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Healthcare in contexts of poverty and conflict

Sara Valente de Almeida
Student 17077

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under the supervision of Professor:

Pedro Pita Barros

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Abstract

This dissertation is composed by a set of studies on access to and preventive healthcare in contexts of poverty, conflict and complex demographic history.

The first chapter dedicates to traditional healing practices and their role in the modern world. Using data from Indonesia, results show demand for traditional treatment changes with medical treatment prices and supply, which should be considered for policy purposes. The second chapter studies the introduction of a co-payment component in hospital costs for Palestine refugees living in Lebanon. Patients changed their healthcare provider after the policy and evidence suggests inequalities in access to care deepened. The third chapter describes the type of households living in these camps and identifies differences between male and female-headed families in terms of budget management and mental health. We find evidence that women leaders are more fragile in terms of income and mental health compared to their male peers. The fourth and final chapter evaluates the impact of an inter-sectoral intervention to tackle substance abuse among teenagers in Brazil. The experiment decreased the adolescents consumption frequency and we believe more actions of this type should be considered for similar settings.

Keywords: global health, access to healthcare, traditional healing, co-payments, gender inequalities, substance use.

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Dedication

To Beirut.

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Introduction

The year of 2020 was a turning point for public health at a global level. We exponentially improved our information and medical technology services, high quality vaccines were developed at a record speed, hospitals were built in a matter of weeks.

While the Global Pandemic is affecting everyone, health systems, structures and financial resources vary significantly across countries and communities. These differences will define the extent to which inequalities in terms of health outcomes and well-being will deepen even further in the near future.

This dissertation includes four chapters that study access to healthcare and health outcomes in different regions of South East Asia, Middle-East and Latin America, where access to jobs, hospitals with beds, doctors and equal access to healthcare are nothing but a wishful thought. Chapter 1 uses an extensive dataset to find empirical evidence of interactions between traditional and medical practices as a way to use local cultures to the benefit of their own health systems. The second and third chapter look closely into health services provided by the United Nations Agency for Palestine refugees living in Lebanon (UNRWA), analysing the introduction of hospitalization costs co-payment schemes and inequalities in access to health care, respectively. The last chapter travels all the way to Brazil to study the impact of an inter-sectoral intervention to reduce substance consumption among teenagers. All chapters share the characteristic of looking into relevant aspects of access to health care in atypical settings (from non-OECD countries).

The first chapter looks into Indonesia, a country with a strong culture for traditional healing practices, and studies price elasticity of demand for these services, in a time where formal medical care is continuously expanding. As the population continues to grow and several countries are still struggling to achieve Universal Health Coverage, using local and historically established entities to support the provision of healthcare has the potential to become a key service in the future to support National Health Systems. We combine an extensive longitudinal panel dataset from 2000, 2007 and 2014, with individual and community level information. During the period of analysis, each agent reported whether they got any treatment, which provider they chose and how many times, decisions which we recreate with patient decision models. We adapted a set of multinomial logit and negative binomial response estimations with year and island fixed-effects to fit our interpretation of the decision process. Taking advantage of the rich dataset in use we also measure the impact of building a new health facility on traditional practitioners (natural experiment). To study whether patients benefit from the collaboration between medical and traditional services, we also make a first attempt at measuring determinants of objective and subjective health outcomes (BMI and SAH) in this setting. In general, we found that Traditional Practitioners (TP) demand can decrease from the increase in provision of formal medical care, but both services continue to be used in parallel. TP costs are associated with an increase in the probability of visiting a private clinic; and healthcare costs at public centres are negatively related with the probability of visiting a TP. Since public health centres are typically cheaper than private clinics, it is interpreted as possible that medical and traditional services are used as complements by the wealthiest and as substitutes by the poorest. These results make an argument for national health plans in these settings to consider the relevance of traditional practices, something that is rather unnoticeable in OECD countries. Having local authorities completely engaged in the development of Health Plans - often made to the image of richer countries and influenced by international organizations - can make them more suited to the characteristics of the population, and thus more efficient.

In the second chapter, while still looking into potential consequences of investing in Universal Healthcare Coverage (UHC), we assess the impact of introducing co-payments for hospital care for Palestine refugees in Lebanon. Using a complete population dataset, we analyse how charging 10% of treatment costs (provided for free until then) to patients in specific hospitals can affect their choice of provider. This project relies on multinomial logit, negative binomial, and linear regression models. Results show a shift in demand from hospitals in which the co-payment was implemented - private and public - towards hospitals that continued to provide free care - Palestine Red Crescent Society hospitals (PRCS). The latter are also the ones known to have more financial constraints and that face more challenges to provide quality health care services. Moreover, the probability of changing provider was higher for patients with severe health conditions and financial constraints. For UNRWA, this is an important result because the institution was not expecting that charging 10% in secondary care costs would have a strong impact - probability of choosing a PRCS hospital increase by 18 pp - even if followed by an increase in coverage for tertiary care (which is less used). At the time, this policy was so polemic that users were demonstrating against it at UNRWA's facilities.

Our findings suggest that sharing costs between provider and patients can have a strong negative impact on the accessibility of care and thus, when necessary, should be implemented with responsibility and awareness. These changes contribute to deepen inequalities among patients, in this case leaving the poorest and sickest with less options of care, which can be particularly problematic in a context of conflict.

For the third chapter we continue exploring the features of healthcare supply in Palestine refugee camps. We now look into gender differences in an extremely patriarchal community where women have less access to informal networks, jobs and general support to sustain their household. This cross section analysis looks into gender differences in terms of household healthcare expenses and mental health issues associated with being head of household. We use different estimation methods to compare households headed by men and women, including two-part probit and glm, propensity score matching and binary models. This study estimates differences in price elasticities between both groups and makes a thoughtful attempt to disentangle stigma from preferences effects. Following previous literature, findings show that expenditure in healthcare as percentage of total spending is higher in female-headed households (FHH). Female leaders, specially widows, are more likely to have poorer mental health, showing, however, slight improvements from 2010 to 2015.

For the fourth chapter of this thesis the focus is on preventive healthcare and risk behaviours. We study a randomized control trial among teenagers in the tri-border area of Iguazu in Brazil. The experiment consisted in an inter-sectoral intervention to create focus groups between randomly selected students (locals and migrants), teachers and professionals from social institutions. Each group then developed a set of extra-curricular activities, that were later delivered to students both in the treatment and control groups. These activities were created in the spotlight of health education related subjects and the project was implemented between 2017 and 2019. The impact evaluation used a difference-in-differences model to measure alcohol, tobacco, and cannabis consumption among participants. The intervention was successful in decreasing the probability of consuming once a month, but not for heavier consumption patterns. Nonetheless, it improved the impact of participating in all activities and peer effect turned out as an important driver of consumption for all substances.

This dissertation brings together a set of public health issues that emerged in adverse conditions, all in regions with difficult demographic challenges, in conflict or post-conflict areas, which are actually, and unfortunately, common to may countries in the world. This thesis makes thus a relevant contribution to subjects and communities not often under the scope of economics studies and hopes to provide a meaningful insight for future research.

Chapter 1

Traditional Healing: Does the past have a future?

Abstract

Traditional practitioners have managed to survive the spread of modern health-care practices, but how these two worlds have interacted until today is a rather unexplored subject with important implications for the design of National Health Plans. To study this issue we use data from Indonesia, the largest country in Southeast Asia, currently investing in Universal Health Coverage, and with one of the strongest and well known cultures for traditional healing. This study estimates the price elasticity of demand for traditional practitioners, while conventional medicine continued to spread, using an extensive longitudinal panel data from 2000, 2007 and 2014. Demand is measured using patient decision models to predict treatment seeking attitudes, type of treatment and number of visits to each provider. We also use a natural experiment to measure how TP demand reacts to the construction of a new health facility and measure health outcomes related to using both modern and traditional health services. Estimation procedures use probit, negative binomial and multinomial logit response models with year and island fixed-effects.

Results show that while demand for traditional practitioners is negatively affected by the expansion of the health-care system, patients continue to resort to both systems simultaneously. An increase of one standard deviation in TP costs is associated with an increase in the probability of visiting

a private clinic by 8.9 pp, while an increase of one standard deviation in public healthcare costs relates to a decrease in the probability of visiting a TP by 4.1 pp. Medical and traditional services are thus used as complements and substitutes, depending on the type of system used.

Promoting national health plans in these settings without understanding the role of TP will most likely create unnecessary inefficiencies and potentially allow for conflictual treatments. More dialogue between the relevant agents and data are needed to understand how a collaboration between both systems could benefit everyone involved, from patients, to providers and the public healthcare system.

1.1 Introduction and Motivation

In a world still striving to provide basic health-care coverage for all, it is key to understand the nations' societal and cultural features that can contribute to a well-functioning health care system. Traditional medicine practices naturally emerged from a need to provide medical assistance in places with strong spiritual beliefs and surrounded by a rich biodiversity. The curative abilities of the traditional health practitioners (TP) allied to their spiritual connection allow them to create a bond with the patients difficult to reach for most conventional doctors. Moreover, vulnerable groups and indigenous communities need health care services that are fast and accessible in remote areas, which is still a challenge for many public health systems. [1]

The Global Market for Herbal Supplements and Remedies is projected to grow from USD 104.6 billion in 2020 to USD 166.2 billion in 2027, at a record growth rate (CAGR) of 8.1%. [2] This speculation alone should be enough to call the attention of national governments, specially in low and middle income countries (LMICs), where these practices are common and where we expect that more than 90% of urban population growth will happen, until 2050. [3]

A great setting to study this subject can be found in Indonesia, home to one of the richest cultures of TP in the world and that since 2014 is actively investing on achieving universal access to healthcare [4] - which has much more to it than just expanding its geographic presence. Taking advantage of this ‘perfect storm’, this study goes deeper into one particular aspect of expanding healthcare and well being: the prevalence of and interactions with traditional healing practices during that process. According to the Indonesian Ministry of Health, traditional health practitioners include (1) massage, broken bones, circumcision, acupuncture, chiropractor, and others; (2) traditional healers using herbal remedies; (3) indigenous healers with a religious approach; and (4) indigenous healers with a supernatural tint. In this study we study TP practices in the first two categories, which report to the Ministry of Health. The 3^{rd} category is the responsibility of the Ministry of Religious Affairs, and the 4^{th} of the local district municipality. [5]

Despite the statement in the Indonesian Basic Health Law of 1960 that all citizens had a right to be physically, mentally and spiritually healthy, and the undeniable presence of TP in the health care market, the debate on whether TP should be included in the National Health Plan is rarely addressed, even less from an economic point of view. Studying the potential substitution or complementary effects between both systems sheds light on the impact of non-conventional practices on families. On one side, there might be deficiencies in the provision of health care services that TP are compensating for, producing a positive externality for the health system and reducing pressure on public services, while on the other, TP may contribute for delaying the conventional treatment, thus worsening the patients condition. Since both mechanisms may be interacting at the same time, the reality will never be possible to understand without exploring the details.

K. Leonard has made an exceptional contribution for the literature on this topic in the context of African countries. In ‘African Traditional Healers:The Economics of Healing’, the author points out that Traditional Healers are integrated for so many generations in certain societies that they can neither be the answer to all healthcare problems in the community, nor useless agents taking advantage of cultural believes for their own benefit. [6] To develop a formal health care system exclusively on a scientific basis in these contexts, places patients in a constant and not necessarily beneficial dilemma.

The present chapter uses an extensive database from a household and community survey with several waves (Indonesian Family Life Survey, IFLS, 2000 to 2014) to analyse the relationship between conventional and traditional practices (complements vs. substitutes) and estimate the impact of TP provision on patients' health in Indonesia. This constitutes innovative research by contributing with empirical evidence to the debate on whether TP should be included in National Health Plans in specific countries, from an economic and social perspective.

Indonesia is considered one of the herbal medicine centres of the world, where traditional medicine is an important and ancient feature of society. Constituted by more than 17,000 islands and the fourth most populated country in the world, Indonesia is extremely wealthy in biological resources and ethnic diversity. In such a complex framework at geographic and social level the design and implementation of any national-level policy becomes challenging. [7] In the early 90's a Health Law Act placed Complementary and Alternative Medicine (CAM) as part of curative and nursing care, highlighting the need for increasing supervision of traditional medicine. Since then, some clinical studies focused on how could CAM be supervised and standardized, but the scientific evidence available is still very limited. Evidence is even more scarce in what concerns economic impacts or determinants of healthcare provision. [8]

Despite the existence of regulation and the national acknowledgement of the practice, traditional health services have been rather at the margin of the national health discussions. To build up a relationship between traditional healers and other health-care providers needs more than a mindset change. Most of traditional medicine practices were established on an informal basis, creating several barriers to the standardisation of their methods. It is important to stress that Traditional Medicine provides an important source for self-care with a focus on health and healing rather than disease treatment by itself. In Indonesia, CAM is still used by around 40% of the population (up to 70% in rural areas) and the share of users continues to increase. [9] On the other hand, estimates on CAM usage are mostly outdated and it is unclear to what extent conventional medicine will substitute traditional practices in terms of healthcare needs once its access is universally ensured. [10]

The National Health Insurance scheme (NHIS) was established in Indonesia around 2014 and in three years became the largest single-payer health insurance scheme in the world. [11] As part of the National Health Plan, the Indonesian Government committed to achieve universal healthcare coverage (UHC) until the end of 2019. Medical health-care provision was thus in the spotlight of investment, with a growing number of health-care facilities and workers, and Traditional Practitioners (TP) suffered from unprecedented threats to their market. While both services co-exist, how sensitive were users to these changes? Did demand for traditional healing practices, deep-rooted in the local culture, change with the progressive increase in supply for conventional medicine? To address these questions, the present analysis estimates determinants and relationships between the two services and patients' health using a patient-decision theoretical framework and non-linear econometric models.

The overall findings suggest that the provision and utilisation of medical services can affect the demand for traditional practitioners in Indonesia, and vice-versa. Both poor and rich families continue to use TP services, but while the richest use both services as complements, the poorest are more likely to have to chose between both. A one positive standard deviation in TP costs is associated with an increase in the probability of visiting a private clinic by 8.9 pp and a similar change in costs at public health centres relates to a 4.1 pp lower probability of visiting the TP. This evidence is also supported by other results from different estimations. This evidence follows Thorsen and Pouliot (2015) [12] where demand for traditional medicine is related to higher levels of household income. In terms of health outcomes we find education to be a relevant driver of good health outcomes, and that patients visiting both private and TP services are associated with healthier BMI levels.

The remaining of the study is organised as follows: section 1.2 covers the relevant literature on the subject; section 1.3 describes the data, including descriptions of the dependent and explanatory variables used in the estimation procedures; section 1.4 explains the methods used; section 1.5 presents the main results and, finally, section 1.6 presents the discussion and section 1.7 concludes the analysis.

1.2 Literature Review

According to the latest estimates, about four billion people, (80% of the World population) use herbal medicine for primary health-care. This is a largely quoted statement in the literature, presented by the World Health Organization (WHO) at the WHO Traditional Medicine Strategy $2002-2005$. [13] In this report WHO not only recognises the important role of traditional medicine in our society, but also the need to define a strategy for addressing issues of policy, safety, efficacy, quality, access and rational use of alternative medicine. Nonetheless, these estimates are known to come from an estimate of a 1983 WHO textbook which makes this percentage quite outdated.

Most of the available research on the topic of traditional medicine focuses on clinical and experimental trials. [8] Bodeker and Kronenberg highlight that there is a need to understand how the presence of traditional healers has an impact at social, political and economic levels. There is a range of social and cultural factors that influence the use of traditional and alternative medicine that health policy decision makers should take into account. According to that study, particularly in LMICs, patients still resort to traditional and alternative medicine for its affordability, availability, and cultural familiarity. While it is not always true that traditional treatment is less costly or geographically closer (depending on the patient and the treatment), the proximity to cultural and family values gives traditional healers a very peculiar and relevant advantage relative to other health care providers. This fact brings us closer to the point that traditional healers have a very important role in their communities and their practice could be acknowledged by collaborating with national health systems.

Patient satisfaction and how it should influence decisions in the health care services management is a rather popular topic in health-care literature. Patient satisfaction can be achieved at several levels and public opinion is often not completely taken into account in the design of health care policies. [14] In this context, traditional healers seem to understand well their patients needs and requirements. In a concrete example, healer credibility is pointed out as one of the main reasons why breast cancer survivors resorted to traditional medicine in a small sample study conducted in Malaysia. [15], [16], [17] Such studies look into the traditional healers contingent-based payment scheme and the importance of motivating patients to strive and follow treatment. Evidence shows that there is a whole cultural and social dependence on TP that can be explored, aside from the characteristics of the practice. Moreover, both studies agree that there is room to explore how TP techniques can be used to further improve health-care services.

In 1998, after the hit of the financial crisis, a particular project under Social Safety Net (SSN) program in Indonesia provided the most vulnerable households with health cards. The program entitled a price subsidy to all household members and an extra budgetary support to health care facilities providing subsidised care. [18] The researchers produced an impact evaluation of this project to estimate the effect of a household receiving a health card and a health clinic receiving a subsidy. That allowed to better understand the context of the Indonesian society and to have some background on an impact evaluation exercise on public health. According to the results, demand for traditional medicine seems to follow the trends of public health services in general, which supports the idea that both branches target the same public. The Health program was only somewhat successful as the population that benefited the most were actually the non-poor. The authors highlight the need to clearly understand incentive mechanisms for health care providers and be more objective in the allocation of public spending investments to health care.

On the relative role of TP in health-care provision, Banerjee, Deaton and Duflo found that in a rural area of India visits to traditional healers still account for a relative large share of total outpatient care visits (19%) and household expenditure (12%). [19] Here, richer households tend to resort less to traditional healers and villages served by health facilities that are closed more often have higher demand for these services.

Several studies have associated demand for traditional medicine to poor and disadvantage or the less educated patients. [20],[21] However, more recent studies on treatment seeking show these assumptions are not always verified. [12] Thorsen and Pouliot suggest a framework to analyse treatment seeking determinants in peri-urban and rural Nepal using factors such as age, wealth and medical plant knowledge, that we believe to suit our objectives as well. They find evidence that having a more educated household leader decreases the probability of seeking a traditional healer, while higher income has the opposite impact. Also characteristics of bio-medical health-care services provision, traditional practices credibility, strong cultural identities and disease understanding have been considered as more important drivers of traditional healers demand. [22] In addition, evidence from Indonesia and Tanzania shows that suffering from more severe and chronic illnesses such as asthma, diabetes and hyper-tension can also increase the demand for traditional treatment. [23] In general, health care demand can be influenced by several factors including demographics, socioeconomic status, health care supply and environmental conditions. [24], [25] This makes individual characteristics such as age, marital status, reported health and education as important variables to include in the healthcare demand estimation.

When visiting a certain physician patients have to make an initial choice of seeking care, which type of physician they need and how often this visit will occur depending on the diagnosis and the doctor's opinion. These decisions are determined by different decision-making processes, a first one that only depends on the patient, a second step that also depends on the supply and costs of health care available, and the last one depending on the physician's judgement. To model patient demand in different stages, health economics commonly uses two-part models that treat these stages separately. One of the first applications of this method happened in 1995. [26] Pohlmeier and Ulrich developed a negative binomial hurdle model that estimates the discrete choice of visiting a physician as different process of that of the number of visits. Following their results, two-part models are highly recommended to estimate two different decision processes, since not treating them separately would lead to misinterpreting reality. A more recent study also looks into healthcare decisions in Nigeria with a two-part model. [27] Their focus is the decision of seeking treatment and which physician to chose. In a setting of adverse economic conditions these decisions become even more conflicting by forcing constant trade-off in budget management to maximize the household's utility. The study concludes that severity is the most important determinant of healthcare demand, highlighting the use of a Nested Logit Model as the most appropriate method. In addition, the study raises awareness for the relevance of traditional practitioners in the health system, who charge the highest treatment costs among all healthcare and well-being providers and yet continue to exist.

Kayombo and colleagues analyse an initial collaboration between bio-medical practitioners and traditional healers in Tanzania.[28] Due to the burden of HIV/AIDS in the region, mobilising resources from the two health systems to collaborate is extremely important to tackle the spread of this disease. In the study a research team conducted an open ended questionnaire identifying traditional healers providing health-care to HIV/AIDS patients. Results show it will be a long process to achieve a meaningful collaboration between traditional healers and bio-medical practitioners. In a related study, the authors conducted a survey to nineteen TP to assess their knowledge and willingness to collaborate with the national tuberculosis (TB) programme in Vanuatu.[29] The findings show TP also treated lung diseases and that many had already collaborated with the Government funded health care system. Healers could actually help providing a faster identification and care of TB cases, which favours the inclusion of traditional healers in TB treatment management. With a similar strategy, another study leaded by Maputle focused the use of traditional medicine during pregnancy in a South African province. [30] Results show that it is necessary to increase collaboration between health care providers and follow up of traditional medicine treatment to prevent potentially harmful effects of incompatible treatments.

While literature shows that traditional medicine still has an important role in several communities, the sector's dimension is difficult to measure and the social, political and economic implications of its presence have not been fully explored. Traditional medicine can be more affordable than medical treatment, is typically more available in rural areas and TP have an unique proximity with the population that gives them credibility, makes patients feel understood and closer to their family values. We found existing evidence that demand for traditional care has different motivations than demand for medical care, but with parallel trends over time. Even if they differ in their essence, traditional and medical treatment seem to answer very correlated needs, like having more need to feel cared for when being sick. In addition, the few studies that tried to understand the consequences of increasing collaboration between the two types of services showed positive results. It is thus possible that traditional and medical care behave as complement goods, rather than substitutes.

Most of the mentioned studies rely on survey analysis and descriptive statistics, without showing an objective evidence on the impact of co-existent bio-medical health care centres and TP nor how this can affect the population. In the present study, we try to fill this gap using a series of methods to model patients decision processes, using an extensive dataset and a natural experiment.

1.3 Data and Statistics

The quality of the database and the data treatment process are paramount features of this study. We use data from 2000, 2007 and 2014 which corresponds to waves from 3 to 5 of the Indonesian Family Life Survey (IFLS).

IFLS is a panel survey part of an on-going project that collects data at individual, household and community levels. The first wave, in 1993, interviewed 7,224 households in 13 provinces, which represented about 83 per cent of the Indonesian population. This wave was collected using multi-stage probability sampling and constitutes the base framework for the remaining ones. The survey waves that followed were also designed in a way that it was possible to track respondents through time, even those who commute in between. As such, in IFLS 2 the same respondents as in IFLS 1 were interviewed four years later. IFLS 3, in 2000, was also fielded on the full sample. Later, IFLS 4 and IFLS 5 were published in late 2007 and 2014, respectively, interviewing the same set of IFLS households. This means 16,204 households and 50,148 individuals were interviewed. In addition, another 2,662 individuals who died since IFLS 4 had exit interviews with a designated person that was close to them. [31] With less than 6 per-cent household level attrition between the baseline and first follow-up (four years later) and a cumulative attrition between the baseline and second follow-up (five years) is 5 percent. [32]

The content of IFLS covers multiple subjects of study, providing complete and detailed information on each of them. The conducted surveys allow to collect information on a broad range of characteristics inherent to individuals, households, and communities. In what concerns health and health-care services, the IFLS contains sections on subjective and objective health measures and demand for health services at individual and household level. All waves contain extensive information about health status. A limitation to this study is that this information is not exactly the same across surveys. Indeed, besides self-reported health and few reported ability to perform activities of daily living, the health section varies significantly with time. For this reason, the analysis was reduced to the year 2000 and thereafter using individual level data from the Household survey, merged with information at community level, health facilities and traditional practitioners. [1]

Table 1.1 provides some descriptive statistics at the individual level. The sample is balanced in terms of gender and living area in every wave. Reported health is generally high across time as the share of respondents answering to be at least somewhat healthy is close to 80%. The highest degree of education attained is increasing through time, reaching 9% of respondents with university education level in 2014. The level of household expenditure, presented in logarithm, can be considered proxy to household income, also increases with time. This last factor was computed and provided directly by IFLS.

Table 1.1: Individual Summary Statistics

	2000	2007	2014
Age	33.38	40.03	46.12
	(19.49)	(19.31)	(19.00)
Female	0.52	0.52	0.52
Married	0.62	0.65	0.75
Urban	0.42	0.45	0.54
SAH	0.72	0.86	0.75
Log(HH exp.)	12.03	12.93	12.89
	(0.75)	(0.69)	(0.89)
Education			
- Elementary	0.50	0.44	0.44
- Junior High	0.18	0.19	0.19
- Senior High	0.24	0.27	0.25
- College	0.03	0.04	0.03
- University	0.04	0.06	0.09

Note: IFLS Households survey 2000, 2007, 2014. This table presents mean and standard deviation (in parentheses) of each variable in the sample, using individual survey weights. Female, married and urban are binary variables and give the percentage of individuals that are female, married and living in urban areas. Self-Assessed Health (SAH) obtains the value 1 if the respondent considers to be at least somewhat healthy and 0 otherwise.Education dummy variables show the respondents share that attained each education level.

The community-level IFLS surveys considered in this study were conducted among community leaders, health centres workers and traditional healers. These sections capture aggregated characteristics of respondents in the same community, as well as of particular services and institutions responsible for ensuring the well-being of the

[1] The different database are merged based on household, individual and communities identifiers (hhid, pidlink and commid)

community. Indonesia has a vast variety of health-care services.[2] Following IFLS strategy we focus on attendance to only three types of providers/establishments: Health Centres or Health Sub-centres (Puskesmas or Puskesmas Pembantu), Private Clinics and Traditional health workers (TP). To control for the construction of a new facility we generalise the concept to health facilities, that includes any of the previous type of providers mentioned except from TP.

The survey conducted to TP is only available for the IFLS waves published in 1993, 2007 and 2014. Since this project only uses data from 2000 and thereafter, only 2007 and 2014 data are considered. These data have valuable information on TP practices and characteristics, including whether a TP prescribes modern medication or has any other occupation besides traditional medicine - see Table 1.2. This allows for producing an analysis of the practice and learn some characteristics of this type of provider.

Table 1.2: TP Summary Statistics

	2007	2014
Age	60.7	59.63
	(12.78)	(14.12)
Female	0.8	0.76
Medicinal Herbs	0.36	0.44
Modern medication	0.06	0.04
Other Work	0.26	0.37
Charge	0.55	0.44
Midwive	0.49	0.30
Education		
Elementary	0.76	0.69
Junior High	0.10	0.14
Senior High	0.12	0.12
College	0.01	0.00
University	0.02	0.04

Note: IFLS Traditional Health Practitioners Survey 2007, 2014. This table presents mean and standard deviation (in parentheses) values for each variable. All dummy variables represent the percentage of individuals. Education dummy variables show the respondents share that attained each education level.

TP in this sample are generally women around 60 years of age. About half of the practitioners in the sample have other jobs besides being a TP and around half also works as a mid-wive.[3] Not all of them state to charge for their consultations, which can

[2]See table A3 in Appendix.

[3]See Table A3 for the definition of mid-wive.

indicate the use of alternative payment methods such as food or personal favours or even by voluntarily contribution.[33] Regarding treatment, medicinal herbs are much more prescribed than modern medication, as it would be expected. These traditional medicines can be either produced by individual persons at home industries or produced and packed on a commercial scale. The first type may not be registered and are made by TP themselves for use by their own patients - giving TP another income source. If it is the second type, the medicine must be registered and licensed before they may be sold at a formal vendor. [34]

The estimation procedure that follows consists in estimating healthcare demand indicators, using health and healthcare supply related variables as determinants. We start by identifying the main drivers of having visited a TP in the last 4 weeks and secondly, we use the number of visits as the dependent variable, adding more explanatory variables related to costs and number of facilities. For the natural experiment stage we perform a third specification including a binary variable that indicates whether a healthcare centre was built since the last survey wave. Lastly, we try to assess how healthcare supply affects the population's health status by measuring how it relates to the BMI and reported SAH by participants. The next section provides a more detailed description of the variables of interest used.

1.3.1 Dependent Variables

The main variables of interest measure demand for treatment type. This is measured as a categorical variable that indicates whether an individual visited a public HC, a private clinic or a TP during the 4 weeks preceding the time of the interview. The variable is obtained from a survey question present in all IFLS waves with the same formulation.

Figures 1.1 and 1.2 show how the average share of respondents that visited a TP in the four weeks before taking the survey changed from 2000 to 2014, by province. In 2000, only the provinces of South Sulawesi, South Sumatera, North Jawa and North Nusa Tenggara have a percentage of visitors above 5%. In 2014, the average share of the respondents that visited the TP by province was 23.63%. Despite the fact that we are using self reported measures and there can be an effect of people being more and more comfortable with acknowledging that they visit the TP, that alone is already a sign that times are changing and the presence of TP services is not showing signs of disappearing. In comparison with other services, between 2000 and 2014, the percentage of TP patients increased from 3 to 21%, whereas the share of participants that visited a public health center was around 30% in all waves (table A1 in Appendix).

Figure 1.1: Percentage patients reporting to visit TP in **2000**

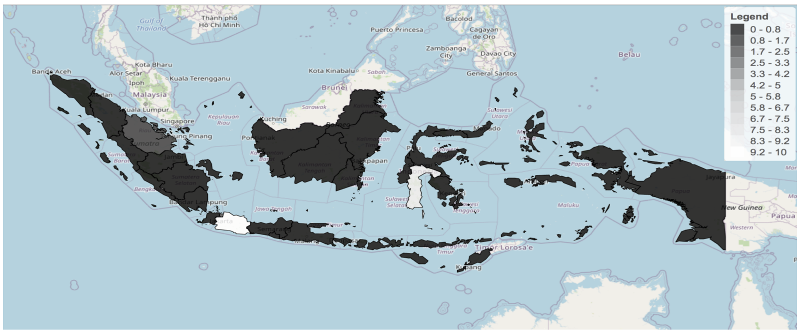
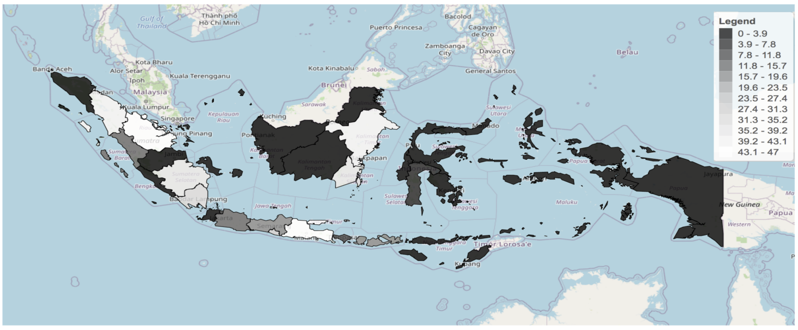
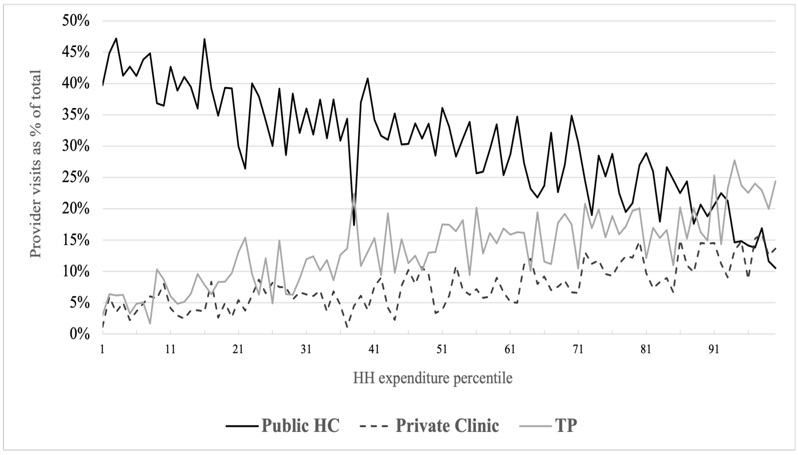


Figure 1.2: Percentage patients reporting to visit TP in **2014**



The pattern in this question confirms that TP services are still being used by the local population and that attendance seems to be increasing. In Figure 1.3 the average proportion of participants visiting the TP, public and private health services is measured by expenditure (as proxy of income) percentile. The tendencies show that private and TP usage is increasing with the level of total household expenditure, whereas attendance to public services has the opposite relation. As both private care and TP are paid services, this relationship was expected. Nonetheless, this could be offset if poorer families living in more isolated areas would visit the TP more due to lack of alternatives. Following this line of thought, in the estimation section we will try to understand better what is behind the determinants of TP demand and how it varies with other services utilization.

Figure 1.3: Proportion of participants visiting the public, private clinics and TP measured by percentile of expenditure (in log, as a proxy for income)



In the literature there are also several examples of studies that consider the number of visits to each facility as determinant of treatment demand ([35], [36]). Table 1.3 shows the average number of visits to the public health centre, private clinic and TP in the last four weeks, by year and age. Older patients on average visit the TP more frequently, which is expected given that they are also more likely to have more and more severe health issues, as well as more free time. The number of visits does not vary significantly with the type of provider, indicating that people resort to traditional medicine as frequently as they do for medical providers. Eventually, they may even resort to both services for the same condition (i.e. as complements). However, this cannot be confirmed with this survey.

Table 1.3: Number of visits to healthcare centres, private clinics and TP in the last 4 weeks, by year

	Public			**Private**			**TP**		
	2000	2007	2014	2000	2007	2014	2000	2007	2014
15-24	1.325	1.406	1.319	1.425	1.092	1.172	1.334	1.270	1.886
	(0.692)	(0.657)	(0.789)	(0.701)	(0.440)	(0.469)	(0.644)	(0.661)	(1.461)
25-44	1.469	1.795	1.562	1.376	1.160	1.316	1.596	1.538	1.547
	(0.831)	(2.249)	(1.119)	(0.858)	(0.644)	(0.750)	(0.877)	(1.327)	(1.260)
45-64	1.470	1.697	1.588	1.980	1.322	1.625	1.686	1.351	1.551
	(0.765)	(1.196)	(1.184)	(1.208)	(1.930)	(0.929)	(1.138)	(1.206)	(1.542)
65-79	1.287	1.796	1.920	1.391	1.050	1.348	1.195	2.217	1.644
	(0.631)	(1.151)	(1.096)	(0.623)	(0.220)	(0.680)	(0.632)	(4.425)	(1.207)
80+	1.514	1.790	1.432	1.390	1.752	2.302	1.500	1.206	1.657
	(1.412)	(1.445)	(0.755)	(0.597)	(0.443)	(1.616)	(0.707)	(0.572)	(0.942)

Note: IFLS Community Survey 2000, 2007, 2014. Number of visits average and standard deviation (in parentheses) of respondents who affirm to have visited a public health centre, private clinic or a TP in the last 4 weeks, by age group.

On the supply side, Table 1.4 shows average numbers of facilities available in each village over time, as reported by the community leader/representative. Note that both public health centres correspond to medical treatment, and just counting for these two services, together they more than double the number of traditional practices. Although due to lack of data we will not use information on number of hospitals, the average number available for each person also grew from 2.02 in 2000 to 4.18 in 2014, making medical care much more present in the country.

Table 1.4: Number of facilities available to the residents

	2000	2007	2014
Health Center	2.22	2.15	2.16
Priv. Clinic	4.78	4.30	5.45
TP	2.51	3.02	3.97

Note: IFLS Community Survey 2000, 2007, 2014. Average number of facilities available to the participants from each village/township. Public health centres and Private clinics are considered medical treatment.

Regarding the reasons for visiting each provider, data in Table 1.5 shows that for both public health centres and private clinics the purpose that more people reported for their visit is treatment of illness and consultation. Massages and physiotherapy are the top two reasons for visiting a TP. Since 2000, the share of TP users for massage, physiotherapy and consultation increased 68, 15.7 and 14.5 pp respectively. While this may indicate that patients use both services as complements for different treatments, the share of users resorting to TP for consultation, with illnesses and even injuries has been increasing since 2000.

Table 1.5: Purpose of visit by type of provider

	Public		**Private**		**TP**	
		Δ pp $(00-14)$		Δ pp $(00-14)$		Δ pp $(00-14)$
Check up	**40%**	**-2.5**	**9%**	**2.1**	**3%**	**2.6**
Consultation	**29%**	**-12.4**	**10%**	**-5.0**	**8%**	**14.5**
Family	14%	-15.0	4%	2.0	2%	-0.5
Immun	44%	50.0	0%	0.0	0%	0.0
Injection	30%	-10.7	5%	0.9	3%	8.1
Massage	**4%**	**-5.4**	**2%**	**-2.7**	**99%**	**15.7**
Medical	32%	4.3	9%	2.7	5%	8.3
Other	24%	-5.5	9%	8.9	14%	-5.8
Physiotherapy	**13%**	**12.0**	**8%**	**8.0**	**57%**	**68.0**
Prenatal	24%	-0.8	9%	5.6	4%	4.4
Treatment of illness	**34%**	**0.5**	**10%**	**4.8**	**6%**	**6.1**
Treatment of injury	25%	2.9	8%	-0.1	13%	13.4
Total	29%	-6.5	8%	2.2	14%	17.6

To understand further the relationship between the three types of health care providers mentioned we analyse communities where a health facility was built as a natural experiment to measure the impact of a conventional medicine supply shock. Due to data availability constraints, we cannot use a propensity score matching (regions are too heterogeneous) and thus, the best option is to perform a simple differences exercise, as explained in the 1.4 section.

In the last estimation we look into health outcomes. We use two health outcome measures, the Body Mass Index (BMI) and Self Assessed Health (SAH), both considered to be reliable determinants of morbidity (e.g., [37], [38], [39]; and [40]). However, the relationship between both indicators is not straightforward as they seem to capture different morbidity predictors.[40] The BMI is a formal measure of physical well-being given by the ratio between weight and the square of the body height (expressed in units of kg/m^2). This index was constructed using data on anthropometric measures provided in the Household Survey for all waves. The dependent variable is unordered categorical and obtains the value 1 when the individual's BMI is underweight (below 18), 2 when normal (between 18 to 25), 3 when overweight (over 25) and 4 for obese (above 30). [41], [42], [43], [44] As for the SAH, the dependent variable is binary with the value 1 if an individual reports to be (maximum) somewhat healthy and 0 otherwise, based on a Likert scale of 5 levels, from very bad to very good. This question from the IFLS survey is present in all survey waves and thus allows us to compare subjects in different waves.

BMI is a relatively objective health measure, but that can also depend on cultural aspects related to food habits and healthy standards. Moreover, because of its non-monotonic property, both low and high values are undesirable, which makes it more complex to use. In turn, SAH relates to the way each individual feels at the moment of the interview. Both self reported health or BMI can be biased, either by each personality and culture or by excess fat or highly developed muscle mass. [45] Using both variables, with the caveats and advantages they imply, the estimation exercise aims at understanding how patients' health status change with healthcare usage and existence of modern and traditional health-care services in simultaneous, as it happens in Indonesia.

Table 1.6 below shows the descriptive statistics by BMI level including the good health indicator. Those who are underweight report an average health status 7 percentage points lower relative to the full sample. By contrast, those in the overweight and obese BMI levels have the highest average reported health. In LMICs, wealthier families are associated with higher weight, since being financially stable also means having more resources to buy food, healthcare and having better treatments than poorer families. Culturally, being overweight can also be a form of ostentation, which makes some unhealthy habits actually being appreciated and desired. The average age of those with normal BMI is 2 years lower than the total average, which can be due to several factors. As people get older in this context probably they become less active, have lower income, slower metabolisms and care less about themselves, which makes them less healthy either by lack or excess of weight.

