Doctoral School of Social Sciences

Doctoral programme in Development Economics and Local Systems

Curriculum in Development Economics

The visible and invisible dimensions of gender inequality in the Global South

Three essays on time use, mental load, and depression

a dissertation submitted in partial fulfillment of the requirements for the Doctoral degree (Ph.D.) doctoral programme in Development Economics and Local Systems

Sveva

Vitellozzi

XXXV Cycle

Supervisor – Prof. Gianna Claudia Giannelli

Doctoral committee:

- Professor Luca Piccoli, University of Trento
- Professor Francesca Gagliardi, University of Hertfordshire
- Dr. Antonio Scognamiglio, Food and Agriculture Organization

Abstract

This thesis investigates gender inequalities in low- and middle-income countries. Even though the topic has been largely analyzed in the literature, the main novelty of this work is the focus on the invisible dimension of these inequalities. Exploiting longitudinal, satellite, and experimental data, this thesis analyzes causes and consequences of three important dimensions of gender inequalities: the unequal division of time between spouses; mental load (the management behind household activities); and depression. What emerges is that exogenous shocks can positively challenge the unequal allocation of time between domestic and market activities within the household, leading women to engage more in income-generating activities and increasing their empowerment. However, if not paired with a more gender-equal division of roles in the household, an increased participation in the labor market risks enhancing mental load, which in turn reduces women's labor productivity and increases the likelihood of choosing a less cognitively demanding, and less remunerative job. Especially in low-income contexts, the burden of mental load is strictly correlated with mental disorders such as anxiety, chronic stress, or depression. Suffering from depression affects economic preferences and leads women to alter their health and saving behaviors in ways that could be detrimental in the long-run. Ultimately, this thesis shows that these dimensions of gender inequalities are more interconnected than they appear in reality, and that they need to be addressed jointly to better understand their persistence worldwide.

Keywords: gender; poverty; inequality; time use; mental load; depression
JEL Classification: J16; J22; J24; D91

Per amare la cultura occorre una forte vitalità. Perché la cultura – in senso specifico o, meglio, classista – è un possesso: e niente necessita di una più accanita e matta energia che il desiderio di possesso.

— P.P.Pasolini

Acknowledgements

Now that the moment to write down the acknowledgments has come, I am fully realizing the importance of the incredible human beings who have shared this experience with me. I feel that the least I can do is to take some time to express my sincere gratitude to all of you for having been there with me until the end of this Ph.D.

First of all, I would like to thank my supervisor, Professor Gianna Claudia Giannelli, for having guided me the whole time throughout this experience; for having been always supportive of my research ideas and projects, even when they were "unconventional" or hard to put in practice; for having been always there whenever I needed help; and for the academic and human support she always offered me during these three years. My heartfelt gratitude also goes to Professors Chiara Rapallini and Francesco Cecchi, for all their support in one of the chapters of this thesis. Without them, I would not have been able to conduct the experiment in Kenya and live the incredible experience that was the fieldwork in Nairobi.

I would like to thank my reviewers, Professors Karine Marazyan and Selene Ghisolfi, for the very useful comments that substantially increased the quality of this work.

During these three years, I have met countless colleagues that marked this experience in a positive and invaluable way. Among them, I profoundly acknowledge my Ph.D. colleagues, that shared with me most of the joys and sorrows of this journey. Thanks to all of you, Simona, Niccolò, Margherita, Giulia, and Marco, for the mutual help, the support, the brainstorming sessions, the laughs, and, most importantly, for your friendship. Meeting you has been a gift of this Ph.D. A special thanks go to Carlo Azzarri, who encouraged me to apply for the Ph.D. and has helped and guided me ever since we first started working together. Thanks to Miguel Purroy, who has always been there to help me without expecting anything in return. Lastly, thanks to Nathan Prior and Fredrick Achar, for their invaluable support during my experience in Kenya.

Let me conclude with some personal acknowledgments. Thanks to my lifelong friends: my support network in all the moments of my life. Thanks for your incredible energy, you have no idea how refreshing your presence has been during the darkest and brightest moments of this Ph.D. Lastly, I would like to thank my family, the ultimate core of my life. Without my parents and my brother, I would have never been able to come along this way. Thank you for

your constant presence and unconditional love, you gave me the strength to believe in myself and the courage to pursue all my ideas and projects, no matter how hard or ambitious they seemed from the outside.

Thank you all, really. No (wo)man is an island, and I never realized how true this was until I started (and finished) this Ph.D.

Table of Contents

Introduction

Despite the advances made over the past century, gender inequalities still pervade numerous aspects of our everyday lives (World Bank, 2012). Women are more disadvantaged than men in terms of education and health, life expectation, labor market outcomes, as well as political representation and social mobility (World Bank, 2012). In low- and middle-income countries, such inequalities are even more exacerbated: women are more vulnerable than men to negative shocks (e.g., natural shocks, income shocks); they are at higher risk of being victimized; and they are subjected to gender norms that confine their roles in the society to daughters, wives, and mothers, with few possibilities of expressing independent goals or aspirations (Nolen-Hoeksema, 2001; Asfaw and Maggio, 2018; Solotaroff, 2019).

In these contexts, women are mostly responsible for unpaid domestic work, and they have to divide their time between market and domestic activities, which partly explains the structure of gendered labor markets and the persistence of inequalities in terms of employment opportunities, earnings, and productivity among others (World Bank, 2012). For instance, women are more likely than men to be employed in the informal sector, which guarantees time flexibility but is also characterized by high instability and income volatility (Perry, 2007). Time is a resource and, when domestic activities are considered, it is unequally divided between men and women worldwide (Anxo et al., 2011; Ferrant et al., 2014). In low- and middle-income countries however, the time women devote to unpaid domestic work is particularly burdensome, and it limits their lives under several aspects (Bardasi and Wodon, 2006; Wodon and Blackden, 2006; Gammage, 2010; Arora, 2015; Arora and Rada, 2017).

This unequal division of time can be analysed under two angles. The former is visible, and reveals that women spend a disproportionate amount of time compared to men in domestic activities, which in turn limits the time they can devote to work (whether employed or self-employed), to leisure and rest, and to pursue their own goals (World Bank, 2012; Solotaroff et al., 2019). The latter is invisible, and it refers to the "mental" time women spend in planning, organizing, and thinking about the management of the household (i.e., the so-called "mental load") (Daminger, 2019; Dean et al., 2022). Living with these constant thoughts and worries in the background of the mind can undermine several aspects of women's lives, from their productivity and occupational choices, to their empowerment and overall well-being. When considered in a broader (patriarchal) context that strictly defines the role of women in the society and their spheres of activity, these factors are likely to negatively affect their mental health, by increasing their risk of suffering from depression, stress, and anxiety (Jenkins and Good, 2014). Mental disorders can potentially reinforce gender inequalities by altering women's decision-making processes, productivity, preferences, and daily behaviors in ways that could be detrimental for them both in the short and long term.

This thesis examines three seemingly unrelated dimensions of gender inequalities in low- and middle-income countries, with the scope of unfolding their differences and demonstrating how interconnected they are in reality. Starting from the visible dimension of time use, this study first analyses the impact of exogenous shocks on time allocation of men and women, and on women's empowerment. Then, it digs deeper into the invisible dimension of gender inequalities by investigating the gender-differentiated impact of mental load on productivity and occupational choices. Finally, it looks at the association between depression and economic behaviors under a gendered perspective. Through the adoption of panel, satellite, and experimental data, this work answers different research questions that lie at the intersection of applied microeconomics, behavioral development economics, and feminist economics in three different settings: Bangladesh, Kenya, and Mexico. In all the three chapters, sociological and anthropological studies integrate the economic literature, with the aim of better understanding the gender relations underlying the research context in which the study was conducted.

The first chapter, co-authored with Gianna Claudia Giannelli, "Thriving in the rain: natural shocks, time allocation, and empowerment in Bangladesh", analyzes the impact of two severe flooding events that occurred in Bangladesh in 2014 and 2017 on time (re)allocation of women and men, and on women's empowerment. The literature shows that women are more vulnerable than men to climate change (Terry and Sweetman, 2009), and that natural shocks influence the allocation of time within the household between men and women (Halliday, 2012; Kamei, 2019; Garg et al., 2020). On the one hand, as men engage more in market activities after the disaster, women may find themselves to spend more time in domestic and reproductive activities. On the other hand, women may engage more in paid activities to contribute to the increased household's expenses (Canessa and Giannelli, 2021), thus reallocating their time from domestic to leisure and market activities. This last channel may also lead to a long-lasting change in the acceptability of women's work and in prevailing gender norms, and an increase in women's empowerment (Bradshaw and Fordham, 2013; Moreno and Shaw, 2018). The aim of this study is to understand whether and to what extent the flood that occurred in 2017 shapes women's and men's time allocation. Following a recent paper (Canessa and Giannelli, 2021) showing that the flood in 2014 leads to an increase in women's empowerment, this paper asks then whether this increase persists over time and whether influences the reaction to the flood in 2017.

The second chapter, co-authored with Francesco Cecchi and Chiara Rapallini, "Under pressure: the impact of mental load on women's productivity and occupational choices - experimental evidence from Kenya", focuses on the psychological invisible dimension of gender inequalities in urban areas in Kenya (i.e., Nairobi). Mental load has been defined as the combination of cognitive labor (i.e., the management behind household activities), and emotional labor (i.e., the caring and responsibility of other household's members well-being) (Dean et al., 2022). Most often held by women, this load risks holding important drawbacks in terms of gender inequalities. The literature on scarcity states that poverty, by constantly loading individuals with pressing thoughts related to financial worries, negatively affects cognitive functions and a series of economic outcomes (de Bruijn and Antonides, 2021). Building on these notions, this study asks whether mental load, by worrying individuals with pressing concerns related to the household, has negative consequences on their labor productivity and leads them to self-select into less remunerative and cognitively-demanding jobs. It hypothesizes also that the impact of mental load is gender-differentiated (that is, stronger for women than for men), and that it differs among women with different income levels. We identify two potential mechanisms through which mental load can operate: an increase in stress, and a decrease in attentional resources.

Finally, the last chapter, "Depression and economic behavior through the lens of gender. Lessons from Mexico", examines the association between depression, economic preferences, and daily behaviors under a gendered perspective in Mexico. Women are more likely than men to suffer from depression (Nolen-Hoeksema, 2001; Jenkins and Good, 2014), and mental disorders are associated with a different willingness to take risks and to defer future gratifications, impaired cognitive abilities, reduced performance and women's empowerment, among others (Ridley et al., 2020). Mexico is a country with a high incidence of mental disorders and violence, where local norms follow the principles of the so-called "machismo", according to which men hold the power within the household and marriage is built on the premise of the wife's respect for her husband (Belló et al., 2005; Knapp et al., 2009). In this context, women are at a high risk of suffering from mental disorders. This analysis focuses solely on women, and it asks whether depression shapes women's risk aversion, time discounting, and cognitive functions. Then, it investigates whether these changes in economic preferences translate in changes in daily behaviors, namely investment in children's education, investment in physical health (i.e., smoking and sport habits, and sleep deprivation), and credit and saving decisions.

Finally, a mediation analysis investigates what are the main depressive symptoms shaping economic preferences.

As already stated, this thesis adopts different data and empirical methods to answer the above-mentioned research questions. The first chapter relies on the analysis of the Bangladesh Integrated Household Survey (BIHS), a three-waves panel dataset national representative of the rural areas of the country, for a total of 6,500 sampled household. Data were collected in 2012, 2015, and 2018, and they are particularly suitable for this study because they allow to consider both shocks in the analysis, and because they contain detailed time use information collected under the form of time diaries. To construct the treatment variable, we rely on the NASA Flooding Map, a product composed of 250-mt resolution images, that defines flooded areas as water observations falling outside normal water levels. The treatment variable, i.e., the intensity of exposure to the flood for each sampled household, is then defined as the share of pixels identified as "flooded" in a 5-km radius for each household (Gröger and Zylberberg, 2016).

The second chapter relies on experimental data collected between April and May 2022 in Nairobi, Kenya. More specifically, we run a lab-in-the-field experiment to identify the impact of mental load on productivity and occupational choices with a final sample of 720 participants. The treatment consists of triggering in the mind of participants thoughts related to mental load (Cohn et al., 2015). To measure productivity and self-selection, participants in the treatment and control group were given 30 minutes to perform an incentivized effort task, that were divided in three time slots of 10 minutes each. We asked them to perform two different tasks: a menial (i.e., dividing black form red beans) and a more cognitively-demanding one (i.e., the Tower of Hanoi (TOH)). For the first two time slots, participants had to divide as many black from red beans as possible, and to complete as many TOH with 4 disks as possible. To account for self-selection, before starting the last round of the effort task we increased the difficulty of the TOH (i.e., from 4 to 5 disks) along with its economic incentive (i.e., from 20 to 100 KSH for each completed Tower), and we asked participants to choose between the cognitively demanding task with increased difficulty and the menial task.

The last chapter relies on the Mexican Family Life Survey (MxFLS), a national representative panel dataset of the Mexican population at the national, urban, rural, and regional level. The data provide information for a period of 10 years, and it has been collected in three waves: in 2002, in 2005-2006, and in 2009-2012 for around 35,000 individuals. The analysis relies only on the last two waves because in the first wave information on risk attitudes and time discounting were not collected. The data contain also a module on emotional status that provides information on self-reported depressive symptoms. It consists of 20 questions asking how often in the past 4 weeks the individual has experienced feelings such as sadness, stress, fear, loneliness, or irritability. The questions are based on the Generalized Health Questionnaire, and they have been already validated in Mexico (Calderón-Narváez, 1997; Schmeer and Kroeger, 2011). Finally, the data contain information on cognitive abilities, measured through the Raven's matrixes.

Given the different nature of the research questions, this thesis adopts three different empirical methodologies. In the first chapter, to assess the impact of the natural shocks on the outcomes of interest, the identification strategy consists of a Difference-in-Difference methodology, that allows to identify a treatment and control groups based on the exposure to the flood. The second chapter adopts an Ordinary Least Squares (OLS) specification and the Heckman Selection Model to account for self-selection into more or less cognitively-demanding jobs. Finally, the last chapter relies on a Fixed Effects Model, exploiting two out of three waves of the data. While in the first two chapters a causal mechanism is identified, the last chapter aims at providing robust correlations on the association between depression and economic outcomes.

Each chapter provides interesting and important results for gender inequalities in low- and middle-income countries. The first chapter shows that, in rural Bangladesh, natural shocks operate through the second, indirect channel in the reallocation of time between men and women. After the shock in 2017, women are more likely to engage in paid activities, they spend on average 55 minutes less in domestic work, 90 minutes more in leisure activities, and they are less likely to be time poor. Men, by contrast, for substituting for women's work within the household increase the time spent in domestic activities by 74 minutes, and they are more likely to be time poor. A heterogeneity analysis shows that these results are conditional to having experienced the flood in 2014 or not. Results are confirmed only for those women that experienced both floods, while for women that experienced only the flood in 2017 the results go in the exact opposite direction: they spend a disproportionate amount of time in domestic work, the time spent in market activities decreases, and they are more likely to be time poor. Finally, we find that the increase in women's empowerment caused by the flood in 2014 persists over time and it is likely to shape women's response to the flood in 2017.

The lab-in-the-field experiment shows that mental load impacts both productivity and occupational choices. More specifically, results show that mental load significantly reduces productivity in the automatic task (i.e., dividing the beans), but not in the cognitively demanding task. At the same time, treated participants self-select more often into the former. The gender-disaggregated heterogeneity analysis shows that mental load reduces productivity for women, and not for men, but that the self-selection into the less cognitive, and less remunerative task is stronger for men (women are more likely to select into it regardless of treatment status). We are not fully able to identify the mechanisms that drive the results, but we find suggestive evidence that mental load operates through a reduction in attention for men, and an increase in stress for women. Finally, we find that the effect on productivity is similar above and below the median of income distribution in our sample, with an insignificantly stronger effect for non-poor participants.

The last chapter shows that depression is significantly correlated with attitudes towards risk aversion and time discounting. More specifically, women suffering from depression exhibit a lower probability of being risk averse as well as of being impatient both in the short and distant future. The mediation analysis shows that the increase in patience is driven mainly by anhedonia, i.e., the inability to derive pleasure from activities perceived as enjoyable by others, while the decrease in risk-aversion is mainly driven by negative beliefs about the future. These changes in preferences translate in changes in daily behaviors: depression leads women to invest less time in children's education, to smoke more and practice less sport, to sleep less, and to be significantly less likely to save in informal institutions. The heterogeneity analyses show that more marginalized groups (i.e., depressed women living under the poverty line, and depressed mothers) risk being more vulnerable to the consequences of mental health on their economic outcomes.

This thesis addresses the visible and invisible dimensions of gender inequalities and it shows how interconnected they are in reality. Exogenous shocks can lead to a reallocation of time within the household and to an increase of women's economic empowerment. However, this increased engagement in paid activities risks translating in an increase in mental load. Having to think, plan, and organise all the activities in the household, women may find themselves with no time left to think about their own selves. This lack of time negatively impacts economic outcomes (e.g., productivity), and it can also increase the risk of suffering from mental disorders, which in turn affect employment, preferences, and daily behaviors among others. Under this perspective, women risk finding themselves in a loop that, in the worse scenario, could trap them into poverty.

The three most important takeaways of this work are the following: first, when a positive change in women's empowerment occurs endogenously, it brings about long-lasting changes that affect the behaviors of spouses within the household. This result is particularly important because it shows that when local norms are challenged (e.g., after the flood women are more likely to engage in paid activities to contribute to the increased household's expenses) in favor of a more gender equal division of roles within the household, the effect is sustainable over time. Second, mental load is an invisible, important psychological dimension of gender inequality that we need to investigate more because, other than productivity, it may be affecting other economic outcomes that could contribute explaining the persistence of gender inequalities worldwide. More importantly, it is particularly relevant understanding which interventions would be effective in lowering mental load in poor settings, where its burden is particularly heavy. Lastly, the gender gap in mental health may be an additional factor explaining gender differences in preferences and economic behaviors that needs to be acknowledged and addressed properly by the economic literature, especially when focusing on low- and middle-income countries. More generally, since women suffer more than men from mental disorders, conducting gender-disaggregated analyses when investigating the economics of mental health seems especially relevant to better tackle this (in)visible problem and to better understand which aspects of the cultural system we live in differently affect mental disorders for women and men.

References

Anxo, D., Mencarini, L., Pailhé, A., Solaz, A., Tanturri, M. L., and Flood, L. (2011). Gender Differences in Time Use over the Life Course in France, Italy, Sweden, and the US. *Feminist Economics*, 17(3):159–195.

Arora, D. (2015). Gender Differences in Time-Poverty in Rural Mozambique. *Review of Social Economy*, 73(2):196–221.

Arora, D. and Rada, C. (2017). A gendered model of the peasant household: Time poverty and farm production in rural mozambique. *Feminist Economics*, 23(2):93–119.

Asfaw, S. and Maggio, G. (2018). Gender, weather shocks and welfare: Evidence from malawi. *The Journal of Development Studies*, 54(2):271–291.

Bardasi, E. and Wodon, Q. (2006). Measuring time poverty and analyzing its determinants: concepts and application to guinea. *Gender, time use, and poverty in Sub-Saharan Africa*, 73:75–95.

Belló, M., Puentes-Rosas, E., and Medina-Mora, M. E. (2005). Prevalencia y diagnóstico de depresión en población adulta en méxico. *Salud pública de México*, 47.

Bradshaw, S. and Fordham, M. (2013). Women and girls in disasters.

Calderón-Narváez, G. (1997). Un cuestionario para simplificar el diagnóstico del síndrome depresivo. *Revista de Neuro-psiquiatría*, 60(2):127–135.

Canessa, E. and Giannelli, G. C. (2021). Women's Employment and Natural Shocks. page 55.

Cohn, A., Engelmann, J., Fehr, E., and Maréchal, M. A. (2015). Evidence for Countercyclical Risk Aversion: An Experiment with Financial Professionals. *The American Economic Review*, 105(2):860–885. Publisher: American Economic Association.

Daminger, A. (2019). The Cognitive Dimension of Household Labor. *American Sociological Review*, 84(4):609–633.

de Bruijn, E.-J. and Antonides, G. (2021). Poverty and economic decision making: a review of scarcity theory. *Theory and Decision*, pages 1–33.

Dean, L., Churchill, B., and Ruppanner, L. (2022). The mental load: building a deeper theoretical understanding of how cognitive and emotional labor over load women and mothers. *Community, Work & Family*, 25(1):13–29.

Ferrant, G., Pesando, L. M., and Nowacka, K. (2014). Unpaid Care Work: The missing link in the analysis of gender gaps in labour outcomes. page 12.

Gammage, S. (2010). Time Pressed and Time Poor: Unpaid Household Work in Guatemala. *Feminist Economics*, 16(3):79–112.

Garg, T., Gibson, M., and Sun, F. (2020). Extreme temperatures and time use in China. *Journal of Economic Behavior & Organization*, 180:309–324.

Gröger, A. and Zylberberg, Y. (2016). Internal labor migration as a shock coping strategy: Evidence from a typhoon. *American Economic Journal: Applied Economics*, 8(2):123–53.

Halliday, T. J. (2012). Intra-household labor supply, migration, and subsistence constraints in a risky environment Evidence from rural El salvador. *European Economic Review*, page 19.

Jenkins, J. H. and Good, M.-J. D. (2014). Women and global mental health: Vulnerability and empowerment. *Essentials of global mental health*, pages 264–281.

Kamei, A. (2019). Who is Walking More for Water? Climate-Shock on Women's/Children's Domestic Work Using Ugandan Panel Time-Use. *Climate-Shock on Women's/Children's Domestic Work Using Ugandan Panel Time-Use*, (July 2019):63.

Knapp, J., Quiros, A., and Muller, B. (2009). Women, men, and the changing role of gender in immigration.

Moreno, J. and Shaw, D. (2018). Women's empowerment following disaster: a longitudinal study of social change. *Natural hazards*, 92(1):205–224.

Nolen-Hoeksema, S. (2001). Gender Differences in Depression. *Current Directions in Psychological Science*, 10(5):173–176.

Perry, G. (2007). *Informality: Exit and exclusion*. World Bank Publications.

Ridley, M., Rao, G., Schilbach, F., and Patel, V. (2020). Poverty, depression, and anxiety: Causal evidence and mechanisms. *Science*, 370(6522).

Schmeer, K. K. and Kroeger, R. A. (2011). Union Type and Depressive Symptoms Among Mexican Adults. *Journal of Family Issues*, 32(12):1597–1621. Publisher: SAGE Publications Inc.

Solotaroff (2019). *Voices to Choices: Bangladesh's Journey in Women's Economic Empowerment*. The World Bank Group. OCLC: 1117903096.

Solotaroff, J. L., Kotikula, A., Lonnberg, T., Ali, S., and Jahan, F. (2019). *Voices to choices: Bangladesh's journey in women's economic empowerment*. World Bank Publications.

Terry, G. and Sweetman, C., editors (2009). *Climate Change and Gender Justice*. Practical Action Publishing, Rugby, Warwickshire, United Kingdom.

Wodon, Q. and Blackden, C. M. (2006). *Gender, time use, and poverty in sub-Saharan Africa*. The World Bank.

World Bank (2012). *World development report 2012: Gender equality and development.* The world bank, 2012 edition.

Chapter 1

Thriving in the rain: natural shocks, time allocation, and empowerment in Bangladesh

Sveva Vitellozzi[1,2] , Gianna Claudia Giannelli[2]

1 University of Trento

2 University of Florence

Abstract

Differences in time use patterns between men and women are particularly pronounced in low- and middle-income countries, and they can be exacerbated by climate change and natural shocks. By employing georeferenced and longitudinal panel data, this paper investigates the impact of the dramatic flood that occurred in Bangladesh in 2017 on time use patterns of both men and women and on women's empowerment. Results show that the shock led women to engage more in market activities, to decrease their time spent in domestic work, and to be more empowered, while men decreased their time spent at work and they engaged more in housework substituting for women's domestic work. To further understand the mechanisms behind this shift in time allocation, we then exploit another flooding event that occurred in 2014 and we conduct a heterogeneity analysis. There are significant differences in time use patterns and empowerment measures between women affected by the flood in 2014 and those who were not. These findings suggest that the shock in 2014 led to an increase in women's empowerment that persists over time and that influences the response to the shock in 2017 for both men and women.

JEL Classification: J16; J22; J43

Keywords: time allocation; time poverty; natural shocks; empowerment

1.1 Introduction

Gender differences in time use represent a major source of gender inequality worldwide: women tend to work more than men when both domestic and market activities are considered (Anxo et al., 2011; Ferrant et al., 2014); they tend to specialize more in housework and care activities, while men in market activities (Solotaroff, 2019); and they tend to be more time-poor than men, i.e., to lack the time to rest and leisure after considering the time spent at work, whether in the labor market or at home (Bardasi and Wodon, 2006; Wodon and Blackden, 2006; Gammage, 2010; Arora, 2015; Arora and Rada, 2017). In low- and middle-income countries, such inequalities are even more exacerbated and they are shaped by several factors, including natural shocks (Halliday, 2012; Kamei, 2019; Garg et al., 2020).

In the aftermath of a natural shock, women may engage more in paid activities to contribute to the household's increased economic expenses, reallocating their time from domestic work to market and leisure activities (Canessa and Giannelli, 2021; Lee et al., 2021). By increasing women's labor supply, exogenous negative shocks can lead to long-term changes in women's economic position within the household, and they can shape prevailing social norms through the disruption of the traditional replication of gender roles within the household (Bradshaw and Fordham, 2013). Indeed, while women engage more in paid activities as a risk-coping mechanism (Canessa and Giannelli, 2021), the social acceptability of women's employment may grow, followed by a more gender-equal division of time within the household (Moreno and Shaw, 2018).

Understanding these mechanisms is critical for a better design of policies encouraging a gender-driven response to adaptation to climate change. This paper asks whether and to what extent extreme weather shocks differently impact women and men's time allocation, time poverty, and women's empowerment. More precisely, by combining detailed panel data with high-precision satellite data, this study seeks to assess the impact of a severe flood that occurred in Bangladesh in 2017 on the reallocation of time between men and women. Then, this paper aims at deepening our understanding of the long-term impacts of natural shocks on women's empowerment. By relying on a recent paper showing that the flood that occurred in 2014 in Bangladesh led to an increase in women's engagement in paid activities and in their empowerment (Canessa and Giannelli, 2021), this study asks whether this increase persists over time and whether it leads men and women to react differently to the shock in 2017.

The analysis relies on georeferenced data from NASA satellites to measure the impact of the flood as the share of inundated areas for each sampled household (Gröger and Zylberberg, 2016; Canessa and Giannelli, 2021). We match these data with the Bangladesh Integrated Household Survey (BIHS), a panel dataset representative of rural Bangladesh collected by the International Food Policy Research Institute (IFPRI) in 2012, 2015, and 2018. These data are particularly suited for the study for three reasons. First, they allow us to conduct the analysis of time allocation in the aftermath of the shock. Indeed, the second and third waves were collected in a period ranging from three to nine months from the occurrence of the flood, depending on the month of interview. Second, they include an extensive module on time use administered to both spouses in the household. Third, they allow for including both shocks in the analysis.

The identification strategy relies on a Difference-in-Difference approach. The treatment variable is the share of inundated areas in 2017 around each sampled household. Thanks to the nature of the data, we are able to conduct an in-depth analysis of the impact of repeated shocks on time use. Indeed, we estimate distinct equations at the individual level for men and women to assess the impact of the flood. Since potential spillover effects of the flood of 2014 risk to bias the results on the impact of the flood in 2017, we then conduct the analysis on two sub-samples of the population: those individuals that were exposed to the flood in 2014 and those who were not. We then check whether the increase in women's empowerment induced by the flood in 2014 persists in 2018, employing as treatment variable the share of inundated areas around each sampled household in 2014. It is worth noticing that the empirical analysis is conducted using only the waves in 2015 and in 2018, as we are mostly interested in analysing the impact of each shock separately[1].

Results show that the flood in 2017 significantly impacts time allocation for both men and women. Women spend less time on domestic labor and more time on leisure activities, and they become less time poor, whereas men spend less time working outside the home and more time on domestic chores, and they become more time poor. The flood leads women to work more and significantly increases their empowerment, measured through the Women's Empowerment in Agriculture Index (WEAI). When we disentangle these impacts for individuals who experienced the flood in 2014 and those who did not, the findings are confirmed only for those households who experienced both shocks. Indeed, among the households only affected by the 2017 flood, women spend more time in domestic chores, become more time poor, and spend less time on reproductive agricultural activities. Men, on the other hand, spend more time in

[1] We are interested in understanding the impact of the shock on time allocation between men and women in the short-term, and the impact on women's empowerment in the long-term. As shown in Table 12 in the Appendix, the shock in 2014 has no impact on time use variables for women in 2018, but it affects men's engagement in domestic and leisure activities. This is most likely due to the fact that the 2014 flood also reduced men's likelihood of being employed in the 7 days prior to the interview in 2018.

market and leisure activities, and less in domestic work. Finally, we find that the 2014 flood had a positive and significant impact on women's empowerment in 2018, but this increase appears to be limited to those who have been affected by both floods.

This work contributes to the literature in two ways. First, it is one of the first studies to investigate the gender-specific impact of extreme weather events on time use and time poverty. Time use data are particularly useful for conducting in-depth analyses of individual and social behaviors, as well as for gaining a better understanding of policy impacts on women, men, and children (Floro and King, 2016). This research expands on the use of such data to better understand how people react to recurrent climatic shocks. Extreme weather occurrences are becoming more common as a result of climate change, particularly in developing countries (Guiteras et al., 2015). To build more effective, gender-differentiated, and informed policies, it is necessary to have a thorough understanding of how households respond to shocks and how such shocks influence the daily activities of men and women differently.

Second, it provides quantitative estimates of natural shocks long-term influence on women's empowerment and employment. Building on a recent research that shows that the 2014 flood in Bangladesh leads to an increase in women's paid labor and empowerment (Canessa and Giannelli, 2021), this analysis corroborates and expands on these findings by demonstrating that such changes are structural and persist over time. Indeed, using the third wave of the panel released in October 2020, this research examines the medium-term impact of the 2014 flood and it assesses the impact of the 2017 disaster on time use and women's empowerment. According to the findings of this study, the increase in women's empowerment brought about by the flood in 2014 has persisted over time, leading women to engage more on market rather than reproductive activities. This finding has far-reaching policy implications, as it demonstrates that, when endogenous, an increase in women's empowerment actually persists over time and leads to long-term changes in women's and men's behaviors within the household.

The paper proceeds as follow: Section 2 describes the context of the study; Section 3 presents the data employed for the study; Section 4 explains the empirical methodology adopted for the analysis; Section 5 introduces the results; Section 6 provides robustness checks to strengthen the analysis; and Section 7 concludes.

1.2 The context: gender norms and time allocation in Bangladesh

Bangladesh is a patriarchal society where men control property, income, and women's labor (Cain et al., 1979). Women in rural Bangladesh find themselves trapped in a circle that sees their role changing from daughter, to wife, to mother with little possibility to express independent goals or aspirations (Solotaroff, 2019). Patriarchy generates a system in which men feel allowed to claim power over women's lives. The major example of such control is "purdah" (i.e., seclusion), a common practice that confines women's sphere of activities within the homestead, limiting their access to economic and social opportunities (Kabeer, 1988; Solotaroff, 2019). For instance, the strict application of purdah prevents women to cultivate land themselves or to go to the market, and all these tasks have to be interceded by male household members (Kabeer, 1988; Solotaroff, 2019). Purdah also hinders women's access to the labor market, as they have to engage in income-generating activities within the compound (Cain et al., 1979; Kabeer, 1988). These patriarchal norms have engendered a highly segregated labor market and a rigid division of labor that still persists nowadays (Cain et al., 1979; Heintz et al., 2018).

Another common practice in rural Bangladesh is exogamy, i.e., marrying the daughter to a man living in another village (Cain et al., 1979; Kabeer, 1988). The application of exogamy makes women vulnerable and powerless. Indeed, when they marry, women move to the village where their husband lives, weakening their ties with their family of origin (Cain et al., 1979). Once married, women's autonomy is particularly limited because they are subjected to the will and supervision not only of their husband, but also of their mother-in-law, who plays an essential role within the family (Solotaroff, 2019). More generally, the practice of exogamy makes parents to invest less in their daughter's education, as she will leave the household at an early stage of her life (Solotaroff, 2019). In addition, women tend to claim less their land inheritance because they live away from their father's property and have to rely on others to represent their interests (Kabeer, 1988).

These norms define a strict division of labor within the household. Women employ most of their time in domestic work, to which men mainly contribute by shopping for consumer goods, since purdah severely limits women's mobility to go to the market (Cain et al., 1979). While men specialize in the stage of the agricultural production carried out in public space, women instead engage in activities carried out within the home (Kabeer, 1988). Consequently, women tend to specialize in activities that keep them close to the homestead, such as food processing and preparation, animal husbandry, and household maintenance (Cain et al., 1979). As for agricultural work, while men specialize in harvest and pre-harvest activities, women specialize in post-harvest activities (Cain et al., 1979). Women's peak periods of agricultural activity are in December-January, and in June-July, while they engage more in income-earning activities during February-March, which is a busy period in gardens cultivation, hut repair, and handicrafts (Cain et al., 1979).

These well-defined gender roles make women particularly vulnerable to negative shocks (Islam et al., 2017; Solotaroff, 2019). Indeed, they are not only at higher risk of being physically injured by disasters like floods (Cannon, 2002), but their coping strategies are also less effective because they lack access to crucial productive assets and resources (Solotaroff, 2019). Women are usually denied access to land (Solotaroff, 2019), and even if they are legally entitled to part of the inheritance, they usually trade this right with their kin in exchange of support in times of potential distress (Kabeer, 1988). Since land is usually not registered in their names, women cannot claim any compensation for any crop loss due to regular flooding and erosion (Thomas, 2004).

During floods, women have to plan and implement measures to mitigate disasters and risks. These measures include, but are not limited to, activities like preserving fuels and storing food, prepare portable mud stoves for future use, collect and store firewood in dry places, and store fodder for domestic animals (Khandker, 1988). In the aftermath of the shock, women mitigate household's risk induced by the flood by involving in food processing and selling in local markets, rearing catting and poultry, doing small business and saving for children's education (Khandker, 2007).

1.3 Data

1.3.1 GIS Data and floods

Between 2011 and 2018, Bangladesh experienced two severe flooding events, in 2014 and 2017. From mid-August 2014 until the end of September 2014 heavy rains and overflows from the Brahmaputra and Ganges rivers caused severe flooding that affected almost 3 million people, with an estimate of 275,000 individuals displaced. The flood was particularly intense in the northeastern part of the country, where more than 10,000 acres of crops were inundated and more than 600 schools remained closed. This event was registered as the worst event hitting the country since the flood in 2007 [2].

In August 2017 until mid-September 2017, Bangladesh was hit again by a dramatic flood recorded as one of the worst flooding events in recent history, affecting almost 7 million people and 9,000 villages. The overflows of the Brahmaputra and Ganges rivers led to the inundation of 31 districts in the northern part of the country. The flood caused significant damages to housing and infrastructures, in particular schools, roads, and railways, which resulted in the inundation of additional areas that would have been protected otherwise. The flood particu-

[2] https://reliefweb.int/sites/reliefweb.int/files/resources/a-i7876e$_0$.pdf

larly damaged the agricultural sector, causing losses in food crops (including the main staple rice), and livestock and fish stocks [3].

The treatment is defined as the households' exposure to the floods. Following the literature (Gröger and Zylberberg, 2016; Canessa and Giannelli, 2021), we adopt georeferenced data to construct the treatment variable. More specifically, we adopt the NASA Flooding Map, a product composed of 250-mt resolution images, that defines flooded areas as water observations falling outside normal water levels [4]. As in Canessa and Giannelli (2021), we adopt a composite image for an interval of 15 days, that defines an area as flooded if it is recognised as such for at least 2 days. This time-span of the composite image overcomes the issue of cloud coverage, providing more detailed data. We construct two treatment variables for the analysis, one for each flood. To decide which reference period to consider for the flood, we follow the information reported in the Official Reports in 2014 and in 2017 of the Bangladesh Water Development Board of the National Government. In 2014, the report states that the flood reached its highest peak at the end of August and during the first 10 days of September, while in 2017 during the last two weeks of August.

The units of analysis for the shock are the 6,500 sampled households, that are nationally representative of the country's rural areas. While Canessa e Giannelli (2021) define their treatment at the village level, for this study we had access to the georeferenced coordinates of the households, released with the Harmonized Bangladesh Integrated Household Survey in September 2017. The treatment variable is then defined as the share of pixels identified as "flooded" in a 5-km radius for each household in the sample. As robustness checks we repeat the analysis for 2- and 10-kms radius. The 5kms-radius allows for including the areas of agricultural activities of rural households (Gröger and Zylberberg, 2016; Canessa and Giannelli, 2021). Indeed, data in Table 1.1 show that the average distance of the land from the homestead is about 0.5-kms.

In 2017, with the treatment specification of the 5-km radius, the mean share of inundated areas corresponds to 9 percent, with the maximum reaching 93 percent. In normal times (i.e., the first two weeks of July 2017), the mean share is very low, around 1 percent, while the maximum reaches 22 percent. Figure 1.1 shows the average share of flooded areas for selected intervals before (1st to 14th of July 2017), during landfall (16th to 29th of August 2017), and in two periods after the landfall (29th to 11th of September 2017, and 15th to 30th of September 2017). It shows that 9 percent of the median household is inundated during the last two weeks

[3]https://reliefweb.int/disaster/fl-2014-000117-bgd

[4]All data are publicly available at the following link: https://floodmap.modaps.eosdis.nasa.gov/index.php

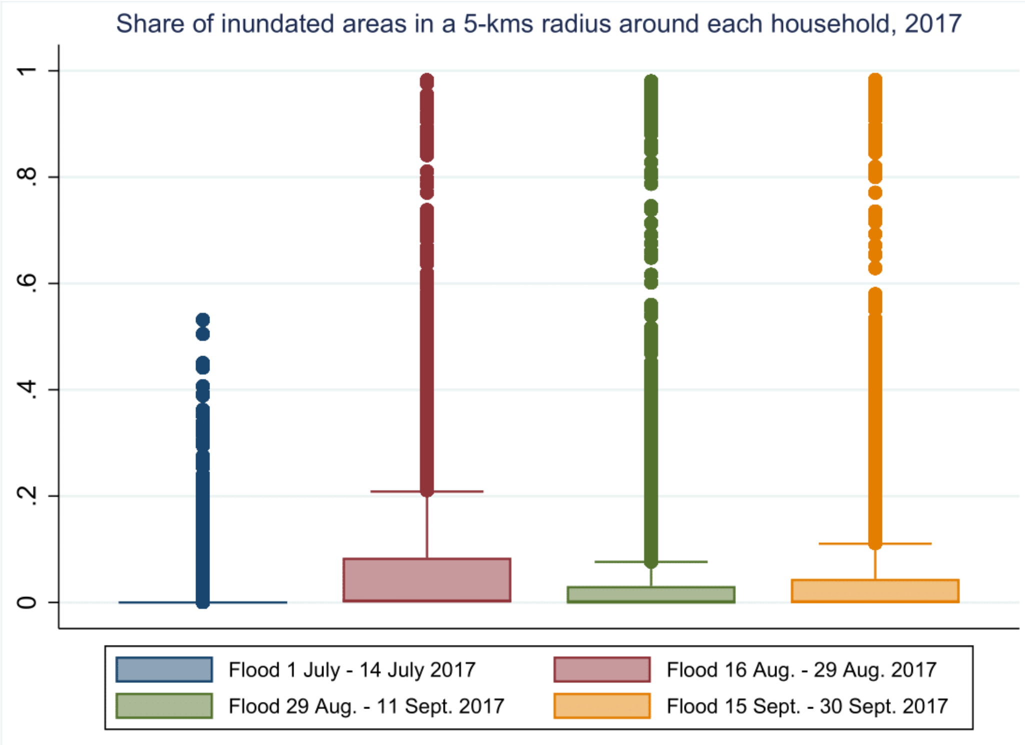


Figure 1.1: Share of inundated areas, 2017

of August. This number reaches 98 percent for the most affected households. It is important to notice that, after one month, around 7 percent of the households are still inundated, probably because of differences in soil absorption. This may impact differently time allocation among household members. in the Appendix, Figure 1.2 shows the incidence of the flood during the last 2 weeks of August 2017.

