estout CMP_5Eq_Namibia using Appendix_5Eq_Namibia.html, label cells(b(star fmt(3)) ///
    se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
    label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//MARGINAL EFFECTS
margins, dydx(*) predict(pr) force
margins, dydx(*) predict(pr eq(#2)) force
margins, dydx(*) predict(pr eq(#3)) force
margins, dydx(*) predict(pr eq(#4)) force
margins, dydx(*) predict(pr eq(#5)) force

//LR TEST OF INDEP
drop M_R
gen M_U4= e(ll)

quietly cmp (ConsiderSuicide_Yes= $xlist3 ) ///
    (PlanSuicide_Yes= $xlist3 ) ///
    (AttemptSuicide_Yes= $xlist3 ) ///
    (MentalHealth= $xlist3 ) ///
    (UsedDrugs_Yes= $xlist3 ) ///
    [pweight=weight] if Country==4, ///
        indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_probit) ///
        vce(robust) cov(independent)
gen M_R= e(ll)

di "chi2(10) = " 2*(M_U4-M_R)
di "Prob > chi2 = "chi2tail(10, 2*(M_U4-M_R))
//////////////////////////////////////////////////////////////////////

//Peru
cmp (ConsiderSuicide_Yes= $xlist3 ) ///
    (PlanSuicide_Yes= $xlist3 ) ///
    (AttemptSuicide_Yes= $xlist3 ) ///
    (MentalHealth= $xlist3 ) ///
    (UsedDrugs_Yes= $xlist3 ) ///
    [pweight=weight] if Country==5, ///
        indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_probit) ///
        vce(robust)
estat ic
estimate store CMP_5Eq_Peru
```

```
estout CMP_5Eq_Peru using Appendix_5Eq_Peru.html, label cells(b(star fmt(3)) ///
      se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
      label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//MARGINAL EFFECTS
margins, dydx(*) predict(pr) force
margins, dydx(*) predict(pr eq(#2)) force
margins, dydx(*) predict(pr eq(#3)) force
margins, dydx(*) predict(pr eq(#4)) force
margins, dydx(*) predict(pr eq(#5)) force

//LR TEST OF INDEP
drop M_R
gen M_U5= e(ll)

quietly cmp (ConsiderSuicide_Yes= $xlist3 ) ///
      (PlanSuicide_Yes= $xlist3 ) ///
      (AttemptSuicide_Yes= $xlist3 ) ///
      (MentalHealth= $xlist3 ) ///
      (UsedDrugs_Yes= $xlist3 ) ///
      [pweight=weight] if Country==5, ///
           indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_probit) ///
           vce(robust) cov(independent)
gen M_R= e(ll)

di "chi2(10) = " 2*(M_U5-M_R)
di "Prob > chi2 = "chi2tail(10, 2*(M_U5-M_R))

/////////////////////////////////////////////////////////////////////////////

//Morocco
cmp (ConsiderSuicide_Yes= $xlist3 ) ///
      (PlanSuicide_Yes= $xlist3 ) ///
      (AttemptSuicide_Yes= $xlist3 ) ///
      (MentalHealth= $xlist3 ) ///
      (UsedDrugs_Yes= $xlist3 ) ///
      [pweight=weight] if Country==6, ///
           indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_probit) ///
           vce(robust)
estat ic
estimate store CMP_5Eq_Morocco

estout CMP_5Eq_Morocco using Appendix_5Eq_Moroc.html, label cells(b(star fmt(3)) ///
      se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
      label(Observations Log-Likelihood Chi-2 AIC BIC))replace
```

```
//MARGINAL EFFECTS
margins, dydx(*) predict(pr) force
margins, dydx(*) predict(pr eq(#2)) force
margins, dydx(*) predict(pr eq(#3)) force
margins, dydx(*) predict(pr eq(#4)) force
margins, dydx(*) predict(pr eq(#5)) force

//LR TEST OF INDEP
drop M_R
gen M_U6= e(ll)

quietly cmp (ConsiderSuicide_Yes= $xlist3 ) ///
    (PlanSuicide_Yes= $xlist3 ) ///
    (AttemptSuicide_Yes= $xlist3 ) ///
    (MentalHealth= $xlist3 ) ///
    (UsedDrugs_Yes= $xlist3 ) ///
    [pweight=weight] if Country==1, ///
        indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_probit) ///
        vce(robust) cov(independent)
gen M_R= e(ll)

di "chi2(10) = " 2*(M_U6-M_R)
di "Prob > chi2 = "chi2tail(10, 2*(M_U6-M_R))
drop M_R

////////////////////////////////////////////////////////////////////////////
//LR TEST REGARDING POOLED DATA NO DUMMIES (USING MVPROBIT
COMMAND)
    //Saying that the coefficients (4*5) are the same across all 6 countries

//UNRESTRICTED
cmp (ConsiderSuicide_Yes= $xlist3 ) ///
    (PlanSuicide_Yes= $xlist3 ) ///
    (AttemptSuicide_Yes= $xlist3 ) ///
    (MentalHealth= $xlist3 ) ///
    (UsedDrugs_Yes= $xlist3 ) ///
    [pweight=modified_weight], ///
        indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_probit) ///
        vce(robust)
estat ic
estimate store CMP_5Eq_POOLED_NODUMMIES

gen M_U_NoDummy=e(ll)

gen M_R = M_U1+M_U2+M_U3+M_U4+M_U5+M_U6
```

```
//
di "chi2(6*4*5) = " 2*(M_U_NoDummy-M_R)
di "Prob > chi2 = "chi2tail(120, 2*(M_U_NoDummy-M_R))      //Chi2=46584663, Prob>Chi2=0

///////FIGURES/////////////////////////////////////////////////////////////////////

//SUICIDAL TENDENCY BY COUNTRY (FIGURE 3.3)
gen SuicideAPC_Yes100=SuicideAPC_Yes*100
graph bar (mean) SuicideAPC_Yes100 [pweight=weight], over(Country) title("Suicidal
Tendency") asyvars blabel(bar)

//SUICIDAL INTENSITY BY COUNTRY (FIGURE 3.4)
graph bar (mean) TimesAttemptSuicide if AttemptSuicide_Yes==1 [pweight=weight],
over(Country) ///
    title("Suicidal Intensity") asyvars blabel(bar)

//BULLYING (FIGURE 3.5)
gen Bullied_Yes100=Bullied_Yes*100
graph bar (mean) Bullied_Yes100 [pweight=weight], over(Gender) over(Country) ///
    title("Bullying Incidence") asyvars blabel(bar)



//POSITIVE PARENTING BY REGION (FIGURE 3.6)
gen Region=1 if Bangladesh==1|Indonesia==1
replace Region=2 if Namibia==1|Morocco==1
replace Region=3 if CostaRica==1|Peru==1
label define Regiond 1 "Central Asia/Middle East" 2 "Africa" 3 "Central/South America"
label values Region Regiond

kdensity ParentalTrustEngage if Gender==1 & Region==1, title("Central Asia/Middle East")
bwidth(1) ///
    addplot(kdensity ParentalTrustEngage if Gender==0 & Region==2, bwidth(1))      ///
    name(RegionA)

kdensity ParentalTrustEngage if Gender==1 & Region==2, title("Africa") bwidth(1) ///
    addplot(kdensity ParentalTrustEngage if Gender==0 & Region==2, bwidth(1))      ///
    name(RegionB)

kdensity ParentalTrustEngage if Gender==1 & Region==3, title("Central/South America")
bwidth(1) ///
    addplot(kdensity ParentalTrustEngage if Gender==0 & Region==3, bwidth(1))      ///
    name(RegionC)

grc1leg RegionA RegionB RegionC, legendfrom(RegionA) ///
    title("Figure 5: Positive Parenting By Region") ycomm
```

```
********************************************************************************
********************************************************************************

