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City, University of London

Essays on the Economics of Non-Communicable Diseases

A Thesis submitted in fulfilment of the requirements of
Doctor of Philosophy

by

Chandanee Wasana Kalansooriya
Department of Economics

Supervised by
Prof. Mireia Jofre-Bonet
Dr. Victoria Serra-Sastre

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To my loving
Amma
(Mum)

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Abstract

This doctoral thesis is a collection of three papers that study topics related to Non-Communicable Diseases (NCDs) - the key cause of death globally, challenging health systems and economies.

First, we analyse the dietary changes, a major risk factor of NCDs in Low and Middle-Income Countries (LMICs) and examine the role of education as a mechanism to improve healthy food demand. We use the food consumption data of Sri Lanka. Using the demand elasticities estimated from the Almost Ideal Demand System (AIDS), we prove that the enhancement of the living standards of the people has led them towards a rather unhealthy diet. This adds economic evidence to the literature on the occurrence of nutritional transition leading to the growth of NCDs in LMICs. Further, the study fills the dearth of evidence in the literature on the role of education in dietary choices in LMICs. We show that education plays a significant role in enhancing healthy food demand, however, it does not help to discourage the demand for unhealthy food. Yet, education helps to improve diet quality when individuals have diet-related diseases, i.e. diabetes. We show the possibility of effective use of price policies to encourage healthy consumption and discourage unhealthy consumption in LMICs.

Second, we investigate the household consumption impact of out-of-pocket healthcare expenditures arising from chronic NCDs (C-NCDs) and how it changes according to the shifts in public health expenses. We use a matching method to estimate the crowding-out effect and a Matched Difference-in-Difference (MDID) method to identify the changes in the crowding-out effect according to changes in public healthcare expenses. We use the data of Sri Lanka, an LMIC, and show that the out-of-pocket healthcare expenses arising from C-NCDs have grown faster than such expenses of other health conditions during the last two decades. We show that public healthcare provision plays a significant role in C-NCD care, and a reduction in public spending leads to a further increase in the household burden of the treatment cost. The increasing out-of-pocket expenses due to C-NCDs are crowded-out on households' basic needs, such as food and clothing, particularly in low and middle-

income households. Accordingly, the study highlights that the lessening of public spending and the absence of health insurance to cover healthcare costs of C-NCDs care generate adverse impacts on household welfare.

Third, we provide novel evidence on how the livelihood of people with NCDs was affected by COVID-19. We explore the impact of COVID-19 on the labour market outcomes of individuals with NCDs using the data from the *Understanding Society COVID-19 Study* in the UK. The difference-in-difference estimates reveal that the pandemic negatively affected the likelihood of engaging in work and the work duration of people with NCDs. We show that their probability of engaging in work negatively relates to the severity of the pandemic, whereas the amount of work hours gradually decreases throughout the pandemic resulting in a significant gap between the pre and post-Covid work amount. The work loss is higher for the upper age group of the workforce and the individuals with riskier health conditions to Covid-19. Although the pandemic did not cause it to deteriorate further, the low mental and physical health of individuals with NCDs may lead them to exit the labour market, raising concerns about their welfare during the post-covid period.

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Chapter 1

Thesis Introduction

Non-Communicable Diseases (NCDs) are the key cause of death as they kill 41 million people each year, equivalent to 74% of all deaths globally, and 17 million people with NCDs die prematurely (WHO, 2022). NCDs, also known as chronic diseases, are health conditions that tend to be of long duration, do not pass from person to person, and result from a combination of genetic, physiological, environmental and behavioural factors. The main types of NCDs include but are not limited to, cardiovascular diseases, cancers, chronic respiratory diseases and diabetes. People of all age groups, regions and countries are affected by NCDs. NCDs are considered a growing threat to the health systems in the world with population ageing and increasing life expectancy (Bamford and Serra, 2011).

Besides being a challenge to human health, the loss to the economy from NCDs is enormous. It challenges the well-being of individuals, households and the wider economy. The ill-health caused by NCDs reduces labour productivity and thus erodes household income (Abegunde and Stanciole, 2006; Chand et al., 2020; Kumara and Samaratunge, 2018). In the absence of public healthcare provision at adequate quality and quantity, the cost of NCD treatment and care has to be borne by households (Kien et al., 2017; Murphy et al., 2020; Wang et al., 2015) and thus impedes their overall consumption (Datta et al., 2018; Kumara and Samaratunge, 2017). The increasing cost to the government for NCD care also puts more pres-

sure on public finance (Adeyi et al., 2007). Considering all these costs, in 2010, the World Economic Forum estimated that the cumulative output loss due to four major NCDs during the 2011-2030 period could be US$ 47 trillion, which is 75% of the global GDP in 2010 (Bloom et al., 2011). These projections do not include the cost of premature deaths among people with NCDs during the recent COVID-19 pandemic[1].

NCDs disproportionately affect people in Low- and Middle-Income Countries (LMICs), where 77% of all NCD deaths and 86% of premature deaths occur (WHO, 2022). These higher death rates are attributed to the limited access to comprehensive services for chronic disease prevention, treatment and management in those countries. The health systems of LMICs are less prepared for faster-growing NCDs and have smaller increases in national health spending (Bollyky et al., 2017). As a result, the majority of NCD treatment and care cost passes to the household budget. The total out-of-pocket healthcare spending more than doubled in LMICs from 2000 to 2017, whereas, for high-income countries, this increase was only 46% (WHO, 2019). The reduction in labour productivity due to ill-health and increasing healthcare outlay push those people in LMICs towards poverty challenging those countries to achieve sustainable development goals (Bloom et al., 2011; Sirag and Mohamed Nor, 2021).

High-income countries also carry a large economic burden of NCDs. However, their economies can abide the healthcare cost, and health systems are much more developed to provide advanced care for people with NCDs. Yet, in the occurrence of external shocks such as COVID-19, NCDs bring them new challenges. Their healthcare systems confront difficulties in providing necessary care for people with NCDs with the overwhelming pressure on healthcare demand (PAHO, 2021; Pécout et al., 2021; WHO, 2020a). Similarly, the adverse impacts of such shocks on people

[1]People with NCDs had a greater risk of getting severely infected with COVID-19, and the death rates due to COVID-19 were much higher for individuals with NCDs than healthy people (Nikoloski et al., 2021; Pal and Bhadada, 2020; Roncon et al., 2020)

with NCDs affect the economy at a larger scale when the percentages of people with NCDs are high in those high-income countries.

Accordingly, this thesis focuses on the risk factors of NCDs and NCDs-related issues in both LMICs and high-income countries. It consists of three papers that provide comprehensive studies of three topics related to NCDs. A brief introduction to each paper is given below.

The first paper of this thesis focuses on the dietary behaviour of people in LMICs and the factors that modify it. Most NCDs are the result of behavioural factors[2]. Nutritional transition[3] - the changes in consumption patterns from a traditional healthy diet to westernized unhealthy diets, is identified as one of the leading causes of rising NCDs in LMICs (Kelly, 2016; Popkin, 2015; Rhee, 2015). Rapid urbanization, globalization and economic growth in LMICs during the last two decades fueled the nutritional transition, and those consumption changes happened at a faster rate in LMICs than in high-income countries (Breewood, 2018; Popkin, 2001), resulting in the elevation of NCDs. Hence, using evidence from Sri Lanka, a country that underwent significant economic and social changes during the last two decades[4], we aim to assess the changes in food consumption behaviour from healthy choices to unhealthy choices by modelling household food demand. Further, we identify how education modifies those consumption behaviours, and analyse the disparity in food consumption of households having individuals with diabetes- one of the most prominent diet-related diseases.

[2]These behavioural factors include tobacco use, physical inactivity, unhealthy diet and the harmful use of alcohol.

[3]The model "nutritional transition" explains the evolution of the world's food consumption pattern. It follows five stages: hunter-gatherer lifestyles; early labour-intensive agriculture with periods of famine; receding famine as agriculture becomes more industrialised; "Western"-style diets with high intakes of calories, sugar, animal fat and processed foods, and sedentary lifestyles associated with rising incomes; and finally, healthier diets and more active lifestyles (Breewood, 2018).

[4]Sri Lanka has entered the fourth stage of nutritional transition, characterised by nutrition-related NCDs (Weerahewa et al., 2018), and is in an advanced state of epidemiological transition, with the disease burden shifting from communicable diseases to NCDs (Mehta, 2016a). 83% of deaths in Sri Lanka are from NCDs (Organization et al., 2018). These transitions are accompanied by economic growth in the country as the per capita income more than doubled during the last two decades (The World Bank, World Development Indicators, 2022)

We use data from household income and expenditure surveys in Sri Lanka in 2006 and 2016. Using the food demand elasticities estimated from the Almost Ideal Demand System (AIDS), we assess the changes in elasticities during the two periods. Our results show that households increase their consumption of both healthy and unhealthy food with growing income, partially confirming the nutritional transition. We find that education increases the demand for healthy food with income increase, but it does not decrease unhealthy food demand. Further, we show that diabetic people only slightly change their food choice towards a healthier diet.

Our study is the first to show economic evidence of the nutritional transition using food demand elasticities. It also fills the dearth of evidence in the literature for the impact of education on dietary behaviour in LMICs and the food consumption behaviour of people with diabetes. The study provides policy guidance to tackle a leading risk factor of NCDs- unhealthy diet. It is important to invest in diet-related education to guide people towards a healthy diet, and price policies should be used as an effective tool in demand management towards healthier choices.

The second study of the thesis concentrates on the out-of-pocket healthcare expenses of NCDs and their impacts on other household consumption in LMICs. Our focus is on five main chronic NCDs (C-NCDs)- heart disease, diabetes, high blood pressure, cancer, and asthma- that have been growing fast during the last two decades (WHO, 2022). As we indicated earlier, out-of-pocket expenses for healthcare are the primary strain for households in LMICs arising from NCDs (Alam and Mahal, 2014; McIntyre et al., 2006; Murphy et al., 2020). It has been shown that out-of-pocket expenses due to ill-health crowd-out on other household consumption (Datta et al., 2018; Nguyen et al., 2012; Wang et al., 2006). However, the household burden of healthcare expenses depends on the availability of public healthcare services (Correa-Burrows, 2012; Xu et al., 2003). Therefore, consumption depletion due to ill-health may also vary according to the availability of public health services. Hence, in this paper, we aim to estimate (1) the crowding-out effect of out-of-pocket

healthcare spending caused by the C-NCDs on all other household consumptions, (2) the changes of the crowding-out effect according to the changes in public healthcare provision, and (3) to compare the above effects related to C-NCDs with the effects related to other types of NCDs.

We use data from Sri Lanka. The prevalence rates of C-NCDs have been increasing sharply in Sri Lanka during the last two decades (Ediriweera et al., 2018; Mehta, 2016b). Despite the rising health burden, the public healthcare provision in the country has been compressing[5] placing a higher burden on household budget[6] (Kumara and Samaratunge, 2016; Pallegedara, 2018). Accordingly, we use three waves of household income and expenditure survey data in Sri Lanka, in 2006, 2012 and 2016. Using the matched-difference-in-difference method, we could estimate the changes in the crowding-out effect, which we derived using a matching estimator for the average treatment effect of C-NCDs. Our results revealed that the higher out-of-pocket healthcare expenditure that the households with C-NCDs had at the beginning of the reference period was increasing at a higher rate than it was for other types of NCDs. The highest burden of out-of-pocket expenditures was placed when the public spending on health care was at its lowest. Higher out-of-pocket spending crowds-out on some consumptions, especially food consumption; however, the crowding-out varies on household income as the adverse effect is striking in low-income households.

The study provides novel evidence on the changes in the crowding-out effect of the out-of-pocket healthcare payments for C-NCDs according to the changes in public healthcare provision. Similarly, the study differs from the existing literature related to the crowding-out effect estimations as we distinguish the impact of C-NCDs and other types of NCDs, and in the estimation method -instead of modelling in regression, we used a matching method to estimate the average treatment effect.

[5]Public health expenditure as a percentage of GDP was 1.97 in 2006, and it declined to 1.15 by 2012, followed by a slight increase to 1.55 by 2016 (CBSL, 2007, 2013, 2017)

[6]A 53% of the total healthcare spending of the country is financed as household out-of-pocket expenditures (MoH, 2018).

In the third paper of the thesis, we relate our topic to the COVID-19 pandemic. COVID-19 made a disproportionate impact on people with NCDs. They had a greater risk of getting severely infected with COVID-19 (ISDS, 2020; Roncon et al., 2020; Simonnet et al., 2020), and the death rate of COVID-19 for people with NCDs was higher than the healthy individuals infected (Alqahtani et al., 2020; Nikoloski et al., 2021; Pal and Bhadada, 2020; WHO, 2020c). COVID-19 created unprecedented pressure on health services and regular NCD care was severely interrupted (Jones et al., 2020; Pécout et al., 2021; WHO, 2020b). COVID-19 and related lockdown restrictions created a favourable atmosphere for several behavioural risk factors for NCDs, such as unhealthy diet, alcohol use, lack of physical activity and higher stress levels, triggering new health issues, including mental health issues, among individuals with NCDs and the healthy (Aknin et al., 2021; Nassereddine et al., 2021; Pécout et al., 2021; Serrano-Alarcón et al., 2022). COVID-19 hindered the labour market performances of individuals in general. (Aygun et al., 2021; Borland and Charlton, 2020; Lemieux et al., 2020; Powell et al., 2022; Singh et al., 2022; Vassilev and Hamilton, 2021). Owing to the disproportionate impact, the labour market activities of individuals with NCDs may have been affected more, however, it has not been investigated yet. Hence, in this paper, we aim to analyse the effects of COVID-19 on the labour market outcomes of individuals with NCDs in a high-income country context.

We use the data of the UK Understanding Society COVID-19 study, which consists of nine waves from April 2020 to September 2021. The average treatment effect of COVID-19 at different stages of the pandemic was estimated using a difference-in-difference method. Our results show a significant negative impact of COVID-19 on the work probability and the work hours of individuals with NCDs. The impact varies at different stages of the pandemic, and by age and the work type of individuals with NCDs. The riskiness of the NCD condition to COVID-19 has a positive link with the work loss of people with NCDs.

Accordingly, our study provides new evidence on how the livelihood of people with NCDs was affected by COVID-19. It shows important insights into the current labour market issues in the UK while emphasizing the importance of protecting the quality of life of the people with NCDs who were adversely affected in the labour market during COVID-19.

The thesis consists of the above three studies and is organised as follows. We present our first paper titled "Nutritional transition and demand for a healthy diet: An analysis using Almost Ideal Demand System" in the Second chapter. The third chapter presents the paper titled "The crowding-out effect of healthcare expenses of chronic Non-Communicable Diseases on household consumption and the role of public healthcare spending". Our third paper titled "COVID-19, Non-Communicable Diseases and Labour Market Outcomes" is presented in chapter four. Chapter five gives an overall summary and the conclusion of the thesis.

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Chapter 2

Nutritional transition and demand for a healthy diet: An analysis using Almost Ideal Demand System

2.1 Introduction

Non-communicable Diseases (NCDs) are the key cause of morbidity and mortality across the globe, with disproportionate impacts in low and middle-income countries (LMICs) (WHO, 2022). Besides the health risk, NCDs generate extensive pressure on the economies of LMICs by consuming a large volume of resources, both private and public, for healthcare and limiting the funds available for other consumptions and investments (Lee et al., 2015; Murphy et al., 2020; Xu et al., 2003). The rapid rise in NCDs increases the poverty in LMICs and impedes the achievement of sustainable development goals (Bloom et al., 2011).

The nutritional transition that accompanies economic growth, urbanisation, globalisation of lifestyles and demographic changes, is one of the leading factors in growing NCDs in LMICs (Kelly, 2016; Popkin, 2015; Rhee, 2015). Nutritional transition is a term associated with the changes in consumption patterns from “traditional" diets toward “Western” diets rich in fats, sugars, meat, and highly processed foods, and it is accompanied by a rise in sedentary lifestyles (Breewood, 2018). Though this transition occurred gradually in high-income countries, it has been taking place in compressed periods of about two decades in most LMICs (Breewood, 2018; Pop-

kin, 2001), resulting in a sharp increase in metabolic disorders due to the inability of individuals' metabolic capacity to endure new consumption changes. (Chan et al., 2009; Ramachandran et al., 2012; Yoon et al., 2006).

Although economic and social forces push society towards nutritional transition, some factors may offset the impact. Education is one such significant factor that could affect changing an individual's dietary choices. The literature has long provided evidence of the positive influence of education on changing individuals' behaviour, especially when it is related to health (Brunello et al., 2016; Cutler and Lleras-Muney, 2010; Li and Powdthavee, 2015). Education reduces individuals' obesity and the prevalence of diabetes and hypertension (Bomberg et al., 2019; Ma et al., 2018). However, the education effect on individuals' dietary behaviour shows mixed evidence. Some confirm higher education positively links with better dietary choices (Hiza et al., 2013; Li and Powdthavee, 2015) whereas some shows a negative or no link between the level of education and dietary habits (Braakmann, 2011).

Accordingly, this study aims to assess the changes in food consumption behaviour from healthy choices to unhealthy choices by modelling household food consumption behaviour during a period of nutritional transition and identifying how education might modify those consumption behaviours. Further, we analyse the disparity in food consumption of households having individuals with diabetes, one of the most prominent diet-related diseases.

Our study focuses on Sri Lanka, an LMIC in an advanced state of epidemiological transition, with the disease burden shifting from communicable diseases to NCDs (Mehta, 2016). NCDs account for 83% of total deaths in Sri Lanka (Organization et al., 2018), and nearly 1 in 5 people who die prematurely are from NCDs (WB, 2017). The higher prevalence rates of NCDs compound some inherent risk factors. While belonging to the Asian genotype, more vulnerable to metabolic disorders (Ramachandran et al., 2012; Yoon et al., 2006), significant dietary behaviour changes in Sri Lanka during the past two decades have contributed to the growth

in prevalence (Weerahewa et al., 2018; Weerasekara et al., 2018). The country has entered the fourth stage of nutritional transition, characterised by nutrition-related NCDs (Weerahewa et al., 2018). This transition is attributed to the country's income growth, as the per-capita income has more than doubled during the last two decades.[1].

We use repeated cross-sectional data obtained from the household income and expenditure survey (HIES) of Sri Lanka conducted in 2006 and 2016. We follow Roglic et al. (2016); Salas-Salvadó et al. (2011) to categorise food as healthy or unhealthy and model household food consumption behaviour on a group of healthy/unhealthy foods. We estimate food demand elasticities using an Almost Ideal Demand System (AIDS) and assess changes in elasticity by education and diabetes prevalence.

This study contributes to the literature in three aspects. First, it provides economic evidence for a nutritional transition using food demand elasticities. Although many studies have modelled food consumption behaviour in different countries, those studies are limited to the data of one particular year and not based on disaggregated categories that reflect healthy vs unhealthy food. Hence the changes in food demand behaviour that show the nutritional transition have not been scrutinized (Chern et al., 2002; Ecker and Qaim, 2011; Lasarte Navamuel et al., 2014; Lokuge et al., 2019). Secondly, the estimation of elasticities across educational categories indicates how food consumption patterns vary by education in an LMIC. The literature on the effect of education on dietary behaviours mostly focuses on dietary changes in developed countries (Berry et al., 2012; Brunello et al., 2016; Cutler and Lleras-Muney, 2010; Hiza et al., 2013; Li and Powdthavee, 2015; Ma et al., 2018), and the studies related to the education and healthy food consumption in LMICs is limited (Mayen et al., 2014; Thi Nguyen et al., 2022). Finally, the study provides evidence of the disparity of food demand behaviour for the subset of patients diag-

[1]The GDP per capita (PPP) of Sri Lanka was $6155 in 2000, it increased to $9441 in 2010 and $13584 by 2017 (GDP per capita,PPP(constant 2017 international $) (The World Bank, World Development Indicators, 2022)

nosed with diabetes. Since diabetes remains a risk factor for other NCDs(Márquez and Bajdan, 2021), it is important to pin down the dietary behaviour of these individuals.

Our results indicate that households increase their consumption of both healthy and unhealthy food with growing income. Income responsiveness has risen during the ten years between HIES surveys, providing evidence of the occurrence of the nutritional transition in the country. We find that education increases the income responsiveness of healthy food, but it does not decrease the demand for unhealthy foods. Further, our results show that having diabetes affects only slightly the choice of healthier diets in Sri Lankan households. The study emphasises the importance of investing in education while well-designed price policies used as an effective tool to increase healthy consumption and decrease unhealthy consumption in Sri Lanka.

The remainder of this paper proceeds as follows: in section 2, we discuss the literature related to food consumption behaviour and NCDs. section 3, explains the methodological approach and section 4 describes the data used for the analysis. In section 5, we present the results. We discuss our results in section 6, and section 7 concludes.

2.2 Literature review

Below, we discuss the literature related to food consumption changes and health behaviours. We summarise the literature under three sections; the nutritional transition and metabolic disorders in LMICs, the effect of education on health behaviours, and diabetes and diet.

2.2.1 Nutritional transition and diet-related diseases in LMICs

The model "nutritional transition" explains the evolution of the world's food consumption pattern. As Breewood (2018) explains, nutritional transition follows five

stages: hunter-gatherer lifestyles; early labour-intensive agriculture with periods of famine; receding famine as agriculture becomes more industrialised; "Western"-style diets with high intakes of calories, sugar, animal fat and processed foods, and sedentary lifestyles associated to rising incomes; and finally, healthier diets and more active lifestyles. These five patterns do not refer to specific historical periods; each stage can occur at different times in different places. For example, high-income countries generally began the shift towards diets high in oils, sugar and processed food around the late nineteenth century (the time of the industrial revolution) (Grigg, 1995), while most LMICs did not begin that dietary shift until the 1980s to 90s (Popkin et al., 2012).

Most LMICs are currently in the fourth stage of nutritional transition (Ramachandran et al., 2012; Rhee, 2015), shifting dietary patterns to energy-dense diets with high fat and sugar (Rahati et al., 2014). These patterns are combined with a decline in energy expenditure associated with a sedentary lifestyle, for example, motorised transport, labour-saving devices at home, the phasing out of physically demanding manual tasks in the workplace, and leisure time devoted to physically undemanding activities (Wilkinson and Marmot, 2003). Unlike the gradual transition in nutrient availability and lifestyle changes in developed countries, those changes happened rapidly in many LMICs (Chan et al., 2009; Yoon et al., 2006), allowing less time for adjustment in gene frequencies to the new consumption (Ramachandran et al., 2012).

In some populations, especially in Asia, poor nutrition in earlier life and overnutrition in later life contribute to the increase in diet-related diseases (Chan et al., 2009). The biological cut point to resist diet-related diseases with increasing consumption is set at a lower level for Asian genotypes (Ramachandran and Snehalatha, 2010). They are generally more insulin resistant and metabolically obese than other races (Ambady et al., 2010; Ramachandran et al., 2012). Hence, diabetes and other metabolic diseases, which are highly related to obesity, are common among normal-

weight individuals and at a younger age in the Asian countries (Chan et al., 2009; Yoon et al., 2006). As a result, more than 60% of the people with diabetes live in Asia and the growth of type 2 diabetes in South Asia has been estimated at more than 150% between 2000 and 2035 (Nanditha et al., 2016).

Socioeconomic and environmental factors such as income changes and urbanisation are associated with the nutritional transition in LMICs (Yoon et al., 2006). Individuals' socioeconomic status (SES) is directly linked to their diet. As literature demonstrates, individuals with higher SES consume more healthy food such as whole grains, lean meats, fish, low-fat dairy products, and fresh vegetables and fruits than individuals with lower SES. In contrast, refined grains, legumes and added fats are associated with a diet of lower SES (Alkerwi et al., 2015; Darmon and Drewnowski, 2008; Gómez et al., 2021). However, in LMICs, groups of higher SES consume more unhealthy food such as fats, salt, and processed food than individuals in low socioeconomic status (Allen et al., 2017). This is more prevalent in urban areas. People in urban areas experience faster dietary changes than in rural areas, given that they often have a greater choice of food at lower prices, proximity to supermarkets and access to technologies such as refrigeration and microwaves (Hawkes et al., 2017). Accordingly, unlike in high-income countries, the prevalence of metabolic diseases is frequent among high SES groups than lower groups in LMICs (Ambady et al., 2010; Popkin, 2001).

2.2.2 Education and health behaviours

Education is identified as a crucial factor that modifies behavioural and environmental risk factors related to health. Having healthy food, better health habits, less stressful occupations, being physically active, avoiding risky health behaviours, better residential neighbourhood, and undergoing more preventive health checks are the benefits associated with better education (Böckerman and Maczulskij, 2016; Brunello et al., 2016; Cutler and Lleras-Muney, 2010; Li and Powdthavee, 2015; Ma

et al., 2018).

There is a positive impact of education on preventing metabolic diseases, especially in developed countries. In general, more educated individuals have better self-reported health (Arendt, 2005; Brunello et al., 2016). Years of schooling show a negative association with the prevalence of diabetes and hypertension (Li and Powdthavee, 2015; Ma et al., 2018). The impact of genetic risk on diabetes prevalence is smaller among the people with more years of schooling (Liu et al., 2015). Also, there are lower number of diabetic patients within the same household when household head has a higher education (Bomberg et al., 2019). Education also reduces obesity, a crucial risk factor for diabetes and hypertension (Böckerman and Maczulskij, 2016; Cohen et al., 2013).

Education affects the quality of the diet individuals consume. However, research on the effect of education on dietary choices shows mixed evidence. Li and Powdthavee (2015) show that education improves people's diet with higher weekly consumption of fruit, vegetables and low-fat milk, coupled with a tendency to avoid risky health behaviours. Hiza et al. (2013) show that higher education is associated with consuming both healthy foods and unhealthy food. Braakmann (2011) finds education has no impact on health-related behaviours, including dietary choices. Johnston et al. (2015) link the effect of education on health behaviours through individuals' ability to acquire health-related knowledge, and show that additional years of schooling do not generate a significant increase in health-related knowledge.

The literature that discusses the associations between education, health, and health behaviours mostly concentrates on developed countries. Studies related to developing countries are limited. In a cross-country analysis, Hosseinpoor et al. (2012) show both wealth and education are inversely associated with many NCDs in LMICs except diabetes. They report higher diabetes prevalence among the wealthier and more educated in those countries. A study on socioeconomic inequalities in NCDs risk factors indicates that poor physical activity, alcohol consumption and

overweight are more likely to be seen among the non-poor, while smoking and poor diet quality are concentrated among the poor (Keetile et al., 2019). Another study shows that teenage boys who stay in school longer delay the onset of heavy drinking, and reduce smoking at age 18 (Jensen and Lleras-Muney, 2012). However, more studies are required to determine the association between education and diet choices in LMICs.

2.2.3 Diabetes and diet

Type 2 diabetes can be prevented mostly through diet and lifestyle modification (Hu, 2011). Several dietary practices, which include a high intake of saturated fatty acids, high total fat intake, inadequate consumption of dietary fibre, and high intake of sugar-sweetened beverages, are linked to unhealthy body weight, therefore, type 2 diabetes (Roglic et al., 2016). Studies show that food consumption patterns consisting of red and processed meat, refined grains, high-fat dairy, and fried products are positively associated with diabetes, whereas patterns characterized by vegetables, legumes, fruits, poultry, and fish are inversely associated with diabetes (Jannasch et al., 2017; Korat et al., 2014). A Mediterranean dietary pattern rich in olive oil, fruits and vegetables, whole grains, pulses and nuts, low-fat dairy, and moderate alcohol consumption-mainly red wine is identified as the best strategy to decrease diabetes risk (Salas-Salvadó et al., 2011). However, there is no universal dietary strategy to prevent diabetes or delay its onset, but most of the traditional food patterns are not significantly associated with type 2 diabetes (Reeds et al., 2016). Moreover, most dietary components influencing diabetes risk have a similar effect on biomarkers of cardiovascular risk (Salas-Salvadó et al., 2011).

Although guidelines suggest individuals with diabetes should follow a balanced diet, adherence to a healthy diet is possibly the most challenging task in diabetes management. (Delamater, 2006). Many studies indicate that individuals with low socioeconomic status are more likely to have type 2 diabetes than those with high

socioeconomic status (Hwang and Shon, 2014; Kyrou et al., 2020; Suwannaphant et al., 2017). Hence maintaining a healthy diet would be difficult for them. Bomberg et al. (2019) show that households with diabetic individuals are more food insecure, while Berkowitz et al. (2014) points food insecurity is associated with lower overall dietary quality and poor glycemic control. However, Oster (2018) reveals that US households with diabetic patients demonstrate significant but relatively small calorie reductions, primarily related to unhealthy foods, suggesting they reflect genuine efforts to improve their diet.

In contrast, the socioeconomic gradient of diabetes prevalence is mostly positive in LMICs (Corsi and Subramanian, 2019; Niessen et al., 2018; Seiglie et al., 2020). However, when it comes to glycemic control, it is poorer in individuals with diabetics having low SES than in those with higher SES (Rahman et al., 2020). Yet, the consumption of fat, salt and processed foods is not lower among the high-risk for diabetes. For example, Rathnayake et al. (2014) show that individuals with obesity, a major risk factor of diabetes, consume more fast foods than their lean counterparts. However, more evidence is required to distinguish the dietary behaviour of individuals with diabetes in LMICs.

2.3 Empirical Approach

2.3.1 Almost Ideal Demand System (AIDS)

In this study, we model household expenditure patterns, including healthy and unhealthy foods, and estimate price and income demand elasticities[2]. To do so, we use an Almost Ideal Demand System (AIDS), proposed by Deaton and Muellbauer (1980). AIDS has many desirable properties for demand system estimation. The AIDS model automatically satisfies the aggregation restriction, while homogeneity

[2]Here, the income elasticities are approximated by expenditure elasticities. However, later in the analysis, we distinguish the difference between these two types of elasticities

and symmetry can be imposed with simple parametric restrictions (Moschini, 1995). We use Linear Approximate Almost Ideal Demand System (LA/AIDS) in modelling our demand system, an approach commonly used in empirical studies, owing to its simplicity (Akinbode, 2015; Bhuvandas and Gundimeda, 2020; Guerrero-López et al., 2017). It has been proved that price and expenditure elasticities from both AIDS and LA/AIDS systems are identical if the prices in the system are normalised to one (Asche and Wessells, 1997).

The basic AIDS model is developed from a particular expenditure function taken from the general class of "price-independent, generalised logarithmic" (PIGLOG) cost function, and the basic AIDS demand function in budget share form takes the following functional form (Deaton and Muellbauer, 1980):

$$w_i = \alpha_i + \sum_{j=1}^{k} \gamma_{ij} \ln p_j + \beta_i^* \ln(\frac{m}{P}) + \mu_i \tag{2.1}$$

where, w_i is the expenditure share of the i^{th} good, p_j is the price of j^{th} good, m is the total expenditure of all goods included in the model and P is the translog price index defined by,

$$\ln P = \alpha_0 + \sum_{i=1}^{k} \alpha_i \ln p_i + \frac{1}{2} \sum_{i=1}^{k} \sum_{j=1}^{k} \gamma_{ij} \ln p_i \ln p_j \tag{2.2}$$

Due to the estimation difficulty of Equation 2.1 owing to nonlinearity of parameters, Deaton and Muellbauer (1980) suggest to replace Equation 2.2 by the Stone's price index:

$$\ln P^* = \sum_{i=1}^{k} w_i \ln p_i \tag{2.3}$$

where, p_i is the price of the i_{th} good. Since our study is based on food groups, the mean price of each food group is calculated using,

$$p_i = \sum_{k=1}^{m} w_{ki}(p_{ki}) \tag{2.4}$$

where, w_{ki} is the share of expenditure of k^{th} food out of the total expenditure of i^{th} food group and p_{ki} is the price of k^{th} food in i^{th} food group. Substituting the Stone index in Equation 2.1, the LA/AIDS is given as:

$$w_i = \alpha_i + \sum_{j=1}^{k} \gamma_{ij} \ln p_j + \beta_i \ln(\ln m - \sum_{i=1}^{k} w_i \ln p_i) + \mu_i \tag{2.5}$$

Pollak and Wales (1981) show the possibility of adding linear demographic characteristics, incorporating $D(\eta) = \sum_k^n \delta_{ik}\eta_k$ into the demand system, where, $\delta_{ik}\eta_k$ are the demographic variables[3] and associated parameters, as follows:

$$w_i = \alpha_i + \sum_{k}^{n} \delta_{ik}\eta_k + \sum_{j=1}^{k} \gamma_{ij} \ln p_j + \beta_i \ln(\ln m - \sum_{i=1}^{k} w_i \ln p_i) + \mu_i \tag{2.6}$$

This model satisfies the following aggregation restriction and with parametric restriction, homogeneity and symmetry can be imposed.

$$\sum_{i=1}^{K} \alpha_w e = 1 \quad \sum_i \delta_{ik} = 0 \quad \sum_{i=1}^{k} \beta_i = 0 \quad \sum_{i=1}^{k} \gamma_{ij} = 0 \tag{2.7}$$

Some households have zero consumption for some food categories. In order to address this problem, zero shares were censored by an unobservable latent variable obtained through a Heckman two-step estimation procedure (Heckman, 1977). In the first stage, the probability that a given household consumes the food item is estimated using a probit regression as follows,

$$P(x = 1) = \tau_w e z_{ih} + v_{ih} \tag{2.8}$$

where z_{ih} is the vector of exogenous variables included in the model. This probit

[3]The demographic variables added to the model are: sector, ethnic background, education level of the household head, household size, age of the household head, and having diabetic, hypertension and CVD patients in the household

regression is used to estimate the inverse mills ratio (I) of each household

$$I_i = \frac{\phi_i(\tau_w ez_{ih})}{\Phi_i(\tau_w ez_{ih}} \tag{2.9}$$

where ϕ_i and Φ_i are the probability density and cumulative functions respectively. The inverse mills ratio is then used as an instrument in Equation 2.6. Accordingly, the functional form of LA/AIDS becomes:

$$w_i = \alpha_i + \sum_{k}^{n} \delta_{ik}\eta_k + \sum_{j=1}^{k} \gamma_{ij} \ln p_j + \beta_i \ln(\ln m - \sum_{i=1}^{k} w_i \ln p_i) + I_i + \mu_i \tag{2.10}$$

The estimated parameters of Equation 2.10 are used to derive the demand elasticities of each good. Accordingly, following Green and Alston (1990) we use the below formulas to calculate expenditures and price elasticities of each food category.

1. Expenditure elasticity of each food category i:

$$\mu_i = 1 + \frac{1}{w_i}(\frac{\partial w_i}{\partial \ln m}) = 1 + \frac{\beta_i}{w_i} \tag{2.11}$$

2. Price elasticity (Uncompensated)[4]:

$$\epsilon_{ij} = -\delta_{ij} + \frac{1}{w_i}(\frac{\partial w_i}{\partial \ln p_i}) = -\delta_{ij} + \frac{\gamma_{ij}}{w_i} - \frac{\beta_i}{w_i} w_j \tag{2.12}$$

where $-\delta_{ij}$ is the Kronecker delta that is unity if i=j, and zero otherwise.

2.3.2 Quality income elasticity

As with many household expenditure surveys, HIES does not provide market prices for each food item. Hence, we derived a proxy for the price, which is the unit value of each food category by dividing the expenditure of a food category by the respec-

[4]Both uncompensated and compensated price elasticities are derived using AIDS model. However, for simplicity, we use only uncompensated price elasticities

tive quantity. However, these unit values may substantially vary from the actual market prices since the calculated unit values reflect both market price and consumers' choice of food quality (Cramer, 1973; Deaton, 1988; Huang and Lin, 2000). For example, the food category lean meat includes different qualities of meat such as whole chicken, breast, thighs or wings and the prices of these varieties are different. Generally, the better the quality, the higher the price of the product (Olbrich and Jansen, 2014) and the higher the consumers' expenditures. So, our unit values derived from expenditure reflect the quality of the products that each household consumes. Households included in the survey do not purchase homogeneous products in terms of quality. We expect better-off households to spend more on costly, better-quality foods (Skoufias et al., 2011).

Apart from food quality, there are some other factors that deviate unit values from actual market prices such as regional differences in the food prices induced by transportation costs. Accordingly, following Huang and Lin (2000), we state the equation for unit values as:

$$\log p_i = \pi \log m + \sum_k \gamma_{ik} z_k \tag{2.13}$$

where, p_i is the unit value of i^{th} food category, m is the income approximated by total household expenditure, and z_k is the vector of dummy variables included in the demand system to represent socio-demographic characteristics of households affecting unit values. The coefficient π shows the percentage change in price according to a percentage change in income, which we define as the elasticity of quality[5]. (Cramer,

[5]The derivation of the elasticity of quality can be described using an expenditure function given as, m_i=$q_i p_i$, where, m_i is the expenditure of a particular good, q_i is the quantity, and p_i is the unit value. If we differentiate the log term of the above equation by income (μ), we can derive the expenditure elasticity, which consists of income elasticity and quality income elasticity.

$$\frac{\partial \log m_i}{\partial \log \mu} = \frac{\partial \log q_i}{\partial \log \mu} + \frac{\partial \log p_i}{\partial \log \mu} \tag{2.14}$$

If p_i is a constant, then the expenditure elasticity should be equal to the income elasticity. If it is not, then there will be a positive/negative quality income elasticity, and the elasticity of expenditure would not be equal to income elasticity (Huang and Lin, 2000)

1973; Houthakker, 1952).

2.4 Data

We employ data from two waves of the HIES conducted by the Department of Census and Statistics in Sri Lanka in 2006 and 2016. HIES is a nationally representative survey, and it follows a two-stage stratified sampling method. Urban, Rural and the Estate[6] sectors in each district of the country are the selection domains of the sample design. The survey is generally conducted over 12 consecutive months to capture variations in income and expenditure patterns in Sri Lanka. It collects data from households and records information about each household member. Demographics and income data are recorded for each individual respondent and expenditure data is collected at the household level. After cleaning the data, our sample consists of 18,509 households from the 2006 survey and 21,741 households from the 2016 survey.

Sample design of the survey is two stage stratified and the Urban, Rural and the Estate sectors in each district of the country are the selection domains

2.4.1 Socio-demographic and health status of households

Socio-demographic characteristics and the health status of the sample are given in Table 2.1. Approximately two-thirds of households lived in a rural area in 2006, with the proportion growing to three-quarters by 2016. Sinhala represents the ethnic group with the largest representation. However, the Sri Lankan Tamil community represented in the survey rose by 2016, mainly due to the geographical scope of the survey expanding to the North and East of the country, with the ending of the civil war. Nearly 70% of household heads have education at least up to Ordinary-levels, while the percentages for higher education levels increase from 2006 to 2016.

[6]Estate sector refers to geographical areas that consist of all plantations (tea, rubber, coconut etc) which are 20 acres or more in extent with ten or more resident labourers. The socio-economic characteristics of the Estate sector population are different from the other two sectors (CBSL, 2020)

Table 2.1: Socio-demographic and health status of households

Variable	Definition	2006	2016
Region	*Urban*	24.98%	15.76%
	Rural	65.72%	79.95%
	Estate	9.3%	4.29%
Ethnicity	*Sinhala*	75.02%	72.52%
	Sri Lankan Tamil	9.64%	15.06%
	Indian Tamil	5.66%	3.62%
	Moors	9.07%	8.39%
	Other	0.61%	0.4%
Education household head	*No education*	6.53%	3.89%
	Primary	27.53%	22.39%
	Up to O/L	52.42%	56.74%
	Up to A/L	11.25%	14.24%
	Degree	2.27%	2.75%
Heath Status	*Hbp*	10.46%	13.88%
	Diabetes	7.76%	11.72%
	Heart disease	4.64%	5.34%
Age of the household head		50.46	52.62
Household size		4.39	3.81

Notes: Table shows the socio-demographic characteristics and the health status of the sample. Age of the household head and household size are their mean values. All other values are percentages from the total sample.

Household size has been diminishing while the age of the household head rose during the period.

HIES records the health conditions of each individual in the household. Accordingly, 26% of households in the 2006 survey and 31% of households in the 2016 survey reported that they have at least one individual with a chronic illness. Of all chronic diseases, we considered three major NCDs related to diet (Kraemer et al., 2016), which are high blood pressure (hbp), diabetes and heart diseases. Those are the most common NCDs in households, showing prevalence rates of 14%, 12% and 5% respectively in 2016. The rates are respectively 4, 4 and 1 percentage points higher in 2016 than that in 2006. Some households report more than one individual with these diseases, and individuals with more than one of these diseases are also reported.

2.4.2 Household expenditures

HIES recorded expenditure data under two categories, food and non-food expenditures (DCS, 2016). Nearly half of the total expenses of a household go to food consumption. Under food expenditures, the survey gathered data for around 200 food items under 19 headings. We re-categorised the food items according to our study purpose. Following the literature related to dietary guidelines relevant to the prevention and control of diabetes and other metabolic diseases (Roglic et al., 2016; Salas-Salvadó et al., 2011), we grouped food items into 14 food categories, classified as healthy and unhealthy. Our classification also accounted for the local food consumption behaviour in Sri Lanka (Jayawardena et al., 2013; Samaranayake et al., 2011). For example, since rice is the staple food in Sri Lanka, it is required to identify healthy rice varieties according to the glycemic index (GI). Therefore, we classified rice and other cereal varieties into two groups as High GI cereals and lower/medium GI cereals, following the glycemic load values of each food (Atkinson et al., 2008; Hettiarachchi et al., 2014). Accordingly, cereals (low/medium GI), pulses, fish, lean meat, egg, fruits and vegetables are classified as healthy food, while cereals (high GI), red meat and processed meat, prepared food, sugar, sugar-sweetened beverages (SSBs), confectioneries, and fat and oil are classified as unhealthy.

The mean expenditure shares of each food category out of total food expenditures are given in Table 2.2. Households spend the highest share of spending on cereals, especially for high GI cereals. Fish accounts for 20% of food expenses. Food consumption shares show some differences across regions. For example, expenditure on all cereals is lower in the urban sector, whereas the share is higher in the estate sector. Expenditure shares for prepared food, fish, lean meat, red meat, fruits, confectioneries and sugar-sweetened beverages are high in urban households compared to others. Similarly, the mean shares are different according to the educational level of the household head. Households spend higher percentages on fish, meat, fruits, confectioneries and soft/fruit drinks, and lower shares on cereals, pre-

Table 2.2: Mean food expenditure shares and prices

2006	**All**	**Urban**	**Rural**	**Estate**	**No education**	**Primary**	**O/L**	**A/L**	**Degree**	**Diabetes**	**Unit price**
Food (% of total household expenditures)	52.9%	47.4%	53.2%	65.0%	65.4%	57.5%	43.4%	37.7%	31.6%	45.8%	
Healthy food											
L/M GI cereals	8.9%	5.5%	9.2%	16.3%	12.2%	11.6%	8.2%	5.3%	4.0%	6.4%	58.78
Vegetables	11.3%	9.6%	11.9%	11.9%	11.8%	11.6%	11.2%	10.8%	11.0%	10.8%	67.03
Fruits	5.2%	6.4%	5.1%	2.7%	3.7%	4.0%	5.3%	7.5%	9.8%	6.4%	12.14
Pulses	6.2%	5.2%	6.4%	7.8%	6.6%	6.3%	6.2%	6.0%	5.8%	6.0%	109.26
Fish	21.4%	25.3%	21.3%	11.8%	15.8%	19.7%	22.4%	23.5%	23.9%	23.9%	261.29
Lean meat	3.8%	5.4%	3.3%	3.2%	2.1%	2.8%	4.0%	5.7%	7.1%	5.4%	263.36
Egg	1.6%	1.9%	1.6%	1.6%	1.2%	1.4%	1.7%	2.0%	1.9%	1.6%	7.96
Unhealthy food											
High GI cereals	21.6%	17.8%	22.2%	27.4%	25.3%	23.0%	21.1%	19.3%	17.1%	20.5%	74.43
Prepared food	2.3%	3.4%	1.9%	2.0%	3.2%	2.2%	2.2%	2.2%	2.0%	2.2%	20.30
Red/processed meat	1.9%	3.3%	1.5%	0.6%	1.6%	2.0%	1.8%	1.8%	2.2%	2.4%	287.46
Sugar	7.3%	7.0%	7.5%	6.7%	8.4%	7.7%	7.2%	6.2%	5.2%	6.2%	60.94
Confectioneries	4.2%	4.8%	4.1%	3.2%	3.3%	3.3%	4.3%	5.7%	6.1%	4.1%	192.25
SSB	0.4%	0.6%	0.3%	0.1%	0.2%	0.3%	0.4%	0.5%	0.7%	0.5%	81.90
Fat & oil	3.9%	3.7%	3.9%	4.8%	4.5%	4.1%	3.9%	3.4%	3.2%	3.7%	125.97
2016											
Food (% of total household expenditures)	49.1%	43.8%	49.6%	59.5%	61.3%	54.5%	41.6%	36.8%	29.1%	44.0%	
Healthy food											
L/M GI cereals	10.8%	7.5%	11.0%	17.9%	13.1%	12.6%	10.6%	8.7%	7.3%	10.3%	138.73
Vegetables	10.4%	8.6%	10.8%	10.7%	11.4%	10.8%	10.3%	10.3%	10.1%	10.5%	142.99
Fruits	4.4%	5.8%	4.2%	2.3%	3.0%	3.3%	4.2%	6.2%	7.9%	5.0%	23.74
Pulses	6.3%	5.2%	6.4%	8.6%	6.6%	6.4%	6.4%	6.1%	5.8%	6.2%	254.97
Fish	21.3%	22.7%	21.6%	10.5%	17.5%	19.7%	21.7%	22.5%	23.5%	23.4%	611.09
Lean meat	4.9%	6.7%	4.5%	4.7%	3.4%	3.9%	5.0%	6.0%	6.8%	5.2%	494.83
Egg	1.7%	1.7%	1.7%	2.2%	1.4%	1.6%	1.7%	2.0%	1.8%	1.6%	17.19
Unhealthy food											
High GI cereals	21.9%	19.7%	22.1%	26.2%	23.8%	23.7%	22.0%	19.5%	17.2%	20.2%	99.45
Prepared food	2.7%	5.1%	2.4%	1.4%	3.2%	2.4%	2.7%	3.0%	3.2%	2.6%	48.94
Red/processed meat	1.3%	2.6%	1.1%	0.3%	0.9%	1.3%	1.4%	1.3%	1.7%	1.6%	687.98
Sugar	4.5%	4.0%	4.6%	4.2%	6.6%	5.1%	4.4%	3.6%	3.3%	3.9%	104.43
Confectioneries	4.8%	5.2%	4.7%	4.8%	4.0%	4.1%	4.7%	5.9%	6.0%	4.5%	422.33
SSB	0.5%	1.2%	0.4%	0.1%	0.4%	0.3%	0.5%	0.7%	1.4%	0.5%	152.32
Fat & oil	4.5%	4.2%	4.4%	5.9%	4.9%	4.7%	4.4%	4.1%	4.1%	4.4%	312.16

Notes: Table shows the mean expenditure shares of each food category out of total food expenditures.

pared food, pulses, vegetables and sugar when household heads are educated up to Advanced-Level or degree level. The expenditure share of high GI cereals is lower for households with diabetes compared to all households; however, other shares are not much different from overall figures.

Expenditure shares for some food categories have considerably changed from 2006 to 2016. Percentages for low/medium cereals, lean meat, prepared food and fat and oil were higher in 2016, whereas the shares for fruit, vegetables and sugar were lower. There are heterogeneous changes in expenditure shares across different sectors, education and health status.

The last column in Table 2.2 shows the mean prices of each food group. Since more than one food item is grouped into one category, the unit value of each food group is calculated by giving a weight according to the share of each item within the group as in equation 4. The measurement scales of food groups are different as prices for some goods are calculated as the price per 1 kilogram/litre, while some are recorded as the price per item. Prices of all food groups have increased over time, with most prices doubling from 2006 to 2016. Increasing food shares of some foods from 2006 to 2016 may be attributed to changes in prices. However, shares for some food categories remain unchanged or decrease even with a higher price increase.

2.5 Results

We estimated a modified LA/AIDS model for the demand system of 14 food categories, classified as healthy and unhealthy and then calculated price and income demand elasticities. Before estimating the LA/AIDS model, we needed to address the problem of zero consumption of some food categories. Therefore, we ran a probit regression for each food group to calculate the inverse mill ratio, which was then used as an instrument in the LA/AIDS model to correct for zero consumption. The results of the Probit regression is presented in Appendix 2.A . The LA/AIDs model

parameters are estimated by applying a seemingly unrelated regression method using STATA 15.1. For parsimony, we do not include the results of the estimated LA/AIDS model, but this is available in Appendix 2.B.1.

Table 2.3: Elasticity coefficients derived from LA/AIDS

	Expenditure elasticities		**Own price elasticities**	
	2006	**2016**	**2006**	**2016**
Healthy food				
L/M GI cereals	1.603***	1.095***	-2.884***	-2.618***
	(0.008)	*(0.001)*	*(0.026)*	*(0.021)*
Vegetables	1.060***	1.147***	-0.657***	-0.542***
	(0.000)	*(0.001)*	*(0.002)*	*(0.003)*
Fruits	2.512***	2.214***	-0.851***	-0.861***
	(0.015)	*(0.012)*	*(0.002)*	*(0.002)*
Pulses	0.619***	0.700***	-0.179***	-0.323***
	(0.003)	*(0.002)*	*(0.007)*	*(0.005)*
Fish	0.392***	0.519***	-0.810***	-0.975***
	(0.006)	*(0.004)*	*(0.001)*	*(0.000)*
Lean meat	0.750***	0.791***	-1.013***	-0.959***
	(0.002)	*(0.001)*	*(0.000)*	*(0.000)*
Egg	1.332***	1.344***	-0.582***	-0.550***
	(0.003)	*(0.002)*	*(0.003)*	*(0.007)*
Unhealthy food				
High GI cereals	0.803***	0.863***	-2.103***	-1.834***
	(0.002)	*(0.002)*	*(0.013)*	*(0.010)*
Prepared food	1.245***	1.209***	-2.056***	-1.218***
	(0.003)	*(0.002)*	*(0.013)*	*(0.002)*
Red/processed meat	0.866***	0.833***	-1.091***	-1.012***
	(0.002)	*(0.004)*	*(0.002)*	*(0.001)*
Sugar	1.934***	2.020***	-1.258***	-1.072***
	(0.005)	*(0.010)*	*(0.001)*	*(0.000)*
Confectioneries	0.875***	0.547***	-1.555***	-1.419***
	(0.001)	*(0.005)*	*(0.005)*	*(0.004)*
SSBs	0.977***	1.219***	-1.417***	-1.954***
	(0.000)	*(0.000)*	*(0.009)*	*(0.017)*
Fat & oil	1.312***	1.662***	-0.038***	-0.360***
	(0.002)	*(0.004)*	*(0.006)*	*(0.004)*

Notes: Table shows the expenditure elasticity of each food group. The elasticities were calculated based on the estimated coefficient of the LA/AIDS model. Standard errors are in parentheses. Significance levels : $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Based on the estimated coefficient of the LA/AIDS model, the income and price elasticities coefficients of each food category are calculated. Table 2.3 shows the expenditure elasticity and respective standard errors of each food group in both periods. All the expenditure elasticities are positive, reflecting that all food cate-

gories are either normal or luxury goods. The highest expenditure elasticity, which is nearly two, is recorded for fruits in both years. Accordingly, a 1% of increase in income would increase the demand for fruits by more than 2%. Low-GI cereals, eggs and vegetables are the other foods that record higher elasticity under healthy food category. Under unhealthy food, sugar has the highest expenditure elasticity. Fat and oil, prepared food and SSBs are also recorded as greater than one expenditure elasticity in both years. The elasticities for pulses and fish are relatively low, with a 1% income increase leading to a 0.6-0.7% increase in pulses and a 0.4-0.5% increase in demand for fish.

