FINANCING HEALTHCARE IN INDIA: AN EMPIRICAL ANALYSIS OF HOUSEHOLD EXPENDITURE DATA

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DOCTOR OF PHILOSOPHY

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By

Gaddam Rohin

Registration No: 16SEPH09

School of Economics
University of Hyderabad
Hyderabad-500046

January 2023

School of Economics
University of Hyderabad
Hyderabad - 500046

DECLARATION

I, **Gaddam Rohin**, hereby declare that this thesis entitled **"Financing Healthcare in India: An Empirical Analysis of Household Expenditure Data"** submitted by me under the guidance and supervision of **Dr. K. Ramachandra Rao**, School of Economics, is a bonafide research work, which is also free from plagiarism. I also declare that it has not been submitted previously in part or full to this University or any other University or Institution for the award of any degree or diploma. I hereby agree that my thesis can be deposited in Shodganga/INFLIBNET.

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Registration No. **16SEPH09**

(Signature of the Supervisor)

DR. K. RAMACHANDRA RAO

Supervisor,

School of Economics

University of Hyderabad

School of Economics
University of Hyderabad
Hyderabad - 500046

Date: 31 January 2023

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This is to certify that the research work embodied in the present thesis entitled **"Financing Healthcare in India: An Empirical Analysis of Household Expenditure Data"** has been carried out by **Gaddam Rohin (Registration No. 16SEPH09),** in partial fulfilment of the requirement for the award of the degree of Doctor of Philosophy in Economics, under my supervision. This thesis or a part thereof has not been previously submitted for the award of any degree or diploma at this or any other University/Institute. This thesis is free from plagiarism and has not been submitted previously in part or in full to this or any other University for award of any degree or diploma. The candidate has satisfied the UGC Regulations of publications and conference presentations before the submission of this thesis. Details are given below:

A. Publication

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(Prof. R.V. Ramanamurthy)

Dean, School of Economics

(Dr. K. Ramachandra Rao)

Supervisor, School of Economics

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LIST OF ABBREVATIONS

AB-PMJAY	Ayushman Bharat Pradhan Mantri Jan Arogya Yojana
ARDL	Autoregressive Distributed Lag
CHE	Catastrophic Health Expenditure
GDP	Gross Domestic Product
GHE	Government Health Expenditure
HCE	Health Care Expenditure
LMIC	Low-to-Middle Income Countries
NHA	National Health Accounts
NSSO	National Sample Survey Organisation
OECD	Organisation for Economic Cooperation and Development
OOP	Out-of-Pocket
OOPHE	Out-of-Pocket Health Expenditure
THE	Total Health Expenditure
UHC	Universal Health Care
UHI	Universal Health Insurance
WHO	World Health Organisation

CHAPTER I

INTRODUCTION

1.1. BACKGROUND

Health economics has been an applied field of economics since the publication of Kenneth J. Arrow's article 'Uncertainty and the Welfare Economics of Medical Care' in 1963 where he drew a distinction between health and other goods. Major factors distinguishing health from other goods are extensive government intervention, barriers to entry, asymmetric information (knowledge gap between the physician and patient), externalities (infections), and the presence of the third part (physician) who has a heavy influence on the decision and purchase making of the individuals. This sub-discipline has been having an increasing impact on academia, medical terminology, and policy during the past 40 years.

Health is an essential factor in human happiness and well-being. It is understandable that alleviating illness and maintaining physical and mental health are considered to be essential for human welfare. But Health is not a mere absence of illnesses (physical and mental) but the ability of the individuals to reach their full potential in their lives. Thus, health can be viewed as an asset to the person. By preventing, diagnosing, and treating human disease, illness, injury, and other physical and mental impairments, healthcare aims to maintain or improve overall health. Healthcare is delivered by the health professionals (physicians and practitioners) in various allied fields of medicine, from general medicine to specialized practices like cardiology, neurology, dentistry, optometry, psychology etc. So, in economic sense 'Healthcare' is the viewed as a consumption good for maintaining good 'Health'.

It is a popularly accepted relation that the more developed the country is, the better is the health. But the reverse is also true, the healthier the people are, the better the country develops. Because a healthy person can work more efficiently, and so the healthier the population, the more efficient the nation. Thus, health has intrinsic value in itself but it also does possess an instrumental value in the sense that a healthy individual can work more efficiently. Thus, healthcare becomes a final good as well as investment good.

Historically, the improvements in health status and economic growth have been positively correlated which is why we see better health indicators in developed countries. It is basic knowledge that poverty, through malnourishment and mortality drastically reduces the life expectancy. Thus, national income has a direct effect on life expectancy. For instance, according to the WHO Commission on Macroeconomics and Health study, the national income played a significant role in determining health spending in 1997 for a panel of 167 nations. (Sachs, 2001). Also, improvements in population nutrition was found to be the major driver in the economic growth of England in past 200 years (Fogel, 2004).

Similarly, It is obvious how health affects development. It is more difficult for nations with poor health and educational systems to experience long-term growth. Economic data does really show that an increase in economic growth of between 0.3% and 0.4% per year is correlated with a 10% increase in life expectancy at birth. (Sachs, 2001). So, it becomes an essential part of the government's duty to make sure the necessary healthcare services are easily accessible to all.

1.2. HEALTH AS A PUBLIC GOOD

According to Paul Samuelsson, Public goods have two characteristics:

- Non-Excludability: No person can be excluded from the consumption of the good
- Non-Rivalrous: The consumption of one individual does not reduce or prevent the consumption of another person.

So, a Public good can be described as a product that anyone can consume as much as they want without reducing the amount available for others. Some basic examples of public goods include air, lighthouses, national defence, etc. The Private good, hence becomes a stark opposite with the product being Excludable and Rivalrous. The public good can be excluded from using (through price) and the consumption of the good by one person reduces the amount available for the others. According to these definitions, a public good is not necessarily associated with the public sector, and vice versa for a private good.

Public goods suffer from the problem of 'free rider'. Since, the public goods are non-excludable the benefits of the good can be enjoyed by the person not contributing to the cost of production of that good. Even if the producer is able to make the product excludable, under-consumption arises due to the non-rivalrous nature of the public goods. But if there is no charge

towards a non-rivalled good, there will be no incentive to supply the product and ultimately results in under-supply. According to traditional economic theory, the creation of public goods can result in a market failure, an imbalance that appears when a free-market economy fails to provide outcomes that are efficient for the entire economy. Because of this, governments frequently provide public goods rather than private firms, and the cost is shared by everyone.

By the definition, Health is typically not regarded as a public good because those who do not pay (for health insurance, nutritious food, etc.) would not be able to maintain excellent health. The pursuit of universal health coverage will bring healthcare one step closer to being a public good. Adoption of social insurance systems or other publicly funded health insurance, where all citizens are covered and can use healthcare services whether they have the money or not, raises the possibility that insured health services will then become non-excludable and non-rivalrous, more closely resembling a public good.

1.3. HEALTHCARE STATUS IN INDIA

In an overpopulated developing country like India, effective delivery of healthcare services can prove to be a substantial problem. Income inequalities and rural-urban disparities have only complicated it further. It is reflected in the poor health status with life expectancy and infant mortality rate below the global averages.

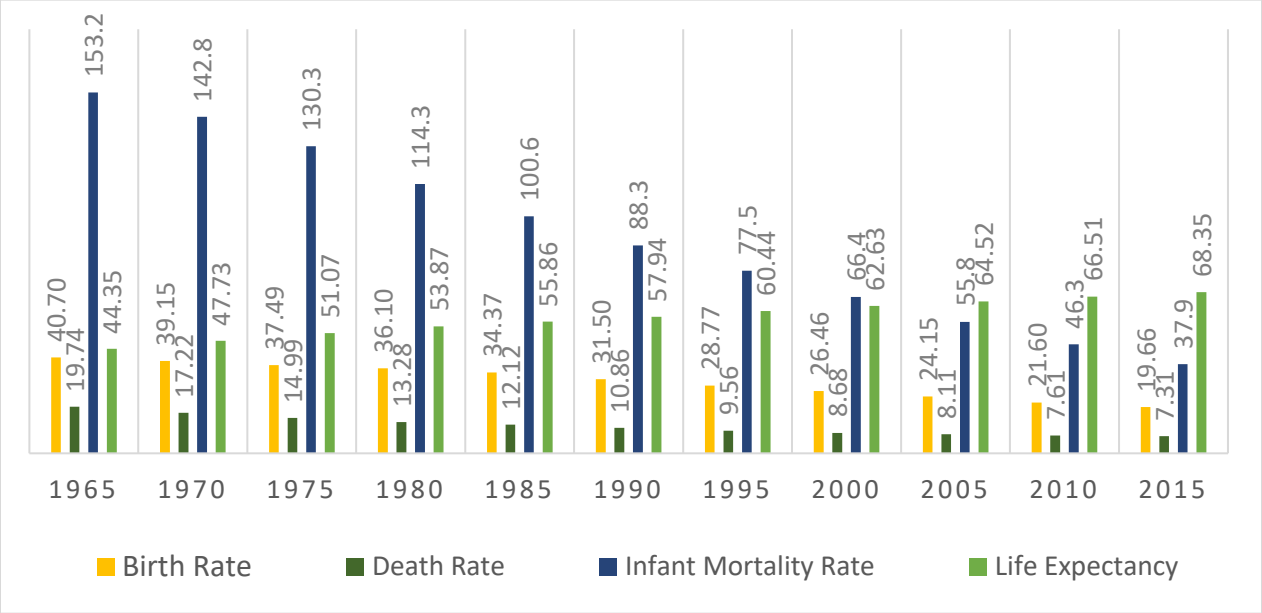

Figure 1.1. Birth and Death Rates, Infant Mortality Rate, and Life Expectancy

However, the situation is not too dire. As can be seen from the above figure, the trends in these basic indicators show that India is in a Transformation stage characterized by decrease Birth and Death rates, followed by a significant and consistent fall in infant mortality rate, and a gradual increase in the life expectancy. This shows that there is potential for achieving better health outcomes albeit with a good push. This is where the concept of Universal Health Care (UHC) comes in to play.

1.4. UNIVERSAL HEALTH CARE

Promoting human welfare and sustained economic and social development is an important agenda for any nation. Health can be supported and promoted in a variety of ways. Some factors that are outside the purview of the health system, such as adequate food and housing, improved education, and stable employment, have an impact on health and as a result, the reduction of inequalities in these factors aids in the decrease of inequalities in health. However, timely access to health care, which include a combination of promotional, preventive, therapeutic, and rehabilitative services, is essential. In 2005, the member states of the World Health Organization (WHO) have committed to setting up financial systems to provide healthcare access to all without any financial burden on them. This is called as the ‘Universal Health Coverage’.

Universal Health Care means that all people have an impartial access to quality health services with protection against any financial hardships arising through the illnesses. So, in retrospect, UHC comprises of 3 main goals:

- Equitable access of health services – irrespective of wealth or other social inequalities.
- Quality of services thus provided be of good quality to improve the health status.
- Minimising financial risks in order to prevent people from suffering financial harm as a result of the expense of using health services (Catastrophic Health Expenditure).

Almost the whole continent of Europe has universal healthcare that is either publicly funded, controlled, or publicly provided. Some nations' public insurance programmes only offer fundamental or "sick" care; for more comprehensive coverage, their residents can purchase supplemental insurance. Australia, Austria, Belarus, Canada, Croatia, Czech Republic, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Luxembourg, Moldova, Netherlands, Norway, Portugal, Romania, Russia, Serbia, Spain, Sweden, Switzerland, Thailand,

Ukraine, United Kingdom and New Zealand are among the nations that have universal healthcare. Most other countries, even those without a universal health coverage system, have a public funded health plan that caters to the needs of the population that cannot afford the health services. India too has several central and state government funded insurance schemes that cover the health needs of the people below poverty line.

1.5. THEORETICAL FRAMEWORK ON DEMAND FOR HEALTH CARE

According to Gary Becker (1964) investment in human capital in the form of education, health, and on-job-training are considered to be important for the individual well being and economic development. Following Gary Becker (1964, 1965) human capital theory and Kevin Lancaster (1966) characteristics approach to demand, Michael Grossman (1972a) developed his model of demand for health. According to Grossman the individual make investment or demand health because health is both consumption good as well as investment good. As consumption good it enters into the utility function of the individual and augments the utility level (health itself creates happiness) of the individual. However, health as a commodity or good is not directly available in the market from where the individual can purchase it, rather the individual purchase health care or medical care from on the presupposition that it restores or augments the stock of health. Similarly, as an investment good it gives a flow of services and help in enhancing the productivity or earning and welfare of the people. Hence economists take a different approach to define health. According to them health is a capital stock or durable capital good that provides services and the flow of services derived from capital stock health consumes over the lifetimes (Grossman, 1972a and 1972b). Every person is taken to have a certain stock of health at the beginning of their lives, which over time depreciates with age and may be increased by investments in medical services. When a person's level of health drops to a critical minimum, death results. Naturally, the stock of health and the rate of deterioration differ from person to person and substantially depend on numerous circumstances, some of which are uncontrollable. Therefore, people demand health care or utilise health care and other health related inputs in order to reduce illness or augment their health and to improve their well being. The investment in health capital is considered to be crucial for the individual and nation because it improve the returns to investment in other sector of the economy as well. Even the return to education is dependent on the investment in health. For instance, performance of the children in school is dependent on the health condition of the children which

in turn determined by investment in health. Above all, the investment in health is started even before the birth of a baby.

However, the demand model developed by Grossman (1972a) in his paper comprised one individual who planned investments in health over the lifecycle in a world without uncertainty (Muurinen 1982; Dardanoni and Wagstaff, 1990). Most of the times people encounter with an unexpected period of illness during their life. In most of the time illness is not serious enough to induce the individual to receive treatment or stay away from work. In some cases, it restricts the individual from work and in the event of illness; the rate of depreciation is even faster thus illness call for a measure (curative health care) to restore the level of health. Sometimes the rate of depreciation is so high that it exceeds the rate of return of health investment, in such case the individual/household has left with no option other than death. The curative health care is taken with the purpose of restoring the stock of health therefore different from other measures such as preventive and promotive health care. For instance, preventive and promotive measures such as check-up visits to a physician, physical exercise etc. are taken in order to maintain health or reducing the risk of becoming ill. Hence the demand for health care increases following increased uncertainty over the incidence of ill health (Dardanoni and Wagstaff, 1990). Moreover, the amount curative health care is needed, must take a point of departure that curative health care is not welfare enhancing per se, but rather it is used as a tool for achieving or restoring a certain level of health.

1.6. FINANCING HEALTH SYSTEMS

The aim for any healthcare system is to provide timely access to health services to the people. This cannot be achieved without a well-functioning healthcare finance system (WHO 2010). In the recent years, there has been a growing commitment to achieve Universal Health Care (UHC) whose 3 main goals are: equitable access, quality of service and protection against financial catastrophe from payments for the services. So, health policies should not only concern about providing equitable access to health services to the population but also make the essential service affordable for them. A big concern in this regard is the impact of health expenditure on the economic status of the households who face illness. Most high-income developed countries have insurance policies in place to ensure the services are provided fairly equitable and affordably (Thomson et.al., 2009). However, in low-to-middle-income (LMIC) countries like India

affordability is a major concern, especially in the absence of prepayment systems where the payments for health services happen primarily on an out-of-pocket basis.

How to pay for such a health system is a major concern of governments working toward UHC. A universal health care system can be financed in one of two ways: by the government or the market. Everyone in the nation has access to coverage that is funded by the government and that gives some form of fundamental medical care. Taxes and other fees are the main ways that people finance these systems. For instance, the *single-payer* system used in the United Kingdom sees the government paying for healthcare services directly. In other situations, the government only covers a portion of the cost through taxes, leaving the balance to be covered directly by the employees and businesses.

Conversely, in a market-based model, the cost of services is paid by private parties such as employers and individuals. In these markets private insurers have a huge role for example like in the United States where 220 million people pay for through employer funded or privately funded health insurance policies (U.S. Census Bureau, 2020). In a market-based system, care is also usually provided by private organizations and due to the private nature, in theory, competition among the different players improve the overall performance due to profit motives–since a better performing hospital can have more patients and thus more revenues. Coordination of care can be difficult, and some duplication of services may happen in a system where clinicians and patients have freedom of choice. The competition from the market-based system also ensures that new medical advancements are incentivized and makes the improvements available to patients sooner.

But if there are insufficient safeguards ensuring a basic level of health coverage, some people might not have access to the care they need. Thus, *safety-net* programmes that provide government-funded protection to people who cannot afford to buy insurance on the commercial market, such as the elderly, the underprivileged, or those who are disabled, are typically seen in market-based health care systems. Examples of safety net programmes include the 3M programmes in Singapore, the Sistema Unico de Saude in Brazil, Medicare, Medicaid, and the State Children's Health Insurance Program (SCHIP) in the United States. There are 27 million people in the United States without health insurance, thus safety net services might not be able to cover everyone who is uninsured. Many are low-wage workers who cannot afford insurance, while others are healthy individuals who opt to forgo coverage (Kaiser Family Foundation, 2021).