//CHAPTER 3 MAIN ANALYSIS REPEATED WITH MENTAL TURMOIL OPROBIT
ESITMATION (APPENDIX TABLE 3.A7)////////////////////////////////////////////////////////

use Chap3_LabeledData.dta

//EXPLANATORY VARIABLES
//ONLY POSITIVE PARENTING

tab ParentsKnowWhereGo
recode ParentsKnowWhereGo (1=5) (5=1) (2=4) (4=2)
label define ParentsKnowWhereGo3 1 "Never" 2 "Rarely" 3 "Sometimes" 4 "Most Times" 5
"Always"
label values ParentsKnowWhereGo ParentsKnowWhereGo3

tab ParentsGoThruStuff
recode ParentsGoThruStuff (1=5) (5=1) (2=4) (4=2)
label define ParentsGoThruStuff4 1 "Always" 2 "Most Times" 3 "Sometimes" 4 "Rarely" 5
"Never"
label values ParentsGoThruStuff ParentsGoThruStuff4

tab ParentsKnowWhereGo
tab ParentsGoThruStuff
tab ParentsCheckHmwk
tab ParentsUnderstandWorries

gen
ParentalTrustEngage=ParentsKnowWhereGo+ParentsGoThruStuff+ParentsCheckHmwk+Parents
UnderstandWorries
gen PeerIndex=Bullied_Yes+CloseFriends_No

gen MH= TroubleSleeping+FeltLonely
sum MH
xtile MentalTurmoil= MH, nq(4)

label define MentalTurmoild 1 "Normal" 2 "Moderate" 3 "High" 4 "Extreme"
label values MentalTurmoil MentalTurmoild
tab MentalTurmoil

//Indonesia
xtile MentalTurm1=MH if Country==1, nq(4)
label values MentalTurm1 MentalTurmoild
tab MentalTurm1
```

```
//Costa Rica
xtile MentalTurm2=MH if Country==2, nq(4)
label values MentalTurm2 MentalTurmoild
tab MentalTurm2

//Bangladesh
xtile MentalTurm3=MH if Country==3, nq(4)
label values MentalTurm3 MentalTurmoild
tab MentalTurm3

//Namibia
xtile MentalTurm4=MH if Country==4, nq(4)
label values MentalTurm4 MentalTurmoild
tab MentalTurm4

//Peru
xtile MentalTurm5=MH if Country==5, nq(4)
label values MentalTurm5 MentalTurmoild
tab MentalTurm5

//Morocco
xtile MentalTurm6=MH if Country==6, nq(4)
label values MentalTurm6 MentalTurmoild
tab MentalTurm6


global xlist3 ParentalTrustEngage PeerIndex Age Gender
global xlist7 ParentalTrustEngage PeerIndex Age Gender CostaRica Bangladesh Namibia Peru
Morocco

cmp setup
//////////////////////////////////////////////////////////////////////////////////////////////////////
//
cmp (ConsiderSuicide_Yes= $xlist7 ) ///
	(PlanSuicide_Yes= $xlist7 ) ///
	(AttemptSuicide_Yes= $xlist7 ) ///
	(UsedDrugs_Yes= $xlist7 ) ///
	(MentalTurmoil= $xlist7 ) ///
	[pweight=modified_weight], ///
		indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_oprobit) ///
		vce(cluster grand_cluster)

estimates store CMP_5Equations_Pooled_MT

estout CMP_5Equations_Pooled_MT using CMP_5Equations_Pooled_MT.html, label
cells(b(star fmt(3)) ///
	se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
```

```
    label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//LR TEST OF INDEP
gen M_U_ALL= e(ll)

quietly cmp (ConsiderSuicide_Yes= $xlist3 ) ///
    (PlanSuicide_Yes= $xlist3 ) ///
    (AttemptSuicide_Yes= $xlist3 ) ///
    (UsedDrugs_Yes= $xlist7 ) ///
    (MentalTurmoil= $xlist7 ) ///
    [pweight=modified_weight], ///
        indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_oprobit) ///
        vce(cluster grand_cluster) cov(independent)
gen M_R_ALL= e(ll)

di "chi2(10) = " 2*(M_U_ALL-M_R_ALL)
di "Prob > chi2 = "chi2tail(10, 2*(M_U_ALL-M_R_ALL))

//////////////////////////////////////////////////////////////////////
//Indonesia
cmp (ConsiderSuicide_Yes= $xlist3 ) ///
    (PlanSuicide_Yes= $xlist3 ) ///
    (AttemptSuicide_Yes= $xlist3 ) ///
    (UsedDrugs_Yes= $xlist3 ) ///
    (MentalTurm1= $xlist3 ) ///
    [pweight=weight] if Country==1, ///
        indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_oprobit) ///
        vce(robust)
estat ic
estimate store CMP_5Eq_Indonesia_MT

estout CMP_5Eq_Indonesia_MT using Appendix_5Eq_Indo_MT.html, label cells(b(star fmt(3))
///
    se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
    label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//LR TEST OF INDEP
gen M_U1= e(ll)

quietly cmp (ConsiderSuicide_Yes= $xlist3 ) ///
    (PlanSuicide_Yes= $xlist3 ) ///
    (AttemptSuicide_Yes= $xlist3 ) ///
    (UsedDrugs_Yes= $xlist3 ) ///
    (MentalTurm1= $xlist3 ) ///
    [pweight=weight] if Country==1, ///
        indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_oprobit) ///
        vce(robust) cov(independent)
```

```
drop M_R
gen M_R= e(ll)

di "chi2(10) = " 2*(M_U1-M_R)
di "Prob > chi2 = "chi2tail(10, 2*(M_U1-M_R))
/////////////////////////////////////////////////////////////////////////

//Costa Rica
cmp (ConsiderSuicide_Yes= $xlist3 ) ///
     (PlanSuicide_Yes= $xlist3 ) ///
     (AttemptSuicide_Yes= $xlist3 ) ///
     (UsedDrugs_Yes= $xlist3 ) ///
     (MentalTurm2= $xlist3 ) ///
     [pweight=weight] if Country==2, ///
          indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_oprobit) ///
          vce(robust)
estat ic
estimate store CMP_5Eq_CostaRica_MT

estout CMP_5Eq_CostaRica_MT using Appendix_5Eq_CR_MT.html, label cells(b(star fmt(3))
///
     se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
     label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//LR TEST OF INDEP
drop M_R
gen M_U2= e(ll)

quietly cmp (ConsiderSuicide_Yes= $xlist3 ) ///
     (PlanSuicide_Yes= $xlist3 ) ///
     (AttemptSuicide_Yes= $xlist3 ) ///
     (UsedDrugs_Yes= $xlist3 ) ///
     (MentalTurm2= $xlist3 ) ///
     [pweight=weight] if Country==2, ///
          indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_oprobit) ///
          vce(robust) cov(independent)
gen M_R= e(ll)

di "chi2(10) = " 2*(M_U2-M_R)
di "Prob > chi2 = "chi2tail(10, 2*(M_U2-M_R))

/////////////////////////////////////////////////////////////////////////

//Bangladesh
cmp (ConsiderSuicide_Yes= $xlist3 ) ///
     (PlanSuicide_Yes= $xlist3 ) ///
     (AttemptSuicide_Yes= $xlist3 ) ///
```

```
    (UsedDrugs_Yes= $xlist3 ) ///
    (MentalTurm3= $xlist3 ) ///
    [pweight=weight] if Country==3, ///
        indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_oprobit) ///
        vce(robust)
estat ic
estimate store CMP_5Eq_Bang_MT

estout CMP_5Eq_Bang_MT using Appendix_5Eq_Bang_MT.html, label cells(b(star fmt(3)) ///
    se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
    label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//LR TEST OF INDEP
drop M_R
gen M_U3= e(ll)

quietly cmp (ConsiderSuicide_Yes= $xlist3 ) ///
    (PlanSuicide_Yes= $xlist3 ) ///
    (AttemptSuicide_Yes= $xlist3 ) ///
    (UsedDrugs_Yes= $xlist3 ) ///
    (MentalTurm3= $xlist3 ) ///
    [pweight=weight] if Country==3, ///
        indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_oprobit) ///
        vce(robust) cov(independent)
gen M_R= e(ll)

di "chi2(10) = " 2*(M_U3-M_R)
di "Prob > chi2 = "chi2tail(10, 2*(M_U3-M_R))

////////////////////////////////////////////////////////////////////////////////////

//Namibia
cmp (ConsiderSuicide_Yes= $xlist3 ) ///
    (PlanSuicide_Yes= $xlist3 ) ///
    (AttemptSuicide_Yes= $xlist3 ) ///
    (UsedDrugs_Yes= $xlist3 ) ///
    (MentalTurm4= $xlist3 ) ///
    [pweight=weight] if Country==4, ///
        indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_oprobit) ///
        vce(robust)
estat ic
estimate store CMP_5Eq_Namibia_MT

estout CMP_5Eq_Namibia_MT using Appendix_5Eq_Namibia_MT.html, label cells(b(star
fmt(3)) ///
    se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
    label(Observations Log-Likelihood Chi-2 AIC BIC))replace
```