Table 1.6: Individual Statistics by BMI level - Mean (SD)

	All subjects	Underweight	Normal	Overweight	Obese
Age	40.77 (16.27)	43.80 (20.62)	38.62 (16.59)	42.22 (13.96)	42.19 (13.12)
Weight	54.63 (11.50)	41.20 (5.75)	49.84 (5.68)	60.95 (7.17)	76.97 (10.16)
Height	154.25 (7.92)	155.01 (8.61)	154.86 (7.82)	153.61 (7.48)	152.42 (8.63)
BMI	22.96 (4.53)	17.04 (1.21)	20.74 (1.25)	25.79 (1.90)	33.09 (3.16)
Good health	0.67 (0.47)	0.60 (0.49)	0.66 (0.47)	0.70 (0.46)	0.66 (0.47)

Note: IFLS Community Survey 2000, 2007, 2014. This table presents mean and SD values for BMI across the sample. BMI is given by the ratio between weight and the square of the body height

1.3.2 Explanatory Variables

Following the literature review, the first group of explanatory variables introduced in the estimation model relate to the respondents' characteristics including age, marital status, reported health and education, measured as the highest level attained from Elementary school to University. [46] The model also includes a set of variables that measure preferences and self-reported costs for health-care services (health centre, private clinic) and TP. The direction of these cost variables give us the relationship between different types of services - if higher costs of service 1 increase demand for service 2, they are substitutes and if the relationship is the opposite, they are complements. In addition, in the survey village chiefs are asked whether there was an important event in the village, in particular the construction of a health facility, a new school or a new road. These variables allow to grasp how TP services can be affected by an increase in the provision of the national health-care system and general development. The data for this variable are aggregated by district (Kecamatan), the 3^{rd} out of 4 levels in the Indonesian regional subdivision scale. As a regional heterogeneity indicator, we control for living in an urban area, which is of main importance in a country like Indonesia.

To measure the relationship between the availability of health-care services and participant's health outcomes, as before, the first variables added control for individual and environment characteristics which tend to be relevant predictors of health related habits. The model is then extended to include number of each type of health-care facilities and TP. These variables are added as an alternative to attendance to different type of health services, which is endogenous to the health status itself - the dependent variable. These factors show how the existence of traditional and medical health-care facilities can affect health outcomes and give some information on the trend for TP to collaborate or not with the national health system.

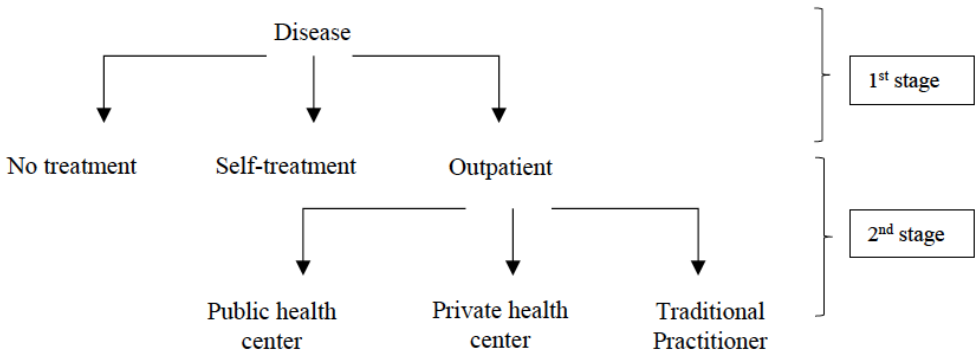
1.4 Methods

This study relies on an extensive individual level longitudinal short (3 years) panel data-set. As aforementioned, this data-set was constructed by gathering information on households, communities and health practitioners across 3 IFLS waves of data collection. While most of the survey structure is constant over time, there are differences in the questions included and in their formulation that need to be taken into account. Different-level database were merged using community, household, and individual identifiers available in IFLS for tracking the respondents over time. The data on communities and households is replaced with repetition for each individual. The complete dataset is a panel with a very large number of observations (N) and a very small time horizon (T). Within this framework, recent literature as shown that fixed effects models provide biased results.[47]

1.4.1 Two-part model for seeking treatment

For the purpose of modelling the first patient's choices we consider a two part model to analyse the different processes the decision-maker goes through. This strategy follows a health-care decision making processes, for which the data are perfectly suited by including information on whether each participant visited a physician, which type and how many times [27]. Figure 1.4 shows the diagram of the decision process.

Figure 1.4: Patient choice, two-step model



The decision to seek treatment or not is nested on the first level of decision, followed by the choice of type of provider, determined by a set of individual characteristics and other variables. Decisions are taken simultaneously, based on the option that maximizes the individual's utility at each level. The first decision on whether to seek outpatient, self-treatment or no treatment may be modelled as a multinomial logit decision. If the individual decides to seek outpatient treatment, then at the second stage the decision is to select which type of practitioner to visit. [48]

The approach that describes demand for the initial contact reflects the decision of the patient to seek treatment, which results from the patient's utility maximization problem and is focused on the intensity of the illness [49]. In this setting, the decision to seek treatment depends on the severity of their condition.

Assume individual i has $j + 1$ alternative health care decisions. The individual chooses between alternatives based on the utility associated with each choice. The conditional utility of choosing option j is:

$$U_{ijk} = \alpha + X_{ijk} + year^{FE} + island^{FE} + e_{ijk} \tag{1.1}$$

Where j $\in N = 0, 1, 2..., J$ and k $\in P = 0, 1, 2..., K$

Patient's i utility from first node (treatment) j, and second node (provider) k, is thus a function of socio-demographic characteristics, health status and providers characteristics represented by X_{ijk}, as well as island and year fixed effects and e_{ijk}, the i.i.d. error term. X_{ijk} represents the set of observed attributes that vary with each decision level. Any attribute that varies among the first stage will lead to variation among the second, i.e., the severity of the health condition that helps the patient make their first decision will also feed the following on which type of practitioner to chose. While the first stage decision depends only on socio-demographic characteristics and health status variables, at the second stage decision makers also take into account the provider characteristics such as costs and services available, that will be part of the attributes in X_{ijk}. [50] Cost variables correspond to the cost reported by each respondent (costs reported by the providers were frequently missing), which is important for interpretation purposes and allows for variation at individual level.

To define the observed choice that results from individual utility maximization, consider the indicator function that follows:

$$Prob(option_{ijk}|U_{ijk}) = \begin{cases} 1 & \text{if } U_{ijk} > U_{ilm}, \forall \text{ j} \neq \text{l and k} \neq \text{m} \\ 0 & \text{otherwise} \end{cases} \tag{1.2}$$

Both for this and the previous expressions, the options included in the dependent variable are mutually exclusive and exhaustive, i.e., we are just including patients who opted for one of the options.[51] The behavioural model in the second stage assumes that the patient does not determine the provider according to medical criteria alone, but also according to economic incentives.

Table 1.7 describes what variables are included as socio-demographic, health status and providers characteristics (X_{ijk}). On socio-demographics, education indicates the highest level attained and expenditure is included in logarithm transformation. The health variables enter the specification as binary, except for BMI which is categorical and enters the model with 3 out of 4 levels (3 binary variables), so that there is one base level, which is omitted.

Table 1.7: Variables description

Set of variables (X_{ikj})	**Description**	**Level**
Socio-dem.	Gender, marital status, highest education level, expenditure (as a proxy for income), living in an urban area	Individual
Health status	BMI levels, having felt acute morbidity symptoms in the last week, having had a negative health shock in the last year or having been hospitalized in the last week	Individual
Health services	Number of facilities available for each provider type, distance from nearest facility	Community
Costs	Patient self-reported cost of treatment at public health centers, private clinics and TP in logarithm	Community

As an additional specification, a vector b is included as one time-varying independent variable with coefficient vector γ. This corresponds to a binary variable that identifies when an individual belongs to a district where a health facility was built since the last wave (1) or not (0). We also add a similar variable for natural disasters, new schools and roads to control for general progress and development. Note that this does not correspond to a differences-in-differences model because within each community every individual had access to the health centre that was constructed and this event happened in different years for different communities. As such, we can only compare indicators before and after the construction. One possible strategy to overcome this issue is to perform a propensity score matching exercise to create an artificial control group in a village where an health facility was not recently built. However, in such an heterogeneous country like Indonesia and with the data available we could not find enough balanced categories between different areas to produce valid estimates.

Results of the simple differences model will be presented as marginal effects which quantify how the probability of the dependent variable varies with a one unit change in the explanatory variable.

Heckman selection model for costs estimation

To measure substitution and complement relationships between traditional and medical practices, we needed to add treatment costs to the specification. However, in IFLS these values are self-reported by patients, and thus, only larger than zero for those who attended treatment. This means that instead of having costs by disease or treatment, we have per individual who attended healthcare services. Specifically, survey participants were asked how much they spent in each service during the previous 4 weeks. By dividing this value by the corresponding number of visits we get average costs by visit, for those who visited any service. To reach an average value of treatment costs by provider for all individuals in the sample we then produced estimates of the average individual treatment value based on personal characteristics - our proxy for treatment prices.

Consider visiting a healthcare centre, ν_i is a dummy variable with the value one when patients seek outpatient treatment at a specific service and costs, c_i, to be truncated variables such that:

$$c_i^* = x_i\beta + \nu_i \tag{1.3}$$

And:

$$s_i = \begin{cases} 1, & \text{if } \upsilon_i\lambda + \epsilon_i > 0 \\ 0, & \text{if } \upsilon_i\lambda + \epsilon_i \leq 0 \end{cases} \tag{1.4}$$

Then, $c_i = c_i^*$ when $s_i = 1$. With this strategy we estimated costs using a Heckman selection model with very few characteristics (x_i) - age, education, SAH and distance to nearest health service. This strategy is only possible because costs are self-reported and vary individually. The selection variable s_i for private clinics and TP is whether the person visited or not these services. For public providers, since some treatments are procured by the national government, we define the selection variable as a person being ensured and feeling acute disease symptoms in the last week. All variables included in the selection model were not used in the multinomial estimation, since they will be already controlled for in the costs prediction.

After having the model predictions, for a matter of simplification costs per visit were standardized and averaged by household.

1.4.2 Negative Binomial model for number of visits

The third stage of the decision model consists in estimating the number of visits to each provider as in [26]. Here we estimate a panel count data model using the negative binomial regression method to find relevant determinants of TP demand in terms of number of visits and health care utilization (visits and number of health centres available). The negative binomial estimator is designed to explicitly handle overdispersion, as it is the case of the dependent variables on the number of visits to the TP or HC and, in fact, most count variables.[52] The covariates included are the same as for the probit regression with robust standard errors.

Robustness checks will be presented in Appendix, using different sample restrictions and different indicators to ensure the validity of the results. This robustness checks include Conditional mixed-process (CMP) models.

1.4.3 Multinomial logit for Health outcomes

The final estimation exercise focuses on health outcomes using Self Assessed Health (SAH) and the Body Mass Index (BMI), as mentioned before. BMI is estimated using a multinomial logit model controlling for year, province and island fixed effects. For this case, an ordered probit model would not suit this estimation because the dependent variable, does not follow an order, both very low and very high values are not desirable from a health point of view.

The multinomial logit model specifies that:

$$p_{ij} = \frac{exp(x\prime_i \beta_j)}{\sum_{j=1}^{m} exp(x\prime_i \beta_j)} \quad \text{where j=1,...,m} \tag{1.5}$$

where $x\prime_i$ are case-specific regressors, here individual health characteristics and community health care provision services. The model ensures that $0 < p_{ij} < 1$ and $\sum_{j=1}^{m}= 1$. For identification purposes, β_j is set to zero for one of the categories, and the coefficients are interpreted with respect to that category.[52]

All the analyses were conducted using Stata version 14 (StataCorp LP, College Station, TX).

1.5 Results

Tables 1.8 and 1.9 summarise the main estimation results for the demand estimation two-step approach using multinomial logit models, controlling for year and island fixed effects.

The probability of seeking treatment depends, as expected, positively on the disease indicators. Namely, feeling worse compared to the previous year (negative health shock) is associated with a higher probability of seeking treatment by 9.3 percentage points (pp) and having been hospitalized in the last 12 months by 10.6 pp. The seeking treatment variable is given by whether a participant visited any health facility or received a visit by a health professional in the last four weeks, whether hospitalization refers to patients who received inpatient care in the last 12 months. The hospitalization is thus more likely to have happened before the decision to seek treatment.

Socio-demographic variables also have a relevant impact. Income proxied by household expenditures (in log) has a positive impact on the decision to seek treatment, as well as living in an urban area. A one percent increase on expenditures is related to a 3.2 pp higher probability of seeking outpatient treatment and living in an urban area relates to a 1.1 pp lower probability of seeking treatment (self-treatment or outpatient) ($p < 0.01$). These results show that individuals deciding whether to get treatment or not are more influenced by their health status, rather then by income and geographic disparities (the variable of intent is income proxied by expenditures). At the same time, seeking outpatient also implies more expenditure on healthcare services, so this result must be analysed with care and together with the remaining evidence.

Table 1.8: 1^{st} step - Seek treatment (Mult. Logit (marginal effects))

Base outcome: No treatment	Self-treatment	Outpatient
Married	-0.002	-0.032***
	(0.006)	(0.006)
HH size	0.001***	0.001***
	(0.000)	(0.000)
Log(pce)	0.009***	0.032***
	(0.001)	(0.001)
Higher education	-0.018***	0.015***
	(0.002)	(0.001)
Woman	-0.019***	0.068***
	(0.001)	(0.001)
Urban	0.009***	0.003***
	(0.001)	(0.001)
Acute	**0.046*** **	**0.049*** **
	(0.001)	**(0.001)**
BMI - good	**-0.000**	**0.001**
	(0.001)	**(0.001)**
BMI - high	**0.005*** **	**0.026*** **
	(0.001)	**(0.001)**
Good health	**-0.025*** **	**-0.103*** **
	(0.001)	**(0.001)**
Worse	**0.012*** **	**0.093*** **
	(0.001)	**(0.001)**
Hospitalized	**-0.020*** **	**0.106*** **
	(0.006)	**(0.004)**
Observations	1,488,563	
Pseudo R-sq.	0.052	

*** p<0.01, ** p<0.05, * p<0.1
Note: Robust standard errors in parentheses. This table presents the estimation results of a multinomial logit model with year, province and island fixed effects, using IFLS Community Survey data from 2000, 2007, 2014. The dependent variable is a categorical variable with value 0 if the patient did not seek treatment (outcome 1), 1 if used self-prescribed medication (outcome 2) and 2 if used medical care (outcome 3). Options are mutually exclusive and results show marginal effects for outcome 2 and 3.

The second estimation results show that treatment costs (as proxy for prices), household expenditure (as a proxy for income) and health status are relevant for patients to decide on the type of treatment. To get the age marginal impacts we estimate the effects for visiting a TP for participants at 20, 35 and 70 years of age (see Appendix table A5). As a participant gets older the impact of having been hospitalized becomes stronger and the impact of distance to the next facility larger, which can both be associated to higher fragility and mobility difficulties with age. As for costs, the impact becomes less relevant for older ages, indicating price elasticity is decreasing with age.

Table 1.9: 2^{nd} step - Outpatient visit last week (Mult. Logit (marginal effects))

Base outcome: Public HC	(1) Visit Priv	(2) Visit TP
Log(pce)	0.097***	0.014***
	(0.004)	(0.003)
Higher education	0.072***	-0.002
	(0.012)	(0.008)
Woman	-0.049***	-0.082***
	(0.005)	(0.003)
Acute	0.000	-0.013***
	(0.006)	(0.004)
BMI - good	0.024***	0.029***
	(0.007)	(0.005)
BMI - high	-0.006	0.033***
	(0.007)	(0.005)
Good health	-0.051***	0.022***
	(0.007)	(0.005)
Hospitalized	0.085***	0.010
	(0.021)	(0.020)
Insurance	-0.068***	-0.063***
	(0.005)	(0.003)
Cost public	**-0.004**	**-0.041*** **
	(0.012)	**(0.008)**
Cost private	**-0.023***	**-0.013**
	(0.013)	**(0.009)**
Cost TP	**0.089*** **	**0.048*** **
	(0.013)	**(0.009)**
N. Public HC	0.003	-0.021***
	(0.002)	(0.001)
N. Priv.	0.007***	-0.010***
	(0.001)	(0.001)
N. TP	0.001	0.009***
	(0.001)	(0.001)
Distance	0.092	0.223**
	(0.118)	(0.087)
Observations	65,588	
Pseudo R^2	0.143	

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.
Note: Results using a multinomial logit model with year, province and island fixed effects and data from 2000, 2007, 2014. The dependent variable is categorical: Service type has the value 0 if the individual visited a public health centre during the last week (outcome 1), 1 if the individual visited a private clinic (outcome 2) and the value 2 if the patient visited a TP (outcome 3). Options are mutually exclusive and results show marginal effects for outcomes 2 and 3. Full table in Appendix, A6

Since cost variables are in standardized values, coefficients indicate how much the probability of each outcome changes when costs differ from their mean by one standard deviation (a "typical" deviation). For TP, a typical increase in costs is associated with a 4.8 pp (p<0.01) increase in the probability of having visited that service in the last week. This positive relationship may result from two main potential mechanisms. Either costs depend strongly on the severity of disease and this implies higher costs or there is a quality and recognition signal for more expensive TP. TP costs are also positively related to private clinics demand. Following the significant and positive impact of household expenditure, visiting a more expensive TP is associated with using a more expensive clinic as well. A typical increase in public costs decreases the probability of visiting a TP by 4.1 pp ($p<0.01$), this time evidencing the presence of a substitution effect. Having national insurance also has a negative impact on the probability of visiting TP, which is expected since insurance covers visits to the public health centres and not to the TP. The number of TP available in the community has a small positive impact of 0.9 pp ($p<0.01$) on demand and distance to the nearest health facility has a positive and statistically significant impact of 22.3 pp ($p<0.05$) on the demand for TP. As mentioned in section 1.4, treatment costs used for this estimation are predictions from the Heckman model (results in Appendix - Table A4) , standardized and averaged by household, based on self-reported costs, not tabulated by procedure.

As a robustness check, we performed a Seemingly Unrelated Regression (SUR) for healthcare demand. Results are presented in Appendix, Table A10 and present similar evidence in terms of health outcomes and relationship between costs and demand. The positive impact of TP costs on their own demand can be a sign of disease severity (despite controlling for hospitalization, having an acute disease and feeling worse than last year), high expenditure levels of its typical users or that patients see costs as a quality indicator.

Turning now to the impact of a new medical health facility (HF) on the TP demand, the multinomial results are presented in Table 1.10. In provinces where a health facility was built, it was 8 pp ($p<0.01$) less likely for participants to have visited a TP in the last 4 weeks. All variables related to progress have a positive impact on the probability of visiting a private clinic and negative for TP, with public services visits as the base outcome. Natural disasters have a significant negative impact for both the demand for private and TP.

The results using number of visits and the negative binomial model provide similar evidence (Table 1.11). With this model the dependent variables are not mutually exclusive, thus visiting other services can be added to the explanatory variables. Having visited either a

Table 1.10: Natural experiment results - New HC

	(1) Visit Priv.	(2) Visit TP
New HF	**0.054*****	**-0.076*****
	(0.012)	**(0.009)**
Treatment road	0.021***	-0.020***
	(0.006)	(0.004)
Treatment school	0.064***	-0.055***
	(0.008)	(0.005)
Natural disaster	-0.015***	-0.010***
	(0.005)	(0.004)
Observations	60,365	
Pseudo R^2	0.152	

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.
Note: Results from a multinomial logit model with year, province and island fixed effects and data from 2000, 2007, 2014. The dependent variable is categorical: Service type has the value 0 if the individual visited a public health centre during the last week (outcome 1), 1 if the individual visited a private clinic (outcome 2) and the value 2 if the patient visited a TP (outcome 3). Options are mutually exclusive and results show marginal effects for outcomes 2 and 3.

public or a private healthcare facility in the last 4 weeks decreases the probability of having one more visit at the TP and the effect is stronger for public services (21.7 pp ($p<0.01$)). Treatment costs of other services also have a relevant impact on the dependent variable. A typical increase in treatment private costs is associated with a decrease in the probability of going one more time to the TP by 8.2 pp ($p<0.05$). A typical increase in treatment costs at public facilities have a similar effect.

Using a CMP model to estimate TP costs in a first stage and number of visits in a second stage provides supporting evidence of the previous results. (Appendix table A9)

More expensive healthcare usually means more severe health conditions and less resources to visit the TP. For those who use public facilities, who are more likely to live under strong budget constraints, TP turns out as a substitute good - the increase in medical costs, is associated with a lower demand for TP. The positive impact found for household expenditure (as a proxy for income) and the evidence that TP demand decreases with costs in public services follows the evidence in previous literature that demand for TP in Indonesia is driven by income.[53],[12] Overall, results show that individuals when

Table 1.11: Number of visits to the Traditional practitioner (Neg. Binomial - Marginal effects)

Dep. variable: N. Visits TP	(1)	(2)
Log(pce)	0.084***	0.083***
	(0.009)	(0.012)
Higher education	-0.088***	0.009
	(0.019)	(0.034)
Urban	-0.052***	-0.025*
	(0.013)	(0.015)
BMI - overweight	-0.047**	-0.045*
	(0.023)	(0.027)
Good health	-0.062***	-0.103***
	(0.013)	(0.020)
Hospitalized	-0.013	0.083*
	(0.033)	(0.050)
Insurance	-0.112***	-0.066***
	(0.013)	(0.015)
Visit Pub.		-0.217***
		(0.018)
Visit Priv.		-0.147***
		(0.031)
Cost public		-0.106***
		(0.040)
Cost private		-0.082**
		(0.036)
Cost TP		0.068*
		(0.036)
N. Public HC		-0.015***
		(0.006)
N. Priv.		-0.023***
		(0.003)
N. TP		0.019***
		(0.003)
Distance	-0.188***	0.927**
	(0.044)	(0.420)
Observations	33,319	20,053
Pseudo R-sq.	0.081	0.114

*** p<0.01, ** p<0.05, * p<0. Robust standard errors in parentheses. Note: Estimation results using a Negative Binomial model with year, province and island fixed effects, using IFLS Community Survey data from 2000, 2007, 2014. The dependent variable, Number of visits to TP, is a count variable that indicates the number of visits to the TP in the last month. Treatment costs are predictions from the preliminary linear model and Heckman estimation, in logarithm. Full table in Appendix A7.

seeking care consume both TP and medical care, with some income driven differences: wealthier families consume both services as complement goods, while the financially fragile are more likely to have to chose between both.

To analyse expenditure differences, let us distinguish households between lowest and highest expenditure quantiles (households in the middle quantile were not included).

Results presented in Table 1.12 show supporting evidence that treatment demand is very much influenced by expenditure. Having been hospitalized has a positive impact on TP demand for low spending participants and on private for high spenders. Average treatment costs in general have a negative and significant impact on TPs. TP costs are associated with a decrease in the probability of a low spender patient visiting the private clinic, but relates to a higher probability of visiting the TP.

Table 1.12: 2^{nd} step - Outpatient visit last week (Mult. Logit (marginal effects) - by expenditure quantiles)

	Low quantiles		Top quantiles	
	Private clinic	TP	Private clinic	TP
Log(pce)	-0.024**	0.057***	0.153***	0.014**
	(0.010)	(0.008)	(0.009)	(0.006)
Higher education	0.219***	-0.135***	-0.030*	0.076***
	(0.029)	(0.022)	(0.017)	(0.010)
BMI - normal	-0.039***	0.029***	0.035**	0.057***
	(0.010)	(0.007)	(0.014)	(0.008)
BMI - overweight	-0.061***	0.029***	-0.005	0.048***
	(0.011)	(0.007)	(0.015)	(0.009)
Good health	-0.058***	0.023***	-0.002	0.036***
	(0.011)	(0.008)	(0.013)	(0.009)
Hospitalized	-0.051	0.203***	0.261***	0.026
	(0.054)	(0.032)	(0.035)	(0.022)
Insurance	-0.023***	-0.089***	-0.013	-0.041***
	(0.009)	(0.006)	(0.009)	(0.006)
Cost public	**0.105*** **	**-0.140*** **	**0.109*** **	**0.005**
	(0.020)	**(0.014)**	**(0.020)**	**(0.013)**
Cost private	**0.146*** **	**-0.069*** **	**-0.056*** **	**-0.071*** **
	(0.023)	**(0.016)**	**(0.022)**	**(0.013)**
Cost TP	**-0.095*** **	**0.157*** **	**0.106*** **	**0.048*** **
	(0.024)	**(0.016)**	**(0.023)**	**(0.013)**
N. Public HC	-0.012***	-0.017***	0.018***	-0.016***
	(0.004)	(0.002)	(0.003)	(0.002)
N. Priv.	0.012***	-0.020***	0.014***	-0.009***
	(0.001)	(0.001)	(0.002)	(0.001)
N. TP	0.005***	0.011***	0.014***	0.009***
	(0.002)	(0.001)	(0.002)	(0.001)
Distance	-1.633***	1.372***	-0.505**	0.184
	(0.201)	(0.151)	(0.204)	(0.122)
Obs.	20,982		19,599	
Pseudo R-sq.	0.145		0.128	

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.
Note: Estimation results using a Multinomial Logit model to estimate the number of visits to the TP, respectively. Estimation performed separately for households in the first two (low) and the last two (high) quantiles of monthly expenditure. Families in middle quantile are not included. This includes year, province and island fixed effect, using IFLS Community Survey data from 2000, 2007, 2014. Results show marginal effects for each coefficient in all specifications. The full table is provided in Appendix, Table A8.

Turning to the health outcome estimation the models now focus on how the provision of healthcare and TP can have an impact on patient's health, measured by SAH and BMI indicators (Table 1.13). Household expenditure (as a proxy for income) is related to a higher probability of reporting a good health status, but also of being overweight in terms of BMI. Results show that a 1 percent increase in household expenditure is related to a 4 pp increase in the probability of being obese. Women are less positive about their health assessment, as well as respondents who engage in self-treatment and living in more urban areas.

Table 1.13: BMI and good self assessed health (SAH) (Multinomial and Probit results - Margins)

	BMI - Underweight	BMI - Overweight	Good health (SAH)
Log exp.	-0.030***	0.038***	0.008***
	(0.001)	(0.001)	(0.001)
Woman	-0.048***	0.092***	-0.020***
	(0.001)	(0.001)	(0.001)
Self-treat	-0.005***	0.003***	-0.047***
	(0.001)	(0.001)	(0.001)
Urban	-0.014***	0.037***	-0.014***
	(0.001)	(0.001)	(0.001)
BMI - Normal			0.030***
			(0.001)
BMI - Overweight			0.031***
			(0.002)
Symptoms	0.006***	0.002	-0.073***
	(0.001)	(0.001)	(0.001)
N. Public HC	**0.014*** **	**-0.007*** **	**-0.012*** **
	(0.002)	**(0.001)**	**(0.002)**
N. Priv.	**-0.010*** **	**0.006*** **	**-0.004** **
	(0.002)	**(0.001)**	**(0.001)**
N. TP	**-0.014*** **	**-0.016*** **	**-0.018*** **
	(0.002)	**(0.002)**	**(0.002)**
N. Public x TP	**-0.017*** **	**0.011*** **	**0.016*** **
	(0.002)	**(0.001)**	**(0.002)**
N. Private x TP	**0.014*** **	**0.000**	**0.009*** **
	(0.001)	**(0.001)**	**(0.001)**
Observations	887,556		887,556
Pseudo R^2	0.087		0.12

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.
Note: Estimation results using a Multinomial logit and Probit models to estimate the likelihood of being under or over the BMI healthy level (categorical) and SAH (binary). This includes year, province and island fixed effect, using IFLS Community Survey data from 2000, 2007, 2014. Results show marginal effects for each coefficient in all specifications. The interaction variable is used to grasp and the effect of having a modern health-care facility built in a district with a given number of TP. The full table is provided in Appendix, Table A11.

Health care services and TP supply are here measured as the number of facilities for each. Variables are included in logarithm transformation so it is easier to interpret their impact. A one percent increase in the number of TP relates to a decrease in the probability of being under or overweight by 1.4 pp and 1.6 pp, respectively, who are generally people with more co-morbidities and less healthy. The effect on SAH is negative, as it is for public and private medical care. The number of public facilities is associated with underweight respondents, while the probability of being overweight is associated to the number of private clinics - which should be another income related effect. The interactions between the number of TP and the other facilities is not always associated with better health (in terms of BMI), but have a positive impact on the probability of reporting a good health status, of 1.6 pp for public health centres and 0.9 pp for the interaction with private clinics. All results mentioned are significant at a 1% level.

1.6 Discussion

The results for income, education, distance and urban coefficients in the different specifications suggest TP are providing care for the richest and for those in more rural and remote areas. At the same time, it is clear that medical and traditional services are related and that TP are being (mostly) negatively affected by conventional practices.

Insured families are registered in the national insurance scheme, created in 2014. These patients have most of healthcare services for free and thus should be able to afford TP if they wanted to. However, we find a negative and significant impact of being registered in the insurance scheme and visiting TP, meaning that it can be providing incentives for the poorest to resort more to medical treatment and less to the alternative options available. It is also possible that even with access to healthcare, these families still struggle with budget constraints as they are also more likely to suffer from more severe physical health issues. Even though our results show that the new public insurance scheme was successful in bringing users to the public healthcare system, since our data stops exactly on the year the scheme was implemented, those that were already insured had just been offered free healthcare treatments (health care supply shock) and the programme had not yet been completely widespread. If more data on later years is available one could study how this effect changes in time and whether having free access to healthcare increases the available budget for TP among the most financially constrained.

Another interesting result we find is that being hospitalized is associated with a higher TP demand for low income participants. For participants in the highest income quantiles being hospitalized is associated with higher demand for private clinics. Note that, because we cannot argue for causality, it is possible that more visits to the TP and to the private clinic are worsening the patients condition and not the other way around. However, the survey question on hospitalization refers to the 12 months previous to the survey, i. e., patients were asked if they were hospitalized at any moment in the 12 months previous to the survey. In turn, the question on seeking any treatment (health centre, private clinic or TP) refers only to the week previous to the survey. From the way both questions are asked to the participants, the hospitalization episode most likely happened before the decision to seek treatment, and not after. Hospitalizations are typically related to more severe conditions and can happen at private or public hospitals. If hospitalization services are not be enough for the patient to feel safe and cured or if the condition requires for rehabilitation, this leads patients to search for other sources of care. The wealthier can go to private clinics, but for the families in the lowest income quantiles the TP can be the cheapest and most accessible way of getting more and more personalized treatment, including services are not covered by insurance at public health centres. This could be an explanation for why having been hospitalized is associated higher demand for private clinics by the richest families and higher demand for TP by the poorest. This mechanism could also explain the increasing share of patients seeking TP for physiotherapy, illness and injury treatment (section 1.3.1). Such dynamics can be worrying and constitute another argument in favour of increasing collaboration between systems. If the country reaches universal healthcare coverage, but services and medicines quality do not follow, TP may become an alternative for families looking for rehabilitation services, specially among the less wealthy.

We believe further research is needed to understand inequities in access to wellness and healthcare in similar contexts to further grasp the role of TP in the community and how they could be included in the National Health Plans.

Despite this thorough analysis, there are some caveats to the study. The first is that, although our data sample is representative of the Indonesian adult population, we lack a field intervention to measure the interactions between different services in a controlled environment, which does not allow us to argue for causality. Secondly, the complexity and extension of this dataset created a serious challenge to have harmonized data. For example, as treatment costs are self reported, the values used for treatment prices are predictions from a Heckman model. Which we consider to be valid (by our robustness checks), but still do not correspond to real pricing information per se. In addition, survey questions and their numbering change between waves, which required a long and intensive study of what questions to use over the years. Finally, we also need to take into account the attrition between survey waves, a common disadvantage of longitudinal datasets, even if IFLS teams make a huge effort to follow families that moved residence from one year to another. [32]

1.7 Conclusion

The use of traditional and complementary medicine services lasts for centuries in several cultures around the world. Traditional Practitioners create an important reputation among their communities which makes them potential key agents for the future of public health. While some steps have been taken towards the regulation and formalisation of the practice, little is known on how TP have been adapting to social development or whether they have been affected at all.

Using Indonesia as a case study, our findings show that, although modern health-care has been spreading through the country, TP are still generally used and have strong interactions with private and public health care providers. Private services and TP are used as complements by higher income families and as substitutes by low income families, likely due to budget constraints. The most significant determinants of TP demand are health conditions and willingness/availability to pay.

Overall, there is evidence that Traditional Practitioners are affected by the provision of medical health-care, but the population seems to use both services in a very consistent way. This study provides an innovative contribution to the literature that argues towards a more integrated health system in a cultural-rich environment as Indonesia. From the results obtained and the whole analysis described, the future of health policy design should take into account the potential power of cultural values and beliefs to complement and improve treatment and the general well being of the population.

Further analysis is needed to understand how modern and the traditional health systems could be integrated, how available are both sides to negotiate that integration, always ensuring the populations health and healthcare access are a priority.

Chapter 2

Co-payments and equity in care

- Enhancing hospitalization policy for Palestine refugees in Lebanon[1]

Abstract

This paper measures the impact of introducing a 10% co-payment on secondary care hospitalization costs for Palestine refugees living in Lebanon (PRL) in all UNRWA contracted hospitals, except for the Red Crescent Society. This ex-post analysis provides a detailed insight on the direction and magnitude of the policy impact in terms of demand by hospital type, average length of stay and treatment costs. With a complete population episode level dataset, we use multinomial logit, negative binomial, and linear models to estimate impacts on the different dependent variables, controlling for disease, patient and hospital characteristics.

After the implementation patients were 18% more likely to choose a Red Crescent Society hospital for secondary care, instead of one with co-payment (p<0.01). This impact was stronger for episodes with longer stays, which were also the more severe and expensive cases. Average length of stay decreased in general and we did not find a statistically significant impact of the co-payment on costs, for the provider or for the patient.

Findings suggest that introducing a 10% co-payment for secondary hospital care had an impact on patients' health care budget, leading to demand shifts towards cheaper options - i.e., patients had to chose care based on financial constraints rather than on their treatment preferences. Before

[1] with Gloria Paolucci, Akihiro Seita and Hala Ghattas

changing healthcare payment schemes in different types of hospitals, facilities offering free of charge treatment should be assessed and prepared for potential demand shifts to avoid overcapacity and the collapse of health care services for such a fragile population. In addition, exemptions from co-payments should be considered for patients with severe health conditions and financial constraints, who, according to our results, are the most likely to change their pattern of care due to an increase in treatment costs.

2.1 Background

Palestine refugees are the oldest and one of the largest refugee groups in the world, having been displaced since 1949 and accounting for around 5.5 million people spread across Jordan, Lebanon, West Bank and Gaza.[54] Particularly in Lebanon, Palestine refugees are not recognized as citizens, living with extremely restricted access to the job market (not entitled to work in as many as 39 professions) and without property rights. The United Nations Relief and Works Agency for Palestine Refugees in the Near East (UNRWA) provides essential development and humanitarian assistance to Palestine refugees including education, primary health care, relief and social services, amongst other services. However UNRWA has faced financial challenges in the last few years. [55][56][57]

The Lebanese healthcare system has been under increasing pressure since the Syria conflict, which started in 2011 and forced local communities to be displaced to the neighbouring countries, including Lebanon.[58] Implementing the most appropriate and sustainable payment schemes in healthcare is thus as complex as it is key to ensure general access to health care and healthy lives in this context.

In terms of secondary health care, UNRWA has historically covered health expenses of Palestine refugees through the partial reimbursement of costs, incurred at any contracted hospital (private, public, UNRWA and NGO hospitals). The amounts covered vary across operation areas and are managed at the local level by the Health Department of the respective field office or headquarters. In the beginning of 2016, due to severe budget constraints, UNRWA in Lebanon explored alternative health financing arrangements and implemented new policies adjusting the co-payment coverage scheme, reducing secondary care cost coverage from 100% to 90% in private and public hospitals, while maintaining all costs covered at the Palestine Red Crescent Society hospitals (PRCS).

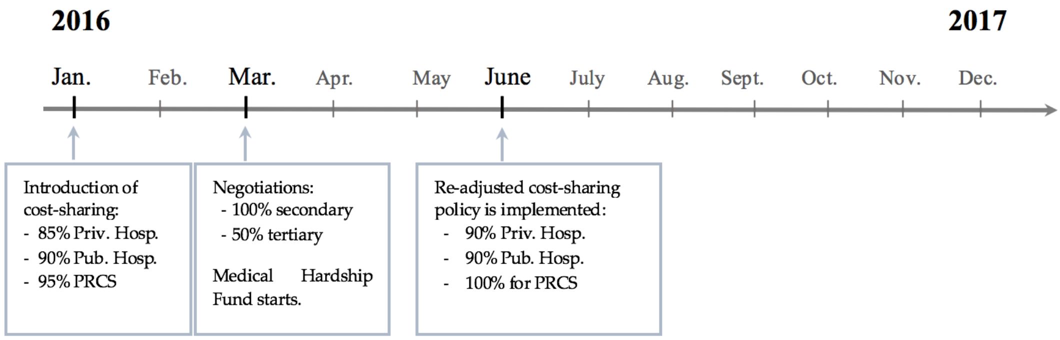
This study goes into the details of this policy change and aims to shed light on its impact on demand and supply of healthcare. This work contributes to the literature on the effect of co-payments in healthcare with a complete population database in a limited resource context, and provides specific insights to inform policies to improve access to healthcare for Palestine refugees in Lebanon (PRL).

UNRWA Hospitalization policy changes: a natural experiment

The policy change of interest in this study had a long and complex path towards implementation. In January 2016, UNRWA increased tertiary care coverage from 50 to 60% and reduced secondary care coverage from 100% to 80% in private, 85% in public and 95% in PRCS hospitals. Additionally, by the end of February 2016, UNRWA announced the creation of a Medical Hardship Fund (MHF), a program designed to ensure access to treatment for those living in extreme poverty and suffering from catastrophic health conditions - including support at the secondary healthcare level (in 2016 the percentage of UNRWA hospitalization accessed by MHF was of 18.4% [59]). Nonetheless, under these new conditions most patients had to cover a larger share of their hospitalization costs out of pocket which raised strong concerns and led to protests against the Agency's decision.

UNRWA contracts services from thirty-five private hospitals, five Palestine Red Crescent Society and four public hospitals in Lebanon. Since the access to the most available hospitals became more expensive, users had less options for treatment - in 2016 the average cost of an appendectomy (surgical removal of the appendix) was around 734 USD in public and 683 USD in private hospitals. With UNRWA covering 90% this means the patient would still have to pay around 70 USD, which can be a significant cost for a family already in financial distress. The resulting tensions led UNRWA to open the matter to negotiations and suspend the cost-sharing policy between April and June 2016, changing coverage back to 100% for secondary care in all hospitals (as it had been until December 2015).[60] This period gives us pre-policy implementation data to use as a natural experiment for the analysis. After the negotiations were concluded, UNRWA re-adjusted the policy to meet partially demands of the population. On June 1^{st} 2016, the percentage of the Agency's coverage for secondary care was set to 90% for government and private hospitals and 100% for PRCS hospitals, maintaining the 60% coverage for tertiary care in all contracted hospitals (up to a ceiling of 5,200 USD per admission) (see Figure 2.1). Together with this last policy, UNRWA revised the monitoring process for length of stay at the geographical area level (geographical areas of operation are formally defined by UNRWA). Each patient diagnosis and expected length of stay were confirmed by an Area Hospitalization Medical Officer (AHMO) (who produced an approval in accordance) and later extensions had to be approved by UNRWA. Unjustified stays were not covered by the institution, which provided an incentive for hospitals to comply.