Because of the high reach of the government financed system, they have to limit the care given to patients to reduce the costs. As such under these plans, it frequently takes longer for new developments to be approved, paid for, and made accessible to physicians and patients (Danzon et.al., 2005). Consequently, the diagnostic and treatment procedures differ a lot between the government financed and market-based health systems. For instance, in the market-based U.S. system, people undergo cancer diagnostic tests more frequently and earlier than they do in Europe (Thorpe et al., 2007).

Thus, Market-based and government-financed models to health care funding each have their own benefits and drawbacks, and neither is ideal across every situation. There is no one-size-fits-all model for financing health systems. All societies must decide how widely to make basic and specialized healthcare accessible, how much to spend for healthcare, and which advances to make available to patients. However, India does not have a single payer system nor is the private insurance market is integrated enough to achieve this.

1.7. HEALTH CARE FINANCING IN INDIA

In this section, we take a close look at the healthcare expenditures in India and will take a look at the trends and composition to get a better look at how the healthcare is finance in India.

Table 1.1: Total & Percapita Healthcare Expenditure (Current US$)

Years	in million current US$	total (% of GDP)	per capita (current US$)
2000	19,549.18	4.03	18.45
2001	21,282.51	4.26	19.72
2002	22,123.80	4.24	20.14
2003	24,451.06	4.01	21.88
2004	28,313.54	3.96	24.92
2005	31,750.95	3.79	27.50
2006	34,454.50	3.63	29.39
2007	42,425.44	3.52	35.66
2008	45,483.92	3.51	37.69
2009	46,643.05	3.49	38.12
2010	55,702.83	3.27	44.90

2011	60,768.87	3.25	48.32
2012	61,955.15	3.33	48.61
2013	71,878.80	3.75	55.67
2014	73,945.53	3.62	56.57
2015	77,190.12	3.60	58.35
2016	80,269.13	3.50	59.96
2017	77,049.67	2.94	56.90
2018	78,995.49	2.86	57.70
2019	83,911.64	2.94	60.67
2020	79,075.57	2.96	56.63

Source: NHA Database, Global Health Expenditure Database

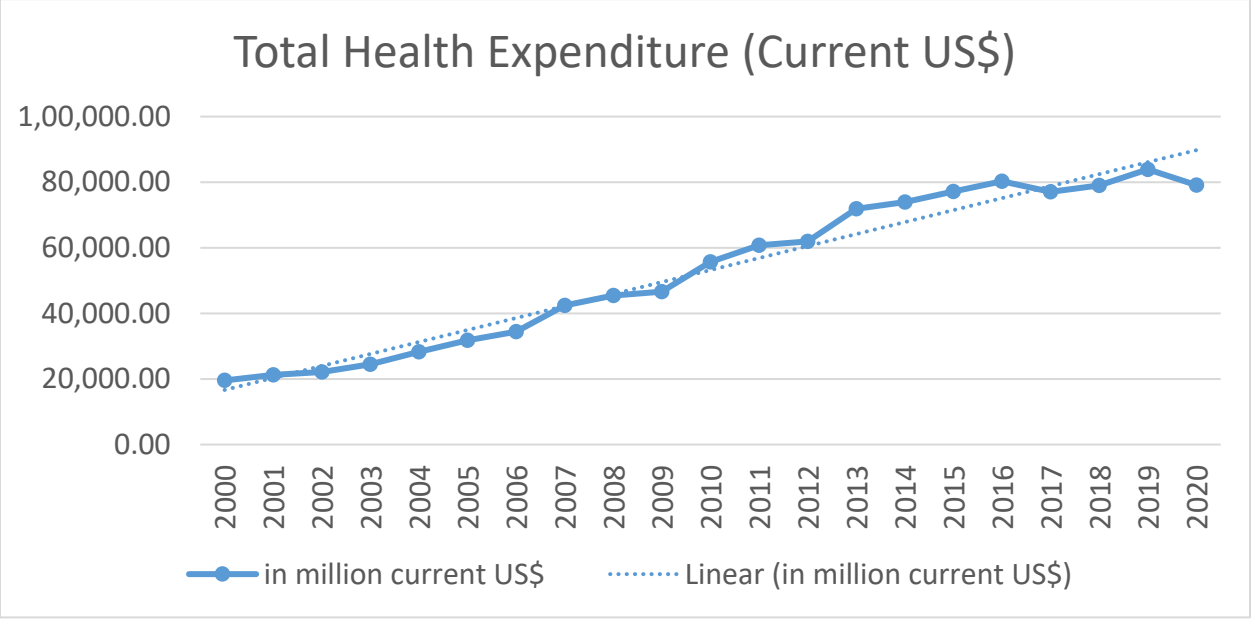

Figure 1.2. Total Healthcare Expenditure (Current US$)

Figure 1.2 shows the total expenditure on health (in current million USD) in India over the period of 2000-2020. The total expenditure on health has risen slowly overtime, from 19,549.18 million USD in 2000 to 83,911.64 million USD in 2019 but has seen a slight dip to 79,075.57 million USD in 2020. But since 2004 the increase has been more substantial from 30,193.40 million USD in 2004 to 97,139.88 million USD in 2014. Percapita health expenditure has followed the same pattern as the total expenditure, rising from 15.82% in 1995 to 74.99% in 2014. But the

Indian GDP too has increased substantially during this period, which is the reason why in spite of the increase in absolute spending the share of health expenditure in GDP has remained around 4%.

Figure 1.3 shows the percapita health expenditure (in current USD) over the past 20 years in India. Since percapita is just a ratio of total expenditure to total population, the numbers show a similar increase in the percapita health expenditure. The percapita health expenditure increased from 18.45 USD in 2000 to 56.63 USD in 2020. In spite of the monetary increase in expenditure the share of health expenditure in GDP has gone down in this period from 4.03% in 2000 to 2.96% in 2020. This reduction significance of a decreasing demand for healthcare in India.

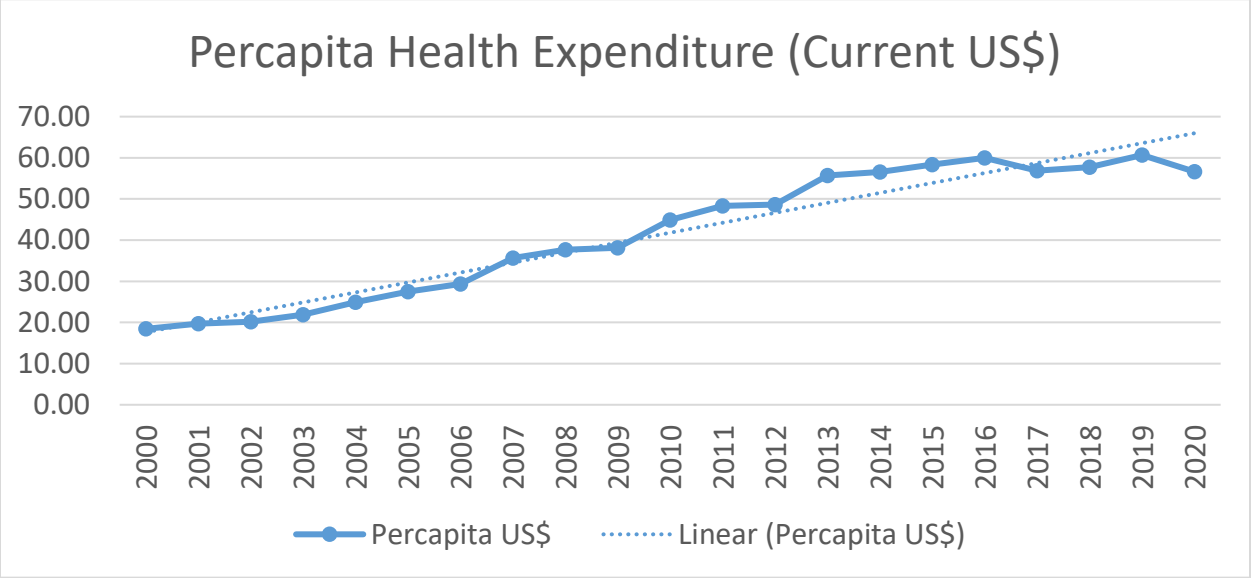

Figure 1.3. Percapita Healthcare Expenditure (Current US$)

We have seen that the expenditure on health as a share of GDP is very low in India. But what's more concerning is that the public/government share in this expenditure is very low. Ideally, it is the responsibility of the state to provide healthcare services and to maintain their quality. But in India we find that most expenditure is private, and a lot of this private expenditure come out-of-pocket.

Table 1.2: Expenditure distribution in India (as % of total health expenditure)

Year	Govt. Expenditure on Healthcare	Private Expenditure on Healthcare	Out-of-Pocket Healthcare Expenditure
2000	20.68	76.64	71.70
2001	18.88	78.79	74.11
2002	18.16	79.38	73.37
2003	18.72	79.76	73.42
2004	17.98	79.78	72.48
2005	20.13	78.34	73.15
2006	20.51	78.06	72.26
2007	20.90	77.59	70.82
2008	22.63	75.50	69.15
2009	25.61	73.37	66.76
2010	26.21	72.82	65.18
2011	28.87	70.26	62.22
2012	27.99	71.07	63.00
2013	23.07	76.66	69.07
2014	23.66	75.59	67.01
2015	25.64	73.65	64.66
2016	26.84	72.52	63.21
2017	32.95	66.46	55.11
2018	34.29	65.25	53.23
2019	33.48	65.65	53.38
2020	36.65	62.36	50.59

Source: NHA Database, Global Health Expenditure Database

Table 1.2 shows the distribution of healthcare expenditure between private and public expenditure. As can be seen from the above table, the healthcare is mostly financed privately in India, over 60% of the total expenditure on healthcare is private, and over half coming out-of-pocket with 50.59% of the total expenditure being out-of-pocket expenditure, as of 2020. There has been a significant change in shares since 2007, The private expenditures have gone down from 77.59% in 2007 to 62.36% 2020.

The governments face a fundamental question in striving to attain universal health coverage. That is, how to finance such a health system? WHO have found three major barriers in moving towards a universal coverage. They are: lack of resources, overreliance on direct payment

for the services at the time of need, and inequitable and inefficient use of resources. WHO suggests improving the efficiency of the revenue collection to increase the funds available to purchase health services on behalf of the population, along with reprioritizing government budgets to allot for health. Development assistance from developed countries to low-income countries is another possible remedy to the deficiency of resources to health. While enough funding is essential, it will be hard to attain anything close to universal coverage if people have financial difficulties or are deterred from receiving services because they must pay upfront. Most nations impose some kind of direct payment, often known as cost sharing, albeit the percentage of overall spending that is funded in this way increases with country wealth. This dependency on direct payments can only be lessened by creating a risk-pooling prepayment approach where the people pay for illnesses in advances, which are then pooled into a healthcare service fund that can be used to purchase the services for all covered. Such a pooling mechanism makes the goal of universal health coverage more realistic.

Healthcare expenditure in India is mostly private and for majority part is out-of-pocket expenditure. This can be seen from the below table.

Table 1.3: Expenditure distribution in India (2019)

	As % of total health expenditure	**In terms of percapita USD (PPP)**
Public	32.79	69.18
Private	66.38	140.06
Out of Pocket	54.78	115.59

Source: World Bank Database 2015.

World Bank data suggests that 66.38% of the total healthcare expenditure is private and 54.78% of total health expenditure is out-of-pocket payments. This is in averse to the goal of Universal Health Coverage where the idea is to alleviate the burden of healthcare financing for all. Poor healthcare spending, especially the public sector spending, lack of sufficient infrastructure and human resources in health are the major observable deficiencies in Indian healthcare system.

Significance of Health Expenditure

Healthcare expenditure, or the amount of money spent on healthcare, is essential for ensuring that individuals have access to the medical care they need to maintain and improve their health. The importance of healthcare expenditure can be seen in several key areas.

First, healthcare expenditure is necessary for ensuring access to basic healthcare services. These services include preventive care, such as vaccinations and screenings, as well as treatment for illnesses and injuries. Without adequate healthcare expenditure, many individuals would not have access to these essential services, leading to poor health outcomes and increased rates of preventable diseases.

Second, healthcare expenditure is essential for the development and advancement of medical technology. Medical research and development require significant funding, and healthcare expenditure can provide the necessary resources for these efforts. This can lead to the development of new treatments and technologies that can improve the quality and effectiveness of healthcare.

Third, healthcare expenditure is important for addressing health disparities and reducing inequality. Many individuals from marginalized groups, such as low-income communities and racial minorities, face barriers to accessing healthcare. Adequate healthcare expenditure can help to reduce these disparities by increasing access to healthcare for these communities.

Fourth, healthcare expenditure is important for economic growth and development. A healthy population is essential for a strong economy, and healthcare expenditure can help to ensure that individuals are able to stay healthy and productive. Additionally, healthcare expenditure can create jobs and stimulate economic activity in the healthcare sector.

Despite its importance, healthcare expenditure can also be a significant burden for individuals and governments. High healthcare costs can lead to financial strain for families and can impede economic growth. It is therefore important for healthcare systems to strike a balance between ensuring access to necessary care while also controlling costs.

In conclusion, healthcare expenditure is essential for ensuring access to basic healthcare services, advancing medical technology, addressing health disparities, and promoting economic

growth and development. However, it is important to find a balance between ensuring access to necessary care and controlling costs.

1.8. RESEARCH GAP & OBJECTIVES

Health is central to human happiness and well-being. It also enables the economic progress through more production by creating healthy individuals that live longer. So, in all sense, Health is an essential commodity for everyone in a nation. In an ideal universal health care setting, health becomes accessible to poor and rich alike. But in countries like India the access becomes harder for poorer sections of the nation and the ever-increasing costs of medical care only strengthen the financial burden on the poor. Therefore, the present study aims at evaluating the financial burden of medical care on household level in India. A look the literature review reveals that although there is an extensive amount of quantitative research on the healthcare expenditure on a global scale, the contributions from India are few.

The long-run relationship between healthcare expenditure and income in Indian states was tested only till early 2000s (Bhat and Jain (2006); Narayan et.al. (2010)) and there is a need to check for the later period. Also, there is a need to check for the causality between the HCE and Income to better understand the relation between the two. Similarly, the studies on OOP and CHE in India have used NSSO data from over 10 years old (Ghosh (2011); Pal (2012); Gupta and Joe (2013)) and have not used the recent surveys on Consumption Expenditure from 2014 and 2018. So, there is a need to study the incidence of CHE and determinants of OOP health expenditure in India with the latest data.

With this understanding, the current study has the following objectives.

- Testing the long-term relationship between growth and health (health-led growth hypothesis) in India.
- Finding the determinants of Out-of-Pocket Healthcare Expenditure in India.
- Estimating the incidence and determinants of Catastrophic Health Expenditure (CHE).
- Estimate the level and determinants of impoverishment due to Out-of-Pocket Healthcare Expenditures.

1.9. DATA AND METHODOLOGY

The required data for the current study will be secondary data in nature. The data for the healthcare expenditures and GDP will be acquired from various government publications. And the data for household expenditures, and other social indicators like income, age composition and social status will be acquired from the NSS 75th Round[1], 71st Round[2], NSS 60th Round[3] and 52nd Round[4].

In order to approach the objectives, we have found the following methods from the detailed literature review.

The long-term relationship between HCE and Income will be tested using Government HCE of the Indian states and their respective State-GDP. The long-term relationship between the two can be tested using ARDL cointegration technique. The determinants of OOP HCE will be found using the 2 part-models suggested by Hitiris (1992) and Matsaganis (2009). For the purpose of estimating health expenditure catastrophe and impoverishing burden, Multiple Logistic Regressions were used on the Household expenditures data.

1.10. ORGANISATION OF THESIS

The current thesis is organised into five chapters. Chapter 1 deals with the introduction of the thesis. In chapter 2 the long run relationship of the health expenditure and GDP is tested to check for the significance of health expenditure to the growth of the economy (health-led growth hypothesis) in India. In chapter 3 a look at Indian demographics, their health care utilisation and expenditure patterns are analysed along with the determinants of out-of-pocket health expenditures by households. Chapter 4 deals with the incidence and determinants of catastrophic and impoverishing burden of out-of-pocket health expenditures on Indian households. The final chapter 5 attempts to summarise the findings from all the chapters while also suggesting any policy recommendations stemming out of those findings.

[1] "India - Household Social Consumption: Health, NSS 75th Round Schedule-25.0: July 2017-June 2018."
[2] "India - Social Consumption - Health Survey: NSS 71st Round, Schedule 25, January - June 2014."
[3] "India - Survey on Morbidity and Health Care: NSS 60th Round, Schedule 25, January 2004 - June 2005."
[4] "INDIA - Survey on Health Care July - June 1995-96, NSS 52nd Round."

CHAPTER II

LONG RUN RELATIONSHIP BETWEEN GDP AND HEALTH EXPENDITURE

2.1. INTRODUCTION

In the current chapter an attempt has been made to test the importance of healthcare investments in the process of economic development. The health-led growth hypothesis is the idea that improvements in health can lead to economic growth. The hypothesis is based on the idea that healthy individuals are more productive and have a greater ability to work, learn, and innovate, which in turn drives economic growth. The hypothesis also suggests that investments in health can have positive externalities, such as reducing poverty and inequality, and promoting social and economic development (Hansen and King, 1996; Hartwig, 2010).