```
//LR TEST OF INDEP
drop M_R
gen M_U4= e(ll)

quietly cmp (ConsiderSuicide_Yes= $xlist3 ) ///
      (PlanSuicide_Yes= $xlist3 ) ///
      (AttemptSuicide_Yes= $xlist3 ) ///
      (UsedDrugs_Yes= $xlist3 ) ///
      (MentalTurm4= $xlist3 ) ///
      [pweight=weight] if Country==4, ///
            indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_oprobit) ///
            vce(robust) cov(independent)
gen M_R= e(ll)

di "chi2(10) = " 2*(M_U4-M_R)
di "Prob > chi2 = "chi2tail(10, 2*(M_U4-M_R))

/////////////////////////////////////////////////////////////////////////////

//Peru
cmp (ConsiderSuicide_Yes= $xlist3 ) ///
      (PlanSuicide_Yes= $xlist3 ) ///
      (AttemptSuicide_Yes= $xlist3 ) ///
      (UsedDrugs_Yes= $xlist3 ) ///
      (MentalTurm5= $xlist3 ) ///
      [pweight=weight] if Country==5, ///
            indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_oprobit) ///
            vce(robust)
estat ic
estimate store CMP_5Eq_Peru_MT

estout CMP_5Eq_Peru_MT using Appendix_5Eq_Peru_MT.html, label cells(b(star fmt(3)) ///
      se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
      label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//LR TEST OF INDEP
drop M_R
gen M_U5= e(ll)

quietly cmp (ConsiderSuicide_Yes= $xlist3 ) ///
      (PlanSuicide_Yes= $xlist3 ) ///
      (AttemptSuicide_Yes= $xlist3 ) ///
      (UsedDrugs_Yes= $xlist3 ) ///
      (MentalTurm5= $xlist3 ) ///
      [pweight=weight] if Country==5, ///
            indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_oprobit) ///
```

```
            vce(robust) cov(independent)
gen M_R= e(ll)

di "chi2(10) = " 2*(M_U5-M_R)
di "Prob > chi2 = "chi2tail(10, 2*(M_U5-M_R))

////////////////////////////////////////////////////////////////////////////

//Morocco
cmp (ConsiderSuicide_Yes= $xlist3 ) ///
      (PlanSuicide_Yes= $xlist3 ) ///
      (AttemptSuicide_Yes= $xlist3 ) ///
      (UsedDrugs_Yes= $xlist3 ) ///
      (MentalTurm6= $xlist3 ) ///
      [pweight=weight] if Country==6, ///
            indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_oprobit) ///
            vce(robust)
estat ic
estimate store CMP_5Eq_Morocco_MT

estout CMP_5Eq_Morocco_MT using Appendix_5Eq_Moroc_MT.html, label cells(b(star fmt(3))
///
      se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
      label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//LR TEST OF INDEP
drop M_R
gen M_U6= e(ll)

quietly cmp (ConsiderSuicide_Yes= $xlist3 ) ///
      (PlanSuicide_Yes= $xlist3 ) ///
      (AttemptSuicide_Yes= $xlist3 ) ///
      (UsedDrugs_Yes= $xlist3 ) ///
      (MentalTurm6= $xlist3 ) ///
      [pweight=weight] if Country==6, ///
            indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_oprobit) ///
            vce(robust) cov(independent)
gen M_R= e(ll)

di "chi2(10) = " 2*(M_U6-M_R)
di "Prob > chi2 = "chi2tail(10, 2*(M_U6-M_R))

drop M_R

////////////////////////////////////////////////////////////////////////////
//LR TEST REGARDING POOLED DATA NO DUMMIES (USING MVPROBIT
COMMAND)
```

```
//UNRESTRICTED
cmp (ConsiderSuicide_Yes= $xlist3 ) ///
      (PlanSuicide_Yes= $xlist3 ) ///
      (AttemptSuicide_Yes= $xlist3 ) ///
      (UsedDrugs_Yes= $xlist3 ) ///
      (MentalTurmoil= $xlist3 ) ///
      [pweight=weight], ///
            indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_oprobit) ///
            vce(robust)
estat ic
estimate store CMP_5Eq_POOLED_NODUMMIES_MT

gen M_U_NoDummy2=e(ll)

gen M_R = M_U1+M_U2+M_U3+M_U4+M_U5+M_U6

//
di "chi2(6) = " 2*(M_U_NoDummy2-M_R)
di "Prob > chi2 = "chi2tail(6, 2*(M_U_NoDummy2-M_R))

****************************************************************************
****************************************************************************

//CHAPTER 3 MAIN ANALYSIS REPEATED WITH SUICIDE MEASURE AS ONE VARIABLE
**RESULTS NOT REPORTED (BUT STATE THEY ARE AVAILABLE UPON REQUEST

use Chap3_LabeledData.dta

//EXPLANATORY VARIABLES
//ONLY POSITIVE PARENTING

tab ParentsKnowWhereGo
recode ParentsKnowWhereGo (1=5) (5=1) (2=4) (4=2)
label define ParentsKnowWhereGo3 1 "Never" 2 "Rarely" 3 "Sometimes" 4 "Most Times" 5 "Always"
label values ParentsKnowWhereGo ParentsKnowWhereGo3

tab ParentsGoThruStuff
recode ParentsGoThruStuff (1=5) (5=1) (2=4) (4=2)
label define ParentsGoThruStuff4 1 "Always" 2 "Most Times" 3 "Sometimes" 4 "Rarely" 5 "Never"
label values ParentsGoThruStuff ParentsGoThruStuff4

tab ParentsKnowWhereGo
tab ParentsGoThruStuff
```

```
tab ParentsCheckHmwk
tab ParentsUnderstandWorries

gen
ParentalTrustEngage=ParentsKnowWhereGo+ParentsGoThruStuff+ParentsCheckHmwk+Parents
UnderstandWorries
gen PeerIndex=Bullied_Yes+CloseFriends_No

gen MentalHealth=1 if TroubleSleep_Yes==1| Lonely_Yes==1
recode MentalHealth (.=0)


global xlist3 ParentalTrustEngage PeerIndex Age Gender
global xlist7 ParentalTrustEngage PeerIndex Age Gender CostaRica Bangladesh Namibia Peru
Morocco

cmp setup

//
cmp (SuicideAPC_Yes= $xlist7) ///
    (MentalHealth= $xlist7 ) ///
    (UsedDrugs_Yes= $xlist7 ) ///
    [pweight=modified_weight], ///
        indicators($cmp_probit $cmp_probit $cmp_probit) ///
        vce(cluster grand_cluster)

estimates store CMP_3Equations_Pooled

estout CMP_3Equations_Pooled using CMP_3Equations_Pooled.html, label cells(b(star fmt(3))
/// se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
    label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//LR TEST OF INDEP
gen M_U_ALL= e(ll)

quietly cmp (SuicideAPC_Yes=$xlist3 ) ///
    (MentalHealth= $xlist3 ) ///
    (UsedDrugs_Yes= $xlist3 ) ///
    [pweight=modified_weight], ///
        indicators($cmp_probit $cmp_probit $cmp_probit) ///
        vce(cluster grand_cluster) cov(independent)
gen M_R_ALL= e(ll)

di "chi2(3) = " 2*(M_U_ALL-M_R_ALL)
di "Prob > chi2 = "chi2tail(3, 2*(M_U_ALL-M_R_ALL))

/////////////////////////////////////////////////////////////////////////
```

```
//Indonesia
cmp (SuicideAPC_Yes= $xlist3 ) ///
	(MentalHealth= $xlist3 ) ///
	(UsedDrugs_Yes= $xlist3 ) ///
	[pweight=weight] if Country==1, ///
		indicators($cmp_probit $cmp_probit $cmp_probit) ///
		vce(robust)
estat ic
estimate store CMP_3Eq_Indonesia

estout CMP_3Eq_Indonesia using Appendix_3Eq_Indo.html, label cells(b(star fmt(3)) ///
	se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
	label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//LR TEST OF INDEP
gen M_U1= e(ll)

quietly cmp (SuicideAPC_Yes= $xlist3 ) ///
	(MentalHealth= $xlist3 ) ///
	(UsedDrugs_Yes= $xlist3 ) ///
	[pweight=weight] if Country==1, ///
		indicators($cmp_probit $cmp_probit $cmp_probit) ///
		vce(robust) cov(independent)
gen M_R= e(ll)

di "chi2(3) = " 2*(M_U1-M_R)
di "Prob > chi2 = "chi2tail(3, 2*(M_U1-M_R))