Estimated price elasticities (own price elasticities) of each food group is also presented in Table 2.3. Own price elasticities of all goods are negative complying with the demand theory. The highest price elasticity is recorded for the demand for low/medium GI cereals. Similarly, high GI cereals, prepared foods, lean meat, red or processed meat, confectioneries, sugar and SSBs also record more elastic demands implying that price increase would decrease the demand for those foods more. However, demand elasticities of some healthy foods such as vegetables, fruits, pulses, and fish show inelastic demands reflecting the difficulty in increasing demand using price policies.

Cross-price elasticities for each food category were also calculated, and the results are presented in Appendix 2.C.1. The cross-price elasticities reveal that high GI cereals and low/medium GI cereals highly substitute for each other. Hence, a price increase in any of those two foods would increase the demand for other goods. Therefore, the price increase for high GI cereals would be a better policy from a health perspective since it would decrease its demand and increase the demand for healthy cereal varieties. Vegetables and pulses are complementary to cereals, reflecting the nature of the Sri Lankan diet since those are usually consumed with rice as a base. Most of all other foods are complementary to each other. Notably, an increase in the price of any other food decreases the demand for fruit, highlighting

fruit is not considered as a main food in the Sri Lankan diet.

2.5.1 Consumption changes from 2006 to 2016

The differences in price and expenditure elasticity between 2006 and 2016 show that households respond differently to the same price and income increase during the two periods. Compared to 2006, expenditure elasticities are slightly higher in 2016 for some healthy foods such as vegetables, pulses, fish and lean meat. However, the expenditure elasticity for fruits and low and medium GI cereals are considerably lower in 2016 than in 2006, meaning that households would not increase their demand for those foods with income increases in 2016 as much as they did in 2006. Under unhealthy foods, high GI cereals, sugar, fat and oil and SSBs recorded higher expenditure elasticities in 2016 than in 2006. Sugar records an expenditure elasticity of nearly two in both years. Households would buy more fat and oil in 2016 than in 2006 with the same income increase. The expenditure elasticity for prepared food and red meat is only slightly lower in 2016 than in 2006, indicating that income responsiveness has not changed much during the period. In essence, the changes and the intensity of the demand sensitivity with an income increase during this period appeared to be more towards unhealthy foods providing evidence for nutritional transition.

Compared to 2006, most unhealthy food categories' price elasticities are lower in 2016 except SSBs. This implies that when price increases consumers did not decrease their demand for unhealthy food in 2016 as much as they did in 2006. However, an increase in the price of SSBs decreased the demand by a higher percentage, and that is more prominent in 2016 than in 2006, showing the effectiveness of price policies in changing the demand for SSB in 2016. For the healthy food group, only pulses and fish showed a substantial increase in price elasticities in 2016 compared to 2006, indicating price increase would decrease the demand for those foods more in 2016. The elasticity of low GI cereals, which has the highest price sensitivity, decreased

marginally by 2016.

2.5.2 Food consumption by education

In Table 2.4 and 2.5 we report the coefficients of the socio-demographic variables for each food group estimated through LA/AIDS model. The results reveal significant variations in the food demand across socio-demographic and health status. Compared to urban households, rural and estate sector households spent more shares on cereals, pulses, vegetables and sugar. They spent less on prepared food, fish and fruits and SSBs in both years. Compared to 2006, urban households in 2016 spent more on unhealthy food such as prepared food and SSBs than rural and estate sector households. Significant ethnic differences can also be found in food expenditure shares. Compared to Sinhalese households, other ethnic groups spent lower shares on most food groups. However, Sri Lankan Tamils consumed more healthy food such as low/medium GI cereals fish and lean meat than Sinhalese households. Moors spent more on prepared food and red meat, which are unhealthy than Sinhalese households.

The effect of education and health status on food expenditure shares are also presented in Table 2.4 and 2.5, The results indicate a significant impact of education on shares spent on different food categories. The shares spent on fruits and fish, categorised as healthy, are significantly higher at higher education levels than at no education. The shares spent for both types of cereals are significantly lower with a higher level of education. However, the allocation for high GI cereals is much lower at higher education levels than the low GI cereals. The share paid on sugar is significantly lower at a higher level of education. Households with degree-level education spent 3% lower shares on sugar in 2006. However, educated households spent higher shares on confectioneries and fat and oil. The share allocated for SSBs and prepared foods has not been linked with education in either year.

The impact of education on food shares in 2016 is mainly similar to 2006 except

Table 2.4: Results of the LA/AIDS model : Coefficients of the demographic variables - 2006

	Rural sector	***Estate sector***	***Sri Lankan Tamil***	***Indian Tamil***	***Moors***	***Primary***	***OL***	***AL***	***Degree***	***Diabetes***
Healthy food										
L/M GI cereals	0.036***	0.059***	0.033***	0.084***	-0.002	0.002	-0.012***	-0.019***	-0.025***	-0.005*
Vegetables	0.014***	0.009***	0.002	0.001	-0.028***	-0.002	-0.005***	-0.009***	-0.005	-0.002
Fruits	-0.024***	-0.041***	-0.028***	-0.059***	-0.004**	0.004*	0.027***	0.064***	0.089***	0.017***
Pulses	0.004***	0.020***	-0.011***	-0.000	-0.019***	-0.001	-0.001	-0.001	0.001	-0.001
Fish	-0.025***	-0.086***	0.028***	-0.023***	-0.007**	0.020***	0.028***	0.036***	0.043***	0.007**
Lean meat	-0.001	0.001	0.011***	0.012***	0.005**	-0.004*	-0.003	0.002	0.008**	0.006***
Egg	-0.002***	-0.001	0.003***	0.002*	0.004***	0.001	0.003***	0.005***	0.004***	0.000
Unhealthy food										
High GI cereals	0.025***	0.055***	-0.006*	0.013***	-0.032***	-0.012***	-0.029***	-0.057***	-0.075***	-0.011***
Prepared food	-0.026***	-0.030***	-0.009***	-0.010***	0.029***	-0.008***	-0.005**	-0.005*	-0.015	0.005**
Red/processed meat	0.001	0.006***	0.002*	0.006***	0.060***	-0.003**	-0.004***	-0.004**	-0.002	0.001
Sugar	0.007***	0.001	-0.009***	-0.018***	0.003**	0.009***	0.004**	-0.016***	-0.027***	-0.018***
Confectioneries	-0.008***	-0.002	-0.012***	-0.009***	-0.008***	-0.003*	0.001	0.012***	0.016***	-0.001 1
SSB	-0.001***	0.001	-0.000	0.001	-0.000	-0.001	-0.001	-0.001	0.000	0.001*
Fat & oil	-0.001	0.009***	-0.002*	0.002*	-0.003***	-0.001	0.003***	0.008***	0.012***	0.000

Notes: The table shows the impact of sociodemographic characteristics on the consumption of food items categorised as healthy/unhealthy in 2006. The reference categories are urban sector, Sinhala ethnic category, households with non-educated household heads, and the households without diabetes patients.
Significance levels: $^{+}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 2.5: Results of the LA/AIDS model : Coefficients of the demographic variables -2016

	Rural sector	***Estate sector***	***Sri Lankan Tamil***	***Indian Tamil***	***Moors***	***Primary***	***OL***	***AL***	***Degree***	***Diabetes***
Healthy food										
L/M GI cereals	0.024***	0.065***	0.009***	0.040***	-0.015***	-0.004	-0.011***	-0.012***	-0.014***	0.011*** *
Vegetables	0.013***	0.015***	-0.019***	-0.006*	-0.029***	-0.007***	-0.011***	-0.012***	-0.013***	0.001
Fruits	-0.017***	-0.020***	-0.017***	-0.035***	-0.009***	0.007***	0.019***	0.039***	0.056***	0.007***
Pulses	0.003***	0.017***	0.001	0.007***	-0.010***	-0.002	-0.001	-0.003	-0.003	-0.001
Fish	-0.009***	-0.081***	0.016***	-0.016***	-0.007**	0.013***	0.027***	0.039***	0.049***	0.014***
Lean meat	-0.006***	-0.002	0.009***	0.009**	0.013***	0.000	0.001	0.003	0.008**	-0.001
Egg	0.000	0.002*	-0.001**	0.005***	0.002***	0.001	0.002**	0.005***	0.002*	-0.000
Unhealthy food										
High GI cereals	0.023***	0.048***	0.034***	0.019***	-0.036***	0.003	-0.012***	-0.040***	-0.063***	-0.019***
Prepared food	-0.039***	-0.061***	0.003**	-0.007**	0.055***	-0.001	0.002	0.005*	0.012***	0.005***
Red/processed meat	0.002**	0.005**	0.003***	0.005**	0.062***	0.000	-0.000	-0.001	0.001	-0.001
Sugar	0.012***	0.004*	-0.031***	-0.022***	-0.017***	-0.014***	-0.015***	-0.024***	-0.042***	-0.001
Confectioneries	-0.005***	0.006*	-0.010***	-0.007**	-0.008***	0.002	0.001	0.008***	0.011***	-0.003*
SSB	-0.004***	-0.005***	0.002***	-0.001	0.001	-0.001	-0.001	-0.002	0.002	-0.002**
Fat & oil	0.002**	0.006***	0.001	0.010***	-0.004***	0.001	-0.000	0.005***	0.007***	0.000

Notes: The table shows the impact of socio-demographic characteristics on the consumption of food items categorised as healthy/unhealthy in 2016. The reference categories are the urban sector, Sinhala ethnic category, households with non-educated household heads, and households without diabetes patients.
Significance levels : $^{+}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

for a few variations. For example, prepared food consumption was significantly higher for higher education levels in 2016, although there was a negative or no significant impact in 2006. The negative impact of education on claims of sugar is higher in 2016 than in 2006. However, the positive impact of education on fruit consumption was lower in 2016 than in 2006.

Table 2.6: Expenditure elasticity by education: 2006

	2006				
	No education	**Primary**	**O/L**	**A/L**	**Degree**
Healthy food					
L/M GI cereals	1.067***	1.388***	1.568***	1.547***	1.520***
	(0.004)	*(0.011)*	*(0.011)*	*(0.019)*	*(0.033)*
Vegetables	1.063***	1.036***	1.034***	0.983***	0.811***
	(0.002)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.006)*
Fruits	2.341***	2.918***	3.000***	2.671***	3.020***
	(0.050)	*(0.035)*	*(0.027)*	*(0.045)*	*(0.125)*
Pulses	0.884***	0.597***	0.651***	0.668***	0.587***
	(0.004)	*(0.006)*	*(0.004)*	*(0.008)*	*(0.023)*
Fish	0.308***	0.352***	0.480***	0.586***	0.616***
	(0.026)	*(0.012)*	*(0.006)*	*(0.009)*	*(0.016)*
Lean meat	0.771***	0.667***	0.602***	0.578***	0.567***
	(0.009)	*(0.005)*	*(0.004)*	*(0.009)*	*(0.018)*
Egg	1.236***	1.281***	1.321***	1.253***	1.218***
	(0.009)	*(0.005)*	*(0.003)*	*(0.006)*	*(0.009)*
Unhealthy food					
High GI cereals	1.115***	0.712***	0.694***	0.812***	0.794***
	(0.006)	*(0.007)*	*(0.005)*	*(0.006)*	*(0.017)*
Prepared food	2.155***	2.728***	2.365***	2.539***	1.240***
	(0.096)	*(0.042)*	*(0.021)*	*(0.052)*	*(0.018)*
Red/processed meat	0.854***	0.787***	0.796***	0.763***	0.749***
	(0.009)	*(0.005)*	*(0.004)*	*(0.011)*	*(0.028)*
Sugar	2.051***	1.733***	1.735***	1.669***	1.894***
	(0.023)	*(0.007)*	*(0.005)*	*(0.012)*	*(0.044)*
Confectioneries	-0.586***	0.712***	0.890***	0.920***	1.338***
	(0.063)	*(0.005)*	*(0.001)*	*(0.002)*	*(0.019)*
SSBs	0.958***	0.911***	0.983***	0.948***	1.275***
	(0.004)	*(0.004)*	*(0.001)*	*(0.002)*	*(0.024)*
Fat & oi	1.149***	1.253***	1.186***	0.909***	1.474***
	(0.004)	*(0.003)*	*(0.002)*	*(0.002)*	*(0.021)*

Notes: Table presents the expenditure elasticities by education. A LA/AIDS model was estimated for each education category and the elasticities were calculated based on the estimated coefficient. Standard errors are in parentheses. Significance levels : $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

To find the expenditure elasticities at different education levels, we estimated the LA/AIDS model for each education category and calculated the elasticities. (The

Table 2.7: Expenditure elasticity by education: 2016

	2016				
	No education	**Primary**	**O/L**	**A/L**	**Degree**
Healthy food					
L/M GI cereals	1.072***	1.044***	1.052***	0.875***	0.807***
	(0.005)	*(0.001)*	*(0.001)*	*(0.004)*	*(0.011)*
Vegetables	1.082***	1.153***	1.128***	1.070***	0.956***
	(0.003)	*(0.002)*	*(0.001)*	*(0.001)*	*(0.001)*
Fruits	1.892***	2.861***	2.811***	3.314***	2.182***
	(0.043)	*(0.040)*	*(0.021)*	*(0.065)*	*(0.059)*
Pulses	0.762***	0.686***	0.687***	0.770***	0.692***
	(0.008)	*(0.005)*	*(0.003)*	*(0.004)*	*(0.014)*
Fish	0.555***	0.500***	0.491***	0.561***	0.530***
	(0.018)	*(0.008)*	*(0.005)*	*(0.008)*	*(0.018)*
Lean meat	0.960***	0.675***	0.614***	0.579***	1.025***
	(0.001)	*(0.005)*	*(0.003)*	*(0.007)*	*(0.001)*
Egg	1.263***	1.328***	1.338***	1.379***	1.394***
	(0.011)	*(0.005)*	*(0.003)*	*(0.007)*	*(0.016)*
Unhealthy food					
High GI cereals	0.775***	0.847***	0.910***	0.893***	0.364***
	(0.012)	*(0.004)*	*(0.001)*	*(0.003)*	*(0.041)*
Prepared food	0.810***	1.975***	2.158***	1.962***	1.635***
	(0.014)	*(0.024)*	*(0.016)*	*(0.026)*	*(0.036)*
Red/processed meat	0.970***	0.815***	0.768***	0.735***	0.978***
	(0.003)	*(0.009)*	*(0.007)*	*(0.018)*	*(0.002)*
Sugar	3.404***	2.550***	2.418***	2.414***	4.128***
	(0.066)	*(0.015)*	*(0.009)*	*(0.020)*	*(0.096)*
Confectioneries	0.533***	0.096***	0.424***	0.411***	0.937***
	(0.026)	*(0.018)*	*(0.007)*	*(0.022)*	*(0.003)*
SSBs	0.446***	1.034***	1.034***	1.114***	1.210***
	(0.067)	*(0.002)*	*(0.001)*	*(0.005)*	*(0.019)*
Fat & oi	1.106***	1.556***	1.695***	1.596***	1.656***
	(0.003)	*(0.007)*	*(0.005)*	*(0.009)*	*(0.022)*

Notes: Table presents the expenditure elasticities by education. A LA/AIDS model was estimated for each education category and the elasticities were calculated based on the estimated coefficient. Standard errors are in parentheses. Significance levels : $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

result of the LA/AIDS model in one education category is presented in Appendix 2.D.1). Table 2.6 and 2.7 present the expenditure elasticity by education category for the two years. Statistical tests for the mean difference between education levels are presented in Table 2.8. For healthy foods, the highest expenditure elasticity is recorded for fruits, and it remains a luxury food for all education levels. The elasticities for fruits are higher at higher education levels, implying that more educated individuals spend more on fruits. Although inelastic, fish and lean meat elasticities

Table 2.8: Tests for the mean difference between education categories

	Primary with no education	O/L with no education	A/L with no education	Degree with no education	O/L with primary	A/L with primary	Degree with primary	A/L with O/L	Degree with O/L	Degree with A/L
2006										
L/M GI cereals	0.320***	0.501***	0.479***	0.452***	0.180***	0.159***	0.132*	-0.021	-0.048	-0.027
Vegetables	-0.027***	-0.028***	-0.080***	-0.251***	-0.00144	-0.052***	-0.224***	-0.051***	-0.223***	-0.171***
Fruits	0.577***	0.659***	0.329***	0.678***	0.082	-0.247***	0.101	-0.329***	0.019	0.348*
Pulses	-0.287***	-0.233***	-0.216***	-0.297***	0.054***	0.071***	-0.010	0.016	-0.064***	-0.08***
Fish	0.043	0.171***	0.277***	0.307***	0.128***	0.234***	0.264***	0.106***	0.135***	0.029
Lean meat	-0.104***	-0.168***	-0.192***	-0.203***	-0.064***	-0.088***	-0.099***	-0.023*	-0.034	-0.010
Egg	0.045***	0.084***	0.017064	-0.01757	0.039***	-0.028***	-0.063***	-0.067***	-0.102***	-0.034
High GI cereals	-0.403***	-0.421***	-0.303***	-0.321***	-0.018	0.099***	0.081***	0.117***	0.099*	-0.01778
Prepared food	0.573***	0.210	0.383***	-0.914***	-0.363***	-0.189**	-1.487***	0.173**	-1.124***	-1.298***
Red/processed meat	-0.066***	-0.058***	-0.091*	-0.104***	0.008	-0.024	-0.037	-0.033***	-0.046	-0.013
Sugar	-0.318***	-0.315***	-0.382***	-0.156***	0.002	-0.064***	0.161***	-0.066***	0.159***	0.225***
Confectioneries	1.297***	1.475***	1.505***	1.923***	0.177***	0.208***	0.625***	0.030*	0.447***	0.417***
SSBs	-0.046***	0.024**	-0.010	0.316***	0.071***	0.036***	0.363***	-0.034***	0.292***	0.326***
Fat & oi	0.104***	0.036***	-0.239***	0.325***	-0.067***	-0.344***	0.220***	-0.276***	0.288***	0.564***
2016										
L/M GI cereals	-0.028***	-0.019***	-0.197***	-0.265***	0.008***	-0.169***	-0.237***	-0.177***	-0.245***	-0.068***
Vegetables	0.070***	0.045***	-0.011	-0.126***	-0.025***	-0.082***	-0.197***	-0.057***	-0.171***	-0.114***
Fruits	0.968***	0.919***	1.422***	0.290	-0.049	0.453***	-0.678***	0.502***	-0.629***	-1.132***
Pulses	-0.075***	-0.075***	0.007	-0.069***	0.000	0.083***	0.006	0.082***	0.005	-0.077***
Fish	-0.055	-0.063**	0.006	-0.024	-0.008	0.061***	0.030	0.070***	0.039	-0.030
Lean meat	-0.284***	-0.345***	-0.380***	0.065***	-0.061***	-0.096***	0.349***	-0.035***	0.411***	0.446***
Egg	0.064***	0.075***	0.115***	0.130***	0.010	0.051***	0.066***	0.040***	0.055***	0.014
High GI cereals	0.071***	0.135***	0.117***	-0.410***	0.063***	0.046***	-0.482***	-0.017***	-0.546***	-0.528***
Prepared food	1.164***	1.348***	1.151***	0.825***	0.183***	-0.012	-0.339***	-0.196***	-0.522***	-0.326***
Red/processed meat	-0.154***	-0.201***	-0.234***	0.008	-0.046***	-0.079***	0.163***	-0.033	0.209***	0.243***
Sugar	-0.854***	-0.985***	-0.990***	0.723***	-0.131***	-0.136***	1.578***	-0.004	1.709***	1.714***
Confectioneries	-0.437***	-0.109*	-0.122*	0.404***	0.327***	0.315***	0.841***	-0.012	0.513***	0.526***
SSBs	0.588***	0.588***	0.668***	0.764***	-0.000	0.079***	0.176***	0.079***	0.176***	0.096***
Fat & oi	0.449***	0.589***	0.490***	0.550***	0.139***	0.040***	0.100***	-0.098***	-0.038	0.059

Significance levels : $^{+}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

are also higher at a higher level of education. Low and medium GI foods remained a luxury for all education levels in 2006, but it became normal for households with higher education levels by 2016. However, the expenditure elasticities for pulses and vegetables are lower at a higher level of education.

Expenditure elasticities for unhealthy foods also vary across education levels. The highest expenditure elasticity, nearly two, is for sugar, and it had increased in 2016 than in 2006 for all education levels. However, by 2016, a slight downward tendency of the elasticity appears with education. The expenditure elasticities for confectioneries, SSBs and fat and oil, are considerably higher at higher education levels, implying that educated individuals spend more on those foods with their income increase. The expenditure elasticity for prepared food across education is also alarming since there is an upward tendency of elasticities with education levels in 2016. The expenditure elasticities for high GI cereals and red meat are generally inelastic at degree-level education.

2.5.3 Food consumption by diabetes prevalence

Table 2.4 and 2.5 which report the coefficients of the socio-demographic variables estimated through LA/AIDS model further show the effect of diabetes on expenditure shares of each food category. Accordingly, significant effects appear in a few food categories. For example, households with diabetes patients spend lower shares on high GI cereals, which are unhealthy for diabetes patients, compared to other households. On the other hand, they spent higher shares on low and medium GI cereals in 2016. The share allocated to sugar by households with diabetes was significantly lower in 2006, but it did not show significant relation in 2016. However, those households spent slightly lower shares on confectioneries and SSBs in 2016. Likewise, households with diabetes spent slightly higher shares on fruits and fish than other households in both years. Although the effect is small, the results also show that households with diabetes spent higher shares on prepared food, which is

categorized as unhealthy.

We estimated the combined effect of diabetes prevalence in the household and education, and the results are presented in Table 2.9. It reveals significant changes in food choices among households with diabetes across education levels. Compared to lower levels, households with diabetes in higher levels of education spent lower shares for some unhealthy food such as high GI cereals and sugar. Similarly they spent higher shares on healthy food, especially fruits and fish.

To identify the differences in food demand elasticities between households with diabetes patients and the rest, we calculated the expenditure elasticity of each food category for households with diabetes and without diabetes. We tested the mean difference of the elasticities, and the results are presented in Table 2.10. Accordingly, in 2006, expenditure elasticities for sugar, the major concern for diabetes, is 11% lower in households with diabetes than in non-diabetes. Similarly, confectioneries and red meat elasticities are 1% lower in households with diabetes. However, the elasticities of other unhealthy food for diabetes, such as high GI cereals, prepared food and SSBs, are not significantly varied between households with diabetes and the rest. Still, households with diabetes show significantly higher expenditure elasticities for some healthy foods. However, the elasticities towards healthy food choices of households with diabetes have been deprived by 2016.

2.5.4 Quality income elasticity

In addition to the expenditure elasticities obtained from LA/AIDS model, we estimated the quality income elasticity of each food group using unit values obtained from expenditures and quantities. Thus, the unit value of a food item was regressed on the household total income and other socio-demographic variables as in Equation 13. The estimated quality elasticities are presented in Table 2.11. These quality income elasticity coefficients give information about the unit value responsiveness of each food according to household income change. Most of the quality elasticities in

Table 2.9: Results of the LA/AIDS model: Coefficients of the diabetes-education variables

	2006				
	Diabetes & No education	**Diabetes & Primary education**	**Diabetes & O/L**	**Diabetes & A/L**	**Diabetes & Degree**
Healthy food					
L/M GI cereals	0.000	-0.003	-0.010***	-0.002	-0.015
Vegetables	0.009	0.001	-0.003*	-0.004	0.009
Fruits	0.011	-0.001	0.018***	0.048***	0.086***
Pulses	-0.005	-0.002	0.000	0.003	-0.004
Fish	-0.019	0.006	0.013***	0.001	0.008
Lean meat	0.001	0.004	0.002	0.014***	0.011
Egg	0.001	-0.002	0.000	0.001	-0.003
Unhealthy food					
High GI cereals	0.005	0.003	-0.011***	-0.039***	-0.045***
Prepared food	-0.004	0.000	0.007***	0.006	-0.009
Red/processed meat	-0.004	-0.003	-0.000	-0.001	0.000
Sugar	-0.031***	-0.011***	-0.015***	-0.034***	-0.050***
Confectioneries	0.025***	-0.007*	-0.003	0.008*	0.014*
SSB	0.002	0.001	0.001*	0.001	0.005
Fat & oil	0.010**	0.001	-0.001	-0.003	-0.006
	2016				
	Diabetes & No education	**Diabetes & Primary education**	**Diabetes & O/L**	**Diabetes & A/L**	**Diabetes & Degree**
Healthy food					
L/M GI cereals	0.022*	0.006	0.007***	0.012**	0.002
Vegetables	0.014**	0.000	-0.001	0.000	0.001
Fruits	-0.007	-0.004	0.007***	0.019***	0.027***
Pulses	-0.001	-0.001	-0.001	-0.002	-0.003
Fish	0.005	0.005	0.016***	0.028***	0.038***
Lean meat	-0.014*	-0.002	-0.001	-0.000	0.002
Egg	0.000	0.000	-0.000	0.000	-0.002
Unhealthy food					
High GI cereals	-0.004	-0.004	-0.016***	-0.045***	-0.067***
Prepared food	-0.008	-0.008**	-0.003	-0.002	0.008
Red/processed meat	-0.010**	-0.001	-0.001	-0.000	0.007*
Sugar	0.006	0.004**	-0.000	-0.008***	-0.021***
Confectioneries	-0.006	0.002	-0.005***	0.004	0.008
SSBs	0.000	-0.001	-0.001**	-0.001	0.003
Fat & oil	0.003	0.004***	0.000	-0.005***	-0.003

Notes: The table shows the impact of diabetes with each education category on the consumption of food items categorised as healthy/unhealthy. The reference category is the households without diabetes patients.
Significance levels : $^{+}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 2.10: Expenditure elasticity of households with diabetes and non-diabetes

	2006			2016		
	Diabetes	**Non-Diabetes**	**Difference**	**Diabetes**	**Non-Diabetes**	**Difference**
Healthy food						
L/M GI cereals	1.825	1.584	0.241***	1.103	1.093	0.01***
			(0.031)			(0.004)
Vegetables	1.064	1.06	0.004*	1.148	1.147	0.001
			(0.002)			(0.003)
Fruits	2.496	2.445	0.051*	2.15	2.203	0.004
			(0.03)			*(0.034)*
Pulses	0.589	0.622	-0.033***	0.682	0.702	-0.02***
			(0.011)			*(0.007)*
Fish	0.487	0.384	0.102***	0.564	0.513	0.051***
			(0.02)			*(0.012)*
Lean meat	0.752	0.75	0.002	0.779	0.792	-0.013***
			(0.006)			*(0.004)*
Egg	1.382	1.328	0.054***	1.376	1.339	0.037***
			(0.009)			*(0.007)*
Unhealthy food						
High GI cereals	0.813	0.802	0.011	0.845	0.865	-0.02***
			(0.008)			*(0.005)*
Prepared food	1.252	1.244	0.008	1.205	1.209	-0.004
			(0.01)			*(0.007)*
Red/processed meat	0.854	0.868	-0.014**	0.826	0.834	-0.009
			(0.007)			*(0.011)*
Sugar	1.916	2.03	-0.114***	2.365	2.398	-0.033
			(0.019)			*(0.031)*
Confectioneries	0.859	0.876	-0.017***	0.512	0.552	-0.04***
			(0.004)			*(0.014)*
SSBs	0.978	0.977	0.002	1.02	1.019	0.001
			(0.002)			(0.001)
Fat & oil	1.332	1.311	0.021***	1.7	1.657	0.043***
			(0.008)			(0.012)

Notes: The table shows the expenditure elasticities of food categories for households with diabetes and rest of the households. Elasticity coefficients were calculated based on the LA/AIDS estimates. Standard errors are in parentheses. Significance levels : $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

the table are positive, indicating that an increase in household income would increase the unit value which reflects the quality of the food. This is particularly significant for healthy food categories such as L/M GI cereals, fish and fruits. However, the estimated elasticities are small, indicating that income increase would affect only slightly on the quality of the food.

The quality income elasticities are higher in 2016 compared to 2006 reflecting

consumers consider more about the quality of the food when income increases in 2016. For example, fruit and vegetables were not quality sensitive to income in 2006 whereas they were in 2016. However, we found negative quality income elasticities for some food categories showing that an increase in income has decreased the unit values. This means that when a household's income increases, they buy those food at a lower price. This could be due to bulk purchasing of food items when income increases since those negative coefficients relate to food categories that bulk purchases could be applied for. i.e. pulses, high GI cereals and sugar.

Further, we estimated the quality income elasticity of food demand for households with the head having different education levels. The results are presented in table Appendix 2.E.2. Seemingly, there is a link between education levels and the elasticity of the quality of different food. When the household head is at a higher education level, those households concern more about the quality of the food they consume. For example, in 2016, a 1% increase in income would increase the unit value of L/M GI cereals by 0.08% for households with degree-level education whereas it is only 0.01% for households with primary-level education. The quality income elasticity progresses with higher education for healthy foods such as L/M GI cereals, vegetables, fruits and fish, as well as unhealthy foods of high GI cereals and fat and oil. Generally, the quality elasticities were slightly higher in 2016 than in 2006.

2.6 Discussion

The study provides evidence of changes in household food consumption behaviour in Sri Lanka between 2006 and 2016. Between these years, the country underwent significant economic and social changes contributing to speeding the nutritional transition. During that period, economic growth accelerated, per capita income doubled, living standards improved, market globalization expanded, and food availability and diversity widened. Meanwhile, Sri Lanka has recorded higher NCD prevalence rates

Table 2.11: Results of the Unit value regression : quality income elasticities

	2006	2016
Healthy food		
L/M GI cereals	0.020***	0.031***
	(0.003)	(0.004)
Vegetables	0.002	0.035***
	(0.002)	(0.002)
Fruits	0.009	0.038***
	(0.006)	(0.008)
Pulses	-0.007***	0.000
	(0.002)	(0.003)
Fish	0.017***	0.032***
	(0.003)	(0.003)
Lean meat	-0.001**	-0.002*
	(0.001)	(0.001)
Egg	-0.003***	-0.000
	(0.001)	(0.001)
Unhealthy food		
High GI cereals	-0.024***	0.018***
	(0.004)	(0.002)
Prepared food	0.005	0.030***
	(0.004)	(0.004)
Red/Processed meat	0.001	0.003***
	(0.001)	(0.001)
Sugar	-0.001**	-0.002***
	(0.001)	(0.001)
Confectioneries	-0.011***	-0.007*
	(0.003)	(0.003)
SSBs	0.001	-0.002**
	(0.001)	(0.001)
Fat and oil	0.003*	0.020***
	(0.002)	(0.002)

Notes: The table presents the quality income elasticity of each food category. These elasticity coefficients give information about the unit value responsiveness of each food according to household income change. Standard errors are in parentheses. Significance levels : $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

than other LMICs. Inappropriate dietary patterns accounted for a crucial factor affecting NCDs prevalence (Weerasekara et al., 2018). Accordingly, in this paper, we tried to evaluate the changes in food demand behaviour during the above period, using demand elasticities of groups of healthy and unhealthy foods. Then, we identified how education and diabetes prevalence influence these behaviours.

The study finds significant socio-demographic variations in household food demand. Adding evidence to the current literature showing that urbanization triggers unhealthy dietary behaviour (Gomes et al., 2022; Yoon et al., 2006), we found that urban households spend more of their income on unhealthy foods compared to rural and estate sectors. The neighbourhood food environment, work arrangements and life patterns could be crucial factors for this difference. For example, easy accessibility to fast food stores in urban areas would encourage individuals to an unhealthier diet consisting mostly of processed food. The busy livelihood activities that limit the time to prepare home-based food encourage individuals to consume ready-to-eat food made from refined flour. This unhealthy dietary pattern explains why urban households record more diabetes and other diet-related diseases compared to other regions (Ambady et al., 2010; Popkin, 2001).

Therefore, creating healthy food practices in urban areas is necessary to manage diet-related risk factors of NCDs. Launching fast but healthy food stores which comply with urban modish life patterns would be an option. Encouraging a healthy lunch at workplaces and schools can also be applied. However, accessing healthy food sources at a reasonably low cost is a challenge for urban households. It is evident that the poorer households are more vulnerable to unhealthy diets and thereby diet-related diseases (Vilar-Compte et al., 2021; Vozoris and Tarasuk, 2003) Yet, it is found that the recommended healthy diets are cheaper than unhealthy diets. (Love et al., 2018). Since most healthy foods such as fruits, vegetables and fish are entirely produced locally in Sri Lanka, it is possible to apply effective production and pricing policies, i.e. regulating unnecessary profits made by intermediaries, to enhance the availability and accessibility of healthy food in urban areas.

Our results partially support the nutritional transition believed to have occurred during this period. The expenditure elasticities of most unhealthy food categories have increased at a higher rate than healthy food categories from 2006 to 2016. We noticed that the economy has grown at a faster rate during this period and per

capita income has doubled. Therefore, the expenditure elasticity estimation shows that increasing income has been spent more on unhealthy food than healthy food in 2016 compared to 2006. However, it is noteworthy that demand for some healthy food categories positively responds to increases in income. This has important policy implications; whereas income improvements increase healthy food consumption, the impact this will have on unhealthy consumption needs to be counterbalanced.

We found that education is a significant factor that affects food demand. When the level of education of the household head is higher, he/she tends to increase spending share on healthy food. Similarly, the demand responsiveness to income of some healthy food, such as fruit, fish and lean meat, is higher at higher education levels. It is important to see the difference in the income elasticities of high GI cereals and low GI cereals as they are staples in the Sri Lankan diet. The demand responsiveness to income for Low GI cereals is bigger at higher levels of education than at lower levels, whereas, at low levels of education, the demand responsiveness to income for high GI cereals is greater than at more advanced education levels. Therefore, our results confirm the previous findings that show education improves people's diet (Li and Powdthavee, 2015). As Cutler and Lleras-Muney (2010) point out the impact of education is greater at higher education levels than at lower levels. Although we have considered general/formal education, not diet-related education, our results show a positive link between education and diet. This positive connection would come through health knowledge as education improves the capacity to acquire health-related knowledge (Johnston et al., 2015). As widely accepted, education is the array of knowledge, skills, and capacities. On the other hand, if education positively links with earnings, those households with educated heads can buy better quality food at a higher price. That would lead to higher spending on healthy food. The results of our quality income elasticity estimations also prove that better-educated household heads are more concerned about food quality, both healthy and unhealthy. Hence our findings further emphasize the importance of individuals

having higher education to earn better diet habits, encouraging governments to keep investing in education.

However, it has been shown that higher education encourages not only healthy consumption but also some unhealthy consumption Hiza et al. (2013). Our findings also prove that those households with educated household heads tend to spend more share on unhealthy food rich in fat, sugar, and refined carbohydrates. Similarly, the demand responsiveness of those foods to income increase is high among higher educated. The demand for prepared food, usually made from refined carbohydrates and SSBs– a primary factor of diet-related NCDs is noticeable among those. While the demand is higher for those ready-to-eat foods among higher educated, the demand responsiveness has increased in 2016 compared to 2006. That implies the dietary change towards ready-to-eat food has become prevalent among households with higher educated heads. Their busy daily routine that constrains the time for home-made food could be a reason for that, however, it is worth investigating the issue further. However, collaborations between public health policymakers and education experts to incorporate education programmes that stress the consequences of unhealthy food into formal education would be worthwhile to prevent unhealthy diets and, thereby, related diseases.

We further investigated the dietary behaviour linked with diabetes, the most common diet-related disease. Diabetes is connected to a number of other serious health problems, including overweight and obesity, hypertension, cardiovascular disease and stroke. Therefore, dietary discipline is crucial for diabetes individuals to manage the disease. Our findings show that having a diabetes individual in the household does not entirely change the food consumption behaviour of that household towards a healthier diet. It decreases the spending share on sugar and cereals with refined carbohydrates and increases the share spent on healthy food. However, it does not seem to reduce the spending share on prepared food rich in refined carbohydrates and SSBs. There is no significant change in the demand responsiveness

to income of unhealthy foods between households with diabetes and others except for high GI cereals and confectionaries. Again, the issue of prepared food and SSBs arises- the demand for those foods is not lower for households with diabetes individuals, though it should be. Since we considered household consumption instead of individual consumption, one can argue that this may not precisely reflect the diet of the person with diabetes. However, the household food environment is crucial for the dietary behaviour of individuals. Further, since diabetes has a genetic component, adherence to a healthy diet within the household is essential when there is a case of diabetes in the home. The significant role of education can be seen here again as households with diabetes with higher educated heads appear to have more control towards a healthier diet.

Our results of price elasticity estimations provide important policy implications for improving people's diets and thus health. Demand responsiveness to price change is higher for most unhealthy foods than healthy foods except for cereals, implying that price policies can effectively control unhealthy consumption. A slight increase in the price of those unhealthy foods would decrease the demand to a more significant extent. On the other hand, reducing the prices of healthy foods would increase their demand. The demand responsiveness to the price of cereals should be highlighted as it contains the demand for rice which accounts for more than 70% of the Sri Lankan diet. The type of rice they consume is crucial in managing diet-related diseases, especially diabetes. Our findings show that healthy cereals (Low GI) are more price elastic than unhealthy cereals (High GI). Therefore, the demand for healthy rice could boost by reducing its price, which is more effective than suppressing the demand for unhealthy rice by raising the price. Nevertheless, we found that healthy cereals and unhealthy cereals are high substitutes. Therefore, the price change of one has a substantial impact on the demand for the other. Accordingly, our study emphasises the possibility of designing pricing policies - taxing unhealthy food and providing subsidies for healthy food to encourage healthy consumption

while discouraging the potentially harmful ones.

The study has some limitations. First, the food categorization into healthy and unhealthy food was based on the international food guidelines for food types, but not the food quantities that should be included in each diet. However, it is important to identify the consumption of a balanced diet which could be a combination of both healthy and unhealthy food in different proportions. Hence, further analysis could be directed to investigate the demand responsiveness for food for a balanced diet as well. Second, although we used a demand system estimation to analyse food consumption behaviour, there are some limitations to it, especially due to the endogeneity nature of prices. Endogeneity of prices typically means that the actual response to a policy change or supply shock would typically be smaller than the demand system parameter suggest. We attempted to capture some parts of this price endogeneity using quality elasticity. However, further analysis such as choice experiments could be applied to overcome the limitation of the demand system estimations.

2.7 Conclusion

The prevalence rates of NCDs increase year-on-year in LMICs, and changes in dietary patterns have been identified as one of the major drivers of rising NCDs - including obesity, diabetes, cardiovascular diseases, hypertension and some types of cancers. The growing NCDs create a significant challenge to the healthcare system in providing access to treatment and care, loading an additional burden on the national health budgets in those countries. Hence, it is crucial to find remedies for controlling the risk factors, particularly unhealthy diets.

In this study, we analysed the changes in dietary patterns and the factors affecting them in an LMIC context using demand elasticities. The study findings provide significant policy implications for lessening the risk factor of NCDs. We

could prove that the enhancement of the standard of living of the people in LMICs has led these towards a rather unhealthy diet. We showed that education encourages healthy food, but it may be challenging to control unhealthy consumption. The study emphasises that providing diet-related knowledge through formal education and applying effective pricing policies to discourage unhealthy food consumption and encourage healthy choices is key to managing diet-related diseases.

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Appendix

2.A Results of the Probit regression(marginal effects)- 2016

Table 2.A.1: Results of the Probit regression(marginal effects)- 2016

	Cereals (L/M GI)	*Vegetables*	*Fruits*	*Pulses*	*Fish*	*Lean meat*	*Egg*
Sector (Urban=0)							
Rural	0.028***	0.017***	-0.04***	0.016***	0.019***	-0.11***	-0.017*
Estate	-0.008	0.024***	-0.12***	0.063***-0.02	-0.13***	0.012	
Ethnicity (Sinhala=0)							
Sri Lankan Tamil	0.186***	-0.02***	-0.06***	-0.07***	-0.06***	0.002	-0.06***
Indian Tamil	0.235***	-0.002	-0.13***	-0.05***	-0.06***	0.076***	0.063**
Moors	0.15***	-0.03***	-0.06***	-0.21***	-0.009	0.055***	-0.015**
Other	0.039	-0.019	0.012	-0.11***	-0.008	0.248***	0.037
Age of hh head	-0.002	0.015***	0.038***	0.015**	-0.013**	-0.09***	-0.1***
Hh size	0.078***	0.082***	0.075***	0.105***	0.106***	0.135***	0.115***
Education (No education=0)							
Primary	0.016	0.006	0.045**	0.012	0.007	0.029*	0.065***
Up to O/L	0.049***	0.016**	0.128***	0.027***	0.013	0.099***	0.117***
Up to A/L	0.091***	0.023***	0.241***	0.037**	0.018*	0.17***	0.207***
Degree and above	0.122***	0.029***	0.292***	0.043***	0.016	0.206***	0.204***
Diabetes= 1	0.041***	0.007*	0.03***	0.009*	0.012**	0.012	0.013

	Cereals (High GI)	*Prepared food*	*Red and processed meat*	*Sugar*	*Confectionaries*	*SSBs*	*Fat and oil*
Sector (Urban=0)							
Rural	-0.002	-0.13***	-0.03***	0.004	-0.001	-0.02***	0.009*
Estate	0.019***	-0.26***	-0.08***	0.004	0.072***	-0.07***	0.043***
Ethnicity (Sinhala=0)							
Sri Lankan Tamil	0.005*	0.015					
Indian Tamil	-0.012	-0.048*	0.027	-0.008	-0.048*	0.016	-0.036**
Moors	-0.063***	0.217***	0.544***	-0.01***	-0.08***	0.055***	-0.015**
Other	-0.013	0.018	0.235***	-0.036	-0.111**	0.067*	-0.039
Age of hh head	0.016***	-0.12***	-0.04***	0.009**	-0.14***	-0.04***	0.012**
Hh size	0.049***	-0.007	0.029***	0.034***	0.168***	0.032***	0.105***
Education (No education=0)							
Primary	0.018**	0.014	0.023***	0	0.021	0.014	0.023**
Up to O/L	0.028***	0.033*	0.033***	.004	0.053***	0.035***	0.037***
Up to A/L	0.036***	0.063***	0.042***	0.007	0.111***	0.058***	0.051***
Degree and above	0.028***	0.111***	0.076***	0	0.137***	0.104***	0.043***
Diabetes= 1	-0.006	-0.012	0.007	0.003	-0.008	-0.001	0.003

Significance levels : $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

2.B Results of the LA/AIDS model for 2016

Table 2.B.1: Results of the LA/AIDS model for 2016

VARIABLES	L/M GI cereals	Vegetables	Fruits	Pulses	Fish	Lean meat	Egg	
lnP_lmGI	-0.108***	-0.017***	0.002***	-0.002***	-0.009***	-0.000	0.001	
lnP_vegetables	-0.017***	0.035***	-0.000	-0.004***	0.004***	0.007***	0.000	
lnP_fruits	0.002***	-0.000	0.006***	-0.001***	0.002***	-0.002***	-0.000***	
lnP_pulses	-0.002***	-0.004***	-0.001***	0.027***	0.003***	-0.012***	-0.000	
lnP_fish	-0.009***	0.004***	0.002***	0.003***	-0.008***	0.001	0.002***	
lnP_leanmeat	-0.000	0.007***	-0.002***	-0.012***	0.001	0.002	-0.006***	
lnP_egg	0.001	0.000	-0.000***	0.019***	0.002***	-0.006***	0.026***	
lnP_highGI	0.131***	-0.040***	-0.003***	-0.021***	-0.005***	0.009***	-0.001	
lnP_prepfood	0.002***	0.001**	0.001	-0.000	-0.005***	-0.003***	-0.000	
lnP_fattyprotien	-0.002***	0.000	-0.001***	-0.004***	-0.003***	0.002	-0.001	
lnP_sugar	-0.002***	0.009***	0.001***	-0.002***	0.013***	0.004**	-0.018***	
lnP_confectionaries	0.004***	0.006***	-0.004***	-0.000	-0.002*	-0.003***	0.001**	
lnP_softfruitdrinks	0.003***	0.002***	-0.000	0.001*	0.001***	0.003***	0.001	
lnP_fatandoil	-0.004***	-0.004***	0.000	-0.002***	0.005***	-0.001	-0.005***	
lnX_stoneP	0.006***	0.011***	0.041***	-0.012***	-0.075***	-0.021***	0.008***	
ln_age	-0.006**	0.010***	0.001	0.007***	0.016***	-0.007***	-0.006***	
ln_hhsize	0.024***	-0.017***	-0.038***	0.000	0.042***	0.008***	-0.004***	
rural	0.024***	0.013***	-0.017***	0.003***	-0.009***	-0.006***	0.000	
estate	0.065***	0.015***	-0.020***	0.017***	-0.081***	-0.002	0.002*	
SLtamil	0.009***	-0.019***	-0.017***	0.001	0.016***	0.009***	-0.001**	
Intamil	0.040***	-0.006*	-0.035***	0.007***	-0.016***	0.009**	0.005***	
Moors	-0.015***	-0.029***	-0.009***	-0.010***	-0.007**	0.013***	0.002***	
primary	-0.004	-0.007***	0.007***	-0.002	0.013***	0.000	0.001	
OL	-0.011***	-0.011***	0.019***	-0.001	0.027***	0.001	0.002**	
AL	-0.012***	-0.012***	0.039***	-0.003	0.039***	0.003	0.005***	
degree	-0.014***	-0.013***	0.056***	-0.003	0.049***	0.008**	0.002*	
diabetes	0.011***	0.001	0.007***	-0.001	0.014***	-0.001	-0.000	
hbp	0.005**	0.002	0.005***	-0.000	0.004*	-0.002	-0.001	
heartd	0.009***	0.000	0.001	0.002	0.000	-0.003	-0.002**	
morethan_one_disease	-0.012**	-0.003	-0.003	-0.002	0.002	-0.002	0.000	
imr_lmGI	0.072***							
imr_vegetables		-0.019***						
o.morethan_one_disease			-0.000					
imr_fruits				0.036***				
imr_pulses					-0.048***			
imr_fish						-0.091***		
imr_leanmeat							-0.035***	
imr_highGI								0.011**
imr_prepfood								
imr_fattyprotien								
imr_sugar								
imr_confectionaries								
imr_softfruitdrinks								
imr_fatandoil								
Constant	0.076***	0.030***	-0.045***	0.113***	0.334***	0.163***	0.074***	0.095***

Significance levels : $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

→ |							
VARIABLES	High GI cereals	Prepared food	Red/ processed meat	Sugar	Confectionaries	SSB	Fat & oil
lnP_lmGI	0.131***	0.002***	-0.002***	-0.002***	0.004***	0.003***	-0.004***
lnP_vegetables	-0.040***	0.001**	0.000	0.009***	0.006***	0.002***	-0.004***
lnP_fruits	-0.003***	0.001	-0.001***	0.001***	-0.004***	-0.000	0.000
lnP_pulses	-0.021***	-0.000	-0.004***	-0.002***	-0.000	0.001*	-0.002***
lnP_fish	-0.005***	-0.005***	-0.003***	0.013***	-0.002*	0.001***	0.005***
lnP_leanmeat	0.009***	-0.003***	0.002	0.004**	-0.003***	0.003***	-0.001
lnP_egg	-0.001	-0.000	-0.001	-0.018***	0.001**	0.001	-0.005***
lnP_highGI	-0.090***	0.009***	0.003***	0.003***	0.008***	0.007***	-0.010***
lnP_prepfood	0.009***	-0.007***	-0.001**	0.003***	-0.003***	0.001***	0.002***
lnP_fattyprotien	0.003***	-0.001**	-0.002	-0.002	0.000	0.008***	0.002**
lnP_sugar	0.003***	0.003***	-0.002	-0.000	0.007***	-0.002*	-0.014***
lnP_confectionaries	0.008***	-0.003***	0.000	0.007***	-0.016***	-0.001	0.003***
lnP_softfruitdrinks	0.007***	0.001***	0.008***	-0.002*	-0.001	-0.031***	0.007***
lnP_fatandoil	-0.010***	0.002***	0.002**	-0.014***	0.003***	0.007***	0.021***
lnX_stoneP	-0.015***	0.007***	-0.012***	0.058***	-0.017***	0.001	0.021***
ln_age	0.030***	-0.030***	-0.000	0.008***	-0.017***	-0.003***	-0.003***
ln_hhsize	0.029***	-0.032***	0.002***	-0.002**	0.005***	-0.003***	-0.014***
rural	0.023***	-0.039***	0.002**	0.012***	-0.005***	-0.004***	0.002**
estate	0.048***	-0.061***	0.005**	0.004*	0.006*	-0.005***	0.006***
SLtamil	0.034***	0.003**	0.003***	-0.031***	-0.010***	0.002***	0.001
Intamil	0.019***	-0.007**	0.005**	-0.022***	-0.007**	-0.001	0.010***
Moors	-0.036***	0.055***	0.062***	-0.017***	-0.008***	0.001	-0.004***
primary	0.003	-0.001	0.000	-0.014***	0.002	-0.001	0.001
OL	-0.012***	0.002	-0.000	-0.015***	0.001	-0.001	-0.000
AL	-0.040***	0.005*	-0.001	-0.024***	0.008***	-0.002	-0.005***
degree	-0.063***	0.012***	0.001	-0.042***	0.011***	0.002	-0.007***
diabetes	-0.019***	-0.005***	-0.001	-0.001	-0.003*	-0.002**	0.000
hbp	-0.005**	-0.005***	-0.001	0.001	0.000	-0.002***	-0.000
heartd	-0.005	0.002	0.000	0.001	-0.002	-0.002*	-0.002
morethan_one_disease	0.009	0.004	-0.001	0.001	0.002	0.002	0.002
imr_lmGI							
imr_vegetables							
o.morethan_one_disease							
imr_fruits							
imr_pulses							
imr_fish							
imr_leanmeat							
imr_highGI	0.011**						
imr_prepfood		0.063***					
imr_fattyprotien		-0.018***					
imr_sugar				0.770***			
imr_confectionaries					-0.023***		
imr_softfruitdrinks						-0.005***	
imr_fatandoil							0.025***
Constant	0.095***	0.139***	0.077***	-0.231***	0.195***	0.016***	-0.036***

Significance levels : $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

2.C Cross price elasticities - 2016

Table 2.C.1: Cross price elasticities - 2016

	L/M GI cereals	Vegetables	Fruits	Pulses	Fish	Lean meat	Egg
L/M GI cereals	-2.62***	-0.26***	0.02***	-0.03***	-0.15***	-0.01***	0.01***
Vegetables	-0.24***	-0.54***	-0.01***	-0.06***	0.02***	0.08***	0.00***
Fruits	-0.07***	-0.13***	-0.86***	-0.12***	-0.21***	-0.12***	-0.04***
Pulses	-0.01***	-0.07***	-0.02***	-0.32***	0.13***	-0.28***	0.47***
Fish	0.00***	0.08***	0.03***	0.05***	-0.97***	0.03***	0.02***
Lean meat	0.01***	0.09***	-0.01***	-0.11***	0.05***	-0.96***	-0.05***
Egg	-0.01***	-0.02***	-0.04***	-0.03***	0.02***	-0.25***	0.05***
High GI cereals	1.26***	-0.36***	-0.02***	-0.19***	-0.02***	0.09***	-0.00***
Prepared food	0.05***	0.02***	0.01***	-0.03***	-0.21***	-0.11***	-0.02***
Red/processed meat	-0.01***	0.02***	-0.00***	-0.05***	-0.01***	0.04***	-0.02***
Sugar	-0.26***	0.08***	-0.05***	-0.18***	-0.01***	0.02***	-0.63***
Confectionaries	0.17***	0.21***	-0.08***	0.02***	0.05***	-0.07***	0.03***
SSB	0.08***	0.07***	-0.01***	0.03***	0.04***	0.10***	0.04***
Fat & oil	-0.19***	-0.21***	-0.03***	-0.12***	0.02***	-0.07***	-0.16***

→	High GI cereals	Prepared food	Red/ processed meat	Sugar	Confectio naries	SSB	Fat & oil
L/M GI cereals	1.94***	0.03***	-0.03***	-0.03***	0.06***	0.04***	-0.06***
Vegetables	-0.56***	0.01***	0.00***	0.11***	0.07***	0.03***	-0.07***
Fruits	-0.35***	-0.01***	-0.04***	-0.01***	-0.18***	-0.01***	-0.05***
Pulses	-0.45***	-0.00***	-0.10***	-0.03***	0.01***	0.02***	-0.04***
Fish	0.08***	-0.02***	-0.01***	0.10***	0.01***	0.01***	0.06***
Lean meat	0.13***	-0.03***	0.03***	0.05***	-0.02***	0.04***	-0.00***
Egg	-0.09***	-0.02***	-0.06***	-0.75***	0.01***	0.05***	-0.20***
High GI cereals	-1.83***	0.09***	0.03***	0.04***	0.08***	0.06***	-0.09***
Prepared food	0.25***	-1.22***	-0.04***	0.09***	-0.10***	0.03***	0.05***
Red/processed meat	0.07***	-0.01***	-1.01***	-0.02***	0.01***	0.11***	0.04***
Sugar	-0.30***	0.06***	-0.09***	-1.07***	0.13***	-0.09***	-0.53***
Confectionaries	0.31***	-0.06***	0.01***	0.20***	-1.42***	-0.01***	0.10***
SSB	0.20***	0.03***	0.24***	-0.07***	-0.02***	-1.95***	0.21***
Fat & oil	-0.47***	0.05***	0.06***	-0.46***	0.06***	0.22***	-0.36***

Significance levels : $^{***}p < 0.01$.