1.3.2 BIHS Data

The Bangladesh Integrated Household Survey (BIHS) is a panel dataset collected by the International Food Policy Research Institute (IFPRI) in three rounds, the first in 2011 (October 2011 – June 2012), the second in 2015 (January-June 2015), and the third in 2018 (November 2017 – March 2018). The survey is nationally representative of the rural areas in all seven divisions of the country and it follows approximately 6,500 households over the three waves. The attrition rate at the household level is 4.4 between the first and the second wave, and 6.7 between the second and the third wave.

The data provide detailed information at the household and individual level on socioeconomic characteristics, as well as agricultural production and practices, dietary intake, anthropometric measurements, and data to measure the Women's Empowerment in Agriculture Index (WEAI). The modules of the WEAI include a module on time use administered to both the household's head and the spouse. Data are collected using time diaries, in which respondents are asked to recall the time spent on activities in the 24 hours prior to the interview, starting at 4:00 am of the day before the interview. Thanks to their sequential nature paired with a very short recall period (i.e., 15 minutes), time-use diaries are more likely than stylized questions to avoid the recall bias because they help respondents to accurately remember their daily activities (Seymour et al., 2020). The main problem of time-use diaries in low- and middle-income countries is that a 24-hour recall does not consider adequately all factors of time allocation, especially in an agricultural setting. For instance, time-use diaries do not capture seasonal variations, or they do not account for festivities – if the day prior to the interview was a holiday, the data may not capture the actual dimension of individuals' workload (Alkire et al., 2013; Seymour et al., 2020). To account for the former concern, we add dummy variables to control for the month of interview in the analysis. As for the latter concern, in the sample only 6 percent of the respondents reported that the day before the interview was an holiday.

Our sample consists of 16,224 observations at the individual level, respectively 2,684 women and 2,684 men per year. We include in the sample only individuals that were present in all the three waves and that reported being the household head or the spouse in the time-use module, which is supposed to be administered to the main respondents of the household. In this way, around 20 percent of observations of the original sample are dropped. Being the allocation of time particularly gender-differentiated among household members in Bangladesh, we decided to focus only on household heads and spouses to have more detailed information on time use differences between men and women. Table 1.1 represents the summary statistics of the sample at baseline (2012). As we can notice, women spend disproportionately more time than men in domestic activities, while men are mostly engaged in market work activities. Men are also more likely to be time-poor than women, and they spend almost the same amount of time in leisure activities.

Table 1.1: Descriptive statistics at baseline (2012)

Variables	Obs	Mean	Std. Dev.	Min	Max
Women					
Minutes spent on domestic work	2705	497.074	141.249	0	960
Minutes spent on work	2705	53.473	108.710	0	720
Leisure time	2705	76.420	79.512	0	660
Time poverty line	2705	0.246	0.431	0	1
WEAI	1985	0.533	0.148	0.079	0.979

Table 1.1 continued from previous page

Working in paid activities	2705	0.635	0.481	0	1
Age	2663	35.402	10.501	16	99
Men					
Minutes spent on domestic work	1985	180.438	174.006	0	870
Minutes spent on work	1985	413.146	232.794	0	1050
Leisure time	1985	82.587	120.758	0	750
Time poverty line	1985	0.479	0.500	0	1
Age	2705	43.492	12.247	18	95
GIS Data					
Flood 16 Aug. - 29 Aug. 2017	5410	0.090	0.189	0	0.982
Flood 1 July - 14 July 2017	5410	0.009	0.040	0	0.532
Flood 28 Aug. - 10 Sept. 2014	5410	0.080	0.187	0	0.978
Flood 1 July - 14 July 2014	5410	0.037	0.113	0	0.854
Self-reported shock (dummy)	2816	0.105	0.307	0	1
Shock 2017 - Dummy	5408	0.612	0.487	0	1
Shock 2017 - Dummy	5408	0.590	0.491	0	1
Distance from plots - kms	5410	0.524	0.993	0	35
Household assets					
Number of electric iron owned	5410	0.053	0.257	0	4
Number of metal pots owned	5410	10.374	7.406	0	110
Number of stove owned	5410	0.023	0.184	0	4
Number of tv owned	5410	0.279	0.477	0	3

The outcome variables for time use patterns are the time (measured in minutes) spent in the last 24 hours in domestic work, in market work, and in leisure activities. Domestic work activities include caring for children and the elderly, cooking and cleaning, and shopping/getting services. The activities considered for market work are working as employed or for own business work, fishing, working in construction, farming, and commuting. Leisure activities include watching TV and listening to the radio, exercising, and engaging in social and religious activities. Time poverty is defined following Alkire et al. (2013) and Bardasi and Wodon (2006). In this study, an individual is time-poor if she worked more than 10.5 hours in the day prior to the interview. As in Canessa and Giannelli (2021), to look whether the floods had an impact on women's likelihood to engage in paid activities, we refer to the question "Are you now doing any work or business that brings in cash, additional food, or allows you to accumulate assets for your household?". To measure women's empowerment, we construct the WEAI, a survey-based index used to assess women's empowerment in agricultural settings[5]. The index is composed by two sub-indexes : the *Five domains of empowerment (5DE)* and the *Gender Parity Index (GPI)*, that weigh respectively 90 and 10 percent in the final index. The 5DE score is a weighted average of 10 indicators grouped in five domains: (1) decisions over agricultural production, (2) access to and decision-making power over productive resources, (3) control over use of income, (4) leadership in the community, and (5) time allocation (Alkire et al., 2013). Women are considered *adequate* on each indicator if their score is equal to or higher than a specified threshold for each domain (Alkire et al., 2013).

1.4 Empirical methodology

1.4.1 Impact of the flood in 2017 on time use and women's empowerment

The identification strategy relies on the assumption that the flood, given its exogenous nature, is not correlated with other omitted determinants of time allocation within the household. To estimate the impact of the flood on time use patterns of men and women we adopt a difference-in-difference methodology, controlling for time-invariant unobserved individual characteristics of the respondents to the "time-use module" common to the three waves. The treatment is a continuous variable for the share of inundated areas in 2017 in a range of 5-kms around each sampled household. We estimate the following specification for men and women separately:

$$Y_{ihrt} = \beta_0 + \beta_1 \, (T_h * t_{=2018}) + \beta_2 \, (P_h * t_{=_{2018}}) + \beta_3 \, W_r t + \beta_4 \, X_{iht} + \beta_5 \, D_t + \beta_6 \, Z_{ht} + \alpha_i + \varepsilon_{ihrt}$$

Where Y_{ihrt} are the outcome variables for each individual i in household h residing in region r at time t; T_h is the treatment variable, i.e., the share of inundated pixels in a buffer of 5-kms for each household; t is the time variable; and β_1 is the difference-in-difference coefficient of the treatment, which gives us the difference in the outcome of interest after the flood between the treatment and the control group. Following the literature (Gröger and Zylberberg, 2016; Canessa and Giannelli, 2021), P_h is the household propensity to be inundated in normal

[5]For a comprehensive explanation of the index components and its construction, please refer to Alkire et al. (2013)

times, measured by the percentage of water coverage in a buffer of 5-kms for each household during the first two weeks of July 2017. This control aims at identifying changes in time allocation due to the treatment for those households that have the same propensity to be inundated in normal times. W_{rt} are interactions between wave and regional fixed effects to account for changes in regional characteristics over time; D_t are the dummy variables of the month of interview, taking as reference January to avoid any problem of collinearity. X_{iht} are individual and household socio-economic characteristics that may shape time-use patterns, namely the number of members under the age of 15, the age and education of both spouses. We control also for household's durable, agricultural, and livestock assets, as measured by the Principal Component Analysis. We control for the level of wealth rather than for yearly income or expenditure estimates because the latter are usually prone to the recall bias, which makes the available information less accurate (Arthi et al., 2016). Z_{ht} is a set of control variables that may influence the home production function, i.e., the number of electric irons owned by the household, the number of gas stoves, the number of cooking stoves, and the access to electricity. Since individuals seem to spend most of their time of leisure activities by watching television, we also added as a control the number of televisions owned by the household. To control for the household's probability of being inundated, we also control for the house's distance from the river, the soil slope, and the soil type. The fixed effects at the individual level are α_i , and ε_{ihrt} is the error term. For the heterogeneity analysis the identification strategy is the same, but we repeat the analysis separately for men and women for two sub-samples of the population, i.e., those individuals that have experienced the flood in 2014 and those who have not.

1.4.2 Long-term impact of the flood in 2014 on women's empowerment

The study also looks at whether the shock in 2014 has led to a persistent increase of women's empowerment over time and whether it influences time allocation between men and women after the shock in 2017. We estimate the same identification strategy as before, employing as dependent variable the WEAI and as treatment variable the share of inundated areas around each sampled household in 2014:

$$\text{WEAI}_{ihrt} = \beta_0 + \beta_1\,(T_h{*}\,t_{=2014}) + \beta_2\,(P_h{*}\,t_{=2014}) + \beta_3\,W_r t + \beta_4\,X_{iht} + \beta_5\,D_t + \beta_6\,Z_{ht} + \alpha_i + \varepsilon_{ihrt}$$

To check whether results differ between women that have been exposed to both shocks or only to the first one, we run a heterogeneity analysis dividing the sample of women on those that experienced both floods and those who experienced only the one in 2014. Control variables are the same than in the main analysis.

1.5 Results

This section presents the estimated effects of the flood on time allocation of men and women, on time poverty, on the likelihood of women to engage in paid activities, and on their empowerment as measured by the WEAI. We first present the results of the impact of the flood occurred in 2017, then the results of the heterogeneity analysis, and lastly the results for the long-term impact of the shock in 2014 on women's empowerment and time allocation.

1.5.1 The impact of the flood in 2017 on time allocation

Table 1.2: Impact of the flood of 2017 on time use variables for women and men

	Women				**Men**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Domestic work	**Market work**	**Leisure**	**Time poverty**	**Domestic work**	**Market work**	**Leisure**	**Time poverty**
Year 2018	3.631	10.65	38.15***	0.043	-3.681	-18.33	35.14***	-0.010
	(13.90)	(10.22)	(9.587)	(0.0295)	(7.278)	(15.05)	(11.52)	(0.0318)
Treat	**-55.55****	**-12.42**	**93.65*****	**-0.063**	**73.49*****	**-61.68**	**-28.63**	**0.171****
	(26.86)	**(27.29)**	**(22.47)**	**(0.084)**	**(20.13)**	**(37.57)**	**(25.19)**	**(0.0828)**
Year#July 2017	203.6*	-46.09	-157.8	0.279	-19.31	-136.3	-91.98	-1.076***
	(106.8)	(99.40)	(97.93)	(0.364)	(92.51)	(154.2)	(109.4)	(0.412)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,352	4,997	5,352	5,352	5,352	5,240	5,352	5,352
R-squared	0.061	0.077	0.091	0.033	0.018	0.013	0.034	0.010
Number of id	2,684	2,680	2,684	2,684	2,684	2,684	2,684	2,684

Note: Clustered standard errors at the household level in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The reported time use variables denote the minutes spent in domestic work, in market work, in leisure activities and time poverty, defined as a dummy equals to 1 if the individual worked more than 10.5 hours in the previous day. Control variables are those reported in Section 1.4.1. Missing observations for the variable "Market Work" are for those individuals that reported not being employed in any work activities the day before the interview.

As shown in Table 1.2, the flood of 2017 significantly impacts time use variables. In the aftermath of the shock, women engage 55 minutes less in domestic work, while men increase their time spent in housework by 74 minutes. Men also decrease their time spent in market activities, and they reduce their time spent in leisure activities, even if not significantly. Such increased engagement in domestic activities leads them to be 14 percentage points more likely to be time poor, if compared to men that did not experience the flood. By contrast, women increase their time spent in leisure activities by 94 minutes, and they are less likely to be time poor by 12 percentage points. These first general results corroborate the hypothesis that, after the shock, women engage less in domestic work and more in market and leisure activities as a risk-coping strategy (Canessa and Giannelli, 2021; Lee et al., 2021). The results show also that men reallocate their time from market to domestic activities, and they are 17 percentage points more likely to be time poor. To better understand this reallocation of time, we also look at the impact of the flood on women's empowerment, as measured by the WEAI, and on their probability of engaging in paid activities.

Table 1.3: Impact of the flood of 2017 on women's employment and women's empowerment

	(1)	(2)
	Paid activities	**WEAI**
Year 2018	0.102***	-0.033***
	(0.022)	(0.010)
Treat	**0.373*** **	**0.035***
	(0.060)	**(0.026)**
Year#July 2017	-0.455*	-0.009
	(0.247)	(0.114)
Control	Yes	Yes
Observations	5,352	5,352
R-squared	0.090	0.033
Number of id	2,684	2,684

Note: Clustered standard errors at the household level in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The dependent variables are defined as a dummy equals to 1 if the woman reported being engaged in paid activities, and the Women's Empowerment in Agriculture Index (WEAI), as defined by Alkire et al. (2013). Control variables are those reported in Section 1.4.1.

Table 1.3 shows that the shock significantly increases women's likelihood of being employed in paid activities by 37 percentage points, confirming the results of Canessa and Giannelli (2021), and women's empowerment significantly increases by 0.035 points (the index ranges between 0 and 1). Following Anderson and Eswaran (2009), we speculate that this reallocation of time is due to the increased engagement of women in paid activities. According to the authors, as the wife's unearned income increases, so does her time spent on reproductive activities and leisure, while her time devoted to earning income declines. On the other side, as the wife's implicit wage rate rises, she contributes less to domestic duties, while men spend more time on housework to substitute for women's work (Anderson and Eswaran, 2009). These results are also in line with the recent paper showing that the 2014 flood led to an increase in women's empowerment and in their labor supply (Canessa and Giannelli, 2021) [6].

1.5.2 Heterogeneity analysis

To check whether the exposure to the flood in 2014 affected the response to the flood in 2017, we conduct a heterogeneity analysis on two sub-samples of the population, i.e., those individuals that experienced the flood in 2014 and those who did not. Results show significant and opposite effects for the two groups for both women and men.

As shown in Tables 1.4 and 1.5, the impact of the flood in 2017 on time use variables is confirmed only for women that experienced both shocks: they significantly decrease their time spent in domestic work by 100 minutes and increase the time spent in leisure activities by 122 minutes, and their likelihood of being time poor decreases by 21 percentage points. They are also more likely to engage in paid activities by 22 percentage points. On the other hand, women that did not experience the flood in 2014 show the opposite reaction to the flood in 2017. They disproportionately increase their time spent in domestic work and reduce their time spent in market activities by 270 minutes, the time spent in leisure activities decreases by 138 minutes, even if not significantly, and they are more likely to be time poor. When disentangling the effect of the flood for these two groups, the effect on women's empowerment is not significant anymore. As shown in Canessa and Giannelli (2021), the flood may have an indirect impact on empowerment through the channel of their engagement in paid activities.

[6] It is worth noticing that the engagement in paid activities does not imply that women are working more outside the household. As already stated, women's mobility in rural Bangladesh is particularly limited by the practice of purdah. From the data, it appears that women mostly engage in paid activities that are carried out within the homestead. This implies that they reallocate their time from reproductive to productive agricultural activities that do not require them to leave the household (e.g., crop processing). Unfortunately, the data do not allow for a deeper investigation on the type of activities women engage in.

Table 1.4: impact of the flood of 2017 on time use variables, heterogeneity analysis - women

	Flood 2014 = yes				Flood 2014 = no			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Domestic work	Market work	Leisure time	Time poverty	Domestic work	Market work	Leisure time	Time poverty
Year 2018	13.47	39.77***	37.09***	0.158***	26.51*	43.14***	32.50***	0.162***
	(18.44)	(13.83)	(13.26)	(0.0384)	(15.10)	(15.36)	(12.50)	(0.0461)
Treat	**-100.1*** **	**-14.76**	**122.4*** **	**-0.213** **	**466.2*** **	**-277.1** **	**-73.77**	**0.711* **
	(30.41)	**(31.89)**	**(26.47)**	**(0.0934)**	**(155.2)**	**(152.3)**	**(126.2)**	**(0.506)**
Year#July 2017	236.7**	-79.50	-185.7*	0.242	-445.7	370.6	-298.4	3.90
	(109.6)	(99.84)	(99.35)	(0.360)	(1986.2)	(1855.3)	(1583.15)	(7.44)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,152	2,908	3,152	3,152	2,202	2,091	2,202	2,202
R-squared	0.085	0.142	0.099	0.057	0.068	0.148	0.081	0.060
Number of id	1,582	1,578	1,582	1,582	1,103	1,103	1,103	1,103

Note: Clustered standard errors at the household level in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The reported time use variables denote the minutes spent in domestic work, in market work, in leisure activities and time poverty, defined as a dummy equals to 1 if the individual worked more than 10.5 hours in the previous day. Control variables are those reported in Section 1.4.1. Missing observations for the variable "Market Work" are for those individuals that reported not being employed in any work activities the day before the interview.

Table 1.11 in the Appendix shows that differences between men that have and have not experienced the flood in 2014 are less striking than for women. However, results show that men that were exposed to the shock in 2014 increase their time spent in domestic activities by 55 minutes and decrease their time spent in market activities by 117 minutes. For men that did not experience the flood in 2014 instead, results show a significant impact only in the reduction of time spent in market activities. These findings strengthen the results of Canessa e Giannelli (2021) and they build on them by showing that the impact of the flood in 2014 on women's labor supply and empowerment persists over time and it leads both spouses to react differently to the shock in 2017 [7].

[7] These results also show that for all men in our sample these flooding events increase their likelihood of being unemployed. Whether they experience both floods or not, all men reduce their time spent in market activities. We find a significant difference in means in the likelihood of being employed the 7 days prior to the interview between men that experienced the flood in 2017 and those who did not, regardless on whether they experienced the flood in 2014 or not. These results strengthen the hypothesis that the shock in 2014 is not directly influencing time allocation in 2018.

Table 1.5: impact of the flood of 2017 on women's empowerment and employment, heterogeneity analysis - women

	Flood 2014 = yes		**Flood 2014 = no**	
	(1)	**(2)**	**(3)**	**(4)**
	Paid activities	**WEAI**	**Paid activities**	**WEAI**
Year 2018	0.0864***	-0.0268**	0.163***	-0.0505***
	(0.030)	(0.013)	(0.033)	(0.013)
Treat	**0.204*** **	**0.0250**	**0.214**	**-0.142**
	(0.069)	**(0.029)**	**(0.377)**	**(0.132)**
Year#July 2017	-0.459*	0.003	-9.606**	0.004
	(0.244)	(0.115)	(4.761)	(1.432)
Control	Yes	Yes	Yes	Yes
Observations	3,152	3,152	2,200	2,200
R-squared	0.153	0.028	0.081	0.054
Number of id	1,582	1,582	1,102	1,102

Note: Clustered standard errors at the household level in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The dependent variables are defined as a dummy equals to 1 if the woman reported being engaged in paid activities, and the Women's Empowerment in Agriculture Index (WEAI), as defined by Alkire et al. (2013). Control variables are those reported in Section 1.4.1.

It is interesting to notice also the differences in the impact of the control variable for "normal times". As already mentioned, women in Bangladesh usually engage in specific activities to prepare for the flood, like collecting firewood, storing food, and securing the household. This preparation is reflected in the impact that the control variable for normal times has on the time spent in domestic work, which increases by 236 minutes for women that experienced the flood in 2014. For the other group, the effect is not significant and, by contrast, the time women spend in domestic work is reduced. The same results are valid for leisure activities: women already hit by the flood in 2014 engage less in leisure activities in July 2017, while for those that were not hit in 2014 there is no significant effect. Moreover, women that already experienced the shock reduce their time spent in market activities, while for those that did not experienced the shock in 2014 their time spent in productive work increases, even if not significantly. The only similar effects are found in the probability of engaging in paid activities, that decreases for both groups.

These results suggest the presence of an adaptive capacity to climate change, which translates in a learning-by-doing adaptation strategy (Adger et al., 2003; Davidson-Hunt and Berkes, 2003). Adaptive capacity is a dynamic notion of adaptation, which enhances the importance of learning about risks, exchanging information, and sharing knowledge to anticipate, forecast, and react more efficiently to future weather shocks (McGray et al., 2007; Osbahr, 2007; Tschakert and Dietrich, 2010). In this case, it seems that, after experiencing the first shock in 2014, women respond more promptly to the flood in 2017.

1.5.3 Impact of the flood of 2014 on women's empowerment

Table 1.6 shows that, when looking at the whole sample of women, the 2014 flood has a persistent impact on both women's empowerment and employment. In 2018, the 2014 shock still affects women's probability of engaging in paid activities by 29 percentage points, and it increases their empowerment by 0.06.

Table 1.6: impact of the flood of 2014 on women's empowerment in 2018

	All women		**Flood 2017 = yes**		**Flood 2017 = no**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	WEAI	**Paid activity**	**WEAI**	**Paid activity**	**WEAI**	**Paid activity**
Year 2018	-0.0334***	0.103***	-0.0315**	0.0977***	-0.0351**	0.138***
	(0.0108)	(0.0239)	(0.0138)	(0.0319)	(0.0147)	(0.0359)
Treat	**0.0652***	**0.292*****	**0.0576***	**0.116**	**0.198**	**-3.310****
	(0.038)	**(0.088)**	**(0.040)**	**(0.092)**	**(0.732)**	**(1.573)**
Year#July 2014	-0.0465	0.0793	-0.0443	0.195	1.844	-23.83***
	(0.0616)	(0.149)	(0.0624)	(0.147)	(2.870)	(7.833)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,352	5,352	3,271	3,271	2,081	2,081
R-squared	0.033	0.090	0.029	0.151	0.053	0.062
Number of id	2,684	2,684	1,642	1,642	1,042	1,042

Note: Clustered standard errors at the household level in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The dependent variables are defined as a dummy equals to 1 if the woman reported being engaged in paid activities, and the Women's Empowerment in Agriculture Index (WEAI), as defined by Alkire et al. (2013). Control variables are those reported in Section 1.4.1.

Table 1.9 in the Appendix shows the impact of the flood on the various dimensions of the

WEAI. The flood has a positive and persistent impact on two specific indicators: input in productive decisions and control over use of income. When looking at the other sub-indexes, we can notice that the flood in 2014 reduced women's autonomy in productive decisions, their ownership of assets and access to credit, their membership to social groups, and their perception of leisure time. As the shock leads to an increase in women's engagement in paid activities, it is reasonable to think that the increase on control over use of income and input in productive decisions outweighs the negative effect of the flood on the remaining WEAI's indicators. An increase in empowerment does not imply an increase in well-being: the majority of WEAI's sub-indexes have a negative sign, suggesting that women's overall well-being did not necessarily increased along with empowerment.

As the long-term impact of the first shock may depend on the occurrence of the second one, we conduct the analysis also for women that have experienced the flood in 2017 and those who have not. The results show that, for women that have been exposed to both shocks, the flood of 2014 still increases their empowerment but it has no significant impact on their probability of engaging in paid activities. On the other hand, for those women that did not experience the shock in 2017, the flood in 2014 has a negative and significant impact on their likelihood of being employed, and it has a positive but not statistically significant impact on their level of empowerment.

These results imply that the increase in women's engagement in paid activities is strictly related to a specific period of time, as it increases in the aftermath of the shock to contribute to the increased household's expenses, but it does not last over time. For those women exposed to both shocks, their engagement in paid activities does not increase significantly but neither it decreases. When looking at their empowerment, results suggest that being repeatedly exposed to exogenous negative shocks increases significantly women's empowerment over time. Interestingly, it seems that for women exposed only to the flood of 2014, their empowerment level in 2018 has not decreased along with their probability of engaging in paid activities, but it has remained stable after the shock. This implies that the exposure to negative economic shocks can trigger a persistent change in women's empowerment that would not have happened otherwise. In other terms, when women's economic position is "endogenously" challenged within the household, its increase persists over time and leads to different reactions of men and women to the subsequent shock.

1.6 Robustness checks

1.6.1 Attrition

We perform an attrition analysis to address the problem of potential bias due to the correlation between the occurrence of flooding and the failure to track individuals in the following wave because of displacement of the households or changes in the composition of the family (e.g., men may have migrated to find work in urban areas or women may have became widowers [8]). To account for attrition, we run the analysis for the balanced as well as unbalanced samples and compare the coefficient estimates (Wooldridge, 2010): as shown in Table 1.12 in the Appendix, the coefficients are very similar for the 2017 shock in the balanced and unbalanced samples, thus ruling out the possibility that attrition, in this case, may be selective.

When we look at the impact of the 2014 shock on women's empowerment in 2018 (Table 1.13), the coefficients between the balanced and unbalanced samples are similar but not the same: in the unbalanced sample, the impact of the flood is not significant anymore. However, we observe no differences in the coefficients of the WEAI's sub-indexes between the balanced and unbalanced samples (Table 1.14). These results may raise concerns about a potential sample composition effect: women that experienced the 2014 flood and were interviewed only at baseline may have dropped out of the sample because they did not survive the shock (i.e., they were less empowered). To check for this concern, we look at differences in mean in empowerment at baseline between attritors and non-attritors. Table 1.7 shows that there are no significant differences, suggesting that the reason for dropping out from the survey was not linked to their empowerment levels.

Table 1.7: Mean differences in WEAI between attritors and non-attritors at baseline

	Non attritors	Mean	Attritors	Mean	Diff	St Err	p value
WEAI	4010	.534	2262	.53	.004	.004	.346

1.6.2 Different definitions of the treatment

As a first robustness check of the results, we repeat the analysis with the treatment defined as the share of inundated areas in a radius of 2 and 10-km around each sampled household. As shown in Table 1.15 and Table 1.16 in the Appendix, results confirm that they are robust across different definitions of the treatment.

[8] It is worth noticing that widows constitute 5.5 percent of the unbalanced sample and 4.3 percent of the balanced sample, and the attrition rate for widows in the sample is 2.11 percent.

1.6.3 Self-reported data

As additional robustness check, we also repeat the analysis using as treatment variable the self-reported information of having experienced the flood or not in the year preceding the survey. The data provide detailed information on the shocks the household experienced over the past 5 years. As alternative treatment, we employ a dummy variable equal to 1 if the household reported loss of crops, livestock, productive assets, and consumption assets due to floods in the year prior to the survey of 2018. Results are shown in Table 1.17 and Table 1.18 in the Appendix. Women decrease their time spent in domestic work by 110 minutes, they are 33 percentage points less likely to be time poor, and 12 percentage points less likely to have any input in production decision. For men instead there is no significant impact, even though the sign of the effect of the self-reported shock is consistent with the treatment variable derived from GIS data.

These results confirm that adopting GIS data to study the impact of weather events leads to more accurate, precise, and reliable results. Indeed, self-reported data are prone to several forms of cognitive biases, such recall error and reference dependence (Guiteras et al., 2015). This last bias is of particular concern when studying the impact of flooding events because people may set as a reference point the average exposure conditions and consider then deviations from that specific average. This can translate in different perceptions and, consequently, different report of the magnitude of the shock between households that are frequently exposed to floods and those who are not (Guiteras et al., 2015).

1.6.4 Parallel trends

To check for ex-ante correlation between the treatment and the trends of our variables of interest, we follow (Gröger and Zylberberg, 2016). We first perform a balance test at baseline (i.e., 2015), to check for mean differences between treated and untreated individuals before the occurrence of the shock. Table 1.19 in the Appendix shows that the treatment variable is correlated with some of the outcomes of interest. To make sure that such correlations are not driven by the flood that occurred in 2014, we repeat the analysis in 2011. As shown in Table 1.8, except for the time spent in leisure activities for men, and the likelihood of being time poor for women, results are not significant, suggesting that in the absence of the shock the treatment and the control group would have followed the same path. To directly test for the presence of parallel trend assumption, we then run a placebo test between the first two waves, in 2011 and 2015. We replicate the benchmark strategy as if the flood hit in 2015, and we estimate the follow specification:

$$Y_{ihrt} = \beta_0 + \beta_1 (T_h * t_{=2015}) + \beta_2 (P_h * t_{=2015}) + \beta_3 W_r t + \beta_4 X_{iht} + \beta_5 D_t + \beta_6 Z_{ht} + \alpha_i + \varepsilon_{ihrt}$$

Results are reported in Table 1.8. For women the hypothesis of parallel trends seems to be confirmed except for one outcome variables, i.e., the probability of engaging in market work. Since this variable is likely to reflect the persistent impact of the flood in 2014, we add as a control variable the share of inundated areas in 2014. Results show that the impact of the treatment on the outcome is not significant anymore. For men the hypothesis of ex-ante correlations between the outcomes of interest and the treatment is not significant except for two variables, i.e., the time spent in domestic work and the probability of being time poor. As before, to check whether such results are driven also by the impact of the flood that occurred in 2014, we add as control variable the share of inundated areas in 2014. While the impact of the flood in 2017 is not significant anymore on the time spent in domestic work, it is still significant for the variable capturing time poverty.

Table 1.8: placebo test with first two waves on the impact of the flood in 2015

		Women	**Men**
		Year 2015#Flood 2017	**Year 2015#Flood 2017**
(1)	Domestic work	14.38	-115.7***
		(30.36)	(39.73)
(2)	Market work	44.89	21.71
		(27.89)	(66.67)
(3)	Leisure time	-22.60	40.35
		(17.72)	(41.26)
(4)	Time poverty	0.0954	-0.297**
		(0.0980)	(0.121)
(5)	WEAI	0.0170	
		(0.041)	
(6)	Paid activities	-0.217**	-
		(0.0844)	
Control for flood in 2014			
(7)	Paid activities	0.121	
		(0.144)	
(8)	Domestic work		-28.25

			(55.77)
(9)	Time poverty		-0.427**
			(0.175)
	Number of observations	4,944	4,335
	Number of id	2,678	2,676

Note: Clustered standard errors at the household level in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively.

1.7 Conclusion

Social and cultural norms highly influence time use differences between men and women worldwide. In low- and middle-income countries, while men usually engage in productive activities, women are in charge of reproductive work, which includes domestic activities such as cleaning, cooking, and caring for children and agricultural work in household farming. Climate change and extreme weather events risk increasing inequalities in time allocation both in the short and in the long period. In the aftermath of flooding events, women risk finding themselves overloaded by their engagement in both market and reproductive activities. Despite the literature has extensively focused on time use patterns in low-income countries, gender specific responses in time allocation to weather shocks have not received much attention yet.

This study assesses the impact of a dramatic flood that hit Bangladesh in 2017 on time allocation of women and men and on women's empowerment. As the data allow for including another dramatic flood that occurred in 2014, we also analyze the heterogeneous impact of the flood in 2017 distinguishing between individuals that have been previously inundated and those who have not. Building on a recent paper showing that the flood in 2014 led to an increase in women's empowerment in the aftermath of the shock, we also examine whether this increase persists over time in the medium-long term. The use of GIS satellite data and of panel data allows for the identification of the impact of the flood while controlling for unobserved time-invariant characteristics.

The results of the Difference-in-Difference estimation suggest that, after the shock, women's time allocation shift towards market and leisure activities while their time spent in domestic work decreases. On the other hand, men engage less in market activities while substituting women in housework activities, their leisure decreases and they become more time poor. These results are in line with the cross-sectional analysis of Anderson and Eswaran (2009), suggesting that women's autonomy in Bangladesh increases as their engagement in paid activities does. In addition, the authors show that as women engage more in paid employment, men start contributing more to domestic work. The heterogeneity analysis sheds light on the mechanisms underlying such changes in time allocation. Results show that individuals that were exposed the shock in 2014 react differently from those that were not, suggesting also the existence of adaptive capacity to climate change.

When looking into the potential mechanism that may be driving these results, we find that the increase in empowerment induced by the flood in 2014 and documented by Canessa and Giannelli (2021) persists over time, regardless of the exposure to the flood in 2017. These results are particularly relevant because they provide evidence that exogenous shock can challenge prevailing gender norms by increasing women's labor supply and women's empowerment. More importantly, they show that when an increase in empowerment occurs "endogenously", it persists over time and it leads both spouses to behave differently within the household.

One of the strengths of this study is the use of georeferenced data, employed to construct both treatment and control variables. As shown in the robustness checks, GIS data provide more robust and reliable results than self-reported data, which are usually prone to cognitive biases such as the recall bias. We also show that results are robust to different definitions of the treatment. Finally, the use of the first and second waves as a placebo test confirms that the parallel trend assumption holds for this analysis.

From a policy perspective, the findings of this study could have important implications. First of all, this study shows that women's and men's time use patterns react differently to weather shocks and they are influenced by two factors: women's level of empowerment and individuals' adaptive capacity to climate change. Both of them are an important target for the attainment of the Sustainable Development Goals (SDGs), especially SGD 5 and SGD 13. Gender-specific development interventions should be designed to increase women's ability to cope with shocks, to enhance their adaptive capacity, and their empowerment. Policies favoring women's access to labor market are certainly the crucial starting point. Participation to the labor market increases women's opportunities to access credit and, consequently, to productive resources essential for coping with shocks. Adaptive capacity, as considered in its dynamic perspective, could be boosted by skills development programs and farmer-to-farmer extension services.

References

Adger, W. N., Huq, S., Brown, K., Conway, D., and Hulme, M. (2003). Adaptation to climate change in the developing world. *Progress in Development Studies*, 3(3):179–195. Publisher: SAGE Publications India.

Alkire, S., Malapit, H., Meinzen-Dick, R., Peterman, A., Quisumbing, A., Seymour, G., and Vaz, A. (2013). Instructional Guide on the Women's Empowerment in Agriculture Index. page 82.

Anderson, S. and Eswaran, M. (2009). What determines female autonomy? Evidence from Bangladesh. *Journal of Development Economics*, 90(2):179–191.

Anxo, D., Mencarini, L., Pailhé, A., Solaz, A., Tanturri, M. L., and Flood, L. (2011). Gender Differences in Time Use over the Life Course in France, Italy, Sweden, and the US. *Feminist Economics*, 17(3):159–195.

Arora, D. (2015). Gender Differences in Time-Poverty in Rural Mozambique. *Review of Social Economy*, 73(2):196–221.

Arora, D. and Rada, C. (2017). A gendered model of the peasant household: Time poverty and farm production in rural mozambique. *Feminist Economics*, 23(2):93–119.

Arthi, V., Beegle, K., De Weerdt, J., and Palacios-Lopez, A. (2016). *Not your average job: Measuring farm labor in Tanzania*. The World Bank.

Bardasi, E. and Wodon, Q. (2006). Measuring Time Poverty and Analyzing Its Determinants: Concepts and Application to Guinea. page 22.

Bradshaw, S. and Fordham, M. (2013). Women and girls in disasters.

Cain, M., Khanam, S. R., and Nahar, S. (1979). Class, Patriarchy, and Women's Work in Bangladesh. *Population and Development Review*, 5(3):405.

Canessa, E. and Giannelli, G. C. (2021). Women's Employment and Natural Shocks. page 55.

Cannon, T. (2002). Gender and Climate Hazards in Bangladesh. *Gender and Development*, 10(2):45–50. Publisher: [Taylor & Francis, Ltd., Oxfam GB].

Davidson-Hunt, I. and Berkes, F. (2003). Learning as You Journey: Anishinaabe Perception of Social-ecological Environments and Adaptive Learning. *Conservation Ecology*, 8(1). Publisher: Resilience Alliance Inc.

Ferrant, G., Pesando, L. M., and Nowacka, K. (2014). Unpaid Care Work: The missing link in the analysis of gender gaps in labour outcomes. page 12.

Floro, M. S. and King, E. M. (2016). The present and future of time-use analysis in developing countries. *Asia-Pacific Population Journal*, 31(1):5–42.

Gammage, S. (2010). Time Pressed and Time Poor: Unpaid Household Work in Guatemala. *Feminist Economics*, 16(3):79–112.

Garg, T., Gibson, M., and Sun, F. (2020). Extreme temperatures and time use in China. *Journal of Economic Behavior & Organization*, 180:309–324.

Gröger, A. and Zylberberg, Y. (2016). Internal labor migration as a shock coping strategy: Evidence from a typhoon. *American Economic Journal: Applied Economics*, 8(2):123–53.

Guiteras, R., Jina, A., and Mobarak, A. M. (2015). Satellites, Self-reports, and Submersion: Exposure to Floods in Bangladesh. *The American Economic Review*, 105(5):232–236. Publisher: American Economic Association.

Halliday, T. J. (2012). Intra-household labor supply, migration, and subsistence constraints in a risky environment Evidence from rural El salvador. *European Economic Review*, page 19.

Heintz, J., Kabeer, N., and Mahmud, S. (2018). Cultural norms, economic incentives and women's labour market behaviour: empirical insights from Bangladesh. *Oxford Development Studies*, 46(2):266–289.

Islam, M. R., Ingham, V., Hicks, J., and Manock, I. (2017). The Changing Role of Women in Resilience, Recovery and Economic Development at the Intersection of Recurrent Disaster: A Case Study from Sirajgang, Bangladesh. *Journal of Asian and African Studies*, 52(1):50–67. Publisher: SAGE Publications Ltd.

Kabeer, N. (1988). Subordination and Struggle: Women in Bangladesh.

Kamei, A. (2019). Who is Walking More for Water? Climate-Shock on Women's/Children's Domestic Work Using Ugandan Panel Time-Use. *Climate-Shock on Women's/Children's Domestic Work Using Ugandan Panel Time-Use*, (July 2019):63.

Khandker, S. R. (1988). Determinants of Women's Time Allocation in Rural Bangladesh. *Economic Development and Cultural Change*, 37(1):111–126.

Khandker, S. R. (2007). Coping with flood: role of institutions in Bangladesh. *Agricultural Economics*, 36(2):169–180. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1574-0862.2007.00196.x.

Lee, Y., Haile, B., Seymour, G., and Azzarri, C. (2021). The heat never bothered me anyway: Gender-specific response of agricultural labor to climatic shocks in Tanzania. *Applied Economic Perspectives and Policy*, n/a(n/a). _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/aepp.13153.

McGray, H., Hammill, A., Bradley, R., Schipper, L., and Parry, J.-E. (2007). *Weathering the storm: options for framing adaptation and development*. OCLC: 952202181.

Moreno, J. and Shaw, D. (2018). Women's empowerment following disaster: a longitudinal study of social change. *Natural hazards*, 92(1):205–224.

Osbahr, H. (2007). Building resilience: adaptation mechanisms and. page 38.

Seymour, G., Malapit, H., and Quisumbing, A. (2020). Measuring Time Use in Developing Country Agriculture: Evidence from Bangladesh and Uganda. *Feminist Economics*, 26(3):169–199.

Solotaroff (2019). *Voices to Choices: Bangladesh's Journey in Women's Economic Empowerment*. The World Bank Group. OCLC: 1117903096.

Thomas, H. T. (2004). Bangladesh: Gender, Poverty and the MDGs. *Bangladesh Resident Mission and Regional and Sustainable Development Department*, Asian Development Bank:67.

Tschakert, P. and Dietrich, K. A. (2010). Anticipatory Learning for Climate Change Adaptation and Resilience. *Ecology and Society*, 15(2). Publisher: Resilience Alliance Inc.