////////////////////////////////////////////////////////////////////////////

//Costa Rica
cmp (SuicideAPC_Yes= $xlist3 ) ///
	(MentalHealth= $xlist3 ) ///
	(UsedDrugs_Yes= $xlist3 ) ///
	[pweight=weight] if Country==2, ///
		indicators($cmp_probit $cmp_probit $cmp_probit) ///
		vce(robust)
estat ic
estimate store CMP_3Eq_CostaRica

estout CMP_3Eq_CostaRica using Appendix_3Eq_CR.html, label cells(b(star fmt(3)) ///
	se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
	label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//LR TEST OF INDEP
drop M_R
gen M_U2= e(ll)
```

```
quietly cmp (SuicideAPC_Yes= $xlist3 ) ///
      (MentalHealth= $xlist3 ) ///
      (UsedDrugs_Yes= $xlist3 ) ///
      [pweight=weight] if Country==2, ///
            indicators($cmp_probit $cmp_probit $cmp_probit) ///
            vce(robust) cov(independent)
gen M_R= e(ll)

di "chi2(3) = " 2*(M_U2-M_R)
di "Prob > chi2 = "chi2tail(3, 2*(M_U2-M_R))

//////////////////////////////////////////////////////////////////////////////

//Bangladesh
cmp (SuicideAPC_Yes= $xlist3 ) ///
      (MentalHealth= $xlist3 ) ///
      (UsedDrugs_Yes= $xlist3 ) ///
      [pweight=weight] if Country==3, ///
            indicators($cmp_probit $cmp_probit $cmp_probit) ///
            vce(robust)
estat ic
estimate store CMP_3Eq_Bang

estout CMP_3Eq_Bang using Appendix_3Eq_Bang.html, label cells(b(star fmt(3)) ///
      se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
      label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//LR TEST OF INDEP
drop M_R
gen M_U3= e(ll)

quietly cmp (SuicideAPC_Yes= $xlist3 ) ///
      (MentalHealth= $xlist3 ) ///
      (UsedDrugs_Yes= $xlist3 ) ///
      [pweight=weight] if Country==3, ///
            indicators($cmp_probit $cmp_probit $cmp_probit) ///
            vce(robust) cov(independent)
gen M_R= e(ll)

di "chi2(3) = " 2*(M_U3-M_R)
di "Prob > chi2 = "chi2tail(3, 2*(M_U3-M_R))

//////////////////////////////////////////////////////////////////////////////

//Namibia
cmp (SuicideAPC_Yes= $xlist3 ) ///
```

```
    (MentalHealth= $xlist3 ) ///
    (UsedDrugs_Yes= $xlist3 ) ///
    [pweight=weight] if Country==4, ///
        indicators($cmp_probit $cmp_probit $cmp_probit) ///
        vce(robust)
estat ic
estimate store CMP_3Eq_Namibia

estout CMP_3Eq_Namibia using Appendix_3Eq_Namibia.html, label cells(b(star fmt(3)) ///
    se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
    label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//LR TEST OF INDEP
drop M_R
gen M_U4= e(ll)

quietly cmp (ConsiderSuicide_Yes= $xlist3 ) ///
    (PlanSuicide_Yes= $xlist3 ) ///
    (AttemptSuicide_Yes= $xlist3 ) ///
    (MentalHealth= $xlist3 ) ///
    (UsedDrugs_Yes= $xlist3 ) ///
    [pweight=weight] if Country==4, ///
        indicators($cmp_probit $cmp_probit $cmp_probit $cmp_probit $cmp_probit) ///
        vce(robust) cov(independent)
gen M_R= e(ll)

di "chi2(3) = " 2*(M_U4-M_R)
di "Prob > chi2 = "chi2tail(3, 2*(M_U4-M_R))

/////////////////////////////////////////////////////////////////////////////

//Peru
cmp (SuicideAPC_Yes= $xlist3 ) ///
    (MentalHealth= $xlist3 ) ///
    (UsedDrugs_Yes= $xlist3 ) ///
    [pweight=weight] if Country==5, ///
        indicators($cmp_probit $cmp_probit $cmp_probit) ///
        vce(robust)
estat ic
estimate store CMP_3Eq_Peru

estout CMP_3Eq_Peru using Appendix_3Eq_Peru.html, label cells(b(star fmt(3)) ///
    se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
    label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//LR TEST OF INDEP
drop M_R
```

```
gen M_U5= e(ll)

quietly cmp (SuicideAPC_Yes= $xlist3 ) ///
	(MentalHealth= $xlist3 ) ///
	(UsedDrugs_Yes= $xlist3 ) ///
	[pweight=weight] if Country==5, ///
		indicators($cmp_probit $cmp_probit $cmp_probit) ///
		vce(robust) cov(independent)
gen M_R= e(ll)

di "chi2(3) = " 2*(M_U5-M_R)
di "Prob > chi2 = "chi2tail(3, 2*(M_U5-M_R))

///////////////////////////////////////////////////////////////////////////

//Morocco
cmp (SuicideAPC_Yes= $xlist3 ) ///
	(MentalHealth= $xlist3 ) ///
	(UsedDrugs_Yes= $xlist3 ) ///
	[pweight=weight] if Country==6, ///
		indicators($cmp_probit $cmp_probit $cmp_probit) ///
		vce(robust)
estat ic
estimate store CMP_3Eq_Morocco

estout CMP_3Eq_Morocco using Appendix_3Eq_Moroc.html, label cells(b(star fmt(3)) ///
	se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
	label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//LR TEST OF INDEP
drop M_R
gen M_U6= e(ll)

quietly cmp (SuicideAPC_Yes= $xlist3 ) ///
	(MentalHealth= $xlist3 ) ///
	(UsedDrugs_Yes= $xlist3 ) ///
	[pweight=weight] if Country==6, ///
		indicators($cmp_probit $cmp_probit $cmp_probit) ///
		vce(robust) cov(independent)
gen M_R= e(ll)

di "chi2(3) = " 2*(M_U6-M_R)
di "Prob > chi2 = "chi2tail(3, 2*(M_U6-M_R))
drop M_R

///////////////////////////////////////////////////////////////////////////
```

```
//LR TEST REGARDING POOLED DATA NO DUMMIES (USING MVPROBIT
COMMAND)
     //Saying that the coefficients (4*3) are the same across all 6 countries

//UNRESTRICTED
cmp (SuicideAPC_Yes= $xlist3 ) ///
     (MentalHealth= $xlist3 ) ///
     (UsedDrugs_Yes= $xlist3 ) ///
     [pweight=modified_weight], ///
          indicators($cmp_probit $cmp_probit $cmp_probit) ///
          vce(robust)
estat ic
estimate store CMP_3Eq_POOLED_NODUMMIES

gen M_U_NoDummy=e(ll)

gen M_R = M_U1+M_U2+M_U3+M_U4+M_U5+M_U6


//
di "chi2(6*4*3) = " 2*(M_U_NoDummy-M_R)
di "Prob > chi2 = "chi2tail(72, 2*(M_U_NoDummy-M_R))        //Chi2=39706543, Prob>Chi2=0
```

[Chapter 4]

```
//CHAPTER 4 MAIN ANALYSIS ////////////////////////////////////////////////////////////////////////////////

use Chap4_LabeledData.dta

//POOLED DATA
keep if location==5|location==1|location==2
drop if age>20

//PCA INDICES

 //PCA for School Support Index
pca /*ShareWithTeacherYes*/ SchoolHygieneEduYes ProvideHygieneKitYes
SchoolFacilityChangeYes SchoolFacilityWashSoapYes SchoolDustBinForKitsYes
//screeplot
predict p1, score
gen SchoolSupportIndexPhyPca = p1
drop p1

//PCA for Cultural Taboo Index
pca EnterWorshipRoomNo IsolationSeparateBld CulturalParticipartionNo ///
    AllowedMeetFamiliyNo AllowedInKitckenNo
screeplot
predict p1 p2
gen SocIsolationIndexPca1 = p1
gen SocIsolationIndexPca2 = p2
drop p1 p2

rename SocIsolationIndexPca1 CommunityWorshipCulturalPca
rename SocIsolationIndexPca2 IsolationFamilyCulturalPca