2.D Results of the LA/AIDS model for education categories

Table 2.D.1: Results of the LA/AIDS model for education category O/L (2006)

VARIABLES	(1) y1	(2) y2	(3) y3	(4) y4	(5) y5	(6) y6	(7) y7	(8) y8	(9) y9	(10) y10	(11) y11	(12) y12	(13) y13	(14) y14
lnP_lmGI	0.071***	0.012***	-0.001	0.001	0.008***	0.003***	-0.000	-0.093***	-0.014***	0.018***	-0.003***	-0.010***	0.006***	0.004***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
lnP_vegetables	-0.030***	0.023***	-0.009***	-0.008***	0.004*	0.000	-0.009***	-0.040***	0.023***	0.023***	-0.008***	0.033***	0.001	-0.002***
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.001)
lnP_fruits	-0.005***	0.002***	-0.001	0.001**	-0.002**	0.001***	-0.001*	-0.000	-0.002**	0.011***	-0.001	-0.003**	-0.002*	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
lnP_pulses	-0.012***	0.007***	-0.003**	-0.000	-0.000	0.000	0.001	0.011***	-0.004**	0.001	0.036***	-0.029***	-0.007***	0.001
	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
lnP_fish	-0.028***	0.015***	-0.010***	0.003*	-0.001	0.000	-0.001	-0.007***	-0.008***	0.025***	-0.005***	0.029***	-0.010***	0.001
	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
lnP_leanmeat	0.025**	0.009	0.002	0.009	-0.014**	-0.001	-0.002	0.005	0.005	-0.008	-0.006	0.002	-0.022***	-0.003
	(0.011)	(0.006)	(0.005)	(0.005)	(0.006)	(0.002)	(0.003)	(0.009)	(0.006)	(0.006)	(0.004)	(0.011)	(0.007)	(0.002)
lnP_egg	0.055***	-0.008	0.007	-0.010**	-0.015***	-0.004*	-0.003	0.012	0.005	-0.021***	0.000	-0.009	-0.017**	0.009***
	(0.010)	(0.005)	(0.004)	(0.005)	(0.005)	(0.002)	(0.003)	(0.008)	(0.005)	(0.006)	(0.004)	(0.010)	(0.007)	(0.002)
lnP_highGI	-0.125***	0.010***	0.003***	0.010***	0.004***	0.001**	0.001**	0.087***	-0.012***	0.011***	-0.004***	0.006**	0.003*	0.004***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
lnP_prepfood	0.003	-0.024***	-0.004***	0.005***	0.006***	0.000	0.002***	0.008***	0.005***	0.006***	0.002**	-0.007***	-0.003**	0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)
lnP_fattyprotien	-0.005	0.006	-0.021***	0.002	0.004	0.000	0.001	0.001	0.001	0.015***	-0.003	-0.006	0.004	0.003
	(0.008)	(0.004)	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.007)	(0.004)	(0.005)	(0.003)	(0.008)	(0.005)	(0.002)
lnP_sugar	-0.016	-0.007	0.011**	0.018***	0.003	0.003	0.012***	0.041***	0.011	-0.030***	0.009	-0.065***	0.008	0.002
	(0.013)	(0.007)	(0.006)	(0.006)	(0.007)	(0.003)	(0.004)	(0.011)	(0.007)	(0.008)	(0.005)	(0.013)	(0.009)	(0.003)
lnP_confectionaries	0.009***	0.006***	-0.002*	0.007***	-0.022***	-0.002***	0.001	0.007***	0.003**	0.001	0.002	-0.004	-0.007***	0.001
	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
lnP_softfruitdrinks	0.016**	-0.013***	0.005	0.006	-0.016***	-0.014***	0.003	0.007	0.009**	-0.000	0.004	-0.009	-0.001	0.004**
	(0.008)	(0.005)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.007)	(0.004)	(0.005)	(0.003)	(0.008)	(0.006)	(0.002)
lnP_fatandoil	0.005	0.003	0.003	-0.016***	0.000	0.002**	0.028***	0.001	-0.012***	-0.004	0.002	-0.012**	0.001	-0.001
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.004)	(0.002)	(0.003)	(0.002)	(0.005)	(0.003)	(0.001)
lnX_stoneP	-0.033***	0.039***	-0.019***	0.038***	-0.004**	-0.000	0.005***	0.029***	0.003**	0.079***	-0.014***	-0.080***	-0.048***	0.008***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
ln_income	-0.014***	0.004***	0.002***	-0.006***	0.004***	0.001***	-0.001***	-0.005***	-0.001**	0.007***	-0.003***	0.010***	0.004***	0.001**
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
ln_age	0.030***	-0.062***	0.010***	0.009***	-0.020***	-0.003***	-0.004***	-0.006*	0.007***	-0.002	0.009***	0.003	0.008***	-0.005***
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.001)
ln_hhsize	0.060***	-0.066***	0.002	-0.002	-0.005***	-0.002***	-0.003***	-0.005*	-0.007***	-0.060***	0.010***	0.030***	0.010***	-0.004***
	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
rural	0.016***	-0.075***	0.004***	0.006***	-0.005***	-0.000	-0.001*	0.027***	0.014***	-0.015***	0.004***	-0.020***	0.004**	-0.001
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
estate	0.027***	-0.137***	0.012***	-0.007**	-0.006*	-0.000	0.004*	0.069***	0.009**	-0.038***	0.018***	-0.068***	0.005	-0.003*
	(0.006)	(0.004)	(0.003)	(0.003)	(0.003)	(0.001)	(0.002)	(0.006)	(0.003)	(0.004)	(0.003)	(0.007)	(0.004)	(0.001)
SLtamil	-0.002	-0.043***	0.002	-0.005**	-0.010***	0.000	-0.001	0.012**	0.004*	-0.043***	-0.017***	0.027***	0.011***	0.003***
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.005)	(0.002)	(0.003)	(0.002)	(0.005)	(0.003)	(0.001)
Intamil	0.033***	-0.109***	0.007**	-0.008**	-0.003	-0.001	0.008***	0.051***	0.005	-0.082***	0.003	-0.043***	0.005	0.002
	(0.007)	(0.005)	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.007)	(0.004)	(0.005)	(0.003)	(0.008)	(0.005)	(0.002)
Moors	-0.016***	0.103***	0.050***	0.007***	-0.005**	0.001	-0.001	-0.015***	-0.024***	-0.008***	-0.019***	-0.032***	0.006**	0.003***
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.004)	(0.002)	(0.003)	(0.002)	(0.004)	(0.003)	(0.001)
diabetes	-0.010**	0.011***	-0.001	-0.016***	-0.005**	0.000	-0.001	-0.007*	-0.004*	0.016***	-0.000	0.015***	-0.002	-0.000
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.004)	(0.002)	(0.003)	(0.002)	(0.004)	(0.003)	(0.001)
hbp	-0.003	0.002	-0.001	0.001	-0.004*	0.000	-0.001	-0.005	-0.000	0.005**	-0.000	0.005	0.002	0.000
	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.001)
heartd	-0.008	-0.016***	-0.001	0.005*	-0.006*	0.000	0.000	-0.003	-0.001	-0.000	0.000	0.016***	-0.002	-0.001
	(0.005)	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)	(0.005)	(0.003)	(0.003)	(0.002)	(0.005)	(0.004)	(0.001)
morethan_one_disease	0.017*	-0.006	-0.007*	0.001	0.008	0.003	-0.001	-0.001	0.008	0.004	0.006	-0.016*	-0.011	-0.003
	(0.009)	(0.005)	(0.004)	(0.005)	(0.005)	(0.002)	(0.003)	(0.008)	(0.005)	(0.006)	(0.004)	(0.010)	(0.006)	(0.002)
imr_lmGI								0.021***						
								(0.008)						
imr_vegetables									-0.028***					
									(0.002)					
o.morethan_one_disease										-				
imr_fruits										0.165***				
										(0.004)				
imr_pulses											-0.015***			
											(0.003)			
imr_fish												-0.102***		
												(0.003)		
imr_leanmeat													-0.060***	
													(0.001)	
imr_highGI	-0.049***													
	(0.005)													
imr_prepfood		0.337***												
		(0.007)												
imr_fattyprotien			-0.036***											
			(0.001)											
imr_sugar				0.515***										
				(0.007)										
imr_confectionaries					-0.019***									
					(0.003)									
imr_softfruitdrinks						-0.002**								
						(0.001)								
imr_fatandoil							0.015***							
							(0.002)							
Constant	0.518***	-0.360***	0.223***	-0.170***	0.304***	0.048**	-0.103***	-0.119	0.068	-0.486***	-0.018	0.651***	0.380***	-0.063**
	(0.108)	(0.061)	(0.047)	(0.053)	(0.059)	(0.023)	(0.032)	(0.095)	(0.058)	(0.066)	(0.045)	(0.111)	(0.076)	(0.025)
Observations	9,654	9,654	9,654	9,654	9,654	9,654	9,654	9,654	9,654	9,654	9,654	9,654	9,654	9,654

Notes: The table presents the quality income elasticity by education levels. Standard errors are in parentheses. Significance levels : $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

2.E Quality income elasticities: by education

Table 2.E.1: Quality income elasticities: by education (2006)

	2006				
	No education	Primary	OL	AL	Degree
Healthy food					
L/M GI cereals	-0.014	-0.003	0.026***	0.067***	0.081***
	(0.012)	(0.006)	(0.004)	(0.011)	(0.029)
Vegetables	-0.006	-0.006	0.003	0.025***	0.018
	(0.008)	(0.004)	(0.003)	(0.006)	(0.015)
Fruits	0.011	-0.026**	0.019**	0.022	0.141***
	(0.023)	(0.011)	(0.008)	(0.019)	(0.052)
Pulses	-0.003	-0.005	-0.009***	-0.001	0.030
	(0.009)	(0.005)	(0.003)	(0.008)	(0.022)
Fish	-0.001	0.004	0.018***	0.044***	0.071***
	(0.010)	(0.005)	(0.004)	(0.008)	(0.023)
Lean meat	0.002	-0.003**	-0.002*	-0.001	0.003
	(0.002)	(0.001)	(0.001)	(0.003)	(0.008)
Egg	-0.002	-0.001	-0.004***	-0.004	-0.012
	(0.002)	(0.001)	(0.001)	(0.003)	(0.007)
unhealthy food					
High GI cereals	-0.001	-0.029***	-0.025***	-0.026***	0.029
	(0.016)	(0.008)	(0.005)	(0.010)	(0.027)
Prepared food	0.009	0.006	0.007	-0.007	-0.035
	(0.011)	(0.007)	(0.005)	(0.013)	(0.033)
Red/Processed meat	-0.002	0.000	0.000	0.007**	0.001
	(0.002)	(0.001)	(0.001)	(0.003)	(0.012)
Sugar	-0.004*	-0.001	-0.002**	0.002	-0.002
	(0.003)	(0.001)	(0.001)	(0.002)	(0.005)
Confectioneries	-0.008	-0.001	-0.016***	-0.023**	0.022
	(0.008)	(0.005)	(0.004)	(0.011)	(0.032)
SSBs	-0.001	-0.000	0.002*	0.005	-0.011
	(0.002)	(0.001)	(0.001)	(0.004)	(0.011)
Fat and oil	-0.004	-0.005*	0.005**	0.014**	0.008
	(0.006)	(0.003)	(0.002)	(0.007)	(0.019)

Notes: The table presents the quality income elasticity by education levels. Standard errors are in parentheses. Significance levels : $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 2.E.2: Quality income elasticities: by education (2016)

	2016				
	No education	Primary	OL	AL	Degree
Healthy food					
L/M GI cereals	0.009	0.012*	0.030***	0.074***	0.087***
	(0.017)	(0.007)	(0.005)	(0.012)	(0.030)
Vegetables	0.006	0.023***	0.039***	0.040***	0.059***
	(0.010)	(0.005)	(0.003)	(0.007)	(0.020)
Fruits	-0.037	0.008	0.038***	0.088***	0.190***
	(0.037)	(0.016)	(0.011)	(0.022)	(0.052)
Pulses	0.010	0.003	0.001	-0.011	-0.009
	(0.012)	(0.005)	(0.003)	(0.007)	(0.016)
Fish	0.022	0.013**	0.037***	0.040***	0.096***
	(0.014)	(0.006)	(0.004)	(0.007)	(0.016)
Lean meat	-0.002	-0.002	-0.002	-0.001	0.004
	(0.003)	(0.002)	(0.001)	(0.003)	(0.009)
Egg	-0.001	-0.000	-0.001	0.001	0.008
	(0.003)	(0.002)	(0.001)	(0.002)	(0.006)
unhealthy food					
High GI cereals	0.025**	0.006	0.021***	0.018***	0.039***
	(0.010)	(0.004)	(0.002)	(0.005)	(0.014)
Prepared food	0.022	0.027***	0.029***	0.038***	0.053
	(0.018)	(0.008)	(0.005)	(0.012)	(0.032)
Red/Processed meat	-0.000	0.002	0.003**	0.007**	0.016
	(0.003)	(0.002)	(0.001)	(0.003)	(0.010)
Sugar	-0.006	0.001	-0.004***	-0.002	-0.004
	(0.004)	(0.002)	(0.001)	(0.002)	(0.006)
Confectioneries	-0.002	0.000	-0.008*	-0.026**	0.011
	(0.012)	(0.006)	(0.005)	(0.011)	(0.031)
SSBs	-0.001	-0.001	-0.002**	-0.005*	0.011
	(0.003)	(0.001)	(0.001)	(0.002)	(0.008)
Fat and oil	0.001	0.008**	0.018***	0.037***	0.146***
	(0.007)	(0.004)	(0.003)	(0.006)	(0.021)

Notes: The table presents the quality income elasticity by education levels. These elasticity coefficients give information about the unit value responsiveness of each food according to household income change. Standard errors are in parentheses. Significance levels : $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Chapter 3

The crowding-out effect of healthcare expenses of chronic Non-Communicable Diseases on household consumption and the role of public healthcare spending

3.1 Introduction

Non-Communicable Diseases (NCDs) account for 83 percent of total deaths in Sri Lanka (Organization et al., 2018), marking a higher percentage than the other low and middle-income countries (LMICs). The prevalence rates of chronic NCDs (C-NCDs hereafter) such as heart disease, diabetes, high blood pressure, cancer, and asthma have been increasing sharply in the country during the last two decades (Ediriweera et al., 2018; Mehta, 2016) generating a significant economic burden at the individual, household, and society level, besides the health risk. The C-NCDs have placed elevated pressures on public spending by demanding more resources towards public healthcare and the household economy by increasing out-of-pocket spending for healthcare. It is estimated that more than one-third of the total health-care expenditures of the country has devoted to NCDs-related care in 2016 (MoH, 2018).

Out-of-pocket expenditure for treatment is the primary strain on the household

economy in the prevalence of C-NCDs (Kien et al., 2017; Kumara and Samaratunge, 2018; Lee et al., 2015; Murphy et al., 2020; Pati et al., 2014; Wang et al., 2015). Likewise, in Sri Lanka, it is shown that most of the treatment costs are financed privately by individuals even in a situation where a universal public healthcare system is available (Kumara and Samaratunge, 2016; Pallegedara, 2018). The cost of rising healthcare expenditures at the household level generally crowd-out on other household consumptions (Batbold et al., 2021; Datta et al., 2018a; Kim and Yang, 2011; Nguyen et al., 2012; Wang et al., 2006). In protecting consumption at the desired level, households may have even been pushed into indebtedness with higher healthcare spending (Samaratunge et al., 2020). However, the rate of crowding-out healthcare expenditures on other household consumptions depends on many factors.

It is evident that the availability of public health services is a prominent factor in reducing the household burden of out-of-pocket payments for healthcare (Correa-Burrows, 2012; Xu et al., 2003). However, despite the rising rates of C-NCDs prevalence in the country, it is noteworthy that the public healthcare provision in Sri Lanka has been decreasing over the last two decades. For example, public health expenditure as a percentage of GDP was 1.97 in 2006, and it declined to 1.15 by 2012, followed by a slight increase to 1.55 by 2016 (CBSL, 2007, 2013, 2017). This scenario provides an intriguing factor to investigate how the reduction of public healthcare provision has affected the household burden of C-NCD prevalence. Accordingly, this study aims to analyse the crowding-out effect of out-of-pocket healthcare spending caused by the C-NCDs on all other household consumptions and to identify how the changes in public healthcare spending have affected the crowding-out effect during the last two decades in Sri Lanka. Further, we compare the crowding-out effect related to C-NCDs with the effect related to other types of NCDs.

Several studies have examined the effects of ill-health/ NCDs on household consumption in different countries (Datta et al., 2018a; Fang et al., 2012; Kim and Yang, 2011; Pal, 2013; Sparrow et al., 2014; Wang et al., 2006). To the best of

our knowledge, only the study by Kumara and Samaratunge (2017) has examined the link between NCDs-prevalence and household consumption in Sri Lanka. However, our study differs from the above, and it contributes to the literature in several ways. First, this study provides novel evidence on the effect of public healthcare expenditures on changing the crowding-out effect of the out-of-pocket healthcare payments of households. Second, unlike studying the impact of ill-health or broad classification of NCDs on household consumption, our analysis is focused on the impacts of C-NCDs, and we show how it differs from the impact of other NCDs. Third, unlike analysing the overall effect of NCDs on household consumption, we isolate the crowding-out effect of healthcare expenditures on household consumption[1]. Therefore, our theoretical approach is based on the conditional demand for household consumption.

Finally, we adopt a different estimation method to identify the crowding-out effect as a solution for a critical empirical challenge in modelling the impact of ill-health/NCDs on household consumption in previous studies. We observed a potential endogeneity in modelling the consumption effect due to the factors that affect both consumption decisions and NCDs prevalence. For example, the age structure of a household would affect both the presence of individuals with NCDs in the households and the consumption decision of some goods and services. Since the OLS method does not provide an unbiased and consistent estimator in such situations (Blundell and Dias, 2009) we apply a different method, which is a matching method, and derive a matching estimator to identify the crowding-out effect of health expenditures on household consumption. Then, we calculate the matched-difference-in-difference (MDID) estimator to uncover the changes in the crowding-out effect as we intend to identify the effect of changing public healthcare expenditures.

We employed three waves of Household Income and Expenditure Survey (HIES),

[1]NCDs cause a significant reduction in labour force outcome (Kumara and Samaratunge, 2018; Sparrow et al., 2014). Hence, the consumption effect of NCDs on households may arise in two sources: the crowding-out effect of increasing healthcare expenditures and the income reduction effect due to ill-health.

conducted by the Department of Census and Statistics, Sri Lanka, in 2006, 2012 and 2016. Our results revealed that households with C-NCDs individuals spend x higher out-of-pocket payments for healthcare and the rate of increase during the reference period is higher than the households with other types of NCDs. They face a higher burden of out-of-pocket spending when public healthcare spending is at a lower level. Healthcare spending crowds out on some consumptions, especially food consumption; however, the crowding-out of health expenses varies on household income as the adverse effect is more prominent when households have a lower mean income/expenditure.

The rest of this paper is organised as follows. Section 2 reviews the existing literature related to the welfare consequences of NCD prevalence. An overview of the healthcare system in Sri Lanka is provided in section 3. Section 4 provides the theoretical framework and the methods used in the study, and section 5 explains the data sources and descriptive statistics. Section 6 provides the empirical analysis of the study, and section 7 delivers the discussion and conclusion.

3.2 Literature Review

This section summarises the literature connecting to out-of-pocket healthcare expenditure related to NCDs and its welfare consequences on households. First, we discuss how NCDs affect household out-of-pocket expenditures. Then we review the findings of the literature attached to the effect of ill-health/NCDs on household consumption.

3.2.1 NCDs and out-of-pocket expenditures for healthcare

out-of-pocket expenses for healthcare are identified as the main economic constraint in the presence of ill-health (McIntyre et al., 2006; Sirag and Mohamed Nor, 2021). This restraint becomes acute for NCDs since the size and the length of the financial

pressure on individuals/households is larger for NCDs than other types of illness (Sangar et al., 2019). Since NCDs has proliferated in the LMICs, the literature identifies the financial burden of out-of-pocket healthcare expenses of NCDs is severe in LMICs (Alam and Mahal, 2014; McIntyre et al., 2006; Murphy et al., 2020). For example, a study that explores the existing evidence of cost incurred by patients with NCDs and their households shows that the average total costs per year to a patient/household in LMICs of chronic obstructive pulmonary disease, cardiovascular disease, cancers and diabetes were USD 7386.71, USD 6055.99, USD 3303.81, USD 1017.05, respectively (Kazibwe et al., 2021). Considering different country contexts, the out-of-pocket expenditure on chronic NCDs in Malawi comprised 22 percent of monthly per capita expenditures of affected households (Wang et al., 2015). In Bangladesh, healthcare expenditure share is 59 percent higher for NCDs households than non-NCDs households (Datta et al., 2018a). In Sri Lanka, compared to non-NCDs households, chronic NCDs-affected households spend 408 rupees (154 percent) more on health as out-of-pocket expenditure per household member (Pallegedara, 2018).

Catastrophic health expenses (CHE) are the severe version of out-of-pocket expenses for NCDs-related health expenditures. There is a mismatch of the literature in categorising health expenditures as catastrophic; for example, some studies consider expenditures as catastrophic when households' financial contributions to healthcare exceed 40 percent of household income (Murphy et al., 2020; Xu et al., 2003), while some consider it even 10 percent of household income (Datta et al., 2018a; Kastor and Mohanty, 2018; Verma et al., 2021). The prevalence of catastrophic spending and impoverishment is highest among NCDs households in LMICs (Murphy et al., 2020). Poorest households and households in rural areas are more vulnerable to catastrophic payments (Salari et al., 2019). Among catastrophic payments of different health conditions, cancer is identified as the disease with highest CHE (Kastor and Mohanty, 2018). The extreme situation of having catastrophic

expenses ends up in households falling into indebtedness. NCD households are more likely to sell assets or borrow from informal sources to finance treatment costs (Datta et al., 2018b). Households indebtedness probability shows a significantly positive association with NCDs conditions when the household head or at least one other working-age member is diagnosed with NCDs (Samaratunge et al., 2020).

Medication accounts for the most significant part of out-of-pocket payment for healthcare-related NCDs. In India, more than 45 percent of out-of-pocket expenses of NCDs are raised through medicine purchases. The proportion was high as 64 percent and 58 percent for the cases of hypertension and diabetes, respectively (Engelgau et al., 2012). It is similar to the picture in Pakistan as the incidence of catastrophic health expenditures rise by 6.7 percentage points when households consume medications for hypertension and diabetes (Datta et al., 2019). The reason for the overburden of medication cost due to NCDs arise due to several reasons. Essential NCDs medicines are more available in the private sector than in the public sector (Khanal et al., 2019; Robertson et al., 2015; Wang et al., 2017). Hence individuals who seek public healthcare also have to bear the cost of medicine. Similarly, most of the medicines for NCDs are unaffordable due to higher prices (Khatib et al., 2016). A study in LMICs found that retail mark-ups of medicines ranged from 10 percent to 552 percent, and private sector patients pay 9-25 times international reference prices for lowest-priced generic products and over 20 times international reference prices for originator products across WHO regions (Cameron et al., 2009). Kankeu et al. (2013) also point that originator brand medicines lead to higher payments than the necessary cost. For example, in the treatment of diabetes, insulin – when required – represents an essential source of spending, leading to a heavy financial burden on many affected households, especially the poor households when they seek care.

One reason for the increasing burden of out-of-pocket healthcare payments is the health sector reforms in LMICs that occurred since the early 1990s, mainly focusing

on promoting the role of the private sector in healthcare provision and implicating fees for the public sector health services (McIntyre et al., 2006). However, those developments occurred in the unregulated private sector setting where health insurance and pension coverage are still limited (Mahal et al., 2010). The insurance coverage for NCDs is limited, and reimbursement rates are low in existing insurance schemes in these countries (Kankeu et al., 2013). Hence, most of the cost of rapidly growing healthcare needs due to NCDs lay on the hands of individuals/households.

The intensity of the burden of out-of-pocket expenditure arising from NCDs depends on many factors. The presence of multi-morbidity (two or more NCDs) was found to be positively associated with high out-of-pocket expenditures. A systematic review of the literature shows that when the number of NCDs increased from 0 to 1, 2 and 3, annual out-of-pocket payment on medicines increased by an average of 2.7 times, 5.2 times and 10.1 times, respectively (Sum et al., 2018). Household income is identified as the main factor in the occurrence of CHE. Poorer households tend to incur more catastrophic expenses for healthcare than other households (Correa-Burrows, 2012; Verma et al., 2021; Wang et al., 2015). Among other factors that affect out pocket expenditures are the seriousness of the chronic conditions, the type of healthcare use; for example, the availability and the strength of public healthcare services, availability of health insurance and its coverage, presence of elderly in the households, and the terrestrial location of households; for instance whether in an urban or rural area (Correa-Burrows, 2012; Krtilová and Yaya, 2012; Kumara and Samaratunge, 2016; Xu et al., 2003).

3.2.2 Effect of out-of-pocket health expenditures on the consumption of non-health goods

Disregarding the type of illness, many studies that discuss the crowding-out effect of the out-of-pocket expenses raised due to ill-health identify that household food consumption is crowded out by increasing out-of-pocket expenditures for health

(Datta et al., 2018a; Kumara and Samaratunge, 2017; Nguyen et al., 2012; Wang et al., 2006). However, some studies show that despite having a larger share of food expenditure, households tend to protect the consumption of food share in the bundle while facing higher healthcare expenditures Panikkassery (2020). Sometimes those households have even higher food consumption than healthy households (Pal, 2013). The negative impact on non-food consumption is also evident with the increasing out-of-pocket health expenditures (Batbold et al., 2021; Datta et al., 2018b; Pal, 2013; Panikkassery, 2020). Among non-food categories, education, clothing, durables and communication are the most common consumption categories that are affected. However, there is evidence that none of the consumptions is negatively affected due to out-of-pocket healthcare expenditures (Fang et al., 2013). In the presence of catastrophic expenses due to ill-health, the negative impact on household consumption is more significant as all other consumption categories record lower levels than households without catastrophic expenditures (Kim and Yang, 2011).

The link between the out-of-pocket expenditures due to NCDs alone on household consumption has also been analysed previously to a minor extent. A study in Bangladesh shows that households with NCDs have lower expenditure shares on food, clothing, hygiene, and energy than non-NCDs households. Further, it reveals that having NCDs is significantly associated with higher household spending on tobacco and higher-calorie foods such as sugar, beverages, meat, dairy, and fruit, with lower expenditures on fish, vegetables, and legumes (Datta et al., 2018a). A study that analyses the impact of medication expenditure, the more significant part of out-of-pocket expenditure, raised due to hypertension and diabetes alone on the consumption of non-health goods in Pakistan shows that medication expenditures are independently associated with crowding-out of food consumption of affected households (Datta et al., 2020). A study in Sri Lanka (Kumara and Samaratunge, 2017) also reveals that NCDs-prevalence and related hospitalisation compel households to sacrifice basic needs, including food, housing, and clothing consumption.

However, that study does not identify the isolated effect of out-of-pocket health expenditures on consumption, so the consumption effect of income reduction due to ill-health is also included in the estimated impact.

The crowding-out of health expenditures on non-health goods consumption largely depends on household income. A study that investigates the association between out-of-pocket health expenditure and poverty using macroeconomic data from 145 countries shows that when out-of-pocket spending share goes beyond a threshold, which is 29 percent of total health spending, the country's poverty rates increase. Sirag and Mohamed Nor (2021). By reviewing the literature related to the economic impact of household-level health expenditures in LMICs, Alam and Mahal (2014) show that the burden of out-of-pocket health payments is concentrated among the poor. Households that are pushed into poverty due to high medical expenses are forced into deeper poverty when it is combined with a loss of household income due to ill-health (McIntyre et al., 2006). Several country-level studies such as the studies in China (Fang et al., 2012; Wang et al., 2006), Indonesia (Sparrow et al., 2014), Vietnam (Nguyen et al., 2012), Mongolia (Batbold et al., 2021), India (Dhanaraj, 2016), and Sri Lanka (Kumara and Samaratunge, 2017) also confirm the fact that consumption of non-health goods is preliminarily affected by out-of-pocket expenditures in poor households compared to high-income households.

The studies that analyse the crowding-out effect of out-of-pocket health expenditures have used different theoretical and methodological approaches. Some studies used multivariate analyses to build the association between the presence of chronic diseases/ill-health and the share of expenses on non-health goods (Fang et al., 2012; Kumara and Samaratunge, 2017; Wang et al., 2006). Those have split analyses to show the link between inpatient treatment/hospitalization, a proxy for out-of-pocket health expenditures, and consumption expenditures. Datta et al. (2018a) used a system of Engel curves in a Quadratic Almost Ideal Demand System (QUAIDS) framework developed by (Banks et al., 1997) while using the presence of NCDs as

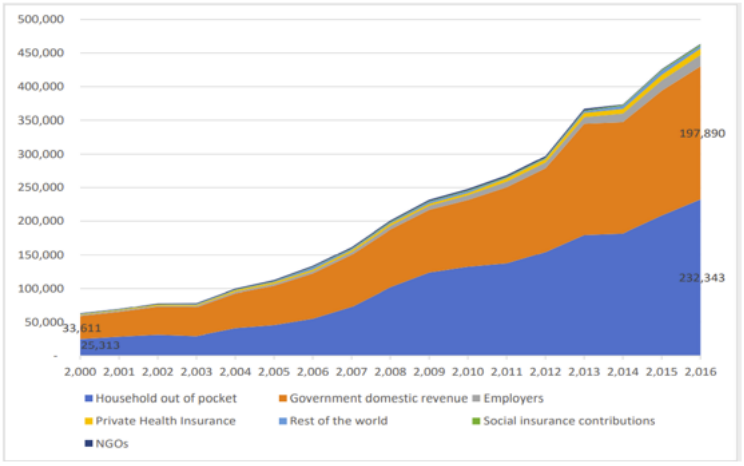
an explanatory variable. However, they did not explore the effect generated by out-of-pocket expenditures of NCDs. Pal (2013) encounters the out-of-pocket expenses to the demand model by estimating the demand system using the conditional quadratic Engel curve.

3.3 An overview of the healthcare system in Sri Lanka

Sri Lanka endowed a universal free healthcare system for primary care since the 1930s, and it was further strengthened with the launch of the 'free health policy' in 1951 following the independence (De Silva et al., 2016). Since then, public healthcare facilities have remained free of charge at the point of use and cover comprehensive healthcare services, including preventive, curative, and rehabilitative care on an inpatient and outpatient basis. Currently, public healthcare provision contributes to 50 percent of outpatient service and 90 percent of inpatient care (Kumar, 2019).

The private sector began to play a significant role in healthcare provision in the early 80s with the liberalization of the economy. It steadily developed in the 90s, and the sector includes large private hospitals, small outpatient clinics, laboratories and pharmacies. Private healthcare provision is mainly focused on providing outpatient services through family practitioners. Most of these private outpatient services are provided by government medical officers working during their off-duty hours. They make an important contribution to healthcare provision as they are often the first point of contact for providing curative care. (Fernando, 2000). The private sector contributes to around 50% of outpatient services, and the service is available in almost all parts of the country. However, inpatient care in the private sector is limited to urban areas, and most private sector hospitals are located in the Western province. However, private-sector healthcare service is barely regulated, and there is no formal link between the private sector and public-sector healthcare services

Figure 3.3.1: Relative contribution for total health expenditures in Sri Lanka (Rs. Million)



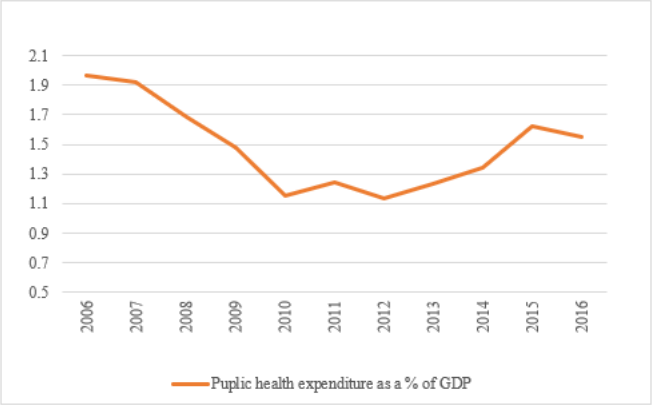
Source: National Health Accounts of Sri Lanka, 2018, Ministry of health

(Rannan-Eliya and Sikurajapathy, 2008).

Receiving healthcare in Sri Lanka is choice based. Patients can seek care in the medical institution of their choice. There are no organized general practitioner services to act as a gatekeeper for accessing hospital services (Rannan-Eliya and Sikurajapathy, 2008). Patients can meet specialists in the private sector without any referrals. Hence, the private provision led to greater inequality of the healthcare system. It is evident that there is a high level of utilization of private healthcare, even by those in the lowest income quantiles (De Silva et al., 2016).

The total healthcare expenditures of the country are financed by several parties, including the government, households, employers, insurance companies, and donors. As figure 01 shows, the public share of health expenditures is contracting gradually while the household-level contribution is expanding. By 2016, 53% of the total healthcare spending of the country was financed by household out-of-pocket expenditures. The government contribution was only 43% of the total healthcare spending (MoH, 2018). The out-of-pocket expenditures for healthcare include payments for private outpatient and inpatient care, prescribed pharmacy drugs and other health-related materials, laboratory investigations, dental care, and costs for

Figure 3.3.2: Public healthcare expenditures as a percentage of GDP



Source: Annual reports, Central Bank of Sri Lanka

indigenous treatments.

Although the private sector plays a significant role in healthcare provision, a national health insurance scheme has not been introduced to date in Sri Lanka. Having health insurance is not compulsory in Sri Lanka. Some private sector corporations provide health insurance for their employees and their family members. There is a monthly premium-based social insurance scheme for government employees, but membership is optional. Other than that households/individuals can purchase health insurance from private insurance providers of their choice, which is rather expensive for many households. Hence the insurance contribution to the total healthcare financing is very low.

As discussed above public sector plays an important role in healthcare provision, however, the public share of health financing is contracting gradually. As figure 02 displays, public healthcare spending as a percentage of GDP is declining to indicate an absolute reduction of public expenditure on healthcare. In 2006 nearly 2% of GDP was allocated for public sector healthcare, and it decreased to 1.1% in 2012. However, with the new challenges to the health sector due to epidemiological and demographic transition, the government identified the vital need to strengthen the existing primary level health care system to reduce the burden on secondary and tertiary care providers (CBSL, 2013). Several international organizations also

emphasized addressing the growing healthcare needs related to NCDs in the country (Engelgau et al., 2010; WB, 2008). As a result, the public healthcare provision started to rise slightly, reaching 1.5% of GDP in 2016.

3.4 Theoretical framework and methods

This section explains the theoretical model - the conditional demand function, the empirical model - the conditional quadratic Engle curve, and the methods used in estimating the crowding-out effect and its evolution.

3.4.1 Theoretical framework: Conditional demand function

Let us assume household preferences, given a vector of characteristics (a), can be represented by a utility function $U = u(x_1 \ldots\ldots x_n; a)$ while the prices of each good given as $p_1 \ldots\ldots p_n$. Then households maximise their utility subject to their budget constraint.

$$U = u(x_1 \ldots\ldots\ldots x_n; a) s.t \sum_{i-1}^{n} p_i x_i = Y \tag{3.1}$$

where x_i denotes the consumption of each good and Y indicates total expenditures. By solving this maximisation problem, one can derive the unconditional demand curve for each good as a function of the prices of all goods and the total expenditure/income, given the vector of household characteristics a.

$$x_i = h(p_1 \ldots\ldots p_n, Y; a) \tag{3.2}$$

However, suppose the consumption of one good - healthcare (H), is predetermined independently of the market mechanism. Once a household member is diagnosed with a C-NCD, the household first decides the amount of healthcare to be consumed and allocates a specific amount of healthcare for treatment. Since the amount con-

sumed by healthcare, say x_H, is already decided or "pre-allocated" by the household, the above maximisation problem will be slightly different (Pollak, 1969), and utility maximisation is now subjected to the excess expenditure available after allocating money for healthcare. We assume that all other $n-1$ goods are available in the market in the new utility maximisation problem, and individuals have no control over the price of these goods. Accordingly, given household characteristics, individuals choose quantities of $n-1$ goods to maximise utility $U = u(x_1.....x_n; a)$ subject to the new budget constraint,

$$\sum_{i=1}^{n-1} p_i x_i = M \tag{3.3}$$

where $M = Y - p_n x_H$ and $p_n x_H$ is the expenditure on healthcare. If x_H is predetermined as x_H^*, the solution of this maximisation problem gives the conditional demand function, which offers the conditional demand for i^th good dependent on the consumption of the healthcare, for each of the $n-1$ goods as follows.

$$x_i = g^{i,n}(p_1 \ldots\ldots p_{n-1}, M, x_H^*; a) \tag{3.4}$$

Thus, the demand for all other goods can be stated as a function of their price, prices of all other goods except healthcare, total expenditures net of expenditures on healthcare expenses and the quantity of healthcare consumed.

3.4.2 The empirical model and methods of estimation

The empirical estimation of the above conditional demand function is challenging when the price information for all goods is not available. Therefore, many cross-sectional studies ended up estimating the Engel curve, which builds the relationship between expenditure shares and income/expenditure, instead of the demand curve (John, 2008; Nyagwachi et al., 2020; Pu et al., 2008). Accordingly, we use the quadratic Engel curve, which provides valuable information regarding the nature

of goods such as luxuries vs necessities, derived from the quadratic almost ideal demand system (QUAIDS), developed by Banks et al. (1997). Since we incorporate the characteristics of the conditional demand curve, derived in Equation 3.4, into the Engel curve relationship, we focus on the conditional quadratic Engel curve. Following Husain et al. (2018); Nyagwachi et al. (2020) who analysed the crowding-out effect of one expenditure category on other household consumptions, our analysis is based on the following functional form.

$$w_{ij} = \beta_{1i} + \beta_{2i} \ln M_j + \beta_{3i} \ln {M_j}^2 + \beta_{4i} d_j + \gamma A + u_{ij} \tag{3.5}$$

where, M_j is household total expenditures net of expenditures on healthcare, w_{ij} is the expenditures of the i^{th} good category of j^{th} household out of total non-health expenditures $(p_i * q_i / M_j)$. A is the vector of household characteristics. The variable d_j is a dummy variable which takes the value one when j^{th} household is having individuals with C-NCDs and zero if the household does not have an individual with NCDs. The coefficient β_{4i} shows how much the expenditure share of i^{th} consumption category of C-NCDs households differs from those households that are not having any kind of NCDs. A significant negative β_4 implies that expenditure shares of C-NCDs households are lower than the households without NCDs, and hence it can be concluded that healthcare expenditures have crowded out the spending of the particular good. u_{ij} is the error term which consists of unobservable factors affecting household consumption. For the comparison purpose, the same functional form is applied for the households with other types of NCDs, in that case, d takes the value one when the household has individuals with any other types of NCDs and zero if the household does not have any individuals with other types of NCDs.

However, like in many observational studies, this study has to address the possible occurrence of econometric issues; selection bias and endogeneity. It occurs since we do not know the consumption decision of households with C-NCDs if they do not have such a condition, and we cannot observe both outcomes simultaneously.

Households are not possibly assigned randomly as C-NCDs, and those households may usually differ from households with non-NCDs even in the absence of being a household with C-NCDs. The health status of an individual depends on many factors related to those individuals and their households. Such factors can be summarised by the observable variables Z, and the unobservable variables v.

$$d_j = g(Z_j v_j) \tag{3.6}$$

There is a possibility of the error term u, which consists of other variables that may affect household consumption decision, in Equation 3.5 is correlated with either Z_j or v_j, the variables that affect the presence of C-NCDs in a household in Equation 3.6. For example, the age structure of a household has a clear link with household consumption decisions, while it relates to the presence of C-NCDs individuals in the household. The data shows that the prevalence rates of C-NCDs are higher at higher age levels. Similarly, we can identify regional or sector-vice differences in expenditure patterns and C-NCD prevalence rates in our data. Thus, we see the term u_{ij} in Equation 3.5 correlates with d_j, the presence of C-NCDs individuals in the household. Similarly, having C-NCD individuals in the household correlates with total household expenditures as the empirical data shows that households with C-NCDs have higher household expenditure/income.

The econometrics literature shows different ways to cope with the endogenous selection bias, and the matching method, the one we use in this study is one such way (Blundell and Dias, 2009). Matching methods explicitly address and eliminate the selection bias, while assuming that selection on unobservables is not a problem in the relevant data under certain assumptions[2] (Moreno-Serra et al., 2007). The matching method has been identified as a more advantageous method over other

[2]unconfoundedness assumption is crucial for the estimation of average treatment effects by matching methods. If two individuals with the same observables differ in their choices regarding exposition to the treatment due to unobservables, this does not necessarily invalidate the unconfoundedness assumption if these different choices are due to unobserved factors that are unrelated to the outcome variable.

methods such as conditioning on other variables in the regression model, or instrumental variables approach (Stuart, 2010). For example, matching avoids making assumptions about the functional form of the regression equation, making analysis more reliable. Matching approaches give a consistent estimate for the average treatment effect (ATE) under the assumption that the selection process depends on observables (Nichols, 2007). A matching method will pair each treatment observation (in this case, households with C-NCD individuals) with the observations of the non-treated group (households that do not have any C-NCD individuals) and construct the correct sample counterparts based on observable variables. The matching assumes that the only remaining difference between the two groups of households has C-NCDs individuals in the household.

Let us define the observable variables X which consist of total household expenditure (health netted) plus the covariate Z that explains a part of the residual term (u) in the expenditure share equation and part of the determinants of having NCDs individuals in a household (d). The covariate Z includes household characteristics such as the region, ethnicity, age of the household head, age structure of the household, household size, and household head education level. Accordingly, following Blundell and Dias (2009), we can re-write the Eqation 3.5 as,

$$\begin{aligned} w_{ij}^{1} &= \beta_{1i} + \alpha d_j(X_j) + \theta(X_j) + (u_{ij} - \theta(X_j)) + (\beta_{4i} d_j - \alpha d_j(X_j)) \\ w_{ij}^{0} &= \beta_{1i} + \theta(X_j) + (u_{ij} - \theta(X_j)) \end{aligned} \tag{3.7}$$

Where, w_{ij}^{1} is the expenditure shares of C-NCDs households and w_{ij}^{0} is the expenditure shares of non-C-NCDs households. $\theta(X_j)$ is the part of the expenditure share that can be predictable from X, and $(u_{ij} - \theta(X_j))$ is what is leftover of the error u_{ij} after conditioning on X. α is the average treatment effect on treated (ATT) over individuals with observable characteristics X and $(\beta_{4i} d_j - \alpha d_j(X_j))$ is the un-

observable household-specific effect.

The average treatment effect estimation under the matching method is built under two assumptions. First, the Conditional Independency Assumption (CIA); assumes that the set of variables in covariate X contains all the information available at the point of selecting a household as a C-NCDs household about the potential outcome in the absence of C-NCDs in that household. Second, it assumes that the observable X does not predict exactly the C-NCD status and leaves some room for unobserved factors that influence the C-NCD status. Formally it can be stated as $p = (d_i = 1|X_i) \leq 1$.

In practice, matching using covariate X is challenging to implement since it is multidimensional (Blundell and Dias, 2009). Hence, following (Rosenbaum and Rubin, 1983), we execute the matching using a propensity score $P(X)$ that estimates each household's propensity to be an NCDs household, given the observable X, using a probit model and match households with similar propensities. Then the matching is done according to the proximity between propensity scores for NCDs and non-NCDs households. Accordingly, the ATT of C-NCDs households is obtained by averaging the difference in expenditure shares among C-NCDs and non-NCDs households with similar characteristics, using the empirical weight of the propensity score distribution among C-NCDs households. Following Blundell and Dias (2009) and Becker and Ichino (2002), the average treatment effect on the C-NCDs household of i^{th} consumption category can be written as,

$$\hat{\alpha}_i = \frac{1}{N^T} \sum_{j \in NCD} \left((w_j^{NCD} - \sum_{k \in NNCD} \omega_{j,k} w_k^{NNCD} \right) \tag{3.8}$$

where, N^T is the number of C-NCDs households, w_j^{NCD} is the expenditure share of j^{th} household if it is a C-NCDs household, w_k^{NNCD} is the expenditure share of k^{th} household if it is non-C-NCDs household and $\omega_{j,k}$ is the weight placed on non-C-NCDs households for C-NCDs households. These weights depend on the matching

method used. In this study, we use kernel matching, and therefore, the weights are the kernel propensity-score weights which take the following form.

$$\omega_{j,k} = \frac{K\left(\frac{p_j - p_k}{h_n}\right)}{\sum K\left(\frac{p_j - p_k}{h_n}\right)} \tag{3.9}$$

As per the second part of the study, we aim to identify the evolution of the crowding-out effect of healthcare expenditures on household consumption. Nyagwachi et al. (2020) applied Matched Difference in Difference (MDiD) method to identify the evolution of the crowding-out effect in a similar setting. Following that, we also applied the MDID approach for our analysis to find the changes in the crowding-out effect. There, we compare the outcome of a treated group with the non-treated group over two time periods t_0 and t_1, where t_0 indicates the first period and t_1 indicates the second period. MDID makes a common trend assumption that if the treated remained untreated, they would have experienced a change in the outcome that equals the observed difference in the actual non-treated. Following Villa (2016), we estimate the MDID estimator that takes the following functional form.

$$\begin{aligned}\mathbf{MDID_i} = E(w^1_{i,t=1}) - \left(\omega^0_{t=1} * E(w^0_{i,t=1})\right) - \left(\omega^1_{t=0} * (E(w^1_{i,t=0})\right) \\ - \left(\omega^0_{t=0} E(w^0_{i,t=0})\right)\end{aligned} \tag{3.10}$$

where, $\omega^0_{t=1}$, $\omega^1_{t=0}$ and $\omega^0_{t=0}$ are the kernel weights of the non-C-NCDs household in the second period, C-NCDs household in the first period and the non-C-NCDs household in the first period, respectively. These three sets of kernel weights are calculated independently according to the estimated propensity score (Villa, 2016). Since our analysis is based on three time periods, 2006, 2012 and 2016, we derive three sets of MDID estimators for the periods 2006-2012, 2012-2016 and 2006-2016. In each period, the prior year is considered as t_0, and the later year is considered as

t_1.