Wodon, Q. and Blackden, C. M. (2006). *Gender, time use, and poverty in sub-Saharan Africa*. The World Bank.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

Appendix

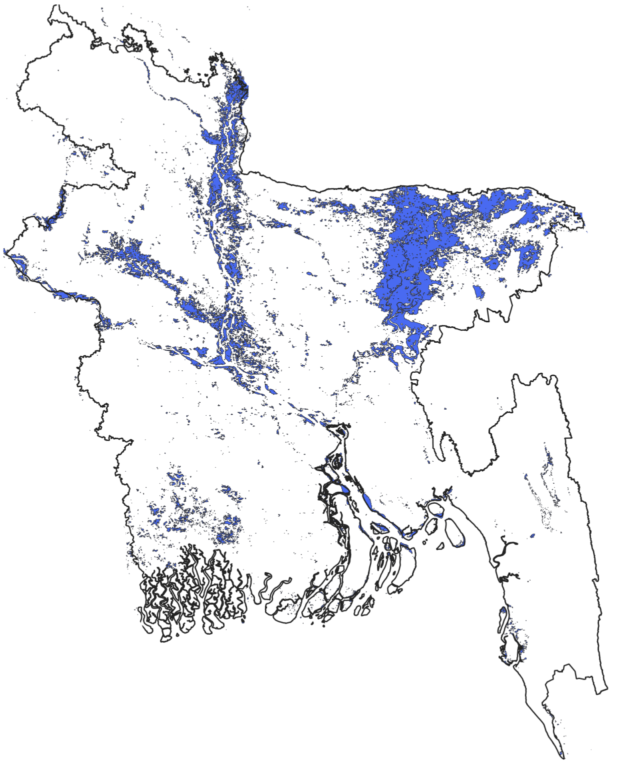


Figure 2: Incidence of the flood, 16-29 August 2017

Table 9: Impact of the flood of 2014 on WEAI's sub-indexes in 2018

	(1) Input	(2) RAI	(3) Asset own	(4) Asset sale	(5) Credit	(6) Control	(7) Group	(8) Speak	(9) Time poverty	(10) Leisure
Year (2018)	-0.0313*	-0.0351	0.00199	0.0371	0.0513*	-0.0114	0.329***	-0.0435	0.0414	0.00678
	(0.0171)	(0.0336)	(0.00219)	(0.0338)	(0.0305)	(0.0215)	(0.0339)	(0.0396)	(0.0295)	(0.0244)
Treat	**0.062****	**-0.509*****	**0.022**	**-0.387*****	**-0.176***	**0.189*****	**-0.0516**	**-0.337*****	**-0.0619**	**-0.245****
	(0.0244)	**(0.109)**	**(0.013)**	**(0.119)**	**(0.095)**	**(0.054)**	**(0.108)**	**(0.120)**	**(0.134)**	**(0.102)**
Year#July 2014	-0.117**	0.236	0.033	0.196	0.215	-0.199**	-0.160	0.094	-0.060	0.571***
	(0.047)	(0.177)	(0.023)	(0.200)	(0.165)	(0.094)	(0.186)	(0.195)	(0.214)	(0.167)
Control	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,352	5,352	5,352	5,352	5,351	5,352	5,352	5,352	5,352	5,352
R-squared	0.035	0.059	0.030	0.052	0.012	0.035	0.321	0.079	0.034	0.096
Number of id	2,684	2,684	2,684	2,684	2,684	2,684	2,684	2,684	2,684	2,684

Note: Clustered standard errors in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The reported variables are, respectively, the following WEAI's subindexes: input in productive decision; autonomy in decisions; ownership of assets; purchase, sale, or transfer of assets; access to and decisions on credit; control over use of income; group membership; speaking in public; workload; and leisure. All these variables have been constructed following Alkire et al. (2013). Control variables are those reported in Section 1.4.1..

Table 10: Impact of the flood in 2014 on time use variables in 2018

	Women				**Men**			
	(1) Domestic Work	(2) Market Work	(3) Leisure	(4) Time Poverty	(5) Domestic Work	(6) Market Work	(7) Leisure	(8) Time Poverty
Year 2018	1.912	10.26	40.42***	0.0338	-4.652	-15.89	35.27***	-0.00615
	(14.01)	(10.22)	(9.463)	(0.0296)	(7.124)	(15.21)	(11.63)	(0.0320)
2018#Flood 2014	**-18.88**	**-35.97**	**-16.89**	**-0.0617**	**62.44****	**-28.55**	**-75.00****	**0.0335**
	(40.88)	**(35.73)**	**(31.63)**	**(0.133)**	**(28.55)**	**(49.32)**	**(37.70)**	**(0.126)**
2018#July 2014	-28.99	-5.657	145.6***	-0.0659	20.18	-143.4*	100.8*	-0.156
	(68.38)	(54.25)	(54.25)	(0.213)	(52.22)	(84.19)	(56.54)	(0.205)
Control	Yes	Yes	Yes	Yes	Yes	Yes		
Observations	5,352	4,997	5,352	5,352	5,352	5,240	5,352	5,352
R-squared	0.061	0.077	0.089	0.033	0.019	0.017	0.034	0.008
Number of id	2,684	2,680	2,684	2,684	2,684	2,684	2,684	2,684

Note: Clustered standard errors in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The reported dependent variables denote the minutes spent in domestic work, in market work, in leisure activities and time poverty, defined as a dummy equals to 1 if the individual worked more than 10.5 hours in the previous day, the Women's Empowerment in Agriculture Index (WEAI), as defined by Alkire et al. (2013), and women's likelihood of being employed in paid activities, defined as a dummy equals to 1 if the woman if the woman reported being engaged in paid activities. Control variables are those reported in Section 1.4.1. Missing observations for the variable "Market Work" are for those individuals that reported not being employed in any work activities the day before the interview.

Table 11: impact of the flood of 2017 on time use variables, heterogeneity analysis - men

	Flood 2014 = yes				**Flood 2014 = no**			
	(1) Domestic work	(2) Market work	(3) Leisure time	(4) Time poverty	(5) Domestic work	(6) Market work	(7) Leisure time	(8) Time poverty
Year 2018	23.45***	-9.600	40.72***	0.0809**	5.624	3.562	29.25*	0.0493
	-8.881	(20.02)	(13.27)	(0.0383)	-8.423	(20.55)	(17.06)	(0.0512)
Treat	**52.12****	**-106.2****	**2.566**	**0.00393**	**80.39**	**-461.9*****	**12.77**	**-0.430**
	(23.21)	**(43.40)**	**(29.30)**	**(0.0923)**	**(71.14)**	**(167.2)**	**(132.8)**	**(0.479)**
2018 Year#July 2017	25.35	-183.5	-86.41	1.209***	-979.2	524.95	-128.26	3.13
	(76.39)	(149.8)	(110.4)	(0.404)	(843.4)	(2028.3)	(1705.8)	(5.567)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,152	3,085	3,152	3,152	2,202	2,156	2,202	2,202
R-squared	0.062	0.031	0.030	0.038	0.040	0.019	0.051	0.023
Number of id	1,582	1,582	1,582	1,582	1,103	1,103	1,103	1,103

Note: Clustered standard errors in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The reported time use variables denote the minutes spent in domestic work, in market work, in leisure activities and time poverty, defined as a dummy equals to 1 if the individual worked more than 10.5 hours in the previous day. Control variables are those reported in Section 1.4.1. Missing observations for the variable "Market Work" are for those individuals that reported not being employed in any work activities the day before the interview.

Table 12: impact of the flood of 2017 on time use variables, unbalanced sample (attrition)

	Women				**Men**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Domestic work	Market work	Leisure time	Time poverty	Domestic work	Market work	Leisure time	Time poverty
Year 2018	-3.380	10.79	48.18***	0.0346	-6.977	-11.68	37.79***	0.00653
	(9.545)	(8.798)	(8.002)	(0.0266)	(6.191)	(12.68)	(9.977)	(0.0295)
Treat	**-59.28****	**-19.81**	**108.8*****	**-0.0770**	**72.01*****	**-61.76***	**-19.96**	**0.105**
	(24.88)	**(25.71)**	**(21.14)**	**(0.0791)**	**(19.20)**	**(35.32)**	**(23.92)**	**(0.0795)**
July 2017	264.4***	-19.39	-242.2***	0.557*	-20.61	-62.42	-104.5	-0.697*
	(96.85)	(91.78)	(85.22)	(0.316)	(79.79)	(144.9)	(102.7)	(0.379)
Constant	246.9***	104.3**	294.1***	-0.163	-34.70	488.0***	237.6***	0.531***
	(59.52)	(46.93)	(54.52)	(0.153)	(46.66)	(91.07)	(74.63)	(0.198)
Observations	7,835	7,317	7,835	7,835	7,614	7,468	7,614	7,614
R-squared	0.063	0.074	0.089	0.031	0.016	0.014	0.031	0.008
Number of id2	4,872	4,767	4,872	4,872	4,716	4,696	4,716	4,716

Note: Clustered standard errors at the household level in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The reported time use variables denote the minutes spent in domestic work, in market work, in leisure activities and time poverty, defined as a dummy equals to 1 if the individual worked more than 10.5 hours in the previous day. Control variables are those reported in Section 1.4.1. Missing observations for the variable "Market Work" are for those individuals that reported not being employed in any work activities the day before the interview.

Table 13: impact of flood 2014 on WEAI, unbalanced sample

	(1)	(2)
	WEAI	Paid activity
Year 2018	-0.035***	0.0799***
	(0.008)	(0.0218)
Treat	0.0432	0.218***
	(0.0344)	(0.080)
July	-0.0150	0.0788
	(0.0555)	(0.138)
Constant	0.544***	0.499***
	(0.0551)	(0.136)
Observations	7,835	7,835
R-squared	0.039	0.099
Number of id2	4,872	4,872

Table 14: Impact of the flood of 2014 on WEAI's sub-indexes in 2018, unbalanced sample

	(1) Input	(2) RAI	(3) Asset own	(4) Asset sale	(5) Credit	(6) Control	(7) Group	(8) Speak	(9) Time poverty	(10) Leisure
Year 2018	-0.00592	-0.0637**	0.0122	-0.00355	0.0224	0.0212	0.326***	-0.0269	0.0363	-0.00715
	(0.00970)	(0.0281)	(0.0264)	(0.00440)	(0.0235)	(0.0152)	(0.0268)	(0.0286)	(0.0267)	(0.0237)
Treat 2014	0.0494**	-0.464***	-0.401***	0.0142	-0.194**	0.155***	-0.142	-0.390***	-0.00237	-0.323***
	(0.0216)	(0.0977)	(0.105)	(0.0117)	(0.0886)	(0.0486)	(0.103)	(0.111)	(0.115)	(0.0926)
July 2014	-0.0883**	0.209	0.278	0.0560*	0.262*	-0.174*	0.0460	0.261	-0.112	0.655***
	(0.0411)	(0.162)	(0.179)	(0.0293)	(0.151)	(0.0894)	(0.175)	(0.183)	(0.187)	(0.152)
Constant	0.989***	0.00654	0.109	0.941***	0.381**	0.590***	-0.0545	0.434**	-0.162	0.794***
	(0.0681)	(0.172)	(0.171)	(0.0330)	(0.154)	(0.0913)	(0.182)	(0.177)	(0.154)	(0.136)
Control	Yes	Yes	Yes	Yes	Yes	Yes				
Observations	7,835	7,835	7,835	7,835	7,831	7,835	7,835	7,835	7,835	7,835
R-squared	0.023	0.057	0.054	0.035	0.015	0.035	0.312	0.072	0.031	0.091
Number of id2	4,872	4,872	4,872	4,872	4,870	4,872	4,872	4,872	4,872	4,872

Note: Clustered standard errors at the household level in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The reported variables are, respectively, the following WEAI's subindexes: input in productive decision; autonomy in decisions; ownership of assets; purchase, sale, or transfer of assets; access to and decisions on credit; control over use of income; group membership; speaking in public; workload; and leisure. All these variables have been constructed following Alkire et al. (2013). Control variables are those reported in Section 1.4.1..

Table 15: robustness check - buffer of 10 kms around each sampled household

		Women	**Men**
		2018#flood 2017_10km	**2018#flood 2017_10km**
(1)	Domestic work	-64.07**	75.91***
		(30.10)	(21.29)
(2)	Market work	-35.58	-75.78*
		(31.89)	(41.55)
(3)	Leisure	97.21***	-19.64
		(0.0917)	(28.84)
(4)	Time poverty	-0.189**	0.154*
		(0.0655)	(0.0921)
(5)	WEAI	0.031	-
		(0.028)	
(6)	Paid activity	0.442***	-
		(0.0454)	
	Observations	5,354	5,353
	Number of id	2,685	2,685

Note: Clustered standard errors in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The reported dependent variables denote the minutes spent in domestic work, in market work, in leisure activities and time poverty, defined as a dummy equals to 1 if the individual worked more than 10.5 hours in the previous day, the Women's Empowerment in Agriculture Index (WEAI), as defined by Alkire et al. (2013), and women's likelihood of being employed in paid activities, defined as a dummy equals to 1 if the woman if the woman reported being engaged in paid activities. Control variables are those reported in Section 1.4.1.

Table 16: robustness check - buffer of 2 kms around each sampled household

		Women	**Men**
		2018#flood 2017_2km	**2018#flood 2017_2km**
(1)	Domestic work	-34.91*	65.98***
		(24.10)	(17.48)
(2)	Market work	-29.32*	-60.60*
		(22.56)	(33.64)
(3)	Leisure	73.22***	-37.61*
		(20.80)	(22.24)
(4)	Time poverty	-0.0803	0.0725
		(0.0748)	(0.0752)
(5)	WEAI	0.034*	-
		(0.023)	
(6)	Paid activity	0.388***	-
		(0.0548)	
	Observations	5,354	5,354
	Number of id	2,685	2,685

Note: Clustered standard errors in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The reported dependent variables denote the minutes spent in domestic work, in market work, in leisure activities and time poverty, defined as a dummy equals to 1 if the individual worked more than 10.5 hours in the previous day, the Women's Empowerment in Agriculture Index (WEAI), as defined by Alkire et al. (2013), and women's likelihood of being employed in paid activities, defined as a dummy equals to 1 if the woman if the woman reported being engaged in paid activities. Control variables are those reported in Section 1.4.1. Missing observations for the variable "Market Work" are for those individuals that reported not being employed in any work activities the day before the interview.

Table 17: robustness checks - impact of self-reported shock on outcome variables, women

	(1) Domestic work	(2) Market work	(3) Leisure time	(4) Time poverty	(5) Paid activities	(6) WEAI
year=2018	13.08	64.60*	24.69	0.113*	0.241***	0.0687**
	(20.71)	(35.29)	(16.17)	(0.0648)	(0.0419)	(0.0306)
year#flood	**-110.8****	**-9.715**	**62.11**	**-0.333****	**-0.0683**	**-0.001**
	(48.41)	**(51.87)**	**(42.18)**	**(0.157)**	**(0.0959)**	**(0.051)**
year#july 2017	145.8	-59.44	-121.5	0.124	-0.134	-0.0523
	(116.1)	(109.6)	(113.0)	(0.376)	(0.213)	(0.0915)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,257	2,902	3,257	3,257	3,257	3,257
R-squared	0.073	0.163	0.113	0.107	0.124	0.038
Number of id	2,68	2,394	2,68	2,68	2,68	2,68

Note: Clustered standard errors in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The reported dependent variables denote the minutes spent in domestic work, in market work, in leisure activities and time poverty, defined as a dummy equals to 1 if the individual worked more than 10.5 hours in the previous day, the Women's Empowerment in Agriculture Index (WEAI), as defined by Alkire et al. (2013), and women's likelihood of being employed in paid activities, defined as a dummy equals to 1 if the woman if the woman reported being engaged in paid activities. Control variables are those reported in Section 1.4.1.

Table 18: Robustness checks - impact of self-reported shock on outcome variables, men

	(1) Domestic work	(2) Market work	(3) Leisure time	(4) Time poverty
Year = 2018	20.41*	26.80	-0.185	0.131*
	(12.07)	(25.53)	(19.68)	(0.0679)
Year#flood	**65.46**	**13.04**	**-23.80**	**-0.0737**
	(40.65)	**(68.47)**	**(42.34)**	**(0.165)**
Year#july 2017	191.9**	-383.1**	-62.48	-1.053**

	(95.91)	(171.6)	(136.5)	(0.503)
Control	Yes	Yes	Yes	Yes
Observations	3,257	3,144	3,257	3,257
R-squared	0.062	0.048	0.053	0.074
Number of id	2,68	2,587	2,68	2,68

Note: Clustered standard errors in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The reported dependent variables denote the minutes spent in domestic work, in market work, in leisure activities and time poverty, defined as a dummy equals to 1 if the individual worked more than 10.5 hours in the previous day, the Women's Empowerment in Agriculture Index (WEAI), as defined by Alkire et al. (2013), and women's likelihood of being employed in paid activities, defined as a dummy equals to 1 if the woman if the woman reported being engaged in paid activities. Control variables are those reported in Section 1.4.1. Missing observations for the variable "Market Work" are for those individuals that reported not being employed in any work activities the day before the interview.

Table 19: balance test at baseline, 2011 and 2015

		OLS at baseline = 2011	**OLS at baseline = 2015**
		Flood 2017	Flood 2017
Women			
(1)	Domestic work	29.96	-22.00
		(34.83)	(36.75)
(2)	Market work	4.904	-15.92
		(27.25)	(21.79)
(3)	Leisure time	5.080	22.49
		(18.82)	(55.46)
(4)	Time poverty	0.237**	-0.242**
		(0.110)	(0.104)
(5)	Paid activities	-.0521	-.0535
		(0.119)	(0.095)
(6)	WEAI	0.052*	
		(0.033)	
	Number of observations	2,277	2,674
Men			

(7)	Domestic work	19.17	-22.00
		(53.73)	(36.75)
(8)	Market work	50.54	-33.12
		(68.74)	(33.88)
(9)	Leisure time	-72.12**	-92.21***
		(35.07)	(29.12)
(10)	Time poverty	0.0926	-0.153
		(0.150)	(0.111)
	Number of observations	1,661	2,674

Note: Clustered standard errors in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The reported dependent variables denote the minutes spent in domestic work, in market work, in leisure activities and time poverty, defined as a dummy equals to 1 if the individual worked more than 10.5 hours in the previous day, the Women's Empowerment in Agriculture Index (WEAI), as defined by Alkire et al. (2013), and women's likelihood of being employed in paid activities, defined as a dummy equals to 1 if the woman if the woman reported being engaged in paid activities. Control variables are those reported in Section 1.4.1. Missing observations for the variable "Market Work" are for those individuals that reported not being employed in any work activities the day before the interview.

Table 20: Impact of the flood of 2017 on time use variables for women and men

	Women				**Men**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Domestic work	**Market work**	**Leisure**	**Time poverty**	**Domestic work**	**Market work**	**Leisure**	**Time poverty**
Year = 2018	3.631	10.65	38.15***	0.043	-3.681	-18.33	35.14***	-0.010
	(13.90)	(10.22)	(9.587)	(0.0295)	(7.278)	(15.05)	(11.52)	(0.0318)
Year#Flood 2017	**-55.55****	**-12.42**	**93.65*****	**-0.063**	**73.49*****	**-61.68**	**-28.63**	**0.171****
	(26.86)	**(27.29)**	**(22.47)**	**(0.084)**	**(20.13)**	**(37.57)**	**(25.19)**	**(0.0828)**
Year#July 2017	203.6*	-46.09	-157.8	0.279	-19.31	-136.3	-91.98	-1.076***
	(106.8)	(99.40)	(97.93)	(0.364)	(92.51)	(154.2)	(109.4)	(0.412)
Year#Central Bengal	-12.98	31.11***	-11.65	-0.018	-7.957	14.31	-17.17	-0.0297
	(11.12)	(11.23)	(8.615)	(0.032)	(7.377)	(14.28)	(10.44)	(0.0324)
Year#North Bengal	-10.25	21.97*	-0.711	0.001	-6.995	25.32*	-28.25**	-0.005
	(11.65)	(11.61)	(8.774)	(0.035)	(8.144)	(15.24)	(11.38)	(0.034)
February	2.644	-25.47***	-3.368	-0.075***	-7.868	-10.79	8.796	-0.019
	(8.763)	(8.834)	(7.005)	(0.027)	(6.385)	(11.81)	(8.705)	(0.027)

March	-9.917	-25.95**	-14.83	-0.102***	-24.84***	-1.414	19.05	-0.039
	(12.74)	(12.85)	(10.01)	(0.038)	(9.159)	(16.37)	(12.73)	(0.038)
April	-22.72	-45.00***	-4.712	-0.229***	-5.725	-42.33*	45.36***	-0.0186
	(15.93)	(16.06)	(12.41)	(0.049)	(11.93)	(21.96)	(15.58)	(0.048)
November	-22.48*	9.053	1.093	-0.060	0.844	24.17	23.47*	0.031
	(13.65)	(13.84)	(10.96)	(0.040)	(8.411)	(16.16)	(12.76)	(0.039)
December	-3.801	-8.884	14.85**	-0.062**	-0.336	17.74	16.11*	0.032
	(9.098)	(9.541)	(7.385)	(0.028)	(6.417)	(12.19)	(9.055)	(0.028)
Members, age <15	44.63***	-11.23**	-12.98***	0.083***	6.737**	5.006	-6.254	0.024*
	(5.049)	(4.628)	(3.740)	(0.014)	(3.416)	(6.421)	(4.733)	(0.013)
HH head education	-0.00270	-0.554*	0.475*	-0.001*	0.373***	-0.603	0.063	-0.001
	(0.318)	(0.333)	(0.267)	(0.001)	(0.144)	(0.390)	(0.386)	(0.001)
Woman education	-0.0207	0.503	0.795*	0.000	-0.0298	-0.185	0.519	0.000
	(0.568)	(0.455)	(0.461)	(0.001)	(0.205)	(0.439)	(0.411)	(0.001)
Woman age	2.998	0.750	-0.759	0.008**	2.119	2.778	0.549	0.009*
	(3.318)	(1.577)	(2.061)	(0.003)	(1.429)	(2.978)	(2.365)	(0.005)
Electricity	15.33*	-16.33*	-6.692	0.009	-0.183	-15.79	-4.858	-0.012
	(8.803)	(9.314)	(7.040)	(0.028)	(6.223)	(12.30)	(8.961)	(0.028)
Dur. asset - quintile	-5.931	-4.429	3.903	-0.0291*	1.203	-2.289	7.694	-0.004
	(5.185)	(5.126)	(4.080)	(0.015)	(3.480)	(6.893)	(4.839)	(0.015)
Prod. asset - quintile	-1.931	4.038	-5.091*	0.014	0.845	2.964	-9.317**	3.06
	(3.779)	(3.862)	(3.089)	(0.012)	(2.697)	(5.507)	(4.015)	(0.011)
Liv. asset - quintile	-3.532	18.88***	-12.50***	0.029***	-1.505	3.487	-6.694**	-0.007
	(3.031)	(3.185)	(2.348)	(0.009)	(2.130)	(4.219)	(3.278)	(0.009)
Female quota hh	-153.6***	14.27	32.91	-0.042	-22.56	-3.532	5.459	-0.068
	(41.79)	(38.94)	(31.82)	(0.124)	(30.67)	(55.83)	(39.27)	(0.115)
Nb.of tv	9.241	35.98***	27.40***	0.105***	-3.409	14.91	10.68	0.027
	(8.665)	(8.425)	(7.102)	(0.026)	(5.761)	(11.67)	(8.814)	(0.026)
Nb. electric iron	-17.89	-9.093	22.55	-0.052	-11.44	2.349	26.26*	0.014
	(16.89)	(13.23)	(14.29)	(0.043)	(10.54)	(20.52)	(14.62)	(0.045)
Nb. metal pots	-0.762	1.187**	0.878*	0.000	0.723**	-0.390	-1.101*	-0.000
	(0.582)	(0.582)	(0.468)	(0.001)	(0.358)	(0.723)	(0.567)	(0.001)
Nb. of stove	-20.09**	1.066	10.72	-0.027	0.636	-8.741	0.355	0.028
	(9.934)	(9.617)	(7.499)	(0.029)	(6.302)	(12.17)	(9.505)	(0.027)
Constant	345.1***	93.59	186.7**	-0.032	-40.50	449.1***	190.0**	0.165
	(128.4)	(62.13)	(80.92)	(0.176)	(58.67)	(124.7)	(95.73)	(0.205)
Observations	5,352	4,997	5,352	5,352	5,352	5,240	5,352	5,352
R-squared	0.061	0.077	0.091	0.033	0.018	0.013	0.034	0.010

Number of id	2,684	2,680	2,684	2,684	2,684	2,684	2,684	2,684

Table 21: Impact of the flood of 2017 on women's employment and women's empowerment

	(1)	(2)
	Paid activities	**WEAI**
year = 2018	0.102***	-0.033***
	(0.022)	(0.010)
Year#Flood 2017	**0.373*** **	**0.035***
	(0.060)	**(0.026)**
Year#July 2017	-0.455*	-0.009
	(0.247)	(0.114)
Year#Central Bengal	-0.073***	0.008
	(0.022)	(0.009)
Year#South Begal	0.075***	0.009
	(0.0232)	(0.010)
february	-0.009	-0.002
	(0.018)	(0.008)
march	-0.042*	-0.0148
	(0.025)	(0.011)
april	-0.0723**	-0.0191
	(0.0341)	(0.0144)
november	0.0177	-0.0121
	(0.0292)	(0.011)
december	0.0312	-0.006
	(0.0207)	(0.008)
Members, age <15	-0.014	-0.001
	(0.010)	(0.004)
HH head education	0.000	0.000
	(0.000)	(0.000)
Woman education	-0.000	-0.000
	(0.000)	(0.000)
Woman age	-0.002	-0.001
	(0.003)	(0.002)

does this household have an electricity connection?	0.029	-0.008
	(0.019)	(0.008)
Dur. asset - quintile	.0090	-0.095**
	(.0106)	(0.004)
Prod. asset - quintile	0.006	-0.004
	(0.008)	(0.003)
Liv. asset - quintile	0.039	-0.003
	(0.006)	(0.002)
Female quota hh	0.024	-0.008
	(0.008)	(0.037)
Number of tv owned by hh	-0.017	-0.001
	(0.019)	(0.008)
Number of electric iron owned by hh	0.027	-0.005
	(0.036)	(0.012)
Number of metal pots owned by hh	0.000	0.000
	(0.001)	(0.000)
Number of stove owned by hh	-0.0408*	0.002
	(0.021)	(0.008)
Constant	0.770***	0.516***
	(0.134)	(0.090)
Observations	5,352	5,352
R-squared	0.090	0.033
Number of id	2,684	2,684

Table 22: impact of the flood of 2017 on time use variables, heterogeneity analysis - women

	Flood 2014 = yes				**Flood 2014 = no**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Domestic work	Market work	Leisure time	Time poverty	Domestic work	Market work	Leisure time	Time poverty
year = 2018	13.47	39.77***	37.09***	0.158***	26.51*	43.14***	32.50***	0.162***
	(18.44)	(13.83)	(13.26)	(0.0384)	(15.10)	(15.36)	(12.50)	(0.0461)
year#flood 2017	**100.1*** **	**-14.76**	**122.4*** **	**-0.213** **	**466.2*** **	**-277.1* **	**-73.77**	**0.711* **
	(30.41)	**(31.89)**	**(26.47)**	**(0.0934)**	**(155.2)**	**(152.3)**	**(126.2)**	**(0.506)**

year#july 2017	236.7**	-79.50	-185.7*	0.242	68.47	2,836	-298.4	5.730
	(109.6)	(99.84)	(99.35)	(0.360)	-2,187	-2,126	-1,617	-6.271
year#Central Bengal	38.11***	26.83*	-13.36	-0.063	23.36	18.01	-3.622	-0.035
	(14.43)	(15.81)	(11.40)	(0.043)	(19.03)	(17.34)	(14.89)	(0.052)
year#North Bengal	-22.41	33.51*	-10.17	0.018	3.497	3.878	4.831	-0.0058
	(17.84)	(18.27)	(14.53)	(0.053)	(15.28)	(15.04)	(11.21)	(0.044)
february	30.59***	-17.81	-8.982	-0.002	-38.05**	-7.00	4.157	0.120***
	(11.10)	(11.72)	-9.130	(0.035)	(14.87)	(14.13)	(11.35)	(0.044)
march	24.52	-29.60	-17.90	-0.039	65.52***	10.17	-10.61	-0.109*
	(16.73)	(18.51)	(14.11)	(0.053)	(20.13)	(18.82)	(15.34)	(0.058)
april	46.01**	84.80***	-14.41	-0.140**	124.1***	24.92	4.108	0.300***
	(20.99)	(21.97)	(16.98)	(0.062)	(25.36)	(24.87)	(18.83)	(0.073)
november	-0.319	9.353	-1.854	-0.032	-45.15**	16.25	-2.676	-0.065
	(17.59)	(19.04)	(15.00)	(0.051)	(22.33)	(21.47)	(15.90)	(0.062)
december	-1.692	2.449	13.76	-0.004	-3.796	-16.94	12.78	-0.074
	(11.21)	(12.57)	-9.246	(0.035)	(15.87)	(15.62)	(12.77)	(0.045)
Members, age <15	53.08***	-14.03**	18.21***	0.095***	27.12***	-0.695	-4.450	0.0498**
	-6.229	-5.830	-4.681	(0.017)	-8.213	-7.329	-6.343	(0.022)
Men education	0.277	-0.868**	0.460	-0.002*	-0.211	0.026	0.450	-2.51e
	(0.322)	(0.367)	(0.312)	(0.001)	(0.574)	(0.672)	(0.456)	(0.001)
Women education	0.107	-0.196	1.024*	-0.001	-0.261	0.701	0.406	0.001
	(0.820)	(0.478)	(0.575)	(0.001)	(0.472)	(0.716)	(0.777)	(0.002)
Women age	3.576	4.638**	-1.015	0.011**	1.506	-0.619	-0.601	0.003
	-4.439	-1.931	-2.865	(0.004)	-1.914	-1.972	-1.854	(0.006)
Electricity	16.68	12.30	-10.29	0.047	9.110	4.931	-6.124	0.093**
	(11.24)	(11.47)	-9.110	(0.036)	(13.97)	(15.65)	(11.08)	(0.043)
Livestock asset index	-21.17**	25.43***	-16.59**	0.029	-6.634	36.82***	23.18***	0.0613*
	-9.542	-9.254	-7.393	(0.031)	(10.34)	(10.05)	-7.711	(0.034)
Productive asset index	-0.341	17.69**	-5.827	0.077***	-2.888	-1.344	-10.85	0.0324
	-7.995	-7.890	-6.763	(0.027)	(11.61)	-9.142	-8.530	(0.036)
Durable asset index	3.171	-10.41	-17.08	-0.084**	51.71***	-6.691	28.58**	0.123***
	(13.45)	(12.36)	(11.20)	(0.040)	(15.89)	(15.72)	(12.62)	(0.047)
Nb. of tv owned by hh	14.53	18.60	34.38***	0.078**	12.30	19.53	22.98**	0.054
	(11.03)	(11.36)	-9.352	(0.035)	(14.11)	(13.80)	(11.67)	(0.041)
Nb. of electric iron owned by hh	-12.40	-9.195	40.52*	-0.021	-6.066	5.085	0.841	0.025
	(23.94)	(17.40)	(21.05)	(0.062)	(22.17)	(18.89)	(18.75)	(0.063)

Nb. of metal pots owned by hh	-1.896**	2.256**	1.015*	6.10e	1.102	0.662	1.313	0.006*
	(0.740)	(0.887)	(0.574)	(0.002)	-1.141	(0.814)	(0.801)	(0.003)
Nb. of stove owned by hh	-19.97	15.60	19.13*	0.028	-16.49	8.31	-2.14	0.034
	(13.45)	(12.92)	(10.47)	(0.037)	(15.23)	(14.23)	(11.34)	(0.042)
Constant	189.0	-48.38	213.1*	-0.182	415.1***	102.8	135.8**	-0.044
	(170.4)	(68.95)	(110.6)	(0.176)	(79.08)	(76.24)	(62.77)	(0.254)
Observations	3,152	2,908	3,152	3,152	2,202	2,091	2,202	2,202
R-squared	0.085	0.142	0.099	0.057	0.068	0.148	0.081	0.060
Number of id	1,582	1,578	1,582	1,582	1,103	1,103	1,103	1,103

Table 23: impact of the flood of 2017 on women's empowerment and employment, heterogeneity analysis - women

	Flood 2014 = yes		**Flood 2014 = no**	
	(1)	**(2)**	**(3)**	**(4)**
	Paid activities	**WEAI**	**Paid activities**	**WEAI**
year = 2018	0.0864***	-0.0268**	0.163***	-0.0505***
	(0.030)	(0.013)	(0.033)	(0.013)
Year#Flood 2017	**0.204*** **	**0.0250**	**0.214**	**-0.142**
	(0.069)	**(0.029)**	**(0.377)**	**(0.132)**
Year#July 2017	-0.459*	0.003	-9.606**	0.004
	(0.244)	(0.115)	(4.761)	(1.432)
Year#Central Bengal	-0.062**	0.0148	0.0393	-0.010
	(0.0293)	(0.012)	(0.038)	(0.016)
Year#North Bengal	0.272***	0.0186	-0.051*	0.001
	(0.0387)	(0.0168)	(0.0284)	(0.013)
february	-0.009	-0.003	-0.048	-0.001
	(0.0239)	(0.0106)	(0.030)	(0.0130)
march	-0.0284	-0.0143	-0.129***	-0.010
	(0.0354)	(0.016)	(0.039)	(0.017)
april	-0.105**	-0.040**	-0.135***	0.0134
	(0.045)	(0.019)	(0.050)	(0.022)

november	-0.0265	-0.0249	0.0938**	0.002
	(0.0376)	(0.015)	(0.044)	(0.018)
december	0.040	-0.003	0.0325	-0.013
	(0.025)	(0.010)	(0.033)	(0.013)
Members, age <15	-0.0154	0.000	-0.0107	-0.004
	(0.0133)	(0.005)	(0.016)	(0.006)
HH head education	0.001*	0.000	-0.000	-5.56
	(0.000839)	(0.000)	(0.001)	(0.000315)
Woman education	-0.000	9.72	0.000	-0.001***
	(0.001)	(0.000)	(0.000)	(0.000)
Woman age	-0.00770	-0.004*	0.003	0.003**
	(0.004)	(0.002)	(0.003)	(0.001)
Electricity	0.0787***	-0.0123	-0.004	-0.002
	(0.0269)	(0.011)	(0.0277)	(0.012)
Livestock asset index: PCA	0.055***	-0.004	0.0328*	-0.00852
	(0.0207)	(0.008)	(0.019)	(0.009)
Productive asset index: PCA	0.0290	-0.0137	-0.005	-0.008
	(0.0199)	(0.00850)	(0.0236)	(0.00992)
Durable asset index: PCA	0.0277	0.00374	0.037	0.009
	(0.028)	(0.011)	(0.032)	(0.015)
Constant	0.796***	0.592***	0.665***	0.341***
	(0.182)	(0.103)	(0.150)	(0.064)
Observations	3,152	3,152	2,200	2,200
R-squared	0.153	0.028	0.081	0.054
Number of id	1,582	1,582	1,102	1,102

Table 24: impact of the flood of 2017 on time use variables, heterogeneity analysis - men

	Flood 2014 = yes				**Flood 2014 = no**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Domestic work	Market work	Leisure time	Time poverty	Domestic work	Market work	Leisure time	Time poverty
year = 2018	23.45***	-9.600	40.72***	0.0809**	5.624	3.562	29.25*	0.0493
	-8.881	(20.02)	(13.27)	(0.0383)	-8.423	(20.55)	(17.06)	(0.0512)

2018.year# flood 2017	**52.12****	**-106.2****	**2.566**	**0.00393**	**80.39**	**-461.9*****	**12.77**	**-0.430**
	(23.21)	**(43.40)**	**(29.30)**	**(0.0923)**	**(71.14)**	**(167.2)**	**(132.8)**	**(0.479)**
2018.year#july 2017	25.35	-183.5	-86.41	1.209***	-1,206*	280.1	-316.6	2.148
	(76.39)	(149.8)	(110.4)	(0.404)	(686.9)	-2,121	-1,707	-5.602
2018.year#Central Bengal	-6.680	7.431	-18.13	0.0106	20.07*	1.845	-26.47	0.00585
	-9.616	(19.28)	(13.78)	(0.0431)	(10.82)	(24.30)	(18.38)	(0.0546)
2018.year#North Bengal	-0.481	55.23**	51.93***	0.163***	-9.561	2.381	-14.36	-0.100**
	(12.78)	(23.22)	(17.65)	(0.0510)	-9.677	(20.43)	(15.38)	(0.045)
february	-11.98	-9.245	12.98	-0.0450	18.08**	-13.04	-1.326	0.016
	-7.679	(14.76)	(11.08)	(0.0351)	-8.902	(19.28)	(14.76)	(0.0447)
march	-22.49*	-21.37	29.35*	0.147***	10.66	12.73	-1.180	0.0599
	(11.95)	(22.16)	(17.27)	(0.0522)	(11.69)	(24.99)	(19.99)	(0.0575)
april	8.570	78.55***	48.43**	-0.0951	2.934	0.321	32.03	0.0261
	(15.30)	(28.15)	(21.43)	(0.0602)	(16.95)	(34.65)	(24.03)	(0.0778)
november	-5.629	50.47**	19.01	0.0431	14.38	-39.18	23.69	-0.0546
	(11.28)	(21.29)	(16.97)	(0.0494)	(10.61)	(25.01)	(19.82)	(0.0599)
december	-2.016	17.52	11.51	0.0254	22.41**	7.660	15.81	0.0235
	-7.621	(15.40)	(11.16)	(0.0348)	-9.188	(20.20)	(15.74)	(0.0462)
Members, age <15	3.135	3.587	-4.423	0.0186	6.382	13.90	-10.19	0.0570***
	-3.924	-7.915	-5.829	(0.0177)	-4.880	(10.57)	-8.272	(0.0220)
Men education	0.231	-0.271	0.687	0.000151	0.298*	-0.297	-0.753	-0.000823
	(0.200)	(0.611)	(0.550)	(0.00133)	(0.155)	(0.468)	(0.470)	(0.00144)
Women education	-0.0498	-0.658	0.528	0.000701	0.103	0.0265	0.658	0.00172
	(0.243)	(0.474)	(0.502)	(0.00174)	(0.197)	-1.145	(0.744)	(0.00307)
Women age	2.214	6.581	-3.250	0.00942*	0.968	-3.071	6.103***	0.00412
	-1.446	-4.047	-2.305	(0.00525)	-1.147	-3.040	-2.310	(0.00924)
Electricity	-5.457	15.97	-8.852	0.0583	-4.713	-5.302	-4.562	-0.0172
	-7.495	(15.61)	(11.69)	(0.0370)	-8.467	(20.01)	(13.91)	(0.0432)
Livestock asset index	-5.051	14.81	-7.889	0.000280	-5.891	0.997	-9.819	-0.0540*
	-7.041	(13.52)	-9.291	(0.0294)	-6.417	(14.02)	(11.72)	(0.0304)
Productive asset index	2.139	25.41**	25.37***	0.0631**	14.43**	-27.07*	-10.24	-0.0272
	-6.062	(11.62)	-8.626	(0.0266)	-5.916	(14.82)	(11.75)	(0.0334)
Durable asset index	-3.739	8.916	7.353	-0.0453	15.33	-20.75	7.920	-0.0319
	-8.642	(16.84)	(13.55)	(0.0354)	-9.343	(20.58)	(15.49)	(0.0477)
Nb. of tv owned by hh	3.805	4.094	3.517	0.0515	-19.65**	13.34	27.05*	0.0106

	-7.164	(16.28)	(11.57)	(0.0357)	-7.817	(17.77)	(14.66)	(0.0411)
Nb. of electric iron owned by hh	-3.455	-16.82	34.84*	0.0771	-3.193	-5.322	17.29	-0.0344
	(14.77)	(31.38)	(20.87)	(0.0657)	(10.12)	(25.68)	(20.39)	(0.0676)
Nb. of metal pots owned by hh	0.650	-0.809	-0.619	-0.000	0.845*	0.968	-1.725*	0.000781
	(0.469)	(0.946)	(0.721)	(0.001)	(0.495)	-1.267	-1.018	(0.00311)
Nb. of stove owned by hh	-3.661	13.50	-5.523	0.0267	-0.308	-22.98	7.484	0.0178
	-7.980	(15.80)	(12.09)	(0.0359)	-9.102	(18.11)	(14.94)	(0.0396)
Constant	-53.18	224.7	303.0***	-0.158	-76.80	696.4***	-1.072	0.243
	(58.62)	(163.0)	(82.87)	(0.201)	(47.64)	(103.6)	(84.88)	(0.318)
Observations	3,152	3,085	3,152	3,152	2,202	2,156	2,202	2,202
R-squared	0.062	0.031	0.030	0.038	0.040	0.019	0.051	0.023
Number of id	1,582	1,582	1,582	1,582	1,103	1,103	1,103	1,103

Chapter 2

Under pressure: the impact of mental load on women's productivity and occupational choices - experimental evidence from Kenya

Sveva Vitellozzi[1,2] , Francesco Cecchi[3] , Chiara Rapallini[2]

1 University of Trento

2 University of Florence

3 Wageningen University

Abstract

Mental load is a widespread but invisible psychological burden. It mainly affects women, by constantly loading them with concerns related to household management and children's well-being. In this study, we investigate whether mental load reduces labor productivity and leads to a self-selection into less cognitive and remunerative jobs, and whether its impact is gender-differentiated. We conduct a lab-in-the-field experiment with more than 700 participants in Nairobi, in which we randomly trigger thoughts related to mental load and then ask to perform a menial or a more cognitively demanding incentive compatible task. Results show that mental load reduces productivity in the menial task, but not in the cognitively demanding one. At the same time, when given the opportunity, treated participants are more likely to self-select precisely into the less remunerative menial task. A heterogeneity analysis shows that mental load reduces labor productivity in the menial task for women alone, while the self-selection effect is driven by men. This study provides evidence of an understudied psychological channel that, by creating a negative performance loop, widens the gender productivity gap and contributes to the reinforcement of the psychological poverty traps identified in the literature.