///////////////////////////////////////////////////////////////////////////////
///MCA EXPLORATIONS
//School Support Index
mca /*ShareWithTeacherYes*/ SchoolHygieneEduYes SchoolFacilityChangeYes
ProvideHygieneKitYes ///
    SchoolFacilityWashSoapYes SchoolDustBinForKitsYes

//Dimension 1: 90.4% explained, principle intertia = 0.0757; Relies more //
    //on Bins, Soap, Kits

//Cultural Taboo Index
mca EnterWorshipRoomNo IsolationSeparateBld CulturalParticipartionNo ///
    AllowedMeetFamiliyNo AllowedInKitckenNo
```

```
//Dimension 1: Inertia= 0.020387, explains 83.6% --> Relies more heavily on
    //Worship, Cultural Participation, & Kitchen
//Dimension 2: Inertia = 0.0003784, explalins 1.55% --> Relies more heavily on
    // Isolation and Meeting Family

gen daysmissedraw=days_miss_m
replace daysmissedraw=1 if days_miss_m==0
replace daysmissedraw=2 if days_miss_m==1.5
replace daysmissedraw=3 if days_miss_m==4|days_miss_m==7
tab daysmissedraw

////////////////////////////////////////////////////////////////////////
//Dissection of Descriptive Stats

//School
sum ShareWithTeacherYes SchoolHygieneEduYes ProvideHygieneKitYes ///
    SchoolFacilityChangeYes SchoolFacilityWashSoapYes SchoolDustBinForKitsYes

sort location
by location: sum ShareWithTeacherYes SchoolHygieneEduYes ProvideHygieneKitYes ///
    SchoolFacilityChangeYes SchoolFacilityWashSoapYes SchoolDustBinForKitsYes


//Cultural
sum EnterWorshipRoomNo IsolationSeparateBld CulturalParticipartionNo ///
    AllowedMeetFamiliyNo AllowedInKitckenNo

by location: sum EnterWorshipRoomNo IsolationSeparateBld CulturalParticipartionNo ///
    AllowedMeetFamiliyNo AllowedInKitckenNo

sum SadLonelyYes

//Additional Statistics for INTRO
tab how_clean

sum pain hot_pack pain_med pain_doct drop_out miss_sch_mom
    //60.1% report having pain
    //13.3% report using a hot-pack
    //21.4% report getting medicine
    //21.3% report going to see doctor
    //42.1% have known someone to drop out of school
    //10% have missed school during Mom's period

//For TABLE 1

sum SadLonelyYes daysmissedraw miss_school Brahman ///
    Madhesi Dalit OtherCaste CurrentUseTypeDisposable CurrentUseTypeOld ///
```

```
      CurrentUseTypeReusable ///
      Wealth_Index MarriedY age agesq PNMHI Purkot Paklihawa

//////////////////////////////////////////////////////////////////////

label variable TotalSchoolSupportSystemIndex2 "School Environment"
label variable CommunityWorshipCulturalPca "Community Cultural Environment"
label variable IsolationFamilyCulturalPca "Family Cultural Environment"
label variable age "Age"
label variable agesq "Age-Sq."
label variable CurrentUseTypeReusable "Reusable Hygiene Product"
label variable CurrentUseTypeDisposable "Disposable Hygiene Product"
label variable Wealth_Index "Wealth Index"
label variable MarriedY "Married"
label variable ShareWithTeacherYes "Counseling at School"

//MODEL FITTING (APPENDIX)

////////////MODEL FITTING- EMOTION
//Base Model, Full Sample, No Control, No Caste, No FE
probit SadLonelyYes CommunityWorshipCulturalPca IsolationFamilyCulturalPca
SchoolSupportIndexPhyPca ///
      age agesq, robust
estat ic
estimate store model1a


//Base Model, Full Sample, No Control, No Caste, Yes FE
probit SadLonelyYes CommunityWorshipCulturalPca IsolationFamilyCulturalPca
SchoolSupportIndexPhyPca ///
      PNMHI Paklihawa age agesq, robust
estat ic
estimate store model2a

//Base Model, Full Sample, No Control, Yes Caste, Yes FE
probit SadLonelyYes CommunityWorshipCulturalPca IsolationFamilyCulturalPca
SchoolSupportIndexPhyPca ///
      Madhesi Dalit OtherCaste age agesq PNMHI Paklihawa, robust
estat ic
estimate store model3a

//Base Model, Full Sample, Yes Control, No Caste, No FE
probit SadLonelyYes CommunityWorshipCulturalPca IsolationFamilyCulturalPca
SchoolSupportIndexPhyPca ///
      CurrentUseTypeDisposable CurrentUseTypeReusable ///
      Wealth_Index MarriedY age agesq, robust
estat ic
```

```
estimate store model4a

//Base Model, Full Sample, Yes Control, No Caste, Yes FE
probit SadLonelyYes CommunityWorshipCulturalPca IsolationFamilyCulturalPca
SchoolSupportIndexPhyPca ///
    PNMHI Paklihawa CurrentUseTypeDisposable ///
    CurrentUseTypeReusable ///
    Wealth_Index MarriedY age agesq PNMHI Paklihawa, robust
estat ic
estimate store model5a

//Base Model, Full Sample, Yes Control, Yes Caste, No FE
probit SadLonelyYes CommunityWorshipCulturalPca IsolationFamilyCulturalPca
SchoolSupportIndexPhyPca ///
    Madhesi Dalit OtherCaste CurrentUseTypeDisposable ///
    CurrentUseTypeReusable ///
    Wealth_Index MarriedY age agesq, robust
estat ic
estimate store model6a


//Base Model, Full Sample, Yes Control, Yes Caste, Yes FE
probit SadLonelyYes CommunityWorshipCulturalPca IsolationFamilyCulturalPca
SchoolSupportIndexPhyPca ///
    Madhesi Dalit OtherCaste CurrentUseTypeDisposable ///
    CurrentUseTypeReusable PNMHI Paklihawa ///
    Wealth_Index MarriedY age agesq, robust
estat ic
estimate store model7a

estout model1a model2a model3a model4a model5a model6a model7a using
ModelFit_ProbitEmotion_April2019_Young.html, label cells(b(star fmt(3)) ///
    se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
    label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//////////////////////////////////////////////////////////////////////
//MODEL FITTING- MISSING SCHOOL (BINARY)

//Base Model, Full Sample, No Control, No Caste, No FE
probit miss_school SadLonelyYes ///
    age agesq, robust
estat ic
estimate store model1b


//Base Model, Full Sample, No Control, No Caste, Yes FE
probit miss_school SadLonelyYes ///
```

```
    PNMHI Paklihawa age agesq, robust
estat ic
estimate store model2b

//Base Model, Full Sample, No Control, Yes Caste, Yes FE
probit miss_school SadLonelyYes ///
    Madhesi Dalit OtherCaste age agesq PNMHI Paklihawa, robust
estat ic
estimate store model3b

//Base Model, Full Sample, Yes Control, No Caste, No FE
probit miss_school SadLonelyYes ///
    CurrentUseTypeDisposable CurrentUseTypeReusable ///
    Wealth_Index MarriedY age agesq, robust
estat ic
estimate store model4b

//Base Model, Full Sample, Yes Control, No Caste, Yes FE
probit miss_school SadLonelyYes ///
    PNMHI Paklihawa CurrentUseTypeDisposable ///
    CurrentUseTypeReusable ///
    Wealth_Index MarriedY age agesq PNMHI Paklihawa, robust
estat ic
estimate store model5b

//Base Model, Full Sample, Yes Control, Yes Caste, No FE
probit miss_school SadLonelyYes ///
    Madhesi Dalit OtherCaste CurrentUseTypeDisposable ///
    CurrentUseTypeReusable ///
    Wealth_Index MarriedY age agesq, robust
estat ic
estimate store model6b


//Base Model, Full Sample, Yes Control, Yes Caste, Yes FE
probit miss_school SadLonelyYes ///
    Madhesi Dalit OtherCaste CurrentUseTypeDisposable ///
    CurrentUseTypeReusable PNMHI Paklihawa ///
    Wealth_Index MarriedY age agesq, robust
estat ic
estimate store model7b

estout model1b model2b model3b model4b model5b model6b model7b using
ModelFit_ProbitSchool_April2019_Young.html, label cells(b(star fmt(3)) ///
    se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
    label(Observations Log-Likelihood Chi-2 AIC BIC))replace
```