For the comparison of the impact of C-NCDs on the consumption of goods and services, we conduct a similar analysis for households that have individuals with other types of NCDs. In that case, the treatment group will be the households with other types of NCDs and the control group will be the households with no NCDs.

3.5 Data

The study uses three waves of Household Income and Expenditure Survey (HIES), in Sri Lanka conducted in 2006, 2012 and 2016. HIES is a repeated cross-sectional survey conducted by the Department of Census and Statistics in Sri Lanka. It is a nationally representative survey and follows a two-stage stratified sampling method to include the urban, rural, and estate sectors[3] and all country districts in the selection domain. At the first stage, primary sampling units (PSUs), which are census blocks, are selected systematically by allocating higher selection probability for the census blocks consisting of a larger number of housing units. Given equal selection probability, the Final Sampling Units (FSUs), which are housing units, are selected at the second stage (DCS, 2016a).

The HIES survey collects individual-level data from each household for demographic, education, income, and health while collecting household-level data for expenditures. The reference unit of this study is the household. Accordingly, after cleaning the data, we used 18544 households from the 2006 survey, 20413 households from the 2012 survey and 21756 households from the 2016 survey for the analysis.

[3]Estate sector is a part of the sectoral composition of the economy of Sri Lanka, and it refers to geographical areas that consist of all plantations (tea, rubber, coconut etc) which are 20 acres or more in extent and ten or more resident labourers.

3.5.1 Socio-demographic characteristics

The socio-demographic characteristics of the sample are summarised in Table 3.5.1. The majority live in rural sector in Sri Lanka. In the 2006 and 2012 surveys, 66% of households were from the rural sector, and it was 80% in the 2016 survey. Accordingly, the composition of the other two sectors, urban and rural, has been reduced in 2016 compared to the other two years[4]. Most households, on average 70%, represent Sinhala ethnic group in all three years. There appears an increase in the Sri Lankan Tamil group in 2012 because the survey coverage expanded to the northern and eastern parts of the country, which previously was under a war situation. The average household size shrunk gradually from 4.4 in 2006 to 3.8 in 2016. The average age of the household head increased during the time from 50.5 to 52.6. More than 60% of households have individuals aged up to 60, while on average, 45% of households have individuals aged over 60. On average, 50-55% of household heads are educated up to grade 10, while 14% of household heads have halted their education with only passing O/Ls. The percentage of household heads that passed A/Ls and entered tertiary education increased gradually from 2012 to 2016.

3.5.2 Health Status

The HIES reports health status data at the individual level, and all health information is self-reported. We identified seventeen disease categories under NCDs. However, only a few of those NCDs are identified as challenging to the health system as they are showing an increasing trend over time. According to WHO (2022) cardiovascular diseases, cancers, chronic respiratory diseases and diabetes are the NCDs which put serious pressure on the health system as those four NCDs account for over 80% of all premature deaths. Our data also shows the prevalence rates of those diseases are increasing over time (Table 3.5.1). Apart from those, high blood

[4]We thoroughly examined whether there is any change in the sampling methodology in 2016 compared to 2012. But there is no such change. Hence we assume that the changes in the percentages reflect the actual change in the sectoral composition.

Table 3.5.1: Socio-demographic characteristics of the sample

Variables	2006	2012	2016
Sectoral composition			
Urban	24.98%	25.07%	15.76%
Rural	65.73%	65.93%	79.95%
Estate	9.29%	9%	4.29%
Ethnic composition			
Sinhala	75.03%	67.83%	72.52%
Sri Lankan Tamil	9.65%	16.34%	15.07%
Indian Tamil	5.65%	6.19%	3.62%
Moors	9.07%	9.21%	8.38%
Other	0.61%	0.41%	0.4%
Average household size	4.38	4.15	3.81
Average age of the HH head	50.48	51.01	52.63
Age structure of the household			
Individuals with			
below 18	70%	66%	65%
18 to 40	75%	71%	69%
40 to 60	63%	63%	60%
Over 60	47%	49%	42%
Education level of the household head			
No education	6%	3.95%	3.46%
Up to grade 5	19.23%	16.03%	15.16%
Upto grade 10	49.96%	53.57%	54.95%
Passed O/L	14.96%	14.53%	14.2%
Passed A/L	7.59%	9.33%	9.48%
Degree or above	2.26%	2.6%	2.74%
Health status			
C-NCDs households	26.53%	28.56%	33.28%
Households with			
Heart disease	4.64%	4.16%	5.35%
HBP	10.46%	12%	13.88%
Diabetes	7.76%	9.16%	11.72%
Asthma	6.24%	5.46%	5.45%
Cancer	0.28%	0.83%	1.05%
other NCDs	21.29%	17.76%	19.59%
Two or more C-NCDs	4.69%	11.27%	7.06%
Household head having c_NCDs	26.16%	24.86%	30.58%

Notes: All the values are percentages of total households.

pressure also shows an increasing trend. Hence we cluster those five diseases into one category as chronic NCDs (C-NCDs), and it consists of heart diseases, high blood pressure (HBP), diabetes, asthma, and cancer. The rest of the NCDs are grouped as other NCDs[5].

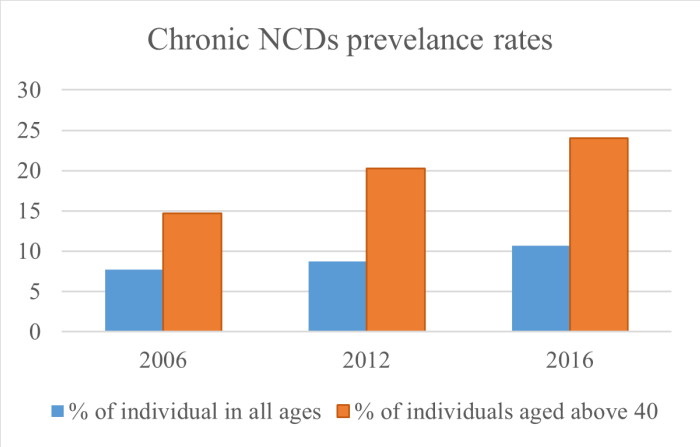
The percentages of households with C-NCDs in all three years are presented in Table 3.5.1. On average, 30% of households have at least one member with C-NCDs, and the percentage increased from 26% to 33% from 2012 to 2016. Figure 3.5.1 shows the changes in prevalence rates of C-NCDs from 2006 to 2016. As it shows the upward trend of the prevalence rates over time, it is particularly prominent among individuals aged over 40. High blood pressure and diabetes are the most common C-NCDs among households. The percentage of households with HBP was 10% in 2012 and it increased to 14% by 2016. Diabetes percentage increased from 8% to 12% during that time. Although the percentage is small the rate of increase in cancer is alarming. The percentage of households with cancer increased by around four times during this period.

While the percentage of households with C-NCDs increased, the percentage of other NCDs decreased by approximately two percentage points from 2006 to 2016. Nearly 5 to 11 percent of households are recorded as having two or more individuals with C-NCDs. The percentage of household heads having C-NCDs has increased from 26% in 2012 to 31% in 2016.

Having an individual with NCDs is linked with several socio-demographic characteristics of the household. Table 3.5.2 shows the variation of socio-demographic characteristics of households with C-NCDs and other types of NCDs for 2016. According to the sectoral composition of households with C-NCDs and non-NCDs, a higher percentage of households with C-NCDs is in the urban sector compared to non-NCDs households. In parallel, the rural and estate sector composition is smaller

[5]These other NCDs include epilepsy, stomach diseases, kidney diseases, arthritis, diseases related to eyes and ears, mental retardation, haemorrhoids, catarrh, severe headache, and naturally disabled or disabled by accident.

Figure 3.5.1: Percentage of individuals with chronic NCDs



Source: Author constructed using data from HIES, 2006, 2012 and 2016

for C-NCD households. Those households are relatively larger in size, and the heads are older than non-NCD households. Significant differences in ethnic composition are also evident in the data. Tamil ethnic group is relatively low, and Sinhala and Moors are higher among households with C-NCD compared to households with no NCDs. Significant differences in the education level between the two types of households exist, but the direction is mixed at the lower level of education. However, the percentages for higher education are larger for C-NCDs than non-NCDs. On average, the households with C-NCDs are richer than the households with no NCDs.

The socio-demographic composition of the households with other NCDs is somewhat different. For those households, the urban composition is lower, and the rural composition is higher. Like in C-NCDs, the average age of the household head is higher in households with other NCDs compared to non-NCDs. Similarly, the Tamil ethnic group has a lower percentage of having other NCDs. There is a significant relationship between education and having other NCD individuals in the household. At higher education levels, there is a lower percentage of households having other NCDs. Unlike C-NCDs, those households with other types of NCDs are poorer than non-NCD households.

Table 3.5.2: Socio-demographic differences of households with chronic NCDs (2016)

	Household with C-NCDs	non-NCDs	Difference	Household with other-NCDs	non-NCDs	Difference
Sector						
Urban	20.32%	14.22%	6.1%***	12.07%	14.22%	-2.15%***
Rural	76.11%	80.88%	-4.77%***	83.82%	80.88%	2.94%***
Estate	35.55%	48.85%	-13.3%***	4.1%	4.88%	-0.78%*
Age of the HH head	57.98	48.31	9.67***	55.09	48.31	6.78***
Household size	3.88	3.75	0.13***	3.73	3.75	-0.02
Ethnic group						
Sinhala	73.29%	70.68%	2.61%***	77.12%	70.68%	6.44%***
Sri Lankan Tamil	13.55%	16.44%	-2.89%***	12.75%	16.44%	-3.69%***
Indian Tamil	3.15%	4.01%	-0.86%***	3.41%	4.01%	-0.6%
Moors	9.38%	8.56%	0.82%*	6.18%	8.56%	-2.38%***
Other ethnic groups	0.61%	0.28%	0.33%***	5.2%	2.88%	2.32%**
Education of the household head						
Not educated	3.43%	3.1 %	0.33%	4.62%	3.1%	1.52%***
Educated up to grade 5	15.6%	13.15%	2.45%***	19.29%	13.15%	6.14%***
Educated up to grade 10	53.34%	55.98%	-2.63%***	55.64%	55.98%	-0.34%
Passed G.C.E.O/L	14.79%	14.62%	0.17%	11.71%	14.62%	-2.91%***
Passed G.C.E.A/L	9.58%	10.39%	-0.81%*	7.02%	10.39%	-3.37%***
Degree or above	3.23%	2.75%	0.48%**	1.69%	2.75%	-1.06%***
Household income	48786	42247	6539***	39358	42247	-2889**

Notes: All the values are percentages of total households.
*** p<0.01, ** p<0.05, * p<0.1

3.5.3 Household expenditures

HIES records expenditure data at the household level under two broad categories: food and non-food expenditures, while the non-food category is split into several expenditure headings. Expenditure data for food is recorded as weekly expenses, while non-food categories are recorded as monthly expenses. Few non-food categories record expenses for the last six months. Therefore, we calculated monthly expenditures for all categories of goods and services. The total household expenditure is the sum of all expenditure categories of a household.

As we study the data of three periods with ten years difference, our data should be adjusted for the price changes during that period. Hence, all expenditure data was deflated using a price index. We used the Colombo Consumer Price Index (CCPI) – the widely accepted price index in Sri Lanka, calculated by the Department of Census and Statistics, which has the base year 2006=100. The CCPI gives the price index for food and non-food categories, and therefore, we deflated food by the food price index and all non-food expenditures by the price index for non-food[6] (DCS, 2016b)

The total household expenditures, after deflating the prices are shown in Table 3.5.3. Significant differences in total spending can be observed between households with C-NCDs and non-C-NCDs. It indicates that the mean total expenditures of households with C-NCDs are significantly higher than those with no NCDs. For example, the average total spending of a household with C-NCDs was 3743 rupees higher than the spending of households with no NCDs in 2006. The mean spending difference between the two types of households in 2012 was higher than that of 2006. However, the mean difference was reduced in 2016. This implies that although households with C-NCDs are more affluent than non-NCDs households, compared to 2012, those households were less affluent in 2016. In contrast, the total expendi-

[6]The price index for food and non-food was 180.92 and 150.4 for 2012, and 221.7 and 165.04 for 2016

Table 3.5.3: Total expenditures

	2006	2012	2016
Total expenditures (SLRs)			
All households	21610	23001	25643
	(166)	(202)	(203)
Households with C-NCDs	24739	26888	29049
	(352)	(562)	(400)
Households with other NCDs	19924	22086	24441
	(301)	(357)	(431)
Households with Non-NCDs	20996	21649	24259
	(223)	(192)	(267)
Difference (c-NCDs - Non-NCDs)	3743***	5239***	4790***
	(405)	(479)	(463)
Difference (other NCDs - Non-NCDs)	-1072***	437	182
	(409)	(400)	(510)
Health-netted total expenditures (SLRs)			
All	20871	22006	24648
	(159)	(188)	(191)
Households with C-NCDs	23595	25197	27425
	(336)	(519)	(363)
Households with other NCDs	18826	20842	22891
	(252)	(338)	(356)
Households with Non-NCDs	20534	21030	23714
	(220)	(181)	(260)
Difference (c-NCDs - Non-NCDs)	3061***	4166***	3711***
	(395)	(446)	(436)
Difference (other NCDs - Non-NCDs)	-1709***	-188	-823*
	(391)	(377)	(479)

*** Notes: All values are price-deflated expenditures. Values are in Sri Lankan rupees.
Standard errors are in parentheses. p<0.01, ** p<0.05, * p<0.1

ture of households with other NCDs was significantly lower than that of non-NCDs households in 2006, and there is no significant difference in other years.

Table 3.5.3 further gives the total expenditures after netted-out of the health expenditures, which relates to the outcome variable of our analysis. The health-netted expenditure follows the same pattern as the total expenditures, where households

with C-NCDs have higher expenditures than households with no NCDs, and the expenditure level of households with other NCDs is significantly lower than that of non-NCDs.

We identified 14 expenditure categories in the total expenditures of a household. Table 3.5.4 gives the mean shares of each expenditure category out of total household expenditures. Further, the table shows the percentage differences between households with C-NCDs and non-NCDs. The data show considerable variations in expenditure shares between households with C-NCDs and non-NCDs. The mean expenditure share on health[7] is higher for households with C-NCDs than the non-NCDs in all three periods. For example, in 2016, a household with C-NCD spent 8% of total expenditures on health on average, whereas a household with no NCDs spent only 3%. The mean spending share for health in households with C-NCD has doubled during the reference period as it was 4% in 2006 and increased to 8% by 2016. The biggest increase happened in the 2006-2012 period as the percentage increased from 4% to 7%.

The food share of households with C-NCD was 4 to 5% lower than that of households with no NCDs. The food share decreased by nearly 10% points for both types of households during the reference period. Accordingly, the shares for almost all other categories increased during that period. Other than the food, the mean shares of education, personal care, clothing and footwear, and non-durable goods were also significantly lower in households with C-NCDs than non-NCDs. On the other hand, on average, the C-NCDs households report higher expenditure shares for housing, transport and recreation, and entertainment than non-NCDs households. As we identified that the households with C-NCDs are located more in urban, and household heads are younger than the households with no NCDs, it is reasonable that those households spend higher shares on housing, transport and recreation.

[7]The health expenses include all spending on health either for western treatment and procedures or for traditional/herbal medicines. There could be situations in which people might use traditional medicines at no cost, but this could be a very small proportion under the advanced health system in the country.

Table 3.5.4: Mean expenditure shares of households with C-NCDs and non-NCDs

	2006			2012			2016		
	c-NCDs	non-NCDs	Difference	c-NCDs	non-NCDs	Difference	c-NCDs	non-NCDs	Difference
Food	50.02%	53.83%	-3.80%***	43.84%	48.65%	-4.81%***	40.11%	44.01%	-3.89%***
Cereals bread and pulses	14.98%	16.44%	-1.46%***	14.04%	15.36%	-1.31%***	12.18%	13.58%	-1.40%***
Fruit, vegetables, and yam	6.12%	6.64%	-0.52%***	5.49%	6.02%	-0.53%***	5.03%	5.39%	-0.36%***
Meat, fish, and egg	7.81%	8.01%	-0.20%**	7.43%	8.06%	-0.63%***	7.05%	7.75%	-0.70%***
Milk and milk products	3.67%	3.72%	-0.05%	3.42%	3.57%	-0.15%***	2.88%	2.90%	-0.02%
Coconut and oil products	3.59%	3.90%	-0.31%***	3.85%	4.33%	-0.48%***	3.46%	3.72%	-0.26%***
Sugar, confectionary, and beverages	4.38%	4.76%	-0.37%***	3.93%	4.53%	-0.60%***	3.58%	4.01%	-0.43%***
Condiments and other foods	6.99%	7.47%	-0.48%***	4.00%	4.47%	-0.47%***	4.06%	4.29%	-0.23%***
Liquor and tobacco	2.47%	3.00%	-0.53%***	1.68%	2.24%	-0.56%***	1.87%	2.31%	-0.44%***
Housing	13.36%	11.72%	1.64%***	15.28%	12.86%	2.41%***	16.38%	14.46%	1.91%***
Fuel and Light	5.78%	5.54%	0.25%***	5.96%	5.73%	0.23%***	4.80%	4.65%	0.15%***
Health	4.24%	2.00%	2.23%***	6.97%	3.02%	3.94%***	7.73%	2.92%	4.81%***
Education	2.25%	2.46%	-0.21%***	3.15%	3.22%	-0.07%***	3.58%	4.03%	-0.44%***
Personal care	1.53%	1.64%	-0.11%***	1.96%	2.13%	-0.16%***	2.17%	2.40%	-0.23%***
Transport	6.27%	5.80%	0.47%***	7.14%	7.12%	0.01%	8.21%	7.94%	0.27%***
Communication	2.13%	1.90%	0.23%***	2.48%	2.42%	0.06%	2.45%	2.41%	0.04%***
Recreation and Entertainment	0.92%	0.78%	0.14%***	1.14%	0.94%	0.20%***	1.55%	1.29%	0.26%***
Clothing and Footwear	3.28%	3.57%	-0.28%***	3.23%	3.90%	-0.66%***	3.62%	4.28%	-0.66%***
Household services	0.21%	0.19%	0.02%	0.30%	0.23%	0.07%***	0.35%	0.24%	0.11%***
Nondurable goods	1.08%	1.12%	-0.03%***	1.08%	1.16%	-0.07%***	1.02%	1.12%	-0.10%***
Durable goods	2.33%	2.52%	-0.19%	1.79%	1.75%	0.04%	2.52%	2.62%	-0.09%
Other	6.59%	6.94%	-0.35%	8.01%	7.88%	0.13%	8.55%	8.78%	-0.23%

Notes: Shares were calculated using price-deflated expenditures
*** p<0.01, ** p<0.05, * p<0.1

The difference in the mean shares between the two types of households is widening from 2006 to 2016 for almost all goods and services except fuel & light, transport and durable goods.

For comparison, we calculated the mean expenditure shares of other types of NCDs as well, and the figures are presented in Appendix 3.A. The expenditure shares of the household with other NCDs have some similarities and differences with the C-NCD category. Such as for C-NCDs, the health share of households with other NCDs increased during the reference period. However, the food share gap between households with other NCDs and non-NCD is smaller compared to that gap for C-NCDs. Unlike, C-NCDs there is no significant difference in the expenditure shares on housing, fuel, personal care and transport between household with other NCDs and non-NCDs.

3.6 Results

3.6.1 Crowding-out effect of health expenditures of chronic NCDs

We obtained the matching estimator that identifies the crowding-out effect of health expenditures resulting from C-NCDs for the years 2006, 2012 and 2016 separately. Kernel matching was used in the estimation with the enforcement of common support. Our treated group is the households with C-NCDs, and the control group is the households that do not have any kind of NCDs[8]. Figure 3.6.1 illustrates the distribution of the treated (C-NCD) and non-treated (non-NCD) propensity scores, and it proves that the matching occurs within the common support region. The density functions of propensity scores of treated and non-treated groups have different shapes, but the distribution range is similar. In practice, the ranges of estimated propensity scores are rarely the same for both the treatment and control groups,

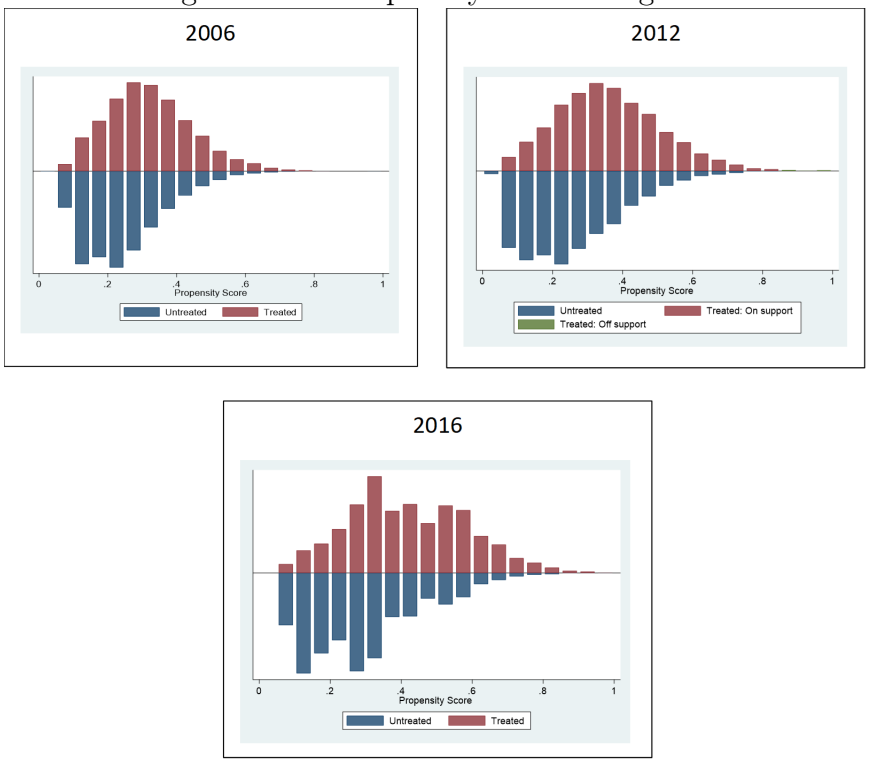
[8]At this stage, we excluded the households with other types of NCDs from the sample.

but they do nearly always overlap (Nichols, 2007). Table 3.6.1 shows the variables used for matching and the t-tests confirm the covariate balance between treated and control groups after matching.

The results of the matching and the ATT of having C-NCDs on each of the consumption categories are presented in Table 3.6.2. Since food accounts for nearly half of the total expenditure, we estimated the ATT for different food categories as well. The estimations have been obtained from the price-deflated expenditures. Hence the average treatment effects are free from price changes across the years. The results indicate that having an individual with C-NCDs in a household significantly affects expenditure shares of some consumption categories. As expected, the health expenditure share is higher for households with C-NCDs compared to households with no NCDs. This is evident in all three years. In 2006, households with C-NCDs spent a 2.8 percentage points higher share on health compared to households with non-NCDs. In 2012 and 2016, it was 5.9 and 6.2 percentage points higher, respectively. In monetary terms, with respect to the mean household expenditures, households with C-NCDs spent 605 rupees, 1375 rupees and 1590 rupees higher amounts on health compared to households with non-NCDs in 2006, 2012 and 2016 respectively.

Similarly, the results indicate that the presence of a C-NCDs individual in the household increases the expenses on housing and transport. Households with C-NCDs individuals spent 0.6 to 0.9 percentage points higher shares on housing and, 0.4 percentage points higher shares on transport. This may be due to these expenditures being linked with the treatment of C-NCDs, such as travelling to the nearest cities for treatments and finding accommodation near hospitals in the case of long-term inpatient treatments. Similarly, households with C-NCD individuals spend higher shares on fuel & light, and recreation & entertainment compared to non-NCDs households. This can be reasonable as we saw that the households with C-NCDs are relatively richer than the households with no NCDs, so they spend a

Figure 3.6.1: Propensity score histograms



Note: The figure illustrates the common support assumption of the propensity score matching. The treated group is the households with C-NCD individuals, and the control group is the households that do not have any kind of NCD individuals.

considerable share on those categories.

The out-of-pocket expenditures raised through C-NCDs have crowded out the spending on some other consumption categories, mainly food expenditures. In 2006, due to C-NCDs, households spent 1.3 percentage points fewer shares on food. Similarly, C-NCDs caused 1.7 and 1.9 percentage points less spending on food in 2012 and 2016, respectively. In monetary terms, with respect to mean household expenditures, households with C-NCDs spent 346 rupees monthly less on food in 2006 due to the extra cost that they have to bear as they have a C-NCD individual in the household. Similarly, those households with C-NCDs spent 391 rupees less in 2012 and 487 rupees less in 2016 for food due to the fact that they have C-NCD individuals in the household. All these monetary values are calculated based on price-deflated expenditures, therefore, the decrease in expenditures reflects the fall in food consumption in real terms.

Among different food items, the highest difference was recorded for cereals, bread, and pulses. Almost all food items except milk & milk products are negatively affected by having C-NCDs individuals in the household. Similarly, the expenditure share of clothing and footwear was 0.4 and 0.2 percentage points lower in 2012 and 2016, respectively. Education was negatively affected by C-NCDs only in 2006 as those households spent 0.2 percentage points less share on education.

3.6.2 Evolution of the crowding-out effect of health expenditures caused by chronic NCDs

Earlier we identified that the expenditure shares of the consumption categories are different between households with C-NCDs and non-NCDs. Accordingly, Figure 3.6.2 shows how the expenditure shares vary between the two types of households from 2006 to 2016. The graphs illustrate the slopes of the trend lines for the treated group (households with C-NCDs households) are different from the control group (Households with no NCDs), indicating that the changes in the expenditure shares occurred differently for treated and control groups. To identify those changes, we estimated the MDID estimator for each consumption category using kernel matching with the enforcement of common support. Since we are analysing three time periods, we estimated three sets of MDID estimators for the 2006-2012 period, 2012-2016 and 2006-2016 period.

Table 3.6.3 presents the result of the MDID estimator for different consumption categories. The MDID estimator shows us the changes in the average treatment effect of C-NCDs. Previously we found that the households with C-NCDs spent significantly higher shares on healthcare in all three periods. Accordingly, the largest change in ATT was also recorded for health expenditures. The ATT of C-NCDs on health expenditure share was higher in 2012 than it was in 2006. Hence the MDID estimator shows that Households with C-NCDs individuals in 2012 spent 3.2 percentage points higher share on health than similar households in 2006. In

Table 3.6.1: Matching variables: Mean values after matching

	2006			2012			2016		
Variable	Treated	Control	Difference	Treated	Control	Difference	Treated	Control	Difference
Household total expenditure (Health netted)									
Below 20000 from	0.5674	0.5806	-0.0132*	0.243	0.249	-0.006	0.1619	0.1675	-0.0056
20000-50000	0.3617	0.3559	0.0057	0.5387	0.5386	0.0001	0.5025	0.5067	-0.0042
50000-10000	0.059	0.0533	0.0057	0.1754	0.1729	0.0026	0.2593	0.2547	0.0045
100000-200000	0.0092	0.0078	0.0014	0.0344	0.0321	0.0023	0.0606	0.0574	0.0032
200000-400000	0.0024	0.0019	0.0006	0.0065	0.006	0.0006	0.0124	0.0104	0.002
Over 400000	0.0004	0.0006	-0.0002	0.0019	0.0014	0.0005	0.0033	0.0032	0.0001
Sector									
Urban	0.2934	0.2849	0.0084	0.3165	0.3063	0.0102	0.1975	0.1859	0.0116
Rural	0.6349	0.64	-0.0051	0.6144	0.6202	-0.0058	0.7682	0.7762	-0.008
Estate	0.0718	0.0751	-0.0033	0.0691	0.0735	-0.0043	0.0343	0.0379	-0.0037
Age	55.877	55.75	0.127	57.018	56.833	0.185	58.391	58.468	-0.077
Number of people aged 40 to 60	1.0724	1.0863	-0.0139	1.0454	1.064	-0.0186	0.9635	0.9786	-0.0151
Number of people age above 60	0.999	0.9754	0.0236	1.0669	1.0499	0.017	0.9065	0.8871	0.0194
Household size	4.627	4.6037	0.0233	4.2633	4.2706	-0.0073	3.9388	3.9393	-0.0005
Ethnicity									
Sinhala	0.7548	0.755	-0.0002	0.7119	0.7064	0.0055	0.7347	0.7286	0.0061
Sri Lankan Tamil	0.0921	0.0919	0.0002	0.1416	0.1431	-0.0016	0.1387	0.1441	-0.0054
Indian Tamil	0.048	0.0498	-0.0018	0.0547	0.0585	-0.0038	0.0309	0.0328	-0.0019
Moors	0.0962	0.0956	0.0006	0.0872	0.088	-0.0008	0.0903	0.0891	0.0012
Other	0.0089	0.0078	0.0012	0.0046	0.004	0.0006	0.0054	0.0054	0
Education									
Not educated	0.0579	0.0613	-0.0033	0.0361	0.0364	-0.0003	0.0352	0.038	-0.0028
Up to grade5	0.1954	0.2007	-0.0053	0.1577	0.1634	-0.0057	0.1659	0.1703	-0.0044
Up to grade10	0.4812	0.4809	0.0003	0.5188	0.5217	-0.0029	0.5304	0.5347	-0.0043
OL	0.1673	0.1618	0.0055	0.165	0.1599	0.0051	0.1459	0.1418	0.0041
AL	0.0728	0.0714	0.0014	0.0941	0.0911	0.003	0.0909	0.0854	0.0055
degree	0.0254	0.024	0.0014	0.0284	0.0276	0.0008	0.0318	0.0299	0.0019

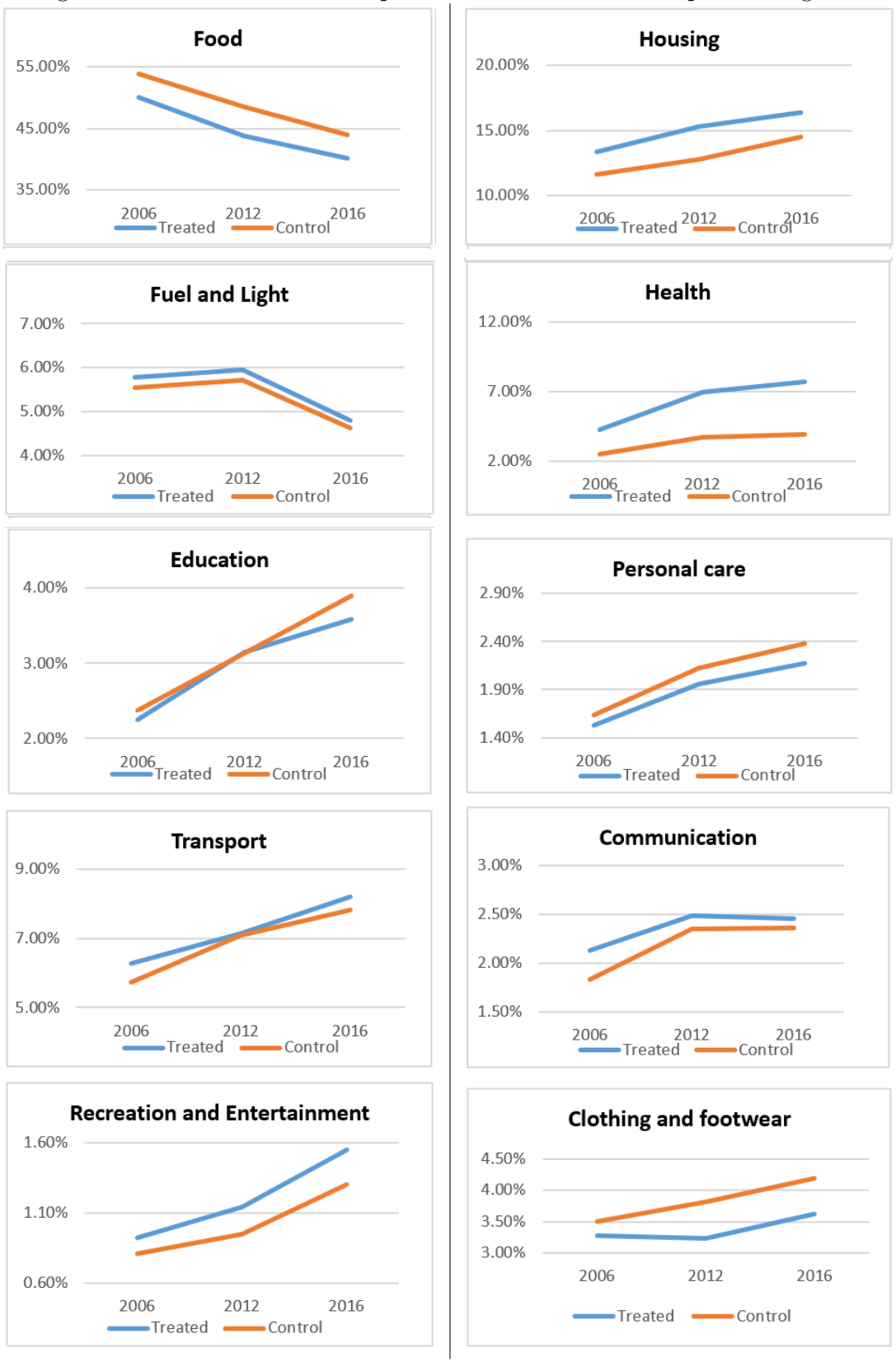
*** p<0.01, ** p<0.05, * p<0.1

Table 3.6.2: Average treatment effect of having C-NCDs on household consumption (Treated group: Households with C-NCDs, Control group: Households with no NCDs)

	2006			2012			2016		
	Control	*Treated*	*Diff (T-C)*	*Control*	*Treated*	*Diff (T-C)*	*Control*	*Treated*	*Diff (T-C)*
Food	0.535	0.522	-0.013***	0.476	0.459	-0.017***	0.44	0.421	-0.019***
Cereals bread and pulses	0.162	0.156	-0.006***	0.149	0.147	-0.002	0.133	0.128	-0.005***
Fruit, vegetables, and yam	0.067	0.064	-0.003***	0.061	0.058	-0.003***	0.055	0.053	-0.002***
Meat, fish, and egg	0.082	0.082	-0.001	0.081	0.078	-0.003***	0.079	0.074	-0.006***
Milk and milk products	0.037	0.038	0.001***	0.035	0.036	0.001*	0.028	0.03	0.002***
Coconut and oil products	0.038	0.037	-0.001*	0.042	0.04	-0.002***	0.037	0.036	-0.001***
Sugar, confectionary, and beverages	0.047	0.046	-0.001*	0.043	0.041	-0.002***	0.039	0.037	-0.002***
Condiments and other foods	0.074	0.073	-0.001	0.044	0.042	-0.002***	0.044	0.043	-0.001**
Liquor and tobacco	0.029	0.025	-0.003***	0.022	0.017	-0.004***	0.023	0.019	-0.004***
Housing	0.131	0.14	0.009***	0.152	0.161	0.009***	0.167	0.173	0.006***
Fuel and Light	0.057	0.061	0.003***	0.059	0.063	0.003***	0.049	0.051	0.002***
Health	0.024	0.052	0.028***	0.047	0.106	0.059***	0.042	0.104	0.062***
Education	0.025	0.024	-0.002*	0.032	0.033	0.001	0.035	0.037	0.002**
Personal care	0.016	0.016	0	0.021	0.021	0	0.023	0.023	-0.001***
Transport	0.061	0.066	0.004***	0.074	0.075	0.001	0.082	0.086	0.004***
Communication	0.022	0.022	0	0.027	0.026	-0.001**	0.026	0.026	-0.001
Recreation and Entertainment	0.008	0.01	0.001*	0.011	0.012	0.001*	0.015	0.016	0.002***
Clothing and Footwear	0.035	0.034	0	0.038	0.034	-0.004***	0.04	0.038	-0.002***
Household services	0.002	0.002	0	0.003	0.003	0	0.003	0.004	0
Nondurable goods	0.011	0.011	0.000***	0.011	0.011	0.000*	0.011	0.011	-0.000***
Durable goods	0.026	0.024	-0.002	0.017	0.019	0.001	0.026	0.026	0
Other	0.069	0.068	-0.001	0.08	0.083	0.004*	0.082	0.089	0.006***

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

Figure 3.6.2: Trends of the expenditure shares of consumption categories



Notes: The graphs show the shares of each consumption category in 2006, 2012 and 2016. The expenditure shares were calculated after deflating each expenditure for price changes.

Table 3.6.3: Results of the Matched difference in difference estimator

	MDID for c-NCDs		
	2006-2012	2012-2016	2006-2016
Food	-0.004	-0.002	-0.006
Cereals bread and pulses	0.004*	-0.003*	-0.001
Fruit, vegetables, and yam	0	0	0
Meat, fish, and egg	-0.002*	-0.003**	-0.005***
Milk and milk products	-0.001	0.001	0
Coconut and oil products	-0.001*	0.001	0
Sugar, confectionary, and beverages	-0.001*	0	-0.001
Condiments and other foods	-0.001**	0.001***	0
Liquor and tobacco	-0.001	0	-0.001
Housing	0	-0.003	-0.003
Fuel and Light	0	-0.002**	-0.002**
Health	0.032***	0.002	0.034***
Education	0.003***	0.001	0.004***
Personal care	0	-0.001**	-0.001*
Transport	-0.004***	0.003*	-0.001
Communication	-0.001	0	-0.001
Recreation and Entertainment	0	0	0
Clothing and Footwear	-0.003***	0.002**	-0.001**
Household services	0.001	0	0.001
Nondurable goods	0	-0.001***	-0.001***
Durable goods	0.003**	-0.001	0.002
Other	0.005*	0.003	0.008***

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

monetary terms, with respect to mean household expenditures in 2012, a household with C-NCD spent 736 rupees more on health compared to a similar household with C-NCDs in 2006. Similarly, in 2016, a household with C-NCD spent 872 rupees more on health compared to a similar household in 2006. Since these values are calculated based on price-deflated expenditures, the changes in amounts are real changes. This suggests that households with C-NCDs spent significantly higher out-of-pocket expenses for health in 2016 than in 2006. This could be due to either increase in C-NCD individuals in the households (multiple C-NCD cases) or C-NCD individuals seeking more private healthcare which leads to higher out-of-pocket spending.

It is noteworthy that the MDID estimator for health expenditures of the 2012-

2016 period is not significant. This means the expenditure increase from 2006 to 2012 is responsible for the total change of out-of-pocket health expenditures during the full period from 2006 to 2016. These results are in line with our data for public health expenditures. We saw that public health expenditure was 2% of GDP in 2006 and it reduced to 1.1% in 2012. In 2016 it increased to 1.5% of GDP. Accordingly, our results of the MDID estimator show that the highest increase in out-of-pocket expenditures of households with C-NCDs occurred during the period that public health provision was decreasing.

As we discussed earlier, the increasing health expenditures due to C-NCDs mostly crowded out the spending on food. However, our MDID estimator does not show any change in the crowding-out of food during the reference period. Instead, it shows that the crowding-out of different food categories was changed. The highest crowding-out was placed on the consumption of meat fish and eggs. For example, households with C-NCDs in 2016 spent 0.5 percentage points less share on meat fish and eggs than similar households with C-NCDs in 2006. The changes in crowding-out of food categories during 2006-2012 are more underlined than in the 2012-2016 period. Compared to 2006, the households with C-NCDs in 2012 spent lower shares on most of the food categories except cereals.

The crowding-out effect of health expenditures due to C-NCDs on non-food consumption has also been changed during the reference period. In 2012, households with C-NCDs spent 0.4 percentage points lower share on transport and 0.3 percentage points lower shares on clothing and footwear than similar households in 2006. Compared to 2012, households with C-NCDs spent 0.2 percentage points lower share for fuel and light in 2016. However, we noted that in 2012 they spent 0.3 percentage points higher share on education than similar households in 2006. Similarly, those households spent 0.1% less share on personal care and non-durable goods in 2016 compared to 2012.

3.6.3 Crowding-out effect by household income

Table 3.6.4 presents the ATT of C-NCDs and the changes of ATT (MDID) by three income groups. The results show that low-income households suffer from higher out-of-pocket healthcare expenditures than high-income families due to C-NCDs. For example, those households with income below 20000 spent 6 percentage points higher share on health when they had C-NCD individuals in the household compared to similar healthy families in 2012. But, for high-income families (50000-10000) the ATT was only 4 percentage points. Considering the changes in the C-NCD impact on health expenses, the ATT of low-income households increased by 3.2 percentage points from 2006 to 2016. There was no increase in the ATT for the highest income category. However, there is a 4 percentage point increase in the ATT of C-NCDs on health expenses of middle-income households (income between 20000-50000) during the reference period. The lower impact on healthcare expenditures of high-income categories could be due to the fact that the probability of having private health insurance is higher for high-income families than for low-income families. Hence they could pay for their healthcare through private health insurance without making out-of-pocket expenses.

Households' coping ability with higher healthcare expenditures relates to household income. As the results indicate, lower-income households (income below 20000) experience a larger crowding-out on food compared to higher-income households due to healthcare expenditures. For example in 2006, the food shares of the lowest-income households crowded by 1.4 percentage points, whereas it improved by 2 percentage points for the highest-income group. It suggests that low-income families may have sacrificed some of their food expenses to cover the healthcare cost of ill members. In contrast, when there are members with C-NCDs in high-income households, they may spend more on healthy food, which is generally expensive, and thereby the food share rises. However, the MDID estimator shows that food shares of high-income families crowded due to C-NCDs in 2016 compared to 2006,

suggesting that healthcare costs become a burden to them as well.

3.6.4 A comparison: Crowding-out effect of health expenditures of other types of NCDs

As an extension of the study, we intend to identify the differential impacts of C-NCDs and other types of NCDs on household consumption. Hence, we conducted the same analysis as above for households with other types of NCDs. In that case, the treatment group is the households with individuals with other types of NCDs, and the control group is the households that do not have any kind of NCD individuals[9].

Table 3.6.5 presents the ATT and the changes of ATT (MDID) of other types of NCDs on each of the consumption categories. The full results of the ATT are given in Appendix 3.B. Similar to the households with C-NCDs, those households with other NCDs also spend a significantly higher share on healthcare, and the shares increased from 2006 to 2016. Compared to non-NCDs households, those households with other NCDs spent 4.8 percentage points higher share on health in 2006, 5.7 percentage points in 2012 and 6.2 percentage points in 2016. It is noteworthy that the health expenditure share of other NCDs was 2 percentage points higher than the C-NCDs in 2006. However, that difference was eliminated by 2016. Unlike households with C-NCDs, those households with other NCDs do not spend higher shares on housing but spend 0.3 percentage points higher shares on transport and 0.1 to 0.2 percentage points higher shares on fuel and light. Further, they spend 0.1 to 0.4 percentage points higher shares on durable and non-durable goods than non-NCDs households.

Considering the crowding-out effect, the healthcare expenditures due to ill-health have crowded out a few other consumptions. Households with other types of NCDs spend 0.5 to 0.6 percentage points lower shares on food compared to non-NCDs households. This is comparably lower than the effect of C-NCDs on food shares.

[9]At this stage, we excluded the households with C-NCDs from the sample

Table 3.6.4: Crowding-out effect of healthcare expenses due to C-NCDs by household income

	Income below 20000				Income 20000 -50000				Income 50000 -100000			
	ATT 2006	ATT 2012	ATT 2016	MDID 2006-16	ATT 2006	ATT 2012	ATT 2016	MDID 2006-16	ATT 2006	ATT 2012	ATT 2016	MDID 2006-16
Food	-0.014***	-0.014***	-0.018***	-0.005	-0.003	-0.008**	-0.003	0.000	0.018**	0.008	-0.011*	-0.029***
Housing	0.011***	0.014***	0.011***	0.000	0.006*	0.004	0.004	-0.002	0.002	0.005	-0.008	-0.010
Fuel and Light	0.004***	0.004***	0.001*	-0.002*	0.004***	0.004***	0.004***	-0.000	0.003	0.003**	0.002	-0.001
Health	0.031***	0.064***	0.063***	0.032***	0.023	0.053***	0.064***	0.041**	0.016*	0.038***	0.044**	0.028**
Education	-0.002***	0	0.001	0.003**	-0.003	0.001	0.002	0.005**	-0.008	0.008	0.007	0.015*
Personal care	0	0	-0.000	-0.000	0	0	-0.000	-0.000	0	0	-0.001**	-0.002
Transport	0.003**	0.001	0.004***	0.001	0.006***	-0.003*	0.001	-0.005	-0.011	-0.004	-0.007	0.004
Communication	0	-0.002***	-0.001***	-0.001*	-0.001	0	-0.001	0.000	0.001	0	0.001	0.001
Recreation and Entertainment	0	0.001***	0.002***	0.002**	0.001	0.001	-0.002*	-0.002*	0.004	0.005	0.008**	0.004
Clothing and Footwear	-0.001	-0.004***	-0.002***	-0.001	-0.002*	-0.005***	-0.002*	0.000	0.007***	-0.002	-0.008***	-0.015***
Household services	0**	0	0.000	0.001**	0	0	0.001**	0.001*	0	-0.004*	-0.002	-0.001
Nondurable goods	0.001***	0***	-0.000	-0.001***	0.001***	0*	-0.000	-0.001***	0	0	0.000	-0.000
Durable goods	0	0	0.000	0.001	-0.004*	0	-0.004**	-0.000	0	0.005	-0.005	-0.005
Other	-0.001	-0.001	0.002	0.003	-0.005	0.005	-0.001	0.003	-0.013	-0.025*	0.021**	0.035**

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

Table 3.6.5: ATT and MDID estimator for households with other types of NCDs

	ATT			MDID		
	2006	2012	2016	2006-2012	2012-2016	2006-2016
Food	-0.005*	-0.006**	-0.006**	-0.001	0	-0.001
Cereals bread and pulses	-0.001	0.004**	0.004***	0.005**	0	0.005**
Fruit, vegetables, and yam	-0.001**	-0.003***	-0.002***	-0.001	0.001	0
Meat, fish, and egg	-0.003***	-0.006***	-0.008***	-0.003**	-0.001	-0.004***
Milk and milk products	-0.001*	0	0.001***	0.001	0.002**	0.002***
Coconut and oil products	0	0	0	0	0	0
Sugar, confectionary, and beverages	0.001	0	-0.001	0	-0.001	-0.001**
Condiments and other foods	0.001	-0.001	0	-0.001	0	-0.001
Liquor and tobacco	0	-0.001	-0.001	-0.001	0	-0.001
Housing	0	0	-0.003*	-0.001	-0.003	-0.004
Fuel and Light	0.001**	0.002***	0.001	0	-0.001	-0.001
Health	0.048***	0.057***	0.062***	0.009**	0.005*	0.014***
Education	-0.002**	0	0	0.001	0.001	0.002
Personal care	0	0.001***	0	0.001**	-0.001**	0
Transport	0.003***	0.003**	0.002	0	-0.001	-0.001
Communication	-0.002***	-0.003***	-0.002***	-0.001	0	-0.001
Recreation and Entertainment	0.002***	0.001*	0.001*	-0.001	0	-0.001
Clothing and Footwear	-0.002 ***	-0.003***	-0.002***	-0.001	0.001	0
Household services	0	0	0.001***	0	0.001	0.001**
Nondurable goods	0.001***	0.001***	0	0	-0.001***	-0.001***
Durable goods	0.002**	0.004***	0.003***	0.002	-0.001	0.001
Other	0.001	0.001	0.005***	0	0.004	0.004

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

Similarly, the crowding-out on different food categories was also relatively insignificant for other NCDs compared to C-NCDs. However, those households spent 0.2 to 0.3 percentage points lower on communication, clothing and footwear than households with no NCDs.

With respect to the Changes in the crowding-out effect, the MDID estimator shows some differences in the expenditure share gap between households with C-NCDs and other NCDs during the reference period. As we noted earlier, the households with C-NCDs spent 3.4 percentage points higher share on health in 2016 compared to 2006, whereas the health expenditure share gap for the households with other NCDs was 1.4 percentage points. The reason for the lower gap is that households with other NCDs spent a higher share on health in 2006 compared to C-NCDs, and by 2016 both types of NCDs caused a similar increase in out-of-pocket health expenses. This suggests that households with C-NCDs spent significantly higher out-of-pocket expenses for health than the households with other NCDs when moving from 2006 to 2016.

Similar to the C-NCDs there is no significant change in the crowding-out effect on food due to other NCDs during the reference period. However, C-NCDs as well as other NCDs households spent lower shares on meat fish and eggs in 2012 and 2016 compared to 2006. We saw that households with C-NCDs in 2012 spent lower shares on most of the food categories compared to 2006, however, that change cannot be seen for households with other NCDs for the same period. Similarly, unlike C-NCDs, the crowding-out effect of health expenditures due to other NCDs on the rest of the consumption categories has not changed much in the reference period.