JEL Classification: J16; J24; C93

Keywords: mental load; gender; poverty; productivity

[1]Special thanks to Fredrick Achar, Amos Tabalia, Salome Njambi, and Alice Wambui for their invaluable help during fieldwork in Kenya. We gratefully acknowledge financial support from the Laboratory for Effective Anti-Poverty Policies (LEAP) at Bocconi University (2021 LEAP Student Grant), from professor Leonardo Boncinelli from the University of Florence, and from Wageningen University.

[2]The experiment was pre-registered on the AEA RCT Registry and can be found at the following: "Cecchi,

2.1 Introduction

Mental load is the combination of cognitive and emotional labor, with the former referring to the management behind household activities and the latter to the caring and responsibility of other family members' well-being (Dean et al., 2022). Most often held by women, this psychological burden risks having a negative impact on their mental health as well as on economic outcomes. Indeed, in the US mental load is associated with interference with women's work sphere, dissatisfaction with their lives, feelings of overload, and stress (Offer, 2014; Ciciolla and Luthar, 2019). Over the past years, mental load has received increasing attention in the literature, but existing studies are based solely on the analysis of qualitative and time-use surveys of dual-earner families in western countries (Offer and Schneider, 2011; Ciciolla and Luthar, 2019; Daminger, 2019a; Dean et al., 2022). In low- and middle-income countries, mental load risks bearing an even larger burden because women lack access to external and domestic facilities that could substitute for their time and their own housework (Floro, 1995).

Because of its invisible nature, the impact of mental load on economic outcomes has not been measured nor quantified yet. However, by constantly loading women with pressing concerns related to the household management, mental load risks impairing their cognitive abilities and stress levels (Schilbach et al., 2016). In doing so, it can affect their labor productivity, earnings, decision-making processes, and preferences, among others (Cettolin et al., 2020; Kaur et al., 2019; Dalton et al., 2020). As is the case for many other low- and middle-income countries, Kenya has made significant progress in female labor participation in recent years.[1] Despite this, gender norms still prescribe women to account for a more than commensurate share of unpaid work (i.e., housework and childcare) while at the same time increasingly engaging in the labor market, especially in casual jobs with a piece-rate pay system (Agwaya and Mairura, 2019; Maina et al., 2019; Oloo and Parkes, 2021). In informal settlements in Nairobi, characterized by poor living conditions and volatile informal labor markets, women divide their time between market and domestic activities with a disproportionate amount of time devoted to domestic work (Maina et al., 2019). Daily performance at work assumes then a specific relevance: given the time constraint they face, women have to be as productive as possible to maximize their daily earnings. Within this context, we believe that understanding whether mental load impacts labor productivity and self-selection into informal, less remunerative jobs is of upmost importance.

In this study, we ask whether mental load reduces productivity and leads to self-select in less cognitively demanding jobs, and we investigate to what extent its impact differs between men and women, and between women with different income levels. We identify two potential mechanisms that could be at place: a decrease in attentional levels and an increase in stress. To test these mechanisms, we conduct a lab-in-the-field experiment in poor, urban settings in Kenya. To quantitatively assess the impact of mental load on our outcomes of interest, we vary its salience in participants' mind. Following a large

Francesco, Chiara Rapallini and Sveva Vitellozzi. 2022. "Under pressure: the impact of women's mental load on labor productivity and occupational choices. Evidence from Kenya." AEA RCT Registry. May 23. https://doi.org/10.1257/rct.9021"

[1] https://data.worldbank.org/indicator/SL.TLF.CACT.FE.ZS?locations=KE

body of the literature in economic and psychological research (see Cohn and Maréchal (2016) for a comprehensive review), our treatment consists of triggering in the mind of the participants thoughts related to mental load. Using a between-subject design, we randomly assign participants to the treatment and control groups and we then ask them to perform a real effort task to proxy labor productivity.

We assign participants to perform either a menial (from here on referred to as 'automatic' task) or a cognitively-demanding task: dividing black from red beans, an effort task frequently used by experimental economists to measure productivity; or the Tower of Hanoi (TOH), a task used in the psychological literature to measure, among others, cognitive abilities (Zook et al., 2004). The effort tasks last approximately 30 minutes and are divided in three 10-minutes intervals. In the first two slots, participants are asked to divide as many black from red beans and to complete as many TOH with four disks as possible, in random order. For the last slot participants may choose between the two tasks. Importantly, in this third slot we limit the learning effects that a previous experience with the TOH may have induced, by increasing the number of disks of each TOH to five (i.e., a substantially more cognitively-demanding task). At the same time, we increase the economic incentive for completion of each TOH, to make it unambiguously more advantageous to select the latter task (mimicking self-selection into a financially more rewarding but intellectually more challenging job).

Results show that mental load significantly reduces productivity in the automatic task (i.e., dividing the beans), but not in the cognitively demanding task. At the same time, treated participants self-select more often into the former. We speculate that the focus required to complete the cognitively demanding task reduces the temporary effect of mental load priming, limiting its effect on productivity. Even so, given the chance treated participants would rather opt for a less cognitively demanding task. The gender disaggregated heterogeneity analysis shows that mental load reduces productivity for women and not for men in the automatic task when the beans are performed as the first task, and when we consider the average income earned from dividing the beans during the whole effort task. When looking at self-selection and productivity in the last round, we find no significant gender differences in results, even though evidence suggests that the self-selection effect is mainly driven by men[2], while the productivity effect by women. We are not able to fully identify the mechanisms that drive the results, but we find suggestive evidence that mental load operates through a reduction in attention for men, and an increase in stress for women. Finally, we find that the effect on productivity is similar above and below the median of income distribution in our sample, with an insignificantly stronger effect for non-poor participants.

This study makes several contributions to the literature. First, it sheds light on a psychological dimension of gender inequalities that contribute to the worsening of the gender productivity gap. Most of the literature explains this gap in terms of the existence of gender-specific barriers to access productive inputs, such as land or fertilizers (Kilic et al., 2015; Mukasa and Salami, 2015; Palacios-López and López, 2015; Singbo et al., 2021), or the existence of specific gender norms that confine women's

[2]We hypothesize that women succumb to gender norms that assign them to the low-paying informal jobs anyway, which may help explain why when given the chance to choose a low or high cognitively demanding job they overwhelmingly opt for the former, and why the self-selection effect is driven by men.

sphere of activity in domestic and reproductive work (Manda and Mwakubo, 2014). Even though we know that reduced cognitive abilities and increased stress negatively impact labor productivity (Skirbekk, 2004; Heineck and Anger, 2010; Kaur et al., 2019), evidence on the psychological dimension of the gender productivity gap is scarce. This paper fills this gap in the literature by showing that mental load negatively impacts women's labor productivity for menial tasks but not men's.

Second, it provides evidence of an understudied psychological phenomenon that creates a negative performance loop that could trap individuals in poverty. From the literature on scarcity we know that living in poverty holds psychological drawbacks that affect economic outcomes and that risks creating a "psychological poverty trap" (Haushofer and Fehr, 2014). However, these studies have focused mainly on the psychological impacts of poverty on over-borrowing, consumption decisions, and economic preferences (de Bruijn and Antonides, 2021). By looking at productivity and occupational choices, our study provides new evidence that cognitive overload reduces productivity in less remunerative tasks that require less cognitive effort, and it leads individuals to self-select into those same tasks. Moreover, we provide interesting insights on the gendered dimension of the problem, showing that mental load reduces productivity only for women but it affects mainly men's job selection choices.

Third, this paper varies the salience of mental load and it measures its impact on economic outcomes. As already stated, the existing literature on mental load focuses on dual-earner families in the US and it is based on the analysis of time-use surveys (Offer, 2014; Ciciolla and Luthar, 2019; Daminger, 2019b; Dean et al., 2022). In this study, we quantitatively assess the impact of mental load on labor productivity and occupational choices and we conduct the analysis in poor, urban areas of a middle-income country, where its magnitude is severely underestimated even though it holds important negative consequences on overall individuals' well-being. Our treatment provides an "intent-to-treat" estimate of the impact of mental load on productivity and job selection, in the sense that: 1) we expect our treatment to trigger increased mental load only for those individuals that are prone to suffering from this burden, and 2) control group individuals may have participated under "endogenously" high mental load levels even in the absence of treatment. The magnitude of effects should therefore be interpreted as a conservatively lower bound.

Lastly, this study analyzes an important but neglected aspect of gender inequalities that could severely undermine women's empowerment. By constantly loading women with pressing concerns, mental load risks impairing their self-efficacy and agency, which are two fundamental dimensions of empowerment (Alkire et al., 2013). On top of that, by making women less productive at work, mental load risks entailing a loss of income that can translate into reduced decision-making power within the household (Angel-Urdinola and Wodon, 2010; Doss, 2013). Moreover, if less productive, women risk spending more time than needed on the performance of paid and unpaid working tasks, thus reducing their time to rest and becoming more time poor (Bardasi et al., 2011).

This study is not without limitations. The technique of priming holds its concerns on its effectiveness and difficulty of identifying the mechanisms behind the hypotheses we are testing. Also, in our experimental design, we did not collect baseline information on participants' mental load levels. We are consequently unable to determine whether the treatment had a bigger effect for people whose baseline levels of mental load were relatively high (i.e., women) or relatively low (i.e., men), thus potentially underestimating the magnitude of our treatment effect. Finally, participants particularly enjoyed one of the tasks we asked them to perform (i.e., the TOH), thus counfouding the potential effects of our treatment on productivity in more cognitively-demanding jobs.

The rest of the paper proceeds as follows: Section 2 explains the context of the study, the causal mechanisms and the research hypotheses being tested; Section 3 focuses on the experimental design; Section 4 describes the data; Section 5 focuses on the empirical methodology; Section 6 reports the results; Section 7 discusses the results; and Section 8 concludes.

2.2 Causal mechanisms, research context, and hypotheses

The main hypothesis of this study is that mental load related issues capture individuals attention by generating intrusive and stressful thoughts that reduce cognitive resource and increase stress and, consequently, affect our productivity and decision-making processes (Mani et al., 2013; Haushofer and Fehr, 2014; Shah et al., 2018; Kaur et al., 2021; Dalton et al., 2020).

2.2.1 Mental load and cognitive functions

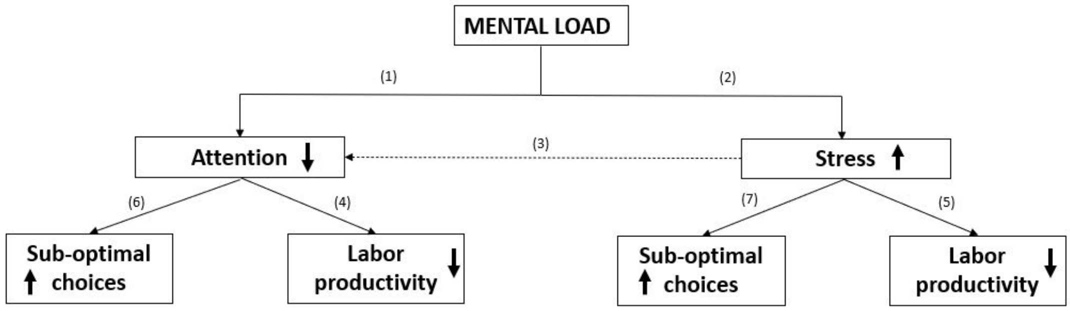
Executive functions are mental processes employed by the brain whenever people need to concentrate and pay attention instead of relying on instinct or intuition (Diamond, 2013). All of them are limited resources and, among other factors, they can be impaired by an increase in cognitive load or stress (Diamond, 2013; Dean et al., 2017).

The literature on scarcity states that poverty, by inducing constant and daily thoughts about financial needs, increases cognitive load and negatively impacts "mental bandwidth", the combination of cognitive capacity (i.e., the total amount of information the brain can absorb at any point in time) and executive control (i.e., the ability to carry out goal-directed behavior employing cognitive functions) (Schilbach et al., 2016). Whenever individuals engage their cognitive capacity in some pressing concern, they are left with less space for less urgent decisions or problems and their cognitive abilities are impaired, leading to behavioral reactions like reduced capacity to exert willpower or to make long-term decisions, reduced self-control, or increased risk aversion (Vohs et al., 2013; Deck and Jahedi, 2015; Allred et al., 2016; Schilbach et al., 2016; Schilbach, 2019). An increase in stress as well can lead to a depletion of attentional resources and working memory (Scott et al., 2015; Tsai et al., 2019), and it may affect our decision-making processes and judgment (Staal, 2004; Morgado and Cerqueira, 2018).

Causal mechanisms

Building on these notions, we hypothesize that mental load can impact labor productivity and occupational choices through its impact on cognitive functions and stress.

Labor productivity



Source: personal elaboration of the authors

Figure 2.1: Causal mechanisms - mental load, productivity, and economic decision-making

Both an impairment in cognitive abilities and an increase in stress can reduce labor productivity (Staal, 2004; Banerjee and Mullainathan, 2008; Henderson et al., 2012; Kaur et al., 2019). Among all cognitive functions, we test for attentional constraints as contributing mechanism: by making it harder for women to focus on other factors than pressing daily concerns related to the household management, mental load reduces their attention at the workplace (channel (1) in Figure 2.1) and, consequently, it negatively affects productivity (4). Depending on individual reactions to stressors, an increase in stress can have a twofold effect on performance: very low or high reactions can lead to a decrease in performance, while a moderate response can increase performance (Henderson et al., 2012). We hypothesize that the increase in stress induced by mental load (2) decreases performance in the effort task (5), and its impact can be "direct" or "indirect", with the latter operating through a reduction of attentional resources of the individual (3).

Decision-making process

Decision-making processes are impaired by both stress and reduced attention (Staal, 2004; Deck and Jahedi, 2015; Morgado and Cerqueira, 2018). We posit that mental load can lead individuals to make more intuitive choices that translate in self-selection in less cognitive and less remunerative jobs, and to a sub-optimal choice in terms of income maximization. An increase in cognitive load reduces attention (2) and it increases the opportunity cost of our reasoning system to "regulate choice", leading to make more intuitive and less reasoned choices (Deck and Jahedi, 2015). Stress as well leads individuals to scan less alternatives and to alter individuals' decision-making processes (Staal, 2004; Morgado and Cerqueira, 2018). Both this mechanisms can lead individuals to make a suboptimal choice (6, 7), engaging in a less remunerative and less cognitive-demanding task even though their predicted income from a more cognitive-demanding task is higher.

2.2.2 The context: labor market, gender roles, and mental load in urban Kenya

The employment structure of the Kenyan labor market reflects the traditional gender division of roles: while men are employed almost equally in all sectors of the labor market, women engage mostly in traditionally female-dominated activities, like the manufacturing and garment industries, or the horticultural industry (Wanjala and Were, 2009). In urban areas, where the informal sector is particularly widespread and is constituted primarily by small-scale economic activities, women engage mainly as self-employed workers, casual workers, or employed workers in small enterprises (Agwaya and Mairura, 2019). This structure of the labor market, paired with local gender norms that place women in charge of managing household activities, entails a gender-differentiated division of mental load. While men's share of domestic work is linked to activities carried out less frequently, such as paying school fees, women's share is linked to those activities carried out daily, like cooking, cleaning, or fetching water. Qualitative interviews in Kibera and Korogocho (i.e., two of the biggest slums in Nairobi) reveal that women's mental load can be grouped in three main dimensions:

- *Time pressure:* women are particularly vulnerable to time management, as they feel that they do not have the time to balance work and family obligations, and they have no time left for themselves. While at work, they think about all the activities that have to be carried out at home before the end of the day;
- *Children's well-being:* women bear most of the emotional labor within the household, as they constantly worry about their children's and husband's well-being, especially when it comes to children's future expectations;
- *Financial worries:* both women and men are constantly worrying about financial needs related to rent, school fees, and food, but women are in charge of managing the household's budget on a daily basis, especially when it comes to deciding what food to buy and how to split money in the next coming days [3].

Table 2.7 in the Appendix shows differences in mean between men and women on a self-reported stress scale including items that could proxy mental load. As we can see, women in our sample reported being more stressed than men on average (p-value 0.001), and to have felt stressed about more items than men in the past 7 days (p-value 0.039). If we look at each item of the stress scale separately, women reported being stressed more times than men about financial worries (p-value 0.019), their children's access to education (p-value 0.051), being victim of violence (p-value 0.06), and the relationship with their spouse (p-value 0.012) and with others (p-value 0.00). Men instead were more likely to feel stressed about a potential business failure (p-value 0.051). These descriptive statistics show that women are on average more stressed about some of the mental load's dimensions we identified in urban areas in Kenya. Both men and women reported being stressed about financial needs, but while for men their concern is mostly related to a business failure, for women it is related to household's financial worries and to access to education of the offspring.

[3] To watch a short documentary on women's mental load in urban and rural Kenya, please click here: `https://youtu.be/3wNBC1JT_kc`

2.2.3 Research hypotheses

Based on the identified causal mechanisms and on the research context, this study tests the following research hypotheses:

1. Mental load reduces labor productivity;
2. Mental load leads to a self-selection in less cognitive-demanding jobs and to a sub-optimal choice;
3. The impact of mental load on labor productivity and self-selection is gender-differentiated, as women carry a higher mental burden compared to men;
4. Mental load has a stronger impact for women living in poverty as they lack access to basic facilities that could help them outsourcing their mental load (e.g., childcare facilities).

2.3 Experimental design

2.3.1 Sample and randomization

A total of 720 individuals participated in the experiment. We sampled participants in urban areas (i.e., Nairobi) with children under the age of 10. By design, half of them are women and half are men. For each household, we sampled only one woman or man, to avoid any potential problem related to intra-household dynamics. The choice of the children under the age of 10 comes from the literature on mental load and the qualitative interviews conducted on the field. A substantial burden of mental load is related to childcare, especially when children are under the age of 10 (Maccini and Yang, 2009). In addition, children above the age of 10 in Nairobi tend to become independent enough to help their parents in the house, going to school by themselves, and to work if needed.

We sampled participants from three different areas of the city: 486 participants are from Kibera and Kawangware, two of the biggest slum areas of the city, where we observe substantial income variation among inhabitants. We sampled the remaining participants from Waithaka, a low- middle-income neighborhood. In this way, we are able to look at differences in the outcomes of interest and in the intensity of mental load based on the income level of the participants while accounting for the facilities they have access to.

2.3.2 Treatment

Following the literature on poverty and cognition, to assess the impact of mental load on productivity and self-selection we adopt the technique of "priming" by triggering in the mind of participants thoughts related to mental load (Mani et al., 2013; Shah et al., 2015; Dalton et al., 2020). Priming interventions do not aim at generating new thoughts, but rather at bringing up to the mind already existing thoughts by making them more salient (Cohn and Maréchal, 2016).

The design of the treatment was based on extensive fieldwork and pilot tests conducted in slum areas in Nairobi to identify the best trigger to increase the salience of mental load. Our treatment consists of three steps:

1. *Time-use module:* we ask participants to fill in a time-use module under the form of time diaries to start triggering the time pressure dimension of mental load;
2. *Psychological prime:* following Callen et al. (2014), we asked participants whether it happens to them to think about household-related thoughts and worries during a normal working day. If the answer was positive, we then asked to tell us about what they were thinking about. More specifically, they were asked the following question:

   "Sometimes it happens that while you are working or doing other things, thoughts about household management responsibilities may come to your mind. They maybe things you have to plan, organize, facilitate or even do by yourself. We are therefore interested in understanding your daily experiences related to the management of the household that may stress or worry you. This could be anything, for example how you manage the time for cooking and cleaning activities, how you manage the household's expenses, or concerns related to your children's well-being. Could you tell us if it happens to you to think/worry about issues such as these ones during the day? "
3. *Video and mental load reporting:* we asked participants to watch a four-minutes video with women and one man from Kibera talking about their household-related worries in relation to a normal working day[4]. To have participants re-experiencing mental load, rather than just reporting it, we then asked them to do the exact same exercise. We asked them to report to the enumerator what they think about and how they feel on a normal working day. Starting from the time-use module administered before, the question would start as "Now I want you to tell me yesterday, from when you woke up until when you went to sleep, what you were thinking about and how you were feeling about it. So you can start by saying '*Yesterday I woke at 6am and I started thinking about XXX...*'"

Our triggers aim at capturing individuals' attention for a period of time long enough to impair their performance during the effort task. The treatment was designed in three steps to be effective in varying the salience of mental load: with the time use module, participants start thinking to the time management related to household's work; with the "emotional trigger", based on Callen et al. (2014), participants think about how they feel in relation to these mental load related worries. Finally, the scope of the video is twofold: on the one hand, it wants to have participants relate to people similar to them on common worries and problems; on the other, it wants to instruct them for the last step of our treatment, which consisted of having them *re-experiencing* their mental load, rather than simply reporting it.

One of the limitations of priming is that it does not allow you to test the mechanisms through which the prime operates (Kaur et al., 2021). We cannot exactly assess how our treatment, particularly the

[4]The video is available at the following link: https://drive.google.com/file/d/1yJDiAEf6P4vz_gYlziAho1azjaqD7oFw/view?usp=sharing

video, affects productivity and decision-making. We believe, however, that the video operates through an emotional channel, based on the information gathered through our qualitative interviews: mental load is particularly burdensome in Kenya, yet nobody talks about it, because there is a stigma on mental health and it is difficult to talk freely about your mental and emotional status. By showing people that they are not alone in struggling daily with these mental load related issues, we believe our video has an impact on productivity by overloading their mind with these thoughts and worries and by increasing their stress levels.

2.3.3 Labor productivity

To measure labor productivity and to account for self-selection, we ask participants to perform an automatic and a proceduralized, cognitively-demanding task, in randomized order. For the former, they had to divide black from red beans. For the latter, they had to complete the Tower of Hanoi (TOH), a puzzle task commonly used to assess individuals' problem-solving abilities and executive functions like working memory or procedural learning (Zook et al., 2004). The effort task lasted in total 30 minutes and it was divided in three time slots of 10 minutes each. During the first two slots, participants were asked to divide as many black from red beans as possible and to complete as many TOH with 4 disks as possible. As already mentioned, the order of these two tasks was randomized for each participant. For the last slot, participants were asked whether they rather divide the beans again or complete as many TOH with 5 disks as possible. The economic incentive was set such that it should always be more rational to choose the TOH. In fact, participants gained 20 KSH for each 100 grams of beans divided (in all three slots), 20 KSH for each TOH with 4 disks completed (in the frist two slots), whilst they were offered 100 KSH for each TOH with 5 disks completed (in the final slot). With this last slot we aimed at investigating whether mental load leads individuals to self-select into less cognitive demanding jobs and to make a non-income-maximizing choice.

2.3.4 Experimental procedure

The data collection was conducted in April, May 2022 (from the 20^{th} of April until the 3^{rd} of June 2022)[5]. The experiment lasted on average one and half hour, and, on top of the show-up fee (i.e., 200 KSH, about 1,67 US dollar), participants gained on average 449 KSH (i.e., about 3,73 US dollars) from the effort task, and we observe no significant differences in total earnings between the treatment and the control group. From our data, the average daily income of participants is about 450 KSH. [6]

The research team was composed by nine enumerators and one supervisor, and they met the recruited participants in three different locations in Kibera, Kawangware, and Waithaka. Recruitment was phone-based and it took place the week before the start of the experiment. We initially selected a

[5]We received ethical approval for the experiment by the University of Florence (Ethical Approval nb. 154) and from AMREF Health Africa in Kenya (ESRC P1169/2022).

[6]While it may seem unethical to increase emotional stress and remunerate participants based on their performance, it is worth noticing that the expected income from the whole experiment (i.e., show-up fee and performance-based compensation) is higher than the average daily income for both participants in the treatment and control group (for an experiment that took no more than two and half hours to complete).

sample of 1000 individuals from an already existing pool of participants of the survey firm. Because of a delay in the IRB approval, we started the data collection three weeks later than expected. For this reason, we had to re-sample about 15 percent of the original sample that was not available anymore. The new recruitment was made mainly through the "snowballing" technique. The main reason for participants who did not show up was work: we collected data only during workdays to capture at best the daily dimension of mental load. Consequently, some of the recruited participants were not able to leave work to come to the experimental session. We do not believe, however, that this attrition was selective.

When recruited, participants were advised that they would have received a show-up fee to cover the transportation costs. Participants engaged in the experiment simultaneously and separately, each of them assigned to one enumerator. The locations were big enough to ensure that there were no spillover effects and that participants had enough space between one another. Each enumerator was provided with headphones to show the video to participants in the treatment group. All data were collected on tablets with KoboToolbox. The random assignment to the treatment or the control group was coded in the questionnaire: as soon as the enumerator inserted the name of the participant, the tablet would automatically assign her/him to the treatment or control group. Data on the TOH were collected online, and they were stored on a separate, independent database[7]. At the end of the experiment, the enumerators reported the total earnings from the effort task and participants received the payment through M-Pesa, a mobile app commonly used in Kenya to transfer money.

After affirming their informed consent, the enumerators explained to all participants the rules of the tasks they had to perform. They explained the Tower of Hanoi with 3 disks and then they asked participants to complete one to make sure they understood the rules, and they explained the rules for dividing the beans. As the effect of priming could last from 15 minutes to one week (Cohn and Maréchal, 2016), we decided to explain the rules before exposing participants to the treatment to avoid any potential drawback with our prime.

Then, participants in the treatment and in the control group were exposed to the same activities but in different orders to ensure that they all spent the same amount of time in the experiment. As shown in Table 2.1, right after the explanation of the effort task participants in the treatment group were first exposed to the treatment and then they were asked to perform the effort task. After the effort task, they were asked to complete a Digit Span Task to measure their attention level (Hale et al., 2002), to self-assess their own stress level[8], and to answer basic socioeconomic questions.

Participants in the control group, on the other hand, were asked to compile the socioeconomic questionnaire first, and then to perform the effort task to make sure that any potential differences in the outcomes of interest are not due to differences in cognitive fatigue. On average, the socioeconomic questionnaire takes the same amount of time as the treatment. After the effort task, they were asked to complete the Digit Time Span and to self-assess their own stress level. We also asked them to complete

[7]The links are publicly available. For more information, update the settings at the following: `https://cheerful-banoffee-e5fb80.netlify.app/admin/`, and then open the following: `https://cheerful-banoffee-e5fb80.netlify.app/`

[8]The order of the two modules was randomized to minimize the risk of getting biased information

a simplified version of the Raven's matrixes. Finally, they were exposed to the first two parts of the treatment, excluding the video.

Table 2.1: Order of tasks in the experiment

Treatment group	**Control group**
1. Treatment	1. Socio-economic questionnaire
2. Effort task (randomized)	2. Effort task (randomized)
3. Stress scale	3. Stress scale
4. Digit span task	4. Digit span task
5. Socio-economic questionnaire	5. Treatment (no video)

2.4 Data

2.4.1 Main outcome variables

The main outcomes variables in this study are labor productivity and self-selection into less cognitively-demanding tasks. Labor productivity is measured as the income earned during each time slot of the effort task. We define productivity in the automatic task as the income earned from dividing the beans, and productivity in the proceduralized task as the income earned from completing TOHs with 4 or 5 disks. Self-selection into less cognitive-demanding tasks is defined as the likelihood of selecting the beans in the third round rather than the TOH with 5 disks based on observable characteristics[9].

As secondary outcomes, we construct a variable to check whether selecting into the beans or the TOH with 5 disks is a sub-optimal choice or not. The sub-optimal choice is a dummy variable equal to 1 that predicts the income in the final round (TOH or beans) based on the performance in the previous rounds. More specifically, we measure the predicted income of the TOH with 5 disks or of dividing beans based on the performance in the first two time slot of the effort task. We then define the choice as being sub-optimal if the participant chooses the task with the lower predicted income.

2.4.2 Descriptive statistics

Table 2.2 presents descriptive statistics on key characteristics of the participants at the individual and the household level. Participants in our sample have on average 31 years, 11 years of education, and 77 percent of them is married. The average number of household members is slightly greater than 4, with almost 2 children under the age of 10. Half of the sample reported being employed in the informal sector, working on average 38 hours per week, and earning 12800 KSH (about 107 US Dollars) per month.

Table 8 in the Appendix reports randomization test between the treatment and the control group. The test shows that the randomization worked properly as the two groups are comparable in terms of observable socio-economic characteristics. The only variable that shows a significant difference in

[9] Differently from the Pre-Analysis Plan (PAP), we do not include as main outcome variable total labor productivity because we find that the joint income effect is insignificant in all our empirical specifications.

Table 2.2: Descriptive statistics

	Std. Dev.	Mean	SE(Mean)	Median	Min	Max
Male	.5	.51	.019	1	0	1
Age	7.654	31.3	.285	30	18	62
Education	2.925	11.173	.109	12	0	20
Muslim	.229	.055	.009	0	0	1
Married	.415	.779	.015	1	0	1
Childcare - school	.406	.208	.015	0	0	1
Childcare - parents	.442	.266	.016	0	0	1
Nb hh members	1.264	4.025	.047	4	2	11
Children < 10	.934	1.868	.035	2	1	7
Female share	.207	.534	.008	.5	0	1
Self-employed	.466	.318	.017	0	0	1
Unemployed	.304	.103	.011	0	0	1
Informal	.5	.51	.019	1	0	1
Working hours	23.589	38.655	.879	40	0	126
Asset index	.999	-.016	.037	-.02	-2.675	4.72
Downward income risk	.311	.404	.012	.429	-1.667	1
Monthly income	16655.1	12792.6	620.2	10000	0	200000
Multitasking	.008	.011	0	.01	0	.03

means is the time spent multitasking the day before the interview. Other characteristics do not show any significant difference, suggesting that the randomization successfully achieved balance across the two groups.

2.5 Empirical specification

To estimate the impact of mental load on labor productivity and occupational choices we proceed by step: we disentangle the effect of the treatment based on the type of task (i.e., proceduralized vs automatic) and based on the rounds of the effort task. For the first two rounds, we adopt an Ordinary Least Squares (OLS) model, while for the last round we adopt the Heckman Selection Model [10].

2.5.1 Impact of mental on labor productivity during the first two rounds of the effort task

We adopt an OLS model to evaluate the impact of the treatment on task performance during the first two rounds. We first estimate the Average Treatment Effect (ATE) on the pooled sample and we then look for heterogeneous treatment effects by interacting the treatment with gender and income levels of participants, as shown in Equations (1), (2), and (3) respectively.

Impact of mental load on labor productivity:

$$Y_i = \beta_0 + \beta_1 TREAT_i + \beta_k \mathbf{X}_{ik} + e_{ik} \tag{2.1}$$

[10] In the PAP the Heckman procedure was not included. We also estimate the impact of mental load on productivity and self-selection using an OLS model, and Table **??** in the Appendix shows no differences in results.

Impact of mental load on labor productivity - gender differences

$$Y_i = \beta_0 + \beta_1 TREAT_i + \beta_2 SEX_i + \beta_3 (TREAT_i \times SEX_i) + \beta_k \mathbf{X}_{ik} + e_{ik} \tag{2.2}$$

Impact of mental load on labor productivity - income differences

$$Y_i = \beta_0 + \beta_1 TREAT_i + \beta_2 POOR_i + \beta_3 (TREAT_i \times POOR_i) + \beta_k \mathbf{X}_{ik} + e_{ik} \tag{2.3}$$

where Y_i is labor productivity measured as the income earned separately during the first two tasks of the effort task (i.e., dividing beans and completing as many TOH with 4 disks as possible). The independent variable is the dummy variable that identifies whether participants are in the treatment (i.e., dummy equals to 1) or in the control group, ($\mathbf{X}_{ik}$) are the control variables at the individual and the household level, and ϵ_{ik} is the error term. The interaction terms in equations (2) and (3) estimate, respectively, the impact of the treatment in relation to being a man, and the impact of the treatment in relation to being above or below the median of the income level. Following the hypotheses we are testing, we estimate equation (3) only for women.

Control variables include the age of the participant, the years of education, the marital status, the religion, the mode of childcare, whether the participant is employed in the formal or informal sector, whether she/he is unemployed or self-employed, the income level, the downward income risk, and the time spent the day previous to the interview in multitasking. At the household level, we control for the household composition, and more specifically the number of children under the age of 10, the number of adults in the household, and the share of female members. Adults are defined as individuals older than 15. We then control for the area of residence (i.e., inside or outside the slums), and for the household's assets, measured through Factor Analysis. Detailed information on the construction of the variables is provided in Table 2.9 in the Appendix. We also control for the order of the effort task (i.e., whether the beans or the TOH was done as the first task) interacted with the treatment in the pooled sample, and with the treatment and the gender in the heterogeneity analysis.

2.5.2 Impact of mental load on occupational choices and labor productivity during the last round of the effort task

To account for self-selection into less cognitively demanding task in the last round, we adopt the Heckman selection model Heckman (1979). This allows us to understand whether the treatment leads participants to self-select into dividing the beans again or the TOH with 5 disks, and to account for it when estimating the impact of treatment in the last round of the effort task

We first estimate the selection equation, which gives us the likelihood of self-selecting into the beans or the TOH with 5 disks based on observable characteristics. For the ATE and the Heterogenous Treatment Effects, we include as observable characteristics being in the treatment or in the control group, the years of education, the average number of wrong moves in the TOH with 4 disks, and the average time needed to complete each TOH with 4 disks in the previous round. Then, following Equations (1), (2), and (3), we include, respectively, the sex of the participants, and the treatment interacted with the sex or the income level of the participants. We, therefore, estimate the following first stages:

$$Selfsel_i = \beta_0 + \beta_1 TREAT_i + \beta_2 SEX_i + \beta_3 Education_i + \beta_4 WrongTOH4_i + \beta_5 TimeTOH4_i + e_{ik} \tag{2.4}$$

$$Selfsel_i = \beta_0 + \beta_1 TREAT_i + \beta_2 SEX_i + \beta_3 (TREAT_i \times SEX_i) + \beta_4 Educ_i + \beta_5 WrongTOH4_i + \beta_6 TimeTOH4_i + e_{ik} \tag{2.5}$$

$$Selfsel_i = \beta_0 + \beta_1 TREAT_i + \beta_2 POOR_i + \beta_3 (TREAT_i \times POOR_i) + \beta_4 Educ_i + \beta_5 WrongTOH4_i + \beta_6 TimeTOH4_i + e_{ik} \tag{2.6}$$

where $Selfsel_i$ is the probability of selecting into the beans or the TOH with 5 disks. From the first stage, we obtain an inverse Mills ratio (λ_{Selfi}) to be included in the second-stage equations:

$$Y_i = \beta_0 + \beta_1 TREAT_i + \beta_k \mathbf{X}_{ik} + \lambda_{Selfi} + e_{ik} \tag{2.7}$$

$$Y_i = \beta_0 + \beta_1 TREAT_i + \beta_2 SEX_i + \beta_3 (TREAT_i \times SEX_i) + \beta_k \mathbf{X}_{ik} + \lambda_{Selfi} + +e_{ik} \tag{2.8}$$

$$Y_i = \beta_0 + \beta_1 TREAT_i + \beta_2 POOR_i + \beta_3 (TREAT_i \times POOR_i) + \beta_k \mathbf{X}_{ik} + \lambda_{Selfi} + +e_{ik} \tag{2.9}$$

where Y_i is either the income earned from dividing the beans in the third round, or from the number of TOH with 5 disks completed; $TREAT_i$ is the treatment dummy variable, interacted with the sex ($TREAT_i \times SEX_i$) or the income level ($TREAT_i \times POOR_i$) of the participants; $\mathbf{X}_{ik}$ are the control variables at the individual and household level; λ_{Selfi} is the Mill ratio from the first stage of the Heckman selection model; and ϵ_i is the error term.

2.6 Results

2.6.1 Average Treatment Effect

Table 2.3 shows the results for the Average Treatment Effect (ATE) on labor productivity and self-selection. Columns (1) and (2) show that mental load reduces productivity in the automatic but not in the cognitive task. It is important to notice however that the effect is confirmed only when participants perform the automatic task in the first round. As already said, we randomized the order of the automatic and cognitively-demanding tasks in the first two rounds of the effort task. The interaction term $2^{nd} round\#Treat$ gives us the effect of being in the treatment group and having done the TOH or the beans as the first task in Columns (1), (2), (4), and (5), respectively. As we can see, it seems that the treatment effect disappears in the second round of the effort task. In other words, it could be that our treatment had an impact only on the performance of the automatic task executed right after the end of the treatment. This is consistent with the literature on priming, stating that its effect could last from

Table 2.3: Average Treatment Effects

	(1) Exogenous task beans	(2) Exogenous task TOH 4 disks	(3) Selection TOH = 1	(4) Endogenous task beans	(5) Endogenous task TOH 5 disks
Treatment	-3.255**	9.313	-0.236**	-10.696**	41.931
	(1.462)	(12.810)	(0.105)	(4.514)	(29.587)
Male	-25.332***	32.328***	0.401***	-23.667***	-33.524
	(0.916)	(11.016)	(0.107)	(4.840)	(31.294)
Age	-0.123	-3.758***	-	-0.391	-5.789***
	(0.120)	(0.530)		(0.247)	(1.624)
Years of education	-0.063	4.173***	0.052***		
	(0.638)	(0.570)	(0.020)		
2^{nd} round#Treat	4.712***	-15.817	-	10.788*	-47.465
	(1.631)	(13.311)		(6.009)	(37.269)
2^{nd} round	7.658	-0.327	-	3.885	-7.077
	(12.122)	(1.424)		(4.424)	(26.016)
Total nb of wrong moves - TOH 4 disks	-	-	0.002	-	-
			(0.005)		
Average time - TOH 4 disks	-	-	-0.006***	-	-
			(0.001)		
Constant	110.070***	150.537***	0.383	112.105***	639.497***
	(12.422)	(22.010)	(0.257)	(14.647)	(75.793)
Observations	720	720	685	685	685
Adjusted R-squared	0.214	0.213	-	-	-
Controls	Yes	Yes	Yes	Yes	Yes

Note: Clustered standard errors at the ward level in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The reported dependent variables denote the income earned when dividing the beans, when completing the TOH with 4 or 5 disks, and the likelihood of self-selecting into a less or more cognitive demanding task. Self-selection is estimated based on observable characteristics: the years of education, the total number of wrong moves when completing the TOH with 4 disks, and the average time needed to complete each TOH with 4 disks. Control variables are those listed in the Appendix. Years of Education are not included in Columns (4) and (5) because they are included in the first stage of the Heckman selection.

10 minutes to one week, and that, when the performance of a task requires a high engagement of our executive functions, the priming effect can be invalidated (Hart et al., 2010; Cohn and Maréchal, 2016). Table 2.10 in the Appendix shows that, when we do not control for the order of the task, the treatment effect is not significant anymore. When we look at the average income earned from dividing the beans or completing the TOHs across the three rounds of the effort task (i.e., Table 2.11 in the Appendix), the treatment has an aggregate impact in reducing productivity in the automatic task only for those who performed the beans first. Overall, when the automatic task is performed after the TOH, the treatment seems to have a positive effect on productivity. We speculate that there are two opposite reasons for this reaction: as reported in the qualitative interviews, we know that part of the participants enjoyed playing the TOH, while others felt stressed about not being able to complete enough towers and earn from the task. Consequently, on the one hand, this positive experience with the TOH may have overcome the negative effect of our priming, increasing productivity in the second round. On the other hand, the negative experience with the TOH may have increased productivity in the automatic task because participants felt more comfortable in performing an easier task.

Column (3) shows that the treatment leads to a negative selection in the cognitive task, i.e., that it increases the probability of choosing the beans rather than the TOH with 5 disks. In the last three columns the sample is reduced. This is because we are missing data for 35 individuals on the number of wrong moves and on the average time needed to complete each TOH with 4 disks. Columns (4) and (5) shows that mental load reduces the income in the third round only in the automatic task, in line with results in the first round. These results confirm our research hypothesis that mental load leads to a reduction in productivity and to self-selection into less cognitively-demanding tasks.