Figure 2.1: Policy timeline

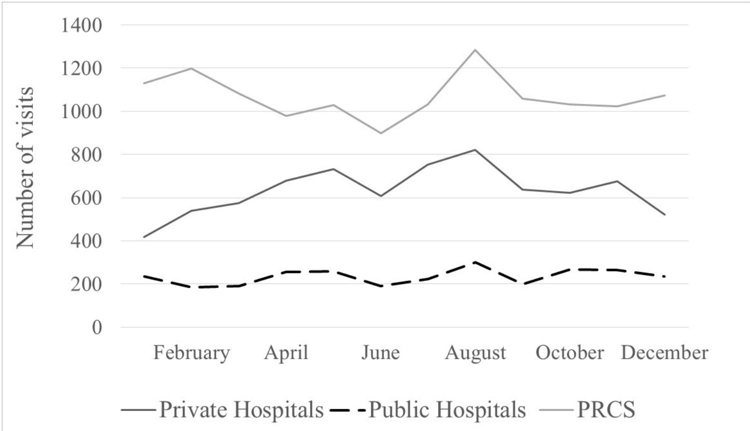


The period after June 2016 will be equivalent to an experiment second-stage when we measure how the 10% co-payment changes demand between the ex post and ex ante stages.

UNRWA is the main official provider of health care for Palestine refugees and almost all refugees are accessing hospitals through UNRWA hospitalization support program.[61] According to Chaaban et al. (2015) the overall health conditions of this population are fragile. Namely, around 37% of the Palestine refugees from Lebanon (PRL) reported to be chronically ill and more likely to be hospitalized, with acute illness and disability percentages around 63% and 10.3%, respectively.

A preliminary look into the data shows PRCS demand in terms of hospital visits was decreasing until June, when the second policy adjustment was put in place, as Figure 2.2 shows. At the same time, demand for private hospitals seems to evolve in an opposite direction from that of PRCS. With the imposition of different cost-sharing levels in different hospitals, June was a turning point in terms of decision making for households with secondary health care needs.

Figure 2.2: Average number of visits, per month, in 2016



A growing body of literature has examined the impact of cost-sharing policy implementation and abolition on health care demand. Nabyonga et al. (2005) presents an impact assessment on the abolition of user fees in Uganda.[62] The authors carried out a longitudinal study in 106 health facilities across the country to explore how demand for health care services reacted to the policy change. The study found an increase in utilization among all population groups, with a relatively higher increase among the poor. Similar evidence was found by De Allegri et al. (2011) who focused on the reduction of user fees for maternal care services.[63] The results of two multivariate logistic regression models suggested that poorer women might have benefited the most from the new financing policy with important implications for decreasing inequalities. Evidence from the Occupied Palestinian Territory also shows that out-of-pocket payments have a regressive effect and increase pre-existing income inequalities.[64] However, in all the above cases user-fees (when known) were higher than the ones imposed by UNRWA in secondary hospitalization in 2016 and in most cases addressed a reduction rather than an increase in out-of-pocket fees.

Notably, one important tool that previous research has found to be effective in the successful implementation of new policies is to provide transparent and complete information to the community. This is especially true in complicated environments, where the population has few resources and is already struggling with day-to-day expenses. Indeed, studies have shown that a gradual introduction plan can be enough to transform a failed implementation into a smooth transition generally accepted by the population and with better results regarding budget saving outcomes.[65], [66], [67]

The introduction of cost-sharing policies is a complex exercise as it has immediate negative implications for the user - costs increase. Nonetheless, some policies of this nature may actually bring important benefits to health care services.[68][69] In UNRWA's case, the new policy was introduced as a strategy adjustment for “greater sustainability and increased support for tertiary care", by shifting part of the coverage from secondary to tertiary level hospitalizations.[70] However, to what extent this policy was effective and what were the implied unforeseen effects is not clear. Of particular interest is whether users change behaviour after the cost-sharing policy is implemented and whether UNRWA is able to contain costs. Throughout this project, we answer these questions by analyzing how the bill value, UNRWA contribution and hospital visits change pre and post-intervention. For this purpose we focused on secondary care data for which we have pre and post policy information. This work is a valuable contribution towards increasing quality of health care for Palestine refugees, while providing a general framework of how hospitalization services are being used.

The overall findings suggest that introducing a 10% co-payment for secondary care for private and public hospitals had a significant impact redistributing demand between types of hospitals. Namely, after this policy change patients were 18% more likely to choose a PRCS hospital for secondary care. In addition, the average number of stay in days decreased in all hospitals, which can be related to the effectiveness of having improved occupancy control at the same time of the policy change.

The remainder of the study is organized as follows: section 2.2 presents the data and concerns of external validity, section 2.3 explains the methods used including the theoretical and empirical models, 2.4 presents the main results and, finally, 2.5 provides conclusions and discussions of the analysis.

2.2 Data set

The data used in this work are part of a broader ongoing program of data collection being conducted by UNRWA in all contracted hospitals with the goal of ultimately constructing a comprehensive time series of hospitalizations. [2]

For a matter of confidentially, the refugee registration number was anonymised, but in a way that allows to follow up of each patient. The data collection was initially piloted in 2013 and started being fully conducted in 2016.

For this project we use a subset of the original data from January 2016 to October 2017 with complete information on all UNRWA hospitalizations (the availability of the data depends on the on-going digitalization process). We focus on Palestine refugees from Lebanon in secondary care for which we have 32,061 observations, not including birth deliveries and MHF cases who benefit from a different financial support program and were differently affected by the policy change. We excluded MHF cases by eliminating observations from patients that got complete coverage using other than PRCS hospitals after June 2016 which is the best identification possible given that data on the MHF cases identifier is not available. The data contains individual level information collected from every hospital in UNRWA areas of operation, Beqaa, Central Lebanon Area (CLA), North Lebanon Area (NLA), Saida and Tyre, from 27 private hospitals, 5 PRCS and 4 public hospitals. The Lebanon map in figure 2.3 shows the distribution of UNRWA contracted hospitals across the country (more detailed maps by region in Appendix 4.4). The available variables include the patients' age and gender, entry and discharge date, diagnosis and surgery description, bill value, UNRWA contribution, patient contribution and hospitals' characteristics. Because we have the complete population data-set, there is no need for sampling and the findings will be robust and representative of the population. This is an important strength of this paper that makes it unique in the literature.

Gender of hospital users is generally equally distributed between males and females however, as seen in Figure 2.4, there are some imbalances when data are stratified by age group. There is a relatively higher number of young males going to the hospital until

[2]Data were provided by UNRWA directly, but all opinions are the responsibility of the researcher.

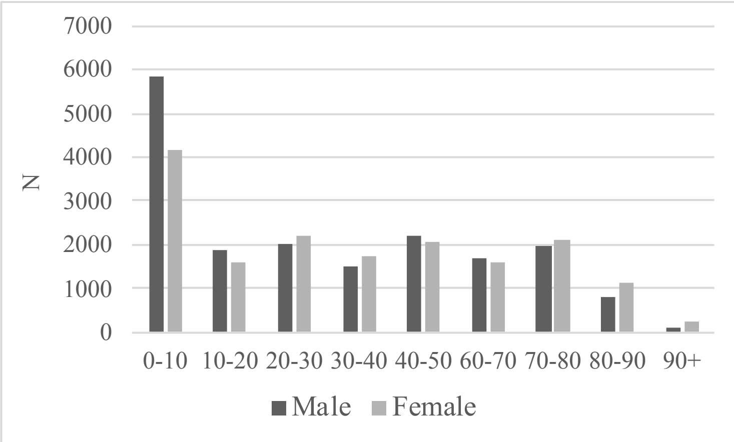
Figure 2.3: Hospitals location in Lebanon

the age of 10 to 20 years. Between 29 and 70 years, the groups are quite balanced and from 70 years onwards women become the majority. Existing evidence on Palestine youth shows that young males tend to have more dangerous behaviors that put their lives at risk, while females spend generally more time at home throughout their lives and end up living longer.[71]

In what concerns regional disparities, CLA is the area with the highest number of hospitals, 12, followed by NLA with 10, Beqaa with 7, Saida with 6 and Tyre with 4. Nonetheless, Saida has the highest number of incidents in the database, most likely due to having the highest population size and density of Palestine Refugees and Ein El Hilweh camp (in Saida), which were exposed to several conflicts during this period of time (Figure 2.5).

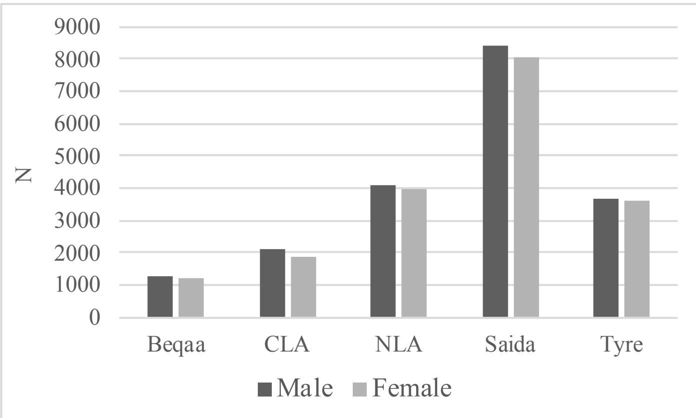
Of the total observations 6,781 are surgical and 25,280 medical cases. Surgical cases are paid fee for service, independently of the number of days patients stay at the hospital. As such, these cases should not be affected by the higher monitoring from UNRWA at the time of the policy change. Regarding seasonality, the number of visits to the hospitals

Figure 2.4: Population by age group and gender



Note: Data from January 2016 to October 2017 for secondary care.

Figure 2.5: Population by region and gender



Note: Data from January 2016 to October 2017 for secondary care.

decreased significantly during Ramadan in both years and, especially because it coincided with the policy change in 2016, it is important for this to be considered in the analysis.

We are able to observe high responsiveness in the data with regards to the timings of policy changes and cultural events. This, combined with its representativeness, suggest a high quality and reliability of the data sources. The progress of the project was closely followed by UNRWA, that supervised and provided guidance on unregistered events and the general results interpretation related to culture and societal-specific features.

2.2.1 External validity

The Palestine community living in Lebanon has a unique culture and has struggled with very particular social and political challenges over time. Although still registered as refugees, Palestine Refugees from Lebanon have been sharing the same geographic area as Lebanese for the last 70 years. On the other hand, this population continues to be marginalized and socially excluded with many living in precarious conditions. Moreover, with the Syrian refugee crisis, services became more crowded and scarcer in the country.

To assess how PRL compare with national averages we use the most recent data published, including the 2009 WHO Data Book for Lebanon , World bank data and the AUB Socieconomic Survey 2015 of Palestine refugees.[72][61]

Comparing AUB 2015 estimates for PRL in Lebanon, the Syrian Arab Republic and the West Bank and Gaza, we see generally a young population with approximately half under 24 years of age and West Bank and Gaza standing out with the highest percentage of population in this age group (Table 2.1).[61]

Table 2.1: Population in % of gender by age groups, 2015

	Lebanon		Syrian Arab Republic		West Bank and Gaza		PRL	
Age groups	Female	Male	Female	Male	Female	Male	Female	Male
0-24	46%	46%	52%	53%	61%	62%	45%	51%
25-64	48%	48%	44%	43%	36%	35%	46%	43%
65+	7%	6%	4%	4%	3%	3%	8%	7%

Poverty affects young Palestine refugees with 74% of adolescents living in poverty and 5% in extreme poverty, in line with recent evidence on the reality of other refugee groups such as Syrian.[73] The overall estimation is that 65% of PRL live below the poverty line, against 68% of Syrian refugees and 28.5% of Lebanese (UN Lebanon annual report 2018). PRL expenditures per month are also lower than the average of their Lebanese counterparts. Nonetheless, the employment rate for Lebanon was 43.9% slightly higher than the estimate for PRL of 37%, very close to the rate for the same year in Syrian Arab Republic and considerably higher than the 33.7% for West Bank and Gaza.

Regarding health indicators, the incidence of NCDs is high and increasing across the Arab world. The reported prevalence of chronic and acute disease among PRL is 37% and 63%, respectively. With heart disease, stroke and diabetes as the top three causes of death in Lebanon, the most common NCDs are similar for both groups and a common issue across the region.[74][75] Infant mortality rates on the other hand, show slightly lower values for PRL at 19 per 1000 births, compared to 21 in Lebanon, 29.6 in Syrian Arab Republic, 21 in West Bank and 23 in Gaza. This is an indicator that is usually strongly correlated with life expectancy.[76] In this sense, these indicators highlight that the PRL population in Lebanon have strong similarities with other countries and refugee populations across the region. This is one of the key factors strengthening external validity and making this policy impact analysis valid in similar contexts.

2.3 Methods

2.3.1 Theoretical model

To understand patient behavior following the introduction of a co-payment in secondary care hospitalization costs, we develop a theoretical model that formalizes a hypothesis on how individuals decide between hospitals. [3]

We are studying the policy implementation as a natural experiment in two stages, the ex ante stage where patients have free access to secondary care, and the ex post stage where treatment in public and private hospitals is charged at 10%, but not in PRCS hospitals. Given this setting, we assume the different hospital types have different quality levels and use a vertical differentiation model to analyze competition and interaction among hospitals. Providers compete in terms of quality, which is valuable because it can result in better health outcomes or improve the treatment process itself.

We start by considering that patients obtain utility from their treatment. This utility is directly influenced by the cost and benefit of treatment, which in turn are dependent on the

[3] The most common types of cost-sharing are: co-payments, payment of a fixed amount for each medical service; coinsurance, payment of a fixed percentage of the health care expenditure; and deductibles, payment of the first need of care each year. [69]

condition's severity level. In this market for health care there are two hospitals, indexed by j=1,2, where hospital 1 is of higher quality than hospital 2 and patients have preferences for these hospitals. The treatment cost share is exogenous and can vary over time and between hospital type. The demand each provider faces is then determined by the preference of the indifferent patient.

Each patient makes the decision to take treatment or not and from which hospital to demand treatment. This said, the patients' utility $U(j, \eta)$, $j = 1, 2$, with disease severity η, when choosing provider i is given by:

$$U(j, \eta) = \theta_j B(\eta) - S_j C_j(\eta) \tag{2.1}$$

where $B(\eta)$ is the benefit of getting treatment, which we assume to be equal for all patients of the same severity whatever hospital they select, and S_j is the share of the total cost, $C(\eta)$ (measured in USD units), that the patient is required to pay, i.e., $S_j C_j(\eta)$ is the out-of-pocket payment, exogenously established. Both $C_j(\eta)$ and $B(\eta)$ are increasing on severity ($B'(\eta) > 0, B''(\eta) < 0, C_j'(\eta) > 0, C_j''(\eta) > 0$), meaning that higher severity corresponds to higher benefits, but also higher cost. The augmented preference for the quality hospital is given by θ, where $\theta_1 > 1$ and $\theta_2 = 1$, such that the benefit of getting treatment at hospitals with higher quality is larger. In this framework, consider that:

- $\eta_1 > \eta_2 \Rightarrow C_j(\eta_1) > C_j(\eta_2), \forall\, \eta$;
- $S_1 > S_2$; and
- $C_1(\eta) > C_2(\eta), \forall\, \eta$;

Then:

1. There exists a η^* such that, for $\eta \geq \eta^*$:
   $B(\eta) \geq S_2 C_2(\eta)$, everyone gets treatment at the hospital;
2. There exists a η^{**} such that,

   For $\eta^* < \eta < \eta^{**}$:

   $\theta B(\eta) - S_1 C_1(\eta) < B(\eta) - S_2 C_2(\eta)$, everyone chooses hospital 2.

And for $\eta \geq \eta^{**}$:

$\theta B(\eta) - S_1 C_1(\eta) > B(\eta) - S_2 C_2(\eta)$, everyone chooses hospital 1.

To study these conditions we need to understand how the thresholds vary with changes in out-of-pocket payments, S_j.

For this purpose, we derive the severity thresholds functions, η^* and η^{**}, in order to S_j, through the application of the Implicit Function Theorem:

If f : $\mathbb{R}^m \times \mathbb{R} \Rightarrow \mathbb{R}$ is a C^1 function, $f(x_0; y_0) = 0$, and $\frac{\partial f}{\partial x} \neq 0$, then for some neighborhood $U \subset \mathbb{R}^m$ of (x_0) there is a C^1 function $g : U \Rightarrow \mathbb{R}$ such that $g(x_0) = y_0$ and $f(x, g(x)) = 0$ for all $x \in U$. The partial derivatives of g at x_0 are given by the formula:

$$\frac{\partial g}{\partial x^i}(x) = -\frac{\frac{\partial f}{\partial x^i}(x_0, y_0)}{\frac{\partial f}{\partial y}(x_0, y_0)}$$

The calculations yield the following results (proofs in Appendix, section A2.1):

<u>Proposition 1</u>

The severity threshold for patients to get treatment, η^*, is positively related to treatment costs at the low quality hospital, $S_2 C_2(\eta)$. This is, as the patients' contribution share increases, S_2, the severity threshold that leads a patient to seek treatment increases.

$$\frac{\partial \eta^*}{\partial S_2}(S_2) = \frac{C_2(\eta^*)}{{\partial B(\eta^*)}/{\partial \eta^*} - S_2\left({\partial C_2(\eta^*)}/{\partial \eta^*}\right)} > 0 \tag{2.2}$$

<u>Proposition 2</u>

An increase in patient contribution charged in hospital 1, S_1, increases the severity threshold that leads patients to change their choice to the high quality hospital, η^{**}.

$$\frac{\partial \eta^{**}}{\partial S_1}(S_1, S_2) = \frac{C_1(\eta^*)}{{\partial B(\eta^{**})}/{\partial \eta^{**}} - S_1\left({\partial C_1(\eta^{**})}/{\partial \eta^{**}}\right)} > 0 \tag{2.3}$$

<u>Proposition 3</u>

An increase in patient contribution charged in hospital 2, S_2, decreases the severity threshold that leads patients to choose the high quality hospital, η^{**}.

$$\frac{\partial \eta^{**}}{\partial S_2}(S_1, S_2) = -\frac{C_2(\eta^{**})}{\partial B(\eta^{**})/\partial \eta^{**} + S_2(\partial C_2(\eta^{**})/\partial \eta^{**})} < 0 \tag{2.4}$$

Proposition 4

An increase (decrease) in patient contribution charged in hospital 1, S_1, decreases (increases) the number of patients going to hospital 1 and increases (decreases) the number of patients going to hospital 2.

$$\frac{\partial W_1}{\partial S_1} < 0; \frac{\partial W_1}{\partial S_2} > 0; \quad \frac{\partial W_2}{\partial S_1} > 0; \frac{\partial W_2}{\partial S_2} < 0 \tag{2.5}$$

Where, W_j is the number of patients going to each hospital. Since from Proposition 3 the severity threshold of going to hospital 1 increases, the average costs and length of stay are also expected to increase at hospital 1.

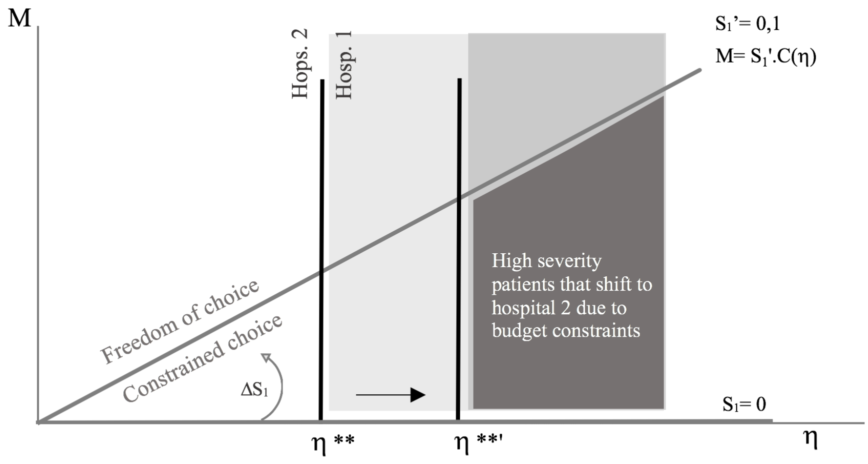
Additionally, because this is a context of strong financial distress, it is important to consider that some heavy users with severe cases at high quality facilities will be forced to shift hospital due to lack of financial resources.[61] In order to include these cases in the model we need to add a budget constraint at the patient level, such that:

- $M > SC(\eta_1)$;

To understand further how this condition interferes with the model, figure 2.6 shows how the increase in patient contribution in hospital 1 from 0 to 10% can affect their choices.

Consider the budget constraint and the increase on patient contribution, S_1. From the above explained theory, there is a threshold severity level η^{**} after which patients will prefer to choose a high quality hospital (hospital 1). We also saw that when S_1 increases, the severity threshold, η^{**}, increases (from η^{**} to $\eta^{**\prime}$ in the graph) and it takes a more severe health condition to make people willing to pay more. Following, the number of patients decreases and the average patient length of stay (LoS) increases at hospital 1. However, from the group of people that are willing to pay more, some will not be able to follow this increase in costs. Taking this into account, more people will shift to hospital 2, and there will be a negative effect on the average LoS at hospital 1. The overall effect on average LoS at hospital 1 will be a trade-off between the two effects described. In Figure 2.6, the light grey area represents the point after which patients choose hospital 1 and the dark grey represents those that are willing to pay, but will choose a low quality hospital because $M < SC(\eta_1)$.

Figure 2.6: Budget constraint dynamics (from $S_1 = 0$ to $S_1^{'} = 0,1$)



Applying this theoretical reasoning to the study, we can consider PRCS hospitals to be hospital type 2 and private and public hospitals to be hospital type 1. We will use the relationships above to interpret the results achieved from the econometric results, in order to understand the rational behind the patients' behavior changes. Let us consider two hypothesis, following the introduction of a 10% co-payment as of June 2016:

- Patients that shift to hospital 2 due to financial constraints were overusing the high quality hospital, when the low quality hospital has enough resources to treat all diseases and conditions with lower costs for UNRWA;
- Patients that shift to hospital 2 due to financial constraints will not have access to sufficient care and this will have negative future impacts in terms of level of morbidity and mortality.

If the first hypothesis is confirmed, the new policy was effective to reduce inefficiencies and allowed UNRWA to contain costs, on the other side, the second hypothesis implies that the policy not only did not allow UNRWA to contain costs, but also made access to healthcare more difficult for poorer families with severe health conditions. The estimation and econometric methods adopted will allow us to explore these hypotheses and understand what is the most plausible scenario according to the data under analysis.

2.3.2 Estimation and econometric methods

The main purpose of this study is to estimate the effect of co-payments on patients' healthcare decisions - PRL - and the providers costs - UNRWA. We exclude the period between January and March 2016 and focus on the shift from full coverage (in force during April and May 2016) to cost-sharing (after June 2016). We use a differences estimation equation, as follows:

$$Y_{it} = \alpha + \beta_1 T + \beta_2 X_{it} + \beta_3 H_{it} + \beta_4 Int_{it} + \epsilon_{it} \tag{2.6}$$

Where i = 1,.., N denotes individuals and t represents time (day). The dependent variable, Y_{it}, corresponds to each outcome of interest: bill value, UNRWA contribution, patient contribution, stay in days and the probability of choosing a PRCS, a public or a private hospital (all monetary variables will be expressed in USD). T is a treatment vector time-varying independent variable with coefficient β_1, such that T=1 if the period is after the last policy change (from June 2016 onward) and T=0 otherwise. Matrix X_{it} includes individual-specific characteristics, including gender and age, H_{it} corresponds to the demographic profile and characteristics of the hospitals (region, distance to refugee camp, type). Finally, we add interaction terms between bill value, UNRWA contribution and patient contribution with variable T, here represented by Int_{it}, and ϵ_{it} is the error term (all estimations were applied in Stata 14.0 with support from Microsoft Office Excel 2016). In simple differences analysis the event under study must be exogenous to the outcome variables, which is verified in this case as the policy change was an exogenous decision taken by UNRWA.

We use a total population, where the individuals are observed each time they use hospitalization services and it is thus not necessary to use fixed effects methods for the results to be robust. [4] Nonetheless, to avoid heterogeneity issues we use clustered standard errors by hospital in all estimations and robust standard errors for further robustness checks presented in Appendix.

Because we wish to identify mechanisms through which the policy change had an impact on several features of hospitalization services we estimate various specifications of the general model in (2.6), with different estimation methods, depending on the dependent variables.

Dependent variables

The policy change under analysis implied different coverage between hospitals that may have had an impact on the patients's choice. With a complete database of hospitalization cases, every individual episode corresponds to one out of the three hospital types - private, public or PRCS. In this framework, we conducted a multinomial logit model, where the outcome variable is hospital type, a categorical with values from 1 to 3, where 1 corresponds to PRCS, 2 to private and 3 to public hospitals. Following the theoretical reasoning in the previous section, this approach assesses the indirect utility of each alternative, assuming that individuals choose the one that provides the greatest utility.[79] The dependent variable is thus the indirect utility of each choice as a function of individual, hospital and unobserved characteristics. The coefficient estimates give the differential effects of the observed characteristics on utility, from which we compute the average marginal effect of each variable.

The second estimation exercise focuses on measuring the policy impact on the Length of stay (LoS) at UNRWA contracted hospitals for secondary care. LoS is calculated as the number of days between the admission and the discharge date of a given patient and can be considered as a severity indicator in the sense that more severe conditions are associated with longer hospitalization periods. In addition, simultaneously with the policy change, UNRWA also increased LoS monitoring for all patients covered by UNRWA. If this measure was efficient, LoS is expected to decrease in all hospitals, potentially

[4] With a total population we are not using the estimated average, but the true parameter. There is no need to estimate time-varying average treatment effects. [77], [78]

decreasing also bill values for medical cases. To perform this estimation we use a negative binomial regression model, largely used for non-negative integer dependent variables with over-dispersion (variance is more than double of the mean), as it is the case. [80][81] As a robustness check we also perform the same regression using multilevel poisson estimation model, presented in Appendix, section A2.3.

Following this, to understand the financial consequences of these changes we turn our focus to the impact on bill value, UNRWA and patient contribution. The bill value corresponds to the total costs health-care by individual, including the procedure's value, doctors services payment, occupancy and medication expenditures (while hospitalized) or a fixed fee in case of surgery. This value is then presented to the patient, who receives financial support from UNRWA that usually corresponds to a fixed share of the total bill value (in secondary care, the sum between UNRWA and patient contribution is generally equal to the total bill value, with some exceptions for when the patient receives support from a third contributor). These three continuous variables present a left-skewed distribution which is common in health-care costs data due to the presence of few heavy users. [82] In order to properly use the Ordinary Least Squares (OLS) model we performed logarithm transformations so that we can use normally distributed variables. For this set of estimations, in equation (2.6) Y_{it} becomes $log(Y_{it})$. Although this implies a loss of accuracy, this method is widely in used in the literature for these situations and studies have proven its robustness. [83]

2.4 Results

Considering the theoretical framework presented, the empirical results explore whether patients are using services more efficiently after the introduction of 10% co-payment costs for certain hospital types, or whether access to hospital services became more difficult for families with severe health conditions and in financial distress. The estimation results in this section will help us achieve the answers.

Table 2.2 shows the results for the multinomial logit model that measures the impact of each explanatory variable on the probability of going to each hospital type. The Policy coefficient had a positive and statistically significant impact on the probability of an episode happening at a PRCS (demand) and the opposite effect for Private hospitals. Namely, after June 2016 patients were around 18% (p>0.01) more likely to choose a PRCS hospital instead of a private or public hospital (note that because it is a multinomial logit, patients are distributed across the three hospital types, as such when the demand changes for one of them it has to fully compensate in at least one of the others). Regarding public hospitals, the database includes 17,287 observations for PRCS, 7,208 for private and 2,679 for public hospitals. Since this is a complete population dataset and there are significantly fewer public hospitals, demand for these hospitals will most likely be driven by particular reasons such as distance (statistically significant - table B1 in Appendix), which can make patients less sensitive to changes in prices.

Table 2.2: Policy impact estimation on demand for hospital type (Multinomial logit - margins), from April 2016 to October 2017

	(1) PRCS	(2) Priv. Hosp.	(3) Pub Hosp
Policy	**0.180***** **(0.061)**	**-0.147***** **(0.032)**	**-0.033** **(0.065)**
UNRWA contribution	2.880*** (0.678)	−1.819*** (0.404)	−1.061* (0.633)
Bill value	−3.001*** (0.717)	1.880*** (0.430)	1.121* (0.661)
Stay in days	0.022*** (0.008)	−0.017*** (0.006)	−0.005 (0.005)
Surgery	0.098** (0.043)	−0.048 (0.030)	−0.050 (0.031)
UNRWA contr. [(at pol.=0) - (at pol.=1)]	−3.26	2.405	1.324
Stay in days [(at pol.=0) - (at pol.=1)]	−0.069***	0.045**	0.022
Observations	32,810	32,810	32,810

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.
Note: The dependent variables are binary variables with the value 1 if the patient is at each hospital type and 0 otherwise. Note that all patients get treatment, thus for each observation at least one option must be selected. Coefficients show average marginal effects for multinomial logit regression results. Standard errors clustered by hospital in parentheses. Policy is a dummy variable that indicates the period after the last policy change (from June 2016 onwards). These model specifications control for individual and hospital specific variables. Full table in Appendix table .

Apart from the general demand shift, the variable for length of stay has opposite signs between PRCS and the other hospital types. Generally, average length of stay is higher for private hospitals, as more severe episodes require more resources. In fact, a simple mean test shows the average value is 0.7 days lower at PRCS and the difference is statistically significant at 1%. This said, the results from the multinomial estimation show a higher average stay in days at PRCS, as an increase in one day at the hospital makes it 2 percentage points more likely to choose a PRCS hospital. We believe this contradicting result comes from controlling for the variable bill value, which is highly correlated with length of stay (0.8) and is also expected to be correlated with disease severity. In this sense, when controlling for this factor, we can consider that length of stay becomes an indicator of efficiency. Since private hospitals are profit oriented, the length of stay should be closer to the optimal number of days necessary for each procedure, and thus lower compared to other type of facilities. There is also a noteworthy preference of surgeries being performed at PRCS hospitals which can be driving the positive and significant coefficient of average stay in days. As for Bill value and UNRWA contribution, the variables have the expected signs and are statistically significant, in PRCS hospitals interventions are cheaper and UNRWA contributes at 100% for all secondary care costs.

To control for non-linearities in cross-products, the interaction coefficients were computed following Karaca-Mandic et al. (2012).[84] The interaction effect allows both the intercept and the marginal effect (slope) of UNRWA contribution and LoS on the expected probability of the dependent variable to be different before and after the policy was implemented. Due to the model non-linearity the marginal effect is not constant over its entire range. As such, the difference between the marginal effect in both moments gives the change in the conditional probability that the outcome variable is equal to one for a unit change in UNRWA contribution, as the co-payment share changes from zero to 10% (policy variable changes from 0 to 1). Regarding UNRWA contribution, the difference the marginal effect before and after the policy is implemented is not statistically significant, which was expected given that all patients were subject to the policy change. In turn, the difference in the marginal effect of LoS before and after the policy is negative for PRCS and positive for private. This means that the effect of staying 1 additional day at the hospital in the probability of going to a PRCS hospital was 0.7 percentage points lower after the policy was in place. At the same time, for private hospitals, one additional day hospitalized has a more positive impact on the probability of a patient choosing this hospital type, after the policy was implemented. As such, while demand increased at PRCS hospitals and decreased for private, staying longer became less likely to happen at PRCS facilities after June 2016. This may indicate that the increase in monitoring of LoS was successful in reducing inefficiencies at PRCS or that, due to the higher demand, services were forced to reduce hospitalization time for patients.

Because LoS distribution is highly skewed to the right and most patients in this sample stay only one day at the hospital, we divide the sample into two groups: the ones that stay one day at the hospital and the ones that stay at least two (there are only 4 observations that stay less than one day at the hospital and they were excluded for this part of the analysis). Following the results in table 2.3, with this specification, after the policy was implemented the probability of going to a PRCS hospital was higher among episodes with longer stays. Considering the aforementioned high correlation between LoS and bill value, such result follows the theoretical hypothesis that for those which the 10% meant a significant cost (i.e. higher bill values), the policy change had a more significant impact. In the t-tests results of the policy marginal effects (specification 1 and 2) equal to 0.117 and 0.181, respectively, the null hypothesis was not rejected.

Table 2.3: Policy impact estimation on PRCS demand by LoS, from April 2016 to October 2017 (with controls)

	PRCS	
	(1) 1 day	(2) 2+ days
Policy	**0.117*****	**0.181*****
	(0.040)	**(0.056)**
Surgery	0.094*	0.111**
	(0.048)	(0.053)
Bill value	−1.983***	−2.724***
	(0.484)	(0.548)
UNRWA contr.	1.886***	2.641***
	(0.444)	(0.520)
UNRWA contr. [(at pol.=0) - (at pol.=1)]	−2.271	−3.674
Observations	16,851	24,495

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.
Note: Dependent variables in log transformations; Estimations include controls for type of hospital, gender, age, Ramadan and LoS. Standard errors clustered by hospital in parentheses. Policy is a dummy variable that indicates the period after the last policy change (from June 2016 onwards).

Looking at the policy impact on LoS, table 2.4 shows a statistically significant IRR coefficient of 0.860, i.e., after the co-payment was implemented the average number of stay in days changed by a factor of 0.860, *ceteris paribus* (p<0.01). This general decrease of the average length of stay can either be a consequence of the policy change or the increase in monitoring that UNRWA implemented at the time of the policy. In particular, in PRCS the change in control and the introduction of a co-payment have two opposite effects. On one side, average stays should be shorter due to the increase in control, on the other, LoS is expected to increase with demand, especially if that demand shift is driven more by heavy users. Going back to the table, the interaction coefficients between hospital types and the policy are below 1 (relative to PRCS). This means, the average number of days at the hospital per episode was higher at PRCS after the policy being implemented, suggesting evidence that even with higher control, patients seem to have stayed hospitalized at PRCS longer than before (on average).

Table 2.4: Policy impact estimation on Stay in Days (Neg. Binomial - IRR), from April 2016 to October 2017 (with controls)

	Stay in days
Policy	**0.860***** **(0.021)**
Surgery	0.678*** (0.057)
UNRWA contr. × Policy	1.001*** (0.000)
Priv. Hosp × Policy	0.778*** (0.051)
Pub. Hosp. × Policy	0.763* (0.123)
Private hospital	1.363*** (0.105)
Public hospital	1.451*** (0.205)
Regional effect	✓
Constant	2.194 * ** (0.138)
Observations	32,811

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.
Note: Coefficients show Incidence Rate Ratios (IRR) for a negative binomial regression results. Standard errors clustered by hospital in parentheses. Policy is a dummy variable that indicates the period after the last policy change (from June 2016 onward). This model specification controls for individual and hospital specific variables. Full table in Appendix, Table B2.

In what concerns costs, table 2.5 shows that the policy change had no significant direct impact on any of the three outcome variables - bill value, UNRWA and patient contribution. If on one side, UNRWA provided less financial support for patients going to more expensive hospitals, on the other, more people are going to the cheapest option (PRCS). If both effects balance out than the impact on costs is expected to be diminished and potentially not significant. In other words, demand reacted to the policy change by changing their hospital choice, which might have been enough to accommodate the changes in costs.

Table 2.5: Policy impact estimation on Bill value, Patient contribution and UNRWA contribution (OLS), from April 2016 to October 2017 (with controls)

	(1) Patient contr.	(2) UNRWA contr.	(3) Bill value
Policy	**0.091**	**0.002**	**-0.001**
	(0.116)	**(0.006)**	**(0.007)**
Stay in days	-0.031**	0.001	0.011**
	(0.014)	(0.002)	(0.004)
Surgery	-0.082	0.010	0.024**
	(0.060)	(0.010)	(0.010)
Private hosp.	0.569	-0.036	0.076*
	(0.390)	(0.033)	(0.039)
Public hosp.	0.615*	0.024	0.007
	(0.302)	(0.018)	(0.013)
Bill value	1.220***	0.960***	
	(0.058)	(0.013)	
UNRWA contr.			0.983***
			(0.011)
Stay in days × policy	0.015	0.001	-0.002
	(0.015)	(0.003)	(0.003)
Priv. Hosp × Policy	-0.296	-0.073**	0.072**
	(0.249)	(0.035)	(0.035)
Pub. Hosp × Policy	-0.502**	-0.109***	0.110***
	(0.232)	(0.009)	(0.010)
Constant	−12.743***	−6.810***	7.328***
	(0.656)	(0.162)	(0.047)
Observations	12,875	32,810	32,810
R-squared	0.900	0.982	0.983

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.
Note: Dependent variables in log transformations; Estimations include controls for type of hospital, gender, age, Ramadan and LoS. Standard errors clustered by hospital in parentheses. Policy is a dummy variable that indicates the period after the last policy change (from June 2016 onwards).Full table in Appendix, table B3.

That said, in relation to the original research questions, our findings show the introduction of a 10% cost-sharing component for secondary care is a potential instrument for redistributing demand, while it shows low effectiveness for containing costs for the provider. Moreover, other than the introduction of co-payments itself, there are several aspects of the policy implementation process that may be behind this result, from timings to lack of information. Nonetheless, to the extent that the data available allows us to show, the policy impact had very low (if any) impact in terms of costs for UNRWA.

Overall, the demand shift towards PRCS and the increase in LoS control had a relevant impact for patients and healthcare services provision. These changes had contradictory impacts on costs and the overall effect on patient and UNRWA contribution was not significant.

2.5 Conclusion

In this study, we examine the effect of introducing a 10% co-payment in hospitalization costs at private and public hospitals, using a natural experiment setting. We find that, after introducing the co-payment component, the probability of going to hospitals where coverage remained at 100% (PRCS) increased. These findings were stronger when looking at patients with longer lengths of stay. Data demonstrate that the provider (UNRWA) costs did not change after the policy implementation and patients are staying longer at the fully covered and cheaper hospitals.

Building on previous evidence, this study contributes to the contemporary debate on the net impact of implementing health care out-of-pocket payments in complex social and political contexts, such as the one of the Palestine refugees living in Lebanon. The analysis provides a general understanding on the demand for hospitalization in secondary care level and a thoughtful insight on how a particular policy change affected health care services from a *lessons learned* perspective. The outcomes of this project provide evidence on the characteristics and determinants of health care demand in UNRWA contracted hospitals, while indicating the magnitude and direction of the cost-sharing policy impact at different levels, enabling the identification of potential issues and advantages of this type of payment scheme in secondary care hospitalization.

According to the results, UNRWA introducing a cost-sharing component for private and public hospitals lead to a demand re-distribution towards PRCS hospitals, where treatment continued to be provided free of charge. This can mean an efficiency gain in case PRCS are able to answer to a higher demand, but also that access to private and public hospitals is now more restricted. We also found a relevant general decrease on average LoS, which can represent not only the policy change but also the fact that UNRWA increased control on the occupancy at the hospitals. This is evidence that increasing control was effective and may have contributed to avoiding (or decreasing) system over-usage (overutilization of UNRWA services is frequently mentioned as a significant challenge for the health programme in official documents.[85] [86]) On the other side, for PRCS in particular, average LoS increased despite being more controlled. In this context, and following our theoretical assumptions, this provides some evidence that patients in more severe financial situations with more severe conditions were affected by the change in policy and face more constraints to chose public or private hospitals, even if it is their preferred option.