Investments in health can also have positive externalities that go beyond the direct economic benefits of improved health. For example, reducing poverty and inequality can lead to more inclusive and sustainable economic growth. Additionally, healthy populations can lead to greater social cohesion and improved social and political stability, which can also contribute to economic growth. Another important argument in favour of the health-led growth hypothesis is that health is a key determinant of human capital, which is an important driver of economic growth. Human capital refers to the knowledge, skills, and abilities of individuals that can be used to produce goods and services. Investments in health can improve the quality and quantity of human capital, which can lead to higher levels of productivity and economic growth.

Despite these arguments, some critics of the health-led growth hypothesis argue that the relationship between health and economic growth is more complex than the hypothesis suggests. They argue that other factors, such as technology and education, may be more important drivers of economic growth. Additionally, some argue that the health-led growth hypothesis may not be applicable to all countries or contexts.

2.2. LITERATURE REVIEW

In their study, Kiymaz, Akbulut et.al. (2006) tried to test the unit root properties of health care expenditure (HCE) and gross domestic product, and their long-term relationship in the Turkish economy. For this purpose, they used the data from OECD health database on private,

public, and total health care expenditure, along with GDP, and growth rate of population, for the period of 1984-98. They used Augmented Dickey-Fuller test (ADF) and Phillips and Perron test to check for the data stationarity and unit root and used Multivariate Cointegration technique to check for cointegration among the variables. The study found unit root properties in the series and non-stationarity in the series. They also found a cointegrating relationship between GDP and healthcare expenditure, and a one-way causality from GDP to healthcare expenditure. They discovered that the total cost of health care would rise by 21.9 percent for every 10 percent growth in the gross domestic product. They discovered that healthcare spending had an income elasticity of more than 1, indicating that it was a luxury good in Turkey.

Sülkü and Caner (2011) tried to retest the relationship between the GDP and HCE in Turkey since the previous study stopped at 1998 data. The Turkish healthcare system has undergone reforms post 1998, so the authors used the same variables as the previous study and extended the dataset from 1984-2006, and converted the data on HCE and GDP to log values, and employed the same multivariate cointegration method and found that contrary to the previous study, the income elasticity of healthcare has gone down, with 10% increase in GDP leading to a 8.7% increase in HCE, indicating that HCE has become a necessity post reforms. But they did find that although income elasticity total HCE went down, the elasticity of private HCE was still more than 1, meaning that private HCE was still a luxury in Turkish economy. But the study concludes that the reforms did reduce the financial burdens of healthcare.

The two previous studies (Kiymaz 2006 and Sülkü 2011) found contradicting results regarding the income elasticity of healthcare expenditure. Yavuz, Yilanci, and Ozturk (2013) thought that although Sülkü and Caner (2011) extend the period of analysis, both studies employ the Johansen multivariate cointegration approach, which is susceptible to small sample bias. Additionally, because both researches only examined gross domestic product and population growth rate to explain changes in the health care expenditures, there exists omitted variable bias. So, the authors added some demand and supply variables to the independent variables. Infant mortality rate and the percentage of people 65 and older in the total population were considered demand side variables. Physician density and the typical length of stay in the hospital were taken into consideration as supply side variables. The dataset for the period 1975-2007 was considered for the study. ARDL bounds testing approach to the cointegration was used to examine the long

run relationship among the variable. According to the findings, while income does not have a long-term effect on health spending, it does have a short-term effect, with a 1% rise in per capita income causing a 0.75 % increase in per capita health spending. However, it has been found that the average length of stay and the number of doctors have negative impacts, the percentage of elderly people has favourable effects, and the newborn mortality rate has no impact on either the short- or long-term costs of healthcare.

Gerdtham and Löthgren (2000) checked for the stationarity and cointegration for the GDP and HCE in the OECD region. They selected 21 countries and the data for the two variables were collected for 1960-1997. The stationarity was tested using ADF as well as Kwiatkowski et al. (1992). Cointegration was tested using Error Correction Model (ECM) and Shin Test. Both the unit root tests found the data to be non-stationary with a conclusion that both HE and GDP are difference stationary I(1) processes. While the panel ECM does not reject the non-cointegration of the two series, the Shin test gives a non-rejection of cointegration. The authors thus conclude that the HE and GDP are in a long run cointegrating relationship.

Many studies have tested the relationship between growth and health but Narayan et.al. (2010) added investment, trade, education, and R&D into the analysis to find which has better long-run relationship with the growth. 5 Asian countries were considered for the analysis (India, Thailand, Indonesia, Sri Lanka, Nepal) and the period of study was 1974-2007. 4 different growth models were formulated. Panel cointegration test was used to find the cointegration and Dynamic OLS technique was used to estimate the long-run relationships between growth and other variables. Under all 4 cases, cointegrating relationship was found between all the variables. Additionally, for the panel of 5 Asian nations, investment and health both statistically significantly and favourably affect per capita income. The range of the health sector's elasticity is merely 0.16 to 0.26, indicating that an increase in health spending as a percentage of GDP only leads to a rise in per capita income of up to 0.26%. The elasticity of per capita investment, on the other hand, ranged from 1.36 to 2.32 and was the greatest. Exports and R&D also have a positive impact on per capita income, with elasticities of 1.41 and 0.07, respectively. Imports have a negative and large influence on per capita income, which decreases by 1.07 percent for every 1 percent rise in imports. However, the correlation between education and per capita income is statistically insignificant.

Hitiris and Posnett (1992) did one of the earliest studies on the determinants of health expenditures. The study used data from 20 OECD countries over a 28-year period of 1960-87. 3 relationships were estimated: the relationship between, percapita HCE and percapita GDP; relationship between PCHCE, PCGDP and Population above 65-year old (share of total); and relation between PCHCE, PCGDP, and crude mortality rate. Using OLS regression technique, the study found a very strong positive relationship between income and health expenditure (income elasticity of 1.16). share of elderly population also showed a positive movement in the total HCE (+0.55). Although very little, a negative relationship was found between mortality rate and HCE (-0.08).

Baltagi and Moscone (2010) tried to retest the long run relationship between the HCE and GDP and to determine the status of HCE as a luxury or necessity good. The test panel consisted of 20 OECD nations and the period of study was 1971-2004. In addition to percapita HCE and GDP, Public HCE as a share of total Government Expenditure; the dependency rates for both young and old persons (calculated as the population aged 0–14; and 65+; divided by the population aged 15–64) were taken for the study. All the variables were converted to natural logarithmic forms. Fixed Effects, Spatial Maximum Likelihood Estimation, and Common Correlated Effects Estimation (CCEP) methods were used. All the three regressions result an income elasticity of less than 1 (FE=0.899; SMLE=0.896; CCEP=0.674) indicating healthcare expenditure is a necessity good in the OECD region.

'Healthcare' is a local 'public good' in each of the respective localities or nations. So, in principle, it is a heterogeneous good due to fiscal decentralization of the nations. So, Lo´pez-Casasnovas and Saez (2007) thought that it is not accurate to compare income elasticities of health expenditures across nations. Using data for 110 locations across 8 OECD nations in 1997, a special sample was created to address the issue of multijurisdictional health care when evaluating income elasticity. A multilevel hierarchical model was used to estimate sample data in order to distinguish between within- and between-country variation as the two main sources of random variation. The main goal was to determine whether nation specificity existed in the various correlations between health care spending and the explanatory variables. Using the dependent variable of Health expenditure (log, $PPP), and the independent variables of percapita GDP (log, $PPP), % of population above 65-year-old (log), and public health expenditure as a share of total (log), a

Restricted Maximum Likelihood (REML) method was used. The results show the following variations between-countries: (i) the rise in the % of population over 65-year-old, and a rise in the share of public health expenditure led to a rise in the total health expenditure; (ii) The income elastic values are very low (around 0.2 for all nations). Within country variability: Higher (relative) income variance causes greater variation in health care spending, which raises the estimated income elasticity.

Bhat and Jain (2006) estimated the income elasticities of health expenditure in India for both private and public expenditure. Their study consisted of two parts: one analysis on public health expenditure (only state governments expenditure) and other on private health expenditure. For the analysis the percapita real terms of income and expenditure were considered. 14 major states, that consisted of about 90% of the total population were taken up by the study. The data period was 1990-2002 and the sources of data were CMIE and other government publications. The public health expenditure was analysed first. After some unit root tests, data was found to be stationery and panel data regression analysis was used. According to the findings, state governments in India aim to spend 0.43 percent of the GSDP on healthcare. Governments will allocate this amount of money into the health sector. In addition, a 1% increase in the GSDP causes a 0.684% increase in health spending. According to an analysis of private health spending, private HE has expanded far more quickly than real wages. The real per capita expenditure on health has increased by 1.95 percent for every 1% increase in real PCI. PHE has increased annually during the past ten years by 18 percent in nominal terms and around 11 percent in real terms. The authors believe that it is questionable whether consumers are getting value for their money with the relatively high out-of-pocket expenditures that households bear, particularly in catastrophic illnesses where the financial burden is high.

Atilgan, Kilic, et.al. (2016) empirically investigated the health-led growth theory in Turkey. For the purpose they used only two variables, Real percapita GDP, and percapita healthcare expenditure. After some stationarity tests, Auto Regressive Distributed Lag (ARDL) model was used to check for the relationship between healthcare expenditure and economic growth for the period 1975-2013. According to their research, a 1 percent increase in per capita health spending results in a 0.434 percent rise in per capita GDP, supporting the health-led growth hypothesis for the Turkish economy.

A large body of theory agrees that accumulation of health capital has a stimulating effect on the economic growth of the nation. Hartwig (2010) tried to test the applicability of this theory in rich countries. For this purpose, he selected 21 countries from the OECD region and the data for real percapita GDP and HCE were collected for the period of 1970-2005 from OECD Health database. The collected data was deflated with a GDP deflator and the health expenditure data was converted to 5-year moving average to remove the cyclical nature. Panel Granger-test was used to find the causality between GDP and HCE. OLS and Generalized Method of Moments (GMM) were used to test for Granger causality and as for robustness tests two variables of life expectancy and alcohol consumption were later introduced but they showed no significance. The final results suggest that the health-led-growth hypothesis does not apply for the high GDP nations while also finding that the growth-cause health expenditure exists in the OECD countries. However, the author also suggests that the results are so because the time period considered for the study might not be large enough to capture the actual effects of the health capital accumulation on economic growth.

Nixon and Ulmann (2006) tried to study the determinants and their effects on the three conventional outcomes, IMR, Life Expectancy at birth in males, and in females. They tried to do this using macroeconomic analysis on European economies. For the purpose of this study, they used a healthcare production function, rather than a Grossman's Human Capital Model. They used the data of 15 EU countries from OECD Health Database for the period 1980-95. The three conventional outcomes were taken as the dependent variables, and the set of independent variables included Percapita health expenditure, health expenditure as a share of GDP, Physician density, Bed density, inpatient admission rate, average inpatient stay, population coverage, unemployment rate, nutrition consumption, alcohol, tobacco intake, and environment pollution. The authors used Ordinary Least Squares (OLS) estimation and found that Health expenditure and Physician density has the most effect on the three outcomes. But they also found that health expenditure is a major factor in lowering IMR but has marginal effect on the life expectancy in males and females. They stated that these results were in line with the findings from other developed countries.

Leiter and Theurl (2012) tried to see if there is any convergence or divergence in the health system financing methods across nations using the OECD countries as a empirical evidence. For this purpose they used two dependent variables, public share of the total healthcare finance and

real public health financing per capita ($PPP). The independent variables included, public health insurance coverage (%), demographic burden, openness of economy, political orientation, percapita GDP, and type of healthcare system. The data on these variables was collected for 22 OECD countries for the period of 1970-2005. The methods used were, σ-convergence, absolute and conditional β-convergence. The study found that the health systems were converging, but the rate of the convergence has been slowing overtime.

Apergis and Padhi (2013) explored the convergence of real percapita GDP and health (public) expenses across Indian states using the panel convergence methodology (Phillips and Sul 2007). For empirical analysis, state-level data from 26 Indian states was collected from Central Statistical Organization, GoI for the period 1981-2005. The data for percapita GDP and public health expenses (as a share of GDP) were taken in 1990 prices. The convergence test results for income convergence reject the convergence hypothesis for the full sample, but the results show the formation of three convergence clusters/groups with 9, 12, and 5 states in those respective clusters. Similar results are seen in health expenditure convergence with no convergence in full sample but 4 convergence groups with 8, 3, 3, and 12 states in each group. However, when transitional graphs were plotted for those 4 groups of states, groups 1&2 converging from above; and groups 3&4 seem to converging from below. But the amount of time it would take for all the groups to converge is still inevident.

Potrafke (2010) tried to empirically evaluate whether political ideology and election motives have an influence on the rising healthcare expenditure in the OECD countries. He wanted to test the existence of theoretical ideas of ‘Political Business Cycle’ and ‘Partisan Theory’. For this purpose, he collected data for 18 OECD countries from OECD health database for the period 1970-2004. Public percapita real healthcare expenditure growth rate was taken as the dependent variable. The independent variables included real GDP percapita growth rate, unemployment growth rate, share of healthcare expenditure as a share of social expenditure, share of underage and elderly population, and a political variable that can account the election timing, political ideology of the government, and government coalition. Panel data methods were used viz. Regression, Unit Root test, and Autocorrelation. The study found that the political ideology had no effect on the healthcare spending. But found that the incumbent candidates did increase the

health spending during the election years to please the voters. This does prove the Political Business Cycle theory, but the Partisan Theory could not be validated in the OECD scenario.

Farag, Nandakumar, et.al. (2012) tried to find the strength of relationship between percapita health expenditure and percapita GDP in high, medium and low income countries. The empirical analysis was done using data for 173 countries for the period of 1995-2006. The data was collected from WHO, World Resource Institute and World Bank. Apart from GDP and health expenditure, data for several exogenous variables like government effectiveness, voice and accountability, GINI coefficient of inequality, life expectancy, physician density and literacy were considered. The study used two-way fixed effects model with OLS regression method for the analysis. The regressions were done separately for income groups and continental groups of the countries. According to the study, health care spending is most responsive to changes in income in middle-income nations (0.874), with high-income countries falling in the middle (0.644) and low-income countries having least response (0. 516). Consequently, in the continental groups South American Nations are the most responsive (0.968) followed by Europe (0.964), Oceania (0.831), North America (0.823), Asian (0.782) and Africans (0.721) having the least response to income changes. The remaining variables taken under the study have returned insignificant effects.

Di Matteo (2010) estimated the fiscal sustainability of ever increasing government health expenditure in the Canadian federation. He used the data from Canadian Institute for Health Information and Statistics for the years 1965-2008. The variables included were GDP, Provincial Population, percapita provincial government health expenditure (GHE), provincial government revenue, population above 65 years age, and provincial federal cash transfers (all in real terms). In order to estimate the future GHE two methods were use, a simple Extrapolation method, and a Pooled Time Series Cross-section Regression with two different scenarios: (i) future values from implied growth rate; (ii) a scenario with low economic growth (50% of the implied growth rate from 1966-2008), and a rapid ageing population (150% of the implied growth rate of population above 65). So, three future values were calculated. By simple extrapolation, The GHE was found to triple by 2035 to reach 10,967CAD percapita compared to 3,604CAD of 2008. Under Scenario I and II, the GHE is estimated to grow to 6,777CAD (8% of GDP) and 5,416CAD (8.8% of GDP) respectively. The author suggests that the extrapolation scenario is unrealistic as, although the GHE has been rising rapidly, the resource (GDP) restrictions will catchup eventually. And that the

regression results show a little impact of ageing population on GHE. But the results also suggest that even if growth rates fall, the GHE burden on GDP will increase.

Utilizing information from 133 low to middle middle-income countries (as defined by the World Bank) for the years 1995, 2000, 2005, and 2006, Farag, Nandakumar, et.al. (2013) examined the effects of health spending on IMR and child mortality. Data on health spending were collected from NHA from WHO; child mortality rates were collected from UNICEF database; and access to improved water and sanitation, physician density, gender parity in secondary school education and literacy rates were considered as control variables, with the data obtained from World Resources Institute. Panel regression was used with a fixed model. The study was divided into two sections; one checks for the impact of total health expenditure on health outcomes and the other checks the impact of public health expenditure (with private expenditure as a control variable). The study calculates elasticities of newborn and child mortality with regard to income of -0.58 and -0.64 respectively, meaning that for every 1% rise in GDP per capita, infant mortality decreases by 0.58 percent and under-five mortality decreases by 0.64 percent, while the health spending elasticities according were -0.13 and -0.15 for infant and child mortality respectively. This indicates that income has better effect than the health spending on IMR and CM. The study found that public health expenditure has better effect (elasticities -0.17 and -0.19) on IMR and CM than private expenditure (elasticities -0.07 and -0.08). Additionally, the study used government effectiveness (as calculated by World Bank) as another control variable and found that government effectiveness has more impact on IMR and CM (elasticities -0.36 and -0.38); and suggests this might be, since government effectiveness is a moderator for government health spending.