We compared the effect of other NCDs on household consumption by household income, and the results presented in Table 3.6.6. Similar to C-NCDs the effect of other NCDs on health expenditures vary by household income; the higher burden of out-of-pocket healthcare expenses is placed when household income is low compared to the middle to high income. With respect to the crowding-out effect on other

Table 3.6.6: Crowding-out effect of healthcare expenses due to other NCDs by household income

	Income below 20000				Income 20000 -50000				Income 50000 -100000			
	ATT 2006	ATT 2012	ATT 2016	MDID 2006-16	ATT 2006	ATT 2012	ATT 2016	MDID 2006-16	ATT 2006	ATT 2012	ATT 2016	MDID 2006-16
Food	-0.008***	-0.005*	-0.009***	-0.001	-0.006	-0.005	-0.003	-0.010***	0.004	0.002	-0.010*	-0.014*
Housing	0.001	0.002	0.003	0.002	0	-0.004	-0.010**	0.003	-0.011	0.004	-0.008	0.003
Fuel and Light	0.001**	0.003***	-0.000	-0.002	0.001	0	0.002**	0.001	-0.001	0	0.002	0.003
Health	0.045***	0.068***	0.073***	0.029***	0.023***	0.035***	0.057***	0.034**	0.016	0.051***	0.045**	0.029
Education	-0.001	0	0.001	0.002	-0.004**	-0.001	-0.000	0.004	0.01	-0.001	0.007	-0.003
Personal care	0	0.001***	0.000	0.000	0	0.001**	-0.000	-0.001	0	0.001*	-0.002***	-0.002**
Transport	0.005***	0.003***	0.005***	-0.000	0.003	0	-0.001	-0.004	-0.031***	0.011	-0.006	0.025*
Communication	-0.001***	-0.003***	-0.002***	-0.001	-0.002***	-0.002***	-0.002**	0.001	-0.002	-0.001	-0.004**	-0.002
Recreation and Entertainment	0.001**	0.001**	0.001***	0.000	0.004***	0.003**	0.001	-0.003*	0.019	0.022	0.006	0.005
Clothing and Footwear	-0.002**	-0.003***	-0.002***	-0.001	-0.002**	-0.003***	0.000	0.003*	-0.001	-0.001	-0.007***	-0.006*
Household services	0	0	0.000***	0.000*	0	0	0.001**	0.001	0.001	-0.003	0.004	0.003
Nondurable goods	0.001***	0.001***	-0.000	-0.001***	0.001***	0**	0.000	-0.001***	0	0	0.000	0.000
Durable goods	0.001	0.001	0.002**	0.001	0.006***	0.006**	0.001	-0.005	0.009	0.026***	0.010	0.000
Other	0.002	-0.001	0.002	0.001	-0.002	0.006	0.010***	0.012**	0.02	-0.039**	0.010	-0.010

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

consumption categories, the negative impacts of C-NCDs on food and clothing are higher than that of other NCDs. For example, in 2016, C-NCDs caused a 2 percentage point reduction in food share in low-income households, while other NCDs caused a 1 percentage point reduction. It is noteworthy that the changes in the crowding-out effect from 2006 to 2016 of middle to high-income earners. Compared to 2006, their food shares are crowded out by 3 percentage points due to C-NCDs in 2016, whereas it was 1.4 percentage points due to other NCDs. The crowding-out effect on clothing increased by 1.5 percentage points due to C-NCDs, whereas it was 0.6 percentage points due to other NCDs.

3.6.5 Sensitivity analysis

Our MDID estimations are based on assumptions. particularly we assumed that the set of variables used for matching contains all the information available about the expenditure patterns at the point of selecting a household as a C-NCDs household. We partially tested the compliance of our estimations with this assumption by estimating the MDID estimators for one particular NCD category, i.e. diabetes. The results are presented in Table 3.6.7. The size and the direction of MDID estimators for the expenditure share of different consumption categories of individuals with diabetes are close to the similar estimators for the c-NCDs group partially suggesting the validity of the variables we incorporated in the model.

3.7 Discussion

This paper aimed to examine the crowding-out effect of out-of-pocket healthcare expenditures on household consumption of other goods and services. We particularly focused on the healthcare expenditures raised through five chronic NCDs (C-NCDs): heart diseases, diabetes, high blood pressure, cancer, and asthma. Those C-NCD prevalence rates have been growing fast during the last two decades in Sri Lanka.

Table 3.6.7: Results of the MDID estimator: Treated group- diabetes

	Diff (T-C)	Diff (T-C)	Diff(T-C)	MDID	MDID	MDID
	2006	2012	2016	2006-12	2012-16	2006-16
Food	-0.02***	-0.023***	-0.019***	-0.003	0.005	0.002
Housing	0.017***	0.012***	0.011***	-0.005*	-0.001	-0.006*
Fuel and Light	0.007***	0.007***	0.004***	0.00	-0.003***	-0.003***
Health	0.026***	0.064***	0.055***	0.038***	-0.009	0.029***
Education	-0.002	0.001	0.00	0.003*	-0.001	0.001
Personal care	0.00**	0.001	-0.001***	0.001**	-0.001***	-0.001**
Transport	0.005***	0.001	0.003*	-0.005**	0.002	-0.003
Communication	0.002***	0.00	0.00	-0.002***	0	-0.001**
Recreation and Entertainment	0.003***	0.001	0.002***	-0.002*	0.002	0.00
Clothing and Footwear	-0.002***	-0.004***	-0.004***	-0.002***	0.001	-0.002**
Household services	-0.001	0.001**	0.00	0.001**	0	0.001
Nondurable goods	0.00	0.00	0.00**	0	0	0.00
Durable goods	-0.005***	0.001	-0.002	0.007***	-0.003	0.003*
Other	-0.004	0.004***	0.005**	0.008**	0.001	0.009***

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

We employed repeated cross-sectional data from Household Income and Expenditure Survey, Sri Lanka in three time periods, 2006, 2012 and 2016. We noticed an overall reduction in public healthcare expenditures during that period, while the reduction is prominent from 2006 to 2012. Hence we examined the evolution of the crowding-out effect of out-of-pocket healthcare expenditures caused by C-NCDs according to the changes in government healthcare expenditures as well. The propensity score matching method was used to find the crowding-out effect of the healthcare expenditures while applying the matched difference-in-difference(MDID) method to identify the changes in the crowding-out effect during the examined period. To distinguish the impact of C-NCDs, we carried out a similar analysis for other types of NCDs and compared the results.

Our descriptive analysis disclosed that the percentage of households with C-NCDs had increased considerably from 2006 to 2016. The highest percentage increase was recorded for cancer. This could be due to the advancement of diagnostic technology that upsurges the identified number of cancer cases, besides the actual rise in cancer incidents. Similarly, the 50% increase in diabetes prevalence is also alarming since diabetes creates an additional risk for individuals' health apart from the disease-specific effects. It has been found that diabetes remains a risk factor for

the prevalence and the of other NCDs(Márquez and Bajdan, 2021) and severity of the infection of infectious diseases such as Covid-19 (Nikoloski et al., 2021; WHO, 2020).

It is noteworthy that the head of the household was diagnosed with NCDs for nearly one-third of families. Therefore, the economy of those households with C-NCDs could be adversely affected due to the negative impacts of ill-health. However, we noticed that the mean expenditure of households, which can be used as a proxy for household income, with C-NCDs was higher compared to the households with healthy individuals, implying that those households are relatively rich. Yet, the mean difference in income between the two types of households decreased from 2012 to 2016 indicating that the C-NCDs households were relatively less affluent in 2016 than similar households in 2012. This downward trend indicates either a decrease in actual income of C-NCDs households due to the ill-health of household members or the prevalence of C-NCDs has become more common among low and middle-income households and thereby the mean value diminished. Either way, this gives an alarming signal that the household economy of C-NCD individuals' is deteriorating.

The results of our primary analysis revealed that having an individual with C-NCDs in the household caused a significant increase in healthcare expenditure shares in all three periods. This finding is in line with the previous literature, which found that NCDs generate higher out-of-pocket expenditures for healthcare within households. (Kien et al., 2017; Kumara and Samaratunge, 2016; Kundu et al., 2018; Lee et al., 2015; Murphy et al., 2020; Pallegedara, 2018; Pati et al., 2014; Wang et al., 2015). The highest impact on out-of-pocket expenses due to C-NCDs was recorded in 2012. It is significant that 2012 was the year that we identified the lowest public healthcare spending on health. Our MDID estimator also revealed that C-NCDs' effect on health expenditure has grown from 2006 to 2012, while there was no significant change from 2012 to 2016 when there was a slight increase in public spending. Accordingly, this evidence discloses that the

highest burden of out-of-pocket healthcare expenditures due to C-NCDs is placed on households when government healthcare expenses are at a deficient level. Therefore, the study confirms that public healthcare provision plays a major role in C-NCD care in the country. It is crucial due to the fact that 90% of inpatient care in the country is financed by the government (Kumar, 2019). Therefore, enhancing public healthcare provision in C-NCD care is crucial to lessen the household burden of out-of-pocket expenditures. However, the limited availability of public funds that the country faces at the macroeconomic level would restrict the public provision of healthcare, so alternative methods should be investigated to minimize the pressure on the household economy.

Our analysis based on different income levels of households shows that low-income families suffer from higher out-of-pocket healthcare expenditures than high-income families due to C-NCDs. These out-of-pocket expenditures rise mainly through private outpatient medication, prescription and testing. Even though free healthcare provided by the government is available for everyone, the pressure on the demand for public healthcare is extensive. Hence seeking private healthcare is common even in low-income households, especially for outpatient care (De Silva et al., 2016). It is crucial that a national health insurance scheme has not been introduced to date in Sri Lanka although the private sector plays a significant role in the healthcare provision (Kumar, 2019). In the absence of health insurance, the healthcare cost is mostly covered as out-of-pocket expenditures by households. On the other hand, occupation-based private health insurance schemes exist in the country, so the ownership of health insurance relates to individuals having better-established jobs linked with higher pay. This could be the reason that high-income families suffer less from higher out-of-pocket healthcare expenditures than low-income families due to C-NCDs. This emphasizes the importance of having national health insurance to cover the healthcare cost of low-income families to reduce the burden of out-of-pocket expenditures.

Further, we found that the impact of C-NCDs on health expenses is rising in middle-income households during the 2006- 2016 period. Previously we suggested that the prevalence of C-NCDs has become more common among low and middle-income households based on the mean income difference between the two groups of households. Hence the rise in overall prevalence rates of C-NCDs during our reference period could be a result of the rise in multimorbidity in middle-income households. These results confirm the findings that show a higher level of health-care utilisation and greater financial burden associated with a higher prevalence of C-NCDs among individuals in middle-income groups (Checkley et al., 2014; Katz-marzyk et al., 2022; Lee et al., 2015).

The presence of individuals with C-NCDs in the household increased not only the healthcare expenses but also some other expenses of the household such as housing, transport, and communication. When a household has an individual with a particular disease, it is reasonable to assume that those households must incur higher costs on transport since they often travel to a hospital for treatment. This is noteworthy when individuals seek private medical care, or specialists care as those services are typically available in main cities. In case of hospitalisation for long-term treatment, the household members may have to find accommodation near the hospital so the housing expenditures will rise. This is particularly the case for cancer patients since cancer treatments are concentrated in only a few hospitals in the country.

We found that the increasing expenditure shares, mainly health expenses, caused by C-NCDs have crowded out the other consumption of other goods and services, especially food expenses. The results for different food categories also confirmed that having C-NCD individuals in the household decrease the consumption of almost all foods, while the impacts on foods such as cereals, bread, pulses, meat, fish and egg are high in 2016 compared to 2012. Other than the food, we observed that the spending on clothing and footwear, personal care and non-durable goods were

also crowded by healthcare spending due to C-NCDs. This implies that overall, household welfare is adversely affected due to C-NCDs, especially because of the out-of-pocket healthcare costs that households have to bear. Hence, a policy which is directed to reduce the household healthcare cost burden is necessary to enhance the welfare of families with C-NCDs.

Our results further show that the coping ability of household consumption level of other goods and services without larger falls due to increasing out-of-pocket expenses depends on household income. Households with higher incomes can manage their normal consumption level of food in the presence of C-NCDs, whereas low-income families sacrifice some of their food expenses to cover the healthcare cost of ill members. In contrast, we saw food shares rising due to C-NCDs in high-income households. Presumably, those high-income households consume more healthy food, which is generally expensive, as the NCD care is combined with a healthy diet (Afshin et al., 2017), and they can afford the cost of those foods. However, moving from 2006 to 2016, we saw that the crowding-out expanded to high-income families as well. This suggests that the upsurge of C-NCD prevalence in the country brought new burdens even to households with high incomes.

We compare the crowding-out effect of out-of-pocket healthcare expenditures caused by C-NCDs with the impact of other types of NCDs. The results revealed that the impact on healthcare expenses due to other NCDs is similar to the impact of C-NCDs. Both types of NCDs increase the household burden of out-of-pocket healthcare expenses, and the burden increased from 2006 to 2016. However, we saw a difference between the C-NCDs and other NCDs in terms of the changes in the impact. There is a larger increase in out-of-pocket health expenses due to C-NCDs than other NCDs during the reference period reflecting the increasing burden of C-NCDs on the household economy. This could be either due to the increasing prevalence of C-NCDs, such as multiple NCD individuals in households or the increase in treatment costs of the existing NCD individuals due to the tendency to-

wards seeking private medical care for NCD treatment. Further, we identified that the crowding-out of healthcare expenses on other consumption categories is different between the two types of NCDs. Food expenditures are crowded-out more due to C-NCDs than other NCDs. The income-specific analysis provides more insights and reveals that the difference in the impact of the two types of NCDs is more prominent among middle to high-income households. At the beginning of the reference period, their food consumption had not been crowded by health expenses. Still, it was crowded by 2016, implying that the C-NCDs burden is high among high-income households than the burden of other NCDs.

The study has some limitations. There could be missing variables that we were unable to incorporate in matching due to the limitation of data. However, we did a sensitivity analysis based on one c-NCD condition to check the impact of the missingness of variables partially. On the other hand, we were unable to fully address the endogeneity of the variable of interest- the C-NCDs status of households. We assumed that conditional on the covariates, the C-NCDs status is exogenous. However, it is very likely that omitted variables that we cannot control are correlated with C-NCDs and outcome variables. For example, the quality of the goods and services that households consume may relate to the C-NCDs. Finally, the health expenditure data that we encountered consist of all measurable expenditures on health. However, other than these direct expenditures on health, people could have used other traditional healers for controlling and treating NCDs. That could lead to underestimating the impact of NCDs on health expenditures.

3.8 Conclusion

This study analysed the crowding-out effect of out-of-pocket healthcare expenses caused by C-NCDs on other consumption categories of a household. Similarly, it examined the role of public healthcare provision in changing the crowding-out effect.

We employed three waves of household income and expenditure survey in Sri Lanka, 2006, 2012 and 2016, and we show that the C-NCD prevalence rates have increased during this time while the public healthcare provision has been contracted. We tried to overcome, although partially, the empirical challenge - the endogeneity of the variables of interest associated with the modelling of household consumption behaviour and applied a matching method to find the crowding-out effect of healthcare expenditures caused by C-NCDs. We used Matched difference-in-difference method to explore the changes in the crowding-out effect during the reference period.

We show that C-NCDs cause a significant increase in out-of-pocket expenditure for the healthcare of households in all three periods while the highest burden was placed on households when government healthcare expenses are deficient. Similarly, we proved that the rise in the healthcare expenses of households is higher due to C-NCDs than other types of NCDs. We found that low-income families suffer from higher out-of-pocket healthcare expenditures due to C-NCDs than high-income families as they do not have an alternative mechanism to cover the healthcare cost. The study adds evidence to the existing literature that discusses the greater financial burden associated with a higher prevalence of C-NCDs among individuals in middle-income groups. We show that the healthcare expenditures caused by C-NCDs have crowded out the consumption of other goods and services, especially food expenses, and that crowding-out is larger than such outcome due to other types of NCDs. The coping ability of a household to maintain consumption levels, in the rising out-of-pocket expenses, depends on household income. However, we noticed that by the later part of the reference period, the crowding-out trickled to the medium to high-income households as well.

In summary, the study urges the importance of addressing the rising healthcare financing issues related to C-NCDs in households that are deprived of household welfare. Public healthcare provisions play a significant role in C-NCD care, and it reduces the household burden of out-of-pocket healthcare spending. However,

with respect to the limited availability of public funds that the country faces at the macroeconomic level, it would restrict the public provision of healthcare, and therefore, the NCDs care should be targeted at the most affected groups- the low and middle-income households. It is an urging requirement to implement national health insurance in the country to cover the healthcare cost of low and middle-income families to reduce their burden of out-of-pocket healthcare expenditures.

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Appendix

3.A Appendix: Difference of the mean expenditure shares of households with other NCDs

Table 3.A.1: Difference of the mean expenditure shares of households with other NCDs

	2006			2012			2016		
	other NCDs	non-NCDs	Difference	other NCDs	non-NCDs	Difference	other NCDs	non-NCDs	Difference
Food	53.49%	53.83%	-0.33	47.37%	48.65%	-1.28%***	43.01%	44.01%	-0.99%***
Housing	11.66%	11.72%	-0.05	12.92%	12.86%	0.06	14.64%	14.46%	0.18
Fuel and Light	5.60%	5.54%	0.06	5.68%	5.73%	-0.05	4.63%	4.65%	-0.02
Health	4.24%	2.00%	2.24%***	7.24%	3.02%	4.22%***	8.11%	2.92%	5.19%***
Education	2.11%	2.46%	-0.35%***	2.83%	3.22%	-0.39%***	3.35%	4.03%	-0.68%***
Personal care	1.61%	1.64%	-0.03	2.10%	2.13%	-0.03	2.29%	2.40%	-0.12%***
Transport	5.61%	5.80%	-0.19	6.94%	7.12%	-0.18	7.66%	7.94%	-0.28%*
Communication	1.62%	1.90%	-0.28%***	2.12%	2.42%	-0.30%***	2.17%	2.41%	-0.24%***
Recreation and Entertainment	0.91%	0.78%	0.13%***	1.03%	0.94%	0.09	1.40%	1.29%	0.12%*
Clothing and Footwear	3.22%	3.57%	-0.34%***	3.42%	3.90%	-0.48%***	3.72%	4.28%	-0.56%***
Household services	0.17%	0.19%	-0.02	0.24%	0.23%	0.01	0.31%	0.24%	0.07%**
Nondurable goods	1.20%	1.12%	0.08%***	1.21%	1.16%	0.05%***	1.10%	1.12%	-0.02
Durable goods	2.49%	2.52%	-0.03	2.03%	1.75%	0.27%**	2.66%	2.62%	0.04
Other	6.06%	6.94%	-0.88	7.30%	7.88%	-0.58%**	8.15%	8.78%	-0.63%***

Notes: Shares were calulated using price-deflated expenditures
*** p<0.01, ** p<0.05, * p<0.1

3.B ATT of having other types of NCDs on household consumption

Table 3.B.1: ATT of having other types of NCDs on household consumption

	2006			*2012*			*2016*		
	Control	*Treated*	*Diff (T-C)*	*Control*	*Treated*	*Diff (T-C)*	*Control*	*Treated*	*Diff (T-C)*
Food	0.564	0.559	-0.005*	0.504	0.497	-0.006**	0.458	0.452	-0.006**
Cereals bread and pulses	0.173	0.172	-0.001	0.159	0.164	0.004**	0.14	0.144	0.004***
Fruit, vegetables, and yam	0.07	0.069	-0.001**	0.064	0.062	-0.003***	0.058	0.057	-0.002***
Meat, fish, and egg	0.082	0.079	-0.003***	0.082	0.076	-0.006***	0.08	0.073	-0.008***
Milk and milk products	0.037	0.036	-0.001*	0.035	0.035	0	0.029	0.03	0.001***
Coconut and oil products	0.042	0.042	0	0.046	0.046	0	0.04	0.04	0
Sugar, confectionary, and beverages	0.049	0.049	0.001	0.046	0.046	0	0.04	0.04	-0.001
Condiments and other foods	0.079	0.08	0.001	0.047	0.046	-0.001	0.046	0.045	0
Liquor and tobacco	0.032	0.032	0	0.024	0.023	-0.001	0.025	0.024	-0.001
Housing	0.122	0.122	0	0.136	0.136	0	0.158	0.155	-0.003*
Fuel and Light	0.057	0.059	0.001**	0.058	0.06	0.002***	0.048	0.049	0.001
Health	0.023	0.071	0.048***	0.042	0.099	0.057***	0.041	0.103	0.062***
Education	0.024	0.022	-0.002**	0.03	0.03	0	0.034	0.035	0
Personal care	0.017	0.017	0	0.021	0.022	0.001***	0.024	0.024	0
Transport	0.056	0.059	0.003***	0.071	0.074	0.003**	0.079	0.081	0.002
Communication	0.019	0.017	-0.002***	0.025	0.022	-0.003***	0.025	0.023	-0.002***
Recreation and Entertainment	0.008	0.01	0.002***	0.01	0.011	0.001*	0.014	0.015	0.001*
Clothing and Footwear	0.035	0.034	-0.002 ***	0.038	0.036	-0.003***	0.041	0.039	-0.002***
Household services	0.002	0.002	0	0.002	0.003	0	0.003	0.003	0.001***
Nondurable goods	0.012	0.013	0.001***	0.012	0.013	0.001***	0.012	0.012	0
Durable goods	0.024	0.026	0.002**	0.017	0.021	0.004***	0.024	0.028	0.003***
Other	0.061	0.062	0.001	0.075	0.076	0.001	0.08	0.085	0.005***

Notes: The table shows the ATT of having other types of NCDs on household consumption (Treated group: Households with other types of NCDs, Control group: Households without NCDs

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

Chapter 4

COVID-19, Non-Communicable Diseases and Labour Market Outcomes

4.1 Introduction

Non-Communicable Diseases (NCDs), also known as chronic diseases, which tend to be of long duration and are the result of a combination of genetic, physiological, environmental and behavioural factors, are the key cause of death across the globe. It accounts for 74% of global deaths and an even higher proportion (75%) of premature adult deaths (WHO, 2022a). Besides their health risk, NCDs cause an extensive burden to the economy at micro and macro levels. The NCDs-driven economic concerns are markedly higher than those for infectious diseases, and it is estimated that the total cost of NCDs for the period 2011-2030 could be US$ 47 trillion (Bloom et al., 2011). However, these estimations need to be revised with the incident of the COVID-19 pandemic as it created disproportionate negative impacts on people with NCDs.

The COVID-19 outbreak started in December 2019 and rapidly spread across the globe, putting unprecedented pressure on human health and people's social and economic behaviours worldwide. The World Health Organization (WHO) officially declared the outbreak a pandemic in March 2020. The pandemic caused millions of deaths worldwide, and millions of people were left with long-term health conditions

(WHO, 2022b). It challenged public health officials in disease control and crisis management mechanisms across the globe, and many countries declared periods of lockdown, shutting many economic services in the economy, and causing a global economic crisis.

COVID-19 is an infectious disease, and it affects people with NCDs in different ways. First, people with NCDs have a greater risk of getting infected with COVID-19, and once they are infected their probability of ending up with severe health complications is high (ISDS, 2020; Roncon et al., 2020; Simonnet et al., 2020). More critically, death rates due to COVID-19 are much higher for individuals with NCDs compared to healthy individuals infected with it (Alqahtani et al., 2020; Nikoloski et al., 2021; Pal and Bhadada, 2020; WHO, 2020d). COVID-19 and NCDs share common risk factors, such as age, obesity, and smoking, and therefore, having one disease increases the probability of the infection of the other (Pan et al., 2021; Sheldon and Wright, 2020).

Secondly, the unprecedented pressure piled on the health sector with COVID-19 hindered NCDs individuals' access to healthcare for treatment and management of their pre-existing conditions. Providing facilities for diagnosis, treatment, and continuous care is at the core of ensuring people with NCDs benefit from the necessary care to control their condition, prevent complications, and ultimately prevent untimely death (PAHO, 2021). However, nearly all WHO member countries experienced a considerable degree of disruption of NCD services, leaving millions of people with NCDs unattended during the pandemic (WHO, 2020c). Health staff providing care for individuals with NCDs were deployed to support COVID-19 related care either fully or partially, creating substantial disruptions to the support for NCD patients (Jones et al., 2020; Pécout et al., 2021). Further, travel constraints and lockdowns limited the individuals' access to preventive services, hospital treatment and prescription medicines for NCDs (WHO, 2020c) and left them unattended by healthcare.

Thirdly, COVID-19-related lockdowns and self-isolation built a more disadvantaged environment for behavioural aspects of NCDs management. That increased exposure of individuals with NCDs to several behavioural risk factors for NCDs such as unhealthy diet, alcohol use, lack of physical activity and higher stress levels, potentially triggering new health issues. A study shows that 50% of NCD patients reported worsening of their medical condition during the pandemic, and 17% developed a new disease (Pécout et al., 2021). It is also found that patients who recover from COVID-19 are more likely to develop long-term chronic conditions (Nassereddine et al., 2021). Other than the deterioration of physical health, COVID-19 triggered mental health problems. Isolation and loss of personal relations hugely affected individuals' mental health, especially among young adults, women, and those with pre-existing mental health issues (Aknin et al., 2021; Knolle et al., 2021; POST, 2021; Serrano-Alarcón et al., 2022).

Large efforts have been devoted to understanding the relationship between COVID-19 and NCDs and have been widely discussed in the literature. However, little attention has been paid to the impact of COVID-19 on labour outcomes for individuals with pre-existing NCDs. The COVID-19 pandemic and related lockdowns hindered the labour market performances of individuals (Aygun et al., 2021; Borland and Charlton, 2020; Lemieux et al., 2020; Powell et al., 2022; Singh et al., 2022; Vassilev and Hamilton, 2021). It has been calculated that the total employment income in European countries decreased by -4.8% in 2020, with the most significant decreases due to absences and reduced work hours (Eurosta, 2020). Owing to the disproportionate risk of COVID-19 on NCD individuals, they were advised to take extra self-isolation measures during the pandemic's early months before the vaccine was introduced. On the other hand, Covid infections brought severe illness to NCD individuals; therefore, the time taken for a normal life would be long for them compared to healthy individuals. All these facts could negatively affect the labour market outcomes of individuals with NCDs.

In this paper we aim to analyse the effects of COVID-19 on the labour market outcomes of individuals with NCDs in the UK [1]. In particular, we examine the impact of the pandemic on (1) the likelihood of being employed or self-employed of individuals with NCDs (extensive margin); (2) the number of working hours they did during the pandemic (intensive margin). We use data from the Understanding Society COVID-19 study, a longitudinal study capturing the experiences and reactions of the UK population to the COVID-19 pandemic. The survey consists of nine waves from April 2020 to September 2021 and is built upon the UK Household Longitudinal Study. The COVID-19 study provides essential advantages to our study as each individual in the survey is linked to the mainstage household survey, allowing us to identify individuals' pre-pandemic socioeconomic and health status, which is essential to identify the impact of COVID-19.

We employ a difference-in-differences approach to estimate the average treatment effect on the treated of the pandemic on NCD individuals' labour market outcomes. We estimate two aspects of this impact: the extensive margin- the probability of employment and the intensive margin- the impact on the working hours. We find that COVID-19 decreased the likelihood of participating individuals with NCDs in the labour market and their labour supply. The impact varies by age, work type, the riskiness of the health condition to COVID-19, and at different stages of the pandemic. The adverse impacts on employment probabilities are linked with the severity of the pandemic whereas the work amount is not. The decline in working hours of people with NCDs continues as the pandemic proceeds, and a substantial reduction in their work is evident at the last stages of the pandemic compared to pre-pandemic levels.

The remainder of this paper proceeds as follows. In section 2, we discuss the literature that discusses the relationship between COVID-19 and NCDs. Section 3

[1]The UK experienced several stages of the COVID-19 pandemic, especially acute during the first and second waves, with several lockdown measures from March 2020 to March 2021, creating severe disruptions to ordinary life. The UK ranks among the first ten countries in the world worst hit by the pandemic.

describes the data used for the analysis, and section 4 explains the methodology we use. Section 5 presents the results, and the discussion is in section 6. Section 7 gives the conclusion of the study.

4.2 Literature

NCDs are long-term chronic health conditions that do not result from an infectious process. Those diseases are linked to genetic, physiological, environmental and behavioural factors. cardiovascular diseases, cancers, chronic respiratory diseases and diabetes are some of the major NCDs. On the other hand, COVID-19 is an infectious disease caused by the SARS-CoV-2 virus. COVID-19, or the novel coronavirus discovered in China in late December 2019, scattered across the world within a few months. By the end of January, the WHO declared the COVID-19 outbreak a public health emergency of international concern, and by mid-March, the outbreak was declared a global pandemic. From mid-March to late April, Europe became the epicentre of the pandemic reporting around 63% of global mortality from the virus within the region (WHOEurope, 2020).

Since the beginning of COVID-19, its impact on people with long-term health conditions or NCDs has been widely discussed. They were affected disproportionately by the pandemic in many aspects. The following literature provides an overview of the studies that have been done in relation to COVID-19 and NCDs.

4.2.1 NCDs and COVID-19

People with underlying health conditions, including cardiovascular diseases, diabetes, hypertension and cancer, have a higher risk of containing the novel coronavirus due to their lower immunity. More importantly, once they get infected by the virus, they have a much higher likelihood of developing a more severe form of the disease or fatal outcomes than an average patient (Nikoloski et al., 2021; PAHO,

2021; Pal and Bhadada, 2020; Wang et al., 2020; WHO, 2020d).

Early pandemic data in Italy shows that 98.8% of COVID-19 fatalities link to at least one comorbidity. 48.6% had at least three comorbidities. Hypertension was the most common comorbidity associated with Covid, as 73.3% of Covid cases reported hypertension (ISDS, 2020). In a study in France, the odds of developing severe COVID-19 were seven times higher in patients with obesity (Simonnet et al., 2020). Current smokers were 1.45 times more likely to have severe complications from COVID-19 and had a higher mortality rate (Alqahtani et al., 2020). Diabetes is the second more frequent comorbidity among COVID-19 patients and diabetic patients with COVID-19 are at higher risk of ICU admission (Roncon et al., 2020). Hypertension, diabetes, COPD, cardiovascular disease, and cerebrovascular disease are major risk factors for patients with COVID-19, as those conditions report 2.29, 2.24 and 5.97 odds ratios for Covid infections (Wang et al., 2020).

NCDs and COVID-19 share common risk factors such as advanced age, male sex, certain ethnicities or races, obesity, smoking, and poverty that reinforce adverse health effects (Pan et al., 2021). Covid -19 and NCDs are two epidemics that are closely connected and act synergistically on morbidity and mortality. Although communicable and Non-Communicable Diseases seem very different, distinguished by transmissibility and chronicity, they can be linked together through the concept of socially transmitted conditions. This means they share social, environmental, and commercial determinants of the prevalence. For example, both COVID-19 and NCDs such as diabetes are driven by urban design, housing, poverty, the availability of tobacco, alcohol, processed foods, and physical inactivity(Sheldon and Wright, 2020).

Evidence shows a two-way causality between major NCDs and severe outcomes of COVID-19. The synergistic relationship leaves people living with NCDs at a higher risk of developing severe COVID-19 complications, and patients who recover from COVID-19 are more likely to develop long-term chronic conditions (Nassereddine

et al., 2021). On the other hand, containment and mitigation measures for COVID-19 accelerate the NCDs prevalence. Mainly, staying at home, social distancing, and travel restrictions contributed to unhealthy lifestyles and risk behaviours such as unhealthy diet, smoking, excessive alcohol drinking, and physical inactivity (Pan et al., 2021). A study conducted in six EU countries (Belgium, France, Germany, Italy, Spain, and the UK) and the USA (Pécout et al., 2021) found that 64% of NCD patients adopted such negative behaviours. Accordingly, 50% of those NCD patients experienced a worsening of their medical condition during the lockdowns, and the main reason was the reduction or stoppage of physical activities. 54% of patients felt completely socially isolated during lockdowns and their stress levels increased. Further, 17% of NCD patients developed a new disease during the first lockdown.

Mental illness is one of the most common NCDs accelerated by COVID-19 (Pécout et al., 2021; Rossi et al., 2020; Vizheh et al., 2020). The pandemic contributed to the development of new mental health issues and the worsening of existing psychiatric symptoms (Vindegaard and Benros, 2020), especially among young people with anxiety(Pécout et al., 2021). Social isolation is the key to developing mental illness during the pandemic. A study of 78 countries found that approximately 10% of the population was suffering from mental health difficulties due to lockdown-related social isolation(Gloster et al., 2020). Pécout et al. (2021) shows that the NCD patients in the UK and the USA were at higher social isolation levels than Europe during the pandemic. Knolle et al. (2021) compared the mental health effect of Covid -19 between Germany and the UK and found that the severity of phycological impact was higher in the UK compared to Germany. Serrano-Alarcón et al. (2022) show that mental health is more sensitive to the imposition of containment policies in the UK than to the evolution of the pandemic itself. Exploiting the difference in the policy responses to COVID-19 in England and Scotland, they show that Scotland, where the lockdown rules were extended, suffered a more significant decline in mental health than England.

4.2.2 Healthcare access of NCDs patients during COVID-19

The emergence of COVID-19 caused broad disruptions to health services related to the screening, treatment and surveillance of NCD patients (Cheung et al., 2020; Jones et al., 2020; Kruse et al., 2022; Pécout et al., 2021; Rusch et al., 2020; Sahoo et al., 2021; WHO, 2020b). These disruptions are particularly problematic for those living with NCDs who need regular care. A WHO survey finds that health services in many countries have been partially or completely disrupted due to COVID-19 (WHO, 2020b). Many country-level studies confirm those disruptions occurred in NCD care during the pandemic. For example, in Latin America, 83% of patients experienced delays in receiving their treatment and care services Kruse et al. (2022). In India, nearly two-thirds of NCD participants encountered challenges in their routine investigation and emergency treatments (Sahoo et al., 2021). In the EU and USA, NCD patients had to change the frequency of their visits to physicians and cancel or reschedule long-planned medical consultations or surgeries (Pécout et al., 2021).

The disruptions to health services particularly affected the health conditions for early diagnosis for which immediate care is crucial, for example, cancer. Screening, case identification, referral in symptomatic cancer diagnosis, and management and follow-up of patients have all been affected by the COVID-19 pandemic in the UK (Jones et al., 2020). Globally, 2.3 million cancer surgeries have been cancelled or postponed during the peak 12-week period of COVID-19 (Organization et al., 2020)

During peak times of the pandemic, hospitals were overwhelmed with Covid patients, and non-urgent treatments were cancelled. Most hospitals and surgical professional societies have recommended the rescheduling or reduction of elective surgeries to conserve anaesthesiology staff, equipment and ICU beds for the COVID-19 response effort (Rusch et al., 2020). There was direct competition for mechanical ventilators between patients with critical COVID-19-related respiratory failure and patients with severe exacerbations of chronic lung disease without COVID-19

infection (Cheung et al., 2020). A study shows a significant reduction in hospital admissions of the acute coronary syndrome in England during March 2020 compared with the weekly average in 2019, suggesting that the reduced number of admissions is likely to have resulted in increases in out-of-hospital deaths and long-term complications. (Mafham et al., 2020).

Not only hospitals but also most medical practices also struggled with providing necessary care for their patients with the new challenges of COVID-19, including a reduced workforce due to illness and self-isolation, reallocation of medical staff for covid care and lacking PPE. Hence the services were scaled down for non-urgent visits (Organization et al., 2020). Similarly, alternative methods for doctor visits, such as telephone and video consultations and telemedicine, emerged instead of in-person GP consultations. However, some people face challenges with these new methods. For example, Kruse et al. (2022) found that 76% of patients faced challenges with electronic prescriptions in Latin America. Similarly, those alternative methods might result in missed cues, reduced examination findings, and loss of the clinician's gut feeling (Jones et al., 2020). Similarly, COVID-19 adds an additional burden on people with pre-existing chronic medical conditions for their self-care, such as dietary precaution, medication adherence, home-based exercises, self-monitoring of blood glucose and blood pressure, self-foot examination, and stress management (Gupta et al., 2020).

Other than the pressure built by the overwhelming pressure on the healthcare system to treat COVID-19-related issues, NCD care was affected by the challenges made by lockdown restrictions. During the first lockdown, it took some time to change how they accessed healthcare, and NCD patients could not access appropriate care during the first lockdown (Pécout et al., 2021). They had difficulty finding an available physician, trouble finding their treatment at the pharmacy and the initial fear towards the infection of COVID-19 also left them absent from regular care in hospitals and medical practices (Sahoo et al., 2021).

4.2.3 Labour market impact during COVID-19

COVID-19 affected the labour market in terms of incidence of working, work hours, earnings, and working mode in almost all countries in the world. For example, in Europe, the labour market slack was 1.2 percentage points, and one percentage point down in employment was reported (Eurosta, 2020). In Australia, COVID-19 induced a 32 percent decline in aggregate weekly work hours among workers aged 20–64 years, alongside a 15 percent decline in employment (Lemieux et al., 2020). In the UK, the employment rates declined throughout 2020 following the start of the pandemic (Powell et al., 2022). Fana et al. (2020) shows that employment impact of COVID-19 is asymmetric within and between countries. In particular, the countries hardest hit by the pandemic (Spain, Italy, and the UK) are the countries more likely to suffer the worst employment implications of confinement.

The COVID-19 pandemic disproportionately impacted different socio- demographic categories. For example, females were more adversely impacted than males by decreased labour demand and other consequences of the labour market (Aygun et al., 2021; Borland and Charlton, 2020; Singh et al., 2022). In Canada, the unemployment likelihood during the pandemic was 1.69 and 1.17 times higher for females than males for those employed full-time and part-time, respectively. Similarly, the work hours gap between female and male full-time workers increased by 6% (Singh et al., 2022). Females were also more likely than males to withdraw from the labour force (Borland and Charlton, 2020). However, Hupkau and Petrongolo (2020) found that men and women were roughly equally affected by the pandemic in the UK at the extensive margin, as measured by the incidence of job loss or furloughing. They revealed that women suffer slightly smaller hours and earning losses overall. In contrast, Crossley et al. (2021) found no evidence of divergence in employment outcomes by gender in the UK.

One reason for the gender difference in the labour market outcomes could be that women needed to attend to children during the lockdown period more. Women with

children constitute the most vulnerable group against employment and income losses during the pandemic (Aygun et al., 2021). At the onset of the pandemic, parents at work were more than twice as likely to report reduced income than non-parents at work (31.7% and 15.1%, respectively) in the UK (Vassilev and Hamilton, 2021).

Other than gender, several other socio-demographic factors link with the disparity of the labour market impact. For example, Borland and Charlton (2020) found significant age disparities in work loss. Young people (aged 15–24) experienced larger decreases in employment and movement out of the labour force during the initial stages of COVID-19. The reason would be that those younger workers engaged in jobs which were most affected by shutdowns due to COVID-19, e.g. the hospitality sector (Lemieux et al., 2020). However, the UK data shows that employment levels have fallen for older workers aged 65+ by a larger percentage than the other age groups (Powell et al., 2022). Nevertheless, the reduction in income was higher among the 30 to 59 years (Vassilev and Hamilton, 2021).

Labour market shocks due to COVID-19 are associated with higher levels of inequality in financial well-being (Botha et al., 2021). Individuals in the lowest part of the income distribution were more likely to report reduced household income during the pandemic (Lemieux et al., 2020; Vassilev and Hamilton, 2021). For example, in the UK, the proportion of economically active people who reported reduced income was 43.8% among those in the lowest income quintile, which compares with only 30.4% of those in the top income quintile in 2020 (Vassilev and Hamilton, 2021). Immigrant workers, employment of ethnic minorities and those with lower education were also affected more due to the pandemic (Aygun et al., 2021; Crossley et al., 2021; Singh et al., 2022)

The impact of COVID-19 on the labour market and income varies by job category. The private sector has driven the fall in employment (Powell et al., 2022). Those most affected by COVID-19 are in public-facing jobs in industries such as accommodation, hospitality, non-essential retail and travel (Lemieux et al., 2020;

Webster et al., 2021). The economic hardship of the pandemic affected the self-employed and informally employed the most (Aygun et al., 2021).

Governments in many countries implement different programmes to protect employees' income. For example, the coronavirus job retention scheme, commonly known as furlough, in the UK, and the job keepers programme in Australia are examples. The deterioration of labour market outcomes of individuals has reversed somewhat through these programmes (Borland and Charlton, 2020). In the UK, the impact on household income was much less than the expected fall due to the reduction in earnings cushioned by the furlough scheme implemented by the UK government (Chowdhury, 2021). It shows that while national income contracted by 15% in the second quarter of 2020, there was only a 3.3% fall in household gross disposable income. However, the employees on the lowest incomes were more likely to be furloughed and paid lower (Chowdhury, 2021).

However, there are some controversies about the labour market impacts of COVID-19. Demena et al. (2022) studied 29 empirical studies related to the labour market impact of COVID-19 conducted in 12 countries and found that large parts of the documented literature exhibit substantial publication bias. After controlling for publication bias, they found almost no meaningful impact of COVID-19 on earnings, hours worked and unemployment. Crossley et al. (2021) also found that the widening of labour market inequalities in the first wave of the pandemic was subsequently reversed in the UK. The significant fall in hours worked with the onset of the pandemic was recovered later for many individuals.

To the best of our knowledge, the differential impacts of the pandemic on labour market outcomes by the long-term health conditions of individuals have not been analysed. Hence, this paper aims to fill this gap.

4.3 Data

We use the data of *Understanding Society COVID-19 Study*, which allows us to explore the impact of the pandemic on individuals across the UK through a large and representative sample of the UK population. The survey was an integral part of *Understanding Society: the UK Household Longitudinal Study*. The COVID-19 study consists of 9 waves, with the first survey conducted in April 2020 followed by monthly waves until July 2020. From September 2020 onwards, the survey is fielded every two months until March 2021, and then the final COVID-19 study was carried out in September 2021. The advantage of using COVID-19 survey data is that we can link individuals to waves prior to COVID-19.

The COVID-19 study includes everyone in households who participated in waves 8 or 9 of the main US survey, which has probability samples of postal addresses. All household members aged 16+ in April 2020 were invited to the COVID-19 study. Everyone eligible in wave 1 of the COVID-19 survey remained eligible in waves 2 to 4, irrespective of whether they had participated in any of the previous surveys. From wave five onwards, only sample members who had completed at least one partial interview in any of the first four web surveys were invited to participate (ISER, 2020). The total number of respondents who participated in each COVID-19 study is given in Appendix 4.A

We used data from all nine waves of the COVID-19 study (ISER, 2021). We considered the individuals who participated in the survey for at least one wave. Accordingly, 19371 individuals were included in the study. Pre-Covid characteristics of individuals were obtained from the US mainstage surveys. We used four previous surveys (waves 7 to 10; 2016 to 2019) to represent the pre-Covid state of individuals. Each individual was linked with at least one of these waves. Similarly, the COVID-19 survey provides some baseline data for January 2020, so we used those data to identify individuals' baseline health and employment status.

We found some significant differences between the mainstage wave 10 sample

and the COVID-19 study sample (Appendix 4.B). Individuals who participated in at least one survey in the COVID-19 study were slightly younger. Still, those who participated in all nine COVID-19 studies were older than the mainstage sample. Compared to the mainstage sample, the respondents in the COVID-19 survey had a higher frequency of females, married, more educated and employed. British people were more likely to respond to the COVID-19 study, and they were more likely to participate in all nine surveys compared to other ethnic groups. The percentage of individuals having NCDs was higher in the COVID-19 study sample, and it was considerably larger in the balanced sample. Due to the differences in the sample composition, we used weights provided in the COVID-19 survey in all our calculations and estimations. All our descriptive analyses and estimations were derived from the full COVID-19 sample used in the unbalanced panel analysis.

4.3.1 Health

The survey provides data on individuals' long-term health conditions that can be classified as NCDs. We combined all the long-term health conditions [2] and considered individuals as having an NCD if they had at least one long-term health condition during the survey period. Accordingly, 48% of individuals had NCDs during the baseline period (January 2020). Further, we identified another group of NCDs which we named as Risky NCDs- the long-term health conditions that resulted in severe covid-illnesses [3]. According to WHO (2020a), we identified five categories of such health conditions: respiratory diseases, cardiovascular diseases, cancer, diabetes and obesity. Those health conditions were classified as Risky-NCDs, and 30% of individuals had risky NCDs during the baseline period.

Table 4.3.1 shows the sample characteristics of respondents with NCDs and with

[2]The long-term health conditions includes; asthma, arthritis, cognitive heart failure, coronary heart disease, angina, heart attack, stroke, emphysema, chronic bronchitis, liver conditions, cancer, diabetes, epilepsy, high blood pressure, multiple sclerosis, COPD, emotional/psychiatric problems, hyperthyroidism, chronic kidney, brain and nerve conditions and overweight.

[3]We do a sub-sample analysis for this group of individuals

Table 4.3.1: Sample characteristics by NCD status

	NCDs	no NCDs
Mean Age	51.2%	38.0%
	(0.180)	(0.159)
Age categories		
Less than 30	15.9%	38.2%
30 to 40	11.8%	18.6%
40 to 50	16.4%	19.2%
50 to 65	31.7%	17.5%
Above 65	24.2%	6.5%
Female	53.7%	50.7%
Urban	76.2%	78.1%
Marital status		
Single/ never married	27.3%	47.1%
Married	51.4%	40.2%
Separated/Divorced	12.2%	6.7%
Widowed	5.7%	1.8%
Ethnicity		
British	87.8%	82.4%
Asian/British	3.9%	7.2%
Black/British	2.1%	2.0%
White	3.4%	4.0%
Education		
College Level	20.6%	24.3%
A level and above	16.1%	16.9%
O level and above	21.9%	29.6%
Employed	40.9%	60.4%
Self-employed	6.1%	8.6%
Having small children	7.1%	13.5%
Work as a key worker	19.8%	28.6%

Notes: The table shows the percentage (weighted) of individuals in each category under two health statuses: having any NCD and without any NCD. All figures were calculated using the full COVID-19 sample, and they are relevant to the baseline (January 2020) employment status. standard errors are in parentheses

Table 4.3.2: Sample characteristics by employment status

	Employed	**Self-employed**	**All Employed/ self-employed/ both**
Mean Age	40.06	47.26	41.15
	(0.126)	(0.312)	(0.117)
Age categories			
Less than 30	34.6%	14.5%	31.6%
30 to 40	20.9%	18.8%	20.8%
40 to 50	23.3%	27.7%	23.9%
50 to 65	20.1%	33.5%	22.0%
Above 65	1.1%	5.5%	1.7%
Female	52.1%	38.0%	50.3%
Urban	79.4%	72.5%	78.6%
Marital status			
Single/ never married	44.5%	27.4%	41.9%
Married	41.9%	58.6%	44.2%
Separated/Divorced	8.6%	8.8%	8.7%
Widowed	0.8%	1.2%	0.9%
Ethnicity			
British	86.0%	81.1%	85.1%
Asian/British	4.7%	6.7%	5.1%
Black/British	1.8%	2.4%	1.9%
White	3.7%	5.8%	4.0%
Education			
College Level	26.6%	31.3%	27.6%
A level and above	18.7%	15.1%	18.2%
O level and above	29.1%	23.4%	28.1%
Respondents with NCDs	38.1%	39.2%	38.2%
Respondents with risky NCDs	24.0%	23.0%	24.0%
Having small children	13.8%	14.2%	13.1%
Work as a key worker	43.7%	15.3%	39.8%

Notes: The table shows the percentage (weighted) of individuals in each category under employment statuses: employed, self-employed and either employed, self-employed or both. All figures were calculated using the full COVID-19 sample, and they are relevant to the baseline (January 2020) health status.

no NCDs. NCD individuals are older than non-NCD individuals. 24% of NCD individuals were aged 65 and above, whereas it was only 6% for the non-NCD group. The majority of NCD individuals, 32%, were aged between 50 to 65 years. The percentage of individuals under 30 years was 16% for NCDs, while it was 38% for non-NCDs.

The proportion of females is higher among NCD individuals than non-NCDs. 54% were females among individuals with NCDs, and it was 51% for those with no NCDs. More than half of NCD individuals were married compared with 40% of non-NCD individuals those married. The percentage of individuals in other ethnic groups was relatively lower among NCD individuals than non-NCD individuals. For example, only 4% of NCD individuals were Asian or Asian British people, whereas it was 7% for individuals with no NCDs. On the other hand, 88% of NCD individuals were British, whereas it was 82% for non-NCDs.

Individuals with NCDs are less educated than non-NCD individuals. Around 60% of individuals with NCDs had more than O-level education. Which means 40% of them had less than O-level education. For non-NCD individuals, around 70% had more than O-levels. The employed percentages are lower among NCD individuals. Only 41% of NCD individuals were employed compared to 60% of non-NCD individuals. Similarly, the self-employed percentage was 6% for people with NCDs and 9% for no NCDs. Only 20% of NCD individuals worked in key worker employment categories, whereas 29% of non-NCD individuals worked in those employments.

4.3.2 Employment

Table 4.3.2 shows the sample characteristics under three employment categories; employed, self-employed and either employed, self-employed or both. The figures indicate that compared to employed, those individuals engaged in self-employment were relatively older. 35% of employed individuals were less than 30 years old,

compared to 14% of self-employed. The percentage of employed individuals between 50 to 65 years was 20%, whereas it was 33% for self-employed. Nearly 6% of self-employed were aged above 65 years.

The gender composition of the two employment categories is varied. The likelihood of females being self-employed is smaller. Only 38% of self-employed were females, whereas it was 52% for employed. Compared to employed, more percentage of self-employed were living in the rural. 27% of self-employed and 21% of employed were living in rural. Individuals who are single or never married were more likely to be employed, whereas married people were more likely to be self-employed. Only 27% of self-employed individuals were single/never married individuals, while 59% were married. On the other hand, 44% of employed individuals were those who were single/never married, whereas only 42% were married. In the total sample, more than 80% of individuals were British, and they were more likely to be employed than self-employed. 86% of employed were British, whereas it was 81% for self-employed. However, for other ethnic communities, the self-employed percentages are higher. For example, the Asian or Asian British proportion among employed was 5%, while it was 7% for self-employed. Similarly, 4% of employed and 6% of self-employed were other white people.

The percentage of individuals with college-level education is higher for self-employed than employed. 31% of self-employed and 27% of employed had college-level education. On the other hand, 29% of employed and 23% of self-employed had education up to O levels. The percentage of individuals having NCDs and risky NCDs are mostly the same in all employment categories. 38% of employed and 39% of self-employed were having any NCDs. 14% of the individuals in both employment categories had small children. 44% of employed workers worked as key workers, and 15 of self-employed also worked as key workers. Among all employed and self-employed, 40% were key workers.