Although we found statistically significant correlations, with this data it is not possible to control for unobservable events happening during the analysis period that could affect the results - conflicts, natural disasters, political crises, etc. As such, one cannot assume direct causality of the policy impact. Additionally, another limitation of this study is that there is not enough data on socio-demographics characteristics or patients benefiting from Social Safety Net (SSN) to understand exactly to what extent the cost-sharing policy is depriving poorest patients from quality health-care. Finally, and probably most importantly, we do not have access to patients health outcomes nor to measures of healthcare service quality. With this information we could have assessed whether there were any signs of overcrowding (or crowding control measures) at PRCS hospitals before and after the policy being implemented. The lack of updated news and information on these hospitals also makes it more difficult to study these services.

Overall, the cost-sharing policy proved to be effective to re-distribute demand across hospital types, indicating that patients are generally price sensitive for secondary care hospitalization services. Nevertheless, the demand adjustment prevented UNRWA from containing more costs than before and the co-payment fee prevented extremely fragile patients from choosing their preferred hospital. This study provides UNRWA with an impact evaluation in-depth exercise, including valuable information on how their policies have an impact in terms of users behavior and cost containment strategies. We believe this analysis can be used for future reference in policy decision making and opens an important precedent of how research and institutions can work together to achieve a greater good for the target population.

Chapter 3

No ordinary leaders and family care

- Evidence from Female-headed households in Palestine Refugee Camps [1]

Abstract

Subject to stigmatization in a community with strong traditional gender roles, female household leaders in Palestine Refugee Camps find themselves with more barriers to provide the basic needs to their families than most. We explore the potential differences in terms of healthcare expenses between male and female-headed households (FHH) in Palestine Refugee camps in Lebanon and make a first approach to assess mental health issues associated with being a female head of household (HoH) in this context. In addition, we measure possible improvements on FHH living standards between 2010 and 2015.

This study produces a deep understanding on the different types of households and of female-headed households, in particular. Data are from AUB Socioeconomic Surveys from 2010 and 2015 with household and individual level information and representative of the refugee population. We perform a cross section analysis using a Two-Part Model (probit and glm) and Propensity Score Matching to understand correlations between household composition and spending decisions, and a probit model to study mental health issues associated with being a female HoH. We also deepen the study on income elasticity to potentially disentangle stigma/preferences effects.

Results show that expenditure in healthcare as a percentage of total spending is 1.4 pp higher for FHH in 2010 ($p<0.05$) and 2.2 pp in 2015 ($p<0.01$). This difference is higher in families headed

[1] with Pedro Pita Barros and Hala Ghattas

by widows or single women. Most mental health indicators are worse for female HoH, of which most are widows. Between 2010 and 2015, female HoH positive feelings indicators show small improvements from one year to the other.

We highlight the need to continue providing financial support to these families, along with a more inter-sectoral approach to protect these families from severe intergenerational psychological damage.

3.1 Background

More than 70 years passed after the entrance of Palestine refugees in Lebanon (PRL), who are still considered as foreigners under the Lebanese law. This status does not grant them any special legal protection and deprives them from economic and human rights, including denial of a permission to work in 39 professions or the right to own property. Most of PRL families still live in precarious conditions and a large share of them still depend on the services of education, social security and health provided by the United Nations Relief and Works Agency for Palestine Refugees in the Near East (UNRWA). [87] Female headed households (FHH) in particular, are a minority of PRL families that, in this context of poverty, have to overcome the cultural and social barriers of ruling a whole family in an extremely patriarchal community.

A recent wave of economics literature has focused on FHH and how they may be subject to a different leadership than most families. [88], [89], [90] This is specially disruptive in societies ruled by strong cultural values that give the default financial responsibility and leadership to the husbands and fathers. Expenditure decisions on health, education or tobacco (and drinking) are all choices typically subject to the influence of the household head (HoH) and that may have long-term effects on the other family members. As such, shifting from the default male leadership, to a woman ruling the household by herself can mean a significant difference in terms of living conditions and well-being. Moreover, since for a large share of FHH the leader is a widow, they also have to overcome all the emotional and financial issues inherent to losing the main income earner.

Having to manage all these challenges creates an extraordinary burden for these household leaders. Studies on food insecurity and health expenditure have shown that females are more likely to show stronger signs of mental distress, compared to male HoH. [91], [92] Having a societal structure that enables mental health issues among a minority is dangerous and can perpetuate structural issues that go beyond financial issues.

In 2010, the AUB Socioeconomic Survey showed that FHH living in Palestine refugee camps were more likely to report severe food insecurity. [93] About 19.2% of FHH experienced severe food insecurity (against 13.8% of MHH) and although they only represent 22.3% of the total population, 30% of households reporting severe food insecurity were FHH. Facing these numbers, together with AUB, between 2010 and 2015, UNRWA changed the policy for distributing the Social Safety Net support (SSN - social protection support for the poorest families) by adding FHH as a relevant criterion to enter the list of beneficiaries. [94] While before FHH were as likely as others to receive this support, now they have better chances. This way UNRWA aimed at improving the fund's effectiveness in promoting equity and fair distribution.

This paper expands knowledge on FHHs in Palestine Refugee camps, starting with the assessment of their budget expenditure patterns and unveiling the factors that make these families different from the rest. In particular, with potential mental health implications for the female HoH here explored. At the same time, this study also analyses potential indicators on whether FHH managed to improve their living standards or changed their preferences after becoming a specific target of UNRWA SSN support. Our findings show that expenditure in healthcare as a percentage of total spending is 1.4 pp ($p < 0.05$) higher for FHH in 2010 and 2.2 pp ($p < 0.01$) in 2015 compared to MHH. However, since women earn less and FHH income is lower, this difference is not enough to achieve the absolute value MHH spend in health. Most mental health indicators are worse for a female HoH and female HoH positive feelings indicators show small improvements between 2010 and 2015. Our study shows that financial support is crucial, but a more intersectoral approach should be considered in order to protect these families from severe intergenerational psychological damage.

The remaining of this study is organised as follows: section 3.2 presents the literature review on the social context of PRL and expenditures and mental health studies; section 3.3 explains the data with focus on topics of interes; 3.4 explains the theoretical approach and econometric models used for this analysis; section 3.5 presents the results, followed by the discussion in section 3.6 and the study limitations in section 3.7, concluding in section 3.8.

3.2 Literature Review

Household expenditure determinants have been a topic of interest for economists for centuries. Several researchers have made important contributions to the understanding of factors associated with consumer choice. [95], [96], [97] Engel suggested that a higher propensity of households experiencing increasing income spend a bigger proportion of the food budget on a diversified diet thus improving the nutritional status of the household members. Engel's original work showed the relevance of income and family size in influencing household expenditure, and later studies confirm that larger families typically have larger budget shares of necessities than smaller families at the same income level. Becker (1965) theory of household production is often used to model household expenditure analysis. [98] The theory extends to consider how households choose the best combination of commodities to maximize utility, while subject to time, resources, and technology constraints. Building on this work, the present study adopts these methods to study differences in household expenditures between FHH and MHH.

Sociology and economics literature have established that historically women and men have different preferences in terms of income expenditures. [99],[100],[101] Moreover, cultural values also have an impact within the family structure and gender roles. [102], [103] Cultures where the family member roles are well established, the HoH is responsible for the household budget and for choosing what is best for every member and thus HoH characteristics and preferences may have relevant consequences on the family well-being. Kennedy and Petters (1992) use data from Kenya and Malawi to evaluate the effects of gender of household head on income, food consumption, and nutrition. [104] Their results suggest that income and gender of the HoH are important determinants of food security and pre-schooler nutritional status. Namely, when income is controlled by women, the household's caloric intake increases. In turn, Akadiri et al. (2017) show evidence that female-headed households in Nigeria and Ethiopia are more likely to experience severe food insecurity, which is very correlated with poverty. [105] This is a cross-sectional study that applies different binary models and finds significant differences in the determinants of food security between male and female HoH. According to this study, female HoH do not manage to benefit as much from improvements in education as the male counterparts. Similar evidence was also found by Mallick and Rafi (2009) in Bangladesh, where the authors also highlight the important role of noneconomic institutions to improve households food security, especially the female-headed ones. [106]

Being HoH is a position of responsibility and leadership that is generally not assumed by choice, but rather by seniority or being the household member that ensures the household income (or a combination of both). Boris et al. (2008) explore mental health and depression among young HoH. [107] The authors find that the Epidemiologic Studies Depression scale for young HoH in Rwanda exceeds the most conservative published cutoff score for adolescents. In the same direction, Audet et al. (2018) conduct a survey across 14 rural districts in central Mozambique in 2014 where 14% of the sample screened positive for depression. [108] While this represents a personal health problem for the HoH, children being raised by a depressed parent/adult tend to develop mental health problems themselves. A 20 and 30-year follow-up study of biological offspring of depressed (high-risk) and non-depressed (low-risk) parents finds that the risks for anxiety disorders, major depression, and substance dependence were approximately three times as high in the offspring of depressed parents as in the offspring of non-depressed parents. [109], [110] In the context of PRL, these children are even more subject to develop depression related diseases due to the economic and social conditions they are living in through their childhood. [111]

The countries covered in the literature above - Kenya, Malawi, Nigeria, Ethiopia, Bangladesh, Rwanda and Mozambique - are all considered as traditionally patriarchal societies, similar to PRL and Palestinians in general. This project contributes to this universe of studies with a detailed description of household typologies present in PRL refugee camps and a thorough study of household expenditure differences at different points in time. Following the evidence mentioned, we also address mental health issues inherent to being a female HoH in this setting. According to the best of our knowledge, having such effects studied in the context of refugees is novel, and likely to be relevant as the number of displaced people in the world is increasing.

3.3 Project description

3.3.1 Data set

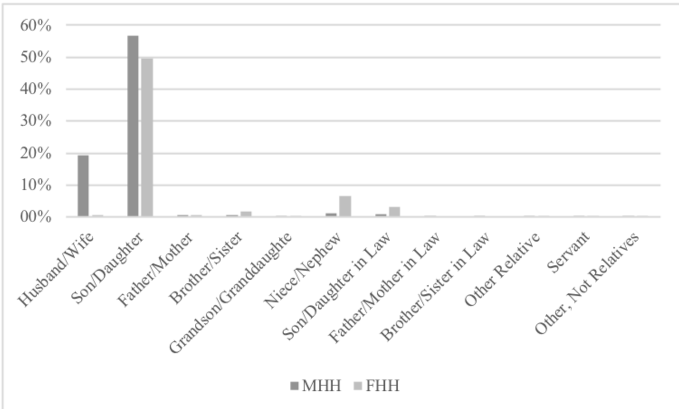
The data are from the AUB socioeconomic survey from 2010 and 2015.[93], [112] This survey includes household and individual level information on Palestine Refugees from Lebanon (PRL), in Lebanon since 1948, and Palestine Refugees from Syria (PRS), that came to Lebanon around 2012 after the Syria crisis. This study is a cross-section analysis restricted to PRL families spanned across 12 refugee camps and areas outside the camps in Lebanon with data on 2,627 randomly selected PRL households in 2010 and 2,974 in 2015. Palestine refugees are distributed over five Lebanese regions, the Beqaa, North Lebanon Area (NLA), Central Lebanon Area (CLA), Saida, and Tyre. Note that since both surveys are 5 years apart and a policy change happened in between through the study we analyse both years separately.

The HoH in this project is the person identified as such by the respondent. This said, the leader is the person seen as the head of the family by the other members, usually the main financial provider and decision-maker of the household. In Muslim societies men are entitled to be responsible for women and children, which means that a female HoH is most likely ruling the family on her own. Of all HoH only 23% in 2010 and 21% in 2015 were women.

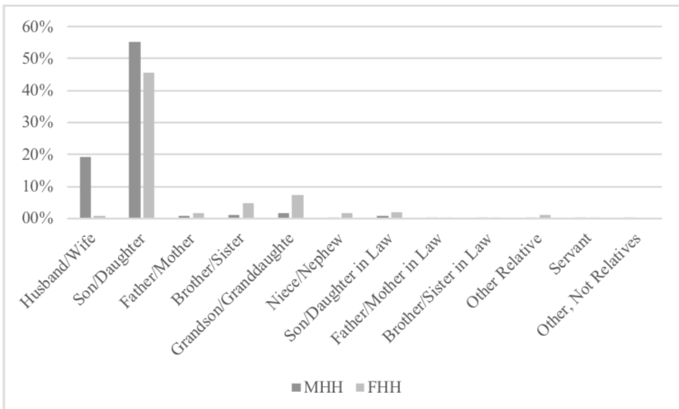
3.3.2 Household typologies

In what concerns household composition, FHH are more diversified than MHH. While MHH are mostly composed by the HoH, the respective wife and sons and daughters, in FHH the share of husbands is almost zero. Female HoH mostly live with their sons and daughters but also with brothers or sisters, nieces or nephews and their son or daughter in law (Figure 3.1). There is also a higher prevalence of chronic disease among FHH for having generally older members.

Figure 3.1: Household composition



(a) 2010



(b) 2015

Note: Data from AUB socioeconomic survey 2010 and 2015. All values were computed using survey weights. We exclude single member households.

Almost all of men HoH are married in both survey years, while the women's marital status changed between both years. The share of single women HoH increased (6 pp) and of being a widow or separated decreased (8 pp) between 2010 and 2015. The traditional family in this sample is larger than the typical FHH. On average, in a MHH there are 5 to 6 sons/daughters with an average age of 15 years old, against 4 to 5 in FHH with an average of 28 years of age. This is interesting as in these families daughters/sons already reached the adult age, but the role of HoH remains with the mother.

Other important differences between both types of HoH are the participation in the labour market and education level. In FHH, the ratio working-to-not-working members is 0.42, against 0.56 for MHH. In addition, almost half of female leaders did not attend education, which is a very high percentage compared to that of men (Table 3.1) - even taking into account the age difference. Household expenditure is lower in FHH, but the differences are smaller in 2015 and the share of FHH with access to UNRWA social support is relatively higher than that of MHH. This higher share of social support to FHH in 2015 can be a result from the increase in the UNRWA efforts to support FHH in particular, following the report from AUB socieconomic survey 2010.

Table 3.1: Descriptive statistics for head of households (AUB Socioeconomic Survey)

	2010		2015	
	Men	Women	Men	Women
Age	49.55	63.02	49.46	61.14
	(14.48)	(13.14)	(14.10)	(13.95)
Marital Satus				
- Single	0.02	0.10	0.02	0.16
- Widow	0.02	0.73	0.02	0.65
- Married	0.89	0.08	0.87	0.11
SAH	0.73	0.53	0.73	0.58
CLA	0.21	0.19	0.23	0.28
Log (HH exp)	6.77	6.33	6.96	6.60
	(0.57)	(0.73)	(0.63)	(0.68)
Social Safety Net	0.31	0.57	0.36	0.54
Education				
- None	0.08	0.47	0.06	0.39
- Elementary	0.39	0.31	0.37	0.30
- Preparatory	0.29	0.14	0.32	0.20
- Secondary	0.09	0.05	0.10	0.06
- Vocational	0.07	0.02	0.06	0.02
- University	0.08	0.01	0.08	0.04
- Post-graduate	0.00	0.00	0.01	0.02

Standard errors for continuous variables in parentheses. Note: Except for age and household expenditure, all variables are binary variables. Values of dummy variables indicate the percentage relative to female or male HoH. All values were computed using AUB Socioeconomic Survey survey weights.

To explore further this subject, we look into differences in average income between female and male HoH. Note that since remittances from abroad, informal jobs and financial aid also provide income, even those who do not engage in work may have some income level. Work is measured as a self-reported variable of whether the respondent has engaged in some form of work during the last week. Table 3.2 shows average income of HoH depending on employment status and gender.

Table 3.2: Income differences between male and female HoH, by year

2010	**Employed**		**Unemployed**	
	Male HoH (I0)	Female HoH (I1)	Male HoH (I2)	Female HoH (I3)
Monthly income (USD)	529.5	322.2	418.1	299.7
Gender gap (I0 - I1)		207.3		
Unemployed gap (I2 - I3)				118.3
2015	**Employed**		**Unemployed**	
	Male HoH (I0)	Female HoH (I1)	Male HoH (I2)	Female HoH (I3)
Monthly income (USD)	628.7	423.8	464.2	398.9
Gender gap (I0 - I1)		204.9		
Unemployed gap (I2 - I3)				65.3

An employed man HoH in 2010 earned on average 111.4 USD more per month than an unemployed peer. At the same time, an employed woman HoH only earned 22.5 USD more than as if she was not working. The figures show similar tendencies in 2015. From unemployment to employment men manage to earn on average 164.5 USD more per month, whereas women earn only 29.4 USD, with an around 50% of jobs being full time for both genders. These simple calculations raise a strong argument that women not only earn less on average, but also that their marginal gain with engaging in some kind of work is much lower than that of men. The low participation and lower wages among women in the labour market illustrate the large gap and inequalities in this sample. Since work opportunities and marginal gain can be related to gender, age and other factors it would be interesting to study the mechanisms behind these differences more in depth in future research.

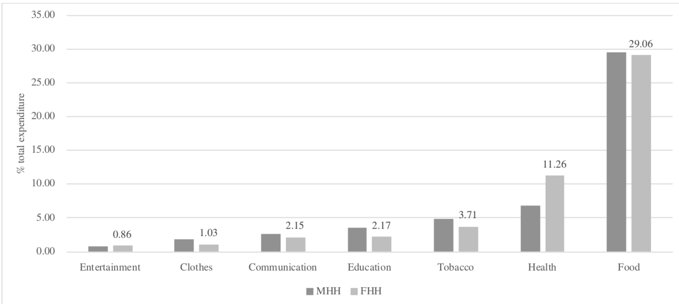
3.3.3 Preferences and mental health

Taking into account the different household compositions that characterize FHH and MHH, let us now look into average changes in expenditures and mental health indicators, which will be the focus of the econometric analysis that follows.

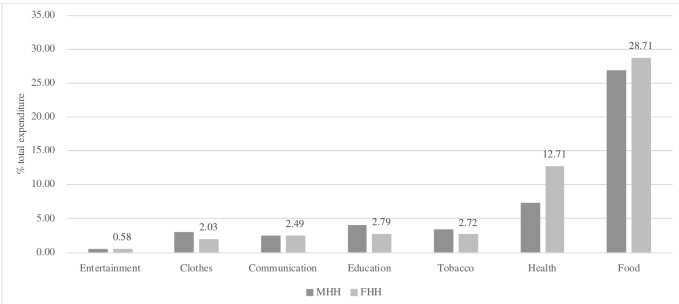
Figure 3.2 shows the percentage of total household expenditure spent in different categories and divided by MHH and FHH. While FHH spend more of their household expenditure on health, the average share spent with education is higher for MHH in both years. Since FHH are generally older, these differences can reflect logistics associated to the household demographic composition rather than preferences. Tobacco expenditure is higher in male headed households for both years and in 2015 MHH are spending a lower share of total expenditure on food.

In absolute values, the average total expenditure per month was approximately USD 1063 and USD 1302 for MHH in 2010 and 2015, while FFH lived with an average of USD 907 and USD 1129 in 2010 and 2015 (excluding single-member families).

Figure 3.2: Household expenditure by category as % of total



(a) 2010



(b) 2015

Note: Data from AUB socioeconomic survey 2010 and 2015. All values were computed using survey weights. We exclude single member households.

The mental health indicators included in this study consist in a set of five binary variables that correspond to feeling calm, happy, depressed, angry or upset. Each variable obtains the value 1 if the respondent had that feeling at least some of the time, and 0 otherwise. Looking into the averages in our sample, there are less female HoH reporting to be happy and calm. The share of male HoH reporting to be happy went from 53% in 2010 to 46%

in 2015 while in 2010 only 40% of female leaders were happy, which dropped to 36% in 2015. Women also report feeling more upset on average, but less angry in both years.

In 2010 the survey was conducted between July and August and in 2015 during April, all warm months outside the Ramadan period, which should not make a significant influence on the responses regarding mental health.

3.4 Methods

3.4.1 Demand for Healthcare - Theoretical Approach

To understand the HoH decision process, let us follow basic economic theory to describe how individuals' preferences determine their demand for healthcare (services and products).

Consider the vector of goods X to be all goods other than health care and the vector H to represent health care services and products consumed. All other goods and services include tobacco, education, food, etc.

Households' preferences (decided by the HoH) can be characterized as $U(X, H)$. This utility function is increasing and concave in goods and healthcare consumption. With this framework, utility increases with consumption, but the marginal increase is lower as consumption increases. Each household leader would like to maximize their household utility, subject to how much of disposable income they have available. With the price of healthcare given by p_h and that of all other goods as p_x, the budget constraint of each household, i, is just $m = ph.h + px.x$, where m is the household income.

Following, the maximization problem is given by:

$$Max\, U(X, H)\; s.t.\; m \leq ph.h + px.x \tag{3.1}$$

In this specification, patients chose the affordable bundle of healthcare and all other goods that maximizes their utility. The affordable set is such that the total expenditure cannot exceed the available income, $m \leq ph.h + px.x$. The equilibrium condition, given by the first order conditions, is the marginal rate of substitution between the consumption of health care and all other goods and services. Assuming households do not save any income at any period of time, their well-being is maximized when their income is completely spent on both types of goods.

FHH Preferences

Previous literature has evidenced that the role of HoH managing the family budget is extremely relevant. [113],[114],[115] Characteristics such as services availability or illness severity can have a negative or a positive impact on health care spending. When it comes to gender, specially in a typically patriarchal society, when a woman becomes the leader of the household the decision maker's preferences change and so does the optimal bundle that maximizes their household utility. Following the evidence from previous studies and the data analysis in section 3.3, this translates in an increased preference for spending more on healthcare in exchange for a larger sacrifice of other goods. The FHH's utility will thus have a marginal rate of substitution different from that of the other households. The balance between this and the income effect explained in the next paragraph will inform the household's optimal bundle.[2]

FHH Income Effect

For both survey years under analysis, FHH had lower disposable income and expenditure levels than that of MHH. While we cannot precisely understand why this happens, it can be associated with the presence of stigma against women in the market, female HoH being less physically strong for some types of job or having less time to dedicate to their profession.

In our sample, most of the employed participants have elementary occupations like street vendors, building caretakers or garbage collectors. Among HoH, 36.14% of males and

[2]See Appendix, sectio A3.1 for a detailed description.

43.75% have this type of occupation. The second most common job for male HoH is crafts and trade worker, while for female is service workers. In terms of hours worked per week, men HoH worked on average around 8h more than women. These differences in terms of occupation can contribute to the wage gap, along with stigma. In fact, they can be extremely correlated. If women are not able to access the most highly paid jobs due to stigma, they will have to work in professions earning less. At the same time probably they cannot work as many hours as men because responsibility at home is not shared equally between male and female members, which is also associated with gender inequalities. For a matter of simplicity, throughout this study we will use the word stigma, bearing in mind that it can incorporate many other factors that are directly or indirectly related to it.

Literature on the impact of stigma, for example HIV-related studies, include stigma as a determinant of income in the sense that it reduces the HoH opportunities of finding a job. [116] As income decreases, the less choices they have available to consume. This can mean a decrease in the healthy choices available, both in terms of food and in terms of health care services. Holding all else constant, a lower income implies a decrease in the budget set, and consequently leads the household to consume less of goods and services, including healthcare. Consider a new budget constraint as:

$$Max\ U(X, H)\ s.t.\ m = ph.h + px.x - s.m \tag{3.2}$$

Where s is the stigma variable ($s \in [0, 1]$), that represents the fraction of income that is negatively affected by stigma if the HoH is female. [3] Thus, compared to the other households, FHH suffer a negative shock on income, that leads to less freedom of choice and worse general well-being.

The remaining of the study estimates statistically significant differences between MHH and FHH in terms of budget management and mental health indicators, using this theoretical background as an important guide through the HoH decision process.

Our hypothesis is that women HoH prefer to spend a larger share of their household budget on healthcare, however that does not translate into better end health outcomes, as other

[3] Note that if m resulted from work this would be a gender gap, but is not restricted to wages here.

elements change at the same time (with an eventual negative impact on health). FHH have lower income available, live in worse conditions and with tougher mental health challenges than the other households. Understanding this mechanism will help explaining what it means to belong to a FHH and inform public policy.

3.4.2 Econometric models

Engel curves

To identify patterns and determinants of household expenditure between MHH and FHH we estimate Engel curves for each household expenditure category using Locally Weighted Regressions. [117] This non-parametric method is based on fitting a linear model to observations in a neighbourhood of a point to estimate the relationship between the share of household expenditure on a particular good and the logarithm of total income or expenditure. The result is a set of graphical analysis that sheds light on different trends of expenditures in health, tobacco, education and food.

Two-part model

There is a vast literature on models for identifying the expenditure determinants. Since our dependent variables are continuous, a simple linear model could be a good first-guess. However, proportions of total expenditure are generally extremely skewed, for which the OLS estimator may not be the most efficient. [118]

In our study sample, around 26% of the individuals belong to households with no healthcare expenditure, 37% with no tobacco expenditure and more than 50% with no education expenditure. Regarding food, education, health and other public services, UNRWA provides part of these services free-of-charge, which explains the distributions. In these cases, literature considers that two-part models as the best fit for these data. [119] A two-part model is designed to estimate variables that have a significant number of observations in the lower bound (zero). Using these models, in the first part, we estimate the variables related to any healthcare expenditure (logit binary model) and in the second part, the model measures factors associated with the quantity of expenditure conditional on the existence of some expenditure (glm). Following Belotti et al. (2014), the general form of a two-part model can be written as follows:

$$E[y|x] = Pr(y > 0) \times E[y|y > 0, x] \tag{3.3}$$

where y is the dependent variable of interest and x is a set of covariates, as aforementioned. [118] The first part of the model is estimated a model for the probability of a positive such as:

$$\Phi(y > 0) = Pr(y > 0|x) = F(x\delta) \tag{3.4}$$

where x is a vector of explanatory variables, δ is the corresponding vector of parameters and F is the cumulative distribution function of an i.i.d. error term, typically chosen to be from the standard normal (probit) or logistic (logit) distributions. For the positive expenditure value, the model can be represented as:

$$\Phi(y|y > 0, x) = g(x\gamma) \tag{3.5}$$

where γ is the vector of parameters of x to be estimated, and g is an appropriate density function for $y|y > 0$. We use the same covariates x for both parts of the model, assuming all of them may affect both parts to some extent. Nonetheless, there are conceptual differences that could justify using a different set of variables in each part. In this case, one can expect that variables like age, household size and having children would be more related to the binary choice part (to spend or not). The youngest and the eldest in the sample are more likely to be sick and to need care, thus having a family member in these groups means having to use health services almost certainly. At the same time, age does not carry a lot of information on how much care each member needs. Health status related variables, like having a chronic condition, would thus be a better candidate to predict the continuos part (how much to spend). While we use the same variables in both parts, we will take these differences into account when discussing the results.

Our estimation uses a logit function for the first part and for the positive part a generalized linear model (GLM) with logarithm function and $Gamma$ distribution, which essentially corresponds to a linear regression via maximum likelihood, commonly used for positive, continuous variables with positive variance. [120]

Propensity score matching

Comparing MHH and FHH is challenging not only for their intrinsic differences, but also because FHH are a minority in the community. This said, we develop a Propensity Score Matching model (PSM) to find similar groups between FHH and MHH within the sample and improve the statistical validity of this comparison. Both groups are comparable in terms of age average, per capita expenditure (in logarithm), area of residence, household size, chronic and acute illness indicators, having direct family abroad and living in a refugee camp.

This model constructs a statistical comparison group based on a propensity score that indicates the probability of being in the treatment or the control group, using observed characteristics. In this case, for the purpose of adapting our study to the model, we consider being a member of a FHH as a natural "treatment" and thus consider MHH as the "comparison group". What we aim at measuring is the average effect of belonging to a FHH, by computing the mean difference in previously selected outcome variables. Using this method, we assume that there are no unobserved factors affecting participation - i.e., being a member of a FHH cannot change due to unobserved factors - and that we are able to find an overlap in the probability of belonging to a FHH across the FHH and MHH in the sample. [121]

To apply the PSM model we start by defining the optimal bandwith and deriving the matching weights with kernel matching. Since we need to include survey weights we then combine matching with survey weights to achieve the final weights. After confirming that the after matching samples are balanced among the covariates chosen, we compute the mean differences between FHH and MHH using a two-part regression model.

Probit

The final estimation exercise consists in a Probit model to estimate the determinants of mental health indicators: feeling, happy, calm, angry, upset and depressed explained in section 3.3. For this purpose, we perform a non-linear Probit model, which follows the expression in equation (3) of the Two-part model.

Results for the Probit model will be presented as marginal effects, which give us the impact (in pp) of a one unit change in the explanatory variables on the probability of the dependent variable being equal to one. We now study indicators of the HoH, instead of household level, as before.

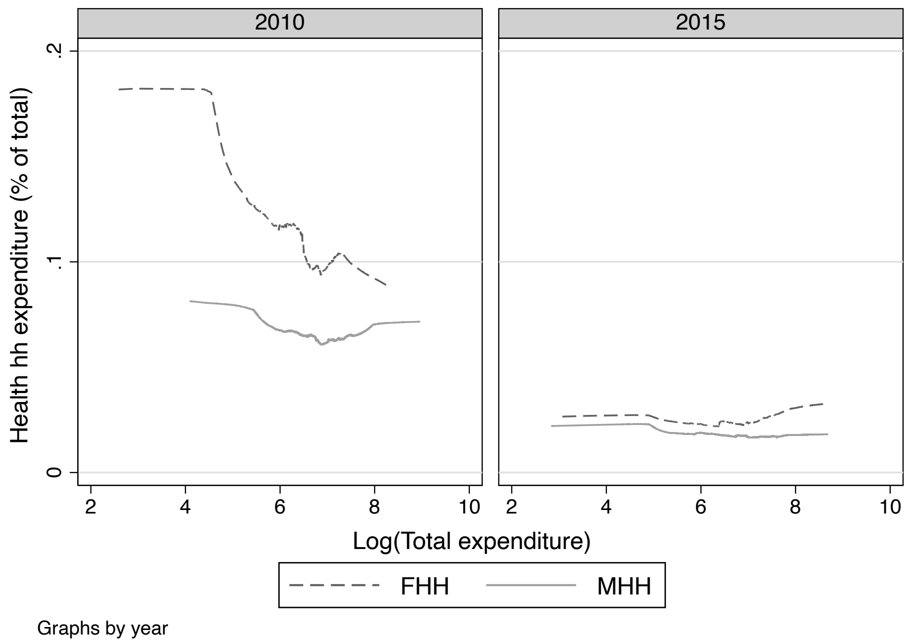
3.5 Results

3.5.1 Engel curves

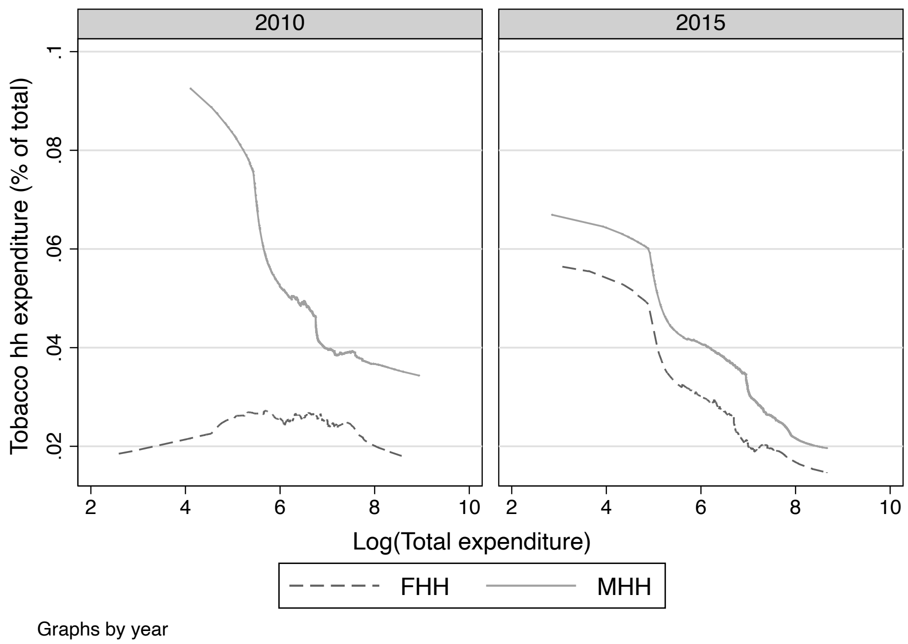
Figures 3.3 and 3.4 show the Engel curves for FHH and MHH for both survey years, 2010 and 2015. There is a clear difference between the FHH and MHH curves for health and tobacco expenditure. At the same levels of expenditure, FHH spend consistently a larger share of their budget on health and smaller on tobacco when compared to MHH. The differences are higher for poorer households as curves seem to converge with higher expenditure levels.

Looking at differences over-time, from 2010 to 2015, FHH with the highest level of expenditure increased the share spent on health and decreased the share spent on education. For FHH that reported lower expenditure levels, the share spent on tobacco in increased considerably from one year to the other. From 2010 to 2015 besides the difference between FHH and MHH being reduced, both groups decreased their expenditure in healthcare (both curves are at a lower level).

Figure 3.3: Share of HH expenditure vs. Total expenditure (log), by category as % of total - Health and Tobacco



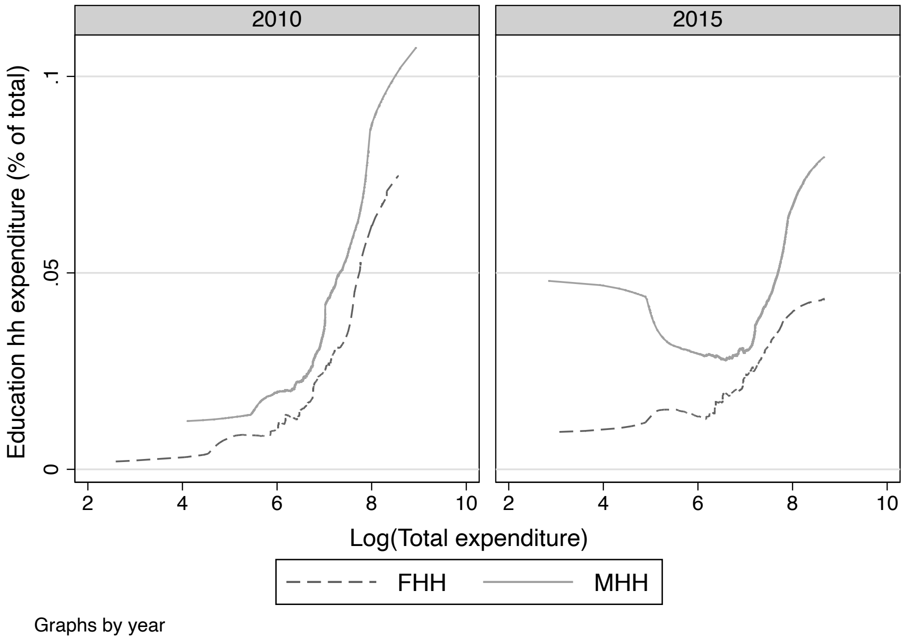
(a) Health



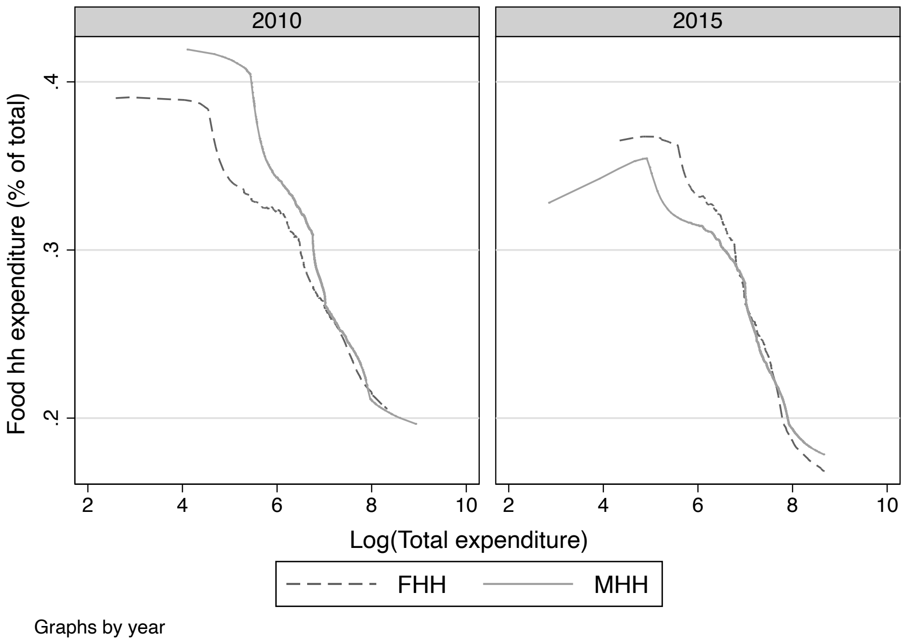
(b) Tobacco

Note: Data from AUB socioeconomic survey 2010 and 2015. All values were computed using survey weights. We exclude single member households.

Figure 3.4: Share of HH expenditure vs. Total expenditure (log), by category as % of total - Education and Food



(a) Education



(b) Food

Note: Data from AUB socioeconomic survey 2010 and 2015. All values were computed using survey weights. We exclude single member households.

3.5.2 PSM model

The PSM two-part model results in tables 3.3 and 3.4 show the intensive, extensive and overall marginal effects for health, tobacco, education and food expenditure as a percentage of total household expenditure (see complete table in Appendix, section A3.2).[4] The overall margin is a combination between the marginal effects from both the probit and glm model, the intensive and extensive margin, respectively. The intensive margin represents the impact on the probability of spending any share of total expenditure, while the intensive margin shows the impact on the share of total expenditure spent in each category. Following the estimation, being in a FHH is related to higher relative levels of healthcare expenditure compared to MHH.

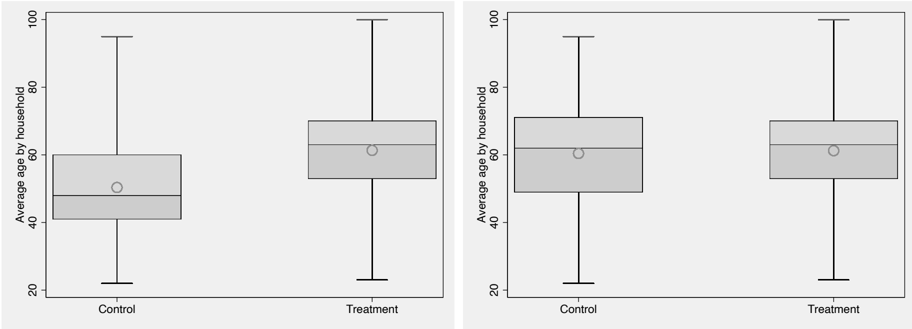
The covariates used in the PSM model include age average at household level, household per capita expenditure (in logarithm), area of residence fixed effects, along with a series of binary variables indicating: a household with more than 4 members in 2010 and 3 members in 2015 (the average household sizes for FHH in each year), at least one household member with a chronic disease, an acute disease, children, being below the low poverty line, having direct family living abroad and living in a refugee camp.