Share of government health expenditure (GHE) in GDP has been rising across all OECD for a few decades but the reasons for such a growth are still unclear. So, Hartwig (2008) tried to test the Baumol's unbalanced growth theory for OECD scenario. The Baumol's theory divides the economy into progressive and non-progressive sectors with productivity growth (due to technical progress) happening only in the progressive sector but the resulting rise in wages happening across both sectors; thus resulting in a rise in prices in the non-progressive sector. Baumol has considered education and health as non-progressive due to their excessive reliance in labour. To empirically test this, the author used the OECD health data from 19 OECD countries for the period 1990-2003. The variables were growth rates of real GDP percapita, real Percapita GHE, and wages and salaries

across sectors in the overall economy. The growth rates were converted to log natural values and OLS regression was employed. The Baumol's theory was captured using a 'Baumol variable' which was the difference between log values of: growth rate of wages and salaries, and growth rate of productivity (real GDP per employee). The empirical results show that the Baumol variable does explain the growth in percapita GHE (coefficient 1.033, with 1% level of significance; Adj. R^2= 0.771) validating Baumol's unbalanced growth theory in the OECD scenario.

The effect of the relative percentages of public and private health spending on income inequality was studied by Bhattacharjee, Shin, et al. in 2017. The theoretical idea of this study is that private health investments lead to increased income inequality since, 'public' health facilities are accessible to all while the 'private' health facilities are accessible only to the richer population that can afford to pay. So, under a private regime the richer are bound to invest more in health and grow faster leaving the poor in a vicious cycle of low health and income levels. This idea is empirically tested using the vaccination sources (private vs public). The data source was 42nd round of NSSO (1986-87) which was done after the Universal Immunization Programme (UIP), as the baseline year and corresponding inequality was measured for the period 1987-2012 using the subsequent NSSO rounds' data. Household expenditure is taken as a proxy for income and was adjusted to constant prices for 1986-87. Gini coefficient (-0.195) was estimated for inequality. Increases in the number of private health care providers are associated with higher levels of expenditure inequality, according to estimates from the OLS and IV models. More specifically, OLS estimates for measles show that an increase in the relative private share of vaccine provision by one standard deviation causes an increase in the Gini coefficient of 1.5 percent, and our IV estimates show that an increase in the relative private share by one standard deviation causes an increase in the Gini coefficient of 2.2 percent.

Any health system should strive to become more responsive to the needs of the public. In their study, Malhotra and Do (2016) calculate the difference in responsiveness between the richest and the poorest people, the proportion of public health spending over all healthcare spending (PPHE), and the responsiveness to the poorest population. Data from the World Health Survey (2002-03) for 63 countries were used for analysis. There are six aspects of responsiveness in outpatient care: quick attention, dignity, choice, information clarity, confidentiality, and standard of basic facilities. The survey comprised of 'vignettes' to reduce response bias and asked

participants to score their experience in each domain on a five-point Likert scale ranging from *very bad* to *very good* Hierarchical Ordered Probit (HOPIT) model was used to estimate the probability of individuals responding with *very good* in each of the domains across the countries. The study found that across the countries, the six domains of responsiveness are positively correlated with the PPHE. Also, the difference in responsiveness between poorest and richest also reduced with an increase in PPHE. A 10% increase in PPHE resulted in reduction the difference in responsiveness across all domains (prompt attention = -0.67, dignity = -1.23, choice = -1.16, clarity of information = -1.99, confidentiality = -1.43 and quality of basic amenities = -2.43).

Studies on the impact of demographics on health expenditure have often indulged in studying the impact of ageing of population on health expenditure, and the studies often suggested that there is very little or no significant impact of ageing population. So, Shiu and Chiu (2008) wanted to extend on this knowledge by including life expectancy as a demographic variable and re-estimate the effects of demographic changes on health expenditure in Taiwan from 1960-2006. The data for GDP, HCE, and Physician ratio were taken from Taiwan national statistical information database, and data age indicators were taken from Taiwanese department of health. GDP and HCE were taken in percapita real terms and converted to log natural values. The life expectancy was divided into three parts with LE65 denoting life expectancy of 65–69-year-olds, LE70 consisting of life expectancy of 70-74 year olds, and LE75 consisting of life expectancy of 75-79 year olds. Age dependency calculated by dividing number of people over 65 years old by number of people between 15-64. Maximum likelihood models and Dynamic OLS estimators were used to estimate to estimate long term impact of GDP, age dependency, life expectancy, and physician ratio on health expenditure. The empirical results return negative coefficients for the life expectancy terms (LE65=6.53, LE70=7.04, LE75=5.93) with high levels of significance. This implies that there is a negative correlation between LE for three age groups and HCE, implying that older people are healthier today than they were in the past and that health care costs would decline as life expectancy increased.

2.3. DATA DESCRIPTION

For the purpose of finding the long run relationship between the health investments and the growth of the nation, the following data sources were used:

- Percapita GDP (in 2011-12 constant prices) – National Accounts, GoI.

- Government Health Expenditure – Ministry of Health and Family Welfare; and budget estimates, GoI.
    - GHE data was deflated using Government Final Consumption Expenditure Deflator.
- Private Health Expenditure – Private Final Consumption Expenditure on Health (in 2011-12 constant prices)

Additionally, PFCE on education and Gross Capital Formation were used to control the effects of investment in education as well as general investments in the economy. These control variables were collected in terms of 2011-12 constant prices. The health expenditures and control/exogenous variables were converted to percapita terms.

Figure 2.1 depicts the trends in percapita national income and percapita health expenditures, both public and private. The percapita incomes have grown constantly from ₹20,662.30 in 1980 to ₹1,08,247.30 in 2020. The government health expenditures have not seen any significant increase from 1980 to 2005. However, there has been a consistent increasing trend in public health expenditure since 2006 from ₹315.68 to ₹968.78 in 2020. The private health expenditures too were constant from 1980 to mid-1990s but started to rise up rapidly around the turn of the millennium. The trend has persisted for a decade when the percapita private health expenditure has reached ₹1,528.31 in 2006. This trend signifies an increase in demand for healthcare from individuals during the time period. The expenditure level has sustained till 2012 post which the expenditures rose rapidly yet again from ₹1600.97 in 2013 to ₹2977.99 in 2020.

Overall trends signify a low public spending and disproportionately high and increasing private expenditure for healthcare.

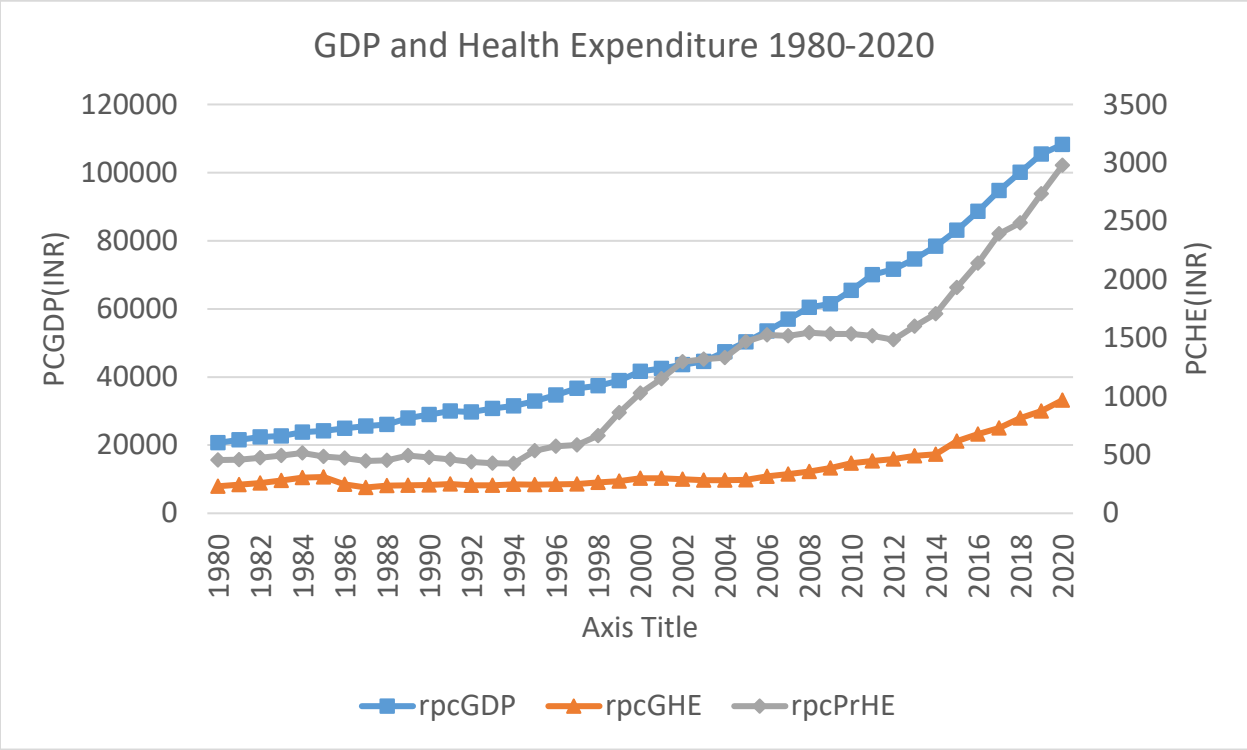

Figure 2.1. GDP and Health Expenditures Per capita (1980-2020)

Table 2.1: GDP and Health Expenditures Per capita (1980-2020)

Year	rpcGDP	rpcGHE	rpcPrHE
1980	20662.30	231.83	455.11
1981	21566.90	245.68	457.49
1982	22432.80	259.86	474.01
1983	22687.90	281.42	492.88
1984	23836.60	304.14	516.29
1985	24211.50	311.22	485.93
1986	24943.60	248.89	473.05
1987	25592.70	220.84	448.54
1988	26033.50	235.33	452.29
1989	27937.30	239.19	495.27
1990	28986.70	242.86	478.18
1991	29970.80	250.89	461.71
1992	29686.00	240.43	439.97
1993	30739.00	239.66	429.35
1994	31477.40	248.49	425.48
1995	32909.30	244.40	536.61
1996	34715.30	248.09	572.37
1997	36625.80	249.57	585.26
1998	37397.50	263.60	662.87
1999	38942.70	275.43	861.39
2000	41625.30	298.50	1028.71
2001	42460.60	300.95	1152.32
2002	43610.20	291.25	1297.90
2003	44583.20	283.41	1318.07
2004	47369.90	283.90	1333.31
2005	50324.90	285.06	1470.04
2006	53477.50	315.68	1528.31
2007	56964.10	336.64	1519.66
2008	60465.80	357.22	1547.30
2009	61468.00	387.56	1534.29
2010	65393.80	428.46	1535.49
2011	69993.60	448.16	1518.58
2012	71609.30	464.01	1486.35
2013	74599.30	492.30	1600.97
2014	78348.30	503.90	1707.04
2015	83091.40	616.98	1933.47
2016	88616.50	676.74	2140.20
2017	94751.30	729.83	2391.68
2018	100034.90	814.17	2486.36
2019	105447.70	874.25	2735.71
2020	108247.30	968.78	2977.99

Source: National Accounts and MoHFW, GoI.

2.4. METHODOLOGY

Using the annual data on the national income and health expenditures, both private and public, the current study inquires the long run relationship between the GDP and health expenditures. For this purpose, a cointegration technique was used. On the purpose of testing for cointegration, Engle-Granger and Johansen cointegration tests are frequently used. However, Yavuz, Yilanci, and Ozturk (2013) and Kilic, Atilgan et.al., (2016) suggest that these tests can only be used under the prior condition that series are integrated to the same order. On the other hand, the Autoregressive Distributed Lag (ARDL) bounds test developed by Pesaran, Shin, and Smith (2001) can be used regardless of whether the variables under investigate are integrated order of one or zero. Besides, the bounds test can be used in small sample sizes. Also, using an ARDL would help understand both the short and long run effects of the independent variables on the dependent, while also indicating the causality of the effect.

So the current study used the annual data from 1980 to 2020 and used an ARDL model with Error Correction Form. The data was collected from National Accounts of GoI. Additionally, we also used Gross Capital Formation (GCF) and Private Education Expenditure as control variables for the model. All the collected data was in constant terms, except for the government health expenditures, which was later deflated using the Government Final Consumption Expenditure (GFCE) deflator. All variables are also converted to percapita terms.

ARDL Model Specification

ARDL is an OLS model consisting of lags of both the dependent variable and independent variable. The general form of ARDL model is:

$$ARDL(p,q): Y_t = \beta_0 + \sum_{i=1}^{p} \beta_1 Y_{t-i} + \sum_{i=0}^{q} \delta_1 X_{t-i} + \varepsilon_t$$

Where, p and q are the lags of the dependent and independent variables respectively. Here, Y_{t-i} term incorporates the lags of the dependent variable and X_{t-i} incorporates the independent variable and its lags, hence the name Autoregressive Distributed Lags model.

2.5. RESULTS

2.5.1. Stationarity Tests

Table 2.2: Stationarity Test Results (ADF)

		I(0)			I(1)		
	Variable	**Level**	**Intercept**	**Trend+Intercept**	**Level**	**Intercept**	**Trend+Intercept**
DV	**ln(PCRGDP)**	7.283	1.016	-3.376	-1.285	-4.535**	-4.612**
IV	**ln(PCRGHE)**	1.906	2.626	0.157	-2.906**	-3.86**	-4.643**
IV	**ln(PCRPFCEH)**	1.818	0.06	-2.418	-3.234**	-3.779**	-3.861
CV	**ln(PCRGCF)**	3.851	0.388	-2.461	-3.156**	-8.507**	-8.517**
CV	**ln(PCRPFCEE)**	6.433	1.532	-2.91	-3.1**	-4.636**	-4.944**

Source: Author's Calculations.

Table 2.2 presents the results of the Augmented Dickey Fuller (ADF) test for stationarity. The results show that all the variables are stationary at first difference and I(1) which allows for the use of the ARDL cointegration test.

2.5.2. F-Bounds Test for Cointegration

Table 2.3: Results of the F-Bounds Test for Cointegration

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Significance Level	I (0)	I (1)
F-statistic	**7.018941**	10%	4.19	5.06
k	2	5%	4.87	5.85
		2.50%	5.79	6.59
		1%	**6.34**	**7.52**

Source: Author's Calculations.

The result of the F Bound test are presented in Table 2.3. The F statistic calculated in the test is matched along the critical values at different values of significance levels. The calculated F statistic is 7.02. Comparing it to the critical values show that the cointegration exist between the dependant and independent values at 1% significance level.

2.5.3. Long-Run Form

Table 2.4: Long Run Coefficients

Variable	Coefficient	Standard Error	t-Statistic	Probability
Selected Model:	ARDL(4, 4, 4)			
PCGHE	0.210759	0.011465	18.38267	0.0000
PCPHE	-0.01486	0.011814	-1.25813	0.2236
EC = PCGDP - (0.2108*PCGHE -0.0149*PCPHE)				

Source: Author's Calculations

Using Akaike Information Criterion (AIC), a lag selection of (4,4,4) was found to be optimal and subsequently an ARDL (4,4,4) was used to calculate the long run and short run coefficients. The long run coefficients for the health expenditures suggest a statistically significant positive effect of public health expenditure on the national income but an insignificant impact of private expenditure on national income. This result suggests that one unit change in government expenditure on healthcare in India helps increase the national income by 21%. However, an increase in private expenditure has statistically insignificant impact on the national income.

2.5.4. Short Run Coefficients and Error Correction Term

Table 2.5: Error Correction Form

Variable	Coefficient	Standard Error	t-Statistic	Probability
Constant	11.76186	2.550128	4.612262	0.0002
D(PCGDP(-1))	0.862783	0.263749	3.271229	0.004
D(PCGDP(-2))	0.500596	0.199408	2.510416	0.0213
D(PCGDP(-3))	0.488277	0.176244	2.770462	0.0122
D(PCGHE)	0.113155	0.047162	2.399277	0.0268
D(PCGHE(-1))	-0.12777	0.046244	-2.76287	0.0124
D(PCGHE(-2))	-0.05811	0.039184	-1.48289	0.1545
D(PCGHE(-3))	-0.13644	0.036362	-3.75232	0.0013

D(PCPHE)	0.007435	0.040772	0.182363	0.8572
D(PCPHE(-1))	-0.07225	0.04435	-1.62903	0.1198
D(PCPHE(-2))	0.083274	0.040373	2.062594	0.0531
D(PCPHE(-3))	-0.12869	0.039011	-3.29879	0.0038
PCGCF	0.135623	0.026616	5.095503	0.0001
PCPEE	0.090228	0.03863	2.335696	0.0306
CointEq(-1)/(ECT)	-1.60905	0.333534	-4.82424	0.0001

Source: Author's Calculations

Table 2.5 shows the results of the short run coefficients as estimated by the model along with the Error Correction Term (ECT). The coefficients show that GHE and PHE have similar effects to that of long run in short run as well. The control variables of GCF and PFCE on education have an expected significant positive impact on national incomes. ECT was estimated at -1.61 meaning that 160% of any deviations from the equilibrium in an year is adjusted for in the subsequent year.