```
//////////
//MODEL FITTING-MISSING SCHOOL (ORDINAL)
//Base Model, Full Sample, No Control, No Caste, No FE
oprobit daysmissedraw SadLonelyYes ///
	age agesq, robust
estat ic
estimate store model1c


//Base Model, Full Sample, No Control, No Caste, Yes FE
oprobit daysmissedraw SadLonelyYes ///
	PNMHI Paklihawa age agesq, robust
estat ic
estimate store model2c

//Base Model, Full Sample, No Control, Yes Caste, Yes FE
oprobit daysmissedraw SadLonelyYes ///
	Madhesi Dalit OtherCaste age agesq PNMHI Paklihawa, robust
estat ic
estimate store model3c

//Base Model, Full Sample, Yes Control, No Caste, No FE
oprobit daysmissedraw SadLonelyYes ///
	CurrentUseTypeDisposable CurrentUseTypeReusable ///
	Wealth_Index MarriedY age agesq, robust
estat ic
estimate store model4c

//Base Model, Full Sample, Yes Control, No Caste, Yes FE
oprobit daysmissedraw SadLonelyYes ///
	PNMHI Paklihawa CurrentUseTypeDisposable ///
	CurrentUseTypeReusable ///
	Wealth_Index MarriedY age agesq, robust
estat ic
estimate store model5c

//Base Model, Full Sample, Yes Control, Yes Caste, No FE
oprobit daysmissedraw SadLonelyYes ///
	Madhesi Dalit OtherCaste CurrentUseTypeDisposable ///
	CurrentUseTypeReusable ///
	Wealth_Index MarriedY age agesq, robust
estat ic
estimate store model6c


//Base Model, Full Sample, Yes Control, Yes Caste, Yes FE
oprobit daysmissedraw SadLonelyYes ///
```

```
      Madhesi Dalit OtherCaste CurrentUseTypeDisposable ///
      CurrentUseTypeReusable PNMHI Paklihawa ///
      Wealth_Index MarriedY age agesq, robust
estat ic
estimate store model7c

estout model1c model2c model3c model4c model5c model6c model7c using
ModelFit_OProbitSchool_April2019_Young.html, label cells(b(star fmt(3)) ///
      se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
      label(Observations Log-Likelihood Chi-2 AIC BIC))replace


//////////////////////////////////////////////////////////////////////////////
//TABLE 4.2
//Emotion on School - SINGLE EQUATION (probit, logit, oprobit/ologit)

//Probit- Emotion
probit SadLonelyYes CommunityWorshipCulturalPca IsolationFamilyCulturalPca
SchoolSupportIndexPhyPca ///
      age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa, robust
estat ic
estimate store Single_Probit_Emotion

//Probit- School
probit miss_school SadLonelyYes age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa,
robust
estat ic
estimate store Single_Probit_School

//OProbit-School
//Oprobit
oprobit daysmissedraw SadLonelyYes age agesq PNMHI Paklihawa, robust
estat ic
estimate store Single_OProbit_School

estout Single_Probit_Emotion Single_Probit_School Single_OProbit_School using
Table2_April2019_Young.html, label cells(b(star fmt(3)) ///
      se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
      label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//////////////////////////////////////////////////////////////////////////////
//TABLE 4.3
//2-Equation - SIMULTANEOUS BI-PROBIT (biprobit, DV binary)


//MODEL 1- NO CASTE
```

```
biprobit (miss_school= age agesq PNMHI Paklihawa SadLonelyYes) (SadLonelyYes= SchoolSupportIndexPhyPca ///
    CommunityWorshipCulturalPca IsolationFamilyCulturalPca age agesq PNMHI Paklihawa), vce(robust)
estat ic
estimate store BiProbit_Model1

//MODEL 2- YES CASTE
biprobit (miss_school= age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa SadLonelyYes) (SadLonelyYes= ///
    SchoolSupportIndexPhyPca CommunityWorshipCulturalPca IsolationFamilyCulturalPca age agesq Madhesi Dalit ///
    OtherCaste PNMHI Paklihawa), vce(robust)
estat ic
estimate store BiProbit_Model2

estout BiProbit_Model1 BiProbit_Model2 using Table3A_CHECK_May2019_Young.html, label cells(b(star fmt(3)) ///
    se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
    label(Observations Log-Likelihood Chi-2 AIC BIC))replace

////////////////////////////////////////////////////////////////////////////////
//2-Equation - SIMULTANOUS CMP (ologit/oprobit & DV Binary; ologit/oprobit & DV Binary)
cmp setup


//Binary DV (TABLE 4.3)
cmp (miss_school= age agesq PNMHI Paklihawa SadLonelyYes) ///
    (SadLonelyYes= SchoolSupportIndexPhyPca CommunityWorshipCulturalPca ///
        IsolationFamilyCulturalPca age agesq PNMHI Paklihawa), indicators($cmp_probit $cmp_probit) vce(robust)
estat ic
estimate store BiProbit_CMP_Model1

cmp (miss_school= age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa SadLonelyYes) ///
    (SadLonelyYes= SchoolSupportIndexPhyPca CommunityWorshipCulturalPca ///
        IsolationFamilyCulturalPca age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa), indicators($cmp_probit $cmp_probit) vce(robust)
estat ic
estimate store BiProbit_CMP_Model2

estout BiProbit_CMP_Model1 BiProbit_CMP_Model2 using Table3A_May2019_Young.html, label cells(b(star fmt(3)) ///
    se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
    label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//Ordinal DV (TABLE 4.5)
```

```
cmp (daysmissedraw= age agesq PNMHI Paklihawa SadLonelyYes) ///
    (SadLonelyYes= SchoolSupportIndexPhyPca CommunityWorshipCulturalPca ///
        IsolationFamilyCulturalPca age agesq PNMHI Paklihawa), indicators($cmp_oprobit
$cmp_probit) vce(robust)
estat ic
estimate store OProbit_CMP_Model1

cmp (daysmissedraw= age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa SadLonelyYes)
///
    (SadLonelyYes= SchoolSupportIndexPhyPca CommunityWorshipCulturalPca ///
        IsolationFamilyCulturalPca age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa),
indicators($cmp_oprobit $cmp_probit) vce(robust)
estat ic
estimate store OProbit_CMP_Model2

estout OProbit_CMP_Model1 OProbit_CMP_Model2 using Table4A_May2019_Young.html,
label cells(b(star fmt(3)) ///
    se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
    label(Observations Log-Likelihood Chi-2 AIC BIC))replace


//MARGINAL EFFECTS

//BiProbit (TABLE 4.4)
//Model 1
cmp (miss_school= age agesq PNMHI Paklihawa SadLonelyYes) ///
    (SadLonelyYes= SchoolSupportIndexPhyPca CommunityWorshipCulturalPca ///
    IsolationFamilyCulturalPca age agesq PNMHI Paklihawa), indicators($cmp_probit
$cmp_probit) vce(robust)
margins, dydx(*) predict(pr) force
margins, dydx(*) predict(pr eq(#2)) force


//Model 2
cmp (miss_school= age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa SadLonelyYes) ///
    (SadLonelyYes= SchoolSupportIndexPhyPca CommunityWorshipCulturalPca ///
    IsolationFamilyCulturalPca age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa),
indicators($cmp_probit $cmp_probit) vce(robust)
margins, dydx(*) predict(pr) force
margins, dydx(*) predict(pr eq(#2)) force


//Ordinal DV (TABLE 4.6)
//Model 1
cmp (daysmissedraw= age agesq PNMHI Paklihawa SadLonelyYes) ///
    (SadLonelyYes= SchoolSupportIndexPhyPca CommunityWorshipCulturalPca ///
```

```
      IsolationFamilyCulturalPca age agesq PNMHI Paklihawa), indicators($cmp_oprobit
$cmp_probit) vce(robust)
margins, dydx(*) predict(pr outcome(#1)) force
margins, dydx(*) predict(pr outcome(#2)) force
margins, dydx(*) predict(pr outcome(#3)) force
margins, dydx(*) predict(pr eq(#2)) force