The resulting groups, one with female ("treatment") and another with male leadership ("comparison group"), are comparable - i.e., are similar in average values, in terms of the above mentioned characteristics. The results that follow show the Average Treatment Effect (ATE) of living in a FHH in the share of total household expenditure spent in each category - health, education, tobacco and food.

Figures 3.5 and 3.6 show before and after matching values for the age average by household for 2010 and 2015. After matching values are achieved using the weights found with the PSM model. To estimate the mean differences in outcomes after matching we perform a two-part model, similar to the one in the previous section.

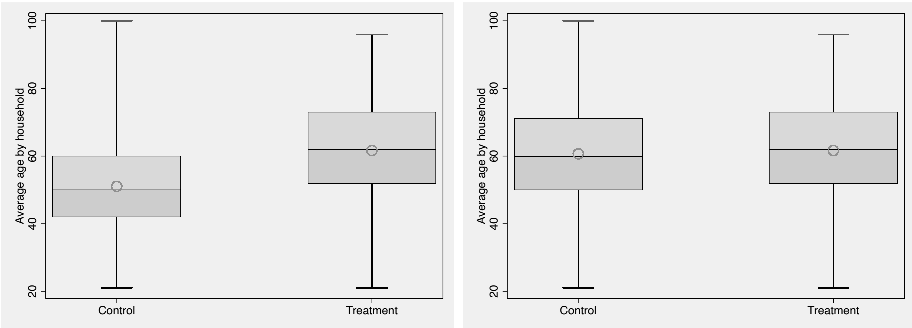
[4] Note that these do not add up to 100% because of other categories, like communication, clothes, entertainment that are not studied in this project, due to lack of consistent data.

Figure 3.5: Average age by household in 2010



(a) Before matching **(b)** After matching

Figure 3.6: Average age by household in 2015



(a) Before matching **(b)** After matching

Note: Data from AUB socioeconomic survey 2010 and 2015. All values were computed using survey weights. We exclude single member households. Results for household expenditure in Appendix, Figure 4.6 and 4.7

Table 3.3 shows the coefficients and marginal effects for both parts of the two-part model and the overall treatment effect using PSM weights for health and tobacco expenditures.

FHH spend on average 1.4 percentage points more of total household expenditure on health than MHH in 2010 ($p<0.05$) and this impact increases to 2.2 pp in 2015 ($p<0.01$). The PSM results indicate that the difference between FHH and MHH is significant only in terms of the share of total expenditure spent, an important difference from the results found with the previous model. This means, both FHH and MHH dedicate part of their household expenditure to health care, but FHH spent a larger share of their expenditures.

In 2010, FHH spent 1.6 pp less of their household expenditure on tobacco than MHH and 0.6 pp less in 2015. Moreover, being in a FHH decreases the probability of spending any part of household expenditure in tobacco by 17.3 pp in 2010 and by 12 pp in 2015.

Table 3.3: PSM ATE results - Health and Tobacco expenditure

	2010					
	Health expenditure			Tobacco expenditure		
	(1)	(2)	(3)	(4)	(5)	(6)
	Probit	GLM	Overall	Probit	GLM	Overall
Treated	0.090	0 .158**		-0.498***	-0.114	
(coef.)	(0.101)	(0.076)		(0.087)	(0.112)	
Treatment effect	**0.023**	**0.020****	**0.014****	**-0.173*****	**-0.023*****	**-0.016*****
(margins)	**(0.025)**	**(0.010)**	**(0.006)**	**(0.030)**	**(0.004)**	**(0.005)**
Observations			9933			10257
Pseudo R-squared			0.148			0.108
Log-likelihood			7.986			7.167
	2015					
	Health expenditure			Tobacco expenditure		
	(1)	(2)	(3)	(4)	(5)	(6)
	Probit	GLM	Overall	Probit	GLM	Overall
Treated	0.038	0.290***		-0.320***	-0.109	
(coef.)	(0.117)	(0.068)		(0.092)	(0.079)	
Treatment effect	**0.009**	**0.031*****	**0.022*****	**-0.120*****	**-0.010*****	**-0.008*****
(margins)	**(0.026)**	**(0.009)**	**(0.006)**	**(0.035)**	**(0.003)**	**(0.003)**
Observations			10375			11192
Pseudo R-squared			0.136			0.0459
Log-likelihood			9.373			9.724

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.

Note: Data from AUB SE 2010 and 2015, using survey weights. All specifications include controls for household age average, per capita expenditure by household (in log), having at least one chronic/acute disease, having 1 child, more than 4 (3 for 2015) people living in the household, having direct family working abroad, living in a camp, having insurance and region.

Table 3.4 holds the results for education and food household expenditures. While most coefficients on education expenditure are not statistically significant at 5%, belonging to a FHH in 2015 is associated with an increase in the probability of spending any share of total expenditure on education by about 1.4 pp, statistically significant at the 10% level. As for food expenditure, belonging to a FHH does not have a statistically significant impact on the share of household expenditure spent with food compared to MHH.

Table 3.4: PSM ATE results - Education and Food expenditure

	2010					
	Education expenditure			Food expenditure		
	(7)	(8)	(9)	(10)	(11)	(12)
	Probit	GLM	Overall	Probit	GLM	Overall
Treated	-0.178*	-0.049		-0.180	-0.002	
(coef.)	(0.097)	(0.119)		(0.238)	(0.032)	
Treatment effect	**-0.047***	**-0.010****	**-0.007**	**-0.003**	**-0.001**	**-0.001**
(margins)	**(0.025)**	**(0.005)**	**(0.005)**	**(0.004)**	**(0.009)**	**(0.009)**
Observations			10588			10578
Pseudo R-squared			0.196			0.274
Log-likelihood			-0.824			4.072

	2015					
	Education expenditure			Food expenditure		
	(7)	(8)	(9)	(10)	(11)	(12)
	Probit	GLM	Overall	Probit	GLM	Overall
Treated	-0.078	-0.054		-0.232	0.048	
(coef.)	(0.119)	(0.173)		(0.326)	(0.033)	
Treatment effect	**-0.020**	**-0.003**	**-0.004**	**-0.002**	**0.012**	**0.012**
(margins)	**(0.030)**	**(0.009)**	**(0.007)**	**(0.003)**	**(0.009)**	**(0.009)**
Observations			11132			8930
Pseudo R-squared			0.228			0.377
Log-likelihood			-0.362			5.911

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.
Note: Data from AUB SE 2010 and 2015, using survey weights. All specifications include controls for household age average, per capita expenditure by household (in log), having at least one chronic/acute disease, having 1 child, more than 4 (3 for 2015) people living in the household, having direct family working abroad, living in a camp, having insurance and region.

Between 2010 and 2015, the overall impact of FHH spending a larger share of expenditure in health increases in 8 pp. On the other hand, the difference between both household groups in terms of tobacco expenditure reduced from one year to the other. As for education and food, we could not find strong differences between household types nor changes in coefficients between survey years.

Tables C9 and C10 in Appendix show similar results using a GLM model without using the PSM weights.

Effects on health expenditure

The distinction between extensive and intensive margin using PSM shows that both MHH and FHH spend part of their budget on healthcare services and thus, the difference between both groups is not so much a matter of 'if', but rather of 'how much' to spend on healthcare.

To further investigate these differences, we used some descriptive statistics and basic calculations. Let us assume a random distribution of illness across the population and that each household will spend a given amount, h, of their budget to pay for treatment. Consider m to be the MHH income and that the share of MHH budget spent on healthcare expenditure is given by h/m. From Table 3.1, in 2015 FHH earnings were 67.4% of that of MHH. FHH income can thus be defined as αm, where $\alpha = 0.674$ and, from Figure 3.2, we have that $h/m = 0.08$. In this framework, the difference between both household groups in terms of healthcare spending as percentage of total income can be given by:

$$\Delta = \frac{h}{\alpha m} - \frac{h}{m} = \left(\frac{1}{\alpha} - 1\right) \times \frac{h}{m} \Rightarrow \Delta = \left(\frac{1}{0.674} - 1\right) \times 0.08 \Rightarrow \Delta = 0.039 \quad (3.6)$$

Without controlling for anything else, if MHH and FHH spent a fixed amount of money on healthcare, FHH would have to spend around 4% more (of their budget) than MHH to match that value. From Figure 3.2, Δ is in fact 0.047 ($0.127 - 0.8 = 0.047$), which is 0.7% more than if the difference in spending were proportional to income. However, the PSM estimates show that in 2015 FHH were associated with a share of health care spending just 2.2 pp above the other families (Table 3.3).

Comparing the estimation value with the mechanical difference one could think that either FHH prefer to spend less than MHH on healthcare or, because their income is lower, the trade-off between different household spending categories leads FHH to spend less than proportionally on healthcare - high income elasticity.

To achieve a parametric version of what is potentially being captured by the PSM, we can estimate the share of income spent on health care as a function of all income related variables. As such, consider a health care demand function $h = f(m, p_x, Z)$ such that $p_x \frac{h}{m} = \theta$ is the share of total income spent on healthcare. We then estimate θ as a function of a trans-log approximation to m. To test income elasticity directly, we also interact the FHH binary indicator with each income-related variable. For a matter of simplification, the cross quadratic terms were set to zero.

As the income elasticity is not constant in this setting, and controlling for all income effects, having a less elastic demand and a larger budget share spent on health care corresponds to a stronger preference for spending more on healthcare. Results in Table 3.5 show that FHH are associated with a share of healthcare expenditure about 3.2 pp larger that the counterparts. At the same time, FHH elasticity coefficients of interaction with age and household size are negative and statistically significant at 5% level.

From the above results, FHH spend less (than MHH) in health care due to income reductions associated with being FHH, even if they have a stronger preference for health. We thus find, in this setting, that the stigma effect mentioned in section 3.4 would surpass that of FHH preferences.

3.5.3 Mental Health

Focusing on the role of female HoH, we conduct a set of five probit models to study each mental health outcome. The results are presented on Table 3.6.

In general, being a woman or a HoH are associated with positive impacts on the mental health indicators selected. At the same time, being a woman and HoH is associated with a lower probability of feeling happy and calm and a higher probability of feeling upset and depressed. These women were 12.2 pp and 7.7 pp less likely to feel happy in 2010 and 2015 ($p<0.05$). Receiving SSN support, which half of FHH do (54%), is also associated with a negative impact on most mental health outcomes. Since SSN families are the most fragile ones (according to UNRWA's criteria), these poorer mental health outcomes may result from living in very bad conditions, making being SSN beneficiaries highly related to

Table 3.5: Linear regression on the share of health care expenditure - using translog

HC expenditure as % of total budget	(1)	(2)	(3)
FHH	0.035***	0.032***	0.032***
	(0.007)	(0.008)	(0.008)
Ln monthly income	-0.013***	-0.012***	-0.011***
	(0.004)	(0.004)	(0.004)
Ln monthly income × Ln age	-0.006	-0.006	0.001
	(0.005)	(0.005)	(0.005)
Ln monthly income × Ln hhsize	-0.021*	-0.025*	-0.011
	(0.013)	(0.013)	(0.014)
Ln monthly income × Ln educ level	-0.005	-0.006	-0.006
	(0.006)	(0.006)	(0.007)
Year × Ln monthly income	0.009	0.008	0.006
	(0.013)	(0.013)	(0.014)
Ln monthly income × FHH		-0.007	-0.016
		(0.009)	(0.012)
Ln monthly income × Ln age x FHH			-0.043**
			(0.017)
Ln monthly income × Ln hhsize x FHH			-0.046*
			(0.027)
Ln monthly income × Ln educ level x FHH			-0.006
			(0.015)
Year x Ln monthly income × FHH			0.017
			(0.031)
Constant	0.051***	0.051***	0.051***
	(0.004)	(0.004)	(0.004)
Observations	16,819	16,819	16,819
R-squared	0.068	0.068	0.070

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses
Note: Data from AUB SE 2010 and 2015, using survey weights. The complete table is presented in Appendix - table C11

poor mental health outcomes in general.

Between both survey years, while positive feelings such as happiness and feeling calm improved, in 2015 female HoH were 10.5 pp more likely to feel upset (p<0.01) and 8.9 pp more likely to feel depressed (p<0.05).

An additional specification is added to control specifically for female HoH who are also widows. Assuming that the female HoH in this situation would not be leading the family in case the husband would still be alive, results presented in table 3.7 show some evidence that this group can be driving the negative impact on the mental health for female HoH.

Table 3.6: Probit results - Mental health (marginal effect)

			2010		
	Happy (1)	Calm (2)	Angry (3)	Upset (4)	Depressed (5)
Woman	0.072***	0.049**	-0.005	-0.022	-0.036*
	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)
HoH	0.113***	0.086***	0.006	-0.051**	-0.053**
	(0.021)	(0.021)	(0.021)	(0.022)	(0.022)
Female HoH	**-0.122*** **	**-0.073** **	**0.001**	**0.022**	**0.032**
	(0.037)	**(0.037)**	**(0.034)**	**(0.038)**	**(0.037)**
Chronic	-0.097***	-0.096***	0.066***	0.095***	0.061***
	(0.017)	(0.017)	(0.016)	(0.017)	(0.018)
Acute	-0.062***	-0.074***	0.068***	0.082***	0.033*
	(0.018)	(0.018)	(0.016)	(0.018)	(0.018)
SSN	-0.111***	-0.169***	0.025	0.044	0.091***
	(0.027)	(0.026)	(0.025)	(0.028)	(0.027)
Obs.	7,748	7,748	7,748	7,748	7,748
Pseudo R-sq.	0.0506	0.0478	0.0307	0.0275	0.0304
			2015		
	Happy (1)	Calm (2)	Angry (3)	Upset (4)	Depressed (5)
Woman	0.076***	0.046**	0.014	-0.083***	-0.075***
	(0.020)	(0.020)	(0.019)	(0.019)	(0.020)
HoH	0.089***	0.058***	0.034	-0.080***	-0.058**
	(0.022)	(0.023)	(0.021)	(0.022)	(0.023)
Female HoH	**-0.077** **	**0.041**	**-0.030**	**0.105*** **	**0.089** **
	(0.038)	**(0.040)**	**(0.034)**	**(0.037)**	**(0.040)**
Chronic	-0.071***	-0.089***	0.048***	0.067***	0.072***
	(0.017)	(0.017)	(0.016)	(0.017)	(0.017)
Acute	-0.069***	-0.091***	-0.007	0.037*	0.004
	(0.020)	(0.020)	(0.019)	(0.020)	(0.020)
SSN	-0.112***	-0.101***	0.077***	0.126***	0.093***
	(0.027)	(0.027)	(0.025)	(0.026)	(0.026)
Obs.	8,082	8,082	8,082	8,082	8,082
Pseudo R-sq.	0.0351	0.0367	0.0223	0.0384	0.0308

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses
Note: Data from AUB SE 2010 and 2015, using survey weights. All specifications include controls for age household size, being married, per capita expenditure (in log), a direct member living abroad, living in a camp, working and region fixed effect.

Table 3.7: Probit results - Mental health (marginal effect), trauma specification

			2010		
	Happy	Calm	Angry	Upset	Depressed
	(1)	(2)	(3)	(4)	(5)
Woman	0.068***	0.049**	-0.006	-0.019	-0.034*
	(0.018)	(0.019)	(0.018)	(0.019)	(0.019)
HoH	0.112***	0.086***	0.005	-0.050**	-0.052**
	(0.021)	(0.021)	(0.020)	(0.022)	(0.021)
Female HoH	**-0.108****	**-0.118****	**0.037**	**-0.035**	**0.006**
	(0.052)	**(0.052)**	**(0.046)**	**(0.052)**	**(0.052)**
Widow	0.146***	-0.020	0.048	-0.096*	-0.091*
	(0.053)	(0.053)	(0.051)	(0.056)	(0.054)
Female HoH x widow	**-0.130***	**0.083**	**-0.088**	**0.156****	**0.108**
	(0.071)	**(0.071)**	**(0.065)**	**(0.073)**	**(0.071)**
Obs.	7,748	7,748	7,748	7,748	7,748
Pseudo R-sq.	0.0515	0.0480	0.0310	0.0281	0.0308
			2015		
	Happy	Calm	Angry	Upset	Depressed
	(1)	(2)	(3)	(4)	(5)
Woman	0.072***	0.041**	0.011	-0.082***	-0.076***
	(0.020)	(0.020)	(0.018)	(0.019)	(0.019)
HoH	0.088***	0.057**	0.032	-0.081***	-0.058**
	(0.022)	(0.022)	(0.021)	(0.022)	(0.023)
Female HoH	**-0.031**	**0.089***	**-0.042**	**0.048**	**0.080**
	(0.049)	**(0.051)**	**(0.044)**	**(0.047)**	**(0.050)**
Widow	0.116**	0.139***	0.071	-0.022	0.011
	(0.052)	(0.053)	(0.050)	(0.054)	(0.053)
Female HoH x widow	**-0.153****	**-0.171****	**-0.025**	**0.112**	**0.007**
	(0.073)	**(0.074)**	**(0.066)**	**(0.072)**	**(0.071)**
Obs.	8,082	8,082	8,082	8,082	8,082
Pseudo R-sq.	0.0359	0.0379	0.0228	0.0389	0.0308

Note: Data from AUB SE 2010 and 2015, using survey weights. All specifications include controls for age household size, being married, per capita expenditure (in log), a direct member living abroad, living in a camp, receiving SSN support, having chronic/acute disease, working and region.

3.6 Discussion

Following previous studies, the results discussed in section 3.5 focus the importance of HoH in expenditures management and the implications in terms of mental health that being in charge of the household decisions may have for women. [122], [123])

Our analysis finds that living in a household with female leadership is related to higher expenditures on health (% total expenditure) - which is widely supported in the literature - and lower expenditures on tobacco. [124],[125], [126] This last analysis of healthcare spending shows that despite FHH having preference for spending more on health care, these families end up spending less than MHH in absolute terms, even if it represents a higher percentage of their available budget. This happens due to a penalty on disposable income associated with being in a FHH and having a less income elasticity.

Glick et al. (2018) conduct a representative survey among Palestinians and argue that risky behaviours such as smoking and drinking are more likely among young men than others. [127] This indicates that male HoH have to spend a larger share of total expenditures on tobacco to sustain their lifestyle, as also suggested by our results. As for education and food expenditure, which are directly related to taking care of children and cooking activities, mothers being involved in these spending decisions also in MHH could be what is driving MHH and FHH to have similar expenditures patterns.

Mental health issues are a very serious problem in contexts of conflict and migration all over the world. [128], [129] For PRL, the emotional burden of living in a country that even after 70 years continues to impose severe restrictions for this community can have severe damages on people's well-being. In addition, literature on the impacts of sickness and wars have shown that factors as such have strong impacts on decision making processes. [130], [131], [132]) In our study, most women HoH are providing for a family after a loss which can be affecting their mental health, rather then the HoH role itself.

Whether due to a traumatic event or not, when a woman becomes HoH her weight in the decision-making process of household expenditures increases and, depending on her preferences, there can be significant differences for the household members. While we find evidence that FHH are more likely to have a healthier lifestyle than MHH - that should translate into better health - , we also find that they spend a larger share of expenditure on health. These contradictory results indicate that FHH may need more care then MHH, most likely due to having worse living conditions, less resources, less hygiene and worse isolation. This hypothesis is also related to the impact of stigma measured in terms of average income. It is also possible that female leaders invest in more expensive treatments, but less likely given their lack of financial resources and stability.

Looking at time trends, between 2010 and 2015 FHH increase further the share of expenditure spent on health relative to MHH and there are small improvements on the education expenditure. Positive feelings also improve for FHH from 2010 to 2015. While these trends cannot provide robust evidence that FHH improved their living standards between both survey years, they can be related to the increase in financial support provided by UNRWA to these families after 2010.

We suggest the need to go beyond financial incentives to FHH and create an inter-sectoral support system that helps the HoH to sustain their families in a more structured way. These policies may consist in providing personalised psychological support and contributing to break stereotypes in the labour market, such as promoting entrepreneurship opportunities that allow women to achieve a stable career and normalize their lives, as much as possible.

3.7 Limitations

The biggest limitation of this study resides in the fact that MHH and FHH are so distinct that comparing both groups is a rather complex task and makes it impossible to argue for causality between belonging to a FHH (or being a female HoH) and the results found. Nonetheless, we overcome this limitation as much as possible by using different models and the PSM, that provided consistent evidence with different specifications. In addition, UNRWA provides financial support for health, education and security that may provide services differently for different types of households. In principle, controlling for SSN families should identify the households receiving more support, but we cannot exclude the hypothesis that we might not be grasping other type of financial supports for which we do not have information (seasonal supports, specific aid programs, among others).

Regarding the mental health section, given that the indicators are based on self reported measures, these depend on how willing are the respondents to answer truthfully. If women tend to complain less about their conditions, they might tend to under-evaluate their status even if they feel miserable. This would give a misleading evidence on the impact of being a woman HoH. Nonetheless, in terms of mental health, these measures are one of the few resources available for researchers to study and literature has shown their ability to predict depression related conditions. [133]

3.8 Conclusion

This article provides an in-depth analysis and uses different methods to understand core differences between female and male headed households living in Palestine refugee camps in Lebanon.

Following the literature, this study uses two-part models using probit and GLM and combines these methods with a Propensity Score Matching model to create artificial treatment and comparison groups. [134] Using these models we find statistically significant differences between household budget management in FHH and MHH. FHH consistently spend more on healthcare, despite showing evidence of having healthier habits. The differences found are stronger in FHH where the HoH is single or widowed.

Regarding mental health indicators, the Probit model results show female HoH are typically less happy, calmer and more depressed then male HoH. Different specifications also show that these negative effects are mostly driven by female HoH who are also widows. Moreover, we find evidence of a strong stigma effect that negatively affects the female HoH's ability to earn income, provide for her families and their general well-being.

We consider it is of utmost importance to continue providing financial support for these families along with psychological support to overcome trauma and severe challenges that are common to the HoH of these families in particular.

Chapter 4

Can intersectoral interventions reduce substance use in adolescence?

- Evidence from a randomized controlled multicentre study[1]

Abstract

We measure the impact of an inter-sectoral intervention entitled “Caiu na rede”, designed to tackle substance use among adolescents in Brazil. The intervention consisted in a multicentre Randomized Controlled Trial study implemented between 2017 and 2019 with students from Brazil, Paraguay, and Argentina. The complete sample was composed by 880 adolescents aged between 14 to 17 years old, enrolled across 23 different institutions that provide extra-curricular activities for young adults after school.

The intervention consisted in joining 5 professionals from each institution to work together with a group of randomly selected students (440 in 2017) to develop a set of activities related to health education, rapid health diagnosis, prevention, and risk behaviours and the attainment of the sustainable development goals. The activities that resulted from this joint exercise were then delivered as part of the institution’s agenda to adolescents both in the treatment and control groups. We use difference-in-differences models measure the impact of the intervention in alcohol, tobacco, and cannabis consumption. We also measure the impact of participating in the activities developed

[1] with Rafael Correa and Judite Gonçalves

during the intervention after involving some of the subjects themselves in the activities design process.

An adolescent in the treatment group is 8 pp less likely to consume tobacco and cannabis ($p<0.01$) and 13pp less likely to consume alcohol at least one day in the last month ($p<0.01$). While the intervention did not have a strong impact on frequent consumption, participating in the activities (complete sample) was associated with lower probability of frequent consumption. Adolescents showed a higher consumption of alcohol in the last 30 days compared to other substances. The frequency of alcohol and cannabis use increases with age and one additional day in the group average consumption leads to a 3 pp increase in the individual alcohol and tobacco consumption (peer effect) ($p<0.01$).

This study shows the relevant and successful impact of an intersectoral intervention to tackle substance use among adolescents. It sheds light on the relevance of getting subjects involved in the design of activities for themselves in a very intercultural region. We believe this type of activities can be a key instrument in decreasing substance use in a very crucial stage of life.

4.1 Introduction

Adolescence is the stage of life when individuals are more likely to engage in risky behaviours and substance use tends to increase.[135] Tobacco, alcohol, and cannabis consumption among teenagers can have devastating health consequences and jeopardize users' professional and personal prospects.[136],[137] Implementation of policies aiming to discourage initiation and decrease substance use should focus on this specific age group, where intervention is likely to be more effective. [138], [139] Moreover, tackling substance use at this critical developmental stage is key for empowering and providing youths with opportunities to grow healthy and successful in both professional and personal aspects of life. This study assesses the effectiveness of an intervention tackling alcohol, tobacco, and cannabis consumption among teenagers in a tri-border region of Brazil, Argentina and Paraguay, a critical environment for substance use.

Engagement in consumption of tobacco, alcohol, and cannabis is associated with a series of psychological and social factors. Being subject to domestic violence or abusive relationships is commonly associated with risky behaviours. Migration can also be a catalyst for (abusive) consumption, partly due to lack of parental control. [140],[141] Peer influence and the social environment are key determinants of substance use and engagement in delinquency, behaviours that in turn contribute to increased levels of crime, violence, and danger. [142] All of these interconnected factors, occurring at such an early stage of life, can jeopardize a person's future, in addition to perpetuating inequalities and impacting on the lives of those around. Governments and social actors must adopt a holistic approach to address the triggers of substance use and provide adequate assistance to teenagers —, inserted in their communities— to prevent initiation and reduce consumption.

Following the World Health Organization (WHO) definition, inter-sectoral actions refer to 'actions affecting health outcomes undertaken by sectors outside the health sector, possibly, but not necessarily, in collaboration with the health sector'. This type of action is a main tool for governments to integrate different services, from coordination structures to funding mechanisms, and develop strategies that aim to improve health outcomes in the population. [143] This implies joint planning by all different agents involved in an intervention, which may include for example governmental and non-governmental organizations, teachers, social workers, and investors. Recently, some inter-sectoral actions have been developed jointly with the subjects of the intervention themselves, as a way to enhance engagement and achieve better results. [144] For instance, including adolescents in the design and co-development of an intervention for them not only allows for a better and more comprehensive understanding of their needs, but also empowers them to promote their own health and well-being.

The United Nations (UN) agenda for sustainable development goals contemplates the legal and political articulation of health systems focusing on the needs of adolescents. [145], [146], [147] Governments should adopt more comprehensive public health strategies, going beyond the traditional approach. Examples of more comprehensive strategies include establishing platforms and multicomponent actions involving adolescents, parents, schools, and communities to address substance use and other health-related issues. [138] Such approach requires long-term planning, intervention, monitoring, and evaluation. Moreover, targeting vulnerable groups living in complex environments should be a priority, in order to create sustainable investments in adolescent health at local, national, and global levels. [148], [149], [145] In order to move forward and building on existing evidence, we need to implement different types of interventions to learn what kind of activities work, at what ages, and how they help adolescents —e.g., by keeping them out of dangerous environments for longer? By providing them with coping mechanisms to prevent initiation of substance use in the first place? Or by helping them not to transition from light to heavy consumption?

The present study analyses an intervention that took place in neighbouring Iguazu River Mouth in Brazil, Puerto Iguazu in Argentina, and Caaguazu in Paraguay. Due to its geographical characteristics and weak local governance, this region constitutes a "perfect storm" of critical factors for criminal activity and socioeconomic disadvantage. [150] The Human Development Index (HDI) in this region is between 0.52 and 0.82 (low and medium Human Development), and the Gini Index between 0.47 and 0.55. [2] The proportion of people with low incomes is between 21% and 25.5%. [151] In this complex environment, the risk factors for early substance use are abundant. We measure the effectiveness of a randomized controlled inter-sectoral intervention tackling alcohol, tobacco, and cannabis consumption among teenagers in this region. The intervention involved students from different social organizations in the design and co-development of a set of activities to raise awareness on substance use and keep them and their peers occupied after classes. Teenagers in the treatment group did this exercise together with teachers and social workers from their institutions, and later participated in the activities. Teenagers in the control group, who belong to the same organizations, participated in the activities but did not take part in their design and co-development. In addition to evaluating the effectiveness of the intervention, we identify the main socio-demographic characteristics associated with substance use.

Results show that the intervention (i.e., development of the activities on top of participation in the activities) reduced the probability of any alcohol, tobacco, and cannabis consumption

[2]The whole Brazil has a Gini Index value of 53.30 and ranks 8^{th} place in the world, according to the World Bank - GINI index (World Bank estimate), Country ranking, *in*: https://www.indexmundi.com/facts/indicators/SI.POV.GINI/rankings

(first time or not), but not the probability of frequent consumption among users —i.e., all decreased but participating in the brainstorming for developing the activities was not critical for the intensive margin.

Participating in the activities, on the other hand was associated with lower probability of frequent consumption. There is room to investigate further how the involvement of the participants in the activities design reduced frequency of use for all students, both in the treatment and in the control group.

This study is organized as follows: section 4.2 presents the background and study design, section 4.3 presents the data and methods, and section 4.4 contains the main results. Section 4.5 discusses the results and concludes.

4.2 Background and Study Design

4.2.1 Literature Review

Both WHO and the European Monitoring Centre for Drugs and Drug Addiction (EMCDDA) have advocated for the importance of integrating education, health, social security, and housing dimensions in substance use prevention strategies, due to proven efficacy in the past. [152], [153] Yet, existing literature shows that fragmented approaches are common, rather than transversal and coordinated strategies to tackle the problem of substance use at an early stage of life. Intersectoral interventions have also proven effective in other fields, such as mental health. [154], [155]

Marsiglia et al., (2019) identified the importance of involving adolescents, their context and relationships, to reach higher levels of effectiveness in preventing substance use among adolescents.[156] Van Ryzin and Roseth (2018) identified the importance of peer support and cooperative learning, and Spoth et al. (2017) and Strøm et al. (2014) the importance of delivering a universal prevention intervention. [157],[158], [159]

Griffin and Botvin (2010) provide an extensive literature review of 46 studies on interventions tackling substance use among teenagers. [139] Interventions developed in schools have shown positive results. School-based interventions including anti-drug information, refusal skills, self-management skills, and social skills training are also known to be effective in reducing combined substance use. The EU-Dap study (European Drug Abuse Prevention trial) is an example of a successful school-based program to prevent tobacco, alcohol, and drug use in seven countries. With a 12-hour class-based comprehensive curriculum on social influence, this intervention reduced consumption, prevented baseline non-smokers or sporadic smokers from moving onto daily smoking, but was not effective in making daily smokers reduce or stop smoking. [160]

Interventions involving preventive measures targeted at the individual, their family and/or community, guided by relevant psychosocial theories, are considered to be the most effective to tackle substance use. [139] Griffin and Botvin (2010) review several school- and family-based prevention programs, along with model community-based prevention approaches. Despite the undeniable effectiveness of these interventions, several challenges were identified in their implementation, including how to reach the most vulnerable families and insufficient resources. Lastly, a qualitative study by Sanders (2000) analyses a family support intervention to prevent risk factors associated with drug abuse in youths, called Triple P-Positive Parenting Program. [161] This program included media interventions with wide reach and intensive behavioural family interventions with narrow reach for high-risk families. The author finds evidence that parenting interventions can have a pervasive impact on the quality of life of families.

Brazil has high prevalence of alcohol, tobacco, and illicit substance consumption among adolescents, which makes it a priority country for substance use prevention. [162] In their national survey, Madruga et al. (2012) report that more than half of adolescents in the sample were regular alcohol users, the mean age of cigarette smoking onset was 14.7 years, and 3% of participants had used at least one illicit drug.

The existing literature presents us with several examples of successful interventions that were developed with and for teenagers, aiming to reduce levels of substance consumption. Our study contributes to the discussion in two main ways. First, we provide evidence on the specific mechanisms behind the negative relationship between extracurricular activities and alcohol, tobacco, and cannabis use —is it increased awareness from the involvement in the co-design of activities, or avoiding risky environments by participating in the activities? Second, as the intervention took place in the tri-border area of Iguazu River Mouth, we can explore the interaction between the intervention and participants' socio-demographic characteristics, specifically immigrant status from Paraguay or Argentina.

4.2.2 Study Design

This study evaluates a multicentre randomized controlled experiment conducted between 2017 and 2019. In total, 880 students from Brazil, Paraguay, and Argentina participated, with around 67% participating in all three data collection waves (see below). The study was approved by the research ethics committee of the State University of the West of Paraná (CAAE 82847418.6.0000.0107) and registered according to the CONSORT (UTN U1111=1252-6877). [162]

We started by identifying 23 institutions and 115 project 'implementers' with different nationalities through meetings with public managers and service providers in the fields of education, health, social assistance and sports. These institutions dedicate to providing teenagers with social support at different levels, including sports associations for promoting physical activity, integrating young immigrants in the community, or social institutions focused on substance abuse. All institutions signed a participation form and provided a list of implementers including managers, parents or guardians, university students, and adolescents. The eligibility criterion for being an implementer was to belong to one of the participating institutions and their role was to support the development of activities with adolescents (as well as responsibility for data collection).

In each institution, classes were randomized into treatment and control classes, with a total of 440 adolescents allocated to treatment classes and 440 to control classes. The final sample was composed of 880 adolescents from 14 to 17 years old: 376 Brazilians (42.7%), 292 Paraguayans (24.1%), and 212 Argentineans (33.2%) (for more details see Table D1 in Appendix).

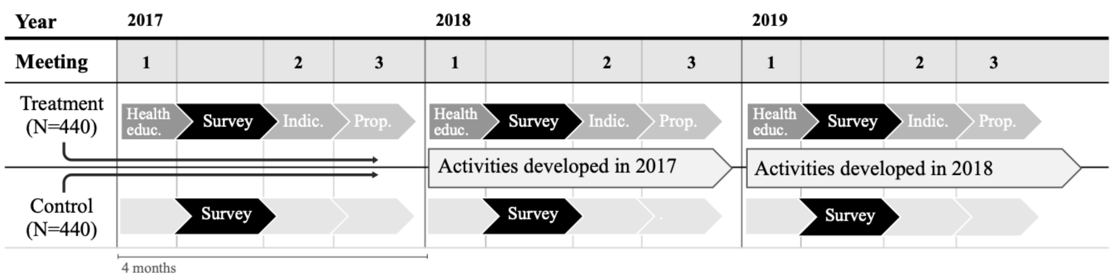
The intervention lasted for three years. In each year, the implementers and adolescents in the treatment group worked together in teams, during a 4-month cycle of health education, brainstorming activities, and strategic planning. The teams thus worked as incubators of new ideas and strategies for improving the activities offered at each institution to make them more suited to the participants' interests and needs. The intervention took place through three monthly meetings in the beginning of each year, lasting 120 minutes each, on the following themes: (1) vulnerability and health care network, (2) analysis of indicators of adolescent health, and (3) strategic planning and development of proposals for future activities. Each year, between the first and the second meeting, the students answered an electronic survey to collect a set of indicators related to their substance consumption, mental health, physical activity, and relationship with their parents. Adolescents in the treatment group participated in all stages of the project with the implementers at their institution, while the control group only answered the electronic survey, without providing any input to what the activities should be and how they should be conducted. Students in the treatment group analysed the survey indicators in the second meeting to define the priorities by institution and action area (see Appendix Table D2), based on the proposal of the National Health Plan. [163]

The formal proposals were developed in the third meeting of the intervention and delivered from 2018 onwards. Both treatment and control group students participated in the activities. In sum, this study measures the effectiveness of involvement in the design and co-development of activities (what the treatment group worked on) on top of participation in the activities (both treatment and control groups). At the beginning of each year, the project team did an assessment of how the intervention was being conducted at the institutions. Figure 4.1 shows the intervention timeline with the meetings, survey and activities happening from 2017 to 2019.

4.3 Data and Methods

Data collection occurred between the first and second meetings, each year (2017, 2018, 2019). An electronic platform was established for the purpose (http://caiunarede.pti.net.br).

Figure 4.1: Average frequency of consumption by gender over age (excluding non-consumers)



Note: Meeting 1- Health education training (Health educ); 2- Survey indicators analysis (Indic.): 3- Development of proposals (Prop.); N participants=880; Meetings are conducted by project implementers.

The virtual environment was accessed by the project implementers on the institutions' computers through an available login and password. The indicators used were self-reported and self-registered, and adapted from instruments of public use validated for the three countries. [164]

Information collected included the student's country, institution, age, and gender, whether they felt lonely in the last year, Body Mass Index (BMI) (classified into underweight, normal weight, overweight, or obese), early initiation of sexual activity (sexual intercourse before the age of 15 [165]), tobacco use in the last 30 days, alcohol use in the last 30 days, cannabis use in the last 30 days, physical activity in the last week, parental connection in the last 30 days (felt understood by their parents), and parental regulation in the last 30 days (parents knew what they were doing on their free time).

We focus our analyses on three main outcomes that capture individual behaviours targeted by the intervention: current tobacco, alcohol, and cannabis use. These consumption indicators are categorical and represent self-reported consumption frequency (in days) over the last 30 days. The seven categories are: never, used in 1 to 2 days, 3 to 5 days, 6 to 9 days, 10 to 19 days, 20 to 29 days, everyday.

4.3.1 Methods

For each relevant outcome, the impact of the intervention was measured by the difference between the measurements before and after the intervention, in the treatment versus the control group, using a differences-in-differences (DiD) estimation model. This method allows us to correct for pre-existing differences between individuals in the two groups (e.g., age, gender, weight, height) when measuring changes in the outcomes. The DiD estimator provides an unbiased estimate of the treatment effect under the assumption that without the treatment, outcomes would have had the same evolution in both groups. [166] This assumption is reasonable thanks to the randomized control study design.

We estimate Probit regressions for each outcome variable as a function of the explanatory variables and the DiD terms, as specified in the following expression [167]:

$$\begin{aligned} &P(Y_{it}^{T,A,C} = 1 \mid Treat_i, Time_t, X) = \\ &\Phi(\alpha + \beta_1 age_{it} + \beta_2 gender_{it} + \beta_3 country_{it} + \beta_4 BMI_{it} + \\ &+ \beta_5 earlySE_{it} + \beta_6 Treat_i + \beta_7 Time_t + \beta_8 Treat_i \times Time_t) \end{aligned} \tag{4.1}$$

In equation 4.1, Y_{it}^{T} is a binary variable indicating consumption of tobacco, Y_{it}^{A} alcohol, and Y_{it}^{C} cannabis in at least 1 out of the past 30 days. A series of individual characteristics (X) are included in the model, not only to control for differences between treatment and control groups, but also to understand their associations with the outcomes. These include age, gender, country, under and overweight BMI levels (below 15 and over 23 if girl and below 16 and over 22 for boys), and risky personality (proxied by early sexual activity). $Treat_i$ identifies individuals in the treatment group. $Time_t$ identifies the period after the intervention (2018 and 2019). The coefficient of main interest is β_8, the coefficient on the interaction term. As the models are non-linear, the impact of the intervention on a specific outcome is obtained by calculating the average marginal effect that corresponds to β_8. Lastly, $\Phi(.)$ denotes the cumulative distribution function of the standard normal distribution. All estimations cluster standard errors at the institutional level to account for correlations between students from the same institution.

As mentioned, our dependent variables $(Y_{it}^{T}, Y_{it}^{A}, Y_{it}^{C})$ are dichotomized and take value one if the respondent consumed alcohol, tobacco, or cannabis in at least one day over the last 30 days, and zero otherwise (i.e., any consumption or consumption on the extensive margin). To investigate consumption along the intensive margin, or in other words to distinguish heavy use from social consumption, we estimate an additional probit model where we exclude those who do not consume and the dependent variable takes the value 0 for those who consumed up to 9 days in the last month and the value 1 for those who consumed in at least 10 days. As a sensitivity check we also performed an ordered probit where the dependent variables are categorical instead of binary and take value 0 for those who did not consume, value 1 for those who consumed in up to 9 days in the last 30, and value 2 for those who consumed in more than 9 days in the last 30 —the heavy consumers.