2.5.5. Diagnostic Tests

Table 2.6: Serial Correlation Test

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	2.082451	Prob. F(4,15)	**0.134**
Obs*R-squared	13.21069	Prob. Chi-Square(4)	0.0103
Null: No Serial Correlation			

Source: Author's Calculations

As part of the analysis, Serial Correlation test and CUSUM/CUSUM Square for testing model stability were used. The results of Breusch-Godfrey LM test is presented in Table 6 and stability test results are presented in Figure 2.2. The results show that no serial correlation exists in the model as the Breusch-Godfrey LM test failed to reject null hypothesis. Also, the CUSUM and CUSUM square plots show that the model is stable at 5% significance.

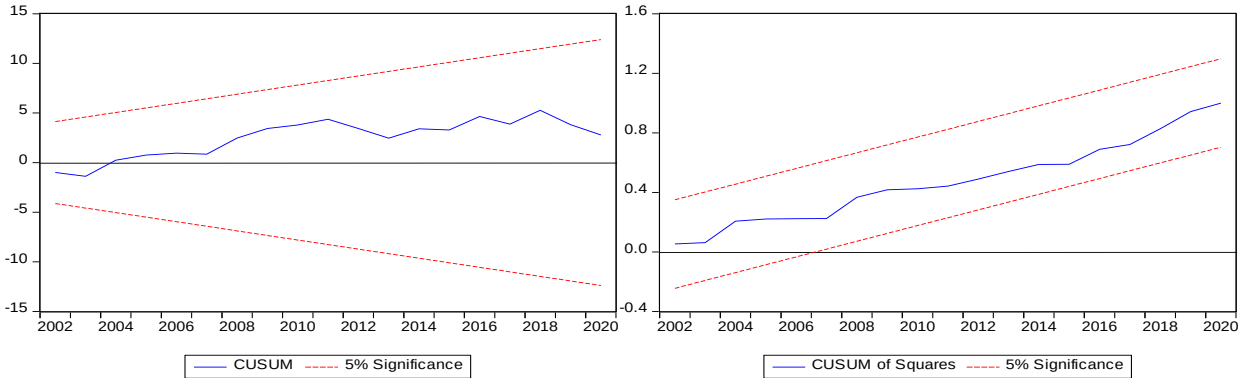

Figure 2.2. CUSUM and CUSUM Square test for Model Stability

2.6 CONCLUSIONS

The current chapter focused on finding the overall long-term relationship between the health expenditures and the GDP of the Indian economy. In doing so the government health expenditure is found to be positively cointegrated with the national income in the long run. This validates that health led growth theory is valid for the Indian economy. However, the private expenditures showed insignificant relationship with the GDP. In conclusion, the analysis establishes that health expenditures from the public sector have a significant impact on economic growth of the Indian economy.

CHAPTER III

OUT-OF-POCKET HEALTHCARE EXPENDITURES AND DETERMINANTS IN INDIAN HOUSEHOLDS

3.1. INTRODUCTION

In the current chapter we see the expenditure patterns of Indian households, especially those payments from out-of-pocket. Indian healthcare system is extensively dependent on OOP payments. So, it is imperative to examine the major risk factors responsible for out-of-pocket health payments among households. In this chapter an attempt has been made to carry out an econometric analysis on the determinants of out-of-pocket health payments. The current chapter also gives an overall picture of the Indian demographics, their healthcare service utilisation patterns along with the expenditures on those services. For this purpose, the unit level data collected by the National Sample Survey Organisation (NSSO) has been used.

3.2. DATA SOURCE

3.2.1 National Sample Survey Organisation Surveys

The data collected in 4 consecutive surveys of NSSO on 'Healthcare Consumption and Morbidity' spread across a period of 23 years. The included rounds are 52nd (July 1995-June 1996), 60th (January-June, 2004), 71st (January-June, 2014) and 75th round (July 2017-June 2018). The National Sample Survey Office (NSSO), the erstwhile National Sample Survey Organisation was set-up by Government of India in 1950 to collect information on various facets of the Indian economy through nationwide sample surveys to assist in socioeconomic planning and policymaking. In its seventh round, NSS made its first effort to gather data on health (Oct 1953-March 1954). The surveys undertaken in the three rounds that followed, from the eleventh to the thirteenth, in 1956–1958, were all explanatory in nature. The basic objective was to obtain a morbidity profile of the country (NSS Report 71st Round, 2015). The surveys under the study are longitudinal, studying morbidity pattern, utilisation of healthcare services and expenses incurred on medical services.

All four surveys included in the study use the same recall period for consumption and healthcare expenditures. A recall period of one month was used for consumption expenditure,

while the recall periods for health expenditures was 365 days for the inpatient care and 15 days for the outpatient care. For the purpose of the study, the expenditure and reimbursements on inpatient and outpatient cases are adjusted to a 30-day reference period. The data contains individual cases of hospitalisation, which are cumulated at the household level to gather a total healthcare expenditure estimate for the households in the survey sample. Similarly, the reimbursements are also aggregated at households and deducted from the total health expenditure to arrive at out-of-pocket health expenditure (OOPHE). Since the survey data also lacks information on income of the households, monthly household consumption expenditure (HHCE) is used as a proxy. For the purpose of economic (Income) class, five wealth quintiles were generated using the per capita HHCE of the households and the households are accordingly arranged in the classes ranging from poorest quintile to the richest quintile. An overview of the four rounds of survey is given in Table 3.1.

Table 3.1: Survey Description and Household Average Expenses

	NSS52	NSS60	NSS71	NSS75
Sample Estimates				
Villages/Blocks	12231	7423	8269	14258
Sample Households	120942	73868	65932	113823
Sample Persons	629888	383339	333104	555115
Average Household Size	4.92	4.82	4.51	4.35
Population Estimates				
Estimated Population	840,392,489 (840 million)	958,922,889 (959 million)	1,121,101,609 (1.12 billion)	1,140,187,554 (1.14 billion)
Average HHCE (INR per household)	1,801.11	2,887.42	7,333.01	9,404.56
Average Health Expenditure	106.63	296.92	886.03	747.64
Average Reimbursement	1.66	6.49	19.31	25.57
Average OOPHE	104.97	290.43	866.72	722.07
Average % Reimbursed	**1.55**	**2.19**	**2.18**	**3.42**

Source: Author's Estimations from NSSO microdata.

Notes: Population Estimations calculated using population weights provided in the data.

Table 3.1 depicts the sample sizes and populations estimates for the 4 rounds of data. Additionally, average consumption expenditures and health expenditures per household are also estimated. Both the consumption and healthcare expenditures have seen a substantial rise from 60th

to 71st round. The HHCE has risen further in the 75th round, however the average health expenditure has gone down in the same period.

3.2.2. Comparability of the Four Rounds of Survey Data

The NSSO used a multi-stage sampling design to gather data on morbidity and medical services for all of India's states and union territories. Since it used an uniform sample technique and had a wide geographic scope, the survey results are comparable. Only treatments for diseases given on medical advice were regarded as medical treatment in the 52nd and 60th NSSO surveys. However, in later rounds, self-medication, medication taken on a pharmacist's recommendation, etc. are also taken into account as forms of medical therapy. This is due to self-pervasive medication's prevalence in India. People with impairments were viewed as sick people in early health surveys. Pre-existing conditions were classified as chronic illnesses in the 71st round if they had been treated for a month or longer during the reference period. In the 71st round, newborns were given a fictitious illness code so that information about the care and costs associated with birthing could be recorded. As is customary, delivery is not seen as a disease. According to the demands of the Ministry of Health and Family Welfare, a more comprehensive and updated illnesses code list was accepted in the 71st round. In the 71st round survey, information on costs associated with treatment was gathered using a paid technique rather than a payable one because it was more easily available. The definitions used in the 71st round apply to the 75th round as well.

3.2.3. Justification for Using the Last Four Rounds of NSSO Data

The objective of the study is to examine utilisation and expenditure patterns of health care and its consequences on the households. The NSSO 52nd, 60th and 71st round surveys are all India comprehensive surveys which collect information on morbidity, utilisation, and expenditure on health care separately for inpatient and outpatient care. These four rounds contain relevant information about morbidity, not all of which were included in the earlier rounds. Unlike the previous round the reference period for both inpatient and outpatient care are same in these four rounds. The same definition of illness, namely any deviation from the state of physical and mental wellbeing is adopted in all the three rounds. One will be treated as sick if one feels sick is itself a subjective judgement of a person’s health. More interestingly, the concepts and methodology are almost same in these rounds. The same concepts and methodology of 52nd round was adopted in 60th round survey. However, in 71st and 75th round surveys there are minor differences in the

concepts and definitions related to some of the variables, but these changes have been taken into consideration while making any comparison with 52nd and 60th rounds. Moreover, these three rounds of NSSO Surveys focus on curative aspect of health care services.

3.2.4. Limitations of NSSO Health Surveys Database

The major limitation of health expenditure data is that it does not capture the actual amount that household incurred for health care. There is a possibility of downward bias in the expenditure because of its fixed reference period. The information related to expenditure on health care beyond the reference period was not captured. The status of ailments are classified into four categories, viz., (a) started before the reference period and still continuing (b) started before the reference period but ended within the reference period (c) started within the reference period and is continuing and (d) started and ended within the reference period. Hence except the last category where ailments started and ended within the reference period the actual expenditure on health care cannot be captured. The same problem arises for inpatient care also. One of the specific problem relevance to household level health surveys data is that it excludes people living in institutions such as hospitals, nursing homes etc. In such cases individuals may well have above average health expenditure. Studies in some countries have suggested that people living permanently in institutions may account for 5-10 percent of overall health use (WHO, 2010). If the survey period is not designed to collect data for the whole year, then there is a significant seasonal variation in the morbidity rate, health care use and expenditure. There are certain non-sampling errors are associated with health survey data. Most of the health surveys rely on the information provided by principal informant, who provides information for other family members. Therefore, if the principal informant is not able to recall the pertinent event then there is high chance of error in the information. Sometimes the number of events forgotten is proportional to the length of recall period. Event with less relevance or impact on the individual are most likely to forgotten.

Despite the limitations mentioned above, NSSO Health Surveys are more comprehensive and widely accepted health surveys which give information on morbidity, utilisation and expenditure on health care at both the national and state level. As far as the latest four rounds (52nd, 60th, 71st and 75th) of health surveys are concerned, the recall periods with respect to inpatient care and outpatient care are same and the concepts and methodology adopted in these three rounds are almost same. Although there are some changes in the concepts used in the 71st

round survey, these differences have been taken into consideration while making comparison with the previous round surveys.

3.3. DEMOGRAPHICS

The microdata from the four successive Health surveys thus collected can be used to ascertain some crucial information about the of Indian population and their trends across the time-period under consideration. As such an attempt has been made to ascertain a picture of the socio-economic distribution of Indian demographics, their healthcare utilisation pattern along with the expenditures on such care.

Table 3.2: Demographic Distribution (1996-2018) in Percentages

Sector	**1996**	**2004**	**2014**	**2018**
Rural	75.83	74.58	70.02	70.53
Urban	24.17	25.42	29.98	29.47
Household Type				
Self-Employed	53.02	51.42	51.97	51.10
Regular Wage/Salaried	10.37	9.74	18.13	17.70
Labour	28.87	30.48	25.30	26.79
Others	7.74	8.36	4.60	4.41
Age Group				
0-5yrs	14.79	13.48	10.78	8.14
6-14yrs	22.01	21.32	18.16	18.23
15-50yrs	51.33	52.50	56.17	58.12
50yrs+	11.88	12.69	14.89	15.51
Gender				
Male	51.58	51.26	51.49	51.69
Female	48.42	48.74	48.51	48.31
Social Group				
Scheduled Tribes	8.54	8.18	9.26	9.07
Scheduled Castes	20.51	20.05	18.85	19.63
Other Backward Classes	-NA-*	40.35	44.25	44.91

Others	70.94	31.42	27.64	26.39
Education				
Illiterate	48.86	42.45	31.53	26.07
Informal Literate	1.35	1.02	1.00	1.04
Up to Primary	27.65	29.17	29.34	28.91
Up to Secondary	16.44	19.84	23.87	25.98
Higher Secondary/Diploma	2.91	3.92	8.17	10.03
Graduation and above	2.79	3.60	6.09	7.97
Religion				
Hinduism		82.65	81.13	81.13
Islam		12.30	13.89	14.13
Christianity		2.14	2.23	2.25
Sikhism		1.77	1.75	1.64
Jainism		0.28	0.20	0.20
Buddhism		0.58	0.50	0.46
Zoroastrianism		0.00	0.01	0.01
Others		0.28	0.30	0.19

Source: Author's Calculations from NSSO microdata; * In 52nd Round, OBC are included as a part of other castes.

Table 3.2 shows the demographic distribution of India across selected socio-economic attributes. Majority of the Indian population reside in rural areas in spite of the marginal decrease of rural share from 75.83 percent of population in 1996 to 70.53 percent in 2018. The urban areas consist of less than 30 percent of total population of India. The majority of the redistribution is observed after the millennium, between the 60th and 71st round.

Majority of the Indian population rely on earnings from self-employment with over 50 percent of population living in houses belonging to the category. the share of regular wage/salaried population has increases over the period from 10.37 percent in 1996 to 17.70 percent in 2018. ~30 percent of the population still rely on casual labour and other forms livelihood. India also has high labour stock with >50 percent of the population in productive age group of 15 to 50 years. Over the years this demographic increased from 51.33 percent in 1996 to 58.12 percent in 2018. This

period also saw a rising demographic burden with population over 50 years age growing from 11.88 percent in 1996 to 15.51 percent in 2018. India is also home to more male than female population with 51.69 percent male and 48.31 percent female population in 2018.

In terms of social group (aka caste) OBCs form the biggest chunk of India with ~45 percent of population while population of general category account to 26.39 percent of the population. Population of Scheduled castes ad tribes account for ~20 percent and ~10 percent of population respectively. India has seen some favourable results in education over the four rounds. The literacy rate has increased from ~51 percent in 1996 to ~74 percent in 2018. Also, the education levels beyond primary education have seem significant improvements. However, 26.07 percent of Indian population are still illiterate in India in 2018. India is primarily a Hindu majority state with over 80 percent people following the religion. Islam as a faith has seen a slight increase in the population share from 12.3 percent in 1995 to 14.13 percent in 2018. Christians and Sikhs form minority of <2.5 percent and <2 percent of population respectively.

Table 3.3: Distribution of Household Type across Sectors in Percentages

	1996			2004			2014			2018		
HHType\Sector	Rural	Urban	Total	Rural	Urban	Total	Rural	Urban	Total	Rural	Urban	Total
Self-Employed	57.61	38.61	53.02	54.45	42.50	51.42	56.72	40.86	51.97	55.71	40.08	51.10
Regular Wage/Salaried	0.00	42.90	10.37	0.00	38.33	9.74	9.68	37.86	18.13	9.11	38.25	17.70
Labour	33.82	13.34	28.87	36.40	13.10	30.48	29.67	15.10	25.30	31.71	15.02	26.79
Others	8.57	5.15	7.74	9.15	6.07	8.36	3.92	6.17	4.60	3.48	6.65	4.41
Total	100			100			100			100		

Source: Author's Calculations from NSSO microdata.

Table 3.3 shows the distribution of household type across the sectors. Although, the self-employed form the majority of the population, their share is higher in rural than in urban. Also, over the period, the self-employed in urban have from 38.61 percent to 40.08 percent and urban salaried population saw a small drop in population share from 42.90 percent in 1996 to 38.25 percent.

Table 3.4: Distribution of Social Group across Sectors in Percentages

	1996			2004			2014			2018		
Social group\Sector	Rural	Urban	Total	Rural	Urban	Total	Rural	Urban	Total	Rural	Urban	Total
Scheduled Tribes	10.34	2.90	8.54	10.12	2.48	8.18	11.78	3.38	9.26	11.69	2.80	9.07
Scheduled Castes	22.30	14.92	20.51	21.43	16.03	20.05	20.94	13.95	18.85	21.72	14.62	19.63
Other Backward Classes				41.92	35.73	40.35	44.69	43.22	44.25	45.32	43.93	44.91
Others	67.36	82.18	70.94	26.54	45.76	31.42	22.59	39.45	27.64	21.27	38.64	26.39
Total	100			100			100			100		

Source: Author's Calculations from NSSO microdata.

Table 3.4 shows distribution of social group across sectors. The urban India was predominantly occupied by other castes in 2004 with 45.76 percent of population but the share has decreased to 38.64 percent in 2018, with OBSs taking the maximum share of 43.93 percent of urban population, which increased from 35.73 percent in 1996. The Scheduled Castes and Tribes witnessed no significant change in population share.

Table 3.5: Distribution of Income Classes across Sectors in Percentages

	1996			2004			2014			2018		
Income Class\Sector	Rural	Urban	Total	Rural	Urban	Total	Rural	Urban	Total	Rural	Urban	Total
Poorest	29.49	8.51	24.41	32.16	6.17	25.56	31.95	9.98	25.36	31.72	6.01	24.15
Poor	25.37	11.77	22.08	25.01	9.30	21.02	27.88	15.00	24.02	27.57	9.37	22.21
Middle	21.22	17.66	20.36	23.02	20.03	22.26	18.60	15.35	17.63	22.27	15.38	20.24
Rich	16.38	24.96	18.45	13.73	24.58	16.49	15.96	24.56	18.54	14.86	27.77	18.67
Richest	7.55	37.11	14.70	6.07	39.91	14.67	5.61	35.10	14.45	3.57	41.47	14.74
Total	100			100			100			100		

Source: Author's Calculations from NSSO microdata.