//Model 2
cmp (daysmissedraw= age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa SadLonelyYes)
///
      (SadLonelyYes= SchoolSupportIndexPhyPca CommunityWorshipCulturalPca ///
      IsolationFamilyCulturalPca age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa),
indicators($cmp_oprobit $cmp_probit) vce(robust)
margins, dydx(*) predict(pr outcome(#1)) force
margins, dydx(*) predict(pr outcome(#2)) force
margins, dydx(*) predict(pr outcome(#3)) force
margins, dydx(*) predict(pr eq(#2)) force


//CHAPTER 4 SENSITIVITY ANALYSIS WITH OLDER SAMPLE INCLUDED/////////////////

use Chap4_LabeledData.dta

//POOLED DATA
keep if location==5|location==1|location==2

//PCA INDICES

 //PCA for School Support Index
pca /*ShareWithTeacherYes*/ SchoolHygieneEduYes ProvideHygieneKitYes
SchoolFacilityChangeYes SchoolFacilityWashSoapYes SchoolDustBinForKitsYes
//screeplot
predict p1, score
gen SchoolSupportIndexPhyPca = p1
drop p1

//PCA for Cultural Taboo Index
pca EnterWorshipRoomNo IsolationSeparateBld CulturalParticipartionNo ///
      AllowedMeetFamiliyNo AllowedInKitckenNo
screeplot
predict p1 p2
gen SocIsolationIndexPca1 = p1
gen SocIsolationIndexPca2 = p2
drop p1 p2

rename SocIsolationIndexPca1 CommunityWorshipCulturalPca
```

```
rename SocIsolationIndexPca2 IsolationFamilyCulturalPca

/////////////////////////////////////////////////////////////////////////
///MCA EXPLORATIONS
//School Support Index
mca /*ShareWithTeacherYes*/ SchoolHygieneEduYes SchoolFacilityChangeYes
ProvideHygieneKitYes ///
    SchoolFacilityWashSoapYes SchoolDustBinForKitsYes

//Dimension 1: 90% explained, principle intertia = 0.083; Relies more //
    //on Bins, Soap, Kits

//Cultural Taboo Index
mca EnterWorshipRoomNo IsolationSeparateBld CulturalParticipartionNo ///
    AllowedMeetFamiliyNo AllowedInKitckenNo

//Dimension 1: Inertia= 0.02598, explains 86% --> Relies more heavily on
    //Worship, Cultural Participation, & Kitchen
//Dimension 2: Inertia = 0.0000412, explalins 0.18% --> Relies more heavily on
    // Isolation and Meeting Family

gen daysmissedraw=days_miss_m
replace daysmissedraw=1 if days_miss_m==0
replace daysmissedraw=2 if days_miss_m==1.5
replace daysmissedraw=3 if days_miss_m==4|days_miss_m==7
tab daysmissedraw

save Chap3AnalysisSample.dta
///////////////////////////////////////////////////////////////////////
//Dissection of Descriptive Stats

//School
sum ShareWithTeacherYes SchoolHygieneEduYes ProvideHygieneKitYes ///
    SchoolFacilityChangeYes SchoolFacilityWashSoapYes SchoolDustBinForKitsYes


//Cultural
sum EnterWorshipRoomNo IsolationSeparateBld CulturalParticipartionNo ///
    AllowedMeetFamiliyNo AllowedInKitckenNo

sum SadLonelyYes


////////////MODEL FITTING- EMOTION
//Base Model, Full Sample, No Control, No Caste, No FE
probit SadLonelyYes CommunityWorshipCulturalPca IsolationFamilyCulturalPca
SchoolSupportIndexPhyPca ///
```

```
    age agesq, robust
estat ic
estimate store model1a


//Base Model, Full Sample, No Control, No Caste, Yes FE
probit SadLonelyYes CommunityWorshipCulturalPca IsolationFamilyCulturalPca
SchoolSupportIndexPhyPca ///
    PNMHI Paklihawa age agesq, robust
estat ic
estimate store model2a

//Base Model, Full Sample, No Control, Yes Caste, Yes FE
probit SadLonelyYes CommunityWorshipCulturalPca IsolationFamilyCulturalPca
SchoolSupportIndexPhyPca ///
    Madhesi Dalit OtherCaste age agesq PNMHI Paklihawa, robust
estat ic
estimate store model3a

//Base Model, Full Sample, Yes Control, No Caste, No FE
probit SadLonelyYes CommunityWorshipCulturalPca IsolationFamilyCulturalPca
SchoolSupportIndexPhyPca ///
    CurrentUseTypeDisposable CurrentUseTypeReusable ///
    Wealth_Index MarriedY age agesq, robust
estat ic
estimate store model4a

//Base Model, Full Sample, Yes Control, No Caste, Yes FE
probit SadLonelyYes CommunityWorshipCulturalPca IsolationFamilyCulturalPca
SchoolSupportIndexPhyPca ///
    PNMHI Paklihawa CurrentUseTypeDisposable ///
    CurrentUseTypeReusable ///
    Wealth_Index MarriedY age agesq PNMHI Paklihawa, robust
estat ic
estimate store model5a

//Base Model, Full Sample, Yes Control, Yes Caste, No FE
probit SadLonelyYes CommunityWorshipCulturalPca IsolationFamilyCulturalPca
SchoolSupportIndexPhyPca ///
    Madhesi Dalit OtherCaste CurrentUseTypeDisposable ///
    CurrentUseTypeReusable ///
    Wealth_Index MarriedY age agesq, robust
estat ic
estimate store model6a


//Base Model, Full Sample, Yes Control, Yes Caste, Yes FE
```

```
probit SadLonelyYes CommunityWorshipCulturalPca IsolationFamilyCulturalPca
SchoolSupportIndexPhyPca ///
    Madhesi Dalit OtherCaste CurrentUseTypeDisposable ///
    CurrentUseTypeReusable PNMHI Paklihawa ///
    Wealth_Index MarriedY age agesq, robust
estat ic
estimate store model7a

estout model1a model2a model3a model4a model5a model6a model7a using
ModelFit_ProbitEmotion_April2019.html, label cells(b(star fmt(3)) ///
    se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
    label(Observations Log-Likelihood Chi-2 AIC BIC))replace

////////////////////////////////////////////////////////////////////////
//MODEL FITTING- MISSING SCHOOL (BINARY)

//Base Model, Full Sample, No Control, No Caste, No FE
probit miss_school SadLonelyYes ///
    age agesq, robust
estat ic
estimate store model1b


//Base Model, Full Sample, No Control, No Caste, Yes FE
probit miss_school SadLonelyYes ///
    PNMHI Paklihawa age agesq, robust
estat ic
estimate store model2b

//Base Model, Full Sample, No Control, Yes Caste, Yes FE
probit miss_school SadLonelyYes ///
    Madhesi Dalit OtherCaste age agesq PNMHI Paklihawa, robust
estat ic
estimate store model3b

//Base Model, Full Sample, Yes Control, No Caste, No FE
probit miss_school SadLonelyYes ///
    CurrentUseTypeDisposable CurrentUseTypeReusable ///
    Wealth_Index MarriedY age agesq, robust
estat ic
estimate store model4b

//Base Model, Full Sample, Yes Control, No Caste, Yes FE
probit miss_school SadLonelyYes ///
    PNMHI Paklihawa CurrentUseTypeDisposable ///
    CurrentUseTypeReusable ///
    Wealth_Index MarriedY age agesq PNMHI Paklihawa, robust
```

```
estat ic
estimate store model5b

//Base Model, Full Sample, Yes Control, Yes Caste, No FE
probit miss_school SadLonelyYes ///
	Madhesi Dalit OtherCaste CurrentUseTypeDisposable ///
	CurrentUseTypeReusable ///
	Wealth_Index MarriedY age agesq, robust
estat ic
estimate store model6b


//Base Model, Full Sample, Yes Control, Yes Caste, Yes FE
probit miss_school SadLonelyYes ///
	Madhesi Dalit OtherCaste CurrentUseTypeDisposable ///
	CurrentUseTypeReusable PNMHI Paklihawa ///
	Wealth_Index MarriedY age agesq, robust
estat ic
estimate store model7b

estout model1b model2b model3b model4b model5b model6b model7b using
ModelFit_ProbitSchool_April2019.html, label cells(b(star fmt(3)) ///
	se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
	label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//////////
//MODEL FITTING-MISSING SCHOOL (ORDINAL)
//Base Model, Full Sample, No Control, No Caste, No FE
oprobit daysmissedraw SadLonelyYes ///
	age agesq, robust
estat ic
estimate store model1c