4.3.2 Descriptive Statistics

Around 49.3% (n=434) of all participants in this study were male, and 450.7% $(n = 446)$ were female. Around 42.7% $(n = 376)$ of the participants were Brazilian, 33.2% $(n = 292)$ Paraguayan, and 24.1% $(n = 212)$ Argentinian. Table 4.1 shows the descriptive statistics for the different years and genders. The sample is quite balanced in terms of gender and age. Nationalities representativeness is quite stable over time, as well as average BMI and early sexual activity. Peer effect is included following the leave-one-out strategy, which consists in including the group average (excluding the individual) as a control in the model (in complementary analyses). [168] In this case, because consumption is a categorical variable, we need to transform the variable such that each level takes the mid-point value (e.g. category 3 to 5 days in the last 30 acquires the value 4), and then compute the leave one out average for each student.

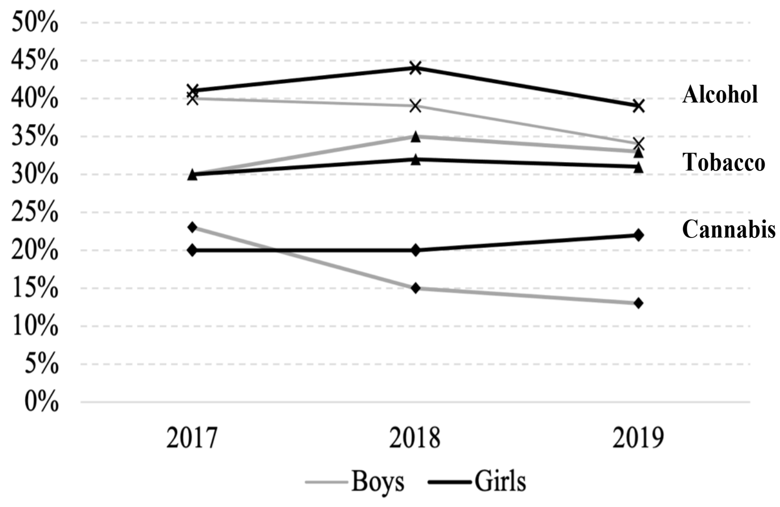
Table 4.1: Descriptive statistics

		2017		**2018**		**2019**	
		Boys	**Girls**	**Boys**	**Girls**	**Boys**	**Girls**
Age	Avg.	15.49	15.32	15.88	15.76	16.40	16.28
Brazil	Prop.	0.42	0.43	0.44	0.50	0.36	0.43
Paraguay	Prop.	0.31	0.35	0.33	0.34	0.35	0.39
Argentina	Prop.	0.27	0.21	0.23	0.17	0.30	0.17
BMI	Avg.	21.96	21.73	22.05	21.82	21.56	21.82
Early sexual activity	Prop.	0.15	0.13	0.15	0.14	0.12	0.16
Peer alcohol cons.	Avg. (days)	3	3	2	2	2	1
Peer cannabis cons.	Avg. (days)	2	2	1	1	1	1
Peer tobacco cons.	Avg. (days)	4	4	3	3	3	3
Total	N	446	434	318	327	223	235

Figure 4.2 shows substance use by gender and over time (any consumption in the past

30 days). Alcohol is the substance that more participants, of both genders, reported to consume at least once in the last month. The proportion of males consuming any tobacco is larger than that of females, whereas cannabis consumption is more common among females in 2018 and 2019. Consumption intensity (frequency of use), by gender and substance is shown in Figure 4.3. Frequency of use is higher for tobacco for both genders (share of students consuming more than 3 days is higher). Female participants show less frequent consumption of alcohol and cannabis (boys share of consuming more than 10 days is larger), but the percentage of students who didn't consume any substance is higher among males. One possible explanation is that girls tend to use more but in more moderate frequency, while the boys either don't consume, or when then do they do it with more intensity (measure in frequency).

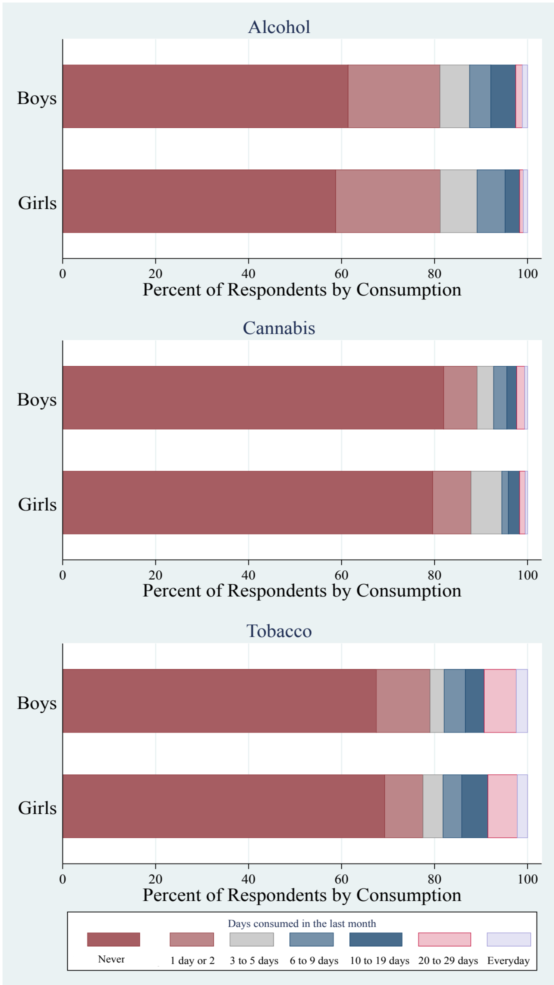
Figure 4.2: Frequency of any consumption in the past 30 days by gender over time



4.4 Estimation Results

The interaction coefficients in the DiD models are statistically significant and show negative impacts of the intervention on all indicators of interest: alcohol, cannabis and tobacco consumption in at least one day in the last month (Table 4.2). The likelihood of a teenager consuming alcohol in at least one day in the last month is 13 percentage points (pp) lower for those in the treatment group compared to the control group after the intervention (p

Figure 4.3: Frequency of consumption in the past 30 days by gender and substance



<0.01). Further, the intervention reduced the likelihood of consuming either tobacco or cannabis in at least one day in the last month by 8 pp ($p < 0.01$). These results indicate that the intervention was successful in decreasing the probability of consuming substances along the extensive margin. The peer effect is statistically significant for all substances. A one day increase in the average frequency of consumption among peers increases the likelihood of consuming substances at least once by 2 pp for alcohol, 4 pp for cannabis and 3 pp for tobacco.

Regarding socio-demographic characteristics, results show that being of Brazilian nationality is associated with a 16 pp ($p < 0.05$) lower likelihood of having consumed cannabis at least once in the last month, compared to foreign participants from Paraguay

Table 4.2: Impacts of the intervention on any consumption in the last 30 days (marginal effects)

	Alcohol		Cannabis		Tobacco	
	(1)	(2)	(3)	(4)	(5)	(6)
Post-treat.	-0.01	0.03	-0.03**	0.03	0.03	0.07***
	(0.03)	(0.04)	(0.01)	(0.04)	(0.04)	(0.02)
Treatment	-0.01	-0.00	-0.02	-0.01	0.02	0.02
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
DiD	**-0.13*** **	**-0.13*** **	**-0.08*** **	**-0.08*** **	**-0.08*** **	**-0.08*** **
	(0.04)	**(0.04)**	**(0.02)**	**(0.02)**	**(0.03)**	**(0.02)**
Girl	0.05	0.05	0.05	0.05	-0.02	-0.03
	(0.07)	(0.07)	(0.05)	(0.04)	(0.05)	(0.06)
Age	0.12***	0.09***	0.07***	0.03*	0.05**	0.03*
	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Brazilian	-0.02	-0.00	-0.16**	-0.13	-0.02	0.02
	(0.05)	(0.06)	(0.08)	(0.08)	(0.05)	(0.05)
BMI_{under}	0.02	0.04	0.04	0.05	-0.12	-0.09
	(0.14)	(0.14)	(0.08)	(0.08)	(0.10)	(0.10)
BMI_{over}	0.01	0.01	0.00	0.00	-0.05**	-0.05**
	(0.04)	(0.04)	(0.03)	(0.04)	(0.02)	(0.03)
Early sex exposure	0.15*	0.15	0.08	0.07	0.15*	0.15*
	(0.09)	(0.09)	(0.06)	(0.05)	(0.08)	(0.08)
Peer tobacco cons.		0.02**		0.04***		0.03***
		(0.01)		(0.01)		(0.01)

Note: Standard errors in parentheses are clustered at institution level.*** p<0.01, ** p<0.05, * p<0.1
Dependent variables are binary with the value 1 if the respondent consumed each substance at least once in the last month; and 0 otherwise. Peer is the (leave one out) average group consumption in days. BMI under and over are binary variables indicating whether each individual has an unhealthy BMI (by deficiency or excess) or not. Results showing the introduction of a peer effect in interaction with the intervention related variables – time, treatment and both (DiD) - had very similar results, presented in Appendix, Table D3.

or Argentina, but the effect loses significance when the peer effect is included. Age is associated wit higher likelihood of consuming all substances — in particular, one more year of age increases the likelihood of reporting having consumed alcohol at least once in 9 pp (p <0.01). Having had an early initiation of sexual activity is associated with higher likelihood of consumption for alcohol and tobacco, but the impact is also reduced when the peer effect is included. Being over the healthy BMI level is associated with lower likelihood of tobacco consumption.

In the second specification, we exclude participants that reported no consumption and compare those who consumed in less than 10 to 19 days in the last month to those who consumed at least that frequently.

Results in Table 4.3 show that the probability of frequent consumption was reduced by the intervention by 15 pp in the case of cannabis, but no impact of the intervention in terms of light or heavy consumption of tobacco or alcohol. Nonetheless, the post-treatment indicator has a negative and statistically significant sign, for all consumption outcomes. This shows the impact of the activities conducted at the institutions for all students during the project duration. This means the activities developed together by the students themselves and the institutions' professionals had a relevant impact to reduce frequent substance consumption among everyone.

Table 4.3: Impacts of the intervention on light vs. heavy consumption (marginal effects)

	Alcohol		Cannabis		Tobacco	
	(1)	(2)	(3)	(4)	(5)	(6)
Post-treat.	-0.16***	-0.06	-0.11**	0.00	-0.17***	-0.10*
	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)	(0.05)
Treatment	-0.01	-0.02	-0.05	-0.03	-0.02	-0.01
	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)	(0.05)
DiD	**0.01**	**0.02**	**-0.15***	**-0.16***	**-0.02**	**-0.04**
	(0.05)	**(0.05)**	**(0.09)**	**(0.09)**	**(0.07)**	**(0.07)**
Girls	-0.06**	-0.05**	-0.01	0.01	0.10***	0.08**
	(0.03)	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)
Age	0.09***	0.02	0.10***	0.03	0.10***	0.06***
	(0.01)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
Brazilian	-0.05*	0.03	0.03	0.09*	-0.33***	-0.24***
	(0.03)	(0.03)	(0.05)	(0.05)	(0.04)	(0.04)
BMI_{under}	-	-	-	-	0.24	0.27*
					(0.15)	(0.15)
BMI_{over}	-0.03	-0.01	-0.04	-0.03	-0.14***	-0.12***
	(0.03)	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)
Early sex exposure	-0.04	-0.05	0.15***	0.12***	0.13***	0.11**
	(0.03)	(0.03)	(0.05)	(0.04)	(0.05)	(0.05)
Peer avg. cons.		0.04***		0.05***		0.03***
		(0.00)		(0.01)		(0.01)
Observations	773	773	371	371	627	627

Note: Standard errors in parentheses are clustered at institution level.*** $p<0.01$, ** $p<0.05$, * $p<0.1$ Dependent variables are binary with the value 1 if the respondent consumed each substance at least 10 to 19 days in the last month; and 0 otherwise. Peer is the (leave one out) average group consumption in days. BMI under and over are binary variables indicating whether each individual has an unhealthy BMI (by deficiency or excess) or not. Complete table in Appendix, Table D4.

Being of Brazilian nationality is associated with less heavy tobacco consumption (33 pp lower probability of heavy use compared to Argentinian or Paraguayan nationality; $p<0.01$). The peer effect has a similar impact as in the previous specification - one day more in the group average frequency of consumption increases the likelihood of consuming alcohol, cannabis and tobacco frequently by 4, 5 and 3 pp, respectively ($p<0.01$). Female gender displays a negative association with heavy use of alcohol, but positive with heavy use of tobacco. Being one year older is now associated with an increase in the likelihood of heavy consumption by 9 to 10 pp ($p<0.01$). Early sexual activity is associated with consuming cannabis and tobacco more frequently at the 1% significance level. Participants that are overweight (have a BMI above healthy level) are 14 to 12 pp less likely to be heavy smokers.

The fact that post-treatment variables and peer effect have a significant and positive impact on heavy consumption shows that there may be positive treatment spillovers to the control group and/or due to the fact that including students in the activities design and development process made them more interesting and engaging for the participants. These results suggest that the intervention had impact for students both in treatment and the control group. Assuming students from both groups interact during the activities and on their daily lives, this positive spillover can result from students in the treatment group changing their consumption and influencing others to follow (peer effect). Another possible hypothesis is that by including some of the students on the development and design processes, the activities became more interesting for all, every participant engaged more and changed their substance consumption.

4.5 Discussion

To summarize, results show that the intervention successfully reduced the use of alcohol, cannabis and tobacco both on the extensive margin (i.e., likelihood of consuming) and, to a lower extent, on the intensive margin (i.e., frequency of consumption among consumers). In addition, consumers in the control group, who only participated in the activities developed by the treatment group, also decreased their consumption frequency. Brazilian students are less likely to engage in heavy tobacco consumption and we find a positive relationship between substance consumption and risky behaviour, proxied by early sexual initiation. Consumption increases with age and average consumption levels of peers.

Similar trends in frequency of alcohol consumption in adolescents, by sex and age, have been identified in other studies. [169], [170], [171], [172] The increase in the consumption of alcohol and other substances among adolescents is still a controversy when discussing the effectiveness of interventions. For example, the intervention described in Valente et al. (2020) showed a decrease in decision-making ability and an increase in substance use in adolescents in the follow-up. [173] The increase in consumption of other substances was also observed after participating in school programs, multicomponent interventions, as well as interventions involving students, parents and teachers. [174], [175], [176]

The change in the likelihood of using substances related to migration and nationality has also been previously studied. Marsiglia et al. (2019) highlight the influence of interpersonal relationship patterns and cultural clashes on consumptions. [176] The authors identified a reduction in substance use among adolescents resultant from an intervention with parental content, that compared the parents' culture of origin and consumption behaviours in Latin America. In our case, students with Brazilian nationality seem to have healthier habits, which can be related to having more stability compared to those with foreign nationality. This evidences the potential lack of integration of foreign students.

As for the peer effect, our results show that the group average consumption frequency influences the consumption frequency of each student, for all substances in almost all specifications. Our study also aligns up with the evidence found in Cordova et al.(2020) on the relationship between risky behaviours and substance consumption. That study showed the impact of a mobile app to change teenagers' behaviours that helped reduce substance consumption and sexual risk behaviours together, highlighting the relationship between both. [177]

While we find robust results that this type of intervention can be a relevant tool to decrease substance consumption among adolescents, we do not have access to an extensive list of socio-demographic and consumption indicators. Household composition, residential area, or parents participation in the labour market may have important impacts on the probability and frequency of consumption, as well as on how the intervention changes the subjects' behaviour. Moreover, since this intervention was implemented in a tri-border area, students may change supplier according to alcohol, cannabis, and tobacco price variations, an important factor that we are not able to include in the estimation.

Overall, we argue that participatory multisector interventions involving the subjects themselves, are effective to decrease substance use among teenagers, with benefits both for the adolescents involved in the development of the activities and the ones that only participate in the activities, potentially by improving the level for awareness, engagement, attractiveness/adequacy of the activities, and integration of foreign and local students.

Recognizing the results of intersectoral initiatives to improve collaboration between students and implementing agents is as important as monitoring and evaluating these programs for their effectiveness. Considering the positive results than have been recently found, this strategy can be a relevant tool for health policy decision makers to tackle substance use at an early stage, with support from different sectors, while avoiding the fragmentation of services and resources.

Based on ours and previous results, we consider this type of intervention to be very effective in engaging participants and reducing harmful behaviours, which may subsequently improve their health outcomes, general well-being, and socio-economic conditions. We believe governments and social institutions should continue to and increase financing of intersectoral interventions at an early stage, while also developing research studies that identify the most effective mechanisms for different individuals and adapt the intervention to their needs.

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Appendix

A1 Chapter 1

A1.1 Additional summary statistics

Table A1: Visited Traditional Practitioner in the last 4 weeks, in percentage of total population sample

	2000	2007	2014
15-24	3.46	10.36	20.28
25-44	3.12	12.74	23.18
45-64	2.24	10.94	20.70
65-79	2.76	7.07	10.51
80+	1.64	4.08	10.78
Total	2.91	11.28	20.68
	(1,646)	(10,270)	(11,710)

Note: IFLS Community Survey 2000, 2007, 2014. Relative percentage and absolute number (in parentheses) of respondents who affirm to have visited a TP in the last 4 weeks, by age group.

Table A2: Community Summary Statistics

	2000		2007		2014	
Urban	0.58	(0.49)	0.60	(0.49)	0.67	(0.47)
Number of						
Health Centres	2.13	(0.93)	2.31	(1.15)	2.26	(1.36)
Private HP	4.78	(2.38)	4.48	(2.29)	5.35	(3.57)
Traditional P.	2.4	(1.7)	2.82	(1.63)	3.64	(2.91)
Hospitals	2.08	(1.14)	2.31	(1.22)	4.03	(2.81)

Note: IFLS Community Survey 2000, 2007, 2014. Table presents mean and standard deviation (in parentheses) values for each variable. Urban shows the share of villages considered urban areas. Apart from this variable, all the others are represented in absolute numbers. Namely, number of health posts, health centres, private health centres, traditional practitioners and hospitals.

Table A3: Type of health facilities in Indonesia

Health facility	Description	Public/Private
A. Multiple-provider facilities		
Public hospital	Public hospital located at the district level	Public
Private hospital	Private hospital located at the district level, national and provincial government enterprises, police, defence forces.	Private
Hospital for women and children	Private hospital for women and children located in the district.	Private
Women's hospital	Private women's hospital located in the district.	Private
Maternity clinic	Private maternity clinics with more than 2 beds.	Private
Health centre	Public health centre located in the district – in general they are located at the sub-district level.	Public
Auxiliary health centre	Public auxiliary health centre – in general they are located at the sub-district level, usually in a village.	Public
Private clinic	Treatment clinic. Before the advent of the puskesmas there were private and public treatment clinics. As the puskesmas was developed the public treatment clinics were incorporated in the puskesmas with the result that only the private balai pengobatan remained. Although they have been ignored by the government and donors they remain a significant source of treatment, especially in urban areas. They are licensed by the local government and must have a doctor as the supervisor. In practice, most of the doctors named as the supervisor seldom visit and nurses, and some midwives, provide most of the health care unsupervised.	Private
B. Solo-provider facilities		
Village midwife (BDD)	BDD is a village midwife who receives a government salary and also may charge for the services she provides and retain the fee herself. Although the village midwife theoretically lives in the village (desa) there are reports indicating that in many villages she lives elsewhere, maybe in a nearby urban area. The services provided by the BDD may be offered in a room in her house or in a structure in that is the property of, and was built by, the village government (polindes). In the polindes the services are provided by the village midwife who charges for the services and retains the fees.	Private
Doctor in full-time private practice.	Doctor whose primary professional activity is private practice and who does not receive a salary from the government.	
Doctor in part-time private practice.	Doctor whose primary professional appointment is with the government to work in a government health facility and who also has a part-time private practice after office hours.	Private
Nurse in part-time private practice	Nurse whose primary professional activity is in a public or private health facility and who has a part-time private practice after hours.	Private
Midwife in full-time private practice	Midwife whose primary professional activity is private practice and who does not receive a salary from the government.	Private

Source: Heywood and Harahap (2009) [180]

A1.2 Additional regression tables

Table A4: Linear regression on treatment costs

	(1) Cost TP	(2) Cost Public	(3) Cost Private
Days in bed	-0.197**	0.219**	0.100*
	(0.096)	(0.093)	(0.057)
Age	0.020*	0.005	0.027***
	(0.011)	(0.011)	(0.007)
Age^2	-0.000*	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)
Higher education	0.361***	0.013	0.309***
	(0.091)	(0.159)	(0.083)
Woman	-0.099*	-0.016	0.059
	(0.058)	(0.074)	(0.045)
Urban	0.149*	-0.196**	0.001
	(0.076)	(0.093)	(0.063)
Constant	9.258***	8.185***	9.442***
	(0.229)	(0.239)	(0.160)
Observations	30,145	44,842	51,860
R-squared	0.046	0.011	0.022

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

Note: Robust standard errors in parentheses. This table presents the estimation results using a linear regression model controlling for year, province and island fixed effects, using IFLS Community Survey data from 2000, 2007, 2014. The dependent variables, cost of TP, public and private healthcare are continuous cost variables that correspond to the reported treatment value by each patient.

Table A5: Multinomial logit results for different age status

Specification (1)

Age	Woman	Urban	Hosp.
20	0.063***	0.002***	0.098***
	(0.001)	(0.001)	(0.004)
35	0.067***	0.002***	0.104***
	(0.001)	(0.001)	(0.004)
70	0.076***	0.003***	0.118***
	(0.001)	(0.001)	(0.004)
Observations	1,488,563	1,488,563	1,488,563

Specification (2)

Age	N Public	N TP	N Priv.	Cost Private	Cost Public	Cost TP	Distance
20	-0.004***	0.003***	0.000	-0.011***	-0.007***	0.004***	0.016**
	(0.001)	(0.000)	(0.000)	(0.002)	(0.001)	(0.001)	(0.008)
35	-0.002***	0.002***	-0.000	-0.004***	-0.005***	0.002***	-0.002
	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)	(0.004)
70	-0.002***	0.002***	-0.001***	-0.000	-0.008***	0.002***	-0.023***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.006)
Observations	49,473	49,473	49,473	49,473	49,473	49,473	49,473

Note: IFLS Community Survey 2000, 2007, 2014. Table presents mean and standard deviation (in parentheses) values for each variable. Urban shows the share of villages considered urban areas. Apart from this variable, all the others are represented in absolute numbers. Namely, number of health posts, health centres, private health centres, traditional practitioners and hospitals.

Table A6: 2^{nd} step - Outpatient visit last week (Mult. Logit (marginal effects))

	(1) Visit Priv	(2) Visit TP
Married	0.084***	0.005
	(0.028)	(0.017)
HH size	0.001	-0.003***
	(0.001)	(0.001)
Log(pce)	0.097***	0.014***
	(0.004)	(0.003)
Higher education	0.072***	-0.002
	(0.012)	(0.008)
Woman	-0.049***	-0.082***
	(0.005)	(0.003)
Urban	0.046***	-0.026***
	(0.005)	(0.004)
Acute	0.000	-0.013***
	(0.006)	(0.004)
BMI - good	0.024***	0.029***
	(0.007)	(0.005)
BMI - high	-0.006	0.033***
	(0.007)	(0.005)
Good health	-0.051***	0.022***
	(0.007)	(0.005)
Worse	0.021***	-0.051***
	(0.005)	(0.004)
Hospitalized	0.085***	0.010
	(0.021)	(0.020)
Insurance	-0.068***	-0.063***
	(0.005)	(0.003)
Cost public	**-0.004**	**-0.041*****
	(0.012)	**(0.008)**
Cost private	**-0.023***	**-0.013**
	(0.013)	**(0.009)**
Cost TP	**0.089*****	**0.048*****
	(0.013)	**(0.009)**
N. Public HC	0.003	-0.021***
	(0.002)	(0.001)
N. Priv.	0.007***	-0.010***
	(0.001)	(0.001)
N. TP	0.001	0.009***
	(0.001)	(0.001)
Distance	0.092	0.223**
	(0.118)	(0.087)
Observations	65,588	65,588

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

Note: Robust standard errors in parentheses. Results using a multinomial logit model with year, province and island fixed effects and data from 2000, 2007, 2014. The dependent variable is categorical: Service type has the value 0 if the individual visited a public health centre during the last week (outcome 1), 1 if the individual visited a private clinic (outcome 2) and the value 2 if the patient visited a TP (outcome 3). Options are mutually exclusive and results show marginal effects for the possible outcomes.

Table A7: Number of visits to the Traditional practitioner (Neg. Binomial - Marginal effects)

Dep. variable: N. Visits TP	(1)	(2)
Age	0.015***	0.019***
	(0.002)	(0.003)
Age squared	-0.000***	-0.000***
	(0.000)	(0.000)
Married	0.061	0.149**
	(0.059)	(0.065)
HH size	-0.006***	-0.007***
	(0.002)	(0.002)
Log(pce)	0.084***	0.083***
	(0.009)	(0.012)
Higher education	-0.088***	0.009
	(0.019)	(0.034)
Woman	-0.084***	-0.073***
	(0.011)	(0.013)
Urban	-0.052***	-0.025*
	(0.013)	(0.015)
Acute	0.012	0.022
	(0.013)	(0.016)
BMI - good	-0.017	-0.019
	(0.023)	(0.026)
BMI - high	-0.047**	-0.045*
	(0.023)	(0.027)
Good health	-0.062***	-0.103***
	(0.013)	(0.020)
Worse	-0.019	-0.019
	(0.015)	(0.018)
Hospitalized	-0.013	0.083*
	(0.033)	(0.050)
Insurance	-0.112***	-0.066***
	(0.013)	(0.015)
Visit Pub.		-0.217***
		(0.018)
Visit Priv.		-0.147***
		(0.031)
Cost public		-0.106***
		(0.040)
Cost private		-0.082**
		(0.036)
Cost TP		0.068*
		(0.036)
N. Public HC		-0.015***
		(0.006)
N. Priv.		-0.023***
		(0.003)
N. TP		0.019***
		(0.003)
Distance	-0.188***	0.927**
	(0.044)	(0.420)
Observations	33,319	20,053
Pseudo R-sq.	0.0810	0.114

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

Note: Robust standard errors in parentheses. This table presents the estimation results using a Negative Binomial model with year, province and island fixed effects, using IFLS Community Survey data from 2000, 2007, 2014. The dependent variable Number of visits to TP is a count variable that indicates the number of visits to the TP in the last month. Treatment costs are predictions from the preliminary linear model.

Table A8: Visits and number of visits to the Traditional practitioner, by expenditure quintiles (Probit and Neg. Binomial - Margins)

	Low quantiles		Top quantiles	
	Private clinic	TP	Private clinic	TP
Married	0.339***	0.149***	0.156***	0.112***
	(0.039)	(0.018)	(0.055)	(0.027)
HH size	-0.009***	-0.004***	-0.002	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Log(pce)	-0.024**	0.057***	0.153***	0.014**
	(0.010)	(0.008)	(0.009)	(0.006)
Higher education	0.219***	-0.135***	-0.030*	0.076***
	(0.029)	(0.022)	(0.017)	(0.010)
Woman	-0.040***	-0.074***	-0.023***	-0.094***
	(0.008)	(0.005)	(0.009)	(0.005)
Urban	-0.008	0.015***	0.087***	-0.008
	(0.008)	(0.006)	(0.009)	(0.006)
Acute	0.017**	-0.022***	-0.011	-0.012*
	(0.009)	(0.006)	(0.010)	(0.007)
BMI - good	-0.039***	0.029***	0.035**	0.057***
	(0.010)	(0.007)	(0.014)	(0.008)
BMI - high	-0.061***	0.029***	-0.005	0.048***
	(0.011)	(0.007)	(0.015)	(0.009)
Good health	-0.058***	0.023***	-0.002	0.036***
	(0.011)	(0.008)	(0.013)	(0.009)
Worse	-0.010	-0.019***	0.044***	-0.024***
	(0.009)	(0.006)	(0.009)	(0.006)
Hospitalized	-0.051	0.203***	0.261***	0.026
	(0.054)	(0.032)	(0.035)	(0.022)
Insurance	-0.023***	-0.089***	-0.013	-0.041***
	(0.009)	(0.006)	(0.009)	(0.006)
Cost public	**0.105*** **	**-0.140*** **	**0.109*** **	**0.005**
	(0.020)	**(0.014)**	**(0.020)**	**(0.013)**
Cost private	**0.146*** **	**-0.069*** **	**-0.056*** **	**-0.071*** **
	(0.023)	**(0.016)**	**(0.022)**	**(0.013)**
Cost TP	**-0.095*** **	**0.157*** **	**0.106*** **	**0.048*** **
	(0.024)	**(0.016)**	**(0.023)**	**(0.013)**
N. Public HC	-0.012***	-0.017***	0.018***	-0.016***
	(0.004)	(0.002)	(0.003)	(0.002)
N. Priv.	0.012***	-0.020***	0.014***	-0.009***
	(0.001)	(0.001)	(0.002)	(0.001)
N. TP	0.005***	0.011***	0.014***	0.009***
	(0.002)	(0.001)	(0.002)	(0.001)
Distance	-1.633***	1.372***	-0.505**	0.184
	(0.201)	(0.151)	(0.204)	(0.122)
Obs.	20,982		19,599	
Pseudo R-sq.	0.1450		0.1280	

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

Note: Robust standard errors in parentheses. This table presents the estimation results using Probit and Negative binomial models to estimate the determinants of having visited the TP in the last 4 weeks and number of visits to the TP, respectively. Estimation separate for households in the first two (low income) and the last two quantiles of monthly expenditure. Families in middle income quantile are not included. This includes year, province and island fixed effect, using IFLS Community Survey data from 2000, 2007, 2014. Results show marginal effects for each coefficient in all specifications. The interaction variable is used to grasp and the effect of having a modern health-care facility built in a district with a given number of TP.

Table A9: Number of visits TP - CMP model

	(1) Cost TP	(2) Number of visits TP
Days in bed	-0.197**	
	(0.096)	
Age	0.020*	
	(0.011)	
Age squared	-0.000*	
	(0.000)	
Higher education	0.361***	
	(0.091)	
Woman	-0.100*	
	(0.058)	
Urban	0.149*	
	(0.076)	
Distance in hours		-0.001
		(0.082)
Log Expenditure		0.038*
		(0.020)
Self-treatment		0.117***
		(0.037)
Visited Public		-0.088***
		(0.029)
Visited private		-0.135***
		(0.035)
Cost Public		0.685***
		(0.184)
Cost Private		-0.446**
		(0.184)
Cost TP		0.591***
		(0.142)
Number of TP		0.021**
		(0.009)
Number of HC		-0.002
		(0.014)
Number of Private HC		-0.005
		(0.007)
New HF		0.151
		(0.168)
New road		0.028
		(0.053)
New school		0.002
		(0.033)
Natural disaster		0.066*
		(0.035)
New HF*Number of TP		0.026
		(0.041)
Year FE	✓	✓
Province FE	✓	✓
Island FE	✓	✓
Constant	9.258***	-7.185***
	(0.229)	(1.875)
Observations	41,805	41,805

Note: Robust standard errors in parentheses. This table presents the estimation results using a cmp model controlling for year, province and island fixed effects and using IFLS Community Survey data from 2000, 2007, 2014. The dependent variables, is a continuous cost variables that correspond to the reported TP treatment value by each patient and number of visits TP indicate the number of visits of each participant during the last month.

Table A10: Seemingly unrelated regression for healthcare demand

	(1) Visit Public	(2) Visit Priv.	(3) Visit TP
Age	0.000***	0.001***	-0.000***
	(0.000)	(0.000)	(0.000)
Married	-0.024***	-0.005	-0.027***
	(0.008)	(0.006)	(0.007)
HH size	-0.002***	0.001***	-0.002***
	(0.000)	(0.000)	(0.000)
Log(HH Exp.)	-0.012***	0.011***	0.006***
	(0.001)	(0.001)	(0.001)
Higher education	0.014***	0.002	-0.002
	(0.002)	(0.002)	(0.002)
Woman	0.015***	0.004***	-0.000
	(0.001)	(0.001)	(0.001)
Urban	0.013***	0.009***	-0.003**
	(0.001)	(0.001)	(0.001)
Acute	0.006***	0.004***	0.005***
	(0.001)	(0.001)	(0.001)
BMI - good	-0.010***	0.009***	0.015***
	(0.002)	(0.001)	(0.002)
BMI - high	-0.009***	0.004***	0.006***
	(0.002)	(0.002)	(0.002)
Good health	-0.021***	-0.019***	-0.013***
	(0.001)	(0.001)	(0.001)
Worse	0.004***	-0.000	0.008***
	(0.001)	(0.001)	(0.001)
Hospitalized	0.049***	0.012**	0.001
	(0.006)	(0.005)	(0.005)
Insurance	0.040***	0.010***	-0.017***
	(0.001)	(0.001)	(0.001)
Number public	0.007***	0.001**	-0.003***
	(0.001)	(0.000)	(0.000)
Number private	0.000	0.001***	0.002***
	(0.000)	(0.000)	(0.000)
Number TP	0.000	0.001***	0.004***
	(0.000)	(0.000)	(0.000)
Cost public	0.106***	-0.002***	-0.003***
	(0.000)	(0.000)	(0.000)
Cost private	-0.003***	0.090***	-0.001***
	(0.000)	(0.000)	(0.000)
Cost TP	0.000	0.001***	0.094***
	(0.000)	(0.000)	(0.000)
Distance	-0.028***	0.022***	-0.001
	(0.006)	(0.005)	(0.005)
Constant	0.246***	-0.070***	-0.043***
	(0.013)	(0.011)	(0.011)
Observations	113,734	113,734	113,734
R-squared	0.790	0.851	0.780

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

Note: Robust standard errors in parentheses. This table presents the estimation results using Seemingly unrelated regression model to estimate the determinants of having visited the different health care providers. This includes year, province and island fixed effect, using IFLS Community Survey data from 2000, 2007, 2014.

Table A11: BMI and good self assessed health (SAH) (Multinomial and Probit results - Margins)

	(1) BMI - Underweight	(2) BMI - Obese	(3) Good health (SAH)
Age	-0.020***	0.016***	-0.001***
	(0.000)	(0.000)	(0.000)
Age sq	0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Log exp.	-0.030***	0.038***	0.008***
	(0.001)	(0.001)	(0.001)
Higher education	-0.011***	0.017***	0.042***
	(0.002)	(0.001)	(0.002)
Woman	-0.048***	0.092***	-0.020***
	(0.001)	(0.001)	(0.001)
Self-treat	-0.005***	0.003***	-0.047***
	(0.001)	(0.001)	(0.001)
Urban	-0.014***	0.037***	-0.014***
	(0.001)	(0.001)	(0.001)
BMI - Normal			0.030***
			(0.001)
BMI - Overweight			0.031***
			(0.002)
Days in bed	0.033***	-0.020***	-0.180***
	(0.002)	(0.001)	(0.001)
Symptoms	0.006***	0.002	-0.073***
	(0.001)	(0.001)	(0.001)
N. Public HC	**0.014*** **	**-0.007*** **	**-0.012*** **
	(0.002)	**(0.001)**	**(0.002)**
N. Priv.	**-0.010*** **	**0.006*** **	**-0.004** **
	(0.002)	**(0.001)**	**(0.001)**
N. TP	**-0.014*** **	**-0.016*** **	**-0.018*** **
	(0.002)	**(0.002)**	**(0.002)**
N. Public x TP	**-0.017*** **	**0.011*** **	**0.016*** **
	(0.002)	**(0.001)**	**(0.002)**
N. Private x TP	**0.014*** **	**0.000**	**0.009*** **
	(0.001)	**(0.001)**	**(0.001)**
Observations	887,556		887,556
Log pseudo likelihood	-5114825.4		-1846862.8
Pseudo R^2	0.087		0.12

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

Note: Robust standard errors in parentheses. This table presents the estimation results using Probit and Negative binomial models to estimate the determinants of having visited the TP in the last 4 weeks and number of visits to the TP, respectively. Estimation separate for households in the first two (low income) and the last two quantiles of monthly expenditure. Families in middle income quintile are not included. This includes year, province and island fixed effect, using IFLS Community Survey data from 2000, 2007, 2014. Results show marginal effects for each coefficient in all specifications. The interaction variable is used to grasp and the effect of having a modern health-care facility built in a district with a given number of TP.

A2 Chapter 2

A2.1 I - Proofs

Proposition 1

Consider condition 1:

$$\begin{aligned} B(\eta) \geq S_2 C_2(\eta) \Leftrightarrow \\ \Leftrightarrow B(\eta) - S_2 C_2(\eta) \geq 0 \Leftrightarrow \\ \Leftrightarrow f(S_2, q) \geq 0 \Rightarrow f(S_2, \eta^*) = 0 \end{aligned} \tag{4.2}$$

Then, by the application of the Implicit Function Theorem: If f : $\mathbb{R}^m \times \mathbb{R} \Rightarrow \mathbb{R}$ is a C^1 function, $f(x_0; y_0) = 0$, and $\frac{\partial f}{\partial x} \neq 0$, then for some neighborhood $U \subset \mathbb{R}^m$ of (x_0) there is a C^1 function $g : U \Rightarrow \mathbb{R}$ such that $g(x_0) = y_0$ and $f(x, g(x)) = 0$ for all $x \in U$. The partial derivatives of g at x_0 are given by the formula:

$$\frac{\partial g}{\partial x^i}(x) = -\frac{\frac{\partial f}{\partial x^i}(x_0, y_0)}{\frac{\partial f}{\partial y}(x_0, y_0)}$$

Then,

$$\begin{aligned} \frac{\partial \eta^*}{\partial S_2}(S_2) = -\frac{\partial f(S_2,\eta^*)/\partial S_2}{\partial f(S_2,\eta^*)/\partial \eta^*} \Leftrightarrow \\ \Leftrightarrow \frac{\partial \eta^*}{\partial S_2}(S_2) = \frac{C_2(\eta^*)}{\partial B(\eta^*)/\partial \eta^* - S_2(\partial C_2(\eta^*)/\partial \eta^*)} > 0 \end{aligned} \tag{4.3}$$

According to this relationship, the threshold for patients to get treatment is positively related to the price of the low quality hospital. This is, as the patients' contribution share increases, more severity is needed for patients to get treatment.