Table 3.5 depicts the distribution of population across income classes and sectors. Overall, the poorer households consists of the higher shares of population compared to the richer. ~24 percent of all population reside in the households belonging to poorest quintile, while ~14 percent of population reside in the richest quintile. The rural areas consists majorly of the households from poorer quintiles while the urban areas have mostly richer quintiles. Additionally, rising share is

seen for rich in urban from 37.11 percent in 1996 to 41.47 percent in 2018. Similar poor in rural have grown from 21.49 percent to 31.72 percent over the same period. This shows the rising income inequalities between the rural and urban settings.

Table 3.6: Distribution of Education Levels across Sectors in Percentages

	1996			2004			2014			2018		
Education\Sector	Rural	Urban	Total	Rural	Urban	Total	Rural	Urban	Total	Rural	Urban	Total
Illiterate	55.24	28.86	48.86	48.10	25.89	42.45	36.05	20.97	31.53	30.23	16.10	26.07
Informal Literate	1.33	1.41	1.35	1.06	0.90	1.02	1.08	0.81	1.00	1.06	0.99	1.04
Up to Primary	27.18	29.13	27.65	29.59	27.92	29.17	30.62	26.34	29.34	30.75	24.50	28.91
Up to Secondary	13.33	26.19	16.44	17.30	27.29	19.84	22.90	26.13	23.87	25.64	26.79	25.98
Higher Secondary/Diplo	1.77	6.49	2.91	2.52	8.01	3.92	6.33	12.46	8.17	8.19	14.43	10.03
graduation and above	1.15	7.90	2.79	1.43	9.99	3.60	3.00	13.29	6.09	4.12	17.19	7.97
Total	100			100			100			100		

Source: Author's Calculations from NSSO microdata.

Table 3.6 depicts the distribution of population across education levels and sectors. A general expected trend is seen here, with urban areas having better education levels overall. The share of illiterate population in rural is around twice as much as that of the urban. The rural sector has seen a significant improvement in overall education levels, but the higher education levels are still lower than the national average and much lower than that of the urban population.

Table 3.7 and 3.8 represent the distribution of household type of the population across different social groups and income classes. Throughout the rounds the distribution of classes by type of livelihood shows that non-vulnerable social groups (OCs) have higher levels of stable incomes especially in the form of regular salaries/wages while the vulnerable groups (ST/SC/OBC) have significantly higher shares of population relying on less stable incomes based on casual labour. A similar correlation between the household type and income class as well. The richer households have higher shares of people relying on regular wage/salaried income while major share of the poor classes rely on earnings from labour which are much less stable in nature. These tables show the interrelationship between the caste, occupation and wealth of the population. Vulnerable social groups rely more on livelihoods that have less stable pay-outs and hence tend to stay in poorer income quintiles. Table 3.9 and 3.10 show that education level is also influenced by this socio-economic class relationship. The people from low social and economic classes tend to

have lower levels of education as well. However, the general education levels have been increasing in the vulnerable classes in the recent rounds. This relationship between social group and income class is revealed in Table 3.11. Non vulnerable OCs form majority of the Richest quintile (48.44% in 2018) across all rounds. The vulnerable SC and ST households form very low share of the rich quintiles (1.07% and 7.74% respectively in 2018).

Table 3.12 depicts the status of Insurance coverage in Indian population. Owing to the lack of data, only the coverage in last two rounds is ascertained with the data. The data shows that medical insurance levels are very low in India. Nearly 85 percent of the overall population is not covered by any form of insurance in both rounds. ~13 percent of all population is covered by health insurance schemes of public nature. Coverage by non-govt. employer and private insurance schemes is only ~1 percent. In total, all types of insurance schemes combined cover only ~15 percent of entire population in all rounds. This low insurance penetration could also be leading to burdens of OOPHE health expenditures in Indian households. Further, across sectors there is a difference in coverage. The proportion of population without insurance is higher in rural. Nearly 86 percent of rural population is uncovered while in urban, it is around 82 percent in 2014 and 81 percent in 2018. Additionally, employer supported and private schemes form ~3 percent of urban population, these schemes have little to no prominence in rural areas with a combined coverage ~1 percent. Almost all the financial support available in rural areas come from schemes sponsored by governments.

Table 3.7: Distribution of Household Types across Social Group in Percentages

	1996					2004					2014					2018				
HHType\Social Group	Scheduled	Scheduled	OBC	Others	Total	Scheduled	Scheduled	OBC	Others	Total	Scheduled	Scheduled	OBC	Others	Total	Scheduled	Scheduled	OBC	Others	Total
Self-Employed	51.77	32.90		59.01	53.04	44.37	34.25	57.05	56.97	51.42	53.35	35.85	56.19	55.74	51.97	52.61	38.07	54.19	55.03	51.10
Wage/Salaried	3.57	7.52		12.02	10.38	3.35	7.84	7.33	15.71	9.74	10.91	16.13	16.10	25.18	18.13	9.88	15.23	16.41	24.40	17.70
Labour	39.69	53.29		20.51	28.87	46.43	50.97	27.85	16.63	30.48	33.79	44.44	23.01	13.08	25.30	34.51	43.29	24.98	14.93	26.79
Others	4.96	6.28		8.46	7.71	5.85	6.94	7.78	10.69	8.36	1.95	3.58	4.71	6.00	4.60	3.00	3.41	4.43	5.63	4.41
Total	100	100		100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Source: Author's Calculations from NSSO microdata.

Table 3.8: Distribution of Household Types across Income Classes in Percentages

	1996						2004						2014						2018					
HHType\Income Class	Poorest	Poor	Middle	Rich	Richest	Total	Poorest	Poor	Middle	Rich	Richest	Total	Poorest	Poor	Middle	Rich	Richest	Total	Poorest	Poor	Middle	Rich	Richest	Total
Self-Employed	48.46	56.39	58.12	55.71	45.11	53.02	46.32	53.31	57.06	55.54	44.39	51.42	51.12	55.76	54.41	52.75	43.15	51.97	51.70	55.73	55.61	49.56	38.90	51.10
Wage/Salaried	1.67	3.69	7.30	14.86	33.48	10.37	1.01	2.25	6.30	15.43	34.53	9.74	7.34	11.62	16.16	25.15	41.31	18.13	6.43	8.96	14.35	25.60	43.88	17.70
Labour	45.82	34.21	26.93	18.76	8.05	28.87	47.82	38.10	28.73	17.68	6.36	30.48	38.36	29.49	25.69	16.37	6.42	25.30	39.09	32.44	26.31	20.23	7.08	26.79
Others	4.05	5.71	7.65	10.67	13.35	7.74	4.85	6.34	7.91	11.35	14.71	8.36	3.18	3.13	3.74	5.73	9.12	4.60	2.78	2.86	3.72	4.60	10.15	4.41
Total	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Source: Author's Calculations from NSSO microdata.

Table 3.9: Distribution of Education Levels across Social Groups in Percentages

	1996					2004					2014					2018				
Education\Social Group	Scheduled	Scheduled	OBC	Others	Total	Scheduled	Scheduled	OBC	Others	Total	Scheduled	Scheduled	OBC	Others	Total	Scheduled	Scheduled	OBC	Others	Total
Illiterate	65.48	59.78		43.70	48.86	57.64	51.84	44.74	29.57	42.45	41.37	37.65	32.76	22.09	31.53	34.36	31.59	26.70	18.03	26.07
Informal Literate	1.37	1.30		1.36	1.35	0.94	0.95	0.91	1.23	1.02	1.23	1.12	0.98	0.89	1.00	1.14	0.97	1.05	1.05	1.04
Upto Primary	23.39	25.62		28.75	27.65	27.73	28.51	29.51	29.52	29.17	30.45	31.47	29.86	26.69	29.34	31.84	30.64	29.08	26.32	28.91
Upto Secondary	8.32	10.91		19.01	16.44	11.21	15.07	19.11	26.08	19.85	19.94	21.37	23.80	27.00	23.87	23.19	24.83	26.51	26.89	25.98
HigherSecondary/ Diplo	0.95	1.52		3.55	2.91	1.67	2.34	3.34	6.25	3.91	4.63	5.47	7.85	11.71	8.17	6.48	7.85	9.95	13.00	10.03
graduation and Above	0.49	0.86		3.62	2.79	0.81	1.29	2.39	7.36	3.60	2.38	2.93	4.76	11.61	6.09	2.98	4.12	6.71	14.71	7.97
Total	100	100		100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Source: Author's Calculations from NSSO microdata.

Table 3.10: Distribution of Education Levels across Income Classes in Percentages

	1996						2004						2014						2018					
Education\Income Class	Poorest	Poor	Middle	Rich	Richest	Total	Poorest	Poor	Middle	Rich	Richest	Total	Poorest	Poor	Middle	Rich	Richest	Total	Poorest	Poor	Middle	Rich	Richest	Total
Illiterate	67.83	56.49	47.63	37.59	21.60	48.86	58.46	50.18	41.98	31.63	16.34	42.45	41.23	36.03	31.92	26.24	13.32	31.53	34.35	30.71	27.19	20.74	10.69	26.07
Informal Literate	1.24	1.43	1.39	1.48	1.19	1.35	1.04	1.05	1.22	0.88	0.81	1.02	1.34	1.05	1.00	0.74	0.67	1.00	1.28	1.27	0.95	0.89	0.62	1.04
Upto Primary	22.75	28.40	30.85	31.29	25.68	27.65	28.44	31.44	31.16	30.54	22.61	29.17	33.55	31.28	31.90	26.09	19.78	29.34	32.53	32.31	29.68	27.02	19.20	28.91
Upto Secondary	7.20	11.68	16.70	22.88	30.58	16.44	10.56	14.90	21.24	27.91	31.91	19.84	19.10	23.71	24.35	28.07	26.53	23.87	23.36	25.23	27.04	29.41	25.60	25.98
HigherSecondary/Diplo	0.68	1.30	2.10	3.80	9.06	2.91	1.05	1.65	2.83	5.58	11.94	3.92	3.46	5.59	7.35	11.44	17.53	8.17	5.77	7.32	9.88	12.52	18.16	10.03
graduation and Above	0.30	0.69	1.33	2.97	11.89	2.79	0.46	0.77	1.57	3.47	16.39	3.60	1.32	2.35	3.49	7.41	22.17	6.09	2.71	3.16	5.26	9.41	25.74	7.97
Total	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Source: Author's Calculations from NSSO microdata.

Table 3.11: Distribution of Social Groups across Income Classes in Percentages

	1996						2004						2014						2018					
(Social group code)	Poorest	Poor	Middle	Rich	Richest	Total	Poorest	Poor	Middle	Rich	Richest	Total	Poorest	Poor	Middle	Rich	Richest	Total	Poorest	Poor	Middle	Rich	Richest	Total
Scheduled Tribes	15.48	9.14	6.7	5.15	2.93	8.54	15.26	8.78	6.44	3.95	2.38	8.18	15.75	9.78	8.66	5.65	2.38	9.26	13.3	8.59	7.05	3.5	1.07	6.12
Scheduled Castes	28.76	23.37	19.69	15.94	9.42	20.52	26.47	23.23	19.9	16.16	8.92	20.05	24.57	20.9	19.62	15.84	8.31	18.85	25.09	23.07	20.1	15.54	7.74	17.49
Other Backward Classes							41.27	43.38	44.09	39.73	29.42	40.35	44.15	46.28	45.38	45.76	37.75	44.25	44.6	42.99	45.13	46.69	42.75	44.4
Others	55.76	67.48	73.61	78.91	87.64	70.94	17	24.6	29.57	40.17	59.27	31.42	15.52	23.04	26.34	32.76	51.57	27.64	17.01	25.35	27.72	34.27	48.44	31.99
Total	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Source: Author's Calculations from NSSO microdata.

Table 3.12: Insurance Coverage in Indian Population

	NSS71				NSS75		
Type of Scheme	Rural	Urban	Total	Type of Scheme	Rural	Urban	Total
All Govt. Schemes	13.12	11.97	12.78	Govt. Sponsored	12.89	8.85	11.7
				Govt. Employer	0.56	3.32	1.37
Non Govt. Employer	0.62	2.42	1.16	Non Govt. Employer	0.26	2.89	1.03
Private Insurance	0.25	3.45	1.21	Private Insurance	0.23	3.79	1.28
Others	0.07	0.18	0.1	Others	0.13	0.21	0.15
No Insurance	85.94	81.98	84.75	No Insurance	85.94	80.94	84.47
Total	100	100	100	Total	100	100	100

Source: Author's Calculations from NSSO microdata.

3.4. UTILISATION

3.4.1. Inpatient Utilisation

Table 3.13: Type of Institute of Inpatient Care in Percentages

	NSS52 (1996)			NSS60 (2004)			NSS71 (2014)			NSS75 (2018)		
InstType	Freq.	Percent	Cum.	Freq.	Percent	Cum.	Freq.	Percent	Cum.	Freq.	Percent	Cum.
Public	11,535.73	44.58	44.58	13,250.71	40.63	40.63	26,089.09	45.41	45.41	47,861.31	50.96	50.96
Private	14,343.27	55.42	100	19,362.29	59.37	100	31,366.91	54.59	100	46,063.69	49.04	100
Total	25,879	100		32,613	100		57,456	100		93,925	100	

Source: Author's Calculations from NSSO microdata.

Table 3.13 shows the overall usage of public and private facilities for inpatient care. The utilisation for inpatient care has been predominantly pro-private facilities in the first three rounds, with a peak of 59.37 percent of inpatient cases being treated in private facilities in 2004. This has come down to 54.59 percent in in the subsequent decade and in 2018, the ratio has come down below 50 percent, with public facilities becoming preferred method of care with 50.96 percent of all inpatient cases being treated.

Table 3.14: Type of Institute of Inpatient Care by Sector in Percentages

	NSS52 (1996)			NSS60 (2004)			NSS71 (2014)			NSS75 (2018)		
Sector	Public	Private	Total	Public	Private	Total	Public	Private	Total	Public	Private	Total
Rural	45.3	54.7	100	41.72	58.28	100	50.26	49.74	100	56.55	43.45	100
Urban	43.08	56.92	100	38.24	61.76	100	35.45	64.55	100	39.13	60.87	100
Total	44.58	55.42	100	40.63	59.37	100	45.41	54.59	100	50.96	49.04	100

Source: Author's Calculations from NSSO microdata.

Table 3.14 depicts the usage of facilities along the two sectors. Rural sector is more reliant on public facilities than the urban sector. The rural households have stated using more public facilities in the 2014 (50.26%) but the urban households have seen a marked rise in public institution utilisation from 35.45 percent in 2014 to 39.13 percent in 2018.

Table 3.15: Type of Institute of Inpatient Care by Household Type in Percentages

	NSS52 (1996)			NSS60 (2004)			NSS71 (2014)			NSS75 (2018)		
HHType	Public	Private	Total	Public	Private	Total	Public	Private	Total	Public	Private	Total
Self-Employed	42.74	57.26	100	36.66	63.34	100	43.76	56.24	100	49.83	50.17	100
Wage/Salaried	41.79	58.21	100	38.11	61.89	100	36.13	63.87	100	40.3	59.7	100
Labour	49.79	50.21	100	49.74	50.26	100	58.98	41.02	100	64.41	35.59	100
Others	42.84	57.16	100	35.86	64.14	100	35.07	64.93	100	38.15	61.85	100
Total	44.58	55.42	100	40.63	59.37	100	45.41	54.59	100	50.96	49.04	100

Source: Author's Calculations from NSSO microdata.

The distribution of utilisation by the type of household is seen in table 3.15. Here the households with stable incomes continue to rely more on the private facilities with 59.7 percent households with salaried incomes going to private facilities in 2018. On the other hand, nearly 2/3rd of households of labour households relying on public facilities in 2018.

Table 3.16: Type of Institute of Inpatient Care by Social Group in Percentages

	NSS52 (1996)			NSS60 (2004)			NSS71 (2014)			NSS75 (2018)		
Social group	Public	Private	Total	Public	Private	Total	Public	Private	Total	Public	Private	Total
Scheduled Tribes	64.58	35.42	100	58.54	41.46	100	67.66	32.34	100	74.59	25.41	100
Scheduled Castes	54.57	45.43	100	54.76	45.24	100	56.98	43.02	100	62.19	37.81	100
Other Backward Classes				36.45	63.55	100	40.6	59.4	100	48.42	51.58	100
Others	40.76	59.24	100	35.74	64.26	100	39.43	60.57	100	41.44	58.56	100
Total	44.56	55.44	100	40.63	59.37	100	45.41	54.59	100	50.96	49.04	100

Source: Author's Calculations from NSSO microdata.

The distribution of utilisation by the social groups is seen in table 3.16. Here the households of vulnerable social groups of ST/SC have relied more on public facilities throughout the rounds. In terms of STs 3/4th of utilisation is public facilities in 2018. SC households also have more than 60 percent utilisation. OBCs and OCs have majority (>50%) relying on private facilities still.