The percentage of individuals who worked during the pandemic is shown in

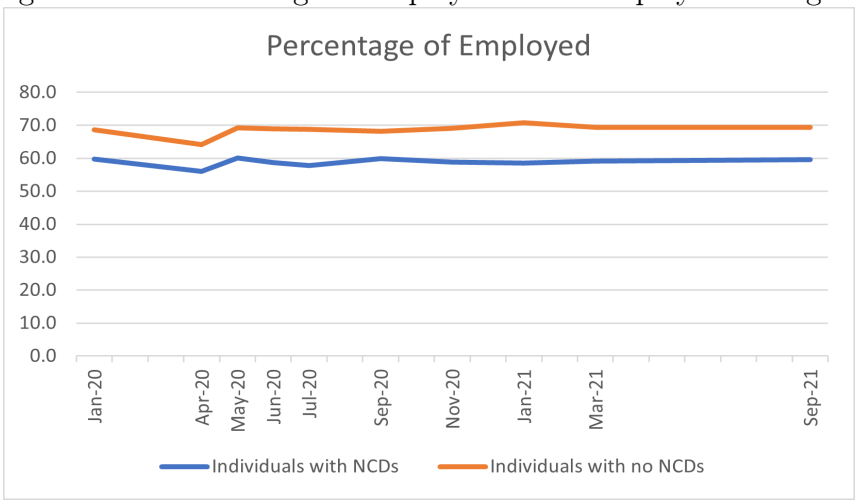
Figure 4.3.1. The figure shows that employment percentages of individuals with NCDs are lower than that of healthy individuals throughout the pandemic. Both employment and self-employment rates dropped at the start of the pandemic but later, it recovered. for example, in April 2020, the employed percentage dropped by around four percentage points for both groups of individuals and by September 2021, the employment rate of healthy individuals exceeded the pre-pandemic level. Compared to employment rates, the self-employment rates fluctuated more during the pandemic.

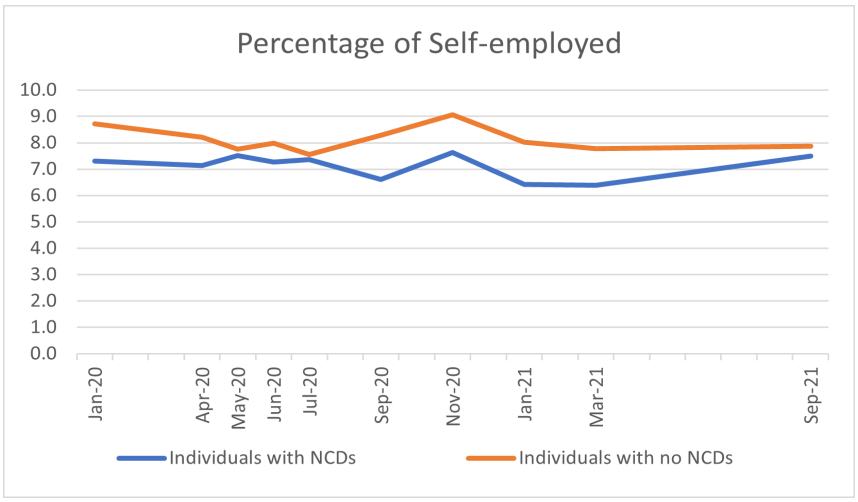
4.3.3 Work hours

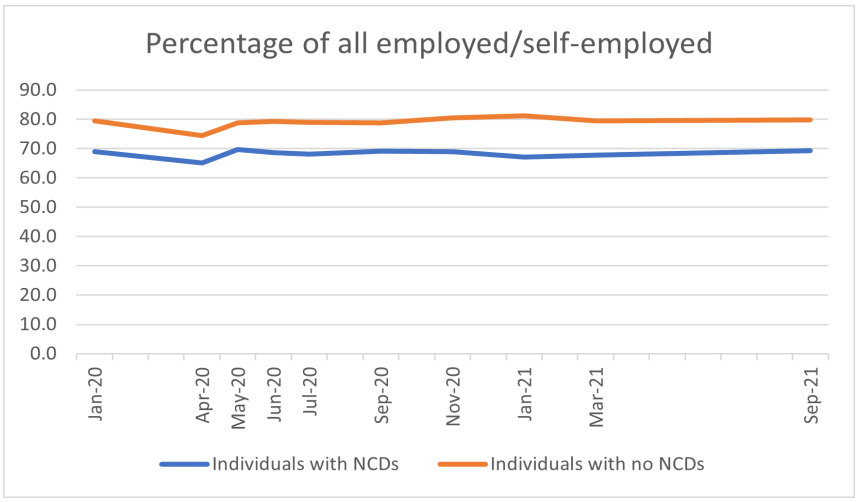
Figure 4.3.2 shows the average weekly work hours of individuals who were employed/ self-employed during the time of COVID-19. It shows that the onset of the pandemic markedly reduced the weekly work hours of both employed and self-employed; however, the reduction is more considerable for self-employed than employed. During pre-Covid time, healthy employees' average work was 34 hours per week. It fell to 22 hours in April. For self-employees, that reduced from 31 hours to 13 hours on average. However, as the pandemic proceeded, the average weekly work increased for both employment categories before falling again after November 2020.

It reflects that the average weekly work hours are linked with national-level lockdowns. The first national-level lockdown was imposed in the country at the end of March 2020 and continued until mid-June. Few local-level restrictions were imposed from July to October, including the Tier system of restrictions. During early November, the second national lockdown, which lasted until mid-December, was set in England. The third nationwide lockdown, which had the toughest restrictions, came into force in the first week of January 2021 and continued until mid-March 2021. During lockdowns, there was an apparent reduction in weekly work. In September 2020, when the economy returned back to the normal after the first lockdown, the work hours of employed increased. Nevertheless the gap between

Figure 4.3.1: Percentage of employed & self-employed during COVID-19 pandemic

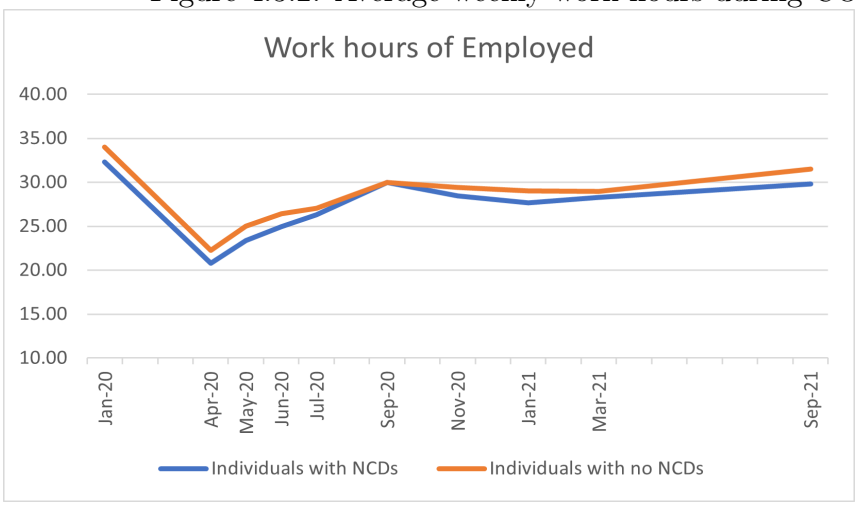


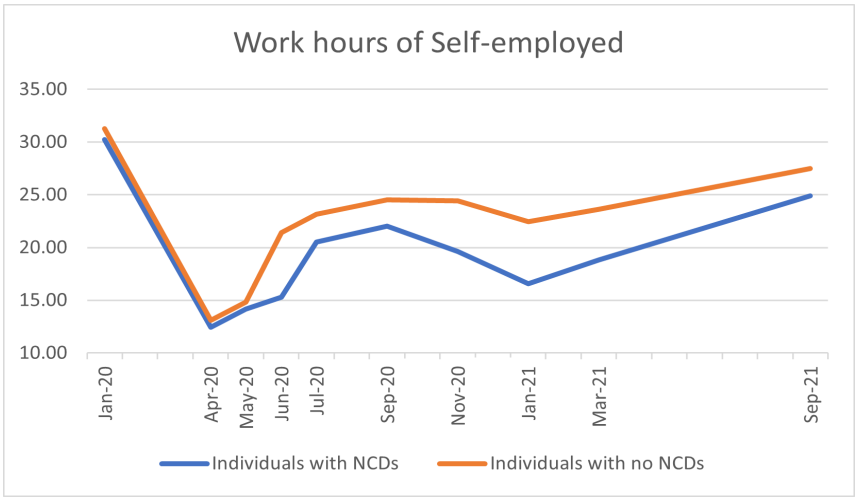


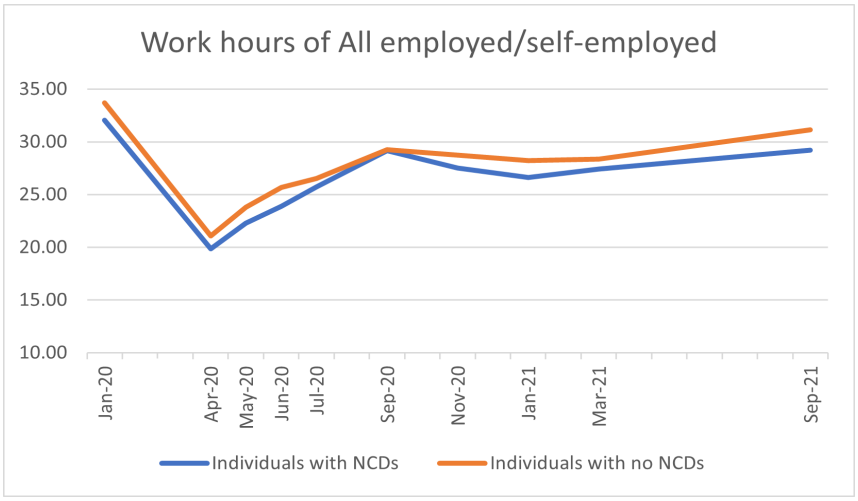


Notes: The figure shows the percentage of employed or self-employed during each COVID-19 survey month. The sample was restricted to all individuals between 16 to 64 years. The X axis shows the month that the COVID-19 surveys were carried out. January 2020 was the baseline period given in the COVID-19 study.

Figure 4.3.2: Average weekly work hours during COVID-19







Notes: The figure shows the means (weighted) of weekly work hours of employed or self-employed during each COVID-19 survey month. The sample was the individuals who were employed or self-employed during the baseline period (January 2020) and aged between 16 to 64. The X axis shows the month that the COVID-19 surveys were carried out. January 2020 was the baseline period given in the COVID-19 study.

the work hours of NCD and healthy individuals eliminated. However, with the second and third lockdowns work hours decreased again. By the end of the pandemic, the work hour average reached 32 hours for healthy employees, but it did not get to the pre-pandemic level. However, note that the baseline (January 2020) weekly work hours were obtained from retrospective data gathered in the first wave of the COVID-19 Study.

The average work hours of individuals with NCDs were consistently lower than those of healthy individuals. Before the pandemic, there was around two hours work gap between the two groups. The pandemic negatively affected both the same magnitudes at the beginning, but in the middle of the pandemic, it acted differently on them[4]. By September 2021, the average work gap between the two groups came back to two hours for employed, but for self-employed, the gap widened more than the pre-pandemic level.

4.4 Methods

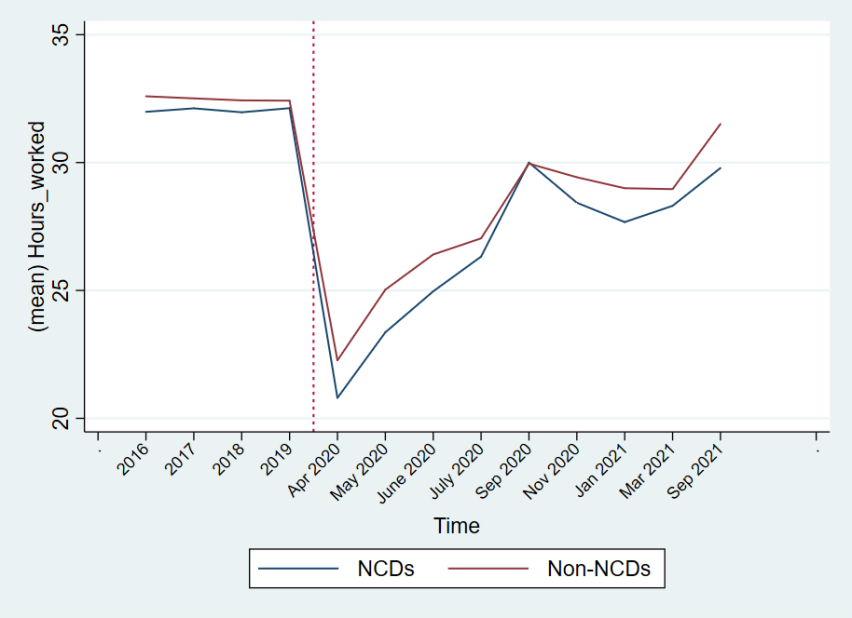
The study aims to identify the heterogeneous effect of COVID-19 on the labour market outcomes of individuals with NCDs. To estimate the effect, we are able to apply a quasi-experimental design, where we have two groups, the group comprised of those individuals with NCDs and a comparison group which includes those individuals with no NCDs, and an exogenous treatment shock defined by the onset of the COVID-19 pandemic. Accordingly, our sample consists of four groups; NCD individuals in the post-Covid period, non-NCD individuals in the post-Covid period, NCD individuals in the pre-Covid period and non-NCD individuals in the pre-Covid period. We refer to the individuals with NCDs in the post-Covid period as the examined/studied group and all other three groups as comparison groups.

Descriptive statistics indicated that the work hours gap between the respondents

[4]The mean difference check was not possible. All mean values were obtained using weights. Stata does not allow the t-test for mean difference with weights.

with NCDs and non-NCDs had widened during the post-Covid period, implying heterogeneous impacts of the pandemic on the outcome variables of the two groups. Therefore, we built a model that estimates the causal parameters to test whether the pandemic effect heterogeneously in the two groups of NCDs and non-NCDs individuals.

Figure 4.4.1: Parallel trend: Weekly work hours of individuals with NCDs and others



The most popular research design used in the literature to evaluate the treatment effects on different groups is Difference-in-Differences (DiD). It can estimate the average treatment effect (ATE) of the COVID-19 pandemic on the outcome variables of the examined group by comparing the average change in the outcome variable of the studied group and the comparison groups. However, the DiD design highly relies on the parallel trend assumption; in the absence of the treatment, the outcome variable of both groups would follow the pre-treatment trend. Visual inspection of trends before the pandemic suggests the parallel trend assumption holds. Figure 4.4.1 shows that the average work hours of NCD individuals were consistently below the average of non-NCD individuals and followed a parallel path during the pre-Covid period. We statistically tested the parallel trend assumption and the results are available in Appendix 4.C. We found that there is no significant change in the

working hour gap between NCD and non-NCD individuals prior to the pandemic. Hence, we could assume that in the absence of COVID-19, the average work hours of NCD individuals and non-NCD individuals would have followed the same parallel path. This permits us to apply a DiD method for our analysis. Mendolia et al. (2022); Serrano-Alarcón et al. (2022) also used a similar approach for their analysis in a similar setting. Accordingly, we apply the following parametric specification:

$$Y_{i,t} = \beta_0 + \beta_1 Covid_{i,t} + \beta_2 NCD_{i,t} + \beta_3 (Covid_{i,t} * NCD_{i,t}) + \delta Z_{i,t} + \epsilon_{it} \tag{4.1}$$

where $Y_{i,t}$ is our outcome variable, i.e. weekly working hours of individual i at time t, NCD_{it} is a dummy variable denoting whether the individual i has any NCD at the time t. $Covid_t$ is a dummy variable that takes the value one for the post-Covid period and zero for the pre-Covid period. $Z_{i.t}$ is the vector of conditioning covariates and ϵ_{it} is the unobserved error term. The coefficient β_3 is our coefficient of interest as it derives the DiD estimator as follows.

Let's denote Y^1 as the outcome variable in the presence of Covid and Y^0 as the outcome variable without Covid. The onset of Covid is at t=1.

$$\begin{aligned} DiD &= E\left[\left(Y^1_{NCD,(t=1)} - Y^0_{NCD,(t=0)}\right) - \left(Y^1_{nonNCD,(t=1)} - Y^0_{nonNCD,(t=0)}\right)\right] \\ &= E\left[(\hat{\beta}_0 + \hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3) - (\hat{\beta}_0 + \hat{\beta}_2) - \left((\hat{\beta}_0 + \hat{\beta}_1) - \hat{\beta}_0\right)\right] \\ &= E\left[\hat{\beta}_3\right] \end{aligned} \tag{4.2}$$

with satisfying the parallel trend assumption,

$$E\left(Y^0_{NCD,t=1} - Y^0_{NCD,t=0}\right) = E\left(Y^0_{nonNCD,t=1} - Y^0_{nonNCD,t=0}\right) \tag{4.3}$$

Accordingly, we first estimate the above-specified standard DiD model, where a single 'post-Covid' variable is included to denote all post-Covid periods. However, we allow for heterogeneous effects of COVID-19 on labour outcomes for NCD and non-NCD individuals. For example, at times the government imposed tighter restrictions, such as lockdowns, that directly impacted the labour market dynamics. Hence it is essential to explore the ATT of the treatment on the studied group at different timings of the post-Covid period.

The two-way fixed-effect (TWFE) event study model is the most favoured method used in the literature to estimate such treatment effect differences in different periods (Alam et al., 2021; Dimitrovová et al., 2020; Tao et al., 2022). However, the TWEF event study model cannot be applied to our context. One of the simplifying assumptions in the event study model is the homogeneous treatment effect across cohorts and time. In contrast, we are trying to identify the heterogeneous effect of the treatment on two groups. Our treatment (COVID-19) applied to both NCD and non-NCD groups, and the ATT of our interest is the coefficient related to the interaction of Covid and NCDs.

In recent methodological developments in DiD design, Callaway and Sant'Anna (2021) provide a framework for estimating average treatment effects in DiD setups with multiple periods. They propose a group time average treatment effect for each treatment period allowing for arbitrary treatment effect heterogeneity and dynamic effects. However, that method highly depends on a 'never treated' or 'not yet treated' group for comparison, which we do not have in our context. The treatment was applied to both groups in our study. Therefore, we continue with the canonical DiD set-up and introduce the time-specific ATT of COVID-19 on NCD individuals' labour market outcomes as follows:

$$Y_{i,t} = \alpha_0 + \alpha_1 Time_{i,t} + \alpha_2 NCD_{i,t} + \alpha_3 Time * NCD_{i,t} + \delta Z_{i,t} + \epsilon_{i,t} \tag{4.4}$$

where $Time_{i,t}$ is the variable representing the time which takes values from 0 to 9, where 0 is for the pre-Covid period, and 1 to 9 is for each post-Covid month. Thus, we compare each Covid-month with the pre-Covid period. As mentioned earlier, $NCD_{i,t}$ is the dummy variable representing that individual who has an NCD. The coefficient of the interaction of Time and NCD (α_3) is our coefficient of interest as it gives the ATT of Covid on NCD individual's outcome variable at different times in the Covid period (the derivation of ATT is similar to the Equation 4.2).

The DiD estimators of β_3 and α_3 in Equation 4.1 and 4.4 are unbiased estimators for the ATT under parallel trend assumption alone. De Chaisemartin and d'Haultfoeuille (2020) point out, the DiD estimator of a standard two-way fixed effect model is unbiased under the parallel trend assumption alone when the treatment is binary, there is a staggered treatment adoption; once treated, always remain treated, and if there is no variation in treatment timing: all treated groups start receiving the treatment at the same date. Our DiD setting satisfies all those three conditions.

The outcome variables of the above DiD models are the labour market outcomes denoted by $Y_{i,t}$. We define labour market outcomes in two stages. First, the probability of being employed/ self-employed during that period. Accordingly, a linear probability model is estimated. Second, if they are employed or self-employed, then their weekly working hours is the outcome variable. In all regression estimations, pre-treatment conditional covariates are used. Individual fixed effects such as gender, race and region, and time-varying individual-specific variables such as age, education, marital status and parents having small children are included in the estimation as conditional covariates. Since the COVID-19 survey does not provide information on education and marital status, we use the most recent data as of 2019 for all post-months.

We apply the same DiD model for several sub-sample analyses to verify the results of our primary analysis. Working as a key worker significantly relates to

the labour market performance during the COVID-19 pandemic, especially during lockdown periods. Hence, we perform a separate analysis for the key worker category. A similar analysis is done for individuals aged 55 and above who are more vulnerable to NCDs and severe Covid infections. Moreover, we do a separate analysis by changing our examined group to individuals with riskier NCDs in the Covid situation instead of considering all NCDs. Finally, we conduct a sensitivity analysis using propensity score matching (PSM) to estimate the ATT of COVID-19 on the work amount of NCD individuals. The support of the parallel trend assumption permitted us to use the PSM method.

4.5 Results

In this section, we present the results of our analysis which examines the effect of COVID-19 on the labour market outcome of individuals with NCDs. Throughout our analysis, we estimate the impact for three employment categories; employed, self-employed and a combined group of all individuals who employed, self-employed or both employed and self-employed.

4.5.1 Overall impact of COVID-19 on the labour market outcomes of NCD individuals

The results of the overall impact of COVID-19 estimated using the DiD model as in Equation 4.1 are presented in Table 4.5.1. We estimated six regressions under three employment categories using the data from four mainstage surveys from 2016 to 2019, and nine COVID-19 surveys from April 2020 to September 2021. The estimations were done in two steps. All respondents aged below 65 years were included in the sample to estimate the probability of work. Only those employed/ self-employed were included in the sample appropriately for the impact on work hours. For the pre-covid period, individuals' employment status was identified as it

was reported in the pre-covid surveys. Still, for the post-covid period, employment status was based on the baseline employment provided in the COVID-19 study.

Table 4.5.1: Overall impact of COVID-19 on the labour market outcomes

	Probability of working			Hours work		
	Any work	Employed	Self employed	All working	Employed	Self employed
NCD	-0.0011	-0.0012	0.0015	-0.1784	-0.2695*	-0.4933
	(0.0028)	*(0.0030)*	*(0.0017)*	*(0.1454)*	*(0.1478)*	*(0.5038)*
Covid	-0.0054***	-0.0281***	-0.0047***	-3.8654***	-2.9756***	-10.6056***
	(0.0019)	*(0.0021)*	*(0.0012)*	*(0.0972)*	*(0.0988)*	*(0.3716)*
Covid_NCD	-0.0445***	-0.0335***	-0.0096***	-1.5942***	-1.5030***	-2.3632***
	(0.0031)	*(0.0032)*	*(0.0018)*	*(0.1647)*	*(0.1682)*	*(0.6057)*

Notes: The table shows the coefficients of six regressions estimated using DiD method. The dependent variable of the first three models is a dummy variable that indicates being employed, self-employed, and either employed or self-employed, respectively. The number of weekly work hours is the dependent variable for the rest of the three models. All models were estimated with conditional covariates for age, gender, living in the urban, education, marital status and having small children.

As the results indicate, the pandemic adversely affected respondents' probability of being employed or self-employed. It caused approximately a 0.5 percentage point reduction in the probabilities of any work. The reduction in the probability of employed is significant as it shows a 5% reduction. Similarly, when they are employed, their working length was also affected by the pandemic. The reduction in work was bigger for self-employed compared to those employed. Self-employed workers lost an average of 8 hours of work per week due to the pandemic, whereas employed people lost about 5 hours of work.

According to the combined effect of COVID-19 and having NCDs, which is the variable of our interest, the pandemic significantly affects NCD individuals' probability of being employed and self-employed. It lowered their probability by around four percentage points of which the larger reduction comes from employed. The pandemic reduced the number of work hours of NCD individuals who were employed or self-employed. Compared to non-NCD workers, NCD individuals worked approximately 1.5 hours less if employed and 2.4 if self-employed.

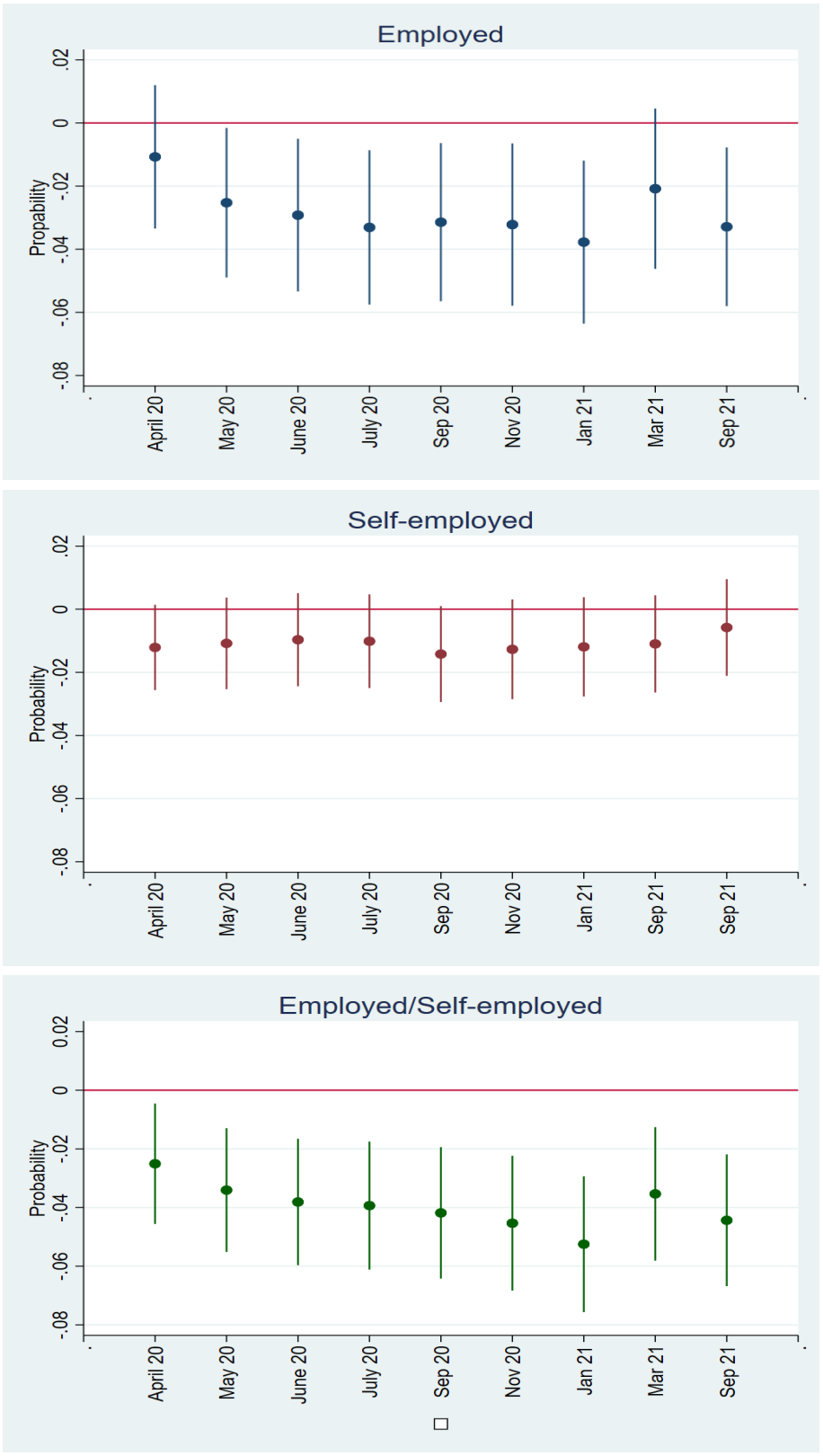
4.5.2 The impact of COVID-19 on the extensive margin: Probability of work

We estimated a linear probability model according to the model specified in Equation 4.4 to capture the heterogeneous effects of COVID-19. The estimated coefficients show the COVID-19 impact on individuals' probability of being employed/ self-employed at different points in time. The sample is restricted to all respondents less than 65 years old to avoid the impact of default retirement. So, our sample consists of individuals between 16-64 years old.

The estimated coefficients for the combined effect of the pandemic and having NCDs are shown in Figure 4.5.1. The coefficients reveal the impact of COVID-19 on work probabilities of people with NCDs. The significance levels of the coefficients are reported in Appendix 4.D. As the figure shows, at the onset of the pandemic, there was no significant difference in the probabilities of being employed between NCD individuals and their non-NCD counterparts. However, in later months, NCD individuals' employment probabilities were more negatively affected by the pandemic than its impact on healthy individuals. Their likelihood of employment was approximately three percentage points lower than the non-NCD individuals at different points during the pandemic period. The highest difference between the two groups was recorded in January 2021 when the UK experienced the peak of the second wave of COVID-19. There, the employment probability of NCD individuals' was four percentage points lower than that of healthy individuals.

The impact of COVID-19 on NCD individuals' self-employment probability is somewhat different from its impact on employment probability. At most points during the pandemic, the self-employment probabilities of NCD individuals were less likely to be affected by COVID-19. There was no significant difference in those probabilities between NCDs and non-NCD people except for one percentage point reduction in the self-employment probability of the NCD group in April and September 2020.

Figure 4.5.1: Effects of COVID-19 on the probability of work of NCD individuals



Notes: Figure shows the DiD coefficient of the linear probability models estimated for employed, self-employed and both.

Considering all categories of employed or self-employed, the estimates indicate a significant negative impact of COVID-19 on NCD individuals' state of being employed or self-employed. Compared to healthy individuals, people with NCDs show a three to five percentage points less chance of being employed or self-employed during the pandemic. The adverse impact increased with time, and by January 2021, NCD individuals reported five percentage points low probability of being employed or self-employed compared to their healthy counterparts.

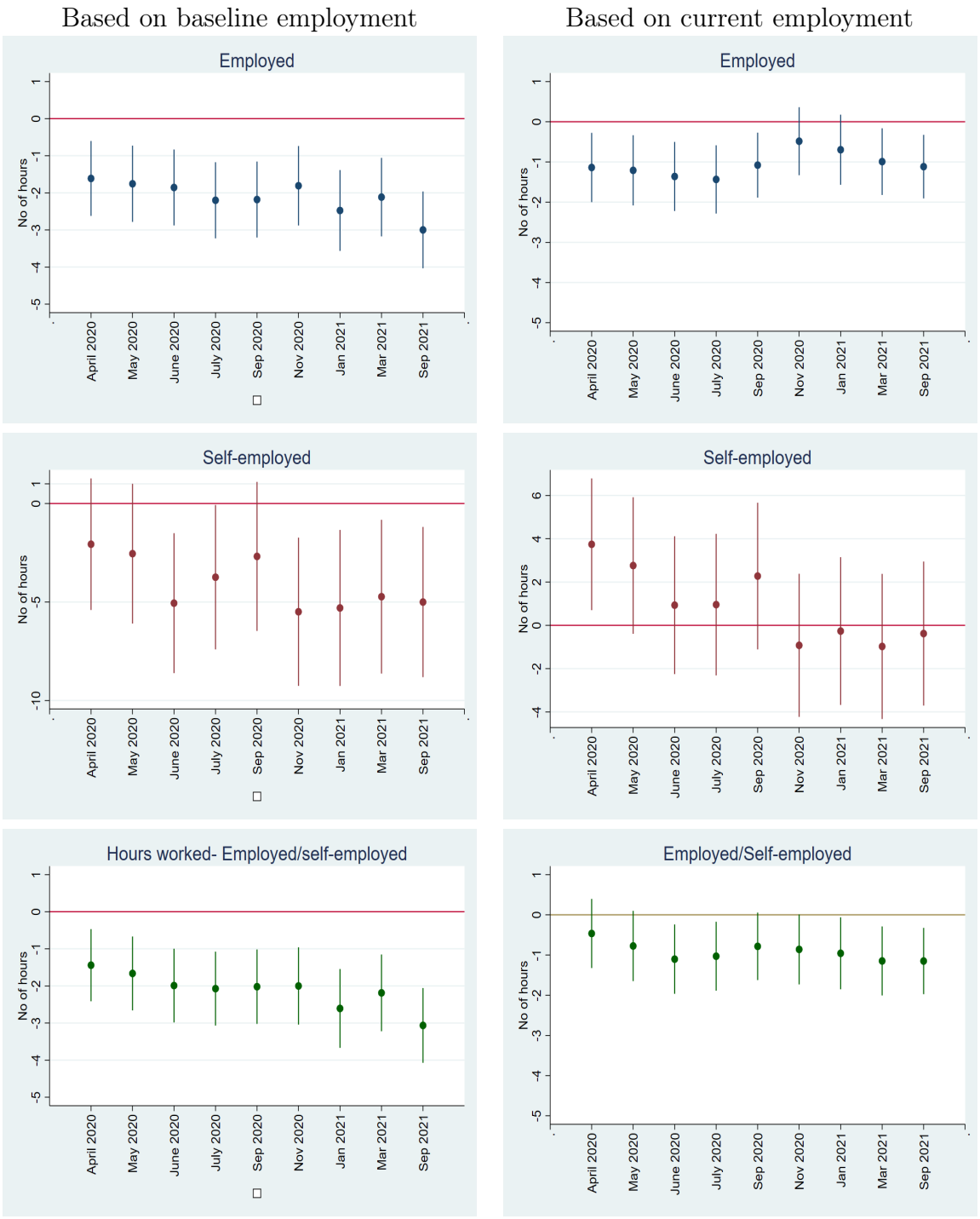
The rest of the results of the linear probability model (Appendix 4.D) indicate that individuals with NCDs had a lower likelihood of being employed or self-employed than those healthy individuals, irrespective of the incidence of COVID-19. In particular, the probability of being employed was four to five percentage points lower among NCD individuals than their healthy counterparts throughout the examined period. The impact on self-employed was smaller as the probability of being self-employed was only one percentage point lower for NCD individuals than healthy individuals. The pandemic negatively affected the likelihood of being employed at the beginning, regardless of their health condition. In April 2020, the employed probability was three percentage points lower than the pre-covid level. The negative impact was eliminated with time, and by September 2020, the probability of being employed was two percentage points higher than the pre-covid level. In contrast, the probability of being self-employed was not affected at the beginning of the pandemic but at the last stages. The self-employment probabilities were approximately one percentage point lower in March and September 2021 compared to the pre-covid level. In general, COVID-19 decreased the probability of working in either category by 1.3 percentage points during the early stage of the pandemic, but later those probabilities were two to four percentage points higher during the rest of the pandemic period compared to the pre-covid level.

4.5.3 The impact of COVID-19 on the intensive margin: Hours of work

The next step of our analysis is to examine the impact of COVID-19 on the extent of work of individuals with NCDs. We used weekly work hours as a measure of the amount of work. Our analysis proceeds in two samples, first, we worked to identify the impact of the pandemic on the work of individuals who had been working at the start of the pandemic. The survey provided data for each individual's employment status at the baseline period, which is January 2020. Accordingly, we restricted the sample to the individuals who were working during the baseline period. However, in some cases, there was a mismatch between baseline employment and current employment status. Therefore, we did a second analysis by restricting the sample based on current employment. So we could identify the impact of the pandemic on the work hours of individuals who were working at that particular time. In both samples, we restricted our selection to people below 65 years old to avoid possible retirement effects.

Figure 4.5.2 presents the results related to the DiD estimator that shows the pandemic-led NCDs' effect on working hours. Those estimators demonstrate the impact of the pandemic on the working hours of individuals with NCDs compared to those with non-NCDs. Accordingly, the pandemic caused a significant decline in the number of work hours of individuals with NCDs compared to healthy individuals. This was evident in both samples that were based on baseline work and current work. According to the baseline employment, the hours lost due to the pandemic was 1.6 hours in April 2020, which increased to 2.2 hours by July for individuals with NCDs. There was a slight reduction in the work hour loss from September to November, but in January, the estimated work loss for people with NCDs was 2.5 hours. Compared to healthy workers, people with NCDs lost 3 hours of work due to the pandemic by September 2021. These working hour losses were slightly lower for the sample based on the current employment; however, the direction of the impact

Figure 4.5.2: Effects of COVID-19 on the weekly work hours of NCD individuals



Notes: Figure shows the coefficient that shows the impact of COVID-19 in NCD individuals' weekly work hours estimated through DiD regressions from the sample based on the baseline employment status and current work status.

was the same.

For self-employed, there is a significant difference between the two samples in the estimated coefficients for the combined effect of NCDs and COVID-19. According to the baseline state of self-employment, self-employed with NCDs lost around five working hours due to the pandemic in several months compared with their healthy counterparts. It was even higher than the work loss of similar individuals who were employed. However, according to the current state of self-employment, self-employed individuals with NCDs were not significantly affected in terms of lost working time. Instead, at the onset of the pandemic, self-employed NCD individuals recorded significantly more work hours than their healthy counterparts.

Considering the broader sample, which is either employed, self-employed or both, the pandemic-led effect of NCDs on individuals' work was negative, implying that the pandemic reduced the work hours of NCD individuals in general. According to the baseline work state, the estimated work loss of people with NCDs due to the pandemic was 1.4 hours in April 2020, and it increased to 3 hours loss by September 2021. The estimations based on current employment show the same direction of the impact, but its magnitude was small.

With respect to the other variables that affected the work hours of individuals, we found that COVID-19 significantly negatively affected the weekly work hours of all employed and self-employed, regardless of their health. The loss of work hours was more significant for self-employed than employed throughout the pandemic. For example, an individual employed during pre-covid lost nearly seven hours of work in April 2020, whereas a self-employed individual lost around 15 hours. The prevalence of NCDs had not significantly affected the work duration of the people, either employed or self-employed, according to the baseline work. However, considering the current state of work, NCDs reduced work time, especially for self-employed. For example, the average work of individuals who worked as self-employed and had NCDs was 2-3 hours fewer than that of healthy individuals. For employed, NCDs

reduced work only in some months. Considering all employment categories, NCDs caused approximately an hour reduction of work in general.

The negative impact of the pandemic on the work hours of NCD individuals was not linked to the severity of the pandemic and related lockdowns. The negative impacts on their work continued to increase as the pandemic proceeded. However, the general impact of COVID-19 was different. It did show a clear link with the severity of the pandemic. The first UK lockdown was in March 2020 and lasted until mid-May. Accordingly, for employed, the loss of the number of work hours was higher in April, and by September 2020, when the economy started to return to normal, the average work hours of people employed increased by one hour compared to the pre-covid level. It regressed again in January 2021, when the UK's second lockdown began. During the last part of the pandemic, by September 2021, the number of work hours improved by 1.3 compared to the pre-covid level. Yet the payoffs of covid on the average work hours of self-employed were always negative. They recorded fewer work hours compared to the pre-covid level even when the economy rebooted (Appendix 4.E and 4.F).

All the above estimations were derived from the full COVID-19 sample used as an unbalanced panel analysis. However, we repeated the analysis for the balanced panel and report the results in Appendix 4.G.

4.5.4 Sub-sample analysis

We did several sub-sample analyses to get an insight into our results of the effect of COVID-19 on the work of NCD individuals. Accordingly, we present the results of those analyses for gender, age categories, different NCD types and age categories. The overall effect of covid-19 on individuals with NCDs in different subsamples are presented in Table 4.5.2

Key workers[5] played a significant role in the labour market during the pandemic

[5]Government identified several employment categories as key workers during the pandemic.

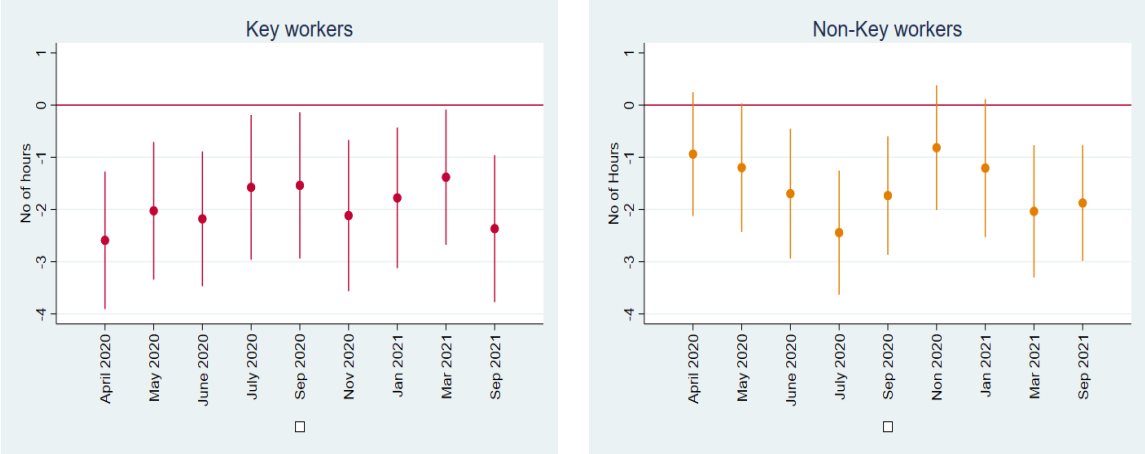
Table 4.5.2: Overall impact of COVID-19 on the labour market outcomes- sub-samples

	Proability of working			Weekly hours worked		
	All	Employed	Self-employed	All	Employed	Self-employed
Female	-0.0435***	-0.0335***	-0.0088***	-1.4160***	-1.2869***	-3.7854***
	(0.0040)	(0.0042)	(0.0022)	(0.2060)	(0.2090)	(0.8881)
Male	-0.0474***	-0.0347***	-0.0112***	-1.9955***	-1.9049***	-1.3434
	(0.0048)	(0.0052)	(0.0032)	(0.2702)	(0.2805)	(0.8227)
Age below55	-0.0311***	-0.0185***	-0.0141***	-1.0392***	-0.8904***	-4.1557***
	(0.0037)	(0.0040)	(0.0022)	(0.1922)	(0.1955)	(0.7952)
Age 55-65	0.0068	0.0103*	0.0053	-1.1476***	-1.7386***	0.1596
	(0.0059)	(0.0059)	(0.0036)	(0.3481)	(0.3597)	(1.0033)
Risky NCD	-0.0311***	-0.0235***	-0.0063***	-1.3625***	-1.3756***	-2.0353***
	(0.0037)	(0.0039)	(0.0022)	(0.2037)	(0.2081)	(0.7518)
Other NCD	-0.0340***	-0.0260***	-0.0078***	-1.0555***	-0.8720***	-1.5128**
	(0.0039)	(0.0041)	(0.0023)	(0.2120)	(0.2175)	(0.7494)
Keyworker				-1.4621***	-1.5109***	-1.9353
				(0.2327)	(0.2285)	(1.8532)
Non-keyworkers				-2.1030***	-1.9038***	-2.5308***
				(0.2306)	(0.2475)	(0.6221)

Notes: The table shows the coefficients of six types of DiD regressions. The dependent variable of the models in the first three columns is a dummy variable that indicates being employed, self-employed, and either employed or self-employed, respectively. The number of weekly work hours is the dependent variable for the rest of the three models.

as they continued their work even during lockdowns. Hence, any work loss of NCD individuals due to the pandemic would be highlighted among the key workers. So, we aimed to identify the pandemic-led impact of NCDs on the working time of individuals in key worker categories. We applied the same DiD regression as above by limiting our sample to only those who worked in key worker categories. For comparison, we did a similar analysis for other employees twho did not work as key workers. The coefficients that show the combined effect of the pandemic and NCDs on work hours of the two groups are presented in Figure 4.5.3. The significance levels of the coefficients are given in Appendix 4.H.

Figure 4.5.3: Effect of COVID-19 on NCD individuals' hours of work: by work type

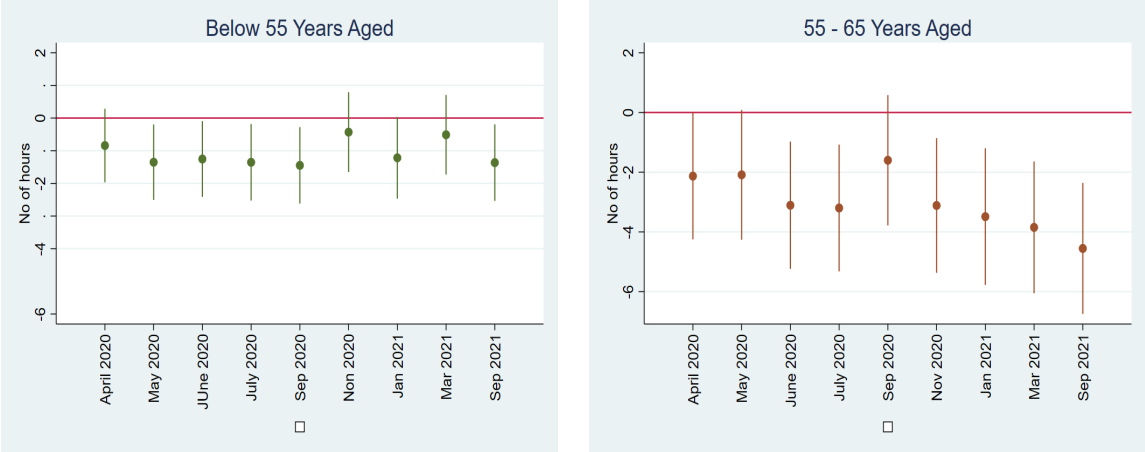


Notes:The figure shows the interaction term coefficients (NCD*Time) estimated from DiD regressions for key and non-key workers.

Our results indicate that the pandemic-led work loss of individuals with NCDs was significantly higher among key workers than for similar non-key workers. There was a robust relationship between the work loss of key workers and the rest of the workers with pandemic-related lockdowns. The most significant impact on key workers was evident during the early stage of the pandemic when the first lockdown was initiated. In April 2020, individuals with NCDs who worked as key workers lost 2.6 hours of work compared to healthy workers and pre-covid work level. With

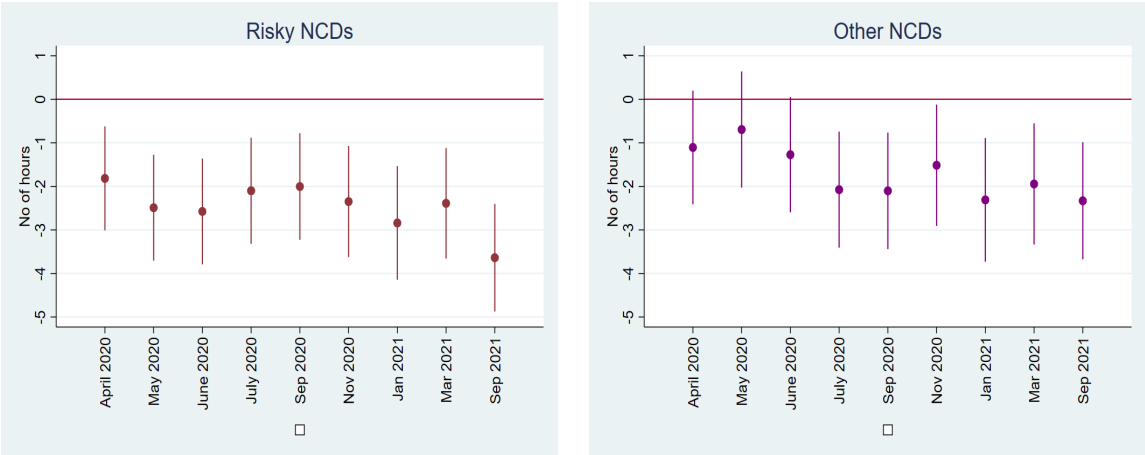
This consist of occupation groups such as, health and social care, education and childcare, utilities and communication, food and necessary goods, transport, key public services, public safety and national security, and national and local governments.

Figure 4.5.4: Effect of COVID-19 on NCD individuals' hours of work: by age groups



Notes: The figure shows the interaction term coefficients (NCD*Time) estimated from DiD regressions for two age groups; individuals aged 55-65 and below 55.

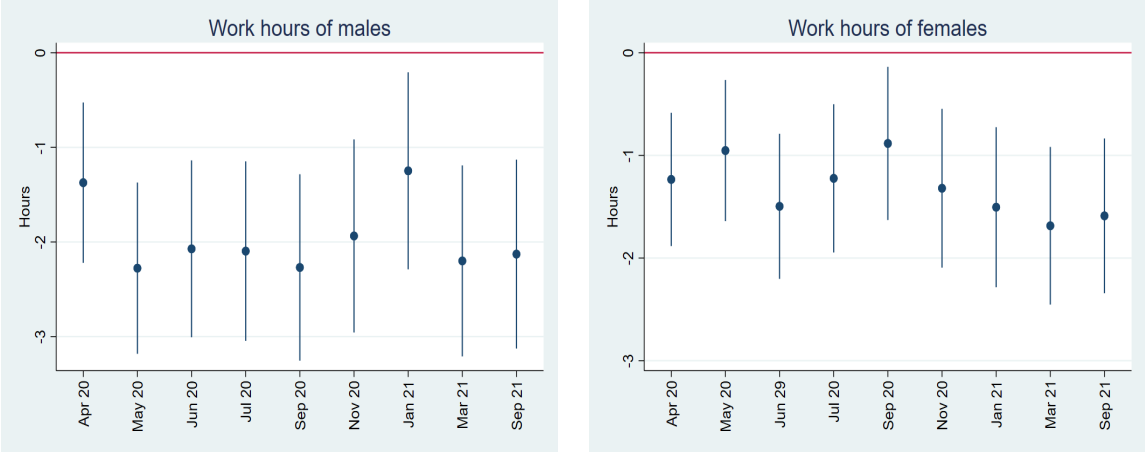
Figure 4.5.5: Effect of COVID-19 on NCD individuals' hours of work: by NCDs type



Notes: The figure shows the interaction term coefficients (NCD*Time) estimated from DiD regressions for two NCDs types: Risky NCDs and other NCDs

the easing of restrictions, by July 2020, their work loss was reduced to 1.6 hours per week. In contrast, the work of non-key workers with NCDs was not affected at the start of the pandemic. Instead, the negative impacts applied during the latter part of the pandemic. In July 2020 they lost 2.4 hours of work weekly compared to healthy workers. In September 2020, when the economy turned back relative to normal, the work loss of non-key workers was larger than that of key workers.

Figure 4.5.6: Effect of COVID-19 on NCD individuals' hours of work: by Gender



Notes: The figure shows the interaction term coefficients (NCD*Time) estimated from DiD regressions for males and females.

Those non-key workers with NCDs lost 1.7 hours per week while key workers lost 1.5 hours. Again when the second lockdown was implemented in November 2020, the work loss of key workers with NCDs turned out to be larger than the work loss of non-Key workers. However, it is important to note that by the end of the pandemic in September 2021, key workers with NCDs still worked around 2.6 hours weekly less than their healthy counterparts. For non-key workers that loss was 1.9 hours weekly.