2.6.2 Heterogeneous effects

Gender differences

Table 2.4: Heterogeneous Effects - gender differences

	(1) **Exogenous task beans**	(2) **Exogenous task TOH 4 disks**	(3) **Selection TOH = 1**	(4) **Endogenous task-beans**	(5) **Endogenous task TOH 5 disks**
Treatment	-7.611***	19.265	-0.075	-11.828**	-5.814
	(2.151)	(14.062)	(0.142)	(5.588)	(42.387)
Male	-30.421***	44.052***	-0.583***	-32.504***	-52.256
	(1.809)	(16.570)	(0.153)	(8.043)	(49.166)
Treat#Male	8.394**	-20.086	-0.354*	4.340	89.064
	(4.089)	(23.607)	(0.211)	(8.985)	(58.426)
Age	-0.117	-3.756***	-	-0.323	-5.614***
	(0.128)	(0.539)		(0.245)	(1.629)
Years of education	-0.060	4.229***	-0.053***	-	-
	(0.631)	(0.520)	(0.020)		
Religion	-0.221	4.925		-2.710	-26.306
	(3.495)	(11.384)		(9.185)	(38.158)
2^{nd} round	-4.101***	13.550		-2.575	5.516
	(1.277)	(9.913)		(5.218)	(37.695)
2^{nd} Round#Treat	10.259***	-24.689*		16.289**	-26.617
	(3.487)	(14.015)		(7.503)	(53.276)
2^{nd} Round#Male	7.422**	-11.753		22.893**	-22.345
	(3.047)	(13.451)		(9.546)	(52.051)
2^{nd} Round#Treat#Male	-10.765**	18.115		-20.506	-38.618
	(5.382)	(16.484)		(12.691)	(73.698)
Total nb of wrong moves – TOH4			-0.002		
			(0.005)		
Time to complete - TOH 4 disks			0.006***		
			(0.001)		
Constant	112.144***	145.286***	-0.298	115.857***	636.125***
	(13.045)	(23.685)	(0.262)	(14.685)	(79.744)
Observations	720	720	685	685	685
Adjusted R-squared	0.214	0.211			
Controls	Yes	Yes	Yes	Yes	Yes

Note: Clustered standard errors at the ward level in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The reported dependent variables denote the income earned when dividing the beans, when completing the TOH with 4 or 5 disks, and the likelihood of self-selecting into a less or more cognitive demanding task. Self-selection is estimated based on observable characteristics: the years of education, the total number of wrong moves when completing the TOH with 4 disks, the average time needed to complete each TOH with 4 disks, and the interaction term between the treatment dummy variable and the gender dummy variable. Control variables are those listed in the Appendix. Years of Education are not included in Columns (4) and (5) because they are included in the first stage of the Heckman selection.

Table 2.4 reports the gender-differentiated impact of mental load on our outcomes of interest. Column (1) shows that mental load reduces labor productivity in the automatic task for women but not for men, confirming our hypothesis that mental load has a gendered effect on productivity, thus contributing to widening the already existing gender productivity gap. As for the results in the pooled sample, the order of the tasks influences productivity: when women perform the TOH first, the treatment actually increases their productivity, while for men it decreases it. In Columns (3) and (4), we find no heterogeneity across gender in self-selection and in productivity during the last round of the effort task, although we find a non-significant stronger effect for men in self-selection, and for women in productivity. Table 2.12 reports the gendered impact of our treatment on the average income earned from dividing the beans. Regardless of the order of the tasks, we find significant differences between women and men, suggesting that our treatment had a negative impact on productivity for women but not for men[11].

In line with the results in Column (3), Table 2.13 in the Appendix shows that men are insignificantly more likely to choose the beans in the third round rather than the Tower of Hanoi, and to make the sub-optimal, non-income maximizing choice. The Wald test (Table 2.14) shows that the effect on men is not significantly different from women, but the effect for men is significantly positive, while for women it is negative but insignificant. These results suggest that the self-selection effect is mainly driven by men[12], while the "productivity effect" in the automatic task is mainly driven by women.

Income differences

Table 2.5: Heterogeneous effects - income differences

	(1) Exogenous task beans	(2) Exogenous task TOH 4 disks	(3) Selection TOH = 1	(4) Endogenous task-beans	(5) Endogenous task TOH 5 disks
Treatment	-9.927***	7.844	-0.075	-13.445*	-24.444
	(3.333)	(12.569)	(0.142)	(6.910)	(55.259)
Poor	-11.105**	1.045		-9.793	-47.654
	(5.380)	(6.082)		(6.588)	(47.352)
Treat#Poor	2.222	19.288		3.873	35.674
	(5.088)	(12.473)		(7.813)	(60.536)
Age	0.143	-2.525***		0.014	-4.482*
	(0.260)	(0.707)		(0.326)	(2.544)
Years of education	0.309	7.087***	0.039		
	(1.038)	(0.906)	(0.027)		
2^{nd} round#Treat	10.028***	-20.373	-	14.370*	-18.947
	(3.841)	(14.385)		(7.419)	(57.698)
2^{nd} round	-4.441***	13.145	-	-1.014	-6.373
	(1.314)	(10.014)		(5.143)	(41.786)
Total nb of wrong moves - TOH 4 disks			-0.002		
			(0.007)		
Average time - TOH 4 disks			-0.005***		
			(0.001)		
Constant	119.604***	67.952***	0.419	100.049***	834.374***
	(20.308)	(23.288)	(0.361)	(22.752)	(132.195)
Observations	353	353	436	591	436
Adjusted R-squared	0.025	0.179			
Controls	Yes	Yes	Yes	Yes	Yes

Note: Clustered standard errors at the ward level in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The reported dependent variables denote the income earned when dividing the beans, when completing the TOH with 4 or 5 disks, and the likelihood of self-selecting into a less or more cognitive demanding task. Self-selection is estimated based on observable characteristics: the years of education, the total number of wrong moves when completing the TOH with 4 disks, and the average time needed to complete each TOH with 4 disks. Control variables are those listed in the Appendix. Years of Education are not included in Columns (4) and (5) because they are included in the first stage of the Heckman selection.

To test our last research hypothesis, we conduct the analysis based on women's income levels: we look at differences between women below and above the median of the weekly income distribution. As

[11] To check whether the order of the tasks influences these results, we also run the analysis without controlling for it but we include the performance in the TOH with 4 disks (i.e., the average time needed to complete each tower and the average number of wrong moves) as a proxy of the participant's experience with the TOH. As shown in Table 2.12, in both analyses the results show a significant gender difference in productivity in the automatic task.

[12] It must be noted, however, that given the initial very low share of women self-selecting into the TOH, to begin with (i.e. the control group) we might be underpowered to observe self-selective pressures on women. In fact, both for women and for men the coefficient is negative, with a drop in the share choosing TOH of about a quarter compared to the control group for women, and of almost half for men.

shown in Table 2.5, we observe a negative but not significant effect on productivity for women below the median of the income distribution, while a negative and significant effect for women above the median of the income distribution (Columns (1) and (4)). Being below the median (i.e., variable "Poor" in the table) significantly reduces productivity in the automatic task by 13 KSH, while the interaction term is statistically insignificant but it has a positive sign.

This result goes against our initial hypothesis, under which we had expected poorer women to face a stronger effect. The possible explanations could be threefold. First, it is simply possible that mental load cuts across income levels, reducing productivity regardless of relative financial deprivation. Secondly, it is possible that the intensity of treatment may be too weak to provide a sufficient trigger to alter the mental load status of already heavily burdened individuals. Thirdly, it could be that for women below the median the effect is somewhat dampened by the simultaneous stress effect, which in other contexts has shown to sometimes have positive effects on productivity. While all three pathways are possible, our qualitative interviews bring suggestive evidence in support of the last mechanism: mental load can lead women to focus more and to work harder to earn more to cover the household's expenses and to stick to the time schedule they have[13].

2.6.3 Mental load, cognitive functions and stress

To better understand which mechanisms are at place, we collected data on self-reported stress after the effort task and we asked participants to perform the Digit Span Task, a task used to measure sustained attention (Hale et al., 2002). We then looked at the impact of mental load priming on these two intermediate variables by estimating the following:

$$Y_{it} = \beta_0 + \beta_1 Treat_i + \beta_k X_{ih} + \varepsilon_i, \qquad (10)$$

where Y_{it} are the outcome variables (i.e., stress, sustained attention) of individual i; $Treat_i$ is the treatment dummy variable, X_{ih} are the control variables at the individual and household level, and ϵ_i is the error term. Depending on the outcome variable, we estimate either a logistic regression (i.e., to estimate the impact of the treatment on stress) or an OLS (i.e., to estimate the impact of the treatment on attention). We conduct the analysis on the pooled sample and then we check for gender differences. As shown in Table 2.6, mental load correctly predicts stress and attention in the pooled sample: it increases stress levels and it reduces sustained attention. If we look at gender differences, results show that mental load affects stress for women, but not for men, while it significantly decreases attention for men.

We also exploited the additional information we collected on the stress scale we computed following Palermo et al. (2020), and on a simplified version of the Raven's matrixes [14]. The stress scale developed and validated by Palermo et al. (2020) is particularly useful for this study because it includes

[13] Qualitative interviews are reported in the Appendix.
[14] Additional information can be found in the Appendix

Table 2.6: Mental load, stress, and cognitive functions

	(1) Self-reported stress	(2) Digit span task	(3) Self-reported stress	(4) Digit span task
Treatment	**0.410***	**-0.031****	**0.407***	**-0.018**
	(0.229)	**(0.013)**	**(0.279)**	**(0.018)**
Male	-0.477**	0.003	-0.420**	0.016
	(0.221)	(0.023)	(0.211)	(0.026)
Treat#male	-	-	**-0.112**	**-0.025***
			(0.389)	**(0.015)**
Constant	0.196	0.463***	0.179	0.459***
	(0.537)	(0.034)	(0.537)	(0.035)
Observations	720	720	720	720
R-squared		0.169		0.171
Controls	Yes	Yes	Yes	Yes

Note: Clustered standard errors at the ward level in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The reported dependent variables denote self-assessed stress of participants and their sustained attention, measured through the Digit Span Task. Control variables are those listed in the Appendix.

questions on stressors that could proxy mental load in urban Kenya, such as financial worries, access to education and food, physical health of the household's members, exposure to violence, alcohol abuse, and the relationship with household's members.

Table 2.15 shows differences in mean in the number of times participants reported being stressed about each item of the scale, and in the number of times they reported being stressed for each scale's item. As we can notice, participants in the treatment group reported to have felt stressed about more items than participants in the control group in the past 7 days. When looking at each item, data show that individuals in the treatment group reported being more stressed about financial worries, business failure, access to the education of the offspring, being victims of violence, and the relationship with the spouse and other family members.

If we disentangle the effect for men and women (Tables 2.16 and 2.17 in the Appendix), we can see that women in the treatment group reported being more stressed about financial worries and access to education of their children, two important dimensions of mental load. Men reported being more stressed about food access, physical health of their children, and their relationship with their spouse. When estimating the impact of mental load on all these variables through a logistic regression, we can see that Tables 2.18 and 2.19 confirm these statistics: the treatment led participants to be more likely to report stress about financial worries, having access to food and education, and the physical health of household members. Even though we find no significant gender differences, evidence suggests that women in the treatment group were more likely to report being stressed about access to education and food, while men for access to food, alcohol consumption of themselves or other household members, and the failure of their own business.

We also look at differences in mean in the Raven's score between participants in the control group that reported thinking "a lot" or not about mental load's related worries. As shown in Table 2.20, those individuals who self-reported a higher burden of mental load exhibit a lower Raven's score and a lower score in the Digit Span Task. If we look at gender differences between men and women, Table 2.20 shows that there is a significant difference in the Raven's score and in attention between men and women, with women performing worse than men. This is in line with the hypothesis that women bear a higher mental burden than men, and that this in turn risks impacting their stress levels and cognitive abilities on a daily basis.

2.7 Discussion of the results

The results presented in the previous Section show that mental load impacts productivity and decision-making, that it holds a gender-differentiated impact, and that it is negatively associated with cognitive abilities and stress.

In the pooled sample, mental load reduces productivity in the automatic task (i.e., dividing the beans) while it has no impact on the more cognitively demanding task. Importantly, the effect of the treatment in the automatic task holds only when participants divide the beans during the first round of the effort task. When they have to complete first the TOH with 4 disks, the treatment seems to have a positive effect. These results are confirmed also when we look at the average income earned from the beans. Also, we find that mental load increases the likelihood of self-selecting into the less remunerative and less cognitively demanding task. Considering the limitation of priming techniques, we conclude that mental load risks reinforcing the psychological poverty trap identified by the literature on scarcity (Haushofer and Fehr, 2014): not only it reduces productivity and earnings in those jobs where individuals living in poverty are usually employed in, but it also leads them to choose those jobs whose productivity is actually reduced by mental load.

The heterogeneity analysis reveals that mental load reduces productivity for women but not for men in the automatic task only when it is performed right after the treatment. In line with the results in the pooled sample, if women engage first in the TOH, then the negative productivity effect of our treatment disappears. When we look at the average income earned from dividing the beans, however, we find that our treatment reduces productivity for women but not for men, regardless of the order of the tasks. These results suggest that mental load reduces productivity for women in those automatic and less cognitively-demanding tasks that reflect the jobs in which they are usually employed (Agwaya and Mairura, 2019). Consequently, women risk finding themselves caught not only in the psychological poverty trap (Haushofer and Fehr, 2014; Schilbach et al., 2016; Ridley et al., 2020), but also in the "mental load trap": by reducing productivity, mental load reduces earnings and income, it increases the financial worries dimension, and it consequently reinforces itself.

In the last round of the effort task, the interaction term is not significant anymore. Mental load leads both men and women to self-select into a less cognitive task, but the effect for men is for about half of those that would have chosen the cognitive task, to desist, while for women it is one in four. We cannot conclude then that gender matters in explaining self-selection or productivity in the last round of the effort task. A possible explanation for these results has to be found in the design of the treatment: by exposing to the same prime all participants, we are "imposing" gender equality in mental load in our sample. Paired with the results in Column (2) of Table 2.12, showing that the treatment had a non-significant but negative impact on the performance of the TOH regardless of gender, the analysis reveals that both women and men responded to the treatment, with the former driving the effect on productivity, and the latter on self-selection. These results are actually of crucial importance because they suggest that, when exposed to it, both women and men are affected by mental load. The problem is that, contrary to our treatment, mental load is not orthogonal to gender outside of the experimental setting. Instead, women usually carry this mental burden because gender norms prescribe them to be responsible for the management of the household. By showing that both men and women respond to mental load when exposed to it, these results imply that this is an invisible, psychological dimension of gender inequality rooted in the patriarchal system that requires more attention.

Looking at the relationship between mental load, stress, and cognitive functions we find that mental load impairs sustained attention and stress in the pooled sample. When we disentangle the effect for gender differences, mental load affects women's self-reported stress, while it significantly reduces attention in men—albeit in both cases only significant at the 10% level. These results have to be interpreted carefully. Because we measured participants' stress and attentional levels after the effort task, we collected "biased" information: the time pressure dimension of the tasks, paired with the economic incentive, may have increased stress levels in participants in the control group and decreased their attention, too, in which case we would be reporting a lower-bound effect. Interestingly, when we look at self-assessed stress for specific stressors in the past week, we find that the treatment increased women's self-reported stress about access to food, their children's education, and financial concerns, and that men reported feeling stressed about more items than women.

This, paired with evidence on self-selection, suggests that our treatment may have been more effective for those individuals that do not usually think a lot about mental load related issues (i.e., more often than not, men). Indeed, while the treatment has a significant impact on men's attention levels but not women's, and men reported being stressed on more items than women, when restricting the analysis to the control group, women that reported thinking "a lot" about mental load related issues exhibit lower scores in the cognitive tests and they report higher self-reported stress than men. All this suggests that our treatment was not equally effective in triggering in minds these thoughts related to mental load, and that we may be severely underestimating the (gendered) impact of mental load on stress, cognitive abilities, and economic outcomes if those most heavily affected by mental load (i.e. most often than not, women) had a weaker response to the treatment.

2.8 Conclusion

Living in poverty substantially increases the mental burden people bear on a daily basis (Haushofer and Fehr, 2014; Schilbach et al., 2016). Despite this, in low- and middle-countries mental load still represents a relatively unexplored and unknown issue. This paper analyzes the impact of mental load on labor productivity and occupational choices in poor, urban areas in Kenya. Previous studies show that mental load has negative effects on women's work sphere, on their stress levels, and on their overall well-being (Offer, 2014; Ciciolla and Luthar, 2019; Daminger, 2019b; Dean et al., 2022), but their analysis is based on qualitative or time-use surveys in the US, and they focus mainly on dual-earner families of the American middle class (Daminger, 2019b). This study contributes to the literature by estimating the causal impact of mental load on labor productivity and occupational choices in a middle-income country, where the conditions people live in worsen the burden of mental load.

We designed a lab-in-the-field experiment in poor areas of Nairobi where we triggered in the mind of the participants thoughts related to mental load and then we asked them to perform a 30 minutes real effort task that was divided in three time slots of 10 minutes each. During the first two time slots, participants were asked to divide black from red beans and to complete as many TOH with 4 disks as possible. To account for self-selection, in the last 10 minutes they were given the choice between dividing the beans again, or completing the TOH with 5 disks with an increased economic incentive.

Kenya is a relevant case to study the relationship between mental load and economic outcomes because of the structure of the labor market and the prevailing gender norms. Over the past years, women have started partaking more in the labor force[15], but they are still predominantly employed in the informal sector and in jobs with a piece-rate scheme (Agwaya and Mairura, 2019). While female labor participation has been increasing, local gender norms still prescribe women to be responsible of the household: they are fully in charge of the domestic work and of the care of their children (e.g., bathing them, helping them with the homework, cooking for them) (Maina et al., 2019). In this context, mental load risks being particularly burdensome, bringing about severe consequences on numerous economic outcomes and, hence, contributing to the persistence of gender inequalities.

The results show that mental load reduces labor productivity in automatic and less remunerative tasks, and it leads participants to self-select into those same tasks. The heterogeneity analysis reveals that gender matters in explaining differences in productivity in the automatic task during the first two rounds of the effort task. When looking at self-selection and productivity during the last round of the effort task, we find that the effect of our treatment on the former is mainly driven by men, while on the latter by women, but we cannot conclude that we find significant gender differences for these two outcomes. Finally, we find that the effects are similar for women above and below the median income in our sample.

Being the first study trying to vary the salience of mental load and to estimate its impact on economic outcomes, this analysis bears its limitations. Despite our prime being effective in triggering mental load for both men and women, it does not allow us to disentangle the causal mechanisms behind our findings nor to understand whether it affects differently individuals with a higher or lower burden of mental load to begin with, increasing the risk of an underestimation of treatment effect. However, even in light of the growing concern in the psychology literature about the reliability of priming techniques (Chivers, 2019; Kaur et al., 2021; Sherman and Rivers, 2021), we still believe that for a lab-in-the-field

[15] https://data.worldbank.org/indicator/SL.TLF.CACT.FE.ZS?locations=KE

experiment, this was the best technique we could use to test our research hypotheses. Another limitation is linked to our effort task: by asking participants to perform a cognitively-demanding task that they enjoyed (i.e., the TOH), we involuntarily vanished the effect of our prime on productivity when the TOH was performed as the first task.

Notwithstanding these limitations, we believe that this study provides exploratory but insightful evidence on mental load, as long as magnitudes of effects are interpreted as intent-to-treat. Indeed, even with an underestimation of our treatment effect and with a small intervention like ours, where we increased participants' emotional stress related to their daily worries, we find significant and worrisome results showing that mental load is an invisible but pressing psychological problem that risks holding individuals in poverty and engendering important drawbacks for gender inequality. What would happen if instead of increasing mental load in individuals we tried to reduce it?

Next steps should involve field experiments to understand which interventions can lower the psychological burden of mental load, and what positive consequences this could lead in terms of productivity, preferences, occupational choices, and well-being more generally. Examples of useful interventions involve access to child-care facilities, paired with conditional cash transfers to lower the dimension of financial worries. Another important aspect to consider relates to the mental health dimension of mental load: in several qualitative interviews, women explained that they tend to take medicines to mitigate the headache when they feel overwhelmed by all their thoughts and worries. In other cases, they do not know how to cope with stress and anxiety and they just loose focus and concentration while working. Mindfulness and meditation techniques are gaining increasing attention also in the economic literature (Economides et al., 2018; Shreekumar and Vautrey, 2022), showing that their benefits are not limited to an overall improvement in mental health, but they include increased performance and less interference of emotions in decision-making (Shreekumar and Vautrey, 2022). From our experience on the field, we believe that such interventions would be extremely helpful in the reduction of negative effects of mental load, while limiting the potential cultural barriers that may arise with, for instance, psychotherapy interventions.

More generally, further analysis on this phenomenon would improve our understanding of the persistence of gender inequalities and it would shed light on an important dimension of women's empowerment (i.e., the psychological one) that has received little attention by the literature when compared to other dimensions. More research is needed to include in time-use surveys questions to proxy mental load to be able to include it in empowerment indexes internationally adopted, such as the Women's Empowerment in Agriculture Index (Alkire et al., 2013).

References

Agwaya, R. and Mairura, S. (2019). *Gender productivity gap in Kenyan informal enterprises*. Kenya Institute for Public Policy Research and Analysis.

Alkire, S., Malapit, H., Meinzen-Dick, R., Peterman, A., Quisumbing, A., Seymour, G., and Vaz, A. (2013). Instructional Guide on the Women's Empowerment in Agriculture Index. page 82.

Allred, S., Duffy, S., and Smith, J. (2016). Cognitive load and strategic sophistication. *Journal of Economic Behavior & Organization*, 125:162–178.

Angel-Urdinola, D. and Wodon, Q. (2010). Income generation and intra-household decision making: A gender analysis for nigeria. *Gender disparities in Africa's labor market*, 381.

Banerjee, A. V. and Mullainathan, S. (2008). Limited attention and income distribution. *American Economic Review*, 98(2):489–93.

Bardasi, E., Sabarwal, S., and Terrell, K. (2011). How do female entrepreneurs perform? evidence from three developing regions. *Small Business Economics*, 37(4):417.

Callen, M., Isaqzadeh, M., Long, J. D., and Sprenger, C. (2014). Violence and Risk Preference: Experimental Evidence from Afghanistan. *American Economic Review*, 104(1):123–148.

Cettolin, E., Dalton, P. S., Kop, W., and Zhang, W. (2020). Cortisol meets garp: the effect of stress on economic rationality. *Experimental Economics*, 23(2):554–574.

Chivers, T. (2019). What's next for psychology's embattled field of social priming. *Nature*, 576(7786):200–203.

Ciciolla, L. and Luthar, S. S. (2019). Invisible household labor and ramifications for adjustment: Mothers as captains of households. *Sex Roles*, 81(7-8):467–486.

Cohn, A. and Maréchal, M. A. (2016). Priming in economics. *Current Opinion in Psychology*, 12:17–21.

Cohn, A. and Maréchal, M. A. (2016). Priming in economics. *Current Opinion in Psychology*, 12:17–21.

Dalton, P. S., Nhung, N., and Rüschenpöhler, J. (2020). Worries of the poor: The impact of financial burden on the risk attitudes of micro-entrepreneurs. *Journal of Economic Psychology*, 79:102198.

Daminger, A. (2019a). The Cognitive Dimension of Household Labor. *American Sociological Review*, 84(4):609–633.

Daminger, A. (2019b). The Cognitive Dimension of Household Labor. *American Sociological Review*, 84(4):609–633.

de Bruijn, E.-J. and Antonides, G. (2021). Poverty and economic decision making: a review of scarcity theory. *Theory and Decision*, pages 1–33.

Dean, E. B., Schilbach, F., and Schofield, H. (2017). Poverty and cognitive function. In *The economics of poverty traps*, pages 57–118. University of Chicago Press.

Dean, L., Churchill, B., and Ruppanner, L. (2022). The mental load: building a deeper theoretical understanding of how cognitive and emotional labor over load women and mothers. *Community, Work & Family*, 25(1):13–29.

Deck, C. and Jahedi, S. (2015). The effect of cognitive load on economic decision making: A survey and new experiments. *European Economic Review*, 78:97–119.

Diamond, A. (2013). Executive functions. *Annual review of psychology*, 64:135–168.

Doss, C. (2013). Intrahousehold bargaining and resource allocation in developing countries. *The World Bank Research Observer*, 28(1):52–78.

Economides, M., Martman, J., Bell, M. J., and Sanderson, B. (2018). Improvements in stress, affect, and irritability following brief use of a mindfulness-based smartphone app: a randomized controlled trial. *Mindfulness*, 9(5):1584–1593.

Floro, M. S. (1995). Women's well-being, poverty, and work intensity. *Feminist Economics*, 1(3):1–25.

Hale, J. B., Hoeppner, J.-A. B., and Fiorello, C. A. (2002). Analyzing digit span components for assessment of attention processes. *Journal of psychoeducational assessment*, 20(2):128–143.

Hart, S. J., Green, S. R., Casp, M., and Belger, A. (2010). Emotional priming effects during stroop task performance. *Neuroimage*, 49(3):2662–2670.

Haushofer, J. and Fehr, E. (2014). On the psychology of poverty. *Science*, 344(6186):862–867.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Econometrica: Journal of the econometric society*, pages 153–161.

Heineck, G. and Anger, S. (2010). The returns to cognitive abilities and personality traits in germany. *Labour Economics*, 17(3):535 – 546.

Henderson, R. K., Snyder, H. R., Gupta, T., and Banich, M. T. (2012). When does stress help or harm? the effects of stress controllability and subjective stress response on stroop performance. *Frontiers in Psychology*, 3:179.

Kaur, S., Mullainathan, S., Oh, S., and Schilbach, F. (2019). Does financial strain lower productivity? Technical report, Working Paper.

Kaur, S., Mullainathan, S., Oh, S., and Schilbach, F. (2021). Do Financial Concerns Make Workers Less Productive? *National Bureau of Economic Research*, No. w28338.:49.

Kilic, T., Palacios-Lopez, A., and Goldstein, M. (2015). Caught in a productivity trap: a distributional perspective on gender differences in malawian agriculture. *World Development*, 70:416–463.

Maccini, S. and Yang, D. (2009). Under the Weather: Health, Schooling, and Economic Consequences of Early-Life Rainfall. *American Economic Review*, 99(3):1006–1026.

Maina, L. W., Kimani, E., Azevedo, A., Parkes, A., and Ndinda, L. (2019). Gendered patterns of unpaid care and domestic work in the urban informal settlements of nairobi, kenya: Findings from a household care survey–2019.

Manda, D. K. and Mwakubo, S. (2014). Gender and economic development in africa: An overview. *Journal of African Economies*, 23(suppl_1):i4–i17.

Mani, A., Mullainathan, S., Shafir, E., and Zhao, J. (2013). Poverty Impedes Cognitive Function. *Science*, 341(6149):976–980.

Morgado, P. and Cerqueira, J. J. (2018). The impact of stress on cognition and motivation. *Frontiers in Behavioral Neuroscience*, page 326.

Mukasa, A. N. and Salami, A. O. (2015). *Gender productivity differentials among smallholder farmers in Africa: A cross-country comparison*. African Development Bank Abidjan.

Offer, S. (2014). The costs of thinking about work and family: Mental labor, work–family spillover, and gender inequality among parents in dual-earner families. In *Sociological Forum*, volume 29, pages 916–936. Wiley Online Library.

Offer, S. and Schneider, B. (2011). Revisiting the gender gap in time-use patterns: Multitasking and well-being among mothers and fathers in dual-earner families. *American Sociological Review*, 76(6):809–833.

Oloo, R. and Parkes, A. (2021). Addressing unpaid care and domestic work for a gender-equal and inclusive kenya.

Palacios-López, A. and López, R. (2015). The gender gap in agricultural productivity: the role of market imperfections. *The Journal of Development Studies*, 51(9):1175–1192.

Palermo, T., Hall, B. J., Cirillo, C., Tanzania PSSN Youth Study Evaluation Team, T. A. C. P. S. T., and in Acknowledgement, G. L. . E. T. (2020). Enhanced life distress inventory: Development and validation in two african countries. *British Journal of Health Psychology*, 25(3):728–753.

Ridley, M., Rao, G., Schilbach, F., and Patel, V. (2020). Poverty, depression, and anxiety: Causal evidence and mechanisms. *Science*, 370(6522).

Schilbach, F. (2019). Alcohol and self-control: A field experiment in india. *American economic review*, 109(4):1290–1322.

Schilbach, F., Schofield, H., and Mullainathan, S. (2016). The Psychological Lives of the Poor. *American Economic Review*, 106(5):435–440.

Scott, S. B., Graham-Engeland, J. E., Engeland, C. G., Smyth, J. M., Almeida, D. M., Katz, M. J., Lipton, R. B., Mogle, J. A., Munoz, E., Ram, N., et al. (2015). The effects of stress on cognitive aging, physiology and emotion (escape) project. *BMC psychiatry*, 15(1):1–14.

Shah, A. K., Shafir, E., and Mullainathan, S. (2015). Scarcity Frames Value. *Psychological Science*, 26(4):402–412.

Shah, A. K., Zhao, J., Mullainathan, S., and Shafir, E. (2018). Money in the Mental Lives of the Poor. *Social Cognition*, 36(1):4–19.

Sherman, J. W. and Rivers, A. M. (2021). There's nothing social about social priming: Derailing the "train wreck". *Psychological Inquiry*, 32(1):1–11.

Shreekumar, A. and Vautrey, P.-L. (2022). Managing emotions: The effects of online mindfulness meditation on mental health and economic behavior. Technical report.

Singbo, A., Njuguna-Mungai, E., Yila, J., Sissoko, K., and Tabo, R. (2021). Examining the gender productivity gap among farm households in mali. *Journal of African Economies*, 30(3):251–284.

Skirbekk, V. (2004). Age and individual productivity: A literature survey. *Vienna yearbook of population research*, pages 133–153.

Staal, M. A. (2004). Stress, cognition, and human performance: A literature review and conceptual framework.

Tsai, N., Eccles, J. S., and Jaeggi, S. M. (2019). Stress and executive control: Mechanisms, moderators, and malleability. *Brain and Cognition*, 133:54–59.

Vohs, K. D., Redden, J. P., and Rahinel, R. (2013). Physical Order Produces Healthy Choices, Generosity, and Conventionality, Whereas Disorder Produces Creativity. *Psychological Science*, 24(9):1860–1867. Publisher: SAGE Publications Inc.

Wanjala, B. M. and Were, M. (2009). Gender disparities and economic growth in kenya: A social accounting matrix approach. *Feminist Economics*, 15(3):227–251.

Zook, N. A., Davalos, D. B., DeLosh, E. L., and Davis, H. P. (2004). Working memory, inhibition, and fluid intelligence as predictors of performance on tower of hanoi and london tasks. *Brain and cognition*, 56(3):286–292.

Appendix

Qualitative interviews

Interviews to understand the dimensions of mental load

Leila, Kibera:

"When I'm at work I deeply think: "where is my child? and is my child safe wherever he is? Is he near someone who is safe, I give it a lot of thought, I always want to know, where is my child? And in most cases, has my child eaten? [...] Something else is the daily bread, how will my people eat? How will my people eat? Wherever you are, even if you are at work, how will my family eat? And you have to do it in a way that you have to do the timing so that the children get tired, they go to sleep early so you have to be organized [...] A man can provide anything that he can afford but he won't say a word, you are the one to know how to spend the money, and maybe the amount is too little but you are the one to get a headache " Josephine, Korogocho:

"I also have such thoughts while at my business, first of all I ensure that at least my children are going to school as I don't want them to go through the kind of life I went through. As I wasn't able to even as a grown up and I go through a lot of problems in terms of education, to get a better life. So, every time I'm at work, I usually think of what I can help my children with to ensure they don't live the kind of life I have lived, so that they may live a better life and get better education so that one day they may be able to conduct their businesses with ease. "

Juma, Korogocho:

"[...] There are many things that I go through in this job, sometimes you come to work but no customers, so you wonder what you will eat when you go back to the house because you have children who need to go to school, they need school fees, and sometimes you leave the house and there is nothing to eat, and maybe the day becomes unproductive and you end up being stressed [...]"

Exit interviews to understand the perceptions of the effort task

Florence, treatment group:

"[...] I felt I was under pressure while sorting beans, at some point I thought about my child in school, whether she is okay, then my mind kind of shut down and I mixed the black beans with the red I had sorted. However, during the tower, I was fully focused. While sorting beans, I thought about my child in school and her safety, I was to pick her up in school and I was afraid I would be late. [...]"

Eva, treatment group:

"While sorting beans, the thought of my child came to me. I was thinking of whether she has been fed. During the tower, my mind was fully occupied in the game. [...] The tower was fun, and I thought the game would teach me about how to make hard life decisions. I thought that through the game I would learn skills on how to order competing needs, The game to me was more like the things that happen in daily life. [...]"

Beatrice, control group:

"During the whole session, I was worried about my child in school. I was worried that if I stay here for long I would find that she has been left alone in school when her classmates are picked by their parents. It is my daily duty to pick her and I was worried I would miss the time to pick her. I was also worried that this little one I

have come here with would wake up and start crying and that would disrupt the session here, fortunately she has not woken up."

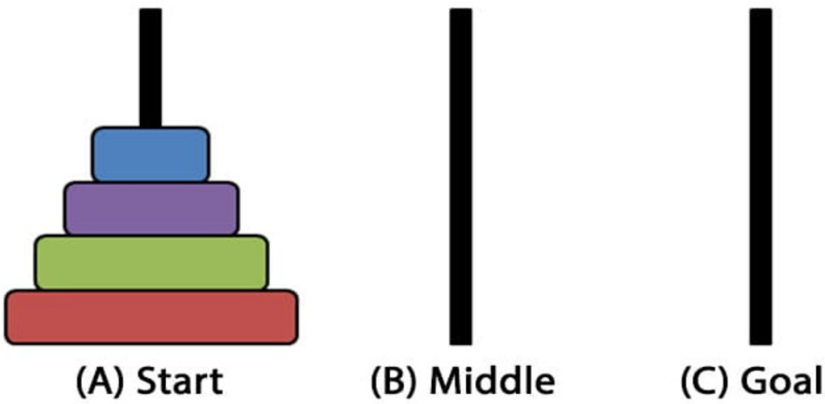
Abdallah, treatment group:

"[...] The things that were spoken in the videos are the things we go through in our daily life. Personally, what worries me most is how the children will go to school (fees), while is more concerned about cooking. For me it is mainly about where the food comes from but not the actual cooking. How I will facilitate food availability, school fees and accommodation (rent) for my household are my biggest concerns. And I also try to compare/balance my working hours and family hours. [...]"

Survey instruments

Tower of Hanoi

Figure 2: Tower of Hanoi



The TOH has three main rules to follow: first, only one disk may be moved at a time; second, the disks can be moved only from one peg to another; and third, a disk may never be place to another smaller disk. The minimum number of moves required to complete the ToH is always $2^n - 1$, where n is the number of disks. To increase the level of difficulty, it is sufficient to add a disk to each round. In our experiment, we developed an online tool to collect precise data on the number of moves needed to complete each TOH in each round of the effort task.

Raven's Matrixes

We asked participants in the control group to solve the following set of 12 Raven's matrixes. The selection of the Matrixes comes from piloting tests to understand the appropriate level of difficulty.

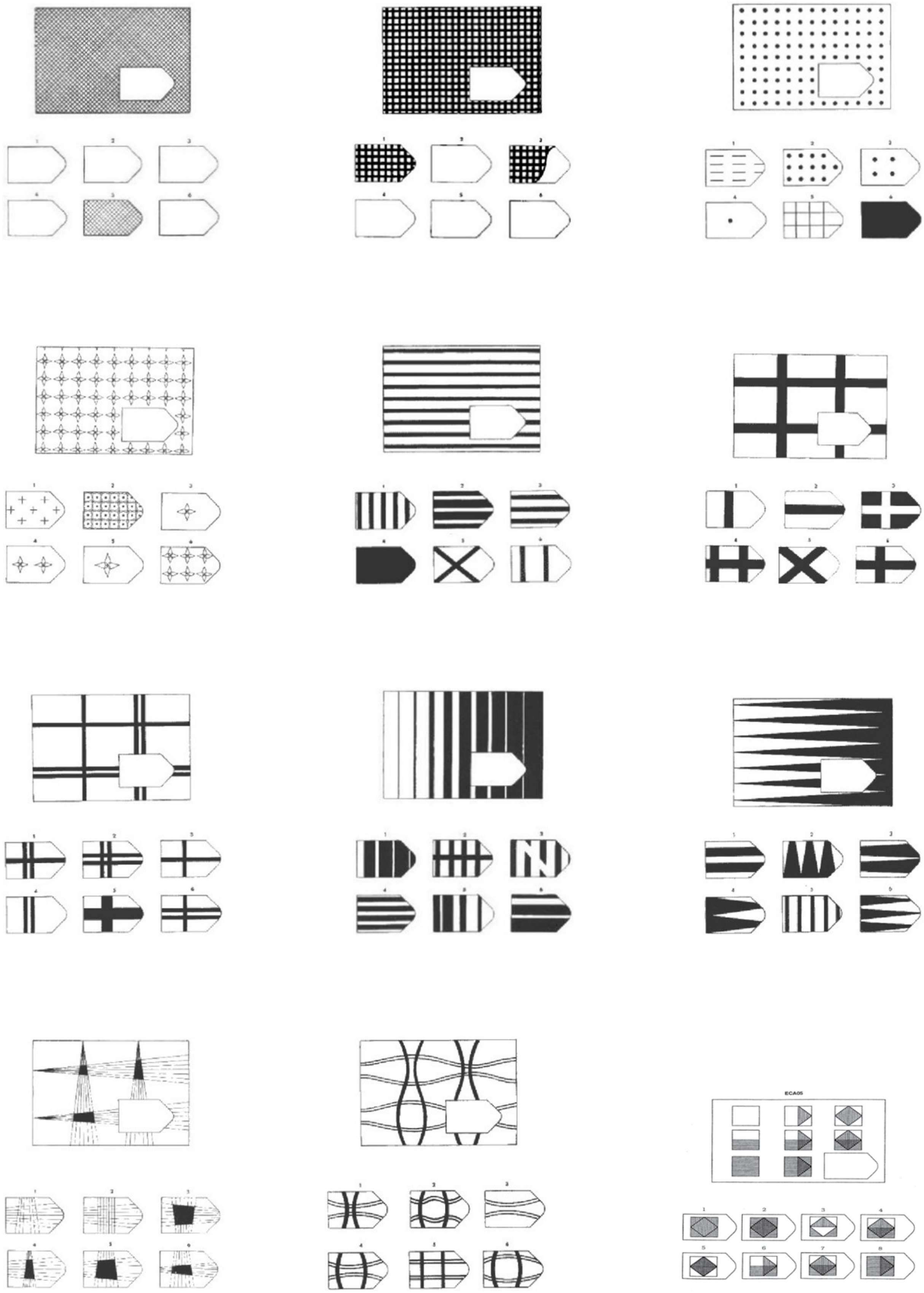


Figure 3: Raven's Matrixes

Additional tables

Table 7: Mean differences in stress between men and women

	Women	Mean	Men	Mean	Diff	St Err	P-value
Stress – self report	**353**	**.581**	**367**	**.447**	**.134**	**.037**	**.001**
Stress - scale	353	11.74	367	11.3	.44	.48	.36
Stress - items	**353**	**6.575**	**367**	**6.144**	**.43**	**.208**	**.039**
Stress – financial worries	**353**	**.966**	**367**	**.926**	**.04**	**.017**	**.019**
Stress – business failure	**353**	**.451**	**367**	**.523**	**-.072**	**.037**	**.051**
Stress - employment	353	.79	367	.787	.003	.03	.924
Stress – access to education	**353**	**.847**	**367**	**.733**	**.114**	**.03**	**0**
Stress – access to food	353	.779	367	.755	.025	.032	.442
Stress – health	353	.638	367	.605	.033	.036	.37
Stress – alcool abuse	353	.209	367	.245	-.036	.032	.256
Stress – violence	**353**	**.258**	**367**	**.199**	**.059**	**.031**	**.06**
Stress – theft	353	.309	367	.33	-.021	.035	.548
Stress – relationship with family member	353	.371	367	.335	.036	.036	.314
Stress – relationship with spouse	**353**	**.368**	**367**	**.281**	**.088**	**.035**	**.012**
Stress – relationship with others	**353**	**.318**	**367**	**.175**	**.143**	**.032**	**0**
Stress – pregnancy	353	.272	366	.252	.021	.033	.53

Note: mean differences in self-reported stress between men and women in the sample. From the bottom, respectively, reported variables indicate: self-reported stress after the effort task, the scale of self-reported stress measured following **?**, the number of items individuals reported to be stressed about; self-reported stress about financial worries, business failure, employment situation of you or the household members, access to education of the household's members, access to food, physical health of you and the household's members, alcool abuse of you and the household's members, being victim of violence, being victim of theft, the relationship with a family member, the relationship with the spouse, the relationship with others, and pregnancy or contraceptive use of you or your spouse.