Table 3.17: Type of Institute of Inpatient Care by Income Class in Percentages

	NSS52 (1996)			NSS60 (2004)			NSS71 (2014)			NSS75 (2018)		
PC_HHCE	Public	Private	Total	Public	Private	Total	Public	Private	Total	Public	Private	Total
Poorest	62.56	37.44	100	54.79	45.21	100	65.56	34.44	100	67.48	32.52	100
Poor	59.2	40.8	100	49.52	50.48	100	55.95	44.05	100	61.38	38.62	100
Middle	48.87	51.13	100	43.38	56.62	100	48.65	51.35	100	52.6	47.4	100
Rich	43.08	56.92	100	36.05	63.95	100	37.29	62.71	100	45.17	54.83	100
Richest	32.29	67.71	100	27.14	72.86	100	22.91	77.09	100	27.02	72.98	100
Total	44.58	55.42	100	40.63	59.37	100	45.41	54.59	100	50.96	49.04	100

Source: Author's Calculations from NSSO microdata.

The distribution of utilisation by the wealth class is seen in table 3.17. Here the household distribution is on the expected lines with poorer population relying more public while the richer classes rely more on private facilities. However, even in the richer classes a increasing utilisation is seen of public facilities from 2014 to 2018. But the indifference in utilisation is stark with 67.48 percent poorest inpatient cases relying on public facilities and 72.98 percent richest cases relying on private facilities in 2018.

Table 3.18: Utilisation of Inpatient facilities by Type of Insurance

NSS71					NSS75			
Type of Insurance	Public	Private	Total		Type of Insurance	Public	Private	Total
All Govt. Schemes	46.77	53.23	100		Govt. Sponsored	53.1	46.9	100
					Govt. Employer	34.19	65.81	100
Non-Gov. Employer	26.27	73.73	100		Non-Gov. Employer	25.63	74.37	100
Pvt. Insurance	6.18	93.82	100		Pvt. Insurance	8.35	91.65	100
Others	28.39	71.61	100		Others	39.89	60.11	100
No Coverage	46.19	53.81	100		No Coverage	52.48	47.52	100
Total	45.38	54.62	100		Total	51.05	48.95	100

Source: Author's Calculations from NSSO microdata.

Table 3.18 shows the inpatient utilisation patterns of Indian population on basis of the type of insurance coverage possessed. The data is limited to the last two rounds since the type of insurance coverage is not collected in precious rounds. The data shows that people covered by

government schemes in were primarily using private health facilities (53.23%) but a further classification into government sponsored and schemes by govt. employer in 2018 shows that people covered under government sponsored schemes rely most on public while those covered by schemes of govt employer tend to favour private facilities. People covered with insurance provided by non-govt. employer predominantly rely on private facilities in both the rounds (73.73% and 74.37%). However, the people with private insurance tend to have the most reliance on private care for hospitalisation (93.82% and 91.65%).

3.4.2. Outpatient Utilisation

Table 3.19: Type of Institute of Outpatient Care in Percentages

	NSS52 (1996)			NSS60 (2004)			NSS71 (2014)			NSS75 (2018)		
treatment))	Freq.	Percent	Cum.	Freq.	Percent	Cum.	Freq.	Percent	Cum.	Freq.	Percent	Cum.
Public	5,296.14	19.41	19.41	7,087.88	23.11	23.11	8,371.94	25.55	25.55	11,870.01	30.16	30.16
Private	21,995.87	80.59	100	23,583.12	76.89	100	24,397.06	74.45	100	27,492.99	69.84	100
Total	27,292	100		30,671	100		32,769	100		39,363	100	

Source: Author's Calculations from NSSO microdata.

Table 3.19 shows the overall outpatient utilisation of Indian households by type of institute. The Indian population primarily relies on private institutes for outpatient care. The overall private usage has come down from 80.59 percent in 1995 to 74.45 percent in 2014 and further to 69.84 percent in 2018. This significant drop in the last two rounds could be a result of patients deterring from high expenditures at private institutes (depicted in next section) and rising public investments in healthcare.

Table 3.20: Type of Institute of Outpatient Care by Sector in Percentages

	NSS52 (1996)			NSS60 (2004)			NSS71 (2014)			NSS75 (2018)		
Sector	Public	Private	Total	Govt	Pvt	Total	Public	Private	Total	Public	Private	Total
Rural	19.78	80.22	100	24.38	75.62	100	28.33	71.67	100	32.55	67.45	100
Urban	18.35	81.65	100	20.26	79.74	100	21.23	78.77	100	26.23	73.77	100
Total	19.41	80.59	100	23.11	76.89	100	25.55	74.45	100	30.16	69.84	100

Source: Author's Calculations from NSSO microdata.

The sector wise utilisation of outpatient care is shown in Table 3.20. Both rural and urban population preferred private facilities for outpatient care in 1995 but the general trend in shift to public usage is seen in both sectors. However, the shift has been more pronounced in the rural areas with the private usage dropping to 67.45 percent and 73.77 percent in rural and urban respectively in 2018. This could be a result of the low-income levels in rural areas that might be forcing usage of public facilities.

Table 3.21: Type of Institute of Outpatient Care by Household Type in Percentages

	NSS52 (1996)			NSS60 (2004)			NSS71 (2014)			NSS75 (2018)		
HHTypeRecode	Public	Private	Total	Govt	Pvt	Total	Public	Private	Total	Public	Private	Total
Self-Employed	16.31	83.69	100	19.73	80.27	100	23.62	76.38	100	28.35	71.65	100
Wage/Salaried	20.94	79.06	100	21.52	78.48	100	22.03	77.97	100	25.95	74.05	100
Labour	22.97	77.03	100	30.83	69.17	100	32.61	67.39	100	37.44	62.56	100
Others	23.44	76.56	100	21.29	78.71	100	26.05	73.95	100	30.02	69.98	100
Total	19.41	80.59	100	23.11	76.89	100	25.55	74.45	100	30.16	69.84	100

Source: Author's Calculations from NSSO microdata.

Table 3.21 shows the utilisation by type of household. The general transitional trend in utilisation to private facilities is seen in all groups but the transition has been slowest in the households who have stable income source of salaries/wages who have the highest utilisation at 74.05 percent in 2018. The drop has been the sharpest in the households relying on labour who has the lowest household consumption expenditures.

Table 3.22 Type of Institute of Outpatient Care by Social Groups in Percentages

	NSS52 (1996)			NSS60 (2004)			NSS71 (2014)			NSS75 (2018)		
Social group	Public	Private	Total	Govt	Pvt	Total	Public	Private	Total	Public	Private	Total
Scheduled Tribes	30.27	69.73	100	36.72	63.28	100	47.94	52.06	100	41.81	58.19	100

Scheduled Castes	19.17	80.83	100	28.02	71.98	100	30.40	69.60	100	34.38	65.62	100
Other Backward Classes				21.9	78.10	100	25.93	74.07	100	32.10	67.90	100
Others	18.56	81.44	100	20.46	79.54	100	18.97	81.03	100	23.90	76.10	100
Total	19.40	80.60	100	23.11	76.89	100	25.55	74.45	100	30.16	69.84	100

Source: Author's Calculations from NSSO microdata.

Tables 3.22 show the outpatient care utilisation patterns of Indian population by social groups. The STs have the highest public facilities utilisation throughout the rounds with 30.27 percent in 1995 and 41.81 percent in 2018. The other vulnerable social groups of SCs and OBCs also have higher than national average utilisation rates for public facilities at 34.38 and 32.10 percent respectively in 2018. Conversely, the non-vulnerable OCs have the highest private utilisation rates in India (>75%) throughout all the rounds.

Table 3.23: Type of Institute of Outpatient Care by Income Class in Percentages

	NSS52 (1996)			NSS60 (2004)			NSS71 (2014)			NSS75 (2018)		
PC_HHCE	Public	Private	Total	Govt	Pvt	Total	Public	Private	Total	Public	Private	Total
Poorest	22.28	77.72	100	29.31	70.69	100	32.19	67.81	100	34.53	65.47	100
Poor	18.37	81.63	100	24.72	75.28	100	31.09	68.91	100	32.32	67.68	100
Middle	20.59	79.41	100	24.04	75.96	100	25.77	74.23	100	33.67	66.33	100
Rich	19.63	80.37	100	22.61	77.39	100	24.01	75.99	100	31.59	68.41	100
Richest	16.84	83.16	100	17.50	82.50	100	19.06	80.94	100	22.17	77.83	100
Total	19.41	80.59	100	23.11	76.89	100	25.55	74.45	100	30.16	69.84	100

Source: Author's Calculations from NSSO microdata.

Table 3.23 depicts the utilisation rates of different economic classes of India in outpatient care. The utilisation rates follow the national trend of movement from private to public in utilisation rates over all the groups. Additionally, the expected trend is seen with richer groups having higher private utilisation than the poorer groups with ~78 percent richest using private facilities and ~65 percent poorest using private facilities in 2018.

Table 3.24: Utilisation of Outpatient facilities by Type of Insurance

	NSS71					NSS75		
Type of Insurance	Public	Private	Total		Type of Insurance	Public	Private	Total
All Govt. Schemes	31.41	68.59	100		Govt. Sponsored	39.02	60.98	100
					Govt. Employer	36.82	63.18	100
Non-Gov. Employer	26.78	73.22	100		Non-Gov. Employer	25.91	74.09	100
Pvt. Insurance	4.39	95.61	100		Pvt. Insurance	5.73	94.27	100
Others	22.65	77.35	100		Others	27.45	72.55	100
No Coverage	24.51	75.49	100		No Coverage	28.74	71.26	100
Total	25.54	74.46	100		Total	30.15	69.85	100

Source: Author's Calculations from NSSO microdata.

Table 3.24 shows the outpatient utilisation patterns of Indian population on basis of the type of insurance coverage possessed. The data shows that people use primarily private facilities irrespective of insurance scheme. People covered by government schemes have least private facilities utilisation rates in both rounds (<70%) but the people covered by private insurance have the maximum private utilisation rate ~95 percent. The uninured population that is around 85 percent of total population, has a public facility utilisation rate of under 30 percent in both the rounds.

Table 3.25: Average Household Consumption and Out-of-Pocket Health Expenditures

	NSS52 (1996)			NSS60 (2004)			NSS71 (2014)			NSS75 (2018)		
	HHCE	**OOPHE**	**HEShare**	**HHCE**	**OOPHE**	**HEShare**	**HHCE**	**OOPHE**	**HEShare**	**HHCE**	**OOPHE**	**HEShare**
INDIA	1801.11	104.9741	5.828301	2887.422	290.4333	10.05857	7333.007	866.7228	11.81947	9404.56	722.0682	7.677853
Rural	1598.202	100.9299	6.315215	2413.581	268.2109	11.11257	6031.051	751.2024	12.45558	7498.69	634.8506	8.466153
Urban	2377.801	116.4683	4.898153	4108.803	347.7079	8.462509	10029.85	1105.973	11.02682	13315.61	901.0482	6.766858
Hindu	1336.074	42.02895	3.145706	2825.448	276.6254	9.790496	7210.357	825.4936	11.44872	9163.931	692.8275	7.560375
Islam	1478.749	87.8694	5.942146	2986.213	341.5588	11.43786	7068.704	946.8071	13.39435	9822.6	790.8665	8.051499
Christian				3589.654	426.2704	11.87497	9325.273	1311.725	14.06635	11003.81	984.4121	8.9461
Others	1954.182	117.8739	6.031877	3734.76	386.4202	10.34659	10551.15	1360.726	12.89647	13783.19	1094.077	7.93776
ST				1997.955	108.4905	5.430079	5179.928	466.8149	9.011997	6865.221	369.1852	5.377616
SC				2313.254	220.6077	9.53668	5924.053	654.6614	11.0509	7867.596	621.7166	7.902243
OBC				2690.837	277.2829	10.30471	7076.292	899.7165	12.71452	8937.716	682.2261	7.633115
Others				3723.606	397.8412	10.6843	9309.345	1080.908	11.611	12093.71	974.961	8.061719
SelfEmploy	1950.627	116.9298	5.994472	3128.165	318.4935	10.18148	7715.213	922.3858	11.95542	9761.034	770.6372	7.895037
Salaried	2572.959	114.9231	4.466574	4575.056	346.8769	7.581915	9657.601	986.8926	10.21882	12654.97	848.3891	6.703997
Labour	1305.836	72.14895	5.525117	2012.111	192.115	9.547931	5126.43	594.2598	11.59208	7074.332	515.9433	7.293173
Others	1718.319	137.4446	7.99878	2667.301	393.0762	14.73685	6404.235	1168.481	18.24545	7365.938	817.7416	11.10166
Poorest	1139.681	51.05448	4.479715	1613.942	161.7758	10.02365	3949.597	570.3948	14.44185	5052.003	475.3406	9.408954
Poorest	1438.134	74.75415	5.197998	2132.789	212.4354	9.960452	5356.02	615.4643	11.49108	6816.689	570.937	8.375576
Middle	1682.665	89.26043	5.304705	2545.365	274.0733	10.76755	6532.799	728.6883	11.15431	8328.545	634.7009	7.620789
Richer	1979.788	115.5991	5.838963	3234.212	343.9462	10.63462	7999.994	990.1863	12.37734	10537.9	908.8088	8.624189
Richest	2766.817	194.3204	7.023247	5076.768	476.1719	9.37943	13192.78	1462.847	11.08824	16304.53	1021.384	6.264415

Source: Author's Calculations from NSSO microdata.

3.5. HOSEHOLD CONSUMPTION AND HEALTH EXPENDITURES

Table 3.25 details the average consumption expenditures and OOP health expenditures of Indian households across the four NSSO rounds over a selection of socio-economic features. At national level, the consumption expenditures rose throughout the rounds with 1,801/- per month in 1995-96 to 9,404/- in 2017-18. However, the OOPHE has increased from 105/- in 1995-96 to 867/- in 2014 and then inexplicably dropped down to 722/- in 2017-18. This led to a much sharper drop in the averages share of OOPHE in HHCE from 11.82% to 7.68% between these two periods.

Urban residents have higher levels of HHCE and OOPHE than the rural households, however, the share of average OOPHE in HHCE is higher in the rural areas throughout the period in consideration. Religious minorities (non-Hindus) are also seen as having higher expenditures in both categories and higher average shares in comparison.

Social groups (Castes) also see differences in expenditures with the vulnerable classes of SC, ST and OBC having lower HHCE and OOPHE across all rounds. Income class (wealth quintile) is an understandably important factor with the subsequent richer sections having higher expenditures. However, in terms of average shares, the richer classes had higher shares in 1995-96, but the situation gradually reversed to the poor having higher shares than the richer in 2017-18. This change can be indicative of an increasing healthcare consumption among the poor as well as an increasing wealth gap the wealthy and the poor. Households with medical insurance have substantially higher expenditures indicating a higher healthcare demand.

Households with male heads also tend to do better with higher expenditures and lower average shares compared to the households with female heads. Also, education level of the head has an impact on the expenditures where higher education levels leading to better consumption and health expenditures. Households relying on regular wages/salaries as a primary source of income tend to have better consumption expenditures and health expenditures and comparatively lower average shares.

Table 3.26: Average Household Expenditures for Inpatient Care in last 365 days

Inpatient Expenses	NSS52			NSS60			NSS71			NSS75		
	Rural	Urban	Total	Rural	Urban	Total	Rural	Urban	Total	Rural	Urban	Total
IPHE365	240.27	402.22	282.42	807.63	1398.89	972.91	3203.12	5443.64	3932.68	2710.1	4543.58	3310.83
IPReim	1.72	33.71	10.05	13.42	134.85	47.36	76.25	475.77	206.34	94.31	641.6	273.63
IPOOP365	238.56	368.51	272.38	794.21	1264.04	925.55	3126.87	4967.87	3726.33	2615.79	3901.98	3037.2

Source: Author's Calculations from NSSO microdata.