The second sub-sample analysis was carried out based on the age of the employed or self-employed workers. Both COVID-19 and NCDs risk was higher at higher age groups, so the impact of Covid on individuals with NCDs should also be higher at higher ages. Complying with our assumption, the result of Figure 4.5.4 indicates that COVID-19 has affected the work hours of NCD people more when their age is more than 55 years (Significance level of the coefficients can be found in Appendix 4.I). For example, in April 2020, an individual aged more than 55 with NCDs worked 2.1 hours less than healthy individuals who worked at that age, whereas there was no post-covid impact of NCDs on the work hours of individuals aged below 55. However, as the pandemic proceeded, the work of under 55 years of age workers was

also affected by the fact they were having NCDs, but that impact was lower than that of the over 55 years group. For example, in June 2020, the post-covid adverse effects of NCDs on work hours were 3.1 hours for those over 55 and 1.3 hours for those under 55. By September 2021, NCD individuals over 55 lost 4.5 hours of work compared to their healthy counterparts, while those under 55 lost only 1.3 hours.

Note that the sample used in this estimation was either employed or self-employed at the baseline period. As our results indicate, compared to the baseline period, the amount of work that individuals aged 55 and over with NCDs had undertaken continuously decreased from April 2020 to September. But the work loss fluctuated during that period for those under 55 years of age. This implies that older individuals with NCDs gradually moved away from the labour market before the average retirement age.

The final sub-sample analysis was done for different NCDs classification. In the primary analysis, we broadly classified NCDs considering all long-term health conditions reported. Now we consider the long-term health conditions that resulted in severe covid -illnesses. We classified those health conditions as Risky-NCDs. Accordingly, we applied the same DiD regression as above by considering the individuals with risky NCDs as the examined group. The sample consisted individuals who were employed, self-employed or both at the baseline period. For comparison, we did the same analysis for the group of individuals who had other NCDs. The results of the post-covid effect are presented in Figure 4.5.5 and the significance levels of the coefficient can be found in Appendix 4.J.

As the results indicate, the effect of risky NCDs on work capacity was more significant and extensive than other NCDs indicating that the COVID-19 pandemic has affected the work capacity of individuals who faced a higher risk due to their ill-health. For example, individuals with risky- NCDs lost at least 1.8 hours of work in April 2020 compared to healthy workers, whereas individuals with other NCDs lost 1.1 hours of work. Those individuals who worked during the baseline period

and had Risky NCDs lost approximately 4 hours of work by the last stage of the pandemic in September 2020.

4.5.5 Mechanisms to explain the labour market impact of COVID-19

In the next step of our analysis, we aim to explore the potential mechanisms which may have caused the adverse labour market outcomes of NCD individuals during COVID-19. We pay attention to two mechanisms. One of the reasons why the pandemic may affect the working hours of NCD individuals is their poor mental health. The literature confirms that the pandemic adversely affected the mental health of people (Rossi et al., 2020; Serrano-Alarcón et al., 2022; Vizheh et al., 2020). So the combination of the pandemic and having NCDs could trigger the adverse effect. We test this mechanism by using the same DiD model as in Equation 4.4) but now with the probability of having good mental health as the dependent variable. The identification of mental health is based on the GHQ-caseness scale, and the threshold we use is 2 to classify poor mental health (Anjara et al., 2020). If NCDs trigger poor mental health during the pandemic, our DiD coefficient should be negative and significant.

The results of Table 4.5.3 indicate that mental health was not affected by NCDs during the pandemic period. In contrast, the mental health of NCD individuals was significantly higher than their healthy counterparts at the very beginning of the pandemic. During the last stage of the pandemic, the NCDs individuals' mental health was negatively affected, but the coefficients are not statistically significant. However, NCD individuals reported poor mental health compared to their healthy counterparts, irrespective of the pandemic (Appendix 4.K)

Individuals' general health (subjective) is the second mechanism we identify as a reason why the pandemic may affect the working hours of NCD individuals. Again, we use the same DiD model as in Equation 4.4 , but now with the probability of

Table 4.5.3: Mechanisms to explain the labour market impact of COVID-19

	Mental health	General health
Apr-20	0.0236**	-
	(0.0116)	
May-20	0.0123	-
	(0.0118)	
Jun-20	0.0077	-
	(0.0119)	
Jul-20	-0.0040	-
	(0.0117)	
Sep-20	-0.0107	-
	(0.0121)	
Nov-20	0.0095	0.0010
	(0.0126)	(0.0134)
Jan-21	0.0166	0.0145
	(0.0128)	(0.0135)
Mar-21	0.0018	0.0072
	(0.0124)	(0.0133)
Sep-21	-0.0064	0.0123
	(0.0121)	(0.0132)

Notes: The table presents the results of DiD coefficients of the two regressions that we used to identify the possible mechanisms of the labour market impact of COVID-19. The outcome variable of the first regression is the probability of having good mental health, whereas the outcome variable of the second regression is the probability of having good general health. The information on general health has not been provided in the early COVID-19 surveys.

having good general health as the dependent variable. The classification of general health or subjective health is based on 'excellent' or 'very good' health reported in the self-assessed general health question in the questionnaire. If NCDs decrease general health during the pandemic, our DiD coefficient should be negative and significant. However, the result of Table 4.5.3 indicates that COVID-19 has not reduced the general health of NCD individuals. Instead, the general health of NCD individuals was always lower than their healthy counterparts, irrespective of the pandemic (Appendix 4.L)

4.5.6 Sensitivity analysis

The primary aim of our analysis was to estimate the average treatment effect of the COVID-19 pandemic on the work hours of individuals with NCDs. We used

Table 4.5.4: Post-covid effect of NCDs on hours worked: Results of the Propensity Score Matching method for full period and sub-samples

	All working	Employed	Self employed
Full sample	-1.039***	-1.997***	-2.214***
	(0.195)	*(0.197)*	*(0.74)*
Female	-1.212***	-0.996***	-3.834***
	(0.25)	*(0.251)*	*(1.046)*
Male	-1.085***	-1.433***	-0.953
	(0.294)	*(0.297)*	*(0.985)*
Age below 55	-0.765***	-0.516**	-4.359***
	(0.214)	*(0.216)*	*(0.923)*
Age 55-65	-0.065	-0.813*	1.59
	(0.472)	*(0.493)*	*(1.394)*
RNCD	-1.444***	-1.427***	-3.193***
	(0.202)	*(0.206)*	*(0.768)*
ONCD	-0.178	-0.025	-1.083
	(0.193)	*(0.193)*	*(0.747)*
Keyworker	-0.91***	-0.629**	-6.966***
	(0.289)	*(0.283)*	*(2.26)*
Non-keyworker	-1.05***	-1.363***	-2.266***
	(0.269)	*(0.285)*	*(0.764)*

Significance levels : $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

DiD method to estimate the ATT. To assess the robustness of our results, we applied another method, propensity score matching (PSM), to estimate the ATT. As shown in Figure 4.4.1, the parallel trend assumption is satisfied, so propensity score matching is validated for the analysis. Matching was done using kernel matching with the common support (Appendix 4.M). Accordingly, we estimated the ATT for the full Covid period and at different points during the pandemic. Similarly, we estimated the impact for different sub-samples. Table 4.5.4 shows the results of the PSM estimators for the full period and different sub-samples. Table 4.5.5 shows the PSM estimators at different points during the pandemic.

The ATT estimated using the PSM method is far more similar to the estimated coefficient of the DiD method. Although there are slight differences in the magnitude of the effect between the two methods, the direction of the outcome is similar. The results of both methods show that the employed workers with NCDs worked fewer

Table 4.5.5: Post-covid effect of NCDs on hours worked: Results of the Propensity Score Matching method

Post-covid period	Employed	Self-employed	Employed/ self-employed
Apr-20	-1.3135**	1.0264	-0.7902*
	(0.5199)	(1.3532)	(0.4241)
May-20	-1.3638***	-0.0146	-1.0086***
	(0.5161)	(1.5115)	(0.348)
Jun-20	-1.6381***	-2.2695	-1.5192***
	(0.4544)	(1.8664)	(0.3775)
Jul-20	-1.8856***	-2.1722	-1.7633***
	(0.491)	(1.4867)	(0.4993)
Sep-20	-1.3328***	-0.3368	-1.0761***
	(0.436)	(1.2653)	(0.393)
Nov-20	-1.6916***	-2.9743*	-1.7709***
	(0.43)	(1.686)	(0.5226)
Jan-21	-1.7207***	-1.5506	-1.5528***
	(0.535)	(1.5859)	(0.5421)
Mar-21	-1.6483***	-1.9442	-1.4607***
	(0.5507)	(1.6795)	(0.4531)
Sep-21	-2.5992***	-4.6814***	-2.7253***
	(0.5644)	(1.4675)	(0.4952)

Notes: The table shows the ATT of the COVID-19 pandemic on NCD individuals estimated through propensity score matching. The ATT was estimated for nine months for three work categories; employed, self-employed and all employed and self-employed. Samples consist of all individuals who worked during the baseline period. Each month of Covid was linked with the baseline period (January 2020) in the PSM matching. The dependent variable was the weekly work hours. The conditional covariates used for matching were age, gender, living in an urban, education, marital status and having small children

hours than healthy workers after the COVID-19 pandemic. Generally, the PSM estimators are slightly lower than DiD estimators. For example, the DiD estimator shows that NCD individuals lost 1.6 hours of work in April, whereas the PSM method indicates that the work loss was 1.3 hours. In the later part of the pandemic, the DiD estimator records 3 hours of work loss for NCD individuals, while the PSM estimator indicates 2.6 hours of work loss.

4.6 Discussion

This paper aims to examine the impact of the COVID-19 pandemic on the labour market outcomes of individuals with NCDs. The Understanding Society COVID-19 study provides extensive data on individuals from the onset of the pandemic to the end, covering nearly two years, using nine surveys. We obtained information on individuals' labour market performances and health from the COVID-19 study and linked the data with the main-stage Understanding Society surveys to distinguish the pandemic-related effects. We used DiD method to capture the average treatment effect of COVID-19 on NCD individuals' labour market variables at different points in time during the pandemic. We conducted several sub-sample analyses to validate our results and checked the robustness using the propensity score matching method.

The results of the overall impact indicate that the COVID-19 pandemic has negatively affected NCD individuals' likelihood of being employed/ self-employed. However, we showed that the effect varies at different points during the pandemic. Since COVID-19 affected all individuals irrespective of their health, the differential impacts on the employment of individuals with NCDs were minor at the onset of the pandemic. But as the pandemic proceeded, the adverse effects on NCD individuals aggravated, and the pandemic kept NCD people out of the labour market. The highest negative impact on the odds of being employed or self-employed was reported in January 2021, when the UK was at the peak of the second wave of COVID-19 with a newly found Beta variant of the virus. Compared to the early variants, the new Covid variant was highly infectious and questioned the effectiveness of the vaccines (Duong, 2021). Similarly, since it was only the beginning of the vaccine roll-out, many NCD individuals were unprotected from the virus, and the UK recorded their highest death rate due to COVID-19 in January 2021. Hence, we could assume that the reason for the lower probability of work of NCD individuals during that time is the risk of them being exposed to the new variant.

We found that COVID-19 adversely affected the work duration of individuals

when they are employed or self-employed. The work loss of self-employed is greater than that of employed. Generally, having NCDs have not affected the working time of individuals. Still, when combined with the pandemic effect, NCDs caused a reduction in employees' work hours. This is more prominent when the work is compared with the baseline employment. NCD individuals who were employed before the onset of COVID-19 worked fewer hours during the pandemic than their healthy counterparts. For the self-employed, when compared with the baseline work status, this work loss is higher than the employed, especially at the later time of the pandemic, However, considering the current employment status, the working time of self-employed individuals with NCDs was not affected by the pandemic. This partially implies some changes in the employment status of self-employed before and after the pandemic.

We proved that the work losses during the pandemic are combined with the pandemic-related lockdowns, irrespective of individuals' health. During the time when tighter lockdown restrictions were enforced, their work loss due to the pandemic was high. However, the NCD individuals' specific work loss due to the pandemic does not relate to the tighter lockdown restriction. Regardless of the easing of lockdown restrictions, their work loss rose when the pandemic proceeded, and the highest work loss appeared at the last stage of our reference period (September 2021).

We found that the work loss due to the pandemic is higher for individuals with riskier health conditions for COVID-19 than those having other types of health conditions. People with NCDs were identified as the high-risk group that the virus can be severely infected. The death rate of COVID-19 infections for people with NCDs was significantly higher than for the healthy people who caught the virus (Alqahtani et al., 2020; Nikoloski et al., 2021; Pal and Bhadada, 2020). Hence NCD individuals lived with extra risk during the pandemic, and they were always advised to take additional measures for protection from the virus. To avoid being exposed

to the virus, some NCD individuals might have chosen to be absent from the labour market. Hence the adverse impact of COVID-19 on the work capacity of people with NCDs could be coupled with the health risk that NCD individuals encountered during the pandemic.

The gradual increase in the work loss of NCD individuals during the pandemic should be investigated. We could think that some people with NCDs who were working before the pandemic have moved out of the labour market gradually, for example, choosing early retirement due to the disadvantaged environment created by COVID-19 for their health. Our sub-sample analysis of age groups gives important insights into this. We found that the pandemic reduced NCD individuals' work hours more for the older age groups compared to younger age, especially during the later part of the pandemic. This implies that those older people are working less than the pre-pandemic level or have moved entirely out of the labour market. This could link to the recent trend of workforce loss in the wider economy of the UK. The UK unemployment rate is close to its lowest level since the mid 70's. Many people leave work to economic inactivity due to sickness, meaning they are not only not working, but they also are not looking for a job either (ONS, 2020). Hence our study suggests that part of the labour loss in the wider economy is linked to the combined effect of NCDs and COVID-19.

Our sub-sample analysis for key workers also gives some important insights into the pandemic's impact on NCD individuals' work. We noticed that key workers with NCDs lost more work hours than their healthy counterparts. Similarly, that work loss is more significant than that of the work loss employees in non-key work sectors. This implies that although the work was compulsory, the NCD individuals might have chosen to voluntarily work less or stayed out of work when there was a higher infectious rate of the virus. Similarly, we saw that by the later part of the pandemic in September 2021, key workers with NCDs still worked fewer hours than healthy workers and even fewer than non-key workers. Accordingly, we could assume

that the pandemic incentivised key workers to move out of the labour market, for example, early retirements. Considering the large workforce loss the UK economy is currently experiencing in some key worker sectors, especially in the health sector (ONS, 2020), we could suggest that the combined effect of NCDs and COVID-19 is responsible for that work loss to some extent.

We identified possible causal channels for the work loss of NCD individuals during the pandemic. We investigated two mechanisms that could lead to lower labour market performances; individuals' mental health and general health. We saw that people with NCDs have lower general and mental health compared to their healthy counterparts, irrespective of the pandemic. However, we do not see that the pandemic has further decreased their general health or mental health. Hence, we could suggest that although the pandemic did not deteriorate the NCD individual's mental or general health further, the existing low levels of health led them to perform less in the labour market as they wanted to minimize the further health risk. However, further investigations are needed to identify other possible mechanisms.

This study has some limitations. The health status is self-reported. Therefore, possible exaggerations of ill-health could exist. Since the COVID-19 vaccine prioritization was linked with long-term health conditions, over-reporting of ill-health could be larger than the normal bias that occurs from self-reported health. Similarly, there was a data limitation on employment status. There were a considerable number of people in the employment category 'both employed and self-employed' in the COVID-19 study data, and the number of individuals in that category increased. However, such a category does not appear in pre-covid surveys. Hence, we could not estimate the impact of the pandemic on their work separately, instead, we combined all employed, self-employed or both together and considered all working people. Finally, there could be missing variables that we could not incorporate into the model due to the data limitation, and therefore the our approach may not be adequate to describe the causal inference. However, we did a sensitivity analysis

using PSM and showed that our findings are consistent with those estimations.

4.7 Conclusion

The literature elucidates how COVID-19 affects people with NCDs, especially their health and healthcare access. However, it has not been discussed the labour market performances of NCD individuals during the pandemic. Hence, Using UK Understanding society COVID-19 study data, we estimate the effect of COVID-19 on labour market outcomes of individuals with NCDs both at the extensive margin and the intensive margin at different stages of the pandemic.

We show that COVID-19 reduced the likelihood of employment and the working time of individuals with NCDs. This impact varies with the employment status and the different stages of the pandemic. COVID-19 negatively affected NCD individuals' probability of being employed, whereas the self-employment probability was not affected much. The highest negative impact on the likelihood of being employed is recorded when the country experiences the peak of the second wave of COVID-19. However, the reduction in the work amount of NCD individuals due to the pandemic does not relate to the severity of the pandemic. Instead, the amount of work decreased continuously throughout the COVID-19 period compared to their pre-pandemic work level, suggesting that some people with NCDs left the labour market after the pandemic. Moreover, we show that the work loss of people with NCDs positively links to the age level and the riskiness of the health condition for severe COVID-19 illness.

The study provides important policy implications. Overall, the lower labour market activities of the people with NCDs led to a contraction of the labour supply after the pandemic. This might have some link with the current shortage of the labour force in the wider economy of the UK. Therefore, identifying the reasons that they quit jobs is important to either bring them back to the labour market or

to prevent such downturns in future. On the other hand, attention should be given to the people with NCDs who left the labour market or worked less due to COVID-19. The plunge of their livelihood could have a direct impact on their quality of life. Hence, this study urges policy actions that protect the welfare of those people with NCDs.

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Appendix

4.A Number of respondents in COVID-19 study

Table 4.A.1: Number of respondents in COVID-19 study

	Apr-20	May-20	Jun-20	Jul-20	Sep-20	Nov-20	Jan-21	Mar-21	Sep-21
Apr-20	17441	13527	12947	12509	12017	11257	11187	11794	11819
May-20		14623	12813	12282	11798	11080	10943	11306	11162
Jun-20			13919	12231	11717	11034	10894	11178	11001
Jul-20				13536	11634	10911	10809	11078	10858
Sep-20					12706	10821	10655	10839	10576
Nov-20						11886	10429	10518	10162
Jan-21							11808	10619	10191
Mar-21								12508	10685
Sep-21									12642

Source: University of Essex, Institute for Social and Economic Research. (2021). Understanding Society: COVID-19 Study, 2020-2021. [data collection]. 11th Edition. UK Data Service. SN: 8644, 10.5255/UKDA-SN-8644-11.

4.B Composition of the COVID-19 study sample

Table 4.B.1: Composition of the COVID-19 study sample

	(1) Wave-10 of the US sample	(2) COVID-19 study sample (All)
Mean Age	49.82	46.6
	(0.101)	(0.119)
Age categories		
Less than 30	15%	20%
30 to 40	14%	16%
40 to 50	18%	21%
50 to 65	29%	29%
Above 65	24%	15%
Female	55%	58%
Urban	75%	77%
Marital status		
Single/ never married	29%	29%
Married	52%	55%
Separated/Divorced	10%	10%
Widowed	6%	3%
Ethnicity		
British	76%	81%
Asian/British	11%	8%
Black/British	2%	3%
White	2%	5%
Region		
North East	3.61	3.38
North West	10	9.85
Yorkshire and the Humber	8.62	8.25
East Midlands	7.29	7.43
West Midlands	8.43	8.38
East of England	8.65	9.63
London	12.31	11.38
South East	11.85	13.71
South West	8.04	9.02
Wales	6.4	5.95
Scotland	8.29	8.61
Northern Ireland	6.47	4.4
Education		
College Level	24%	29%
A level and above	17%	18%
O level and above	21%	21%
Employed	48%	52%
Self-employed	8%	8%
NCD	44%	48%

Notes: The table shows the percentage of respondents in the sample under each category. For Age, mean and standard errors are given. Column (1) shows the sample characteristics of Wave 10 of the main-stage US survey, which consists of 34318 respondents. Column (2) shows the characteristics of the sample that was used for the unbalanced panel study, and it consists of 19371 respondents. Column (3) gives the figures for the sample applied in the balanced panel study, and it consists of 7919 respondents who participated in all nine COVID-19 surveys.

4.C Statistical test for parallel trend

Table 4.C.1: Statistical test for parallel trend

	(1)	(2)	(3)	(4)
VARIABLES	2017	2018	2019	2017 to 2019
NCD	-0.8422***	-0.8615***	-0.8603***	-0.8837***
	(0.2295)	(0.2344)	(0.2367)	(0.2321)
2017	-0.0298			
	(0.1804)			
2018		-0.1927		
		(0.1870)		
2019			-0.3354*	
			(0.1903)	
2017 to 2019				-0.1841
				(0.1511)
NCD*Time	0.3044	0.0813	0.3916	0.2486
	(0.3183)	(0.3223)	(0.3239)	(0.2644)

Notes: The table shows the statistical test for the pre-treatment trend of the work hours of employed individuals. We use the same specification that we used in our main analysis to estimate the DiD estimator. Here, we considered 2016 as the base period. Columns 1-3 show the results of separate regressions which has a dummy variable for each year. Column 4 gives the results of the regression which has a dummy variable that represents all three years (2017-2019). The interaction term (Time*NCD) is statistically insignificant, which means that there are no significant changes in the work hour difference between the individuals with NCDs and non-NCDs with the time.
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.D Probability of employed or self-employed during COVID-19: Results of the linear probability model

Table 4.D.1: Probability of employed or self-employed during COVID-19:Summery of the results of the linear probability models

	Employed			Self employed			Employed or self-employed		
	NCDs	COVID-19	NCDs*COVID-19	NCDs	COVID-19	NCDs*COVID-19	NCDs	COVID-19	NCDs*COVID-19
Apr-20	-0.0518***	-0.0338***	-0.0107	-0.0111**	-0.0040	-0.0121*	-0.0647***	-0.0131**	-0.0251**
	(0.0083)	(0.0074)	(0.0116)	(0.0049)	(0.0044)	(0.0069)	(0.0074)	(0.0067)	(0.0105)
May-20	-0.0436***	0.0143*	-0.0253**	-0.0108**	-0.0018	-0.0108	-0.0555***	0.0348***	-0.0341***
	(0.0082)	(0.0078)	(0.0121)	(0.0050)	(0.0048)	(0.0074)	(0.0073)	(0.0069)	(0.0108)
Jun-20	-0.0435***	0.0108	-0.0292**	-0.0111**	-0.0043	-0.0097	-0.0554***	0.0354***	-0.0381***
	(0.0082)	(0.0079)	(0.0123)	(0.0050)	(0.0048)	(0.0075)	(0.0073)	(0.0071)	(0.0110)
Jul-20	-0.0431***	0.0110	-0.0331***	-0.0111**	-0.0070	-0.0101	-0.0553***	0.0322***	-0.0393***
	(0.0082)	(0.0080)	(0.0125)	(0.0050)	(0.0049)	(0.0076)	(0.0073)	(0.0071)	(0.0111)
Sep-20	-0.0413***	0.0104	-0.0314**	-0.0107**	-0.0065	-0.0142*	-0.0532***	0.0311***	-0.0418***
	(0.0082)	(0.0083)	(0.0128)	(0.0050)	(0.0050)	(0.0078)	(0.0073)	(0.0074)	(0.0114)
Nov-20	-0.0405***	0.0104	-0.0322**	-0.0111**	-0.0012	-0.0127	-0.0529***	0.0354***	-0.0453***
	(0.0082)	(0.0085)	(0.0131)	(0.0050)	(0.0052)	(0.0081)	(0.0073)	(0.0076)	(0.0117)
Jan-21	-0.0390***	0.0167**	-0.0377***	-0.0107**	-0.0080	-0.0119	-0.0507***	0.0353***	-0.0525***
	(0.0082)	(0.0085)	(0.0132)	(0.0050)	(0.0051)	(0.0080)	(0.0073)	(0.0076)	(0.0118)
Mar-21	-0.0403***	0.0061	-0.0208	-0.0107**	-0.0098**	-0.0110	-0.0517***	0.0235***	-0.0353***
	(0.0082)	(0.0081)	(0.0130)	(0.0050)	(0.0049)	(0.0079)	(0.0073)	(0.0073)	(0.0116)
Sep-21	-0.0401***	0.0214***	-0.0329**	-0.0109**	-0.0101**	-0.0058	-0.0517***	0.0383***	-0.0443***
	(0.0082)	(0.0081)	(0.0128)	(0.0050)	(0.0049)	(0.0078)	(0.0073)	(0.0072)	(0.0115)

Notes: The table provides a summary of the results of three linear probability models estimated for three employment categories; employed, self-employed and all employed or/and self-employed. We estimated the model for nine months. Each month of Covid was linked with the pre-covid period (2019) in the DiD regression. The dependent variables of the three models are dummy variables that indicate being employed, self-employed, and either employed or self-employed, respectively. The model was estimated with conditional covariates for age, gender, living in the urban, education, marital status and having small children.

Standard errors in parentheses

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

Table 4.D.2: Regression results of the linear probability model- Employed

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Apr-20	May-20	Jun-20	Jul-20	Sep-20	Nov-20	Jan-21	Mar-21	Sep-21
NCD	-0.0518***	-0.0436***	-0.0435***	-0.0431***	-0.0413***	-0.0405***	-0.0390***	-0.0403***	-0.0401***
	(0.0083)	(0.0082)	(0.0082)	(0.0082)	(0.0082)	(0.0082)	(0.0082)	(0.0082)	(0.0082)
_diff	-0.0107	-0.0253**	-0.0292**	-0.0331***	-0.0314**	-0.0322**	-0.0377***	-0.0208	-0.0329**
	(0.0116)	(0.0121)	(0.0123)	(0.0125)	(0.0128)	(0.0131)	(0.0132)	(0.0130)	(0.0128)
female	0.0508***	0.0491***	0.0512***	0.0526***	0.0424***	0.0428***	0.0429***	0.0421***	0.0438***
	(0.0089)	(0.0093)	(0.0094)	(0.0095)	(0.0097)	(0.0098)	(0.0098)	(0.0097)	(0.0096)
Age	-0.0036***	-0.0048***	-0.0048***	-0.0048***	-0.0051***	-0.0053***	-0.0054***	-0.0052***	-0.0052***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
college_level	0.0936***	0.0874***	0.0851***	0.0885***	0.0863***	0.0882***	0.0925***	0.0917***	0.0928***
	(0.0060)	(0.0062)	(0.0063)	(0.0064)	(0.0065)	(0.0066)	(0.0066)	(0.0065)	(0.0065)
married	-0.0381***	-0.0456***	-0.0479***	-0.0472***	-0.0521***	-0.0530***	-0.0468***	-0.0498***	-0.0433***
	(0.0099)	(0.0101)	(0.0103)	(0.0103)	(0.0105)	(0.0106)	(0.0107)	(0.0106)	(0.0105)
single_nevermarried	-0.0829***	-0.0881***	-0.0863***	-0.0837***	-0.0905***	-0.0949***	-0.0859***	-0.0893***	-0.0812***
	(0.0104)	(0.0107)	(0.0109)	(0.0109)	(0.0111)	(0.0113)	(0.0113)	(0.0112)	(0.0111)
female_smallchildren	-0.0839***	-0.0826***	-0.0857***	-0.0822***	-0.0760***	-0.0865***	-0.0803***	-0.0772***	-0.0791***
	(0.0116)	(0.0124)	(0.0127)	(0.0128)	(0.0131)	(0.0133)	(0.0134)	(0.0131)	(0.0129)
male_married	0.0858***	0.0891***	0.0953***	0.0972***	0.0871***	0.0852***	0.0854***	0.0888***	0.0892***
	(0.0117)	(0.0122)	(0.0124)	(0.0125)	(0.0127)	(0.0129)	(0.0129)	(0.0127)	(0.0126)
Apr-20	-0.0338***								
	(0.0074)								
May-20		0.0143*							
		(0.0078)							
Jun-20			0.0108						
			(0.0079)						
Jul-20				0.0110					
				(0.0080)					
Sep-20					0.0104				
					(0.0083)				
Nov-20						0.0104			
						(0.0085)			
Jan-21							0.0167**		
							(0.0085)		
Mar-21								0.0061	
								(0.0081)	
Sep-21									0.0214***
									(0.0081)
Constant	0.8187***	0.8756***	0.8746***	0.8707***	0.8945***	0.9059***	0.9000***	0.8963***	0.8867***
	(0.0172)	(0.0178)	(0.0182)	(0.0182)	(0.0186)	(0.0188)	(0.0189)	(0.0186)	(0.0185)
Observations	27,528	24,954	24,297	23,974	23,200	22,502	22,383	23,020	23,168

Notes: Dependent variable: Probability of employed
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.D.3: Regression results of the linear probability model- self-employed

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Apr-20	May-20	Jun-20	Jul-20	Sep-20	Nov-20	Jan-21	Mar-21	Sep-21
NCD	-0.0111**	-0.0108**	-0.0111**	-0.0111**	-0.0107**	-0.0111**	-0.0107**	-0.0107**	-0.0109**
	(0.0049)	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0050)
_diff	-0.0121*	-0.0108	-0.0097	-0.0101	-0.0142*	-0.0127	-0.0119	-0.0110	-0.0058
	(0.0069)	(0.0074)	(0.0075)	(0.0076)	(0.0078)	(0.0081)	(0.0080)	(0.0079)	(0.0078)
female	-0.0401***	-0.0411***	-0.0413***	-0.0401***	-0.0413***	-0.0439***	-0.0425***	-0.0440***	-0.0452***
	(0.0053)	(0.0057)	(0.0057)	(0.0057)	(0.0059)	(0.0060)	(0.0060)	(0.0059)	(0.0058)
Age	0.0024***	0.0024***	0.0024***	0.0024***	0.0024***	0.0025***	0.0023***	0.0023***	0.0024***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
college_level	0.0152***	0.0172***	0.0158***	0.0173***	0.0174***	0.0170***	0.0151***	0.0165***	0.0154***
	(0.0036)	(0.0038)	(0.0039)	(0.0039)	(0.0039)	(0.0041)	(0.0040)	(0.0039)	(0.0039)
married	0.0149**	0.0158**	0.0185***	0.0160**	0.0175***	0.0201***	0.0162**	0.0152**	0.0165***
	(0.0059)	(0.0062)	(0.0063)	(0.0063)	(0.0064)	(0.0065)	(0.0065)	(0.0064)	(0.0064)
single_nevermarried	0.0111*	0.0113*	0.0138**	0.0101	0.0107	0.0144**	0.0089	0.0078	0.0099
	(0.0062)	(0.0066)	(0.0066)	(0.0066)	(0.0067)	(0.0069)	(0.0069)	(0.0068)	(0.0068)
female_smallchildren	0.0018	0.0040	0.0053	0.0040	0.0032	0.0069	0.0040	0.0030	0.0089
	(0.0069)	(0.0076)	(0.0077)	(0.0078)	(0.0080)	(0.0082)	(0.0082)	(0.0080)	(0.0079)
male_married	0.0085	0.0109	0.0086	0.0082	0.0086	0.0085	0.0103	0.0068	0.0046
	(0.0070)	(0.0075)	(0.0076)	(0.0076)	(0.0077)	(0.0079)	(0.0079)	(0.0077)	(0.0077)
Apr-20	-0.0040								
	(0.0044)								
May-20		-0.0018							
		(0.0048)							
Jun-20			-0.0043						
			(0.0048)						
Jul-20				-0.0070					
				(0.0049)					
Sep-20					-0.0065				
					(0.0050)				
Nov-20						-0.0012			
						(0.0052)			
Jan-21							-0.0080		
							(0.0051)		
Mar-21								-0.0098**	
								(0.0049)	
Sep-21									-0.0101**
									(0.0049)
Constant	-0.0043	-0.0041	-0.0080	-0.0046	-0.0030	-0.0093	0.0001	0.0022	-0.0010
	(0.0102)	(0.0109)	(0.0111)	(0.0110)	(0.0113)	(0.0116)	(0.0115)	(0.0113)	(0.0113)
Observations	27,528	24,954	24,297	23,974	23,200	22,502	22,383	23,020	23,168

Notes: Dependent variable: Probability of self-employed
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.D.4: Regression results of the linear probability model- all employed or/and self-employed

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Apr-20	May-20	Jun-20	Jul-20	Sep-20	Nov-20	Jan-21	Mar-21	Sep-21
NCD	-0.0647***	-0.0555***	-0.0554***	-0.0553***	-0.0532***	-0.0529***	-0.0507***	-0.0517***	-0.0517***
	(0.0074)	(0.0073)	(0.0073)	(0.0073)	(0.0073)	(0.0073)	(0.0073)	(0.0073)	(0.0073)
_diff	-0.0251**	-0.0341***	-0.0381***	-0.0393***	-0.0418***	-0.0453***	-0.0525***	-0.0353***	-0.0443***
	(0.0105)	(0.0108)	(0.0110)	(0.0111)	(0.0114)	(0.0117)	(0.0118)	(0.0116)	(0.0115)
female	0.0084	0.0050	0.0061	0.0094	-0.0008	-0.0029	-0.0019	-0.0037	-0.0027
	(0.0080)	(0.0082)	(0.0084)	(0.0084)	(0.0086)	(0.0087)	(0.0088)	(0.0087)	(0.0086)
Age	-0.0010***	-0.0023***	-0.0023***	-0.0023***	-0.0026***	-0.0027***	-0.0030***	-0.0028***	-0.0027***
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
college_level	0.1164***	0.1114***	0.1083***	0.1112***	0.1081***	0.1099***	0.1118***	0.1124***	0.1139***
	(0.0055)	(0.0056)	(0.0056)	(0.0057)	(0.0058)	(0.0059)	(0.0059)	(0.0058)	(0.0058)
married	-0.0258***	-0.0310***	-0.0286***	-0.0306***	-0.0325***	-0.0327***	-0.0305***	-0.0342***	-0.0277***
	(0.0089)	(0.0090)	(0.0092)	(0.0092)	(0.0094)	(0.0095)	(0.0095)	(0.0095)	(0.0094)
single_nevermarried	-0.0769***	-0.0818***	-0.0776***	-0.0794***	-0.0832***	-0.0838***	-0.0811***	-0.0849***	-0.0753***
	(0.0094)	(0.0095)	(0.0097)	(0.0097)	(0.0099)	(0.0101)	(0.0101)	(0.0100)	(0.0099)
female_smallchildren	-0.0827***	-0.0775***	-0.0836***	-0.0798***	-0.0776***	-0.0834***	-0.0804***	-0.0789***	-0.0740***
	(0.0105)	(0.0110)	(0.0113)	(0.0114)	(0.0118)	(0.0119)	(0.0120)	(0.0118)	(0.0115)
male_married	0.0934***	0.0973***	0.0989***	0.1025***	0.0922***	0.0889***	0.0918***	0.0921***	0.0914***
	(0.0106)	(0.0109)	(0.0110)	(0.0111)	(0.0114)	(0.0115)	(0.0116)	(0.0114)	(0.0113)
Apr-20	-0.0131**								
	(0.0067)								
May-20		0.0348***							
		(0.0069)							
Jun-20			0.0354***						
			(0.0071)						
Jul-20				0.0322***					
				(0.0071)					
Sep-20					0.0311***				
					(0.0074)				
Nov-20						0.0354***			
						(0.0076)			
Jan-21							0.0353***		
							(0.0076)		
Mar-21								0.0235***	
								(0.0073)	
Sep-21									0.0383***
									(0.0072)
Constant	0.8074***	0.8682***	0.8663***	0.8647***	0.8880***	0.8928***	0.8997***	0.8982***	0.8853***
	(0.0155)	(0.0159)	(0.0162)	(0.0162)	(0.0166)	(0.0168)	(0.0169)	(0.0167)	(0.0165)
Observations	27,528	24,954	24,297	23,974	23,200	22,502	22,383	23,020	23,168

Notes: Dependent variable: Probability of All employed or/and self-employed
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.E Effect of COVID-19 on hours worked (based on baseline work): Results of the DiD regression

Table 4.E.1: Effect of COVID-19 on hours worked (based on baseline work): Summary of the results of DiD models

	Employed			Self employed			Employed or self-employed		
	NCD	Covid	NCD*Covid	NCD	Covid	NCD*Covid	NCD	Covid	NCD*Covid
Apr-20	-0.3744	-6.7051***	-1.6117***	1.4167	-14.1687***	-2.0656	-0.1252	-7.7199***	-1.4413***
	(0.3689)	(0.3149)	(0.5154)	(1.2003)	(1.0547)	(1.7032)	(0.3543)	(0.3037)	(0.4962)
May-20	-0.2410	-4.4363***	-1.7555***	1.3145	-11.0564***	-2.5454	-0.0385	-5.3023***	-1.6637***
	(0.3585)	(0.3247)	(0.5245)	(summary	(1.1366)	(1.8084)	(0.3465)	(0.3154)	(0.5083)
Jun-20	-0.2453	-2.6315***	-1.8553***	1.4056	-7.3929***	-5.0579***	-0.0475	-3.2852***	-1.9907***
	(0.3504)	(0.3225)	(0.5221)	(1.1926)	(1.1443)	(1.8110)	(0.3390)	(0.3140)	(0.5067)
Jul-20	-0.1797	-2.4325***	-2.2005***	1.5227	-5.3757***	-3.7398**	0.0031	-2.8275***	-2.0729***
	(0.3475)	(0.3219)	(0.5237)	(1.2042)	(1.1723)	(1.8694)	(0.3358)	(0.3134)	(0.5082)
Sep-20	-0.0785	0.8672***	-2.1806***	1.2938	-3.6021***	-2.6842	0.0760	0.2902	-2.0207***
	(0.3396)	(0.3246)	(0.5226)	(1.2185)	(1.2132)	(1.9292)	(0.3310)	(0.3183)	(0.5116)
Nov-20	-0.1583	0.0183	-1.8084***	1.7183	-3.4117***	-5.4956***	0.0543 summary	-0.4405	-2.0008***
	(0.3462)	(0.3389)	(0.5467)	(1.1956)	(1.2059)	(1.9188)	(0.3353)	(0.3299)	(0.5314)
Jan-21	-0.1115	-0.6050*	-2.4757***	1.5722	-4.8607***	-5.3012***	0.0711	-1.0170***	-2.6073***
	(0.3502)	(0.3427)	(0.5560)	(1.2256)	(1.2648)	(2.0195)	(0.3395)	(0.3349)	(0.5422)
Mar-21	-0.0824	-0.3606	-2.1155***	1.6651	-4.4716***	-4.7293**	0.1129	-0.7951**	-2.1875***
	(0.3453)	(0.3261)	(0.5399)	(1.2289)	(1.2219)	(1.9901)	(0.3359)	(0.3194)	(0.5277)
Sep-21	0.0544	1.2815***	96FFFB-2.9989***	1.5785	-0.5867	-5.0025**	0.1937	1.2132***	-3.0654***
	(0.3411)	(0.3216)	(0.5281)	(1.2050)	(1.2061)	(1.9442)	(0.3301)	(0.3140)	(0.5144)

Notes: Table provides a summery of the results of DiD regressions for nine months under three categories; employed, self-employed and either employed or self-employed or both. The samples included employed or self-employed individuals during the baseline period (January 2020). Each month of Covid was linked with the pre-covid period (2019) in the DiD regression. The dependent variable was the weekly work hours. The model was estimated with conditional covariates for age, gender, living in an urban, education, marital status and having small children.
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.E.2: Regression results for the DiD model: weekly work hours of individuals employed at the baseline

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Apr-20	May-20	Jun-20	Jul-20	Sep-20	Nov-20	Jan-21	Mar-21	Sep-21
NCD	-0.3744	-0.2410	-0.2453	-0.1797	-0.0785	-0.1583	-0.1115	-0.0824	0.0544
	(0.3689)	(0.3585)	(0.3504)	(0.3475)	(0.3396)	(0.3462)	(0.3502)	(0.3453)	(0.3411)
_diff	-1.6117***	-1.7555***	-1.8553***	-2.2005***	-2.1806***	-1.8084***	-2.4757***	-2.1155***	-2.9989***
	(0.5154)	(0.5245)	(0.5221)	(0.5237)	(0.5226)	(0.5467)	(0.5560)	(0.5399)	(0.5281)
female	-4.0472***	-4.5221***	-4.9607***	-4.8141***	-5.4639***	-5.1267***	-5.1863***	-5.3774***	-5.4911***
	(0.3921)	(0.4004)	(0.3971)	(0.3965)	(0.3944)	(0.4079)	(0.4132)	(0.4018)	(0.3963)
Age	0.1383***	0.1175***	0.1151***	0.1085***	0.0875***	0.1024***	0.0961***	0.0871***	0.0605***
	(0.0127)	(0.0129)	(0.0128)	(0.0128)	(0.0128)	(0.0132)	(0.0134)	(0.0130)	(0.0128)
college_level	5.0855***	4.4978***	3.9468***	3.0034***	3.3076***	3.8598***	4.0034***	3.9004***	3.3043***
	(0.2603)	(0.2640)	(0.2616)	(0.2613)	(0.2597)	(0.2689)	(0.2724)	(0.2646)	(0.2603)
married	-1.5957***	-2.0277***	-1.9598***	-2.5184***	-2.2493***	-2.8017***	-2.5389***	-2.4649***	-2.2761***
	(0.4372)	(0.4409)	(0.4355)	(0.4349)	(0.4306)	(0.4446)	(0.4514)	(0.4417)	(0.4346)
single_nevermarried	-1.5743***	-1.8067***	-1.9988***	-1.7897***	-2.1587***	-2.3636***	-2.1766***	-2.4418***	-2.2533***
	(0.4589)	(0.4638)	(0.4589)	(0.4568)	(0.4538)	(0.4696)	(0.4765)	(0.4648)	(0.4568)
female_smallchildren	-4.6850***	-4.2724***	-4.3962***	-3.9876***	-4.5192***	-4.2660***	-4.2943***	-4.2798***	-5.4209***
	(0.5138)	(0.5335)	(0.5327)	(0.5344)	(0.5329)	(0.5537)	(0.5611)	(0.5447)	(0.5290)
male_married	2.7507***	2.8823***	2.5514***	3.2787***	2.0894***	2.6998***	2.7218***	2.4993***	2.0563***
	(0.5172)	(0.5263)	(0.5216)	(0.5203)	(0.5173)	(0.5356)	(0.5427)	(0.5273)	(0.5192)
Apr-20	-6.7051***								
	(0.3149)								
May-20		-4.4363***							
		(0.3247)							
Jun-20			-2.6315***						
			(0.3225)						
Jul-20				-2.4325***					
				(0.3219)					
Sep-20					0.8672***				
					(0.3246)				
Nov-20						0.0183			
						(0.3389)			
Jan-21							-0.6050*		
							(0.3427)		
Mar-21								-0.3606	
								(0.3261)	
Sep-21									1.2815***
									(0.3216)
Constant	25.6312***	27.2165***	27.8976***	28.4450***	29.8779***	29.0749***	29.0976***	29.7190***	31.1069***
	(0.7842)	(0.7955)	(0.7903)	(0.7842)	(0.7821)	(0.8116)	(0.8219)	(0.7986)	(0.7859)
Observations	18,037	16,498	16,060	15,831	15,307	14,822	14,769	15,203	15,337

Notes: Dependent variable: Weekly work hours. Sample: employed at the baseline
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.E.3: Regression results for the DiD model: weekly work hours of individuals self-employed at the baseline

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Apr-20	May-20	Jun-20	Jul-20	Sep-20	Nov-20	Jan-21	Mar-21	Sep-21
NCD	1.4167	1.3145	1.4056	1.5227	1.2938	1.7183	1.5722	1.6651	1.5785
	(1.2003)	(1.2184)	(1.1926)	(1.2042)	(1.2185)	(1.1956)	(1.2256)	(1.2289)	(1.2050)
_diff	-2.0656	-2.5454	-5.0579***	-3.7398**	-2.6842	-5.4956***	-5.3012***	-4.7293**	-5.0025**
	(1.7032)	(1.8084)	(1.8110)	(1.8694)	(1.9292)	(1.9188)	(2.0195)	(1.9901)	(1.9442)
female	-5.1648***	-4.9591***	-7.5334***	-5.6116***	-5.8260***	-6.4118***	-4.9381***	-5.5228***	-7.3069***
	(1.4186)	(1.5133)	(1.5144)	(1.5401)	(1.5800)	(1.5589)	(1.6225)	(1.6052)	(1.5752)
Age	-0.0265	-0.0018	0.0059	-0.0284	-0.0221	-0.0881*	-0.0934*	-0.0684	-0.0978**
	(0.0433)	(0.0467)	(0.0466)	(0.0475)	(0.0486)	(0.0485)	(0.0501)	(0.0498)	(0.0486)
college_level	3.2997***	3.0180***	1.0062	0.5798	0.4809	2.2671**	2.3010**	2.4297**	0.6956
	(0.8604)	(0.9066)	(0.9038)	(0.9241)	(0.9469)	(0.9379)	(0.9768)	(0.9660)	(0.9447)
married	-1.9463	-4.5065***	-3.0472*	-3.7955**	-3.7587**	-4.1709**	-5.3400***	-4.7235***	-3.9739**
	(1.6089)	(1.7179)	(1.7168)	(1.7308)	(1.7707)	(1.7607)	(1.8158)	(1.8168)	(1.8012)
single_nevermarried	-2.4899	-3.4834**	-2.4504	-2.9019*	-4.1040**	-3.2461*	-4.8906***	-3.1903*	-4.8040***
	(1.5551)	(1.6646)	(1.6724)	(1.6793)	(1.7336)	(1.7174)	(1.7755)	(1.7617)	(1.7420)
female_smallchildren	-3.1185	-2.3985	-2.4632	-2.5301	-5.6877**	-5.6303**	-6.9633***	-5.1780**	-7.6712***
	(2.0640)	(2.2525)	(2.2142)	(2.2823)	(2.3566)	(2.3236)	(2.4586)	(2.4141)	(2.2997)
male_married	2.1421	3.8892**	2.5642	4.7694**	3.9742**	3.7326*	5.1418***	5.4281***	2.5551
	(1.7433)	(1.8515)	(1.8496)	(1.8871)	(1.9336)	(1.9107)	(1.9863)	(1.9659)	(1.9310)
Apr-20	-14.1687***								
	(1.0547)								
May-20		-11.0564***							
		(1.1366)							
Jun-20			-7.3929***						
			(1.1443)						
Jul-20				-5.3757***					
				(1.1723)					
Sep-20					-3.6021***				
					(1.2132)				
Nov-20						-3.4117***			
						(1.2059)			
Jan-21							-4.8607***		
							(1.2648)		
Mar-21								-4.4716***	
								(1.2219)	
Sep-21									-0.5867
									(1.2061)
Constant	31.1648***	31.2608***	32.0808***	32.7616***	33.3663***	36.1192***	36.4329***	34.4433***	38.3798***
	(2.6670)	(2.8642)	(2.8653)	(2.8964)	(2.9794)	(2.9639)	(3.0579)	(3.0311)	(2.9745)
Observations	2,501	2,298	2,215	2,156	2,099	2,066	2,007	2,067	2,065

Notes: Dependent variable: Weekly work hours. Sample: self-employed at the baseline
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.E.4: Regression results for the DiD model: weekly work hours of all individuals employed or/and self-employed at the baseline

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Apr-20	May-20	Jun-20	Jul-20	Sep-20	Nov-20	Jan-21	Mar-21	Sep-21
NCD	-0.1252	-0.0385	-0.0475	0.0031	0.0760	0.0543	0.0711	0.1129	0.1937
	(0.3543)	(0.3465)	(0.3390)	(0.3358)	(0.3310)	(0.3353)	(0.3395)	(0.3359)	(0.3301)
_diff	-1.4413***	-1.6637***	-1.9907***	-2.0729***	-2.0207***	-2.0008***	-2.6073***	-2.1875***	-3.0654***
	(0.4962)	(0.5083)	(0.5067)	(0.5082)	(0.5116)	(0.5314)	(0.5422)	(0.5277)	(0.5144)
female	-3.7880***	-4.2314***	-4.9366***	-4.5703***	-5.1857***	-4.9828***	-4.8995***	-5.1192***	-5.4412***
	(0.3795)	(0.3900)	(0.3871)	(0.3864)	(0.3877)	(0.3981)	(0.4042)	(0.3941)	(0.3869)
Age	0.0826***	0.0701***	0.0710***	0.0659***	0.0442***	0.0521***	0.0488***	0.0418***	0.0214*
	(0.0121)	(0.0124)	(0.0124)	(0.0123)	(0.0124)	(0.0128)	(0.0130)	(0.0127)	(0.0124)
college_level	4.7417***	4.1656***	3.3870***	2.5211***	2.7881***	3.4828***	3.6393***	3.5665***	2.8132***
	(0.2498)	(0.2549)	(0.2530)	(0.2526)	(0.2530)	(0.2602)	(0.2643)	(0.2575)	(0.2524)
married	-2.0191***	-2.6117***	-2.4055***	-2.9122***	-2.6557***	-3.2074***	-3.0302***	-2.9761***	-2.6971***
	(0.4242)	(0.4310)	(0.4268)	(0.4256)	(0.4249)	(0.4360)	(0.4432)	(0.4352)	(0.4268)
single_nevermarried	-2.1106***	-2.3852***	-2.4139***	-2.2002***	-2.7188***	-2.8597***	-2.7716***	-2.8508***	-2.7746***
	(0.4414)	(0.4498)	(0.4461)	(0.4436)	(0.4444)	(0.4563)	(0.4641)	(0.4542)	(0.4449)
female_smallchildren	-4.5044***	-4.1106***	-4.2608***	-3.9035***	-4.6783***	-4.4140***	-4.5010***	-4.3036***	-5.5594***
	(0.5055)	(0.5284)	(0.5279)	(0.5296)	(0.5329)	(0.5500)	(0.5595)	(0.5450)	(0.5259)
male_married	2.8849***	3.2020***	2.7748***	3.7573***	2.6018***	3.0000***	3.1074***	3.0831***	2.3690***
	(0.4962)	(0.5081)	(0.5042)	(0.5029)	(0.5042)	(0.5183)	(0.5264)	(0.5131)	(0.5031)
Apr-20	-7.7199***								
	(0.3037)								
May-20		-5.3023***							
		(0.3154)							
Jun-20			-3.2852***						
			(0.3140)						
Jul-20				-2.8275***					
				(0.3134)					
Sep-20					0.2902				
					(0.3183)				
Nov-20						-0.4405			
						(0.3299)			
Jan-21							-1.0170***		
							(0.3349)		
Mar-21								-0.7951**	
								(0.3194)	
Sep-21									1.2132***
									(0.3140)
Constant	27.7609***	29.0508***	29.7269***	29.9733***	31.5114***	31.0400***	30.9181***	31.3507***	32.7533***
	(0.7534)	(0.7703)	(0.7662)	(0.7603)	(0.7637)	(0.7863)	(0.7990)	(0.7786)	(0.7635)
Observations	21,237	19,425	18,885	18,591	17,990	17,445	17,324	17,854	17,967

Notes: Dependent variable: Weekly work hours. Sample: All individuals employed or/and self-employed at the baseline
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.F Effect of COVID-19 on hours worked (based on current work): Results of the DiD regression.