Table 8: Differences in mean and verification of randomization

	Treat	Mean	Control	Mean	Diff	SE	P-value
Male	368	.511	352	.509	.003	.037	.95
Age of respondent	368	31.392	353	31.204	.188	.571	.743
Years of education	368	11.195	353	11.152	.043	.218	.845
Muslim	368	.063	353	.048	.015	.017	.401
Married	368	.756	353	.804	-.049	.031	.112
Nb of children < 10	368	1.843	353	1.895	-.053	.07	.449
Nb of hh members	368	4.014	353	4.037	-.023	.094	.805
Female share	368	.54	353	.528	.012	.016	.441
Childcare - school	368	.231	353	.184	.047	.03	.122
Childcare - parents	368	.261	353	.272	-.011	.033	.737
Asset index	368	-.007	353	-.026	.018	.074	.805
Weekly work hours	368	39.31	353	37.971	1.338	1.758	.447
Weekly income	368	3367.7	353	3021.3	346.3	310.1	.265
Informal sector	368	.519	353	.502	.018	.037	.637
Unemployed	368	.101	353	.105	-.005	.022	.851
Self-employed - formal	368	.304	353	.332	-.027	.035	.436
Downward income risk	368	.39	353	.419	-.029	.023	.208
Slum	368	.666	353	.621	.045	.036	.204
Multitasking	368	.011	353	.012	-.002	.001	.021

Note: mean differences between the treatment and the control group. Reported variables are: a dummy equals to 1 if the participant is a man, 0 if she is a woman; the age of the respondent; the years of education; a dummy variable equals to 1 if the participant is Muslim, 0 otherwise; a dummy variable equals to 1 if the participant is married, 0 otherwise; the number of children under the age of 10 in the household; the number of household's members; the share of female members in the household; dummy variables equals to one if the mode of childcare is school or leaving the children with the parents; the monthly income measured in KSH; the asset index measured the Factor Analysis; the number of weekly hours worked; a dummy variable equals to 1 if the participants is employed in the informal sector, if he/she is unemployed, and if he/she if self-employed in the formal sector; the downward income risk, measured as 1-(Weekly income below the average Weekly average income); a dummy variable equals to 1 if the participant lives in the slum; and the minutes spent multitasking the day before the interview.

Table 9: definition of outcome and control variables

Outcome variables	**Variables definition**
Labor productivity from automatic and proceduralized tasks	Earnings from each round of effort task accounted separately
Self-selection in less cognitive demanding jobs	Dummy =1 if participant chooses the beans in the third round of effort task
Irrationality	Dummy =1 if the individual does not choose the income-maximizing choice
Control variables	**Variables definition**
Education	Years of education
Male	Dummy =1 if respondent is a man, 0 if she is a woman
Married	Dummy =1 if respondent is married/living together with her/his partner
Formal occupation	Dummy =1 if respondent is employed in the formal sector
Self-employed	Dummy =1 if respondent is self-employed
Unemployed	Dummy =1 if respondent is unemployed
Income level	Monthly income of the participant
Downward income risk	1 − (Weekly income below the average /Weekly average income)
Number of adults in the hh	Total nb. of adults in the household
Number of children under the age of 10	Total nb. of children under the age of 10 in the hh
Share of female members in the hh	Total nb. of female members/Total hh members
Number of hh members earning an income	Total nb. of hh members − nb. of declared dependent children in the hh
Mode of childcare	Dummies = 1 if the main mode of childcare is school or the parents
Asset index	Measured through factor analysis
Slum	Dummy =1 if the participant is living in a slum area, 0 otherwise
Muslim	Dummy =1 if participant is Muslim
Multitasking	Nb. of reported hours of multitasking/24 hours
Randomization effort task	Dummy =1 if participant completed first the TOH and then the beans
Effort task	Dummy =1 if task is the TOH
Stress	Stress scale measured following Palermo et al., 2020
Attention	Performance to the digit span task (tot. nb of correct answer/Tot nb. of questions)
Randomization of Stress and Attention modules	Dummy =1 if first module was stress, 0 otherwise
Poor	Dummy =1 if below the median of the income distribution in the sample

Table 10: Average Treatment Effects without interaction Round # Treat

	(1) Exogenous task beans	(2) Exogenous task TOH 4 disks	(3) Selection TOH = 1	(4) Endogenous task beans	(5) Endogenous task TOH 5 disks
Treatment	-0.783	1.309	-0.236**	-4.628	19.738
	(1.043)	(7.340)	(0.105)	(3.263)	(22.993)
Male	-25.730***	31.396***	-0.401***	-24.205***	-37.868
	(0.867)	(10.853)	(0.107)	(4.961)	(31.150)
Age	-0.123	-3.739***		-0.456*	-5.751***
	(0.121)	(0.536)		(0.251)	(1.631)
Years of education	-0.025	4.255***	-0.052***		
	(0.633)	(0.565)	(0.020)		
Total nb of wrong moves - TOH 4 disks			-0.002		
			(0.005)		
Avg time to complete - TOH 4 disks			0.006***		
			(0.001)		
Constant	109.708***	154.231***	-0.383	115.096***	641.186***
	(11.917)	(22.836)	(0.257)	(14.764)	(74.094)
Observations	720	720	685	685	685
Adjusted R-squared	0.213	0.214			
Controls	Yes	Yes	Yes	Yes	Yes
Constant	110.070***	150.537***	0.383	112.105***	639.497***
	(12.422)	(22.010)	(0.257)	(14.647)	(75.793)
Observations	720	720	685	685	685
Adjusted R-squared	0.214	0.213	-	-	-
Controls	Yes	Yes	Yes	Yes	Yes

Note: Clustered standard errors at the ward level in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The reported dependent variables denote the income earned when dividing the beans, when completing the TOH with 4 or 5 disks, and the likelihood of self-selecting into a less or more cognitive demanding task. Self-selection is estimated based on observable characteristics: the years of education, the total number of wrong moves when completing the TOH with 4 disks, and the average time needed to complete each TOH with 4 disks. Control variables are those listed in the Appendix. Years of Education are not included in Columns (4) and (5) because they are included in the first stage of the Heckman selection.

Table 11: Impact of mental load on the average income earned from the effort task

	(1) Avg income beans	(2) Avg income TOH	(3) Avg income beans	(4) Avg income TOH
Treatment	-1.842	-4.228	-3.993***	10.560
	(1.679)	(8.810)	(1.541)	(15.497)
Male	-25.877***	41.739**	-25.482***	43.673**
	(0.762)	(17.232)	(0.802)	(17.215)
Age	0.097	-5.556***	-0.119	-5.583***
	(0.106)	(0.636)	(0.121)	(0.659)
Years of education	-0.561	4.885***	-0.315	4.712***
	(0.536)	(0.818)	(0.523)	(0.820)
Round	-	-	0.324	11.348
			(1.380)	(14.114)
Round#Treat	-	-	5.085***	-29.665
			(1.139)	(18.527)
Average time to complete – TOH 4 disks	-0.041**	-	-	-
	(0.020)	-	-	-
Total nb of wrong moves – TOH 4 disks	-0.027			
	(0.102)			
Constant	119.237***	278.520***	113.541***	273.345***
	(8.219)	(32.429)	(10.549)	(30.671)
Observations	700	720	720	720
Adjusted R-squared	0.235	0.213	0.228	0.214
Controls	Yes	Yes	Yes	Yes

Note: Clustered standard errors at the ward level in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The reported dependent variables denote the average income earned during the effort task from dividing the beans and from completing the TOH with 4 and 5 disks. Control variables are those listed in Table 8 in Appendix C.

Table 12: Gendered impact of mental load on the average income earned from the effort task

	(1) **Avg income beans**	(2) **Avg income TOH**	(3) **Avg income beans**	(4) **Avg income TOH**
Treatment	-3.905*	-2.246	-9.573***	17.136
	(2.048)	(10.338)	(1.565)	(12.698)
Male	-27.959***	44.148	-31.282***	58.998**
	(1.154)	(29.750)	(2.219)	(23.276)
Treat#Male	4.077*	-4.350	9.828***	-12.880
	(2.251)	(27.532)	(3.655)	(32.330)
Age	0.102	-5.549***	0.094	-5.543***
	(0.106)	(0.635)	(0.112)	(0.663)
Years of education	-0.575	4.877***	-0.579	4.692***
	(0.545)	(0.790)	(0.550)	(0.811)
2^{nd} Round	3.301**	-3.096	-3.204***	23.962*
	(1.328)	(5.652)	(1.237)	(12.706)
2^{nd} Round#Treat	-	-	11.294***	-37.722**
			(3.166)	(14.780)
2^{nd} Round#Male	-	-	7.671*	-24.967
			(4.105)	(23.677)
2^{nd} Round#Treat#Male	-	-	-11.583**	16.168
			(5.757)	(24.982)
Avg time to complete – TOH 4 disks	-0.042**	-	-0.041*	-
	(0.020)		(0.022)	
Total nb wrong moves – TOH 4 disks	-0.023		-0.023	-
	(0.103)		(0.112)	
Constant	119.957***	279.593***	122.756***	264.146***
	(8.675)	(30.972)	(9.140)	(33.863)
Observations	700	720	700	720
Adjusted R-squared	0.235	0.211	0.238	0.212
Controls	Yes	Yes	Yes	Yes

Note: Clustered standard errors at the ward level in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The reported dependent variables denote the average income earned during the effort task from dividing the beans and from completing the TOH with 4 and 5 disks. Control variables are those listed in Table 8 in Appendix C.

Table 13: Gendered impact of mental load on self-selection - OLS analysis

	(1) Endogenous choice	(2) Suboptimal choice	(3) Endogenous choice	(4) Suboptimal choice
Treatment	0.005	0.015	-0.028	-0.009
	(0.021)	(0.021)	(0.041)	(0.047)
Male	-0.224***	-0.211***	-0.227***	-0.225***
	(0.040)	(0.039)	(0.036)	(0.035)
Treat#Male	0.098***	0.084**	0.094***	0.094***
	(0.032)	(0.038)	(0.031)	(0.033)
Age	0.010***	0.003	0.015***	0.006**
	(0.004)	(0.003)	(0.003)	(0.003)
Round			-0.049	-0.065
			(0.079)	(0.067)
Round#Treat			0.040	0.020
			(0.090)	(0.087)
Total nb of wrong moves TOH 4 disks	-0.004**	-0.005***		
	(0.002)	(0.001)		
Average time to complete TOH 4 disks	0.001***	0.001***		
	(0.000)	(0.000)		
Constant	-0.106	-0.009	-0.065	0.031
	(0.110)	(0.132)	(0.112)	(0.137)
Observations	700	700	720	720
Adjusted R-squared	0.151	0.115	0.132	0.087
Controls	Yes	Yes	Yes	Yes

Note: Clustered standard errors at the ward level in parentheses.*, **, *** denote significance at the 10%, 5% and 1% levels respectively. The reported dependent variables are: a dummy variable equals to 1 if the participant chose the beans rather than the TOH with 5 disks in the last round; a dummy variable equals to 1 if the participant made a non-income maximizing choice. Control variables are those listed in Table 8 in Appendix C.

Table 14: Wald test endogenous and suboptimal choice

	Hypothesis testing	F-Statistic	P-value
(1)	Treat + Treat#Male = 0	F(1, 697) = 1.58	Prob >F = 0.2092
(2)	Treat + Treat #Male= 0	F(1, 697) = 2.79	Prob >F = 0.0951

Note: Reported values of the Wald test. Column (1) tests the joint significance of the treatment variable and the interaction term with males for the endogenous choice (i.e., dummy = 1 if the participant chooses the beans), while Column (2) for the suboptimal choice (i.e., dummy = 1 if the participant chooses the task with the lower predicted income.

Table 15: Mean differences in stressors - pooled sample

	Control	Mean	Treat	Mean	St Err	p value
Stress – self report	**368**	**.481**	**353**	**.546**	**.037**	**.077**
Stress - scale	368	11.334	353	11.748	.482	.391
Stress - items	**368**	**6.131**	**353**	**6.606**	**.208**	**.022**
Stress – financial worries	**368**	**.932**	**353**	**.961**	**.017**	**.094**
Stress – employment	368	.483	353	.493	.037	.804
Stress – business failure	**368**	**.764**	**353**	**.816**	**.03**	**.086**
Stress – access to food	368	.777	353	.801	.03	.42
Stress – access to education	**368**	**.712**	**353**	**.825**	**.032**	**.001**
Stress – health	**368**	**.579**	**353**	**.665**	**.036**	**.016**
Stress – alcool abuse	368	.22	353	.235	.032	.631
Stress – violence	368	.207	353	.252	.032	.145
Stress – theft	368	.329	353	.312	.035	.622
Stress – relationship with spouse	**368**	**.318**	**353**	**.391**	**.036**	**.041**
Stress – relationship with hh members	368	.321	353	.329	.035	.82
Stress – relationship with others	368	.226	353	.267	.032	.205
Stress – pregnancy	368	.264	352	.262	.033	.946

Note: mean differences in self-reported stress between participants in the treatment and control group. From the bottom, respectively, reported variables indicate: self-reported stress after the effort task, the scale of self-reported stress measured following **?**, the number of items individuals reported to be stressed about; self-reported stress about financial worries, business failure, employment situation of you or the household members, access to education of the household's members, access to food, physical health of you and the household's members, alcool abuse of you and the household's members, being victim of violence, being victim of theft, the relationship with a family member, the relationship with the spouse, the relationship with others, and pregnancy or contraceptive use of you or your spouse.

Table 16: Mean differences in stress items - women

	Control	Mean	Treat	Mean	St Err	p value
Stress – self report	180	.544	173	.619	.052	.16
Stress - scale	180	11.834	173	11.642	.694	.782
Stress - items	180	6.4	173	6.757	.289	.219
Stress – financial worries	**180**	**.945**	**173**	**.989**	**.019**	**.022**
Stress – business failure	180	.467	173	.434	.053	.533
Stress - employment	180	.761	173	.821	.044	.17
Stress – access to food	180	.828	173	.867	.039	.307
Stress – access to education	**180**	**.739**	**173**	**.821**	**.044**	**.064**
Stress – health	180	.606	173	.67	.051	.206
Stress – alcool abuse	180	.228	173	.191	.044	.395
Stress – violence	180	.245	173	.272	.047	.56
Stress – theft	180	.311	173	.306	.05	.923
Stress – relationship with family member	180	.345	173	.399	.052	.291
Stress – relationship with spouse	180	.372	173	.364	.052	.876
Stress – relationship with others	180	.289	173	.347	.05	.243
Stress – pregnancy	180	.267	173	.278	.048	.821

Note: mean differences in self-reported stress between women in the treatment and control group. From the bottom, respectively, reported variables indicate: self-reported stress after the effort task, the scale of self-reported stress measured following **?**, the number of items individuals reported to be stressed about; self-reported stress about financial worries, business failure, employment situation of you or the household members, access to education of the household's members, access to food, physical health of you and the household's members, alcool abuse of you and the household's members, being victim of violence, being victim of theft, the relationship with a family member, the relationship with the spouse, the relationship with others, and pregnancy or contraceptive use of you or your spouse.

Table 17: Mean differences in stress items - men

	Control	Mean	Treat	Mean	St Err	p value
Stress – self report	180	.544	173	.619	.052	.16
Stress - items	**188**	**5.873**	**179**	**6.43**	**.296**	**.06**
Stress – financial worries	188	.92	179	.933	.028	.641
Stress – business failure	188	.5	179	.547	.052	.364
Stress - employment	188	.766	179	.81	.043	.303
Stress – access to education	188	.729	179	.738	.047	.851
Stress – access to food	**188**	**.686**	**179**	**.827**	**.044**	**.002**
Stress – health	**188**	**.553**	**179**	**.659**	**.051**	**.038**
Stress – alcool abuse	188	.213	179	.28	.045	.139
Stress – violence	188	.17	179	.229	.042	.159
Stress – theft	188	.346	179	.313	.049	.504
Stress – relationship with spouse	**188**	**.292**	**179**	**.38**	**.049**	**.077**
Stress – relationship with hh members	188	.272	179	.29	.047	.683
Stress – relationship with others	188	.165	179	.185	.04	.625
Stress – pregnancy	188	.261	178	.241	.045	.675

Note: mean differences in self-reported stress between men in the treatment and control group. From the bottom, respectively, reported variables indicate: self-reported stress after the effort task, the scale of self-reported stress measured following **?**, the number of items individuals reported to be stressed about; self-reported stress about financial worries, business failure, employment situation of you or the household members, access to education of the household's members, access to food, physical health of you and the household's members, alcool abuse of you and the household's members, being victim of violence, being victim of theft, the relationship with a family member, the relationship with the spouse, the relationship with others, and pregnancy or contraceptive use of you or your spouse.

Table 18: Impact of mental load on stress items - pooled sample

	(1) Stress - financial worries	(2) Stress - business	(3) Stress - employment	(4) Stress - education	(5) Stress - food	(6) Stress - health	(7) Stress - alcohol	(8) Scale - rel. spouse	(9) Stress - rel. hh	(10) Stress - rel. others
Treatment	**1.084*** **	**-0.050**	**0.273**	**0.726*** **	**1.204*** **	**0.524*** **	**-0.037**	**0.287**	**-0.036**	**0.179**
	(0.416)	**(0.257)**	**(0.231)**	**(0.182)**	**(0.246)**	**(0.195)**	**(0.300)**	**(0.182)**	**(0.123)**	**(0.244)**
Male	-0.316	-0.128	0.457	-0.235	0.322**	-0.193	0.320*	-0.517**	-0.413***	-0.960***
	(0.404)	(0.212)	(0.385)	(0.331)	(0.149)	(0.208)	(0.172)	(0.241)	(0.155)	(0.162)
Constant	2.913*	-1.657***	1.803*	-0.890	-0.273	-0.168	-0.756	0.758	-0.780	0.950**
	(1.589)	(0.397)	(1.005)	(0.644)	(1.175)	(0.767)	(0.668)	(0.640)	(0.968)	(0.482)
Observations	720	720	720	720	720	720	720	720	720	720
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: impact of the treatment on self-reported stress between participants in the treatment and control group. From Column 1, respectively, reported variables indicate: self-reported stress about financial worries, business failure, employment situation of you or the household members, access to education of the household's members, access to food, physical health of you and the household's members, alcool abuse of you and the household's members, being victim of violence, being victim of theft, the relationship with a family member, the relationship with the spouse, and the relationship with others. Control variables are those listed in Table 8 in Appendix C.

Table 19: Impact of mental load on stress items - gender differences

	(1) Stress - financial worries	(2) Stress - business	(3) Stress - employment	(4) Stress - education	(5) Stress - food	(6) Stress - health	(7) Stress - alcohol	(8) Scale - rel. spouse	(9) Stress - rel. hh	(10) Stress - rel. others
Treatment	**1.964**	**-0.227**	**0.323**	**0.898*** **	**0.965*** **	**0.378**	**-0.405**	**0.166**	**-0.142**	**0.200**
	(1.420)	**(0.208)**	**(0.217)**	**(0.285)**	**(0.286)**	**(0.332)**	**(0.382)**	**(0.324)**	**(0.147)**	**(0.273)**
Male	0.055	-0.298	0.502	-0.096	0.119	-0.329	-0.016	-0.645***	-0.523***	-0.933***
	(0.520)	(0.224)	(0.461)	(0.430)	(0.126)	(0.286)	(0.181)	(0.204)	(0.192)	(0.200)
Treat#Male	**-1.202**	**0.336** **	**-0.096**	**-0.286**	**0.461*** **	**0.281**	**0.660** **	**0.239**	**0.217**	**-0.049**
	(1.499)	**(0.168)**	**(0.268)**	**(0.420)**	**(0.166)**	**(0.355)**	**(0.313)**	**(0.338)**	**(0.230)**	**(0.366)**
Constant	2.800	-1.597***	1.788*	-0.927	-0.239	-0.122	-0.664	0.794	-0.750	0.949*
	(1.706)	(0.383)	(1.021)	(0.591)	(1.182)	(0.733)	(0.613)	(0.596)	(0.967)	(0.485)
Observations	720	720	720	720	720	720	720	720	720	720
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: impact of the treatment on self-reported stress between participants in the treatment and control group. From Column 1, respectively, reported variables indicate: self-reported stress about financial worries, business failure, employment situation of you or the household members, access to education of the household's members, access to food, physical health of you and the household's members, alcool abuse of you and the household's members, being victim of violence, being victim of theft, the relationship with a family member, the relationship with the spouse, and the relationship with others. Control variables are those listed in Table 8 in Appendix C.

Table 20: Mean differences in stress and cognitive abilities - control group

	No worry	Mean	Worry	Mean	Diff	St Err	P value
Raven - pooled	87	.653	281	.604	.049	.026	.061
Raven - women	37	.604	143	.582	.022	.037	.57
Raven - men	50	.69	138	.627	.063	.036	.083
Attention - pooled	87	.495	281	.426	.069	.018	0
Attention - women	37	.469	143	.419	.049	.026	.065
Attention - men	50	.513	138	.433	.081	.025	.001
Stress - pooled	87	.288	281	.541	-.254	.06	0
Stress - women	37	.271	143	.616	-.345	.088	0
Stress - men	50	.3	138	.464	-.164	.081	.044

Note: mean differences between participants in the control group that reported a high or low burden of mental load. The reported variables indicate, respectively, the score of the Raven's matrixes in the pooled sample, and for women and men separately; the score of the Digit Span Task for in the pooled sample, and for women and men separately; and the self-reported stress after the effort task in the pooled sample, and for women and men separately.

Chapter 3

Depression and economic behavior through the lens of gender. Lessons from Mexico

Sveva Vitellozzi[1,2]

1 University of Trento

2 University of Florence

Abstract

Women are more likely than men to suffer from depression. Gender differences in mental health are associated with biological and social factors, and they are more exacerbated in low- and middle-income countries. In addition to being a major health problem, depression can affect economic preferences and cognitive abilities, and this impact may be gender-differentiated. This study analyzes the relationship between depression, economic preferences, cognitive abilities, and daily behaviors in Mexico under a gendered perspective. This is the first study in a middle-income country to explore these issues using a longitudinal, representative dataset that contains detailed information on risk taking and time discounting behaviors, as well as individuals' emotional status. Results show that depression increases women's risk-taking behavior while decreasing their time discounting. This, in turn, appears to translate into changes in women's health and saving behaviors, and these associations are stronger for women living in poverty. The mediation analysis reveals that, whereas sleep deprivation and fatifue mediate the effect of depression on all the outcomes of interest, anhedonia specifically acts as a mediator for time discounting, while negative beliefs about the future for risk aversion.

JEL Classification: J16; B54; D91

Keywords: depression; economic preferences; cognitive abilities; gender

3.1 Introduction

Depression affects over 4.5 percent of the global population, and women are twice more likely than men to suffer from mental disorders (WHO, 2017). Other than biological factors, gender differences in mental health relate also to social and cultural norms (Jenkins and Good, 2014). Throughout their lives, women are at higher risk than men to experience traumas, such as sexual abuse, harassment, or poverty, which increases the risk of developing mental illnesses (Nolen-Hoeksema, 2001). In low- and middle-income countries, the gender gap in mental health risks being even wider: not only are poverty and depression mutually reinforcing (Ridley et al., 2020), but women also have less control over their lives, they often live in violent environments with a higher risk of assault and victimization (Nolen-Hoeksema, 2001), and they lack access to resources to cope with negative income shocks (Asfaw and Maggio, 2018).

Mental disorders influence individual behaviors on a daily basis: depressive symptoms vary from sadness to loss of interest and pleasure, changes in sleep or appetite, tiredness, reduced attention or difficulty in concentrating, pessimistic beliefs about the future, and anhedonia, i.e., the inability to derive any pleasure from activities perceived as enjoyable by others (de Quidt and Haushofer, 2016; Bayer et al., 2019; Cobb-Clark et al., 2019). In general, women report higher levels of depressive symptoms than men (Salk et al., 2017), and they are more affected by symptoms that fall under Beck's category of "negative attitude", including melancholy, pessimism, and worthlessness (Wu, 2010). Studies show that depression is associated with willingness to take risks or to defer future gratifications, alcohol and tobacco's consumption, the ability to find a job, investments in children's education, and saving and investment decisions (Blanco et al., 2013; Pulcu et al., 2014; Bernheim et al., 2015; Bayer et al., 2019; Schilbach, 2019; Ridley et al., 2020).

Yet, the gendered association between depression, economic preferences, and cognitive abilities has not received much attention, especially in low- and middle-income countries where mental disorders are very common and a substantial gender gap in mental health is observed (WHO, 2017; Ridley et al., 2020). This paper looks at the relation between depression, economic preferences, and cognitive abilities through the lens of gender in Mexico, a country with a high incidence of mental disorders among women[1]. More specifically, this study seeks to answer the following research questions: first, whether and to what extent depression shapes women's attitudes towards risk, time discounting, and their cognitive abilities; second, whether this impact on economic preferences and cognitive functions affects daily behaviors, namely investment in children's education, investment in preventive health, and health and saving behaviors; and third, whether this impact differs between poor and non-poor women, and between mothers and non-mothers.

To answer these questions, I employ the Mexican Family Life Survey (MxFLS), a national representative panel dataset collected in three waves, in 2002, 2005, and 2009. The data provide detailed information at the individual level on emotional well-being, risk attitudes, inter-temporal decision-making,

[1] http://archivos.diputados.gob.mx/Centros_Estudio/ceameg/ET_2013/04_SMDES.pdf

and cognitive abilities for all individuals aged 15 years or more. Since information on risk attitudes and inter-temporal decision making is not available in the first wave, the analysis relies only on the second and the third ones. By exploiting the panel nature of the data, I adopt a Fixed Effects (FE) model that allows for controlling for unobservable characteristics that do not change over time. I then conduct a mediation analysis to better understand which symptoms influence economic preferences.

Results show that depression is significantly correlated with attitudes towards risk aversion and time discounting, while I find no evidence on cognitive abilities. More specifically, women suffering from depression exhibit a lower probability of being risk averse as well as of being impatient both in the short and distant future. Depression also affects daily behaviors: women suffering from depression take more risks in health behaviors (i.e., they smoke more and they sleep less), but they do not invest less in preventive health. When looking at saving and investment decisions, depressed women are significantly less likely to save in informal institutions, while there is no impact on saving or credit decisions in formal institutions. The mediation analysis shows that somatic symptoms (i.e., fatigue and sleep deprivation) mediate the effect of depression on both risk taking and time discounting, whereas anhedonia mediates the effect of depression on time discounting and negative beliefs about the future on risk taking behaviors.

The heterogeneity analysis shows that women living in poverty and suffering from depression are more risk-taking and more patient in the long term than mentally health women, whether living in poverty or not. No significant differences between depressed poor and non-poor women are observed in time discounting in the short term and in cognitive abilities. When looking at differences between depressed mothers and non-mothers, results show that depression does not impact differently their economic preferences. However, mothers with poor mental health spend significantly less time in helping children with their homework, they sleep on average 1 hour less than non-mothers, they are more likely to smoke and have a loan in a formal institution, and they save less in informal groups. No differences are observed in preventive health.

This study makes three main contributions to the literature. First, this is the first study looking the impact of mental health on economic preferences through the lens of gender. Studies show that women are usually more risk averse and more patient than men (Croson and Gneezy, 2009; Dittrich and Leipold, 2014), that they are less likely to engage in competitive behaviors (Niederle and Vesterlund, 2007; Croson and Gneezy, 2009), and that they cope differently with stress (Cahlíková et al., 2020). However, the feminist economics literature claims that these findings are difficult to replicate and not generalizable, and that their main limitation is a failure to consider cultural and societal factors as potential determinants of women's behavior (Nelson, 2016; Becchio, 2019; Sent and van Staveren, 2019). This paper contributes to this strand of the literature by focusing on the invisible and often neglected dimension of gender inequality that is poor mental health, the roots of which have to be found in the patriarchal structure of the society, and by showing that it can contribute in explaining women's preferences and behaviors.

Second, this paper relates to the literature on poverty and cognitive abilities (Mani et al., 2013;

Shah et al., 2015; Schilbach et al., 2016), and on poverty and mental health (Haushofer and Fehr, 2014; Haushofer and Shapiro, 2016; de Quidt and Haushofer, 2016; Baranov et al., 2020; Ridley et al., 2020; Prencipe et al., 2021). Poverty itself is found to reduce cognitive abilities (Mani et al., 2013), and this in turn can impact several economic outcomes, such as employment or saving and investment decisions (Schilbach et al., 2016). Mental disorders can have a similar impact on cognitive functions, for instance by influencing individuals' ability to focus, or by distorting their beliefs about their abilities (de Quidt and Haushofer, 2016; Ridley et al., 2020). By focusing on the gendered dimension of the problem, this paper builds on these findings and it adds on them by showing that depression does affect economic behaviors, and that its effect differs between poor and non-poor women.

Third, this paper looks at the association between depression and economic preferences in a middle-income country, while the scarce existing evidence is mainly based on the analysis of data collected in western societies and clinical settings (Pulcu et al., 2014; Bayer et al., 2019; Cobb-Clark et al., 2019). By relying on a national representative panel dataset, this paper provides insights on the gendered association between mental health, economic preferences, and cognitive abilities in a country where depression is particularly widespread and important gender-differences in mental health are observed (Rafful et al., 2012).

This study is not without limitations. Studying depression with observational data entails a high risk of endogeneity for both reverse causality and the omitted variable bias. Depression is extremely subjective, and it can be correlated with several unobserved factors not captured by the data. In addition, the problem of bad controls arises substantially when studying mental disorders: many variables that can help explaining the outcomes of interest can also be causally affected by depression, thus making it not possible to include them in the regression. The aim of this study is not to identify the causal impact of depression on economic variables, but rather to provide robust and strong correlations on this topic. For these reasons, results should be interpreted carefully, keeping in mind that tackling the causal effect of mental disorders is always a tricky and sensitive issue.

The rest of the paper proceeds as follows: Section 2 revises the literature on women and depression, with a special focus on Mexico; Section 3 describes the data; Section 4 explains the empirical methodology; Section 5 provides the results from the main analysis and the heterogeneity analyses; Section 6 focuses on the mediation analysis; and Section 7 discusses the results and concludes.

3.2 The gendered dimension of mental health

As already stated, women are twice more likely than men to suffer from depression (Nolen-Hoeksema, 2001; WHO, 2017). This gap in mental health can be ascribed both to biological and cultural factors. While the former is linked mainly to hormonal differences between the sexes (Noble, 2005), the latter is linked to the structure of the society that strictly defines women's roles and identity (Chonody and Siebert, 2008; Jenkins and Good, 2014).

Jenkins and Good (2014) focus on three key dimensions that can shed light on gender inequalities in mental health: culture, gender, and power. Culture influences all aspects of mental health as it shapes our way of feeling, thinking, and existing in the world we live in through changing the experience, interpretation, and action we have over reality. Gender, as a cultural factor, is a particularly sensitive aspect of mental health. This cultural construct impacts many areas of women's lives through establishing gender identities and roles within society, such as their access to socioeconomic resources, labor market participation, and risk of victimization. A strict division of gender roles justifies and supports male supremacy in society, as women's spheres of activity is limited within the family, with little prospect of realizing themselves outside of the roles of mothers and spouses. Finally, the component of power addresses the "relationship between institutional and structural arrangements and the agency of persons living under such arrangements" (Jenkins and Good, 2014): women, having less control than men, are more likely to experience stressful and unfavorable situations throughout their life, which risk worsening their mental health (Nolen-Hoeksema, 2001).

Societal and economic factors have been identified to be drivers of women's vulnerability to depression and mental disorders (Jenkins and Good, 2014). Women do, in fact, confront chronic problems on a daily basis that men do not always have to deal with: they are more likely to live in poverty and in poor housing conditions; they earn less than men and are more likely to be unemployed; they have a heavier workload because they have to engage their time both in domestic and market activities; they are responsible for caring for the elderly and children in the household; and, on top of that, they have limited resources to cope with negative shocks (Nolen-Hoeksema, 2001; Jenkins and Good, 2014; Liu et al., 2018). Women have less power not only in society as a whole, but also in their own households: on average, they have less decision-making power within the household than men, are more likely to experience domestic abuse, and are more likely to be time poor, among others (Gammage, 2010; Doss, 2013; Arora, 2015; Kapiga et al., 2019). All of these factors increase their likelihood of developing mental illnesses, contributing to the creation of an additional dimension of gender inequality (Nolen-Hoeksema, 2001; Jenkins and Good, 2014; Baranov et al., 2020).

For women in low- and middle-income countries, the burden of mental disorders risks being even heavier. Among other factors, poverty exposes women to a number of factors that are linked to poor mental health: they are more likely to be victimized both inside and outside the household; they have a lower educational level; they lack access to economic resources to support household expenses; they frequently lack property rights over land; they have less access to the labor market, and thus have fewer opportunities to realize themselves outside the household; and they grow up in cultures where gender roles are strictly defined and confine their sphere of activities in both their personal and social life (Nolen-Hoeksema, 2001; Asfaw and Maggio, 2018; Ridley et al., 2020).

In Mexico, where patriarchy pervades social and cultural norms, women suffer more than men from mental problems (Belló et al., 2005). Gender norms in Mexico expect both women and men to follow the rules of "machismo", a cultural standard stating that men are not supposed to undertake household chores or care for children, as these are roles traditionally assigned to women. Mexican women are expected to assume full care of all aspects of the household, from domestic chores to caring for children and the elderly, to food and nutrition of household members. Marriage is typically built on the premise of the wife's respect for her husband, and it follows a hierarchical power structure in which the woman is subordinated to the "demands" of the males (Knapp et al., 2009). Women in Mexico are also at a significant risk of victimization, including sexual assault and domestic violence (Frías and Agoff, 2015). Depression in Mexico is linked to factors relating to Mexican culture and the its definition of gender roles in the society (Lara et al., 2004). More specifically, women believe that the socialization of the feminine role, which dictates that they should be submissive and bear all of the household chores, is one of the key reasons they are more vulnerable to depression. Furthermore, the obligations of parenting, the workload, and their husband's alcoholism and violence are all variables worsening their mental health (Lara et al., 2004).

Despite the fact that there is a large body of the literature focusing on the qualitative and quantitative (gendered) determinants of mental health, its consequences have received little attention. A recent study looks into the long-term impact of a Pakistani program for depressed pregnant women. Findings show that the treatment improved, along with women's mental health, their financial empowerment, fertility choices, and investments in children (Baranov et al., 2020). Mental health and decision-making are inextricably linked, and it is important to better understand this association through the lens of gender.

3.3 Data

The analysis relies on the Mexican Family Life Survey (MxFLS), a longitudinal dataset representative of the Mexican population at the national, urban, rural, and regional levels. The data provide information for a period of 10 years, and it has been collected in three waves: in 2002, in 2005-2006, and in 2009-2012 for around 35,000 individuals. Because data on risk attitudes and time preferences were collected only in the second and third waves for all individuals aged 15 years or more, the analysis relies on the 2005 (MxFLS2) and 2009 (MxFLS3) waves of the MxFLS. The balanced sample consists of 26,362 observations, 13,181 for each wave. Because I consider only women for this analysis, the final sample consists of 15,282 observations, 7,633, and 7,649 observations for the first and the second wave, respectively.

Depression measure

The module on emotional well-being provides information on self-reported depressive symptoms. It consists of 20 questions asking how often in the past 4 weeks the individual has experienced feelings such as sadness, stress, fear, loneliness, or irritability. The questions are based on the Generalized Health Questionnaire, and they have been already validated in Mexico (Calderón-Narváez, 1997; Schmeer and Kroeger, 2011). By adding up these variables, I derive a depression score ranging between 20 and 80. Individuals are considered to suffer from depression if they reach a score higher or equal to 35. The higher the score, the worse the incidence of depression. Following the literature (Bargain and Zeidan, 2019), to check for the internal reliability of the score I derive the Cronbach's alpha coefficient, that is computed by correlating the score for each scale item with the total score for each observation. The coefficient ranges between 0 and 1: the higher its value, the higher the covariance among the items of the scale, and the higher the probability that they capture the same underlying concept. As we can see from Table 13 in the Appendix, the Cronbach's alpha for both waves is higher than 0.9, suggesting an excellent reliability of the psychometric measure (Bland and Altman, 1997).

Table 3.1: incidence of depression among women in the sample, MxFLS2 and MxFLS3

Depression index	**MxFLS2**	**MxFLS3**	**Total**
1 (20-35)	84.16	82.98	83.57
2 (36-45)	11.03	11.52	11.27
3 (46-65)	2.35	2.64	2.49
4 (66-80)	2.46	2.86	2.66
Total	100.00	100.00	100.00
Obs.	7,633	7,649	15,282

Based on individual scores, I first construct an index ranging from 1 to 4 to assess depression's severity. More specifically, for scores between 20 and 35, individuals are considered to be mentally healthy; for scores between 36 and 45, they are considered to suffer from anxiety; for scores between 46 and 65 , they are considered to be moderately depressed; and for scores between 66 and 80, they are considered to be severely depressed (Calderón-Narváez, 1997). Figure 2 in the Appendix shows mental health's distribution in the sample at baseline. Table 3.1 reports the distribution of depressive symptoms in both waves. As we can notice, in 2009 almost 85 percent of women in the sample is classified as "mentally healthy". For the remaining 15 percent, most of the individuals suffer from anxiety, and less than 4 percent appear to be mildly or severely depressed. In MxFLS3, the incidence of depression in the population increases by less than 2 percent. There is an increase for individuals suffering from anxiety, and for those considered mildly or severely depressed. Based on this categorization, I construct the treatment dummy which is equal to 1 if the index is equal to or higher than 2, and 0 otherwise.

Table 3.2: Transition of depression statuses

	MxFLS3				
MxFLS2	1	2	3	4	Total
1	86.27	9.27	1.85	2.60	100.00
2	64.46	23.90	6.86	4.78	100.00
3	60.57	25.71	8.57	5.14	100.00
4	70.27	22.16	4.86	2.70	100.00
Total	82.85	11.61	2.64	2.90	100.00

Table 3.2 shows us the transitions from one status to the other in the 2005 and 2009 waves. The diagonal shows us that 86 percent of the sample remained in the first category, 23.90 percent were still suffering from anxiety, 8.57 percent remained mildly depressed, and 2.70 percent remained severely depressed. If we look at line 1 in the table, we can see that of those women that were feeling good in 2006, 9.27 percent started suffering from anxiety, 1.85 percent became mildly depressed, and 2.60 percent be-

came severely depressed. When looking at women that were severely depressed at baseline (line 4 in the table), 70 percent of them in 2009 were feeling good, 22 percent passed from being severely depressed to suffering from anxiety, and almost 5 percent passed from being severe to mildly depressed. Of those that were mildly depressed in 2005, nearly 61 percent of them in 2009 changed their emotional status to mentally healthy, 25 percent to suffering from anxiety, and more than 5 percent to being severely depressed. Finally, of those suffering from anxiety, there was an improvement in their emotional status for 64 percent of them, while for more than 10 percent there was a deterioration.

Risk aversion measure

To construct the measure of risk aversion, I rely on data collected through a lottery, where individuals are asked to choose between gambles with different payoffs and with different risk levels. In the Appendix, I present the progression of the questions for each wave. In MxFLS2, the respondent is asked first to choose between receiving a certain amount of $1,000 or receiving either $2,000 or $500 with equal probability, where "$" stands for Mexican pesos. Depending on her choice, the respondent faced an alternative decision. If she chose the first option, she was then asked to choose between $1,000 with certainty, or between $800 or $2,000 with equal probability. If she chose instead the second option, she was asked to choose between that same gamble or between $300 or $3,000. A few more questions were asked following this rationale, and based on their choices, respondents can be classified as risk averse or not.