//Base Model, Full Sample, No Control, No Caste, Yes FE
oprobit daysmissedraw SadLonelyYes ///
	PNMHI Paklihawa age agesq, robust
estat ic
estimate store model2c

//Base Model, Full Sample, No Control, Yes Caste, Yes FE
oprobit daysmissedraw SadLonelyYes ///
	Madhesi Dalit OtherCaste age agesq PNMHI Paklihawa, robust
estat ic
estimate store model3c

//Base Model, Full Sample, Yes Control, No Caste, No FE
```

```
oprobit daysmissedraw SadLonelyYes ///
      CurrentUseTypeDisposable CurrentUseTypeReusable ///
      Wealth_Index MarriedY age agesq, robust
estat ic
estimate store model4c

//Base Model, Full Sample, Yes Control, No Caste, Yes FE
oprobit daysmissedraw SadLonelyYes ///
      PNMHI Paklihawa CurrentUseTypeDisposable ///
      CurrentUseTypeReusable ///
      Wealth_Index MarriedY age agesq, robust
estat ic
estimate store model5c

//Base Model, Full Sample, Yes Control, Yes Caste, No FE
oprobit daysmissedraw SadLonelyYes ///
      Madhesi Dalit OtherCaste CurrentUseTypeDisposable ///
      CurrentUseTypeReusable ///
      Wealth_Index MarriedY age agesq, robust
estat ic
estimate store model6c


//Base Model, Full Sample, Yes Control, Yes Caste, Yes FE
oprobit daysmissedraw SadLonelyYes ///
      Madhesi Dalit OtherCaste CurrentUseTypeDisposable ///
      CurrentUseTypeReusable PNMHI Paklihawa ///
      Wealth_Index MarriedY age agesq, robust
estat ic
estimate store model7c

estout model1c model2c model3c model4c model5c model6c model7c using
ModelFit_OProbitSchool_April2019.html, label cells(b(star fmt(3)) ///
      se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
      label(Observations Log-Likelihood Chi-2 AIC BIC))replace


/////////////////////////////////////////////////////////////////////////////////
//Emotion on School - SINGLE EQUATION (probit, logit, oprobit/ologit)

//Probit- Emotion
probit SadLonelyYes CommunityWorshipCulturalPca IsolationFamilyCulturalPca
SchoolSupportIndexPhyPca ///
      age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa, robust
estat ic
estimate store Single_Probit_Emotion
```

```
//Probit- School
probit miss_school SadLonelyYes age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa,
robust
estat ic
estimate store Single_Probit_School

//OProbit-School
//Oprobit
oprobit daysmissedraw SadLonelyYes age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa,
robust
estat ic
estimate store Single_OProbit_School

estout Single_Probit_Emotion Single_Probit_School Single_OProbit_School using
Table2_April2019.html, label cells(b(star fmt(3)) ///
    se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
    label(Observations Log-Likelihood Chi-2 AIC BIC))replace

////////////////////////////////////////////////////////////////////////
//2-Equation - SIMULTANEOUS BI-PROBIT (biprobit, DV binary)
//MODEL 1- NO CASTE
biprobit (miss_school= age agesq PNMHI Paklihawa SadLonelyYes) (SadLonelyYes=
SchoolSupportIndexPhyPca ///
    CommunityWorshipCulturalPca IsolationFamilyCulturalPca age agesq PNMHI Paklihawa),
vce(robust)
estat ic
estimate store BiProbit_Model1

//MODEL 2- YES CASTE
biprobit (miss_school= age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa SadLonelyYes)
(SadLonelyYes= ///
    SchoolSupportIndexPhyPca CommunityWorshipCulturalPca IsolationFamilyCulturalPca age
agesq Madhesi Dalit ///
    OtherCaste PNMHI Paklihawa), vce(robust)
estat ic
estimate store BiProbit_Model2

estout BiProbit_Model1 BiProbit_Model2 using Table3A_May2019.html, label cells(b(star
fmt(3)) ///
    se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
    label(Observations Log-Likelihood Chi-2 AIC BIC))replace

////////////////////////////////////////////////////////////////////////
//2-Equation - SIMULTANOUS CMP (ologit/oprobit & DV Binary; ologit/oprobit & DV Binary)
cmp setup

//Binary DV (CHECKING)
```

```
cmp (miss_school= age agesq PNMHI Paklihawa SadLonelyYes) ///
    (SadLonelyYes= SchoolSupportIndexPhyPca CommunityWorshipCulturalPca ///
        IsolationFamilyCulturalPca age agesq PNMHI Paklihawa), indicators($cmp_probit
$cmp_probit) vce(robust)
estat ic
estimate store BiProbit_CMP_Model1

cmp (miss_school= age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa SadLonelyYes) ///
    (SadLonelyYes= SchoolSupportIndexPhyPca CommunityWorshipCulturalPca ///
        IsolationFamilyCulturalPca age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa),
indicators($cmp_probit $cmp_probit) vce(robust)
estat ic
estimate store BiProbit_CMP_Model2

estout BiProbit_CMP_Model1 BiProbit_CMP_Model2 using Table3A_CHECK_May2019.html,
label cells(b(star fmt(3)) ///
    se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
    label(Observations Log-Likelihood Chi-2 AIC BIC))replace

//Ordinal DV
cmp (daysmissedraw= age agesq PNMHI Paklihawa SadLonelyYes) ///
    (SadLonelyYes= SchoolSupportIndexPhyPca CommunityWorshipCulturalPca ///
        IsolationFamilyCulturalPca age agesq PNMHI Paklihawa), indicators($cmp_oprobit
$cmp_probit) vce(robust)
estat ic
estimate store OProbit_CMP_Model1

cmp (daysmissedraw= age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa SadLonelyYes)
///
    (SadLonelyYes= SchoolSupportIndexPhyPca CommunityWorshipCulturalPca ///
        IsolationFamilyCulturalPca age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa),
indicators($cmp_oprobit $cmp_probit) vce(robust)
estat ic
estimate store OProbit_CMP_Model2

estout OProbit_CMP_Model1 OProbit_CMP_Model2 using Table4A_May2019.html, label
cells(b(star fmt(3)) ///
    se(par fmt(4))) stats(N ll chi2 aic bic, fmt(3 0 1) ///
    label(Observations Log-Likelihood Chi-2 AIC BIC))replace


//MARGINAL EFFECTS
//BiProbit
//Model 1
cmp (miss_school= age agesq PNMHI Paklihawa SadLonelyYes) ///
    (SadLonelyYes= SchoolSupportIndexPhyPca CommunityWorshipCulturalPca ///
```

```
      IsolationFamilyCulturalPca age agesq PNMHI Paklihawa), indicators($cmp_probit
$cmp_probit) vce(robust)
margins, dydx(*) predict(pr) force
margins, dydx(*) predict(pr eq(#2)) force

//Model 2
cmp (miss_school= age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa SadLonelyYes) ///
      (SadLonelyYes= SchoolSupportIndexPhyPca CommunityWorshipCulturalPca ///
      IsolationFamilyCulturalPca age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa),
indicators($cmp_probit $cmp_probit) vce(robust)
margins, dydx(*) predict(pr) force
margins, dydx(*) predict(pr eq(#2)) force


//Ordinal DV
//Model 1
cmp (daysmissedraw= age agesq PNMHI Paklihawa SadLonelyYes) ///
      (SadLonelyYes= SchoolSupportIndexPhyPca CommunityWorshipCulturalPca ///
      IsolationFamilyCulturalPca age agesq PNMHI Paklihawa), indicators($cmp_oprobit
$cmp_probit) vce(robust)
margins, dydx(*) predict(pr outcome(#1)) force
margins, dydx(*) predict(pr outcome(#2)) force
margins, dydx(*) predict(pr outcome(#3)) force
margins, dydx(*) predict(pr eq(#2)) force


//Model 2
cmp (daysmissedraw= age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa SadLonelyYes)
///
      (SadLonelyYes= SchoolSupportIndexPhyPca CommunityWorshipCulturalPca ///
      IsolationFamilyCulturalPca age agesq Madhesi Dalit OtherCaste PNMHI Paklihawa),
indicators($cmp_oprobit $cmp_probit) vce(robust)
margins, dydx(*) predict(pr outcome(#1)) force
margins, dydx(*) predict(pr outcome(#2)) force
margins, dydx(*) predict(pr outcome(#3)) force
margins, dydx(*) predict(pr eq(#2)) force
```

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