Table 4.F.1: Effect of COVID-19 on hours worked (based on current work): Summary of the Results of the DiD regressions

	Employed			Self employed			Employed/selfemployed		
	NCD	Covid	NCD*Covid	NCD	Covid	NCD*Covid	NCD	Covid	NCD*Covid
Apr-20	-0.5316*	-6.9504***	-1.1380***	-3.1546***	-15.4252***	3.7442**	-0.7887**	-8.0907***	-0.4642
	(0.3072)	(0.2737)	(0.4398)	(1.0765)	(1.0187)	(1.5519)	(0.3088)	(0.2751)	(0.4386)
May-20	-0.4902	-5.4950***	-1.2092***	-3.2204***	-13.0149***	2.7629*	-0.7611**	-6.4340***	-0.7751*
	(0.2997)	(0.2807)	(0.4459)	(1.0812)	(1.0771)	(1.6086)	(0.3026)	(0.2835)	(0.4461)
Jun-20	-0.4270	-3.4382***	-1.3615***	-3.1498***	-8.8447***	0.9323	-0.7163**	-4.1626***	-1.1026**
	(0.2885)	(0.2754)	(0.4385)	(1.0698)	(1.0824)	(1.6240)	(0.2930)	(0.2790)	(0.4401)
Jul-20	-0.4549	-3.1733***	-1.4346***	-3.0182***	-6.7604***	0.9572	-0.7551***	-3.6704***	-1.0296**
	(0.2816)	(0.2703)	(0.4332)	(1.0759)	(1.1075)	(1.6671)	(0.2874)	(0.2756)	(0.4371)
Sep-20	-0.3139	0.6843***	-1.0790***	-3.1437***	-4.9410***	2.2763	-0.6301**	0.0217	-0.7844*
	(0.2618)	(0.2592)	(0.4121)	(1.0940)	(1.1490)	(1.7276)	(0.2752)	(0.2718)	(0.4281)
Nov-20	-0.4070	0.0509	-0.4843	-2.8219***	-5.7747***	-0.9236	-0.6450**	-0.6657**	-0.8602*
	(0.2669)	(0.2706)	(0.4316)	(1.0675)	(1.1260)	(1.6857)	(0.2789)	(0.2815)	(0.4442)
Jan-21	-0.4559*	-0.8682***	-0.6966	-2.8565***	-6.7528***	-0.2645	-0.7132**	-1.4992***	-0.9572**
	(0.2738)	(0.2771)	(0.4449)	(1.0784)	(1.1675)	(1.7404)	(0.2846)	(0.2876)	(0.4568)
Mar-21	-0.4698*	-0.0288	-0.9922**	-2.8598***	-5.0003***	-0.9753	-0.7313***	-0.5632**	-1.1474***
	(0.2650)	(0.2595)	(0.4233)	(1.0730)	(1.1278)	(1.7100)	(0.2774)	(0.2714)	(0.4381)
Sep-21	-0.3685	1.3970***	-1.1170***	-2.9293***	-1.5162	-0.3794	-0.6862**	1.1442***	-1.1497***
	(0.2555)	(0.2480)	(0.4035)	(1.0708)	(1.1313)	(1.6969)	(0.2690)	(0.2614)	(0.4206)

Notes: Table provides a summary of the results of DiD regressions for nine months under three categories; employed, self-employed and either employed or self-employed or both. The samples included individuals who were employed or self-employed in the current period. Each month of Covid was linked with the baseline period in the DiD regression. The dependent variable was the weekly work hours. The model was estimated with conditional covariates for age, gender, living in an urban, education, marital status and having small children.
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.G Effect of COVID-19 on the labour market outcomes of individuals with NCDs: Results of the balanced panel

Table 4.G.1: Results of the balanced panel analysis

	Employed	Self-employed	Employed or self-employed
Probability of work			
(full sample)	0.0018	-0.0083*	-0.0084
	(0.0075)	(0.0045)	(0.0068)
Hours of work			
(Full sample)	-1.8581***	2.0676**	-1.1056***
	(0.3067)	(0.9747)	(0.2995)
Hours worked			
Apr-20	-0.2669	-3.6203	-0.4417
	(0.7617)	(2.4854)	(0.7369)
May-20	-0.3573	-2.1319	-0.4070
	(0.7569)	(2.6621)	(0.7369)
Jun-20	-0.7827	-4.5759*	-0.9326
	(0.7431)	(2.5300)	(0.7195)
Jul-20	-0.7544	-2.1641	-0.6633
	(0.7394)	(2.5436)	(0.7149)
Sep-20	-1.3866*	-1.2385	-1.1728*
	(0.7176)	(2.6360)	(0.7031)
Nov-20	-1.3270*	-4.8433*	-1.5099**
	(0.7309)	(2.6319)	(0.7130)
Jan-21	-1.6199**	-2.8251	-1.6187**
	(0.7465)	(2.6514)	(0.7269)
Mar-21	-2.3934***	-5.5554**	-2.5933***
	(0.7334)	(2.6783)	(0.7168)
Sep-21	-2.5337***	-4.0865	-2.6640***
	(0.7205)	(2.5783)	(0.6999)

The table shows DiD coefficients that obtained using a balanced panel. The table consists of two parts. The upper part of the table shows the DiD coefficients for the entire period of the pandemic. Estimations are for the full sample consist of all employed or self-employed and both. All individuals aged below 65 years were included in the sample for estimating the probability of work. Only those individuals employed/ self-employed/both were included in the estimations of weekly work hours. 2016 to 2019 data were used as the pre-Covid data, and the data from nine surveys of the US COVID-19 study from April 2020 to September 2021 was used as post-Covid data.

The second part of the table shows the time-specific effects of COVID-19 on NCD individuals' work hours. The samples included al employed/ self-employed/ both individuals during the baseline period (January 2020). Each month of post-Covid was linked with the pre-Covid period (2019) in the DiD regression. The dependent variable was the weekly work hours.

All models were estimated with conditional covariates for age, gender, living in the urban, education, marital status and having small children.

Standard errors in parentheses

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

4.H Post-covid effect on hours worked by work categories

Table 4.H.1: Post-covid effect of NCDs on hours worked by work categories: summary of the results of the DiD regressions

Post-covid period	Employed as a key worker	Employed but not a key worker
Apr-20	-2.5899***	-0.9383
	(0.6718)	(0.6045)
May-20	-2.0240***	-1.1978*
	(0.6726)	(0.6278)
Jun-20	-2.1785***	-1.6966***
	(0.6584)	(0.6341)
Jul-20	-1.5763**	-2.4420***
	(0.7072)	(0.6063)
Sep-20	-1.5378**	-1.7335***
	(0.7144)	(0.5784)
Nov-20	-2.1157***	-0.8154
	(0.7383)	(0.6099)
Jan-21	-1.7767***	-1.2062*
	(0.6869)	(0.6744)
Mar-21	-1.3806**	-2.0349***
	(0.6605)	(0.6463)
Sep-21	-2.3665***	-1.8755***
	(0.7180)	(0.5658)

Notes: Table gives the summary of the coefficients of the interaction term (NCD*post-covid) of the DiD regressions for nine months under two categories; Key workers and non-key workers. Each month of Covid was linked with the baseline period in the DiD regression and considered current work status. The dependent variable was the weekly work hours. The model was estimated with conditional covariates for age, gender, living in an urban, education, marital status and having small children.

Table 4.H.2: Regression result of the DiD model: For Key workers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Apr-20	May-20	Jun-20	Jul-20	Sep-20	Nov-20	Jan-21	Mar-21	Sep-21
NCD	0.1971	0.1899	0.2077	0.0931	0.1337	0.1563	0.1180	0.1402	0.3076
	(0.4828)	(0.4721)	(0.4547)	(0.4756)	(0.4721)	(0.4771)	(0.4602)	(0.4513)	(0.4729)
_diff	-2.5899***	-2.0240***	-2.1785***	-1.5763**	-1.5378**	-2.1157***	-1.7767***	-1.3806**	-2.3665***
	(0.6718)	(0.6726)	(0.6584)	(0.7072)	(0.7144)	(0.7383)	(0.6869)	(0.6605)	(0.7180)
female	-4.1577***	-3.9830***	-5.1207***	-4.3449***	-4.3753***	-4.4309***	-4.2716***	-4.3201***	-4.5015***
	(0.5379)	(0.5414)	(0.5296)	(0.5655)	(0.5701)	(0.5821)	(0.5418)	(0.5229)	(0.5685)
Age	0.0226	0.0228	0.0206	0.0456***	0.0253	0.0295	0.0316*	0.0308*	-0.0186
	(0.0165)	(0.0166)	(0.0163)	(0.0174)	(0.0176)	(0.0181)	(0.0169)	(0.0162)	(0.0176)
college_level	2.9886***	2.6734***	2.5338***	1.4545***	2.9164***	3.0474***	3.0701***	3.2173***	2.6963***
	(0.3467)	(0.3450)	(0.3373)	(0.3618)	(0.3641)	(0.3738)	(0.3508)	(0.3367)	(0.3660)
married	-2.3903***	-2.4964***	-2.2002***	-2.4386***	-2.1952***	-2.4005***	-2.3932***	-2.1788***	-2.2406***
	(0.5311)	(0.5297)	(0.5166)	(0.5502)	(0.5528)	(0.5661)	(0.5326)	(0.5160)	(0.5587)
single_nevermarried	-1.6550***	-1.6177***	-2.0059***	-1.3787**	-2.0596***	-1.8701***	-1.9757***	-1.8143***	-2.6668***
	(0.5762)	(0.5748)	(0.5623)	(0.5991)	(0.6048)	(0.6185)	(0.5812)	(0.5607)	(0.6070)
female_smallchildren	-6.0112***	-5.4723***	-5.4316***	-4.6182***	-6.0437***	-5.5817***	-5.8858***	-5.7965***	-6.6246***
	(0.6463)	(0.6678)	(0.6572)	(0.7067)	(0.7138)	(0.7371)	(0.6947)	(0.6602)	(0.7240)
male_married	3.7678***	3.4703***	2.3703***	3.7323***	2.5851***	3.0505***	2.9474***	2.8018***	2.4726***
	(0.6970)	(0.6991)	(0.6835)	(0.7310)	(0.7357)	(0.7535)	(0.7053)	(0.6788)	(0.7374)
Apr-20	-0.5304								
	(0.4173)								
May-20		0.7692*							
		(0.4210)							
Jun-20			2.0712***						
			(0.4114)						
Jul-20				-0.5895					
				(0.4471)					
Sep-20					2.3640***				
					(0.4546)				
Nov-20						2.1714***			
						(0.4718)			
Jan-21							2.6215***		
							(0.4311)		
Mar-21								2.5638***	
								(0.4081)	
Sep-21									1.9881***
									(0.4632)
Constant	32.3703***	32.4389***	33.4929***	31.9131***	32.7109***	32.4334***	32.3181***	32.1832***	34.9937***
	(1.0362)	(1.0365)	(1.0162)	(1.0819)	(1.0942)	(1.1227)	(1.0465)	(1.0045)	(1.0879)
Observations	9,235	8,796	8,560	8,162	7,940	7,689	8,150	8,476	7,874

Notes: Dependent variable: Weekly work hours. Sample: individuals employed as key workers
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.H.3: Regression result of the DiD model: For non-Key workers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Apr-20	May-20	Jun-20	Jul-20	Sep-20	Nov-20	Jan-21	Mar-21	Sep-21
NCD	-0.6743*	-0.6439	-0.5602	-0.5549	-0.3667	-0.4977	-0.5681	-0.5619	-0.5034
	(0.4074)	(0.4003)	(0.3947)	(0.3792)	(0.3541)	(0.3626)	(0.3708)	(0.3599)	(0.3438)
_diff	-0.9383	-1.1978*	-1.6966***	-2.4420***	-1.7335***	-0.8154	-1.2062*	-2.0349***	-1.8755***
	(0.6045)	(0.6278)	(0.6341)	(0.6063)	(0.5784)	(0.6099)	(0.6744)	(0.6463)	(0.5658)
female	-5.6106***	-6.4315***	-6.7031***	-6.3740***	-6.7310***	-6.4736***	-6.6140***	-6.6359***	-6.8258***
	(0.4516)	(0.4622)	(0.4620)	(0.4411)	(0.4162)	(0.4327)	(0.4586)	(0.4406)	(0.4020)
Age	-0.0252*	-0.0272*	-0.0402***	-0.0441***	-0.0692***	-0.0502***	-0.0333**	-0.0376***	-0.0480***
	(0.0137)	(0.0141)	(0.0140)	(0.0133)	(0.0127)	(0.0132)	(0.0140)	(0.0134)	(0.0122)
college_level	6.3084***	5.2553***	4.0912***	3.3791***	2.8077***	3.5879***	3.8176***	3.8511***	2.5459***
	(0.3029)	(0.3112)	(0.3106)	(0.2964)	(0.2805)	(0.2913)	(0.3067)	(0.2953)	(0.2694)
married	0.0357	-0.5041	-0.6682	-1.4991***	-1.2902***	-1.9776***	-1.2506**	-1.1512**	-1.0587**
	(0.5350)	(0.5433)	(0.5430)	(0.5186)	(0.4879)	(0.5044)	(0.5404)	(0.5240)	(0.4721)
single_nevermarried	-1.5882***	-1.7024***	-1.6144***	-1.9684***	-1.8930***	-2.3335***	-1.5367***	-1.7347***	-1.4762***
	(0.5534)	(0.5642)	(0.5618)	(0.5351)	(0.5043)	(0.5239)	(0.5591)	(0.5396)	(0.4874)
female_smallchildren	-3.7778***	-3.5912***	-3.6653***	-3.7930***	-3.3807***	-3.3063***	-3.1325***	-3.1875***	-3.9628***
	(0.6537)	(0.6761)	(0.6828)	(0.6499)	(0.6195)	(0.6419)	(0.6778)	(0.6586)	(0.5789)
male_married	1.2978**	1.4128**	1.6087***	2.1282***	1.7204***	2.1618***	2.1412***	1.9262***	1.4183***
	(0.5977)	(0.6122)	(0.6123)	(0.5839)	(0.5524)	(0.5738)	(0.6058)	(0.5832)	(0.5321)
Apr-20	-10.9770***								
	(0.3760)								
May-20		-10.0632***							
		(0.3976)							
Jun-20			-7.1076***						
			(0.4007)						
Jul-20				-3.6758***					
				(0.3739)					
Sep-20					0.0464				
					(0.3599)				
Nov-20						-1.1740***			
						(0.3756)			
Jan-21							-3.0843***		
							(0.4118)		
Mar-21								-1.2202***	
								(0.3886)	
Sep-21									1.9269***
									(0.3330)
Constant	33.7554***	34.9652***	36.0943***	36.7796***	38.1624***	37.3498***	35.9684***	36.2234***	37.2919***
	(0.8915)	(0.9124)	(0.9086)	(0.8630)	(0.8160)	(0.8497)	(0.8992)	(0.8666)	(0.7892)
Observations	10,100	9,271	9,013	9,155	8,895	8,656	8,079	8,211	9,075

Notes: Dependent variable: Weekly work hours. Sample: all employed other than key workers
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

4.I Post-covid effect on hours worked by Age groups

Table 4.I.1: Post-covid effect of NCDs on hours worked by age: Summary of the results of the DiD regressions

Post-covid period	Age 55-64	Age below 55
Apr-20	-2.1312**	-0.8410
	(1.0811)	(0.5742)
May-20	-2.0888*	-1.3516**
	(1.1090)	(0.5891)
Jun-20	-3.1074***	-1.2542**
	(1.0869)	(0.5914)
Jul-20	-3.1990***	-1.3540**
	(1.0831)	(0.5977)
Sep-20	-1.6001	-1.4483**
	(1.1133)	(0.5971)
Nov-20	-3.1155***	-0.4303
	(1.1498)	(0.6238)
Jan-21	-3.4884***	-1.2173*
	(1.1679)	(0.6376)
Mar-21	-3.8474***	-0.5110
	(1.1259)	(0.6215)
Sep-21	-4.5543***	-1.3644**
	(1.1200)	(0.5976)

Notes: Table shows the coefficients of the interaction term (NCD*post-covid) of the DiD regressions for nine months under two age groups; Aged below 55 and between 55 to 64 years old. Samples consist of all individuals, either employed or self-employed or both at baseline. Each month of Covid was linked with the baseline period (January 2020) in the DiD regression. The dependent variable was the weekly work hours. The model was estimated with conditional covariates for age, gender, living in an urban, education, marital status and having small children.

Table 4.I.2: Regression result of the DiD model: For Aged 55-64

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Apr-20	May-20	Jun-20	Jul-20	Sep-20	Nov-20	Jan-21	Mar-21	Sep-21
NCD	1.3092*	1.3745*	1.4596*	1.4296*	1.3389*	1.3007*	1.3401*	1.3601*	1.5155*
	(0.7773)	(0.7779)	(0.7582)	(0.7520)	(0.7672)	(0.7841)	(0.7998)	(0.7831)	(0.7814)
_diff	-2.1312**	-2.0888*	-3.1074***	-3.1990***	-1.6001	-3.1155***	-3.4884***	-3.8474***	-4.5543***
	(1.0811)	(1.1090)	(1.0869)	(1.0831)	(1.1133)	(1.1498)	(1.1679)	(1.1259)	(1.1200)
female	-3.3784***	-2.2148**	-3.3980***	-3.1566***	-2.9290***	-1.7484*	-1.8701*	-3.2101***	-2.9150***
	(0.9865)	(1.0145)	(0.9945)	(0.9899)	(1.0185)	(1.0501)	(1.0630)	(1.0282)	(1.0253)
Age	-0.7954***	-0.9425***	-0.9364***	-0.9016***	-0.8626***	-0.9075***	-0.9274***	-0.8411***	-1.0870***
	(0.1110)	(0.1136)	(0.1114)	(0.1108)	(0.1135)	(0.1167)	(0.1185)	(0.1146)	(0.1137)
college_level	1.0850*	0.9520	0.0326	-0.4765	-0.3089	0.2076	0.7177	0.5631	-1.1385*
	(0.6075)	(0.6195)	(0.6063)	(0.6056)	(0.6231)	(0.6425)	(0.6512)	(0.6304)	(0.6296)
married	-4.3804***	-5.4286***	-5.1254***	-5.6074***	-6.0031***	-7.0178***	-6.8613***	-6.7328***	-5.9968***
	(0.8056)	(0.8245)	(0.8052)	(0.8049)	(0.8233)	(0.8520)	(0.8631)	(0.8414)	(0.8348)
single_nevermarried	-3.2789***	-3.0617***	-2.6731***	-3.5572***	-4.4563***	-4.1315***	-3.8263***	-3.3301***	-2.4468**
	(1.0230)	(1.0466)	(1.0267)	(1.0213)	(1.0475)	(1.0819)	(1.0943)	(1.0588)	(1.0394)
female_smallchildren	6.4939*	12.2823***	10.0624**	7.2405	-2.4292	3.6981	6.0315	5.5510	-0.8534
	(3.8740)	(4.3323)	(4.3570)	(5.0466)	(4.9286)	(5.8182)	(5.9331)	(5.2433)	(4.4875)
male_married	4.3233***	6.1307***	5.6572***	6.2738***	5.8649***	6.9600***	7.2313***	6.4466***	5.9729***
	(1.1836)	(1.2150)	(1.1912)	(1.1862)	(1.2196)	(1.2580)	(1.2762)	(1.2331)	(1.2294)
Apr-20	-9.3855***								
	(0.7941)								
May-20		-6.7412***							
		(0.8206)							
Jun-20			-4.2723***						
			(0.8030)						
Jul-20				-3.3149***					
				(0.7974)					
Sep-20					-1.7524**				
					(0.8237)				
Nov-20						-2.1709**			
						(0.8492)			
Jan-21							-3.1575***		
							(0.8595)		
Mar-21								-2.7179***	
								(0.8227)	
Sep-21									-1.2041
									(0.8207)
Constant	78.8583***	87.0002***	87.4006***	85.5632***	83.6359***	85.8130***	86.6687***	82.4437***	96.7919***
	(6.6524)	(6.8087)	(6.6733)	(6.6440)	(6.8062)	(6.9944)	(7.1050)	(6.8685)	(6.8125)
Observations	4,087	3,900	3,857	3,821	3,775	3,702	3,721	3,817	3,841

Notes: Dependent variable: Weekly work hours. Sample: All individuals aged between 55-64 and employed or/and self-employed at the baseline
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.I.3: Regression result of the DiD model: For Aged below 55

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Apr-20	May-20	Jun-20	Jul-20	Sep-20	Nov-20	Jan-21	Mar-21	Sep-21
NCD	-0.3524	-0.2688	-0.3015	-0.2023	-0.1888	-0.2497	-0.2681	-0.2517	-0.2232
	(0.4048)	(0.3929)	(0.3844)	(0.3821)	(0.3712)	(0.3746)	(0.3775)	(0.3745)	(0.3647)
_diff	-0.8410	-1.3516**	-1.2542**	-1.3540**	-1.4483**	-0.4303	-1.2173*	-0.5110	-1.3644**
	(0.5742)	(0.5891)	(0.5914)	(0.5977)	(0.5971)	(0.6238)	(0.6376)	(0.6215)	(0.5976)
female	-3.6991***	-4.3787***	-4.8627***	-4.5786***	-5.3972***	-5.3508***	-5.2085***	-5.2104***	-5.5738***
	(0.4122)	(0.4227)	(0.4206)	(0.4218)	(0.4180)	(0.4283)	(0.4334)	(0.4227)	(0.4111)
Age	0.2680***	0.2515***	0.2627***	0.2479***	0.2376***	0.2617***	0.2642***	0.2541***	0.2439***
	(0.0160)	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0167)	(0.0169)	(0.0165)	(0.0161)
college_level	5.1752***	4.5449***	3.8811***	2.9582***	3.2034***	3.9105***	3.9500***	3.9073***	3.2202***
	(0.2760)	(0.2810)	(0.2797)	(0.2803)	(0.2773)	(0.2847)	(0.2884)	(0.2813)	(0.2729)
married	-1.5325***	-2.1683***	-2.0337***	-2.4091***	-1.9113***	-2.3173***	-2.1066***	-2.1174***	-1.9917***
	(0.5163)	(0.5240)	(0.5215)	(0.5212)	(0.5156)	(0.5284)	(0.5368)	(0.5268)	(0.5114)
single_nevermarried	-0.4277	-0.9508*	-0.9826*	-0.5939	-0.8452	-0.8319	-0.7179	-1.0054*	-0.9500*
	(0.5181)	(0.5273)	(0.5253)	(0.5238)	(0.5192)	(0.5325)	(0.5408)	(0.5295)	(0.5143)
female_smallchildren	-4.4962***	-4.0868***	-4.2235***	-3.7643***	-4.3982***	-4.1332***	-4.2836***	-4.1856***	-5.3480***
	(0.5110)	(0.5297)	(0.5297)	(0.5324)	(0.5285)	(0.5430)	(0.5501)	(0.5376)	(0.5150)
male_married	2.9148***	2.9942***	2.6524***	3.5762***	2.3363***	2.6390***	2.7078***	2.8559***	2.0812***
	(0.5552)	(0.5673)	(0.5649)	(0.5658)	(0.5604)	(0.5754)	(0.5826)	(0.5682)	(0.5518)
Apr-20	-7.4581***								
	(0.3292)								
May-20		-4.9305***							
		(0.3415)							
Jun-20			-3.0268***						
			(0.3414)						
Jul-20				-2.6659***					
				(0.3425)					
Sep-20					0.7751**				
					(0.3445)				
Nov-20						-0.0432			
						(0.3573)			
Jan-21							-0.4361		
							(0.3621)		
Mar-21								-0.2104	
								(0.3448)	
Sep-21									1.8486***
									(0.3354)
Constant	19.9400***	21.6866***	21.8410***	22.3850***	23.3442***	22.2362***	21.8826***	22.3562***	23.4241***
	(0.8930)	(0.9117)	(0.9111)	(0.9071)	(0.9017)	(0.9261)	(0.9374)	(0.9152)	(0.8916)
Observations	16,499	14,932	14,436	14,190	13,656	13,192	13,060	13,494	13,595

Notes: Dependent variable: Weekly work hours. Sample: All individuals aged below 55 and employed or/and self-employed at the baseline
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.J Post-covid effect on hours worked by NCDs type: Risky NCDs vs other NCDs

Table 4.J.1: Post-covid effect on hours worked by NCDs type: summary of the results of DiD regressions

Post-covid period	Risky NCD	Other NCD
Apr-20	-1.8160***	-1.1064*
	(0.6085)	(0.6661)
May-20	-2.4894***	-0.6944
	(0.6203)	(0.6803)
Jun-20	-2.5758***	-1.2728*
	(0.6197)	(0.6753)
Jul-20	-2.0997***	-2.0756***
	(0.6216)	(0.6794)
Sep-20	-2.0033***	-2.1023***
	(0.6249)	(0.6824)
Nov-20	-2.3484***	-1.5147**
	(0.6504)	(0.7110)
Jan-21	-2.8397***	-2.3099***
	(0.6653)	(0.7246)
Mar-21	-2.3885***	-1.9449***
	(0.6478)	(0.7097)
Sep-21	-3.6381***	-2.3309***
	(0.6302)	(0.6859)

Notes: Table shows the coefficients of the interaction term (NCD*post-covid) of the DiD regressions for nine months for two treatment groups; individuals with Risky NCDs and Individuals with Other NCDs. Samples consist of all individuals, either employed or self-employed or both at baseline. Each month of Covid was linked with the baseline period (January 2020) in the DiD regression. The dependent variable was the weekly work hours. The model was estimated with conditional covariates for age, gender, living in an urban, education, marital status and having small children.

Table 4.J.2: Regression result of the DiD model: for Risky NCDs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Apr-20	May-20	Jun-20	Jul-20	Sep-20	Nov-20	Jan-21	Mar-21	Sep-21
Risky_NCD	0.2304	0.2726	0.2599	0.3007	0.3597	0.3281	0.3393	0.3631	0.4418
	(0.4377)	(0.4271)	(0.4179)	(0.4142)	(0.4073)	(0.4135)	(0.4185)	(0.4133)	(0.4049)
_diff	-1.8160***	-2.4894***	-2.5758***	-2.0997***	-2.0033***	-2.3484***	-2.8397***	-2.3885***	-3.6381***
	(0.6085)	(0.6203)	(0.6197)	(0.6216)	(0.6249)	(0.6504)	(0.6653)	(0.6478)	(0.6302)
female	-3.8043***	-4.2493***	-5.0128***	-4.7147***	-5.3037***	-5.0754***	-5.0241***	-5.1639***	-5.5535***
	(0.4097)	(0.4216)	(0.4182)	(0.4174)	(0.4183)	(0.4300)	(0.4364)	(0.4236)	(0.4152)
Age	0.0952***	0.0828***	0.0872***	0.0815***	0.0580***	0.0675***	0.0654***	0.0605***	0.0365***
	(0.0132)	(0.0135)	(0.0134)	(0.0134)	(0.0135)	(0.0139)	(0.0141)	(0.0137)	(0.0134)
college_level	4.8453***	4.2544***	3.4422***	2.6295***	2.9315***	3.5866***	3.7301***	3.7510***	2.9282***
	(0.2725)	(0.2780)	(0.2761)	(0.2755)	(0.2756)	(0.2839)	(0.2885)	(0.2798)	(0.2738)
married	-2.0427***	-2.4991***	-2.3050***	-2.7643***	-2.4919***	-3.2518***	-2.9727***	-2.9331***	-2.4730***
	(0.4801)	(0.4884)	(0.4827)	(0.4814)	(0.4806)	(0.4942)	(0.5014)	(0.4896)	(0.4800)
single_nevermarried	-1.9361***	-2.2470***	-2.1214***	-1.8475***	-2.4450***	-2.7316***	-2.5231***	-2.5166***	-2.4475***
	(0.4923)	(0.5026)	(0.4974)	(0.4944)	(0.4952)	(0.5091)	(0.5175)	(0.5036)	(0.4937)
female_smallchildren	-4.4328***	-4.1628***	-4.2391***	-3.9203***	-4.8766***	-4.4503***	-4.5442***	-4.3323***	-5.5998***
	(0.5373)	(0.5616)	(0.5604)	(0.5622)	(0.5656)	(0.5849)	(0.5952)	(0.5772)	(0.5572)
male_married	2.9175***	3.2100***	2.6530***	3.6336***	2.4175***	2.8445***	2.9563***	3.0199***	2.2811***
	(0.5401)	(0.5534)	(0.5493)	(0.5476)	(0.5484)	(0.5648)	(0.5733)	(0.5561)	(0.5442)
Apr-20	-7.7339***								
	(0.3035)								
May-20		-5.3267***							
		(0.3148)							
Jun-20			-3.3184***						
			(0.3136)						
Jul-20				-2.8599***					
				(0.3132)					
Sep-20					0.2515				
					(0.3176)				
Nov-20						-0.4867			
						(0.3301)			
Jan-21							-1.0679***		
							(0.3351)		
Mar-21								-0.8488***	
								(0.3188)	
Sep-21									1.1678***
									(0.3124)
Constant	27.1543***	28.3985***	28.9580***	29.2072***	30.8348***	30.4420***	30.1978***	30.4179***	31.9399***
	(0.8200)	(0.8391)	(0.8344)	(0.8269)	(0.8306)	(0.8564)	(0.8701)	(0.8434)	(0.8266)
Observations	17,702	16,141	15,697	15,488	14,946	14,519	14,428	14,947	14,993

Notes: Dependent variable: Weekly work hours. Sample: All individuals employed or/and self-employed at the baseline
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.J.3: Regression result of the DiD model: for other NCDs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Apr-20	May-20	Jun-20	Jul-20	Sep-20	Nov-20	Jan-21	Mar-21	Sep-21
Other_NCDs	-0.5692	-0.3970	-0.4811	-0.3937	-0.3186	-0.3710	-0.3317	-0.2633	-0.2576
	(0.4726)	(0.4616)	(0.4503)	(0.4459)	(0.4401)	(0.4451)	(0.4506)	(0.4457)	(0.4371)
_diff	-1.1064*	-0.6944	-1.2728*	-2.0756***	-2.1023***	-1.5147**	-2.3099***	-1.9449***	-2.3309***
	(0.6661)	(0.6803)	(0.6753)	(0.6794)	(0.6824)	(0.7110)	(0.7246)	(0.7097)	(0.6859)
female	-3.7819***	-4.4733***	-4.9766***	-4.5750***	-5.3282***	-5.1782***	-4.9572***	-5.1765***	-5.3502***
	(0.4243)	(0.4355)	(0.4305)	(0.4298)	(0.4317)	(0.4419)	(0.4483)	(0.4363)	(0.4274)
Age	0.1170***	0.0953***	0.1065***	0.0973***	0.0789***	0.0889***	0.0868***	0.0748***	0.0669***
	(0.0139)	(0.0143)	(0.0141)	(0.0141)	(0.0142)	(0.0145)	(0.0148)	(0.0144)	(0.0140)
college_level	4.9238***	4.3387***	3.6012***	2.6934***	3.0289***	3.6344***	3.8309***	3.6888***	3.1789***
	(0.2805)	(0.2863)	(0.2828)	(0.2819)	(0.2828)	(0.2902)	(0.2944)	(0.2858)	(0.2797)
married	-2.2628***	-2.9098***	-2.6056***	-3.0796***	-2.9482***	-3.2955***	-3.0001***	-2.9660***	-2.8642***
	(0.4850)	(0.4932)	(0.4866)	(0.4845)	(0.4843)	(0.4961)	(0.5039)	(0.4934)	(0.4834)
single_nevermarried	-2.0792***	-2.6236***	-2.5320***	-2.3211***	-2.9443***	-3.0834***	-2.7014***	-2.9631***	-2.9233***
	(0.5014)	(0.5117)	(0.5054)	(0.5029)	(0.5037)	(0.5165)	(0.5255)	(0.5126)	(0.5009)
female_smallchildren	-4.1199***	-3.6992***	-4.0388***	-3.6602***	-4.1226***	-4.1416***	-4.1591***	-4.0203***	-5.1061***
	(0.5573)	(0.5800)	(0.5762)	(0.5776)	(0.5839)	(0.5988)	(0.6102)	(0.5924)	(0.5698)
male_married	3.1736***	3.2866***	2.9622***	3.9907***	2.7510***	3.0141***	3.2411***	3.2922***	2.6381***
	(0.5573)	(0.5704)	(0.5638)	(0.5618)	(0.5642)	(0.5785)	(0.5869)	(0.5705)	(0.5586)
Apr-20	-7.6893***								
	(0.3036)								
May-20		-5.2687***							
		(0.3151)							
Jun-20			-3.2745***						
			(0.3129)						
Jul-20				-2.8236***					
				(0.3122)					
Sep-20					0.2653				
					(0.3177)				
Nov-20						-0.4630			
						(0.3291)			
Jan-21							-1.0328***		
							(0.3343)		
Mar-21								-0.8055**	
								(0.3184)	
Sep-21									1.2608***
									(0.3125)
Constant	26.3272***	28.3118***	28.3265***	28.7095***	30.2636***	29.7122***	29.2479***	29.9681***	30.7596***
	(0.8493)	(0.8696)	(0.8609)	(0.8556)	(0.8596)	(0.8827)	(0.8976)	(0.8720)	(0.8536)
Observations	16,688	15,214	14,835	14,631	14,148	13,726	13,671	14,169	14,228

Notes: Dependent variable: Weekly work hours. Sample: All individuals employed or/and self-employed at the baseline

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

4.K Regresion results for mental health regression

Table 4.K.1: Regresion results for mental health regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Apr-20	May-20	Jun-20	Jul-20	Sep-20	Nov-20	Jan-20	Mar-20	Sep-21
NCD	-0.1119***	-0.1083***	-0.1085***	-0.1058***	-0.1038***	-0.1079***	-0.1080***	-0.1065***	-0.1055***
	(0.0080)	(0.0079)	(0.0079)	(0.0077)	(0.0077)	(0.0079)	(0.0079)	(0.0078)	(0.0077)
_diff	0.0236**	0.0123	0.0077	-0.0040	-0.0107	0.0095	0.0166	0.0018	-0.0064
	(0.0116)	(0.0118)	(0.0119)	(0.0117)	(0.0121)	(0.0126)	(0.0128)	(0.0124)	(0.0121)
female	-0.1311***	-0.1079***	-0.0988***	-0.0785***	-0.1011***	-0.1048***	-0.0990***	-0.0977***	-0.0983***
	(0.0089)	(0.0091)	(0.0091)	(0.0089)	(0.0091)	(0.0095)	(0.0095)	(0.0093)	(0.0091)
Age	0.0041***	0.0035***	0.0035***	0.0029***	0.0027***	0.0035***	0.0035***	0.0031***	0.0032***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
college_level	-0.0086	-0.0034	-0.0075	-0.0015	-0.0055	0.0008	-0.0004	-0.0004	0.0077
	(0.0060)	(0.0061)	(0.0061)	(0.0060)	(0.0061)	(0.0063)	(0.0064)	(0.0062)	(0.0061)
married	0.0823***	0.0800***	0.0853***	0.0773***	0.0842***	0.0745***	0.0770***	0.0801***	0.0935***
	(0.0098)	(0.0099)	(0.0099)	(0.0097)	(0.0099)	(0.0103)	(0.0104)	(0.0101)	(0.0099)
single_nevermarried	0.0063	0.0042	0.0074	-0.0032	-0.0036	-0.0026	0.0060	-0.0067	0.0114
	(0.0104)	(0.0105)	(0.0106)	(0.0103)	(0.0106)	(0.0109)	(0.0111)	(0.0108)	(0.0105)
female_smallchildren	-0.0106	-0.0110	-0.0027	-0.0023	0.0010	0.0166	-0.0078	0.0013	0.0096
	(0.0117)	(0.0121)	(0.0122)	(0.0121)	(0.0124)	(0.0129)	(0.0131)	(0.0126)	(0.0122)
male_married	-0.0421***	-0.0299**	-0.0279**	-0.0207*	-0.0402***	-0.0352***	-0.0247**	-0.0352***	-0.0401***
	(0.0117)	(0.0119)	(0.0120)	(0.0117)	(0.0120)	(0.0124)	(0.0125)	(0.0122)	(0.0119)
Apr 20	-0.1556***								
	(0.0074)								
May 20		-0.1014***							
		(0.0076)							
Jun 20			-0.0724***						
			(0.0077)						
Jul 20				-0.0033					
				(0.0075)					
Sep 20					-0.0050				
					(0.0078)				
Nov 20						-0.0804***			
						(0.0082)			
Jan 21							-0.1022***		
							(0.0083)		
Mar 21								-0.0479***	
								(0.0078)	
Sep 21									-0.0046
									(0.0077)
Constant	0.6473***	0.6569***	0.6469***	0.6638***	0.6881***	0.6591***	0.6505***	0.6715***	0.6507***
	(0.0173)	(0.0176)	(0.0177)	(0.0172)	(0.0176)	(0.0183)	(0.0185)	(0.0180)	(0.0176)
Observations	25,702	24,351	23,649	23,367	22,508	21,901	21,736	22,383	22,556

Notes: Dependent variable: Probability of having a good mental health
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.L Regression results for general health regression

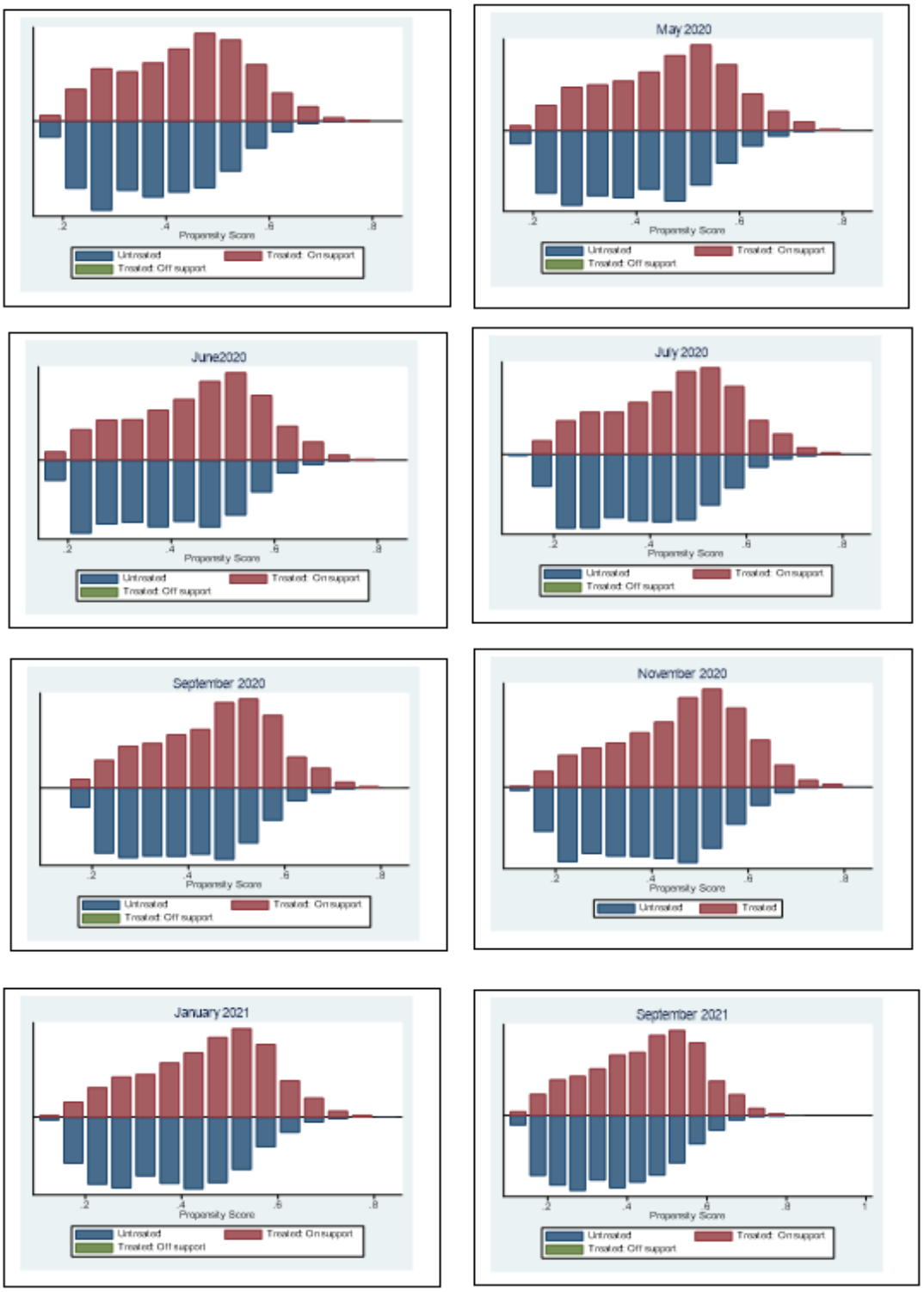
Table 4.L.1: Regression results for general health regression

	(1)	(2)	(3)	(4)
VARIABLES	Nov-20	Jan-21	Mar-21	Sep-21
NCD	-0.2691***	-0.2678***	-0.2650***	-0.2679***
	(0.0084)	(0.0084)	(0.0084)	(0.0084)
_diff	0.0010	0.0145	0.0072	0.0123
	(0.0134)	(0.0135)	(0.0133)	(0.0132)
female	-0.0166*	-0.0156	-0.0180*	-0.0144
	(0.0101)	(0.0101)	(0.0100)	(0.0099)
Age	-0.0021***	-0.0024***	-0.0027***	-0.0023***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
college_level	0.1126***	0.1097***	0.1145***	0.1085***
	(0.0068)	(0.0068)	(0.0067)	(0.0067)
married	0.0811***	0.0802***	0.0682***	0.0688***
	(0.0109)	(0.0110)	(0.0109)	(0.0109)
single_nevermarried	0.0001	-0.0060	-0.0122	-0.0078
	(0.0116)	(0.0117)	(0.0116)	(0.0115)
female_smallchildren	-0.0290**	-0.0331**	-0.0200	-0.0278**
	(0.0137)	(0.0138)	(0.0135)	(0.0133)
male_married	-0.0276**	-0.0293**	-0.0241*	-0.0212
	(0.0132)	(0.0133)	(0.0131)	(0.0131)
Nov-20	0.0723***			
	(0.0087)			
Jan-21		0.0495***		
		(0.0087)		
Mar-21			0.0402***	
			(0.0084)	
Sep-21				0.0063
				(0.0084)
Constant	0.6352***	0.6517***	0.6718***	0.6533***
	(0.0195)	(0.0196)	(0.0193)	(0.0193)
Observations	22,278	22,157	22,732	22,940

Notes: Dependent variable: Probability of having a good general health
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.M Propensity score matching: common support

Figure 4.M.1: Propensity score matching: common support



Notes: Graphs related to the sensitivity analysis: propensity score matching.

Chapter 5

Thesis conclusion

This doctoral thesis is a collection of three papers that deliver comprehensive studies of three topics related to Non-Communicable Diseases (NCDs). The first two papers discuss the issues related to NCDs in the LMIC context, and the third paper discusses new challenges faced by people with NCDs in the labour market in the UK during the COVID-19 pandemic.

In Chapter 2, we analysed the changes in dietary patterns, which is a major risk factor for the prevalence of diet-related NCDs and studied how individuals' education affects food choices in an LMIC context. We used household food consumption data in Sri Lanka for 2006 and 2016, where the country underwent significant economic and social changes contributing to speeding the nutritional transition between these years. The analysis is based on food demand elasticities; thus, the Almost Ideal Demand System was used to estimate the demand elasticities of 14 food categories which were classified as healthy and unhealthy. Our findings confirm the nutritional transition that occurred during this period, which may have led to an increasing NCDs. We show that the enhancement of the living standards of the people has led them towards a rather unhealthy diet. The income responsiveness of most unhealthy food categories has increased at a higher rate than healthy food during the reference period. The demand responsiveness to price changes is also higher for most unhealthy foods than healthy foods, implying that price policies can effectively control unhealthy consumption. Our results partially support the previous findings

that show education improves people's diet. The demand responsiveness to income of some healthy food is higher at higher education levels. However, we saw that education encourages unhealthy consumption as well. Yet, we show that the better-educated household heads are more concerned about food quality, both healthy and unhealthy. Further, we found that having a diabetes individual in the household does not entirely change the food consumption behaviour towards a healthier diet. It decreases the consumption of some harmful food but still consumes a considerable amount of unhealthy and convenient food. However, education plays a significant role as households with diabetes with higher educated heads appear to have more control towards a healthier diet. Overall, the study contributes to the literature by providing evidence related to dietary changes in an LMIC, the role of education in changing diet patterns, and the dietary behaviour of people with diabetes. Similarly, the study highlights important policy implications for improving people's diets and thus health. People in LMICs face the dilemma of using their increasing income towards healthy consumption while counterbalancing unhealthy consumption. Not only investing in education, but a collaboration between public health policymakers and education experts to incorporate diet-related education into the formal education system is required to control the risk factors of NCD prevalence. Government can effectively encourage healthy consumption while discouraging unhealthy ones by designing pricing policies - taxing unhealthy food and providing subsidies for healthy food.

In Chapter 3, we explored the crowding-out effect of out-of-pocket healthcare expenses caused by chronic Non-Communicable Diseases (C-NCDs) on household consumption of other goods and services. We further examined the changes in the crowding-out effect because of changing public healthcare provision. We used the data from three waves of household income and expenditure survey in Sri Lanka, conducted in 2006, 2012 and 2016. Our methodological approach was based on propensity score matching. A matching estimator was used to identify the crowding-out

effect of healthcare expenditures caused by C-NCDs, and a matched difference-in-difference method was used to explore the changes in the crowding-out effect during the reference period. We show that the C-NCD prevalence rates have increased during the reference period while the public healthcare provision has been contracted. Accordingly, C-NCDs caused a significant increase in out-of-pocket healthcare expenditure of households, and the changes in its impact during the reference period are highlighted compared to other types of NCDs. With increasing C-NCD prevalence, low-income families suffer from higher out-of-pocket healthcare expenses than high-income families. Although higher in demand, public healthcare provision plays a major role in NCD care. The reduction in public provision leads to a further increase in the household burden of healthcare expenditures. The increasing out-of-pocket expenses due to C-NCDs crowds out households' basic needs, such as food and clothing. This is particularly alarming in low and middle-income households. Although households with high incomes could bear the cost of healthcare currently without affecting other consumption, the future risk of the pressure on their budget due to C-NCDs is visible. The study provides important policy implications in financing C-NCD-related healthcare costs. Enhancing the availability and the quality of public healthcare service is the best option for minimizing household overburden of healthcare spending. However, the possibility of such a policy is questionable as the country faces huge macroeconomic pressure to reduce public spending. Hence the policies should be targeted at providing C-NCD care for the most vulnerable groups. The wide availability of private healthcare providers and the pressure on the demand for public health services push even low-income households to seek private medical care without having health insurance to cover the cost. Hence implementation of a well-designed national-level health insurance scheme would be an optimal solution for reducing the household burden of C-NCD care costs and enhancing household welfare.

In Chapter 4, we studied the impact of the COVID-19 pandemic on the labour

market outcomes of individuals with NCDs using the data from the Understanding Society COVID-19 study in the UK. We linked the data with the main-stage Understanding Society surveys and applied a difference-in-difference method to distinguish the pandemic-related effects on the labour market outcomes of individuals with NCDs at different stages in the pandemic. Overall, we found that their likelihood of engaging in work and the work duration were negatively affected by COVID-19. However, the impact varies at different stages of the pandemic. The highest negative impact on the probability of being employed/self-employed was reported in January 2021, when the UK imposed tighter lockdown restrictions as it was at the peak of the second wave of COVID-19. However, the loss of work hours due to the pandemic is unrelated to the tightness of lockdown restrictions. Regardless of the easing of lockdown restrictions, the work hours of individuals with NCDs continued to decrease as the pandemic proceeded. We show that the work loss due to the pandemic was higher for individuals with riskier health conditions for COVID-19 than those having other types of health conditions. This implies that the adverse impact of COVID-19 on the work capacity of people with NCDs could be coupled with the health risk that they encounter. We also show that the work loss of people having NCDs is significantly larger for the older age groups compared to younger age signalling that those older people are working less than they did during the pre-pandemic period or they have moved entirely out of the labour market. The lower work hours of key workers with NCDs compared to non-key workers are also highlighted in the study. We tried to identify possible causal channels for the work loss of individuals with NCDs. We suggest that although the pandemic has not deepened their existing low mental or general health further, they may have decided to be less active in the labour market due to their current low health with the combination of being risk averse. Accordingly, the study provides a deeper understanding of the post-covid labour market changes in the UK. The UK economy is currently experiencing a loss in the workforce, and this study suggests that part of the labour

loss could be linked to the combined effect of NCDs and COVID-19. Similarly, this study reveals another aspect of the adverse impact of COVID-19 on people with NCDs. The downturn of their livelihood activities could have a direct impact on their earnings and, thereby, overall consumption. Therefore, actions should be taken to enhance the quality of life of those affected by NCDs.

To conclude, NCDs create diverse challenges to the healthcare system, household budget, individuals' earnings, and the overall economy. This thesis encompasses three studies that discuss those challenges and mechanisms to prevent the risk factors of NCD prevalence. All three studies contribute to the literature and provide important policy implications. First, we discussed household unhealthy dietary behaviour- a major risk factor of NCDs- and highlighted the possibility of using formal education to deliver diet-related knowledge, and the use of effective price policies to improve people's diets. Second, we discussed the consumption crowding of healthcare expenditures and encouraged effective public healthcare provision and the implementation of national health insurance to reduce the household burden of out-of-pocket expenditures. Third, we disclosed the decrease in the labour supply of people with NCDs during the COVID-19 period, indicating a plausible contributor to the decline in the overall workforce in the country. We highlighted the need to protect the quality of life of people with NCDs, whose livelihoods were adversely affected during COVID-19.