MxFLS3 presents the same module on risk aversion but with slight changes between the two waves: while the questions remained the same as in MxFLS2, in MxFLS3 the amounts and the progressions of the lottery changed to improve respondents' comprehension of the module (Brown et al., 2019). In MxFLS3, to first assess whether the respondent had fully understood the mechanism of the lottery, she was asked to choose between receiving either $2,500 or $5,000 with equal probability, or receiving $2,500. If she chose the latter option, she was explained again the task. If the respondent chose the first option, she was then asked to choose between receiving either a sure amount of $2,500, or receiving either $2,000 or $5,000 with equal probability. If she chose the sure amount, then no more questions were asked. If she chose the second option, then a few more questions were asked on the heels of MxFLS2.

Based on this information, I construct an index ranging from 1 to 7 to assess respondents' level of risk aversion (Brown et al., 2019). The higher the index, the more risk-averse the respondent. I identify as risk averse the individuals with a risk aversion index of 5,6, or 7 in both waves. Being these types of measure no perfect predictors of the actual risk aversion of respondents, it would be complicated to isolate small changes in risk aversion from measurement error from one wave to another (Kimball et al., 2009; Brown et al., 2019). Following Brown et al. (2019), I only consider changes at the extremes of the distribution by classifying individuals only as most risk averse or not. The variable of interest is then a dummy variable which takes the value of 1 if the individual is risk-averse, and 0 otherwise. In addition, as the two modules are slightly different, it is important to be careful when interpreting the results: we should interpret them in relative rather than in absolute terms. For instance, if a respondent goes from “not risk averse” to “risk averse” between the MxFLS2 and MxFLS3, this does not necessarily implies that they became more risk averse, but rather that their level of risk aversion is relatively higher if compared to respondents that are “not risk averse” in both waves (Brown et al., 2019).

Table 3.3: index of risk aversion, MxFLS2 and MxFLS3

Index RA	**2005**	**2009**	**Total**
1	2399	1524	3923
	32.56	20.22	26.32
2	375	300	675
	5.09	3.98	4.53
3	531	709	1240
	7.21	9.41	8.32
4	2613	1212	3825
	35.46	16.08	25.66
5	629	2110	2739
	8.54	27.99	18.37
6	165	639	804
	2.24	8.48	5.39
7	657	1044	1701
	8.92	13.85	11.41
Total	7369	7538	14907
	100.00	100.00	100.00

Time discounting measures

To elicit time discounting, the MxFLS provides a set of hypothetical questions about choices between a payment today and a larger payment both in the short (i.e., in a month) and in the distant future (i.e., three years in MxFLS2, and one year in MxFLS3). For instance, the second question asks whether the respondent prefers $1,000 today or $1,100 in a month. The underlying idea is that a more patient individual will be willing to defer future gratification to get the higher amount, while a more impatient individual will not. Depending on the answer, the respondent may be classified in the most patient category (i.e., if she chooses $1,100 in a month) or she will be asked additional questions with increasing amounts. To assess time discounting in the distant future, the questions are the same as in the short one, but the time span changes and the amounts are higher. Respondents are asked whether they prefer $10,000 today or $12,000 in three years, and based on their answer, they are then asked other questions with increasing amounts.

In the MxFLS3, a similar set of questions is included. To assess time discounting in the short term, the amounts change slightly compared to MxFLS2, in order to account for inflation while at the same time ensuring greater heterogeneity in the responses. The questions on preferences in the distant future present more substantial differences with regard to the MxFLS2. The time span changes (i.e., it is one year rather than three), and the amounts are smaller (i.e., they are the same in the short term preferences). Such changes were probably made to collect a more reliable information on time discounting, as it is easier to project one self’s preferences in a year rather than in three.

Table 3.4: time discounting in the short term, MxFLS2 and MxFLS3

Index K1	**2005**	**2009**	**Total**
0	583	820	1403
	7.67	10.72	9.20
1	928	859	1787
	12.20	11.23	11.72
2	774	671	1445
	10.18	8.77	9.47
3	944	1178	2122
	12.41	15.40	13.91
4	807	426	1233
	10.61	5.57	8.08
5	3568	3693	7261
	46.92	48.29	47.61
Total	7604	7647	15251
	100.00	100.00	100.00

Table 3.5: time discounting in the long term, MxFLS2 and MxFLS3

Index K2	**2005**	**2009**	**Total**
0	384	292	676
	5.05	3.82	4.43
1	777	271	1048
	10.22	3.54	6.87
2	775	255	1030
	10.19	3.33	6.75
3	886	577	1463
	11.65	7.55	9.59
4	961	411	1372
	12.64	5.37	9.00
5	3821	5841	9662
	50.25	76.38	63.35
Total	7604	7647	15251
	100.00	100.00	100.00

Based on women's responses, I construct an index ranging from 0 to 5, both in the short and distant future (see the Appendix for further details). As with risk aversion, these measures cannot be considered a perfect predictor of the actual discount rates of the respondents. Therefore, I only use changes at the extreme of the distribution, defining individuals as "most impatient" or not. I construct a dummy variable which is equal to 1 if the respondent is in the fifth category of the index, and 0 otherwise. As we can see from Table 3.4 and Table 3.5, almost half of the sample is classified as "most impatient" at baseline both in the short and distant future.

Cognitive abilities measure

Cognitive abilities are measured through a simplified version of the Raven Standard Progressive Matrices Test, which measures the capacity to think logically and to solve new problems independently of the previous knowledge (Raven, 2000; Mani et al., 2013). The Raven Test provides results that are free of cultural biases and, hence, easily comparable across settings (Rubalcava and Teruel, 2004). In the MxFLS, individuals were asked to solve 8 different puzzles increasing in difficulty: the higher the score, the higher the level of cognitive abilities. The score ranges between 0 and 7 and, as we can see from Table 3.6, at baseline the mean average score is 4.25. Figure 3.2 in the Appendix shows the distribution of cognitive abilities at baseline [2].

Table 3.6: summary statistics of cognitive abilities, MxFLS2 and MxFLS3

Cognitive abilities	Obs.	Mean	SD	Min	Max
MxFLS2	4,390	4.256	2.104	0	7
MxFLS3	4,545	3.474	2.253	0	7

Daily behaviors variables

Women's daily behaviors are captured by investment in children's education, health and saving behaviors. The former is measured as the number of hours women spent in helping children with their homework over the week prior to the interview. Health behaviors include the probability of smoking and doing sport, the average number of sleep hours the week before the interview, and investment in preventive health, which is a dummy variable equals to one if the respondent visited the doctor for vaccination, preventive medical exam, a general health check-up, birth control, family planning, or dental visit. Saving behaviors are captured by three dummy variables equal to one if the respondent has a loan, or a saving account either in a formal or an informal institution. Table 3.7 reports mean differences of such characteristics at baseline according to women's mental health status.

Table 3.7: mean differences of daily behaviors at baseline, MxFLS2

	Mentally well		**Depressed**		**Difference**	
	Obs.	Mean	Obs.	Mean	Diff	P-value
I in children's education	6588	1.188	1045	.936	.2512	.025
Smoke	6588	.045	1045	.087	-.042	0
Sport	6588	.108	1045	.098	.01	.337
Sleep	6579	7.844	1045	7.704	.14	.001
I in preventive health	6466	.106	995	.173	-.067	0
Loan	2132	.165	334	.327	-.161	0
Saving (formal)	6563	.094	1042	.089	.005	.764
Saving (informal)	6560	.081	1042	.092	-.012	.204

Control variables

Other covariates at the individual and the household level are included in the analysis to control for socioeconomic characteristics that can contribute explaining the outcomes of interest while being correlated with the likelihood of being depressed. At the individual level, I control for age, education, sex, and civil status. At the household level, I control for the household's size, the place of residence (i.e., urban or rural), and the income level, measured with a wealth index derived through the Principal

[2] The cognitive abilities module was administered to fewer households compared to other modules. However, the survey documentation does not provide any specific reason for this reduced number of observations.

Component Analysis (PCA). I rely on information on wealth rather than yearly income or expenditure as it is found to be a more reliable measure (Arthi et al., 2018). I then control for household's exposure to violence and to negative shocks, as we know from the literature that such factors influence both economic preferences and depression. (Brown et al., 2019; Baranyi et al., 2021).

Table 3.8: mean differences of sample characteristics at baseline, MxFLS2

	Mentally well		**Depressed**		**Difference**	
	Obs.	Mean	Obs.	Mean	Diff	P-value
Economic decision-making and cognitive abilities						
Risk aversion	6588	.227	1045	.212	.014	.308
Impatience (K1)	6588	.475	1045	.423	.052	.002
Impatience (K2)	6588	.502	1045	.496	.005	.734
Cogn. abilities	**3861**	**4.311**	**529**	**3.862**	**.449**	**0**
Socio-economic characteristics						
Age	**6577**	**39.852**	**1043**	**46.063**	**-6.211**	**0**
HH member	6588	5.157	1045	5.088	.069	.373
Education	5085	3.627	747	3.668	-.041	.663
Married	**6588**	**.264**	**1045**	**.163**	**.101**	**0**
Urban	6588	.578	1045	.569	.01	.553
Violence	**6588**	**.585**	**1045**	**.68**	**-.096**	**0**
Shock	**6588**	**.236**	**1045**	**.342**	**-.106**	**0**
Expenditure	6588	61942.3	1045	53186	8756	.385
PCA asset	6588	312012	1045	277984	34027	.426

Table 3.8 provides differences in mean in the outcomes of interest and in observable characteristics between depressed and non-depressed women at baseline. For the outcomes of interest, significant differences are observed only in cognitive abilities: depressed women exhibit significant lower scores in the Raven test than non-depressed ones. Being a woman and living in urban areas increases the probability of suffering from depression, as well as having been exposed to violent crime or having experienced a negative economic shock, and being not married[3]. There are no significant differences in total expenditure, nor for the wealth index.

Other variables are not included in the analysis to avoid the problem of bad controls, i.e., those variables that can contribute explaining the outcome of interest but that are also causally affected by the explanatory variable. In this analysis, bad controls are the likelihood of being employed, tobacco and alcohol consumption, the number of depressed members within the household, and cognitive abilities when regressing depression on risk aversion and time discounting. All these factors are correlated with the outcome of interest, but at the same time they risk being influenced by the independent variable and, consequently, they cannot be included in the regression.

Table 3.9 instead provides differences in mean in the outcomes of interest between poor and non-poor women, and between mothers and non-mothers. As we can notice, there are significant differences between poor and non-poor individuals in risk aversion and cognitive abilities. When dividing the

[3]It is interesting to notice that not being married is positively correlated with depression. This may be linked to the gender roles defined by the cultural structure of "machismo".

Table 3.9: mean differences in the outcomes of interest at baseline - heterogeneity groups

	Obs.	Mean	Obs.	Mean	Diff	P value
Poverty		**Poor = 0**		**Poor = 1**		
Risk aversion	3927	.205	3706	.246	-.041	0
Impatience (short run)	3927	.469	3706	.467	.002	.878
Impatience (long run)	3927	.504	3706	.498	.007	.577
Cognitive abilities	2459	4.559	1931	3.872	.687	0
Motherhood		**Mother = 0**		**Mother = 1**		
Risk aversion	5646	.232	1987	.204	.028	.009
Impatience (short run)	5646	.48	1987	.434	.045	.001
Impatience (long run)	5646	.519	1987	.449	.07	0
Cognitive abilities	2695	3.928	1695	4.78	-.853	0

sample between women that are also mothers and those who are not, there are significant differences in all the considered variables. Mothers appear to be less risk averse and more patient than non-mothers, and they have a significantly higher score in the Raven's test.

Poverty is measured through an asset-based approach. I do not adopt the money-metric approach based on the poverty line because these measures usually fail to identify multiple dimensions of poverty (Mohamad Azhar and Mohd, 2020). Asset indices, by contrast, provide a more "stable" definition of poverty because they move slowly in time and they are more durable. For these reasons, individuals classified as non-poor according to money-metric measurements can be considered poor if we look at an asset-based definition of poverty. Following the literature (Mohamad Azhar and Mohd, 2020), I compute the wealth deciles and then I define as poor those individuals falling within the 4^{th} decile of the distribution. Table 3.10 shows the different distribution of poor and non-poor individuals in the sample based on this definition.

Table 3.10: distribution of poor individuals in the sample

	MxFLS2	MxFLS32
Non-poor	51.45	72.16
Poor	48.55	27.84
Total	100.00	100.00

3.4 Methodology

The empirical specification exploits the panel nature of the data and relies on a Fixed Effects specification. Even though this does not provide a causal effect of depression on our outcomes of interest, it does guarantee robust correlations. I estimate the following specification:

$$(1) \qquad Y_{it} = \beta_0 + \beta_1 Treat_{it} + \beta_2 X_{it} + \beta_3 Z_{ht} + d_t + \alpha_i + \varepsilon_{it}, \;\; t = 1, 2$$

where Y_{it} are the aforementioned outcome variables for individual i at time t, $Treat$ is the dummy variable which equals 1 if the individual i is depressed at time t, and 0 otherwise, X_{it} and Z_{ht} are the covariates to control for individual and household characteristics, d_t are time fixed-effects, α_i are the time-invariant individual fixed effects, and ε_{it} is the error term.

For the heterogeneity analyses, I include an interaction term to look at the different effect of depression on economic preferences and cognitive abilities between poor and non-poor women, and between mothers and non-mothers. The empirical specification is then the following:

$$(2) \qquad Y_{it} = \beta_0 + \beta_1 Treat_{it} + \beta_2 D_{it} + \beta_3 (Treat_{it} \times D_{it}) + \beta_4 X_{it} + \beta_5 Z_{ht} + d_t + \alpha_i + \varepsilon_{it}, \ \ t = 1, 2$$

where D_{it} is the dummy variable identifying whether the respondent is poor or not or whether she is a morther or not, and $Treat_{it} \times D_{it}$ is the interaction term for the heterogeneity analyses.

3.5 Results

3.5.1 Depression, economic preferences, and cognitive abilities

Table 3.11 reports the results from the FE analysis on the association between depression, economic preferences, and cognitive abilities. As we can see, women suffering from depression are less likely to be risk averse, as well as to be more impatient both in the short and distant future. These findings can be attributed to two depressive symptoms: negative future expectations and anhedonia, as will be explained further in the next section. While producing opposing results, these two symptoms can explain the mechanisms that may be at work. Women who have pessimistic beliefs of the future may be more willing to take risks and defer future gratifications because they fear they will be worse off in the future. On the other side, having lost interest in their surroundings, women may be less concerned with taking chances and deferring future gratifications, leading to increased risk-taking and impatience.

As the literature adopts both binary and continuous definitions of depression (de Quidt and Haushofer, 2016; Cobb-Clark et al., 2019), as robustness checks I run the analysis using different cut-offs to identify depressed women (i.e., subtracting and adding 1 and 2 points to the standard cut-off of 36 points) and using the continuous variable of the mental health score. Figures 3.7 and 3.8 in the Appendix show the results of these analyses: as we can notice, they go in the same direction than the main analysis, but most of the coefficients are not significant anymore. This confirms that the adopted instrument used to assess individuals' mental health has a strong internal validity: when moving from the cut-off validated by researchers from the Mexican Institute of Psychiatry [4], results do not change in sign but they become non-significant, confirming the reliability of the measure used to define depression.

[4] http://www.ennvih-mxfls.org/english/faq.html

Table 3.11: association between depression, economic preferences, and cognitive abilities

	(1) **Risk aversion**	(2) **K1**	(3) **K2**	(4) **Raven**
Depression	**-0.0577***	**-0.0876****	**-0.0508***	**-0.477**
	(0.0328)	**(0.0351)**	**(0.0299)**	**(0.294)**
Age	-0.0162	0.009	0.0109	-0.097*
	(0.010)	(0.011)	(0.011)	(0.050)
HH members	-0.009	-0.0130	-0.0139	0.114
	(0.010)	(0.010)	(0.011)	(0.073)
Education	0.005***	-0.005*	-0.0015	0.019
	(0.002)	(0.003)	(0.001)	(0.0147)
Urban	-0.0841**	0.0512	0.0529	-0.334
	(0.0373)	(0.0415)	(0.0403)	(0.339)
Violence	0.0153	-0.0579**	-0.0370*	-0.0570
	(0.0209)	(0.024)	(0.0215)	(0.194)
PCA index	0.0202	0.007	0.008	0.0153
	(0.017)	(0.017)	(0.017)	(0.105)
Shock	0.025	-0.013	-0.016	0.145
	(0.022)	(0.023)	(0.024)	(0.167)
Marital status	0.046	-0.013	-0.059	-0.092
	(0.048)	(0.056)	(0.054)	(0.293)
Year	0.349***	-0.018	0.217***	-0.307
	(0.047)	(0.050)	(0.051)	(0.240)
Constant	0.922**	0.167	0.156	7.146***
	(0.410)	(0.437)	(0.449)	(1.819)
Observations	11,320	11,320	11,320	6,875
R-squared	0.158	0.009	0.136	0.074
Number of id	6,447	6,447	6,447	5,536

Risk aversion is a dummy variable equals to 1 if the individual is risk averse, and 0 otherwise; K1 is a dummy variable equals to 1 if the individual is impatient in the short run, and 0 otherwise; K2 is a dummy variable equals to 1 if the individual is impatient in the long run, and 0 otherwise; Raven provides the results of the Raven's test, and it ranges between 0 and 7.Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

3.5.2 Depression and daily behaviors

Table 3.14 in the Appendix reports the effects of depression on women's daily behaviors. Everything else being equal, depressed women engage more in risky health behaviors: they are more likely to smoke and, on average, they sleep 45 minutes less than non-depressed women. These findings are consistent with previous research showing that depression leads individuals to take more health risks (Cobb-Clark et al., 2019). Depressed women are also less likely to have a saving account in an informal institution, while the other two credit-related variables show no significant effects. As the mediation analysis will demonstrate, this behavior can be influenced by a specific depressive symptom: anhedonia. Depressed women may have less stimulus in receiving immediate gratifications as a result of their loss of interest in normally rewarding activities. As a result, they are more likely to postpone future gratifications. This is supported by the fact that depressed women do not increase their savings, a behavior that would be consistent with increased patience in the short and long term.

More generally, these behaviors can translate in economic outcomes that can be detrimental in the long run. Adopting health risky behaviors such as smoking more and sleeping less brings about negative consequences on various outcomes other than in terms of physical and mental health. A poor health can negatively impact labor productivity, employment, and overall well-being more broadly. Likewise, adopting riskier behaviors in saving decisions can decrease women's ability to cope with negative unexpected economic shocks.

3.5.3 Heterogeneity analysis

This section provides results from the heterogeneity analyses looking at differences between poor and non-poor women, and between mothers and non-mothers. Living in poverty risks increasing the likelihood of suffering from mental disorders (Patel and Kleinman, 2003), and in societies where gender roles are strictly defined, the experience of motherhood can hold important and negative drawbacks on women's mental health (Jenkins and Good, 2014). Because of this increased vulnerability, it seems particularly important to focus on these two sub-groups of the population for whom mental disorders risk holding even more critical consequences. While looking at the results, it is always important to keep in mind that we are looking at correlations with the aim of providing informative evidence on the addressed issues.

Poor vs non-poor women

Table 3.15 reports the results from the heterogeneity analysis based on the income level of the respondents. The interaction term gives us the difference in the effect of depression between poor and non-poor women. As we can see, poor women suffering from depression are less likely to be risk averse than non-poor depressed women, and they are also more likely to be patient in the long term. Depression reduces cognitive abilities for non-poor women, while we observe no significant impact for poor women. The effect of depression on risk aversion and impatience in the long run differs then according to women's income level. In line with the recent literature, these results suggest that mental health and poverty are correlated, and that they both affects economic behavior.

Table 3.16 in the Appendix shows that women suffering from depression and living in poverty are significantly less likely to practice some sport, significantly more likely to have a credit and a saving accounts in a formal institution. No significant effects are found on the other analyzed behaviors.

Mothers vs non-mothers

Tables 3.19 and 3.20 in the Appendix report the results of the heterogeneity analysis between mothers and non-mothers. The interaction term is interpreted as the additional effect of being a mother when depressed. As we can notice, motherhood does not significantly impact economic preferences and cognitive abilities on top of mental health, while suffering from depression and bearing the role of mother within the household translates in changes in daily behaviors. When combined with motherhood, depression leads women to spend on average almost 12 hours per week less helping their children doing homework, they are more likely to smoke by 18 percentage points, they sleep on average one hour less, they are less likely to have an informal saving account.

3.6 Mechanisms: mediation analysis

To better understand *why* and *how* depression affects economic preferences, I conduct also a mediation analysis, where I include in the regression the treatment dummy together with common depressive symptoms. If the effect of the coefficient of depression (i.e., the main explanatory variable) is reduced or it is not significant anymore, then the considered depressive symptom partly or fully mediate the impact of depression.

The conceptual model of mediation analysis can be formalized as follows (Selig and Preacher, 2009):

$$(3) \qquad M_{it} = \beta_0 + \beta_1 Treat_{it} + \beta_2 X_{it} + \beta_3 Z_{ht} + d_t + \alpha_i + \varepsilon_{it}, \ \ t = 1, \ 2$$

$$(4) \qquad Y_{it} = \beta_0 + \beta_1 Treat_{it} + \beta_2 M_{it} + \beta_3 X_{it} + \beta_4 Z_{ht} + d_t + \alpha_i + \varepsilon_{it}, \ \ t = 1, \ 2$$

Where M_{it} is the mediating variable (e.g., stress, sleep deprivation) of individual i in time t and it is predicted by depression ($Treat_{it}$) in Equation 4. The mediating variable gives the indirect effect of $Treat_{it}$ on Y_{it}. Once M_{it} is included in the regression, there is fully mediation if β_1 is no significant anymore, partial mediation if β_1 is only reduced, or no mediation if the direct effect of β_1 is the same. In other words, with full or partial mediation the effect of depression on time discounting is driven by changes in the mediating variables.

The mediation analysis relies on two steps: first, we need to assess through a logistic regression whether depression correctly predicts the considered symptoms. If its impact is significant, then we can run the mediation analysis by including within the regression each symptom one by one. Table 3.21 in the Appendix shows that depression significantly predicts all the symptoms. I employ the Linear Probability Model (LPM) and I compare the results when depression is considered alone or joint with one of the symptoms. As the Mediation analysis greatly benefits from panel data (Selig and Preacher, 2009), following the literature I conduct the analysis with Fixed Effects.

Table 3.12 shows that fatigue (defined as “waking up tired due to lack of energy or fear"”) and sleep deprivation partly mediate the effect of depression on risk taking behaviors and time discounting both in the short and long run, suggesting that both physical and psychological fatigue associated to poor mental health impair decision-making processes: women adopt what could seem a counter-intuitive behavior, as they exhibit at same time a more patient and risk taking behavior. We can better understand these findings if we look at the mediating effect of anhedonia and negative beliefs about the future. The former partly mediates the effect of depression on time discounting in the short run. These results, combined with those showing a null or negative effect of depression on saving behaviors, suggest that women defer future gratification because of a lack of interest in receiving immediately the hypothetical amount. The latter partly mediates risk-taking behaviors. By believing that they will be worse off in the

Table 3.12: results from mediation analysis

	Risk av.	**K1**	**K2**
Depression	**-0.0151****	**-0.224*****	**-0.0379****
	(0.0711)	**(0.0742)**	**(0.0704)**
Depression, M_{it}: fatigue	**-0.0615***	**-0.0777****	**-0.0531***
	(0.0334)	**(0.0368)**	**(0.0320)**
Depression, M_{it}: sleep deprivation	-0.0538*	**-0.0834****	**-.0404***
	(0.0276)	**(0.0363)**	**(0.0315)**
Depression, M_{it}: stress	-0.0813**	-0.0796***	-0.0556***
	(0.0343)	(0.0366)	(0.0323)
Depression, M_{it}: anhedonia	-0.0784**	**-0.0523***	-0.0606**
	(0.0365)	**(0.0409)**	(0.0350)
Depression, M_{it}: negative beliefs	**-0.0463***	-0.0875***	-0.0729**
	(0.0346)	(0.0368)	(0.0315)

Risk aversion is a dummy variable equals to 1 if the individual is risk averse, and 0 otherwise; K1 is a dummy variable equals to 1 if the individual is impatient in the short run, and 0 otherwise; K2 is a dummy variable equals to 1 if the individual is impatient in the long run, and 0 otherwise.Robust standard errors in parentheses, *** p<0.01, ** p<0.05, *

future, individuals are more likely to take risks as they value more the present than the future. This could translate then into bad choices for oneself, such as increasing the consumption of alcohol and tobacco or making risky investments.

The mediation analysis reveals that economic preferences are shaped by symptoms falling into three of the four categories of depressive symptoms identified by Beck and Alford (2009): cognitive (i.e., pessimistic beliefs about the future), emotional (i.e., anhedonia, or dejected mood), and somatic (i.e., fatigue and sleep deprivation). Then, depression affects women's decision-making processes through interrelated channels (e.g., sleep deprivation can increase anhedonia, while negative beliefs about the future can affect fatigue) that can help us better understand the mechanisms behind mental health and decision-making processes.

3.7 Discussion and conclusion

The aim of this study was to investigate the association between depression, economic preferences, and economic behaviors through the lens of gender. As already stated, it does not attempt to provide a causal impact of mental health on economic outcomes. Its main goal is to provide solid arguments on the importance of focusing on the economics of mental health through the lens of gender, especially in cultures where the patriarchal system keeps shaping women's lives in a pervasive manner. As we have seen from the literature review, studies of anthropology, sociology, economics, and psychology demonstrate the existence of structural problems rooted in the patriarchal society that increase women's likelihood of suffering from mental disorders. While there is extensive evidence on the gendered determinants of mental illness, we still do not know enough about its potential consequences on economic preferences and behaviors.

Results show that, compared to those who are mentally well, depressed women show a more patient and risk-taking behavior. While it may seem counter-intuitive that depression decreases risk aversion along with time discounting, these results are in line with Beck's cognitive model. Economic preferences are likely to be influenced by those that Beck defined as "emotional and cognitive symptoms", e.g., low mood and inability to feel pleasure, anhedonia, and negative feelings about oneself and the future (de Quidt and Haushofer, 2016). While anhedonia reduces sensitivity for immediate financial rewards and for present consumption, thus making individuals more patients, negative beliefs about the future can lead individuals to invest less in their future selves, and to be more risk taking (Pulcu et al., 2014; de Quidt and Haushofer, 2016). These results are in line with other studies showing that depressed individuals are more likely to take health risks (Cobb-Clark et al., 2019) and economic risks (Bayer et al., 2019), and to be more patient (Cobb-Clark et al., 2019). I find non-significant, negative evidence on the effect of depression on cognitive abilities.

To have a broader understanding of the relation between mental health and economic behavior, this study looks at whether suffering from depression translates in changes in daily behaviors. Because the literature states that preferences over risk and time discounting are strictly related to health and saving behaviors (Falk et al., 2018; Cobb-Clark et al., 2019), I include in the analysis variables capturing such dimensions. Then, as mental health affects parental investments in children's outcomes (Lund et al., 2010; Aizer et al., 2016; Baranov et al., 2020), I also include in the analysis women's investment in children's education. Women suffering from depression significantly change their health and saving behaviors: they are more likely to smoke and, on average, they sleep 45 minutes less per week. They are also less likely to have a saving account in an informal institution, while we observe no significant differences in the likelihood of contracting a credit or opening a saving account in formal institutions. These results give us important information on mental health and women's decision-making: they show that depression can shape preferences and daily behaviors, and the gendered analysis overcomes the threat of explaining women's behavior in terms of deviations from men's, by applying masculine values to individual and social behavior and not considering the structures of power underlying these same behaviors (Becchio, 2019).

As poverty influences mental health (Ridley et al., 2020) and women living in poverty are at a particular high risk of suffering from mental disorders (Nolen-Hoeksema, 2001; Belle and Doucet, 2003), I decided to further the analysis to look at differences between poor and non-poor women. Results suggest that there are different mechanisms at place influencing economic behaviors according to women's economic status. From the literature in behavioral development economics, we know that people living in poverty are usually more risk-averse and more impatient, especially in the short-run (Haushofer and Fehr, 2014; Kremer et al., 2019). Several reasons explain such behaviors, from the constant and daily risks they are faced with, as volatile prices and weather shocks, to the limited access to credit markets, or to reduced cognitive abilities and increased stress (Banerjee and Duflo, 2007; Mani et al., 2013; Callen et al., 2014; Haushofer and Fehr, 2014; Schilbach et al., 2016; Janssens, 2017). Our results show that poor women suffering from depression exhibit a greater willingness to take risk and to defer future gratifications in the long run. In terms of daily behaviors, women living in poverty and suffering from depression invest less in their health, and they are more likely to have contracted a credit in an formal institution. Hence, mental health and poverty are two factors that should considered together when investigating (women's) preferences and daily behaviors, as they can be part of the explanation of the results we observe in the literature.

The heterogeneity analysis looks also at differences between women suffering from depression that have children and those who have not. Feelings of overload related to the domestic sphere increase the likelihood of suffering from mental illness (Liu et al., 2018). For this reason, I focus also on this sub-group of the population. While we observe no differences in economic preferences, having children and suffering from depression leads women to spend less time helping them with their homework, they sleep on average one hour less per week, they are more likely to smoke, and to have a saving account in informal institutions. In many traditional societies, women find themselves defined in the role of mothers and wives without many other possibilities of realizing themselves outside the household. In Mexico, where gender roles are strictly defined, women having children and suffering from depression exhibit different behaviors than depressed women without children. It is important then to further analyze the association between mental health and the different roles women can assume throughout their lives, as they can be strictly correlated.

This study has implications for researchers, policy makers, and development practitioners. First of all, further research is needed to evaluate the causal impact of depression on economic decision-making and economic preferences under a gendered perspective. Development economists have been heading in this direction, but mostly to better understand the economic determinants of mental health (Haushofer and Fehr, 2014; Baranov et al., 2020; Prencipe et al., 2021). More attention should be paid to the consequences of mental disorders on economic preferences, with a particular focus on gender differences. Neuroeconomics techniques could be of great help in the study of this topic. By affecting economic preferences, depression could have broader impacts on women's empowerment, on intra-household dynamics between spouses, on labor productivity, and on women's well-being more broadly. With the increasing attention given to women's empowerment worldwide, it seems crucial to include in its definition and measurement a psychological dimension related to mental health. In this way, we would be able to better advise on programs and policies aimed at fighting gender inequalities.

Second, policy makers should pay more attention to the hidden nature of mental disorders. Not only they entail substantial costs both at the individual and aggregate level (de Quidt and Haushofer, 2016), but they have detrimental consequences on individuals' well-being in the long run. Increased access to mental health care services is essential, as well as increasing individuals' awareness on the physical and mental harms that mental disorders can entail in the long run. As women are more vulnerable than men to suffering from mental illnesses, it is important to pay particular attention to this gender difference in the public debate.

Third, development practitioners should focus on the social and cultural determinants of depression in each considered country. For instance, in most low- and middle-income countries social stigma against mental disorders is still very high (Ridley et al., 2020). This can lead individuals to underestimate the problem, and to refuse access to health care because they feel ashamed or judged by others. For women, social stigma can have even worse consequences as they are usually expected to play specific roles defined by gender norms that can reinforce the likelihood of suffering from depression. Boosting the design of programs aimed at fighting social stigma against mental disorders can be a first step in this direction, as they have already been proven to be efficient in improving individuals' mental health (Ridley et al., 2020; Baranov et al., 2020). With the support of researchers, development practitioners should focus on the design of gender-driven programs in the fight against mental health, for instance by offering mental health care in separate shelters or at home, or by offering weekly psychological help by telephone to avoid the social stigma dimension.

References

Aizer, A., Stroud, L., and Buka, S. (2016). Maternal stress and child outcomes: Evidence from siblings. *Journal of Human Resources*, 51(3):523–555.

Arora, D. (2015). Gender differences in time-poverty in rural mozambique. *Review of Social Economy*, 73(2):196–221.

Arthi, V., Beegle, K., De Weerdt, J., and Palacios-López, A. (2018). Not your average job: Measuring farm labor in Tanzania. *Journal of Development Economics*, 130:160–172.

Asfaw, S. and Maggio, G. (2018). Gender, weather shocks and welfare: Evidence from malawi. *The Journal of Development Studies*, 54(2):271–291.

Banerjee, A. V. and Duflo, E. (2007). The Economic Lives of the Poor. *Journal of Economic Perspectives*, 21(1):141–168.

Baranov, V., Bhalotra, S., Biroli, P., and Maselko, J. (2020). Maternal depression, women's empowerment, and parental investment: evidence from a randomized controlled trial. *American Economic Review*, 110(3):824–59.

Baranyi, G., Di Marco, M. H., Russ, T. C., Dibben, C., and Pearce, J. (2021). The impact of neighbourhood crime on mental health: A systematic review and meta-analysis. *Social Science & Medicine*, 282:114106.

Bargain, O. and Zeidan, J. (2019). Heterogeneous effects of obesity on mental health: Evidence from mexico. *Health economics*, 28(4):447–460.

Bayer, Y. M., Shtudiner, Z., Suhorukov, O., and Grisaru, N. (2019). Time and risk preferences, and consumption decisions of patients with clinical depression. *Journal of Behavioral and Experimental Economics*, 78:138–145.

Becchio, G. (2019). Behavioral economics, gender economics, and feminist economics: friends or foes? *Journal of Economic Methodology*, 26(3):259–271.

Beck, A. T. and Alford, B. A. (2009). *Depression: Causes and treatment*. University of Pennsylvania Press.

Belle, D. and Doucet, J. (2003). Poverty, inequality, and discrimination as sources of depression among us women. *Psychology of women quarterly*, 27(2):101–113.

Belló, M., Puentes-Rosas, E., and Medina-Mora, M. E. (2005). Prevalencia y diagnóstico de depresión en población adulta en méxico. *Salud pública de México*, 47.

Bernheim, B. D., Ray, D., and Yeltekin, (2015). Poverty and Self-Control. *Econometrica*, 83(5):1877–1911. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA11374.

Blanco, N. J., Otto, A. R., Maddox, W. T., Beevers, C. G., and Love, B. C. (2013). The influence of depression symptoms on exploratory decision-making. *Cognition*, 129(3):563–568.

Bland, J. M. and Altman, D. G. (1997). Cronbach's alpha. *BMJ : British Medical Journal*, 314(7080):572.

Brown, R., Montalva, V., Thomas, D., and Velásquez, A. (2019). Impact of Violent Crime on Risk Aversion: Evidence from the Mexican Drug War. *The Review of Economics and Statistics*, 101(5):892–904.

Cahlíková, J., Cingl, L., and Levely, I. (2020). How stress affects performance and competitiveness across gender. *Management Science*, 66(8):3295–3310.

Calderón-Narváez, G. (1997). Un cuestionario para simplificar el diagnóstico del síndrome depresivo. *Revista de Neuro-psiquiatría*, 60(2):127–135.

Callen, M., Isaqzadeh, M., Long, J. D., and Sprenger, C. (2014). Violence and Risk Preference: Experimental Evidence from Afghanistan. *American Economic Review*, 104(1):123–148.

Chonody, J. M. and Siebert, D. C. (2008). Gender differences in depression: a theoretical examination of power. *Affilia*, 23(4):338–348.

Cobb-Clark, D. A., Dahmann, S. C., and Kettlewell, N. (2019). Depression, Risk Preferences and Risk-Taking Behavior. page 69.

Croson, R. and Gneezy, U. (2009). Gender Differences in Preferences. *Journal of Economic Literature*, 47(2):448–474.

de Quidt, J. and Haushofer, J. (2016). Depression for Economists. Technical Report w22973, National Bureau of Economic Research, Cambridge, MA.

Dittrich, M. and Leipold, K. (2014). Gender differences in time preferences. *Economics Letters*, 122(3):413–415.

Doss, C. (2013). Intrahousehold bargaining and resource allocation in developing countries. *The World Bank Research Observer*, 28(1):52–78.

Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D., and Sunde, U. (2018). Global evidence on economic preferences. *The Quarterly Journal of Economics*, 133(4):1645–1692.

Frías, S. M. and Agoff, M. C. (2015). Between support and vulnerability: Examining family support among women victims of intimate partner violence in mexico. *Journal of Family Violence*, 30(3):277–291.

Gammage, S. (2010). Time pressed and time poor: unpaid household work in guatemala. *Feminist Economics*, 16(3):79–112.

Haushofer, J. and Fehr, E. (2014). On the psychology of poverty. *Science*, 344(6186):862–867.

Haushofer, J. and Shapiro, J. (2016). The Short-term Impact of Unconditional Cash Transfers to the Poor: ExperimentalEvidence from Kenya*. *The Quarterly Journal of Economics*, 131(4):1973–2042.

Janssens, W. (2017). Be patient when measuring hyperbolic discounting_ Stationarity, time consistency and time invariance in a field experiment. *Journal of Development Economics*, page 14.

Jenkins, J. H. and Good, M.-J. D. (2014). Women and global mental health: Vulnerability and empowerment. *Essentials of global mental health*, pages 264–281.

Kapiga, S., Harvey, S., Mshana, G., Hansen, C. H., Mtolela, G. J., Madaha, F., Hashim, R., Kapinga, I., Mosha, N., Abramsky, T., et al. (2019). A social empowerment intervention to prevent intimate partner violence against women in a microfinance scheme in tanzania: findings from the maisha cluster randomised controlled trial. *The Lancet Global Health*, 7(10):e1423–e1434.

Kimball, M. S., Sahm, C. R., and Shapiro, M. D. (2009). Risk Preferences in the PSID: Individual Imputations and Family Covariation. *American Economic Review*, 99(2):363–368.

Knapp, J., Quiros, A., and Muller, B. (2009). Women, men, and the changing role of gender in immigration.

Kremer, M., Rao, G., and Schilbach, F. (2019). Behavioral development economics. In *Handbook of Behavioral Economics: Applications and Foundations 1*, volume 2, pages 345–458. Elsevier.

Lara, M. A., Acevedo, M., and Berenzon, S. (2004). La depresión femenina vista desde la subjetividad de las mujeres. *Cadernos de Saúde Pública*, 20:818–828.

Liu, L., MacPhail, F., and Dong, X.-y. (2018). Gender, work burden, and mental health in post-reform china. *Feminist Economics*, 24(2):194–217.

Lund, C., Breen, A., Flisher, A. J., Kakuma, R., Corrigall, J., Joska, J. A., Swartz, L., and Patel, V. (2010). Poverty and common mental disorders in low and middle income countries: A systematic reviewq. *Social Science*, page 12.

Mani, A., Mullainathan, S., Shafir, E., and Zhao, J. (2013). Poverty Impedes Cognitive Function. *Science*, 341(6149):976–980.

Mohamad Azhar, N. A. Z. and Mohd, S. (2020). Using asset index to reassess poverty in the Northern States of Malaysia: do the poor stay poor? *International Journal of Social Economics*, 47(4):483–502.

Nelson, J. A. (2016). Not-so-strong evidence for gender differences in risk taking. *Feminist Economics*, 22(2):114–142.

Niederle, M. and Vesterlund, L. (2007). Do women shy away from competition? do men compete too much? *The quarterly journal of economics*, 122(3):1067–1101.

Noble, R. E. (2005). Depression in women. *Metabolism*, 54(5):49–52.

Nolen-Hoeksema, S. (2001). Gender Differences in Depression. *Current Directions in Psychological Science*, 10(5):173–176.

Patel, V. and Kleinman, A. (2003). Poverty and common mental disorders in developing countries. *Bulletin of the World Health Organization*, page 7.

Prencipe, L., Houweling, T. A. J., van Lenthe, F. J., and Palermo, T. (2021). Do Conditional Cash Transfers Improve Mental Health? Evidence From Tanzania's Governmental Social Protection Program. *Journal of Adolescent Health*.

Pulcu, E., Trotter, P., Thomas, E., McFarquhar, M., Juhász, G., Sahakian, B., Deakin, J., Zahn, R., Anderson, I., and Elliott, R. (2014). Temporal discounting in major depressive disorder. *Psychological medicine*, 44(9):1825–1834.

Rafful, C., Medina-Mora, M. E., Borges, G., Benjet, C., and Orozco, R. (2012). Depression, gender, and the treatment gap in mexico. *Journal of affective disorders*, 138(1-2):165–169.

Raven, J. (2000). The Raven's Progressive Matrices: Change and Stability over Culture and Time. *Cognitive Psychology*, 41(1):1–48.

Ridley, M., Rao, G., Schilbach, F., and Patel, V. (2020). Poverty, depression, and anxiety: Causal evidence and mechanisms. *Science*, 370(6522).