Proposition 2

Consider condition 2:

$$\begin{aligned} \theta B(\eta) - S_1 C_1(\eta) \geq B(\eta) - S_2 C_2(\eta) \Leftrightarrow \\ \Leftrightarrow (\theta - 1) B(\eta) - S_1 C_1(\eta) + S_2 C_2(\eta) \geq 0 \Leftrightarrow \\ \Leftrightarrow g(S_1, S_2, \eta) \geq 0 \Rightarrow g(S_1, S_2, \eta^{**}) = 0 \end{aligned} \tag{4.4}$$

Once again, by the application of the Implicit Function Theorem:

$$\begin{aligned} \frac{\partial \eta^{**}}{\partial S_1}(S_1, S_2) = -\frac{\partial g(S_1, S_2, \eta^{**}) / \partial S_1}{\partial g(S_1, S_2, \eta^{**}) / \partial \eta^{**}} \Leftrightarrow \\ \Leftrightarrow \frac{\partial \eta^{**}}{\partial S_1}(S_1, S_2) = \frac{C_1(\eta^{*})}{\partial B(\eta^{**}) / \partial \eta^{**} - S_1 \left(\partial C_1(\eta^{**}) / \partial \eta^{**} \right)} > 0 \end{aligned} \tag{4.5}$$

Proposition 3

Consider condition 2:

$$\begin{aligned} \frac{\partial \eta^{**}}{\partial S_2}(S_1, S_2) = -\frac{\partial g(S_1, S_2, \eta^{**}) / \partial S_2}{\partial g(S_1, S_2, \eta^{**})) / \partial \eta^{**}} \Leftrightarrow \\ \Leftrightarrow \frac{\partial \eta^{**}}{\partial S_2}(S_1, S_2) = -\frac{C_2(\eta^{**})}{\partial B(\eta^{**}) / \partial \eta^{**} + S_2 \left(\partial C_2(\eta^{**}) / \partial \eta^{**} \right)} < 0 \end{aligned} \tag{4.6}$$

Proposition 4

Consider the number of patients going to hospital 1 and 2 as:

$$W_1 = \int_{\eta^{**}}^{\bar{\eta}} f(\eta)d\eta \quad (4.7) \qquad W_2 = \int_{\eta^{*}}^{\eta^{**}} f(\eta)d\eta \quad (4.8)$$

Then, taking into account the above relationships:

$$\begin{aligned} \frac{\partial W_1}{\partial S_1} &= -\frac{\partial \eta^{**}}{\partial S_1} f(\eta^{**}) < 0; \\ \frac{\partial W_1}{\partial S_2} &= -\frac{\partial \eta^{**}}{\partial S_2} f(\eta^{**}) > 0 \end{aligned} \tag{4.9}$$

And:

$$\begin{aligned} \frac{\partial W_2}{\partial S_1} &= \frac{\partial \eta^{**}}{\partial S_1} f(\eta^{**}) - \frac{\partial \eta^{*}}{\partial S_1} f(\eta^{*}) = \frac{\partial \eta^{**}}{\partial S_1} f(\eta^{**}) > 0; \\ \frac{\partial W_2}{\partial S_2} &= \frac{\partial \eta^{**}}{\partial S_2} f(\eta^{**}) - \frac{\partial \eta^{*}}{\partial S_2} f(\eta^{*}) < 0 \end{aligned} \tag{4.10}$$

If average costs are given by:

$$Av.Costs_1 = \frac{\int_{\eta^{**}}^{\bar{\eta}} C(\eta) f(\eta) d\eta}{\int_{\eta^{**}}^{\bar{\eta}} f(\eta) d\eta}, \ C'(\eta) > 0 \tag{4.11}$$

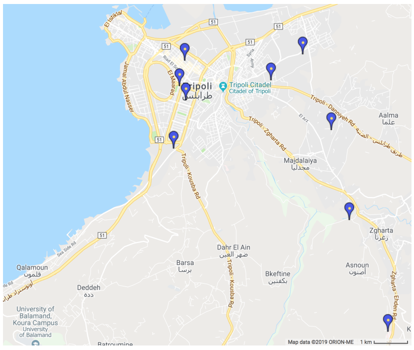
$$Av.Costs_2 = \frac{\int_{\eta^{*}}^{\eta^{**}} C(\eta) f(\eta) d\eta}{\int_{\eta^{*}}^{\eta^{**}} f(\eta) d\eta}, \ C'(\eta) > 0 \tag{4.12}$$

Applying the same reasoning:

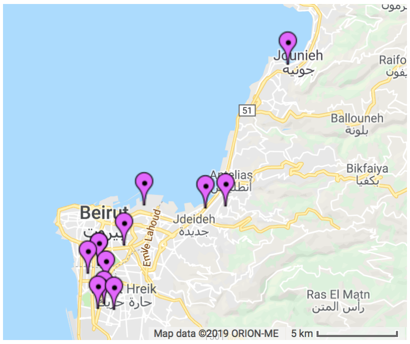
$$\frac{\partial Av.Costs_1}{\partial S_1} > 0; \frac{\partial Av.Costs_1}{\partial S_2} < 0; \ \frac{\partial Av.Costs_2}{\partial S_1} < 0; \frac{\partial Av.Costs_2}{\partial S_2} > 0 \tag{4.13}$$

A2.2 II - Maps

Figure 4.4: Hospitals by enumeration area

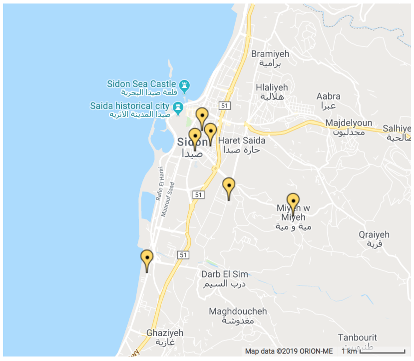


a) North Lebanon Area (NLA) - Tripoli



b) Central Lebanon Area (CLA) - Beirut

c) Beqaa



d) Saida

e) Tyre

A2.3 III - Tables

Results (main) - Standard Errors clustered by hospital

Robustness checks

Trying to further understand the results, in order to also better ensure their reliability, we performed a series of robustness checks to the estimations. These exercises consist in using different clustering methods, different policy shifts, dependent variables and model specifications.

The first check consisted in estimating the probability of changing hospital and assessing how those patients that shifted to a PRCS after the policy change are affecting the results. We created a binary variable for when patients go to a private or public hospital in the first visit before June 2016, but change to a PRCS hospital for the second or further visit after that same date. Note that only 297 patients changed to a PRCS hospital, which corresponds to 1.10% of the sample and does not give us enough power to achieve rigorous estimates. Nevertheless, it can be useful to learn more about this small sample.

Results show that staying one more day hospitalised, slightly (but significantly) decreases the probability of changing to a PRCS hospital. This indicates that people that changed hospital had longer stays on average, which can relate to the theory that patients with more severe conditions - that take longer to treat - have more difficulties covering for the increase in costs. After the policy, patients are 3% more likely to change to a PRCS hospital, highlighting the previous result that demand for PRCS increased with the introduction of the cost-sharing component.

The following estimations replicate the main exercise using data between January and May 2016. This aims at capturing the shift between the first policy change (January to March 2016) and the negotiations period (April to May 2016). During this *first policy*, patients had to cover 5% of their costs for secondary care in PRCS hospitals, 10% in public and 15% in private, whereas during the negotiations, secondary care was free of charge at all

Table B1: Policy impact estimation on demand for hospital type (Multinomial Logit - margins), from April 2016 to October 2017

	PRCS		Priv. Hospital		Pub. Hospital	
	(1.a)	(1.b)	(2.a)	(2.b)	(3.a)	(3.b)
Var. of interest:						
Policy	**0.035****	**0.180*****	**-0.018**	**-0.147*****	**-0.016**	**-0.033**
	(0.015)	**(0.061)**	**(0.017)**	**(0.032)**	**(0.013)**	**(0.065)**
Stay in days	-0.055***	0.022***	0.035***	-0.017***	0.019	-0.005
	(0.016)	(0.008)	(0.013)	(0.006)	(0.015)	(0.005)
Surgery	-0.005	0.098**	0.017	-0.048	-0.012	-0.050
	(0.041)	(0.043)	(0.040)	(0.030)	(0.026)	(0.031)
UNRWA contribution		2.880***		-1.819***		-1.061*
		(0.678)		(0.404)		(0.633)
Bill value		-3.001***		1.880***		1.121*
		(0.717)		(0.430)		(0.661)
UNRWA contr. (at p3==0)		5.745***		-3.547**		-2.198
		(2.226)		(1.582)		(1.621)
UNRWA contr. (at p3==0)		2.016*		-1.142		-0.874
		(1.097)		(0.725)		(0.602)
Difference		-3.26		2.405		1.324
Stay in days (at p3==0)		0.077***		-0.052***		-0.024
		(0.020)		(0.019)		(0.022)
Stay in days (at p3==1)		0.008		-0.007		-0.002
		(0.008)		(0.005)		(0.004)
Difference		0.069***		0.045**		0.022
Controls:						
Age	0.001	0.000	0.001	0.001**	-0.002	-0.001***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Age^2	-0.000	0.000	-0.000	-0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Woman	0.003	-0.004	-0.002	0.002	-0.001	0.003
	(0.006)	(0.004)	(0.006)	(0.004)	(0.004)	(0.004)
Ramadan	-0.016	-0.002	0.012	0.004	0.004	-0.002
	(0.012)	(0.003)	(0.011)	(0.005)	(0.004)	(0.005)
Distance	0.035	0.034	0.023	0.097***	-0.058	-0.131**
	(0.058)	(0.033)	(0.040)	(0.029)	(0.096)	(0.056)
CLA	0.395	0.123**	-0.438	-0.153	0.043	0.030
	(0.317)	(0.055)	(0.301)	(0.109)	(0.116)	(0.109)
Visit	0.005	0.001	-0.005	-0.003	-0.001	0.001
	(0.005)	(0.001)	(0.006)	(0.002)	(0.002)	(0.001)
Observations	32,851	32,810	32,851	32,810	32,851	32,810

Note: Dependent variables are a log transformation of the bill value, unrwa and patient contribution. Specification a does not contain costs related variables and avoids any potential issues of multicollinearity. Policy is a dummy variable that indicates the period of the policy change (from June 2016 onwards). Clustered standard errors by hospital in parentheses;
*** p<0.01, ** p<0.05, * p<0.1

Table B2: Policy 3 impact estimation on Stay in Days (Neg. Binomial/Mult. Poisson - IRR), from April 2016 to October 2017 (with controls)

	Nbreg		Mult. Poisson
	(1)	(2)	(3)
Var. of interest:			
Policy 3	**0.996**	**0.860*** **	**0.906*** **
	(0.029)	**(0.021)**	**(0.020)**
Surgery	0.716***	0.678***	0.694***
	(0.061)	(0.057)	(0.060)
UNRWA contr. × Policy 3		1.001***	1.000***
		(0.000)	(0.000)
Priv. Hosp × Policy 3		0.778***	0.851***
		(0.051)	(0.049)
Pub. Hosp. × Policy 3		0.763*	0.810
		(0.123)	(0.127)
Private hospital		1.363***	1.389***
		(0.105)	(0.113)
Public hospital		1.451***	1.444**
		(0.205)	(0.210)
Controls:			
Age	0.986***	0.994***	0.993***
	(0.003)	(0.001)	(0.002)
Age squared	1.000***	1.000***	1.000***
	(0.000)	(0.000)	(0.000)
Woman	0.968**	0.971**	0.964**
	(0.013)	(0.012)	(0.018)
Ramadan	0.976	0.971*	0.960
	(0.021)	(0.016)	(0.032)
Visit	1.033***	1.017***	1.023***
	(0.011)	(0.006)	(0.006)
Distance	1.008	1.007***	1.011***
	(0.008)	(0.002)	(0.002)
Area		1.014	1.056
- CLA			
		(0.053)	(0.076)
- NLA		1.195***	1.308***
		(0.049)	(0.060)
-Saida		1.110**	1.227***
		(0.052)	(0.066)
- Tyre		0.896***	0.944*
		(0.024)	(0.032)
Constant	2.526***	2.194***	1.758***
	(0.039)	(0.054)	(0.097)
Observations	32,851	32,811	33,402

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

Note: Coefficients show Incidence Rate Ratios (IRR) for a negative binomial and multinomial poisson regression results. Standard errors clustered by hospital in parentheses. Policy 3 is a dummy variable that indicates the period after the last policy change (from June 2016 onward).

Table B3: Policy impact estimation on patients and UNRWA contribution, and Bill value (OLS), from April 2016 to October 2017

	Bill value		UNRWA contr.		Patient contr.	
	(1.a)	(1.b)	(2.a)	(2.b)	(3.a)	(3.b)
Var. of interest:						
Policy 3	**-0.007**	**-0.001**	**-0.040****	**0.002**	**-0.134**	**0.091**
	(0.013)	**(0.007)**	**(0.019)**	**(0.006)**	**(0.102)**	**(0.116)**
Stay in days	0.199***	0.011**	0.193***	0.001	0.191***	-0.031**
	(0.021)	(0.004)	(0.021)	(0.002)	(0.019)	(0.014)
Surgery	0.605***	0.024**	0.590***	0.010	0.935***	-0.082
	(0.085)	(0.010)	(0.086)	(0.010)	(0.095)	(0.060)
Private hosp.	0.732***	0.076*	0.602***	-0.036	1.511**	0.569
	(0.049)	(0.039)	(0.041)	(0.033)	(0.558)	(0.390)
Public hosp.	0.601***	0.007	0.504***	0.024	1.110**	0.615*
	(0.058)	(0.013)	(0.055)	(0.018)	(0.525)	(0.302)
Bill value				0.960***		1.220***
				(0.013)		(0.058)
UNRWA contr.		0.983***				
		(0.011)				
Stay in days ×		-0.002		0.001		0.015
		(0.003)		(0.003)		(0.015)
Priv. Hosp × policy 3		0.148***		-0.109***		0.273
		(0.014)		(0.016)		(0.405)
Pub. Hosp × policy 3		0.118***		-0.085***		0.113
		(0.010)		(0.014)		(0.381)
Controls:						
Age	-0.001	0.000**	-0.001	-0.000**	0.000	0.003**
	(0.001)	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)
Age squared	0.000***	-0.000*	0.000***	0.000**	0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Woman	-0.019**	-0.002	-0.017	0.001	-0.049**	-0.011
	(0.009)	(0.002)	(0.010)	(0.002)	(0.019)	(0.010)
Ramadan	-0.021*	0.004	-0.026**	-0.006	0.007	0.041
	(0.011)	(0.005)	(0.010)	(0.005)	(0.056)	(0.038)
Distance	0.012***	0.001**	0.011***	-0.000	0.010	0.000
	(0.002)	(0.000)	(0.002)	(0.000)	(0.012)	(0.005)
Visit	0.006*	0.001	0.005*	-0.000	0.019**	0.008*
	(0.003)	(0.001)	(0.003)	(0.001)	(0.009)	(0.005)
Area	0.389***	0.066***	0.328***	-0.045***	0.581	-0.162
- CLA						
	(0.099)	(0.015)	(0.092)	(0.013)	(0.422)	(0.284)
- NLA	0.455***	0.043***	0.418***	-0.018	0.672***	0.045
	(0.064)	(0.014)	(0.060)	(0.014)	(0.125)	(0.069)
-Saida	0.387***	0.047**	0.345***	-0.026*	0.740***	0.157**
	(0.069)	(0.018)	(0.058)	(0.014)	(0.163)	(0.072)
- Tyre	0.268***	0.031**	0.241***	-0.016	0.296***	-0.021
	(0.043)	(0.011)	(0.039)	(0.010)	(0.053)	(0.027)
Constant	11.325***	7.328***	4.100***	-6.810***	0.975*	-12.743***
	(0.065)	(0.047)	(0.055)	(0.162)	(0.550)	(0.656)
Observations	32,811	32,810	32,810	32,810	12,875	12.875
R-squared	0.702	0.983	0.675	0.982	0.596	0.900

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

Note: Dependent variable is in log transformation; Policy 3 is a dummy variable that indicates the period after the last policy change (from June 2016 onward). Standard errors clustered by hospital in parentheses;

Table B4: Policy impact estimation on probability of changing hospital type (Probit - margins), from April 2016 to October 2017

	(1) Change
Var. of interest:	
Policy	**0.029***** **(0.010)**
Stay in days	-0.004*** (0.001)
Controls:	
Age	-0.001*** (0.000)
Age^2	0.000*** (0.000)
Woman	-0.006 (0.006)
Visit	-0.005 (0.003)
Surgery	0.011 (0.008)
Area	
-CLA	-0.003 (0.008)
-NLA	0.052** (0.020)
-Saida	0.040*** (0.009)
-Tyre	0.049** (0.021)
Observations	5,823

Note: Dependent variable is a binary variable, equal to 1 if the patient changed from a public or private hospital to a PRCS after the second visit. Policy 3 is a dummy variable that indicates the period after the last policy change (from June 2016 onward). Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

hospitals (as it was for the main estimations). We consider the first three months as the policy 1 and estimate its impact using exactly the same model and estimation strategies as before.

Table B5 to B7 show the results for the three main impact estimations: LoS, hospital demand by hospital type and costs. The results obtained in this section confirm our previous reasoning, in the sense that patients are price sensitive and when they have to cover for a larger share of the costs, demand increases at the facilities where that share is smaller, which also follows the previously developed theoretical framework. Length of stay was higher in public hospitals during policy 1 but significantly lower in private hospitals. Going to a private hospital when policy 1 was in place decreased the rate of stay in days by 0.24, meaning that patients were going less and for shorter stays, as in the case of policy 3 (table B5). Demand for PRCS hospitals was 20% during policy 1, which meant a decrease of almost the same magnitude in the demand for private hospitals, as showed in table B6. In terms of costs, again there is no direct impact of the policy at any level. UNRWA contribution decreased in policy 1 for private and public hospitals, and length of stay during policy 1 affected negatively the bill value, which is mot likely related to the average LoS decrease in the most expensive hospitals. The results for policy 1 follow the general evidence found for policy 3, which was in place after June 2016 and charges 10% of secondary care costs at private and public hospitals.

Table B5: Policy 1 impact estimation on Stay in days (LoS), from January to May 2016

	(1) Stay in days
Var. of interest:	
Policy 1	**1.001***** **(5.19e-05)**
Policy 1 × UNRWA cont.	0.821** (0.065)
Policy 1 × Priv. Hosp.	0.740** (0.11)
Policy 1 × Pub. Hosp.	1.341*** (0.11)
Private hospital	1.478*** (0.20)
Public hospital	0.968 (0.084)
Controls:	
Age	0.993*** (0.002)
Age^2	1.000*** (1.63e-05)
Woman	0.991 (0.020)
Ramadan	1.059*** (0.012)
Visit	0.682*** (0.060)
Surgery	0.909*** (0.016)
Area	
- CLA	1.126 (0.096)
- NLA	1.015 (0.088)
- Saida	0.872* (0.068)
lnalpha	1.982*** (0.17)
Observations	8,295

Note: Dependent variable is a count variable equivalent to the number of days each patient stayed at the hospital in each visit. Policy 1 is a dummy variable that indicates the period of the 1^{st} policy change (from January to March 2016). Robust standard errors in parentheses;
*** p<0.01, ** p<0.05, * p<0.1

Table B6: Policy 1 impact estimation on hospitals' demand, from January to May 2016

	(1) PRCS	(2) Private	(3) Public
Var. of interest:			
Policy 1	**0.202****	**-0.170****	**-0.032**
	(0.095)	**(0.077)**	**(0.030)**
Policy 1 $\times$ UNRWA contribution	-0.002***	0.002***	0.001
	(0.001)	(0.001)	(0.001)
Policy 1 $\times$ Stay in days	0.208***	-0.144***	-0.064
	(0.043)	(0.037)	(0.049)
Stay in days	-0.048***	0.027**	0.021
	(0.011)	(0.012)	(0.015)
Controls:			
Age	0.002	0.001	-0.003
	(0.002)	(0.001)	(0.002)
Age^2	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)
Woman	0.016*	-0.011	-0.005
	(0.008)	(0.009)	(0.003)
Distance	0.042	0.030	-0.072
	(0.064)	(0.042)	(0.105)
Surgical	0.181***	-0.112***	-0.069
	(0.043)	(0.039)	(0.060)
Observations	8,295	8,295	8,295

Note: The dependent variables are binary variables with the value 1 if the patient is at each hospital type and 0 otherwise. Note that all patients get treatment, thus for each observation at least one option must be selected. Coefficients show average marginal effects for multinomial logit regression results. Standard errors clustered by hospital in parentheses. Policy 1 is a dummy variable that indicates the period of the 1^{st} policy change (from January to March 2016). Robust standard errors in parentheses;
*** p<0.01, ** p<0.05, * p<0.1

Table B7: Policy 1 impact estimation on costs, from January to May 2016

	(1) Bill value	(2) UNRWA Contr.	(3) Patient Contr.
Var. of interest			
Policy 1	**0.052**	**-0.039**	**-0.214**
	(0.049)	**(0.044)**	**(0.253)**
Policy 1 × UNRWA cont.	0.000***		0.001***
	(0.000)		(0.000)
Policy 1 × Stay in days	-0.063**	0.002	-0.019
	(0.025)	(0.021)	(0.040)
Private hospital	0.680***	0.616***	1.840***
	(0.058)	(0.063)	(0.298)
Public hospital	0.538***	0.544***	1.918***
	(0.053)	(0.046)	(0.288)
Policy 1 × Priv. Hosp	-0.059	-0.092**	0.146
	(0.036)	(0.043)	(0.298)
Policy 1 × Pub. Hosp	-0.040	-0.086**	-0.424
	(0.057)	(0.039)	(0.281)
Stay in days	0.215***	0.209***	0.156***
	(0.029)	(0.029)	(0.030)
Controls:			
Age	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)
Age^2	0.000***	0.000***	0.000*
	(0.000)	(0.000)	(0.000)
Woman	-0.035***	-0.036***	-0.050**
	(0.011)	(0.010)	(0.022)
Area			
- CLA	0.135	0.112	-0.011
	(0.131)	(0.128)	(0.140)
- NLA	0.205*	0.200*	0.200
	(0.117)	(0.113)	(0.121)
- Saida	0.127	0.118	0.157
	(0.120)	(0.114)	(0.121)
- Tyre	0.094	0.096	0.001
	(0.114)	(0.113)	(0.116)
Surgical	0.505***	0.550***	0.409***
	(0.064)	(0.082)	(0.062)
Constant	11.582***	4.271***	1.633***
	(0.124)	(0.121)	(0.272)
Observations	8,295	8,295	4,628

Robust standard errors in parentheses;
*** p<0.01, ** p<0.05, * p<0.1
Note: Dependent variables are a log transformation of the bill value, unrwa and patient contribution. Policy 1 is a dummy variable that indicates the period of the 1^{st} policy change (from January to March 2016).

The last robustness check, presented in table B8 uses the year of 2017 as proxy for a control year. Facing one of the greatest limitations of this project - not being able to evaluate the before and after trends in a control group of people from the same context - in this estimation we perform the same regression as the main model in 2.4 but with data from 2017 and thus considering a fictional policy change in June 2017. We assume patients in 2017 are equivalent to the patients in 2016, thus a potential control group, that was not subject to a policy change. These results help confirming that the main estimation is not grasping an effect of seasonality associated with the month of June, despite all the control variables. All policy indicators are not significant. Length of stay at private hospitals after June 2017 seems to decrease with a statistically significant impact, but the coefficient is really close to zero (marginal effect of 0.6%).

Table B8: Proxy policy impact estimation on hospital demand, from January to October 2017

	(1) PRCS	(2) Priv. Hosp.	(4) Pub Hosp
Var. of interest			
Policy	**-0.001**	**0.001**	**0.000**
	(0.002)	**(0.003)**	**(0.003)**
UNRWA contribution	1.753	-1.009	-0.744
	(1.126)	(0.702)	(0.569)
Bill value	-1.790	1.019	0.771
	(1.163)	(0.721)	(0.587)
Stay in days	0.005	-0.006*	0.001
	(0.006)	(0.004)	(0.003)
Surgery	0.043	-0.022	-0.021
	(0.044)	(0.025)	(0.026)
UNRWA contr. (at p4==0)-(at p4==1)	0.038	0.008	0.005
Stay in days (at p4==0)-(at p4==1)	-0.001	-0.001	0.001
Controls			
Age	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
Age^2	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Woman	-0.005	0.000	0.004
	(0.005)	(0.005)	(0.005)
Ramadan	-0.004	-0.001	0.005
	(0.003)	(0.004)	(0.004)
Distance	0.023	0.105***	-0.128***
	(0.025)	(0.022)	(0.035)
CLA	-0.002	-0.054	0.056
	(0.027)	(0.112)	(0.096)
Visit	0.000	-0.003	0.002
	(0.001)	(0.003)	(0.003)
Observations	17,524	17,524	17,524

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

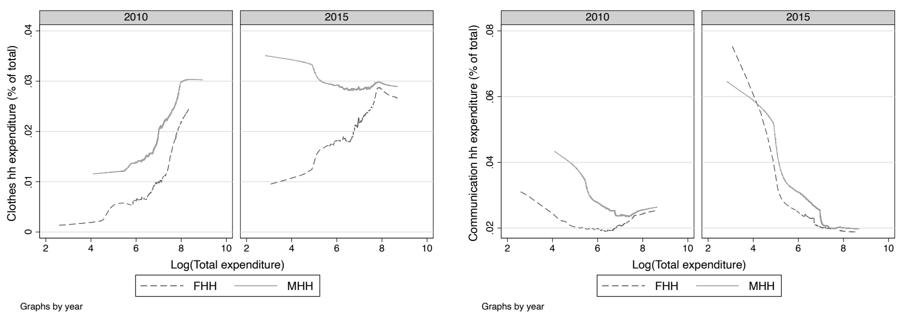
Note: The dependent variables are binary variables with the value 1 if the patient is at each hospital type and 0 otherwise. Note that all patients get treatment, thus for each observation at least one option must be selected. Coefficients show average marginal effects for multinomial logit regression results. Standard errors clustered by hospital in parentheses. Policy is a dummy variable that indicates the period of the 3^{rd} and main policy change if it had happened in 2017 (from June 2017 onward) - Proxy policy.

A3 Chapter 3

A3.1 Optimal bundles

Following the analysis in the Results section, here we look further into Engel curves for clothes and communication expenditure. Expenditure on clothes presents similar patterns to those of education expenditure already mentioned. Regarding communication, 2015 was a year with higher migration levels due to the Syrian conflict. As refugee camps and services became crowded, families had more incentives to move. In addition, since access to borders changed due to the high influx of migrants, it is possible that the opportunities to leave the country for lower income families increased. The relatively high level of spending in communication for FHH in 2015 follows this story line in the sense that historical records have shown that the men of the HH typical leaves first, searching for opportunities abroad, living his household and his wife/mother as the HoH, which would explain why this high level of expenditure is not visible in MHH.

Figure 4.5: Share of HH expenditure vs. Total expenditure (log), by category as % of total



(a) Clothes **(b)** Communication

Note: Data from AUB socioeconomic survey 2010 and 2015. All values were computed using survey weights. We exclude single member households.

Table C1: Determinants of Health-care Expenditure (two-pm model, glm results) - coefficients

Dep. var.: Health care expenditure as % of total	2010 (1) Probit	2010 (2) GLM	2015 (1) Probit	2015 (2) GLM
Treated	0.038	0.290***	0.130	0.131*
	(0.117)	(0.068)	(0.105)	(0.073)
Average age by HH	0.013***	0.011***	0.011***	0.014***
	(0.004)	(0.003)	(0.004)	(0.003)
Log (Percap Exp)	0.798***	0.484***	0.343**	0.161**
	(0.153)	(0.094)	(0.139)	(0.077)
Below lower poverty level	0.159	0.636**	-0.298	0.166
	(0.357)	(0.268)	(0.222)	(0.196)
Having a child	-0.073	-0.051	-0.067	-0.125**
	(0.106)	(0.060)	(0.085)	(0.059)
HH size above 3	0.180	0.143*	0.093	-0.019
	(0.121)	(0.077)	(0.115)	(0.088)
Having one family member living abroad	-0.002	0.041	0.043	0.145*
	(0.110)	(0.069)	(0.125)	(0.088)
Living in a camp	0.011	-0.027	-0.111	0.268***
	(0.127)	(0.069)	(0.119)	(0.076)
Average # chronic disease by HH	0.727***	0.571***	1.064***	0.388*
	(0.172)	(0.143)	(0.136)	(0.202)
Average # acute disease by HH	0.097	0.289***	0.349***	-0.061
	(0.177)	(0.085)	(0.103)	(0.077)
Insurance	0.157	-0.181	-0.099	-0.321***
	(0.183)	(0.117)	(0.190)	(0.119)
Saida	0.600***	-0.040	0.139	0.250**
	(0.168)	(0.095)	(0.151)	(0.126)
Tyre	0.304**	-0.027	0.219	0.302***
	(0.153)	(0.099)	(0.135)	(0.102)
Bekaa	0.166	-0.250**	0.414***	0.354***
	(0.201)	(0.105)	(0.150)	(0.110)
NLA	-0.128	-0.044	-0.103	0.135
	(0.172)	(0.104)	(0.175)	(0.114)
Constant	-5.036***	-6.351***	-2.847***	-4.597***
	(0.934)	(0.544)	(0.746)	(0.476)
Observations	10,375	10,375	9,931	9,931
Pseudo R-squared	0.136	0.136	0.152	0.152
Log-likelihood	9.373	9.373	7.438	7.438

Robust standard errors in parentheses;
*** p<0.01, ** p<0.05, * p<0.1
Note: Data from AUB SE 2010 and 2015, using survey weights. We control for household size and household size squared, age and working status of the HoH and region.

Table C2: Determinants of Health-care Expenditure (two-pm model, glm results) - margins

Dep. var.: Health care expenditure as % of total	(1) Probit	2010 (2) GLM	(3) Overall	(4) Probit	2015 (5) GLM	(6) Overall
Treated	**0.009**	**0.031*****	**0.022*****	**0.033**	**0.020****	**0.013****
	(0.026)	**(0.009)**	**(0.006)**	**(0.026)**	**(0.010)**	**(0.006)**
Average age by HH	0.003***	0.001***	0.001***	0.003***	0.002***	0.001***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Log (Percap Exp)	0.181***	0.075***	0.053***	0.086**	0.034***	0.021***
	(0.034)	(0.012)	(0.008)	(0.035)	(0.010)	(0.007)
Below lower poverty level	0.036	0.059*	0.050**	-0.075	-0.006	0.005
	(0.081)	(0.032)	(0.021)	(0.056)	(0.024)	(0.016)
Having a child	-0.017	-0.008	-0.005	-0.017	-0.015**	-0.011**
	(0.024)	(0.008)	(0.005)	(0.022)	(0.007)	(0.005)
HH size above 3	0.041	0.021**	0.014**	0.023	0.001	0.001
	(0.027)	(0.009)	(0.007)	(0.029)	(0.011)	(0.007)
Having one family member living abroad	-0.000	0.010	0.003	0.011	0.015	0.012
	(0.025)	(0.009)	(0.006)	(0.032)	(0.011)	(0.007)
Living in a camp	0.002	-0.000	-0.002	-0.028	0.022**	0.017***
	(0.029)	(0.009)	(0.006)	(0.030)	(0.010)	(0.006)
Average # chronic disease by HH	0.165***	0.095***	0.058***	0.268***	0.118***	0.057***
	(0.038)	(0.018)	(0.012)	(0.030)	(0.020)	(0.015)
Average # acute disease by HH	0.022	0.027**	0.023***	0.088***	0.017*	0.004
	(0.040)	(0.012)	(0.008)	(0.026)	(0.009)	(0.006)
Insurance	0.036	-0.019	-0.010	-0.025	-0.042***	-0.027***
	(0.042)	(0.013)	(0.009)	(0.048)	(0.013)	(0.010)
Saida	0.125***	0.013	0.009	0.038	0.024**	0.020**
	(0.035)	(0.012)	(0.008)	(0.041)	(0.012)	(0.009)
Tyre	0.072*	0.006	0.005	0.058	0.040***	0.026***
	(0.037)	(0.012)	(0.008)	(0.036)	(0.011)	(0.008)
Bekaa	0.041	-0.015	-0.013	0.103***	0.059***	0.036***
	(0.049)	(0.012)	(0.008)	(0.036)	(0.015)	(0.009)
NLA	-0.036	-0.017	-0.007	-0.030	0.013	0.005
	(0.048)	(0.013)	(0.009)	(0.052)	(0.012)	(0.008)
Observations	10,375	10,375	10,375	9,931	9,931	9,931

Robust standard errors in parentheses;
*** p<0.01, ** p<0.05, * p<0.1
Note: Data from AUB SE 2010 and 2015, using survey weights. We control for household size and household size squared, age and working status of the HoH and region.

Table C3: Determinants of Tobacco Expenditure (two-pm model, glm results) - coefficients

Dep. var.: Tobacco expenditure as % of total	2010 (1) Probit	2010 (2) GLM	2015 (1) Probit	2015 (2) GLM
Treated	-0.498***	-0.114	-0.320***	-0.109
	(0.087)	(0.112)	(0.092)	(0.079)
Average age by HH	-0.014***	0.005*	-0.008**	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Log (Percap Exp)	-0.110	-0.463***	0.014	-0.365***
	(0.096)	(0.126)	(0.117)	(0.113)
Below lower poverty level	-0.448**	-0.403	-0.357	-0.367
	(0.206)	(0.274)	(0.305)	(0.249)
Having a child	-0.092	0.098	-0.085	-0.063
	(0.076)	(0.100)	(0.084)	(0.056)
HH size above 3	0.405***	-0.135	0.327***	-0.332***
	(0.103)	(0.082)	(0.103)	(0.090)
Having one family member living abroad	-0.081	-0.062	-0.036	-0.180**
	(0.109)	(0.085)	(0.098)	(0.081)
Living in a camp	0.157*	0.140	-0.106	0.079
	(0.093)	(0.100)	(0.097)	(0.082)
Average # chronic disease by HH	0.139	0.110	0.074	0.137
	(0.139)	(0.099)	(0.140)	(0.098)
Average # acute disease by HH	0.093	0.072	-0.179	-0.082
	(0.091)	(0.083)	(0.132)	(0.117)
Insurance	0.156	-0.185	0.325**	0.250**
	(0.172)	(0.131)	(0.151)	(0.126)
Saida	0.793***	-0.083	-0.277**	-0.249**
	(0.134)	(0.131)	(0.124)	(0.098)
Tyre	0.607***	0.115	-0.171	-0.198*
	(0.118)	(0.175)	(0.130)	(0.101)
Bekaa	0.300**	-0.516***	-0.316*	-0.267**
	(0.128)	(0.130)	(0.167)	(0.129)
NLA	0.284*	-0.489***	-0.403***	-0.423***
	(0.160)	(0.149)	(0.145)	(0.138)
Constant	1.028*	-0.622	0.914	-0.706
	(0.554)	(0.602)	(0.713)	(0.690)
Observations	10,257	10,257	11,192	11,192
Pseudo R-squared	10257	10257	11192	11192
Log-likelihood	0.108	0.108	0.0459	0.0459

Robust standard errors in parentheses;
*** p<0.01, ** p<0.05, * p<0.1
Note: Data from AUB SE 2010 and 2015, using survey weights. We control for household size and household size squared, age and working status of the HoH and region.

Table C4: Determinants of Tobacco Expenditure (two-pm model, glm results) - margins

		2010			2015	
Dep. var.: Tobacco expenditure as % of total	(1) Probit	(2) GLM	(3) Overall	(4) Probit	(5) GLM	(6) Overall
Treated	-0.173***	-0.023***	-0.016***	-0.120***	-0.010***	-0.008***
	(0.030)	(0.004)	(0.005)	(0.035)	(0.003)	(0.003)
Average age by HH	-0.005***	-0.000	-0.000	-0.003**	-0.000**	-0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Log (Percap Exp)	-0.038	-0.023***	-0.024***	0.005	-0.010***	-0.010***
	(0.033)	(0.007)	(0.007)	(0.044)	(0.004)	(0.004)
Below lower poverty level	-0.156**	-0.034**	-0.028*	-0.134	-0.019**	-0.016*
	(0.071)	(0.015)	(0.015)	(0.114)	(0.009)	(0.008)
Having a child	-0.032	0.000	0.003	-0.032	-0.003	-0.003
	(0.026)	(0.005)	(0.005)	(0.032)	(0.002)	(0.002)
HH size above 3	0.141***	0.005	0.002	0.123***	-0.002	-0.004
	(0.035)	(0.005)	(0.004)	(0.038)	(0.003)	(0.003)
Having one family member living abroad	-0.028	-0.004	-0.005	-0.014	-0.005*	-0.006**
	(0.038)	(0.005)	(0.005)	(0.037)	(0.003)	(0.003)
Living in a camp	0.055*	0.010*	0.010*	-0.040	0.001	0.001
	(0.032)	(0.006)	(0.005)	(0.036)	(0.003)	(0.003)
Average # chronic disease by HH	0.048	0.011*	0.008	0.028	0.005	0.005
	(0.048)	(0.006)	(0.006)	(0.053)	(0.003)	(0.004)
Average # acute disease by HH	0.032	0.004	0.005	-0.067	-0.004	-0.005
	(0.032)	(0.005)	(0.004)	(0.049)	(0.004)	(0.004)
Insurance	0.054	-0.005	-0.005	0.122**	0.013***	0.012***
	(0.060)	(0.007)	(0.007)	(0.057)	(0.005)	(0.004)
Saida	0.283***	0.022***	0.014**	-0.104**	-0.013***	-0.013***
	(0.045)	(0.007)	(0.007)	(0.046)	(0.004)	(0.004)
Tyre	0.220***	0.027**	0.022**	-0.064	-0.010**	-0.010**
	(0.042)	(0.010)	(0.011)	(0.049)	(0.004)	(0.004)
Bekaa	0.109**	-0.007	-0.013**	-0.119*	-0.014***	-0.014***
	(0.046)	(0.005)	(0.006)	(0.063)	(0.005)	(0.005)
NLA	0.103*	-0.006	-0.012*	-0.153***	-0.019***	-0.019***
	(0.058)	(0.006)	(0.006)	(0.055)	(0.004)	(0.005)

Robust standard errors in parentheses;
*** p<0.01, ** p<0.05, * p<0.1
Note: Data from AUB SE 2010 and 2015, using survey weights. We control for household size and household size squared, age and working status of the HoH and region.

Table C5: Determinants of Education Expenditure (two-pm model, glm results) - coefficients

Dep. var.: Education expenditure as % of total	2010 (1) Probit	2010 (2) GLM	2015 (1) Probit	2015 (2) GLM
Treated	-0.178*	-0.049	-0.078	-0.054
	(0.097)	(0.119)	(0.119)	(0.173)
Average age by HH	-0.018***	-0.005	-0.022***	0.003
	(0.004)	(0.005)	(0.004)	(0.006)
Log (Percap Exp)	0.508***	0.420***	0.455***	0.384***
	(0.115)	(0.108)	(0.150)	(0.149)
Below lower poverty level	0.354	0.565**	-0.388	1.413*
	(0.235)	(0.253)	(0.303)	(0.728)
Having a child	0.317***	-0.371***	0.345***	-0.213***
	(0.073)	(0.061)	(0.085)	(0.071)
HH size above 3	1.111***	0.301**	1.362***	0.030
	(0.109)	(0.118)	(0.145)	(0.189)
Having one family member living abroad	0.018	0.158	0.064	0.366**
	(0.116)	(0.139)	(0.124)	(0.176)
Living in a camp	0.004	-0.282**	0.162	0.497***
	(0.104)	(0.128)	(0.123)	(0.162)
Average # chronic disease by HH	-0.346***	-0.063	0.081	-0.378*
	(0.133)	(0.143)	(0.180)	(0.211)
Average # acute disease by HH	0.095	-0.315***	-0.213	0.137
	(0.100)	(0.111)	(0.184)	(0.173)
Insurance	0.413*	0.074	0.163	-0.038
	(0.230)	(0.148)	(0.173)	(0.219)
Saida	-0.340**	0.087	0.410***	-0.114
	(0.146)	(0.181)	(0.151)	(0.204)
Tyre	0.031	-0.338**	-0.021	0.243
	(0.132)	(0.150)	(0.166)	(0.223)
Bekaa	-0.096	-0.164	-0.359*	-0.027
	(0.144)	(0.170)	(0.211)	(0.264)
NLA	-0.179	-0.017	0.241	0.029
	(0.192)	(0.252)	(0.186)	(0.253)
Constant	-2.350***	-4.075***	-2.774***	-5.113***
	(0.671)	(0.693)	(0.942)	(1.004)
Observations	10,588	10,588	11,132	11,132
Pseudo R-squared	0.196	0.196	0.228	0.228
Log-likelihood	-0.824	-0.824	-0.362	-0.362

Robust standard errors in parentheses;
*** p<0.01, ** p<0.05, * p<0.1
Note: Data from AUB SE 2010 and 2015, using survey weights. We control for household size and household size squared, age and working status of the HoH and region.