Rubalcava, L. N. and Teruel, G. M. (2004). The role of maternal cognitive ability on child health. *Economics & Human Biology*, 2(3):439–455.

Salk, R. H., Hyde, J. S., and Abramson, L. Y. (2017). Gender differences in depression in representative national samples: Meta-analyses of diagnoses and symptoms. *Psychological bulletin*, 143(8):783.

Schilbach, F. (2019). Alcohol and Self-Control: A Field Experiment in India. *American Economic Review*, 109(4):1290–1322.

Schilbach, F., Schofield, H., and Mullainathan, S. (2016). The Psychological Lives of the Poor. *American Economic Review*, 106(5):435–440.

Schmeer, K. K. and Kroeger, R. A. (2011). Union Type and Depressive Symptoms Among Mexican Adults. *Journal of Family Issues*, 32(12):1597–1621. Publisher: SAGE Publications Inc.

Selig, J. P. and Preacher, K. J. (2009). Mediation Models for Longitudinal Data in Developmental Research. *Research in Human Development*, 6(2-3):144–164.

Sent, E.-M. and van Staveren, I. (2019). A feminist review of behavioral economic research on gender differences. *Feminist Economics*, 25(2):1–35.

Shah, A. K., Shafir, E., and Mullainathan, S. (2015). Scarcity Frames Value. *Psychological Science*, 26(4):402–412.

WHO (2017). Depression and other common mental disorders: global health estimates. Technical report, World Health Organization.

Wu, P.-C. (2010). Measurement invariance and latent mean differences of the beck depression inventory ii across gender groups. *Journal of Psychoeducational Assessment*, 28(6):551–563.

Appendix

Construction of outcome variables

Figure 1: distribution of depressive symptoms at baseline, MxFLS2

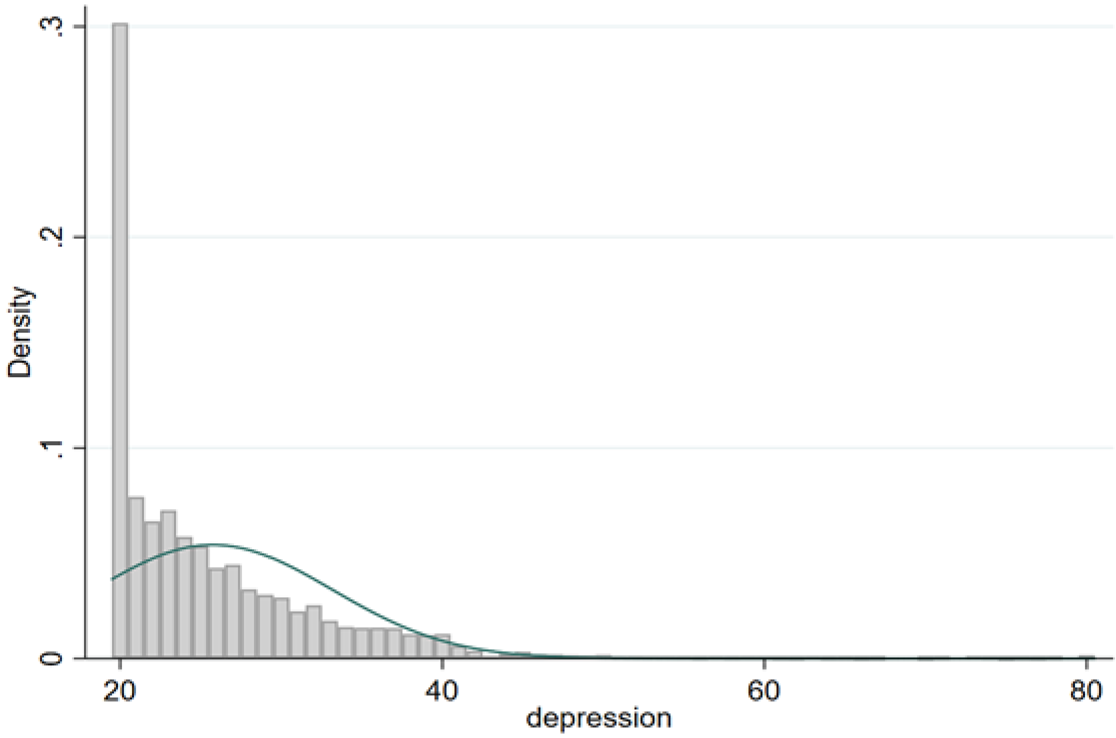


Table 13: Cronbach's alpha, MxFLS2 and MxFLS3

	MxFLS2	**MxFLS3**
Cronbach's Alpha	0.9096	0.9297
Average interim covariance	.1142	.1277

Figure 2: distribution of cognitive abilities at baseline, MxFLS2

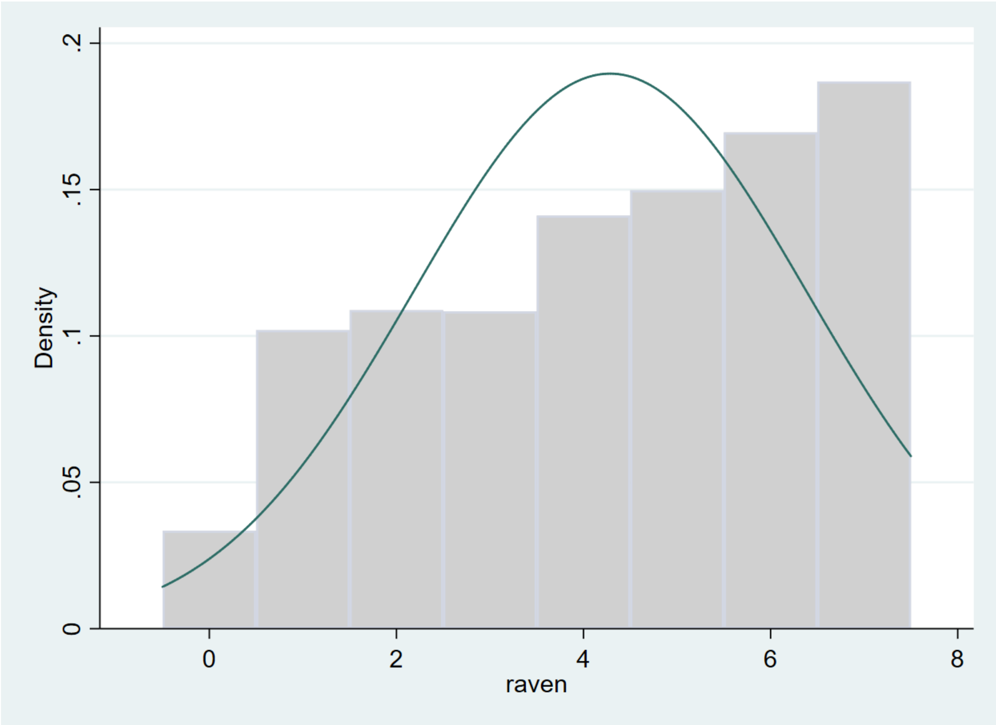
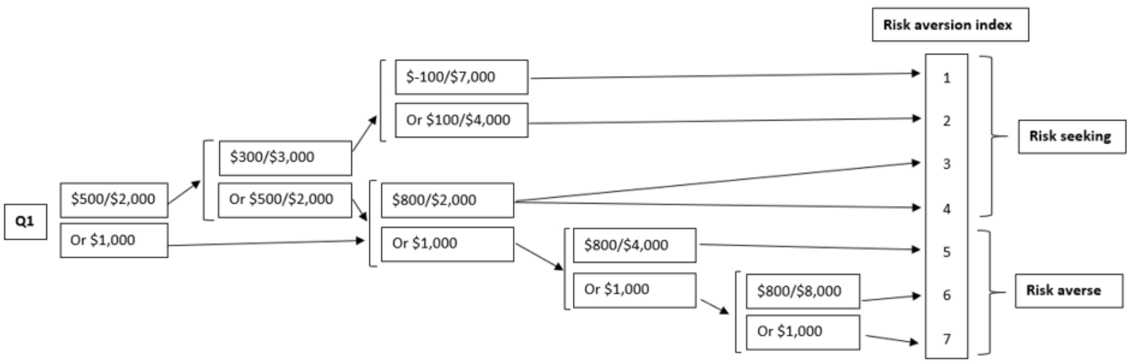
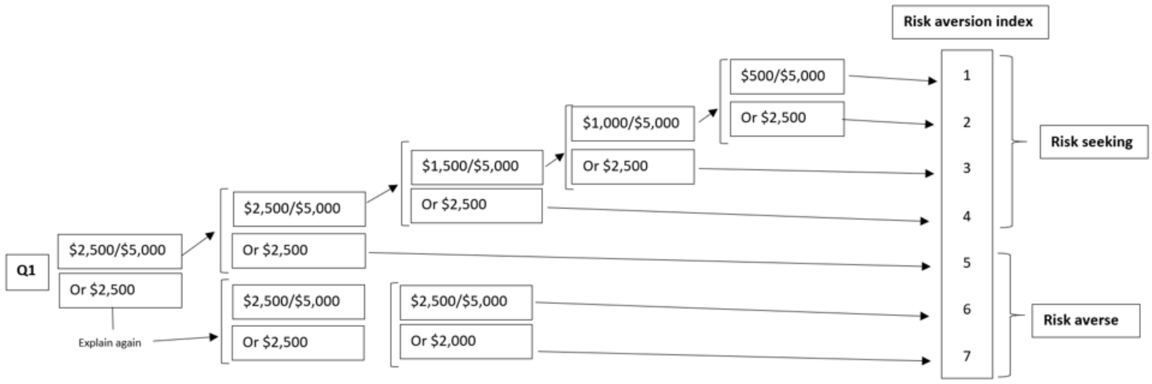


Figure 3: construction of risk aversion index, MxFLS2



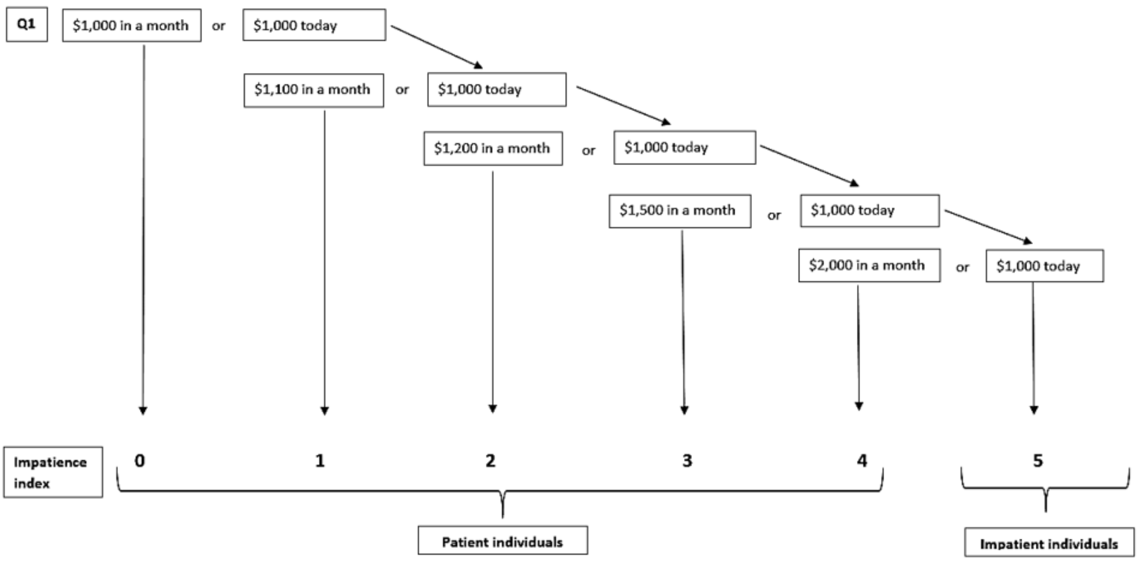
Notes: in Mexico, the symbol "$" stands for Mexican pesos. The risk aversion index goes from 1 to 7, and is increasing in risk aversion. We call "risk averse" those falling in the last three categories of the index (i.e., 5, 6, or 7), and not risk averse those falling in the first four categories of the index (i.e., 1, 2, 3, 4).

Figure 4: construction of risk aversion index, MxFLS3



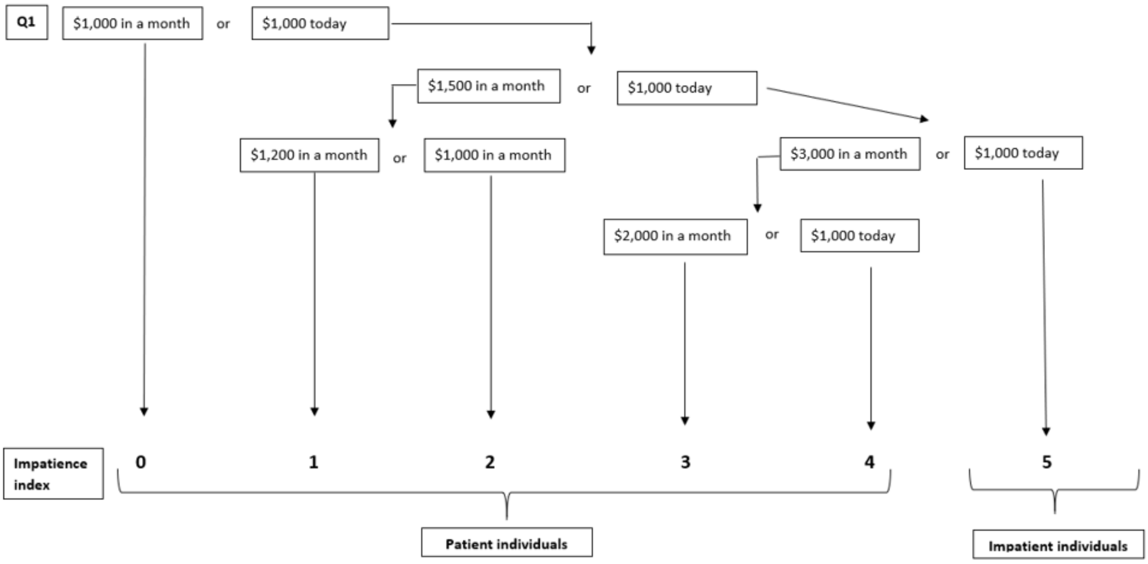
Notes: in Mexico, the symbol "$" stands for Mexican pesos. The risk aversion index goes from 1 to 5, and is increasing in risk aversion. We call "risk averse" those falling in the last three categories of the index (i.e., 5, 6, or 7), and not risk averse those falling in the first four categories of the index (i.e., 1, 2, 3, 4).

Figure 5: construction of impatience index, MxFLS2



Notes: in Mexico, the symbol "$" stands for Mexican pesos. The impatience aversion index goes from 1 to 5, and is increasing in time discounting. We call "impatient" those falling in the last category of the index (i.e., 5), and not risk averse those falling in the first four categories of the index (i.e., 1, 2, 3, 4).

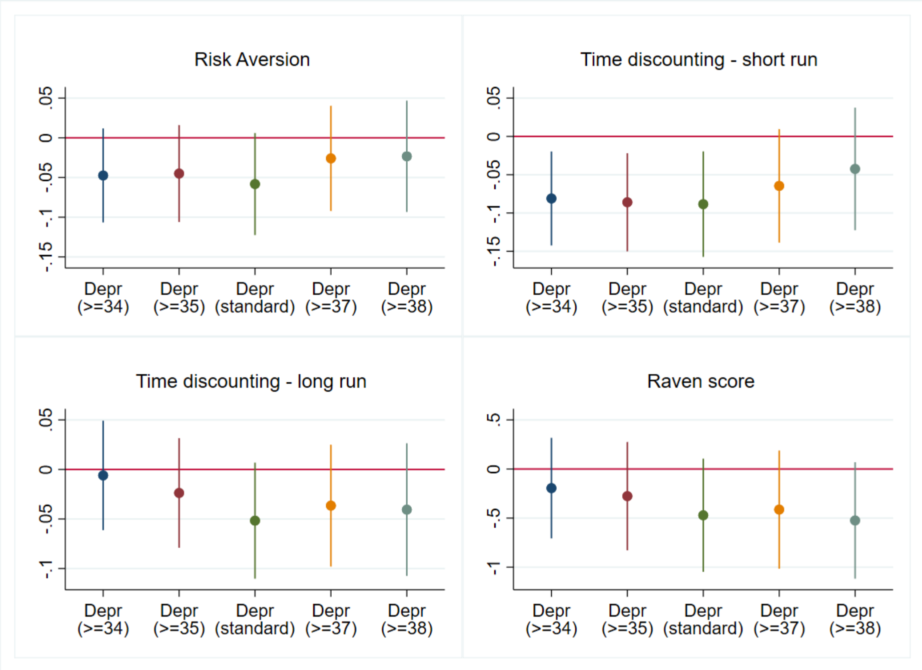
Figure 6: construction of impatience index, MxFLS3



Notes: in Mexico, the symbol "$" stands for Mexican pesos. The impatience aversion index goes from 1 to 5, and is increasing in time discounting. We call "impatient" those falling in the last category of the index (i.e., 5), and not risk averse those falling in the first four categories of the index (i.e., 1, 2, 3, 4).

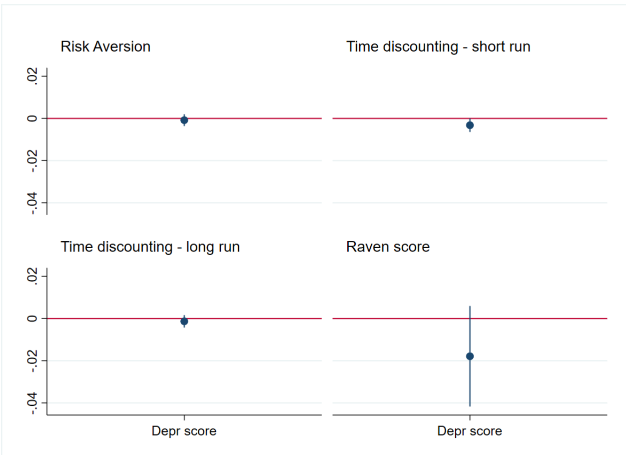
Additional results

Figure 7: Analysis with different cut-offs of depression score



Risk aversion is a dummy variable equals to 1 if the individual is risk averse, and 0 otherwise; K1 is a dummy variable equals to 1 if the individual is impatient in the short run, and 0 otherwise; K2 is a dummy variable equals to 1 if the individual is impatient in the long run, and 0 otherwise; Raven provides the results of the Raven's test, and it ranges between 0 and 7. The reported dependent variables are dummy variables identifiying depressed individuals based on different cut-offs than the standard one (i.e., +/- 1/2 points). Control variables are those included in the main analysis.

Figure 8: Analysis - Depression score and economic preferences



Risk aversion is a dummy variable equals to 1 if the individual is risk averse, and 0 otherwise; K1 is a dummy variable equals to 1 if the individual is impatient in the short run, and 0 otherwise; K2 is a dummy variable equals to 1 if the individual is impatient in the long run, and 0 otherwise; Raven provides the results of the Raven's test, and it ranges between 0 and 7. The reported dependent variable is the mental health score ranging from 20 to 80. Control variables are those included in the main analysis.

Table 14: depression and daily behaviors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Children educ.	Smoking	Sport	Sleep	I prev. health	Loan	Saving (inf.)	Saving
Treat	**0.256**	**0.0784*** **	**-0.015**	**-0.431** **	**-0.003**	**0.102**	**-0.076***	**-0.0142**
	(0.2428)	**(0.026)**	**(0.052)**	**(0.195)**	**(0.031)**	**(0.100)**	**(0.051)**	**(0.030)**
RA	-0.165	-0.016	-0.0026	0.062	0.029	0.128**	-0.013	-0.0537*
	(0.908)	(0.016)	(0.035)	(0.108)	(0.020)	(0.053)	(0.033)	(0.029)
K1	-1.355	-0.009	0.010	-0.222*	-0.012	-0.045	0.016	-0.052
	(0.927)	(0.019)	(0.035)	(0.12)	(0.021)	(0.051)	(0.036)	(0.035)
K2	-2.048	0.025	-0.071*	0.002	0.003	0.026	-0.032	0.028
	(1.389)	(0.018)	(0.038)	(0.140)	(0.024)	(0.046)	(0.038)	(0.031)
Raven	0.568**	-0.005	0.002	0.027	-0.0097*	0.005	-0.004	0.007
	(0.229)	(0.004)	(0.006)	(0.027)	(0.005)	(0.012)	(0.008)	(0.007)
Age	-0.499	-0.009*	-0.008	-0.087	0.020*	0.034	-0.001	-0.003
	(0.505)	(0.005)	(0.014)	(0.065)	(0.012)	(0.026)	(0.012)	(0.012)
HH members	-1.403	-0.010	0.0018	-0.019	-0.025*	-0.033	0.006	-0.009
	(1.362)	(0.007)	(0.015)	(0.061)	(0.014)	(0.027)	(0.012)	(0.014)
Education	-0.028	-0.0014	0.000	0.003	1.77	-0.022	0.003	-0.001
	(0.025)	(0.001)	(0.001)	(0.0107)	(0.001)	(0.025)	(0.003)	(0.000)
Urban	3.666	-0.0806*	0.033	0.015	0.032	-0.033	-0.002	0.186
	(2.830)	(0.045)	(0.064)	(0.315)	(0.037)	(0.084)	(0.058)	(0.124)
Violence	0.036	0.043**	0.079**	0.182	-0.002	0.031	0.083**	0.052
	(0.759)	(0.018)	(0.032)	(0.124)	(0.020)	(0.051)	(0.033)	(0.036)
PCA index	-0.398	-0.003	-0.0542**	-0.043	-0.009	-0.006	0.026	-0.009
	(0.482)	(0.005)	(0.026)	(0.089)	(0.013)	(0.032)	(0.023)	(0.013)
Shock	-1.514	-0.0178	0.020	-0.108	0.031	0.104**	0.003	0.021
	(1.095)	(0.013)	(0.030)	(0.116)	(0.028)	(0.050)	(0.030)	(0.025)
Married	-5.026***	-0.0800	0.156**	-0.436**	-0.138***	-0.053	-0.008	0.0232
	(1.233)	(0.0525)	(0.0617)	(0.180)	(0.0432)	(0.0743)	(0.0563)	(0.0607)
Year	3.659	0.054**	0.108	0.184	-0.208***	-0.116	0.0562	0.0945
	(2.279)	(0.0266)	(0.0664)	(0.318)	(0.057)	(0.114)	(0.0527)	(0.0675)
Constant	28.30*	0.535**	0.291	11.06***	-0.460	-0.896	0.0805	0.0645
	(15.35)	(0.222)	(0.496)	(2.334)	(0.448)	(0.958)	(0.418)	(0.417)
Observations	6,875	6,875	6,875	6,864	6,809	4,481	6,857	6,857
R-squared	0.252	0.043	0.045	0.047	0.152	0.089	0.039	0.025
Number of id	5,536	5,536	5,536	5,533	5,498	4,066	5,524	5,525

Outcome variables are the minutes spent in helping children with their homework over the last week; a dummy variable equals to one if the individual is smoking; a dummy variable equals to one if the individual practice some sport at least once per week; the number of hours slept per night over the last week; a dummy variable equals to one if the individual invests in preventive health; a dummy variable equals to one if the individual has a loan in a formal credit institution; a dummy variable equals to one if the individual has a saving account in an informal institution; a dummy variable equals to one if the individual has a saving account in a formal institution. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 15: heterogeneity analysis, poor vs non-poor women

	(1) **Risk aversion**	(2) **K1**	(3) **K2**	(4) **Raven**
Treat	-0.023	-0.061	0.008	**-0.615***
	(0.040)	(0.043)	(0.037)	**(0.341)**
Poor	0.064**	-0.030	0.006	0.140
	(0.028)	(0.029)	(0.029)	(0.218)
Treat#Poor	**-0.0912***	**-0.063**	**-0.159*****	**0.339**
	(0.060)	**(0.059)**	**(0.056)**	**(0.446)**
Age	-0.0157	0.00941	0.0106	-0.095*
	(0.010)	(0.011)	(0.011)	(0.050)
HH members	-0.0105	-0.0118	-0.0130	0.112
	(0.010)	(0.010)	(0.011)	(0.07)
Education	0.005***	-0.005*	-0.00142	0.0197
	(0.001)	(0.003)	(0.001)	(0.014)
Urban	-0.082**	0.0512	0.0545	-0.339
	(0.037)	(0.041)	(0.040)	(0.337)
Violence	0.0132	-0.056**	-0.036*	-0.058
	(0.020)	(0.0243)	(0.0214)	(0.195)
Index PCA	0.0455**	-0.0113	0.002	0.0997
	(0.021)	(0.021)	(0.022)	(0.142)
Shock	0.0274	-0.014	-0.015	0.152
	(0.021)	(0.023)	(0.024)	(0.166)
Married	0.0423	-0.013	-0.063	-0.0952
	(0.048)	(0.056)	(0.053)	(0.293)
Year	0.358***	-0.025	0.213***	-0.279
	(0.047)	(0.050)	(0.050)	(0.239)
Constant	0.875**	0.197	0.162	7.016***
	(0.406)	(0.435)	(0.445)	(1.799)
Observations	11,320	11,320	11,320	6,875
R-squared	0.161	0.010	0.139	0.076
Number of id	6,447	6,447	6,447	5,536

Risk aversion is a dummy variable equals to 1 if the individual is risk averse, and 0 otherwise; K1 is a dummy variable equals to 1 if the individual is impatient in the short run, and 0 otherwise; K2 is a dummy variable equals to 1 if the individual is impatient in the long run, and 0 otherwise; Raven provides the results of the Raven's test, and it ranges between 0 and 7. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 16: depression and daily behaviors - poor vs non-poor

	(1) Children educ.	(2) Smoking	(3) Sport	(4) Sleep	(5) I prev. health	(6) Loan	(7) Saving (inf.)	(8) Saving
Treat	**-0.925**	**0.0767***	**0.0266**	**-0.425****	**-0.0136**	**-0.0527**	**-0.0300**	**-0.052**
	(1.394)	**(0.0405)**	**(0.0631)**	**(0.199)**	**(0.0363)**	**(0.107)**	**(0.0619)**	**(0.050)**
Poor	1.307	-0.00243	-0.0202	0.0537	-0.0166	0.0189	-0.0029	-0.037
	(1.382)	(0.0186)	(0.0396)	(0.153)	(0.0234)	(0.0494)	(0.043)	(0.036)
Treat#Poor	**1.428**	**0.00416**	**-0.103***	**-0.0105**	**0.0224**	**0.445*****	**-0.112**	**0.0912***
	(1.589)	**(0.0649)**	**(0.0764)**	**(0.345)**	**(0.0515)**	**(0.136)**	**(0.108)**	**(0.066)**
Risk aversion	-0.391	-0.0164	-0.003	0.0619	0.0301	0.143***	-0.0136	-0.0529*
	(0.915)	(0.0170)	(0.035)	(0.109)	(0.0203)	(0.052)	(0.0329)	(0.029)
K1	-1.078	-0.009	0.0082	-0.218*	-0.0137	-0.0352	0.0149	-0.0553
	(0.909)	(0.018)	(0.0359)	(0.127)	(0.0215)	(0.0470)	(0.0363)	(0.035)
K2	-2.244	0.0227	-0.0714*	0.000	0.003	0.0350	-0.0334	0.0313
	(1.396)	(0.0180)	(0.038)	(0.141)	(0.024)	(0.0450)	(0.0382)	(0.031)
Raven	0.511**	-0.0054	0.002	0.0272	-0.009*	-0.00283	-0.0036	0.0074
	(0.244)	(0.0042)	(0.006)	(0.027)	(0.005)	(0.0121)	(0.0081)	(0.007)
Age	-0.484	-0.00979*	-0.00890	-0.087	0.0221*	0.0330	-0.001	-0.002
	(0.552)	(0.005)	(0.0136)	(0.064)	(0.012)	(0.0234)	(0.012)	(0.0124)
HH member	-1.444	-0.0106	0.00213	-0.019	-0.0253*	-0.0228	0.006	-0.009
	(1.357)	(0.007)	(0.0152)	(0.061)	(0.0142)	(0.0268)	(0.012)	(0.014)
Education	-0.0228	-0.001	3.43	0.003	-8.27	-0.006	0.003	-0.001
	(0.0266)	(0.001)	(0.001)	(0.0107)	(0.001)	(0.0219)	(0.003)	(0.000)
Urban	3.792	-0.0810*	0.0367	0.0209	0.0303	-0.0358	0.00251	0.178
	(2.840)	(0.0452)	(0.0656)	(0.314)	(0.0377)	(0.0860)	(0.0585)	(0.124)
Violence	-0.225	0.0434**	0.0785**	0.179	-0.000	0.0372	0.0816**	0.0557
	(0.800)	(0.0184)	(0.0331)	(0.120)	(0.0207)	(0.0485)	(0.0330)	(0.036)
Index PCA	0.468	-0.00440	-0.0691**	-0.0182	-0.0168	0.0600	0.0195	-0.022
	(0.628)	(0.00881)	(0.0328)	(0.112)	(0.0155)	(0.0470)	(0.0281)	(0.016)
Shock	-1.190	-0.0180	0.0190	-0.105	0.0305	0.113**	0.00305	0.0196
	(1.157)	(0.0136)	(0.0302)	(0.118)	(0.0284)	(0.0502)	(0.0300)	(0.0253)
Married	-5.125***	-0.0799	0.157**	-0.438**	-0.137***	-0.0606	-0.00897	0.0254
	(1.297)	(0.0525)	(0.0614)	(0.179)	(0.0433)	(0.0764)	(0.0559)	(0.0609)
Year	3.891	0.0537**	0.104	0.195	-0.211***	-0.117	0.0558	0.0864
	(2.409)	(0.0263)	(0.0671)	(0.312)	(0.0588)	(0.0986)	(0.0507)	(0.0676)
Constant	27.59	0.535**	0.319	11.04***	-0.459	-0.970	0.103	0.0591
	(16.79)	(0.220)	(0.483)	(2.346)	(0.449)	(0.844)	(0.417)	(0.415)
Observations	1,469	6,875	6,875	6,864	6,809	4,481	6,857	6,857
R-squared	0.267	0.043	0.048	0.048	0.153	0.134	0.042	0.027
Number of id2	1,364	5,536	5,536	5,533	5,498	4,066	5,524	5,525

Outcome variables are the minutes spent in helping children with their homework over the last week; a dummy variable equals to one if the individual is smoking; a dummy variable equals to one if the individual practice some sport at least once per week; the number of hours slept per night over the last week; a dummy variable equals to one if the individual invests in preventive health; a dummy variable equals to one if the individual has a loan in a formal credit institution; a dummy variable equals to one if the individual has a saving account in an informal institution; a dummy variable equals to one if the individual has a saving account in a formal institution. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 19: heterogeneity analysis, mothers vs non-mothers

	(1) **Risk aversion**	(2) **K1**	(3) **K2**	(4) **Raven**
Treat	-0.0570	-0.0803**	-0.0436	-0.651*
	(0.0365)	(0.0382)	(0.0336)	(0.377)
Mother	0.114*	0.130*	0.108	-0.229
	(0.0593)	(0.0780)	(0.0703)	(0.494)
Treat#Mother	**0.00390**	**-0.0351**	**-0.0359**	**0.530**
	(0.0820)	**(0.0921)**	**(0.0697)**	**(0.583)**
Age	-0.0160	0.0102	0.0111	-0.0967*
	(0.0104)	(0.0111)	(0.0115)	(0.0501)
HH members	-0.00929	-0.0125	-0.0135	0.114
	(0.0103)	(0.0109)	(0.0117)	(0.0734)
Education	0.00530***	-0.00580*	-0.00150	0.0186
	(0.00197)	(0.00326)	(0.00154)	(0.0146)
Urban	-0.0855**	0.0495	0.0515	-0.331
	(0.0374)	(0.0417)	(0.0404)	(0.340)
Violence	0.0147	-0.0587**	-0.0376*	-0.0425
	(0.0208)	(0.0243)	(0.0215)	(0.195)
PCA Index	0.0206	0.00733	0.00896	0.00609
	(0.0173)	(0.0176)	(0.0177)	(0.103)
Shock	0.0263	-0.0124	-0.0149	0.155
	(0.0220)	(0.0237)	(0.0245)	(0.165)
Married	0.0434	-0.0172	-0.0633	-0.0801
	(0.0488)	(0.0561)	(0.0536)	(0.293)
Year	0.351***	-0.0162	0.219***	-0.312
	(0.0468)	(0.0510)	(0.0510)	(0.238)
Constant	0.881**	0.121	0.118	7.196***
	(0.410)	(0.436)	(0.454)	(1.769)
Observations	11,320	11,320	11,320	6,875
R-squared	0.159	0.010	0.137	0.076
Number of id	6,447	6,447	6,447	5,536

Risk aversion is a dummy variable equals to 1 if the individual is risk averse, and 0 otherwise; K1 is a dummy variable equals to 1 if the individual is impatient in the short run, and 0 otherwise; K2 is a dummy variable equals to 1 if the individual is impatient in the long run, and 0 otherwise; Raven provides the results of the Raven's test, and it ranges between 0 and 7.Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 20: depression and daily behaviors - mothers vs non-mothers

	(1) Children educ.	(2) Smoking	(3) Sport	(4) Sleep	(5) I prev. health	(6) Loan	(7) Saving (inf.)	(8) Saving
Treat	-0.532	0.0258*	0.00402	-0.0830	-0.0274	0.0300	-0.0181	-0.0436
	(1.448)	(0.0188)	(0.0644)	(0.172)	(0.0344)	(0.116)	(0.0522)	(0.0339)
Mother	2.659	0.00138	0.0465	0.530**	0.0752	0.120	0.0917*	-0.104
	(2.005)	(0.0233)	(0.0710)	(0.238)	(0.0763)	(0.117)	(0.0508)	(0.0897)
Treat#Mother	**-11.85*** **	**0.168** **	**-0.0576**	**-1.049** **	**0.0803**	**0.246**	**-0.176***	**0.0825**
	(2.264)	**(0.0685)**	**(0.110)**	**(0.425)**	**(0.0679)**	**(0.207)**	**(0.114)**	**(0.0706)**
Risk aversion	-0.161	-0.0191	-0.00284	0.0673	0.0269	0.127**	-0.0124	-0.0525*
	(0.996)	(0.0170)	(0.0357)	(0.107)	(0.0202)	(0.0532)	(0.0327)	(0.0297)
K1	-1.363	-0.00569	0.00910	-0.249**	-0.0116	-0.0411	0.0112	-0.0498
	(0.929)	(0.0192)	(0.0357)	(0.119)	(0.0215)	(0.0495)	(0.0351)	(0.0348)
K2	-2.217	0.0213	-0.0711*	0.0110	0.00247	0.0359	-0.0314	0.0282
	(1.512)	(0.0180)	(0.0381)	(0.135)	(0.0244)	(0.0470)	(0.0375)	(0.0318)
Raven	0.523**	-0.00592	0.00220	0.0315	-0.00984*	0.00198	-0.00343	0.00708
	(0.225)	(0.00428)	(0.00695)	(0.0266)	(0.00510)	(0.0123)	(0.00806)	(0.00773)
Age	-0.143	-0.00967*	-0.00830	-0.0875	0.0222*	0.0300	-0.00122	-0.00359
	(0.651)	(0.00570)	(0.0138)	(0.0643)	(0.0123)	(0.0251)	(0.0122)	(0.0126)
HH members	-1.552	-0.0104	0.00176	-0.0203	-0.0254*	-0.0331	0.00642	-0.00979
	(1.375)	(0.00700)	(0.0153)	(0.0604)	(0.0141)	(0.0275)	(0.0120)	(0.0142)
Education	-0.0314	-0.00138	0.000239	0.00437	0.000227	-0.0218	0.00379	-0.00137
	(0.0231)	(0.00136)	(0.00141)	(0.00926)	(0.00138)	(0.0257)	(0.00358)	(0.000948)
Urban	3.722	-0.0791*	0.0331	0.00785	0.0338	-0.0401	-0.00403	0.187
	(2.905)	(0.0457)	(0.0648)	(0.310)	(0.0370)	(0.0840)	(0.0578)	(0.123)
Violence	-0.242	0.0457**	0.0769**	0.151	-0.00290	0.0361	0.0782**	0.0564
	(0.682)	(0.0186)	(0.0326)	(0.118)	(0.0215)	(0.0513)	(0.0331)	(0.0373)
PCA Index	-0.469	-0.00464	-0.0528**	-0.0233	-0.00885	-0.00998	0.0299	-0.0124
	(0.512)	(0.00562)	(0.0251)	(0.0856)	(0.0131)	(0.0316)	(0.0233)	(0.0135)
Shock	-1.564	-0.0153	0.0188	-0.130	0.0318	0.110**	-0.000186	0.0236
	(1.167)	(0.0134)	(0.0302)	(0.115)	(0.0285)	(0.0499)	(0.0306)	(0.0259)
Married	-6.467***	-0.0792	0.154**	-0.461**	-0.140***	-0.0491	-0.0128	0.0277
	(1.961)	(0.0521)	(0.0619)	(0.179)	(0.0435)	(0.0766)	(0.0565)	(0.0595)
Year	2.374	0.0566**	0.109*	0.193	-0.204***	-0.0947	0.0577	0.0910
	(2.533)	(0.0269)	(0.0652)	(0.316)	(0.0543)	(0.109)	(0.0530)	(0.0684)
Constant	18.36	0.526**	0.275	10.90***	-0.496	-0.772	0.0534	0.101
	(16.83)	(0.224)	(0.493)	(2.300)	(0.447)	(0.892)	(0.418)	(0.416)
Observations	1,469	6,875	6,875	6,864	6,809	4,481	6,857	6,857
R-squared	0.276	0.054	0.046	0.063	0.157	0.098	0.045	0.027
Number of id	1,364	5,536	5,536	5,533	5,498	4,066	5,524	5,525

Outcome variables are the minutes spent in helping children with their homework over the last week; a dummy variable equals to one if the individual is smoking; a dummy variable equals to one if the individual practice some sport at least once per week; the number of hours slept per night over the last week; a dummy variable equals to one if the individual invests in preventive health; a dummy variable equals to one if the individual has a loan in a formal credit institution; a dummy variable equals to one if the individual has a saving account in an informal institution; a dummy variable equals to one if the individual has a saving account in a formal institution. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 21: correlation between possible mediators and depression, Linear Probability Model

	(1) Sleep depr.	(2) Stress	(3) Fatigue	(4) Anhedonia	(5) Neg. beliefs
Depression	**2.360*** **	**3.105*** **	**2.930*** **	**3.372*** **	**2.382*** **
	(0.133)	**(0.176)**	**(0.163)**	**(0.194)**	**(0.127)**
Age	-0.050	-0.007	0.007	0.067	0.040
	(0.031)	(0.030)	(0.032)	(0.062)	(0.033)
HH size	0.009	-0.005	-0.045	0.072	0.042
	(0.028)	(0.028)	(0.023)	(0.044)	(0.030)
Education	0.004	0.003	0.004	-0.013	0.004
	(0.010)	(0.008)	(0.012)	(0.0191)	(0.0102)
Urban	0.097	0.089	0.107	0.903***	0.288*
	(0.144)	(0.162)	(0.160)	(0.260)	(0.152)
Violence	0.280***	0.443***	0.306***	0.164	0.336***
	(0.060)	(0.065)	(0.067)	(0.106)	(0.066)
Wealth index	0.036	-0.003	0.141***	0.036	0.034
	(0.046)	(0.048)	(0.05)	(0.08)	(0.05)
Shock	0.256***	0.284***	0.241***	0.190*	0.097
	(0.063)	(0.067)	(0.070)	(0.108)	(0.070)
Married	-0.214	-0.0574	-0.0192	0.265	0.296*
	(0.147)	(0.162)	(0.161)	(0.245)	(0.160)
Sex	9.594	-1.505	9.823	12.06	9.704
	(366.5)	(1.979)	(551.2)	(451.3)	(500.3)
Year	0.268*	0.207	-0.153	-0.334	-0.115
	(0.146)	(0.142)	(0.150)	(0.283)	(0.152)
Observations	6,452	6,202	5,678	3,316	5,612
Nb of id	3,226	3,101	2,839	1,658	2,806

The outcome variables are all dummies equal to 1 if the individual suffers from sleep deprivation, stress, fatigue, anhedonia, or she has negative beliefs about the future, and 0 otherwise. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1