Table C6: Determinants of Education Expenditure (two-pm model, glm results) - margins

Dep. var.: Education expenditure as % of total	(1)	2010 (2)	(3)	(4)	2015 (5)	(6)
	Probit	GLM	Overall	Probit	GLM	Overall
Treated	**-0.047***	**-0.010****	**-0.007**	**-0.020**	**-0.003**	**-0.004**
	(0.025)	**(0.005)**	**(0.005)**	**(0.030)**	**(0.009)**	**(0.007)**
Average age by HH	-0.005***	-0.001***	-0.001***	-0.005***	-0.001***	-0.000*
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Log (Percap Exp)	0.133***	0.021***	0.029***	0.115***	0.013	0.025***
	(0.029)	(0.006)	(0.005)	(0.036)	(0.010)	(0.007)
Below lower poverty level	0.093	0.024**	0.031***	-0.098	0.019	0.039
	(0.062)	(0.011)	(0.012)	(0.077)	(0.036)	(0.028)
Having a child	0.083***	0.002	-0.006*	0.087***	0.006	0.001
	(0.019)	(0.003)	(0.003)	(0.022)	(0.005)	(0.003)
HH size above 3	0.290***	0.037***	0.041***	0.343***	0.066***	0.036***
	(0.025)	(0.007)	(0.006)	(0.031)	(0.022)	(0.008)
Having one family member living abroad	0.005	0.006	0.006	0.016	0.011	0.014*
	(0.030)	(0.006)	(0.006)	(0.031)	(0.007)	(0.008)
Living in a camp	0.001	-0.015**	-0.011*	0.041	0.036**	0.021***
	(0.027)	(0.006)	(0.006)	(0.030)	(0.014)	(0.008)
Average # chronic disease by HH	-0.090***	-0.012*	-0.011*	0.021	-0.019	-0.011
	(0.034)	(0.007)	(0.006)	(0.045)	(0.014)	(0.009)
Average # acute disease by HH	0.025	-0.006	-0.009*	-0.054	-0.015	-0.001
	(0.026)	(0.005)	(0.005)	(0.046)	(0.012)	(0.008)
Insurance	0.108*	0.019*	0.014*	0.041	0.021	0.003
	(0.060)	(0.011)	(0.008)	(0.044)	(0.025)	(0.009)
Saida	-0.087**	-0.005	-0.007	0.108***	0.007	0.006
	(0.037)	(0.008)	(0.009)	(0.038)	(0.013)	(0.008)
Tyre	0.009	-0.007	-0.012*	-0.005	-0.001	0.008
	(0.037)	(0.006)	(0.007)	(0.040)	(0.011)	(0.009)
Bekaa	-0.026	-0.001	-0.009	-0.078*	-0.014	-0.009
	(0.039)	(0.009)	(0.008)	(0.045)	(0.009)	(0.008)
NLA	-0.047	0.001	-0.006	0.061	0.001	0.007
	(0.050)	(0.012)	(0.011)	(0.047)	(0.011)	(0.010)
Observations	10,588	10,588	10,588	11,132	11,132	11,132

Robust standard errors in parentheses;
*** p<0.01, ** p<0.05, * p<0.1
Note: Data from AUB SE 2010 and 2015, using survey weights. We control for household size and household size squared, age and working status of the HoH and region.

Table C7: Determinants of Food Expenditure (two-pm model, glm results) - coefficients

	2010		2015	
Dep. var.: Food expenditure as % of total	(1) Probit	(2) GLM	(1) Probit	(2) GLM
Treated	-0.180	-0.002	-0.232	0.048
	(0.238)	(0.032)	(0.326)	(0.033)
Average age by HH	0.007	0.001	-0.051**	-0.000
	(0.010)	(0.001)	(0.021)	(0.001)
Log (Percap Exp)	0.745**	-0.034	0.950**	-0.216***
	(0.320)	(0.038)	(0.438)	(0.045)
Below lower poverty level	-0.340	-0.150	-0.840	-0.168
	(0.536)	(0.095)	(0.863)	(0.181)
Having a child	0.076	-0.001	-0.131	0.087***
	(0.322)	(0.024)	(0.297)	(0.024)
HH size above 3	2.296***	-0.114***	2.035***	-0.152***
	(0.444)	(0.034)	(0.539)	(0.040)
Having one family member living abroad	0.007	-0.073**	0.152	-0.009
	(0.243)	(0.032)	(0.317)	(0.035)
Living in a camp	0.588***	0.203***	0.457	0.052
	(0.224)	(0.035)	(0.368)	(0.031)
Average # chronic disease by HH	0.265	-0.032	0.222	-0.125**
	(0.355)	(0.043)	(0.575)	(0.053)
Average # acute disease by HH	0.072	-0.060**	0.018	0.004
	(0.248)	(0.030)	(0.505)	(0.059)
Insurance	-0.062	-0.126**	-	-0.098*
	(0.350)	(0.053)		(0.052)
Saida	0.454	-0.093**	0.555	-0.048
	(0.388)	(0.042)	(0.409)	(0.044)
Tyre	0.237	-0.017	1.514**	-0.037
	(0.401)	(0.047)	(0.609)	(0.044)
Bekaa	-0.534	-0.157***	1.083**	-0.109**
	(0.326)	(0.040)	(0.525)	(0.046)
NLA	-0.808**	-0.240***		-0.113*
	(0.380)	(0.054)		(0.058)
Constant	-2.212	-1.026***	-0.033	-0.005
	(1.896)	(0.213)	(2.681)	(0.274)
Observations	10578	10,578	8930	8930
Pseudo R-squared	0.274	0.274	0.377	0.377
Log-likelihood	4.072	4.072	5.911	5.911

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

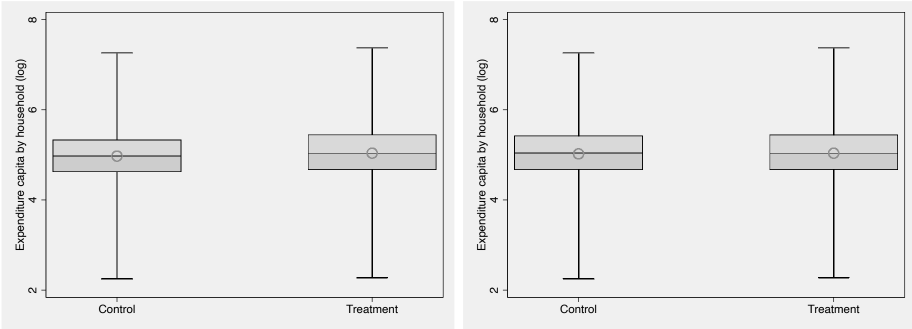
Note: Data from AUB SE 2010 and 2015, using survey weights. We control for household size and household size squared, age and working status of the HoH and region.

Table C8: Determinants of Food Expenditure (two-pm model, glm results) - margins

Dep. var.: Food expenditure as % of total	(1) 2010 Probit	(2) 2010 GLM	(3) 2010 Overall	(4) 2015 Probit	(5) 2015 GLM	(6) 2015 Overall
Treated	-0.003	-0.001	-0.001	-0.002	0.012	0.012
	(0.004)	(0.009)	(0.009)	(0.003)	(0.009)	(0.009)
Average age by HH	0.000	0.000	0.000	-0.001*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log (Percap Exp)	0.011*	-0.005	-0.007	0.010*	-0.054***	-0.056***
	(0.006)	(0.011)	(0.011)	(0.005)	(0.012)	(0.012)
Below lower poverty level	-0.005	-0.046	-0.043	-0.009	-0.045	-0.044
	(0.008)	(0.028)	(0.027)	(0.010)	(0.047)	(0.047)
Having a child	0.001	-0.000	0.000	-0.001	0.023***	0.023***
	(0.005)	(0.007)	(0.007)	(0.003)	(0.006)	(0.006)
HH size above 3	0.035***	-0.027***	-0.026***	0.021**	-0.036***	-0.038***
	(0.013)	(0.010)	(0.010)	(0.009)	(0.011)	(0.010)
Having one family member living abroad	0.000	-0.022**	-0.021**	0.002	-0.002	-0.002
	(0.004)	(0.010)	(0.009)	(0.003)	(0.009)	(0.009)
Living in a camp	0.009**	0.063***	0.059***	0.005	0.014*	0.014*
	(0.004)	(0.010)	(0.010)	(0.004)	(0.008)	(0.008)
Average # chronic disease by HH	0.004	-0.008	-0.008	0.002	-0.032**	-0.032**
	(0.005)	(0.013)	(0.012)	(0.006)	(0.014)	(0.014)
Average # acute disease by HH	0.001	-0.017*	-0.017*	0.000	0.001	0.001
	(0.004)	(0.009)	(0.009)	(0.005)	(0.016)	(0.015)
Insurance	-0.001	-0.037**	-0.036**	-	-0.024*	-0.025*
	(0.005)	(0.016)	(0.015)		(0.014)	(0.014)
Saida	0.004	-0.028**	-0.027**	0.009	-0.011	-0.012
	(0.004)	(0.013)	(0.012)	(0.008)	(0.012)	(0.012)
Tyre	0.003	-0.005	-0.005	0.013*	-0.007	-0.009
	(0.004)	(0.015)	(0.014)	(0.008)	(0.012)	(0.012)
Bekaa	-0.012	-0.048***	-0.046***	0.012	-0.026**	-0.027**
	(0.009)	(0.012)	(0.012)	(0.008)	(0.012)	(0.012)
NLA	-0.025	-0.073***	-0.069***		-0.027*	-0.029**
	(0.017)	(0.015)	(0.014)		(0.015)	(0.015)
Observations	10,588	10,588	10,588	8930	8930	8930

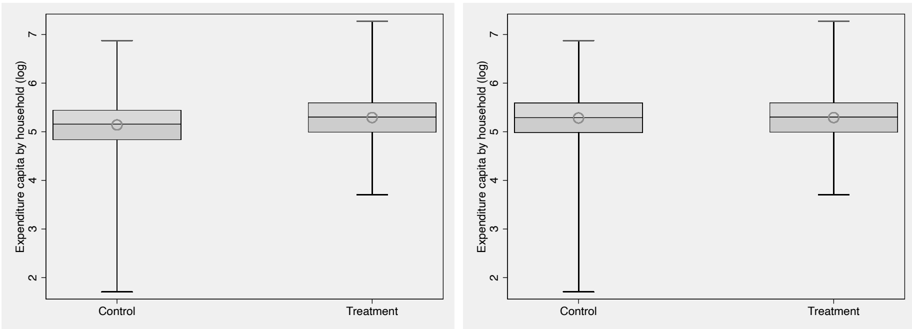
Robust standard errors in parentheses;
*** p<0.01, ** p<0.05, * p<0.1
Note: Data from AUB SE 2010 and 2015, using survey weights. We control for household size and household size squared, age and working status of the HoH and region.

Figure 4.6: Household expenditure in 2010



(a) Before matching **(b)** After matching

Figure 4.7: Household expenditure in 2015



(a) Before matching **(b)** After matching

Note: Data from AUB socioeconomic survey 2010 and 2015. All values were computed using survey weights. We exclude single member households.

A3.2 Complete regression tables

Propensity Score Matching Model

Two-part model

FHH are associated to more 2.1 and 3.1 percentage points (pp) of total expenditure being spent on healthcare in 2010 and 2015. Looking at intensive and extensive margins, FHH are more likely to spend any share of expenditure on health and more likely to spend a larger share as well. This impact is stronger for FHH where the HoH is either a widow or single. Having a chronic disease turn out to be a driver of health care expenditure, more than having acute disease or disability. This can be due to recall periods of chronic diseases or the amount of medication that requires for out-of-pocket spending. Acute and disabilities probably have more expenses at hospital level and less medication, which can be supported by UNRWA.

In what concerns tobacco expenditure, in FHH the share of total expenditure spent is significantly smaller than in MHH for all specifications. Comparing probit with GLM marginal effects, for this category the results are driven by the intensive margins as FHH are 15.4 and 10.6 pp less likely to spend any budget on tobacco in 2010 and 2015.

As follows from the graphical analysis in the previous section, average food expenditure as a percentage of total expenditure does not vary significantly between types of households. The negative impact of FHH on education expenditure is not significant in all specifications nor for all models.

In general, from 2010 to 2015 the coefficients remain mostly the same. One exception is the impact of having a single HoH, which in 2015 reduces the probability of spending any expenditure in education by 38 p.p, with 5% significance level.

A3.3 Robustness check

Table C9: Two-part model results for health and tobacco expenditure - margins

			2010			
	Health expenditure			Tobacco expenditure		
	(1)	(2)	(3)	(4)	(5)	(6)
	Probit	GLM	Overall	Probit	GLM	Overall
FHH	**0.030**	**0.025*****	**0.022*****	**-0.095*****	**-0.012*****	**-0.010*****
	(0.028)	**(0.008)**	**(0.007)**	**(0.031)**	**(0.003)**	**(0.003)**
Obs.			9930			10257
Pseudo R-sq.			0.138			0.0766
Log-likelihood			99378			141527
FHH						
- Married	-0.039	0.034*	0.033*	-0.035	0.000	-0.001
	(0.059)	(0.019)	(0.017)	(0.072)	(0.008)	(0.007)
- Widow	0.054*	0.027***	0.023***	-0.116***	-0.013***	-0.010***
	(0.032)	(0.008)	(0.008)	(0.036)	(0.004)	(0.003)
- Single	-0.030	0.030*	0.025*	-0.080	-0.014**	-0.013**
	(0.053)	(0.016)	(0.013)	(0.062)	(0.007)	(0.006)
- Separated	-0.006	0.008	0.014	-0.084	-0.023**	-0.021***
	(0.059)	(0.027)	(0.027)	(0.088)	(0.009)	(0.008)
Obs.			9930			10257
Pseudo R-sq.			0.139			0.0787
Log-likelihood			99860			142362
			2015			
	Health expenditure			Tobacco expenditure		
	(1)	(2)	(3)	(4)	(5)	(6)
	Probit	GLM	Overall	Probit	GLM	Overall
FHH	**0.028**	**0.024*****	**0.023*****	**-0.093*****	**-0.010*****	**-0.008*****
	(0.032)	**(0.008)**	**(0.007)**	**(0.035)**	**(0.003)**	**(0.003)**
Obs.			11403			12658
Pseudo R-sq.			0.122			0.0338
Log-likelihood			125573			158319
FHH						
- Married	-0.048	0.019	0.020	-0.062	-0.000	-0.001
	(0.066)	(0.016)	(0.014)	(0.076)	(0.007)	(0.007)
- Widow	0.068*	0.030***	0.028***	-0.120***	-0.012***	-0.009**
	(0.038)	(0.009)	(0.008)	(0.042)	(0.004)	(0.004)
- Single	-0.041	0.029*	0.026*	-0.054	-0.010	-0.009
	(0.064)	(0.016)	(0.013)	(0.071)	(0.007)	(0.008)
- Separated	-0.108	-0.003	0.014	-0.066	-0.021**	-0.021**
	(0.067)	(0.035)	(0.032)	(0.107)	(0.009)	(0.008)
Obs.			11403			12658
Pseudo R-sq.			0.125			0.0344
Log-likelihood			126094			158572

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.

Note: Data from AUB SE 2010 and 2015, using survey weights. Marital status variables are dummy variables in interaction with the HoH gender. Each status is compared with the corresponding status of the male leaders. All specifications include controls for household size, household age average, having direct family working abroad, living in a camp, average number of chronic and acute disease per household, having insurance and region fixed effects.

Table C10: Two-part model results for education and food expenditure - margins

	2010					
	Education expenditure			Food expenditure		
	(7)	(8)	(9)	(10)	(11)	(12)
	Probit	GLM	Overall	Probit	GLM	Overall
FHH	**0.002**	**-0.000**	**0.001**	**-0.000**	**-0.009**	**-0.008**
	(0.037)	**(0.007)**	**(0.006)**	**(0.002)**	**(0.010)**	**(0.010)**
Obs.			10588			10575
Pseudo R-sq.			0.204			0.315
Log-likelihood			35119			54676
FHH						
- Married	0.022	0.000	-0.003	-	0.008	0.007
	(0.074)	(0.013)	(0.009)		(0.014)	(0.014)
- Widow	-0.029	-0.002	-0.000	-0.001	-0.004	-0.003
	(0.044)	(0.008)	(0.007)	(0.002)	(0.011)	(0.010)
- Single	-0.088	-0.056**	-0.017	-	-0.017	-0.020
	(0.115)	(0.026)	(0.012)		(0.025)	(0.025)
- Separated	0.161**	0.025*	0.023*	-0.003	-0.039	-0.037
	(0.081)	(0.013)	(0.012)	(0.004)	(0.027)	(0.027)
Obs.			10588			10298
Pseudo R-sq.			0.206			0.329
Log-likelihood			35433			54779
	2015					
	Education expenditure			Food expenditure		
	(7)	(8)	(9)	(10)	(11)	(12)
	Probit	GLM	Overall	Probit	GLM	Overall
FHH	**0.016**	**0.010**	**0.014***	**0.001**	**0.001**	**0.001**
	(0.037)	**(0.010)**	**(0.008)**	**(0.001)**	**(0.008)**	**(0.008)**
Obs.	12562			10471		
Pseudo R-sq.	0.181			0.627		
Log-likelihood	29810			72638		
FHH						
- Married	-0.055	0.013	0.014	-	-0.008	-0.009
	(0.077)	(0.019)	(0.016)		(0.020)	(0.019)
- Widow	0.061	0.012	0.017*	0.001	-0.000	-0.000
	(0.044)	(0.011)	(0.010)	(0.001)	(0.010)	(0.010)
- Single	-0.377**	-0.080*	-0.029*	0.002	0.027*	0.027*
	(0.164)	(0.043)	(0.016)	(0.002)	(0.014)	(0.014)
- Separated	0.049	0.026	0.008	-0.002	-0.025	-0.025
	(0.119)	(0.023)	(0.018)	(0.002)	(0.021)	(0.020)
Obs.			12562			10300
Pseudo R-sq.			0.186			0.635
Log-likelihood			30558			72704

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.

Note: Data from AUB SE 2010 and 2015, using survey weights. Marital status variables are dummy variables in interaction with the HoH gender. Each status is compared with the corresponding status of the male leaders. All specifications include controls for household size, household age average, having direct family working abroad, living in a camp, average number of chronic and acute disease per household, having insurance and region fixed effects.

Table C11: Linear regression on the share of health care expenditure - using translog

HC expenditure as % of total budget	(1)	(2)	(3)
FHH	0.035***	0.032***	0.032***
	(0.007)	(0.008)	(0.008)
Ln monthly income	-0.013***	-0.012***	-0.011***
	(0.004)	(0.004)	(0.004)
Ln age	0.017***	0.017***	0.017***
	(0.002)	(0.002)	(0.002)
Ln hhsize	-0.006	-0.006	-0.007
	(0.006)	(0.006)	(0.006)
Ln educ level	-0.007***	-0.007***	-0.007***
	(0.002)	(0.002)	(0.002)
Ln monthly income × Ln age	-0.006	-0.006	0.001
	(0.005)	(0.005)	(0.005)
Ln monthly income × Ln hhsize	-0.021*	-0.025*	-0.011
	(0.013)	(0.013)	(0.014)
Ln monthly income × educ level	-0.005	-0.006	-0.006
	(0.006)	(0.006)	(0.007)
Ln age × Ln hhsize	-0.043***	-0.043***	-0.041***
	(0.011)	(0.011)	(0.012)
Ln age × Ln educ level	0.001	0.001	0.001
	(0.005)	(0.005)	(0.005)
Ln educ level × Ln educ level	0.002	0.002	0.003
	(0.010)	(0.010)	(0.010)
Year	0.004	0.004	0.005
	(0.005)	(0.005)	(0.005)
Year × Ln monthly income	0.009	0.008	0.006
	(0.013)	(0.013)	(0.014)
Year × Ln age	-0.005	-0.005	-0.004
	(0.006)	(0.006)	(0.006)
Year × Ln hhsize	-0.013	-0.013	-0.016
	(0.020)	(0.020)	(0.022)
Year × Ln educ level	0.002	0.002	0.002
	(0.009)	(0.009)	(0.009)
Ln monthly income × FHH		-0.007	-0.016
		(0.009)	(0.012)
Ln monthly income × Ln age x FHH			-0.043**
			(0.017)
Ln monthly income × Ln hhsize x FHH			-0.046*
			(0.027)
Ln monthly income × Ln educ level x FHH			-0.006
			(0.015)
Year x Ln monthly income × FHH			0.017
			(0.031)
Saida	0.025***	0.025***	0.025***
	(0.007)	(0.007)	(0.007)
Tyre	0.020***	0.020***	0.020***
	(0.005)	(0.005)	(0.005)
Bekaa	0.019***	0.019***	0.019***
	(0.006)	(0.006)	(0.006)
NLA	0.006	0.006	0.007
	(0.006)	(0.006)	(0.006)
Constant	0.051***	0.051***	0.051***
	(0.004)	(0.004)	(0.004)
Observations	16,819	16,819	16,819
R-squared	0.068	0.068	0.070

Robust standard errors in parentheses;
*** p<0.01, ** p<0.05, * p<0.1
Note: Data from AUB SE 2010 and 2015, using survey weights. All specifications include controls for age household size, being married, per capita expenditure (in log), a direct member living abroad, living in a camp, working and region.

A4 Chapter 4

Figure 4.8: Figure A1. Region map

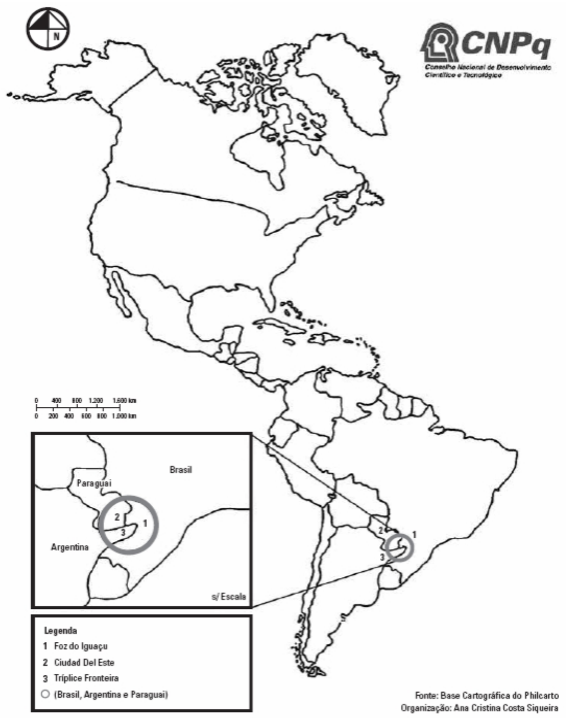


Table D1: Human Development Index by intervention region

Region	Population	HDI
Iguazu River Mouth– Parana, Brazil	264,044 inhab.	0.751
Coronel Oviedo – Caaguazu, Paraguay	117,514 inhab.	0.521
Puerto Iguazu – Misiones, Argentina	80,020 inhab.	0.817

Table D2: Number of adolescents by institution

Inst. Code	Action area	Country	Total enrolled	Participants
1	Social services	Brazil	818	84
2	Social services	Brazil	38	4
3	Social services	Brazil	140	14
4	Social services	Brazil	10	1
5	Social services	Brazil	38	4
6	Education	Brazil	400	41
7	Education	Brazil	327	34
8	Education	Brazil	403	41
9	Education	Brazil	200	21
10	Education	Brazil	291	27
11	Education	Brazil	187	19
12	Education	Brazil	66	7
13	Justice	Brazil	59	6
14	Education	Brazil	326	33
15	Sports	Brazil	40	4
16	Health	Brazil	351	36
17	Health	Brazil	20	9
18	Education	Brazil	320	144
19	Social services	Argentina	20	9
20	Social services	Argentina	20	9
	Justice	Argentina	90	41
	Health	Argentina	170	42
	Justice	Argentina	186	46
21	Social services	Paraguay	100	25
22	Sports	Paraguay	610	150
23	Education	Paraguay	120	29
Total			5350	880

Note:

Figure 4.9: Average frequency of consumption by gender, substance and year

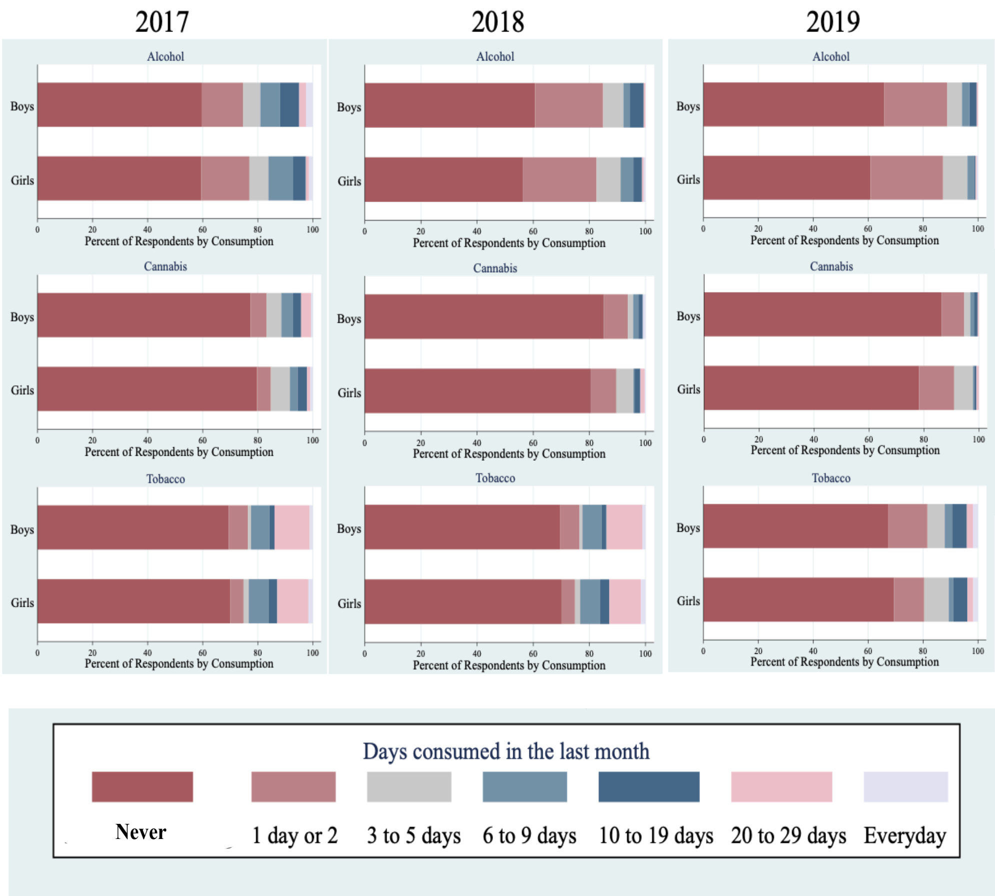


Table D3: Alcohol, tobacco and consumption by gender and year

	0 consump.		1 - 9 days consump.		10 - 30 days consump.	
	(1)	(2)	(3)	(4)	(5)	(6)
Tobacco						
Post-treat.	0.00	-0.09*	-0.00	0.04*	-0.00	0.06*
	(0.04)	(0.05)	(0.01)	(0.02)	(0.02)	(0.03)
Treatment	-0.01	-0.01	0.00	0.01	0.01	0.01
	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)	(0.02)
DiD	0.08***	0.17	-0.03***	-0.06*	-0.05***	-0.10
	(0.02)	(0.10)	(0.01)	(0.04)	(0.02)	(0.07)
Peer		-0.03***		0.01***		0.02***
		(0.01)		(0.00)		(0.01)
Post-treat x Peer		0.01		-0.01		-0.01
		(0.02)		(0.01)		(0.01)
Treatment x Peer		-0.00		0.00		0.00
		(0.00)		(0.00)		(0.00)
DiD x Peer		-0.03		0.01		0.02
		(0.03)		(0.01)		(0.02)
Alcohol						
	0 consump.		1 - 9 days consump.		10 - 30 days consump.	
	(1)	(2)	(3)	(4)	(5)	(6)
Post-treat.	0.06***	0.04	-0.04***	-0.03	-0.02***	-0.01
	(0.02)	(0.06)	(0.02)	(0.04)	(0.01)	(0.02)
Treatment	0.01	0.03	-0.01	-0.02	-0.00	-0.01
	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)
DiD	0.11***	0.10*	-0.07***	-0.07*	-0.03**	-0.03*
	(0.03)	(0.05)	(0.02)	(0.04)	(0.01)	(0.02)
Peer		-0.03***		0.02***		0.01**
		(0.01)		(0.00)		(0.00)
Post-treat x Peer		-0.02		0.01		0.01
		(0.01)		(0.01)		(0.00)
Treatment x Peer		-0.01		0.00		0.00
		(0.01)		(0.00)		(0.00)
DiD x Peer		-0.00		0.00		0.00
		(0.02)		(0.01)		(0.00)
Cannabis						
	0 consump.		1 - 9 days consump.		10 - 30 days consump.	
	(1)	(2)	(3)	(4)	(5)	(6)
Post-treat.	0.05***	-0.01	-0.03***	0.01	-0.02***	0.00
	(0.01)	(0.02)	(0.01)	(0.02)	(0.00)	(0.01)
Treatment	0.03	-0.00	-0.02	0.00	-0.01	0.00
	(0.02)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)
DiD	0.08***	0.12***	-0.06***	-0.08***	-0.03***	-0.04***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Peer		-0.04***		0.03***		0.01***
		(0.01)		(0.00)		(0.00)
Post-treat x Peer		-0.01		0.01		0.00
		(0.01)		(0.01)		(0.00)
Treatment x Peer		0.01		-0.01		-0.00
		(0.01)		(0.01)		(0.00)
DiD x Peer		-0.02		0.02		0.01
		(0.02)		(0.01)		(0.01)
Observations	1.982	1.982	1.982	1.982	1.982	1.982

Note: Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table D4: Probit estimation – light vs. heavy consumers

	Tobacco		Cannabis		Alcohol	
	(1)	(2)	(3)	(4)	(5)	(6)
Post-treat.	-0.17***	-0.18*	-0.16***	-0.15***	-0.11**	-0.00
	(0.05)	(0.11)	(0.03)	(0.05)	(0.05)	(0.10)
Treatment	-0.02	0.04	-0.01	-0.03	-0.05	0.02
	(0.05)	(0.10)	(0.03)	(0.05)	(0.05)	(0.11)
DiD	-0.02	-0.16	0.01	0.07	-0.15*	-0.18
	(0.07)	(0.14)	(0.05)	(0.08)	(0.09)	(0.15)
Peer		0.02*		0.03***		0.06***
		(0.01)		(0.01)		(0.02)
Post-treat x Peer		0.02		0.03**		0.01
		(0.02)		(0.01)		(0.03)
Treatment x Peer		-0.01		0.00		-0.02
		(0.02)		(0.01)		(0.02)
DiD x Peer		0.03		-0.02		-0.00
		(0.03)		(0.02)		(0.04)
Woman	0.10***	0.08**	-0.06**	-0.05**	-0.01	0.01
	(0.04)	(0.04)	(0.03)	(0.02)	(0.04)	(0.04)
Age	0.10***	0.07***	0.09***	0.03*	0.10***	0.03
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)
Brazilian	-0.33***	-0.25***	-0.05*	0.02	0.03	0.08*
	(0.04)	(0.04)	(0.03)	(0.03)	(0.05)	(0.05)
BMI_{under}	0.24	0.27*	-	-	-	-
	(0.15)	(0.15)				
BMI_{over}	-0.14***	-0.12***	-0.03	-0.01	-0.04	-0.03
	(0.04)	(0.04)	(0.03)	(0.02)	(0.04)	(0.04)
Early sex exposure	0.13***	0.12**	-0.04	-0.04	0.15***	0.12***
	(0.05)	(0.05)	(0.03)	(0.03)	(0.05)	(0.05)
Observations	627	627	773	773	371	371

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table D5: Ordered Probit results for tobacco consumption

Tobacco	0 consumption		1 to 9 days		10 days or more	
	(1)	(2)	(3)	(4)	(5)	(6)
Post-treat.	0.00	-0.09*	-0.00	0.04*	-0.00	0.06*
	(0.04)	(0.05)	(0.01)	(0.02)	(0.02)	(0.03)
Treatment	-0.01	-0.01	0.00	0.01	0.01	0.01
	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)	(0.02)
DiD	0.08***	0.17	-0.03***	-0.06*	-0.05***	-0.10
	(0.02)	(0.10)	(0.01)	(0.04)	(0.02)	(0.07)
Peer		-0.03***		0.01***		0.02***
		(0.01)		(0.00)		(0.01)
Post-treat x Peer		0.01		-0.01		-0.01
		(0.02)		(0.01)		(0.01)
Treatment x Peer		-0.00		0.00		0.00
		(0.00)		(0.00)		(0.00)
DiD x Peer		-0.03		0.01		0.02
		(0.03)		(0.01)		(0.02)
Woman	0.01	0.02	-0.00	-0.01	-0.01	-0.01
	(0.05)	(0.06)	(0.02)	(0.02)	(0.03)	(0.04)
Age	-0.07***	-0.03**	0.02**	0.01**	0.04***	0.02**
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Brazilian	0.07	0.01	-0.03	-0.01	-0.04	-0.01
	(0.05)	(0.05)	(0.02)	(0.02)	(0.03)	(0.03)
BMI_{under}	0.09	0.05	-0.03	-0.02	-0.05	-0.03
	(0.11)	(0.10)	(0.04)	(0.04)	(0.07)	(0.06)
BMI_{over}	0.07***	0.06***	-0.03***	-0.02***	-0.04***	-0.04***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Early sex exposure	-0.14*	-0.14*	0.05*	0.06*	0.09**	0.09**
	(0.08)	(0.07)	(0.03)	(0.03)	(0.04)	(0.04)
Observations	1.983	1.983	1.983	1.983	1.983	1.983

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Dependent variable is an ordered variable indicating the frequency of consumption in the last 30 days - with the value 0 for 0 days; value 1 if consumed between 1 and 9 days; value 2 if consumed more than 10 days. DiD is the difference-in-differences coefficient. Peer is the (leave one out) average group consumption in days. BMI under and over are binary variables indicating whether each individual has an unhealthy BMI (by deficiency or excess) or not.

Table D6: Ordered Probit results for cannabis consumption

Drugs	0 consumption		1 to 9 days consumption		10 days or more	
	(1)	(2)	(3)	(4)	(5)	(6)
Post-treat.	0.05***	-0.01	-0.03***	0.01	-0.02***	0.00
	(0.01)	(0.02)	(0.01)	(0.02)	(0.00)	(0.01)
Treatment	0.03	-0.00	-0.02	0.00	-0.01	0.00
	(0.02)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)
DiD	0.08***	0.12***	-0.06***	-0.08***	-0.03***	-0.04***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Peer		-0.04***		0.03***		0.01***
		(0.01)		(0.00)		(0.00)
Post-treat x Peer		-0.01		0.01		0.00
		(0.01)		(0.01)		(0.00)
Treatment x Peer		0.01		-0.01		-0.00
		(0.01)		(0.01)		(0.00)
DiD x Peer		-0.02		0.02		0.01
		(0.02)		(0.01)		(0.01)
Woman	-0.04	-0.04	0.03	0.03	0.01	0.01
	(0.04)	(0.04)	(0.03)	(0.03)	(0.01)	(0.01)
Age	-0.08***	-0.04**	0.05***	0.02**	0.03***	0.01***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
Brazilian	0.16**	0.12*	-0.11**	-0.08*	-0.05**	-0.04*
	(0.07)	(0.07)	(0.05)	(0.05)	(0.02)	(0.02)
BMI_{under}	-0.01	-0.03	0.01	0.02	0.00	0.01
	(0.06)	(0.06)	(0.04)	(0.04)	(0.02)	(0.02)
BMI_{over}	0.00	0.01	-0.00	-0.00	-0.00	-0.00
	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)
Early sex exposure	-0.09*	-0.09**	0.06*	0.06**	0.03*	0.03**
	(0.05)	(0.04)	(0.03)	(0.03)	(0.02)	(0.01)
Observations	1.982	1.982	1.982	1.982	1.982	1.982

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Dependent variable is an ordered variable indicating the frequency of consumption in the last 30 days - with the value 0 for 0 days; value 1 if consumed between 1 and 9 days; value 2 if consumed more than 10 days. DiD is the difference-in-differences coefficient. Peer is the (leave one out) average group consumption in days. BMI under and over are binary variables indicating whether each individual has an unhealthy BMI (by deficiency or excess) or not.

Table D7: Ordered Probit results for alcohol consumption

Alcohol	0 consumption		1 to 9 days consumption		10 days or more	
	(1)	(2)	(3)	(4)	(5)	(6)
Post-treat.	0.06***	0.04	-0.04***	-0.03	-0.02***	-0.01
	(0.02)	(0.06)	(0.02)	(0.04)	(0.01)	(0.02)
Treatment	0.01	0.03	-0.01	-0.02	-0.00	-0.01
	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)
DiD	0.11***	0.10*	-0.07***	-0.07*	-0.03**	-0.03*
	(0.03)	(0.05)	(0.02)	(0.04)	(0.01)	(0.02)
Peer		-0.03***		0.02***		0.01**
		(0.01)		(0.00)		(0.00)
Post-treat x Peer		-0.02		0.01		0.01
		(0.01)		(0.01)		(0.00)
Treatment x Peer		-0.01		0.00		0.00
		(0.01)		(0.00)		(0.00)
DiD x Peer		-0.00		0.00		0.00
		(0.02)		(0.01)		(0.00)
Woman	-0.02	-0.03	0.02	0.02	0.01	0.01
	(0.07)	(0.07)	(0.05)	(0.05)	(0.02)	(0.02)
Age	-0.13***	-0.09***	0.09***	0.06***	0.04***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Brazilian	0.04	0.01	-0.03	-0.01	-0.01	-0.00
	(0.04)	(0.05)	(0.03)	(0.03)	(0.01)	(0.01)
BMI_{under}	0.03	0.00	-0.02	-0.00	-0.01	-0.00
	(0.11)	(0.11)	(0.07)	(0.07)	(0.04)	(0.03)
BMI_{over}	0.00	-0.01	-0.00	0.00	-0.00	0.00
	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)
Early sex exposure	-0.12*	-0.11	0.08	0.08	0.04**	0.04*
	(0.07)	(0.07)	(0.05)	(0.05)	(0.02)	(0.02)
Observations	1.983	1.983	1.983	1.983	1.983	1.983

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Dependent variable is an ordered variable indicating the frequency of consumption in the last 30 days - with the value 0 for 0 days; value 1 if consumed between 1 and 9 days; value 2 if consumed more than 10 days. DiD is the difference-in-differences coefficient. Peer is the (leave one out) average group consumption in days. BMI under and over are binary variables indicating whether each individual has an unhealthy BMI (by deficiency or excess) or not.