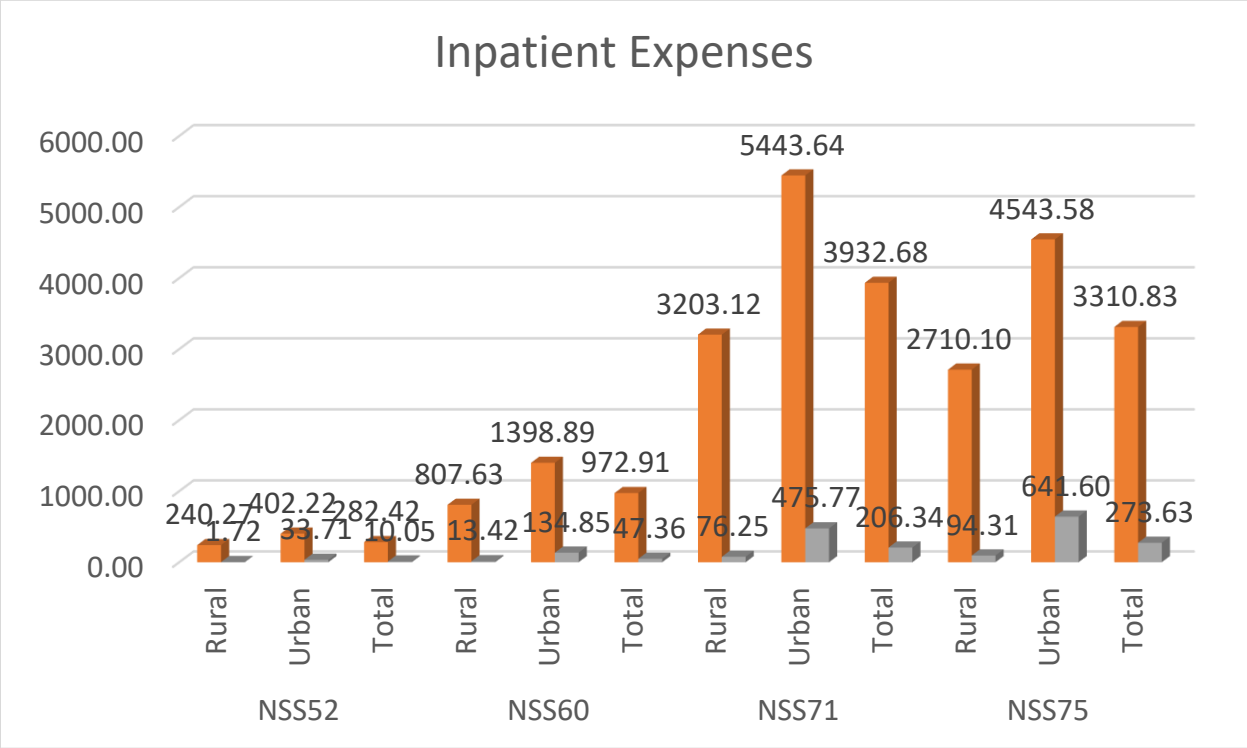

Figure 3.1. Average Inpatient Expenses by Household in Last 365 Days

Table 3.26 (Figure 3.1) and Table 3.27 (Figure 3.2) shows the average inpatient and outpatient out-of-pocket expenditures by the Indian households receiving healthcare services in the period of study. Both inpatient and outpatient expenses have risen significantly in this period. The inpatient expenses rose from INR 282.42/- from 1995-96 to INR 3932.68/- in 2014. Similarly, outpatient expenses increased from INR 41.71/- to INR 281.40/- in the same period. However, both inpatient and outpatient expenses have dropped significantly in the 2017-18 period hinting at a reduction in demand for healthcare services. Significant disparity is also observed in the expenses between rural and urban households. The urban households spend significantly more on ill-

episodes compared to the rural and the disparity has risen drastically during the period of study. The reimbursements for the health expenses are very low in India. Inpatient reimbursements have risen slightly in the period however the outpatient expenses remain inconsequential throughout.

Table 3.27: Average Household Expenditure on Outpatient Care in last 15 days

Outpatient Expenses	NSS52			NSS60			NSS71			NSS75		
	Rural	Urban	Total	Rural	Urban	Total	Rural	Urban	Total	Rural	Urban	Total
OPHE15	40.88	44.07	41.71	101.92	125.39	108.48	247.35	351.92	281.4	210.38	293.95	237.76
OPReim	0.22	0.98	0.42	0.45	3.48	1.3	0.25	3.09	1.18	0.45	3.78	1.54
OPOOP15	40.66	43.09	41.29	101.47	121.91	107.18	247.1	348.83	280.22	209.93	290.17	236.22

Source: Author's Calculations from NSSO microdata.

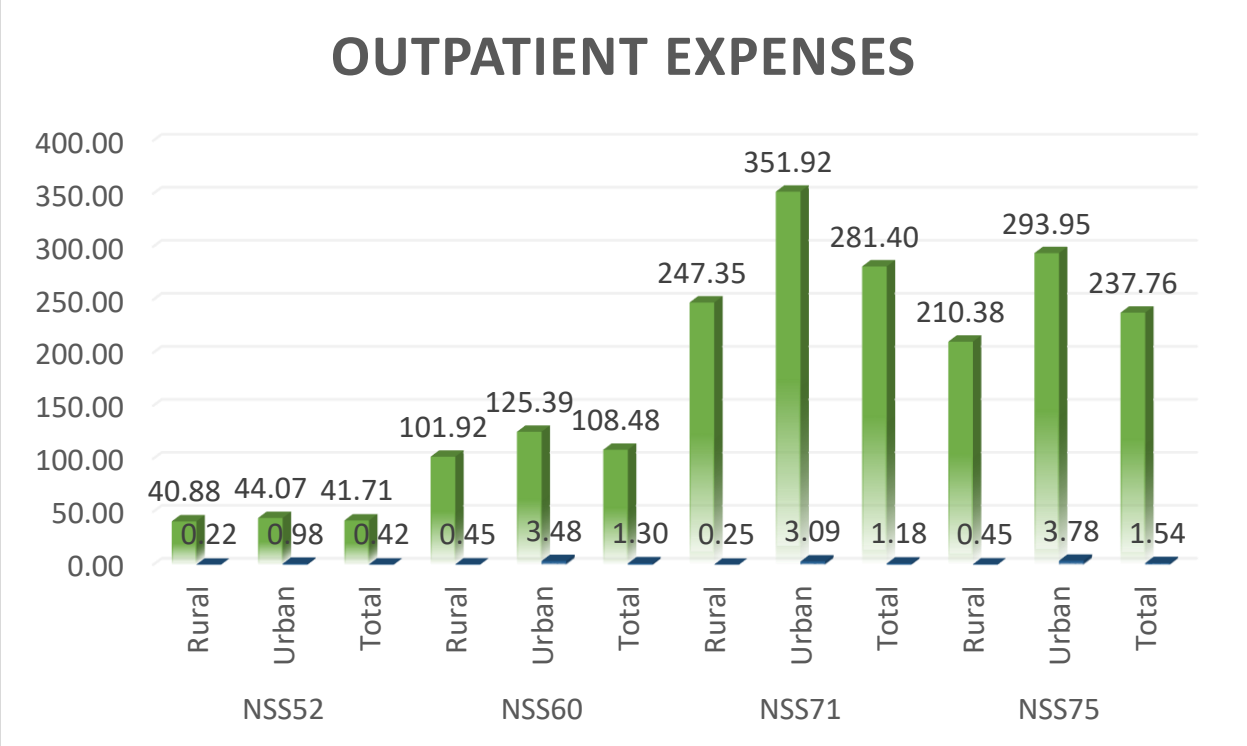

Figure 4 Average Outpatient Expenses by Household in Last 15 Days

Figure 3.3. Composition of Average Inpatient and Outpatient Expenses by the Households

Figure 5 shows the composition of OOP health expenditures by households on inpatient and outpatient services across the rounds. The components of expenditure are not well defined in the 52nd round and hence offer no clear picture of the expenses. In the subsequent rounds, the inpatient expenditure mainly consisted of the physician fee and medicines. Especially in the two recent rounds, the share of physician fee and medicines are higher than the previous rounds. In the same time, majority share of outpatient expenses were spent on medicine. Across the three rounds medicines account for over 55 percent of all outpatient expenditure. The share of physician fee also increased from 9 percent to 12 percent, and expenditure on diagnostic tests doubled from 5 percent to 10 percent respectively from 60th round to the subsequent rounds.

Table 3.28: Expenditures by Type of Institution

	Inpatient		Outpatient	
	Public	Private	Public	Private
NSS52	2116.53	4652.848	138.0676	189.5453
NSS60	3864.269	9352.352	NA	
NSS71	5882.281	26458.25		
NSS75	4488.825	32157.61	469.3758	887.4873

Source: Author's Calculations from NSSO microdata.

NA : Data unavailable for the 60th and 71st round.

Table 3.28 depicts the average expenditures by Indian households on inpatient and outpatient episodes, by the type of institution. The data shows the rising expenses in public and private facilities for inpatient care. However, the rate of growth in private institutions is much higher than the public institutions leading to a huge increase in the gap between public and private healthcare bills. The average inpatient expenditure at public institutes has gone up from 2,117/- to 4,489/- in the period under study and in the same period the private bills went up from 4,653/- to 32,158/-. The average expenditure per inpatient episode in private facility was twice as expensive as public facility in 1995, but in 2018 it was seven times as expensive. This shows the rapid rise in private hospital bills which could be a possible reason for shift in healthcare seeking behaviour from Indian households, especially of economic weaker groups, from private to public facilities. Although, the data is limited for outpatient expenses, the gap between private and public outpatient

expenses have also gone up between 1995 and 2018 with private facilities (469/-) being almost twice as expensive as public in 2018 (887/-).

3.6. DETERMINANTS OF OOPHE IN INDIAN HOUSEHOLDS

3.6.1. LITERATURE REVIEW

Health-care financing in many LMICs including India is heavily relied upon OOP payments of the individuals. Estimates from consumer expenditures survey (CES) of 1999-2000 show that OOP expenditures in India amounts to 5 percent of total household consumption expenditure, ranging from 2 percent in Assam to 7 percent in Kerala (Garg & Karan, 2008). Low levels of utilisation of public health facilities, only 45 percent in inpatient care and 20 percent in outpatient care, leads to seeking health services from private facilities which is another driving factor behind the high OOP expenditures in India (Ramani & Mavalankar, 2006). An analysis of 75th round of NSSO Survey also supports the notion of private facilities increasing OOP burden with ill episode affected households spending 30.4 percent of consumption expenditure on health when visiting public facilities against spending 74.1 percent when visiting private facilities (Yadav et al., 2021). When OOP health spending reaches a particular percentage of overall consumption spending, it becomes catastrophic for the population and imposes a major financial burden (Sangar et al., 2019; Wagstaff & Doorslaer, 2003).

Su, Phokrel, et.al. (2006) conducted a primary survey to find the determinants of household expenditure on western medical care in the country of Burkina Faso. The western institutional medical care was highlighted because, contrary to the western care, payment in kind can be made to other types of providers in the context of rural and semi-urban areas in developing countries. And the authors also assumed that patients treated with western institutional health care tend to be diagnosed correctly and receive appropriate treatment. The survey was conducted in the Nouna health district during 2000-2001. 800 (320 urban, 480 rural) households were selected using two-stage cluster sampling method. The survey consisted of morbidity data and complementary socio-economic data. The morbidity data was collected 4 times during 4 different seasons of the year. Socio-economic data was twice in the year, once in the rainy season and once in the dry season. Logit models were used to find the determinants of illness reporting and provider choice. OLS estimators were used to estimate the magnitude of household health expenditure on western institutional care. 1,549 out of 6,853 respondents said they were sick; 1,019 (66%) said they were

only sick once, and 372 (24%) said they had been sick twice. The remaining 10% reported three times or more. Adulthood, being a woman, being married, and having a disability were all associated with a higher risk of reporting illness. There were 1,176 acute and 1,140 chronic disease occurrences found over the course of the four rounds of data collection. 56 percent of chronic illnesses were not spread by other people. Of the 2,316 illness events, 1,403 (60.6 percent) involved seeking some sort of therapy, while the remaining 913 (39.5 percent) did not. 1,235 of the 1,403 episodes received only one treatment, while 92 received a second treatment and 76 received a third. For all disease episodes, the following provider selection patterns were observed: 275 (11.7%) for western institutional care, 74 (3.2%) for western private care, 117 (5.1%) for traditional healer, 937 (40.5%) for self-medication, and 913 (39.4%) for no care. are. It was more probable to use western institutional care if you had a serious disease, were a member of a home with a female head of household, were literate, and had a greater household income. All other illnesses had a higher likelihood of being treated in a western facility than malaria did, although using western care was connected negatively with chronic illness. The average cost of institutional care in the west was 5,923 CFA (7.67 USD). Being an adult, being married, and contracting an illness during the rainy season all greatly increased health costs. On the other hand, chronic illnesses like malaria were less likely to have an influence on household spending.

Hajizadeh and Nghiem (2011) attempted to find the determinants of OOP expenditure and CHE in the Iranian healthcare system using a nation-wide 2003 Utilisation of Health Services Survey data. A concentration curve inequality study yielded a result of -0.135, indicating that the CHE is concentrated among households with lower socioeconomic status. According to the Heckman selection model's findings, a longer hospital stay, admittance to a hospital run by the private sector or the Ministry of Health and Medical Education, and living in a rural place are all positively correlated with greater out-of-pocket expenses.

In rural areas, OOP expenditure is concentrated among the wealthy, whereas in urban centres, it is fairly distributed according to the ATP of demographic groups. In 1999–2000, approximately 32.5 million people slipped into poverty due to OOP payments, indicating a 3.2 percent increase in overall poverty after accounting for OOP spending (Garg and Karan 2008).

Matsaganis, Mitrakos, and Tsakloglou (2009) attempted to compare the performance of different models in estimating the determining healthcare expenditure in Greece. The authors did

this because Health spending data are known to suffer from a confined range, zero values, skewness, and kurtosis; as a result, numerous approaches, including two-part models and generalised linear models, can be employed to model such data. This study compares the performance of different models using household health expenditure examined in two different specifications: expenditure on all health care (where zero values are rare) and expenditure on hospital services alone (where zero values are common). The data was obtained from the Greek National Statistical Service's 12-month Household Budget Survey (Feb'2004 to Jan'2005). There are 17,913 people living in 6,555 households in the survey sample. The different models compared here were: (i) OLS with log transformed y; (ii) two-part model (2PM) consisted of logit model in the first part, and a OLS in the second; (iii) modified two-part model (M2PM) with logit model in the first part, and a NLS in the second; and (iv) Generalized Linear Model (GLM). 2PM yielded a biased result due to the rejection of homoscedasticity hypothesis. But apart from logOLS, the other models yielded similar results for both the dependent variables. Additionally, the models appeared to meet our primary criterion for fit—mean square error and mean absolute prediction error—equally well. No estimate is best in every situation, according to the authors, who also claim that the majority of alternative estimators are likely to yield findings that are quite comparable.

3.6.2. METHODOLOGY

Out of pocket health expenditure data is usually non-normal, right skewed, and heteroscedastic with variance that increase with mean. Hence, in large scale data set, OLS regression on untransformed data (including the zeros) provides unbiased estimates of the regression parameters (Diehr, P et al. 1999). Two-Part Model is widely used in health economics and health research in such data set (Duan et al. 1984). The use of Two-Part Model assumes that the decision to spend (the participation equation) is independent of the decision on the level of spending (Mocan and Tekin, 2004). Although the model has been criticised on the grounds of restrictive assumption, two-part model provides a good estimate (Manning et al., 1987). If the objective is to predict conditional means and not to make inferences about individual parameters, then Two-Part Model performs reasonably well (Duan et al. 1983). The Two-Part Model has a methodological advantage over other models in case of skewed data on health expenditure (Deb

and Trivedi, 2002) [5]. Part one of the Two Part Model fit the data for all the households, irrespective of whether they spend any amount on health care. It is usually a binary outcome model that distinguishes the households with and without health expenditure. Hence, the first part is modelled by using logit or probit regression, i.e.,

The dependent variable is the incidence of household OOPHE and is classified into two categories: household facing CHE or not facing CHE. Since the dependent variable is a binary variable, a binary logistic model can be applied.

Let the probability distribution of Y_i be:

$$P_i = Prob(Y_i = 1) = \text{Household incurring OOPHE}$$

$$1 - P_i = Prob(Y_i = 0) = \text{Household not incurring OOPHE}$$

So, the probability function becomes,

$$P(Y > 0 | X) = \frac{e^{\alpha+\beta X}}{1+e^{\alpha+\beta X}} \text{----------(3.1)}$$

$$log[\frac{P(Y > 0 | X)}{1-P(Y > 0 | X)}] = \alpha + \beta X + \varepsilon \text{----------(3.2)}$$

where y=0 for household without out-of-pocket health expenditure and y=1 for household with OOPHE, respectively. *P* and *1-P* denote the probability of positive and zero health expenditure respectively. X is a set of explanatory variables.

Now *P/(1-P)* is simply the odds ratio in favour of household facing OOPHE or the ratio of probability that the household will face OOPHE due to health payments to the probability that the household will not face OOPHE. The current study reports the Odds Ratios for the independent variables. An odds ratio of 1 means the 'odds' of the household belonging to the category are the same as that of the reference category. An odds ratio less than 1 indicates lower odds, while more than 1 indicates higher odds of respective category compared to the reference category.

The independent variables used in this study include socio economic characteristics of the households like the sector, religion, social class, type of employment, household size and economic class (5 MPCE quintiles). Demographic burden (people aged 60 and above) is also considered

[5] The model which deals with such skewed health expenditure data is Sample Selection model. However, the main criticism of the sample selection model is based on bi-variate normality assumption between the errors (Duan, N et al. 1983).

along with the medical insurance status of the household. In addition, the gender and education level of the head of the household are used as predictor variables.

The second part of the model predicts the level of health expenditure conditional on positive value by using OLS regression or Generalised Linear Model (Deb, P et al., 2015). However, in health economics literature, the second part is specified as OLS regression of

$$\ln(Y|Y > 0, X)$$

i.e., a log-transformation of Y written as,

$$\ln(Y) = \beta X + e$$

can overcome heteroscedasticity problem (Duan et al. 1983; Manning, 1998). Matsaganis et al. (2009) found that the histogram of the log transformation of non-zero health expenditure data seems to be symmetrical compared to non-transformed data. Figure 6 shows that log-transformation does bring symmetry to the health expenditure data when tested on 75th round NSSO data. Hence, the two-part log-transformed OLS model could be a good estimator. Following Matsaganis et al. (2009) an attempt has been made to estimate the determinants of household health expenditure, where the first and second parts are logit model and log linear model respectively.

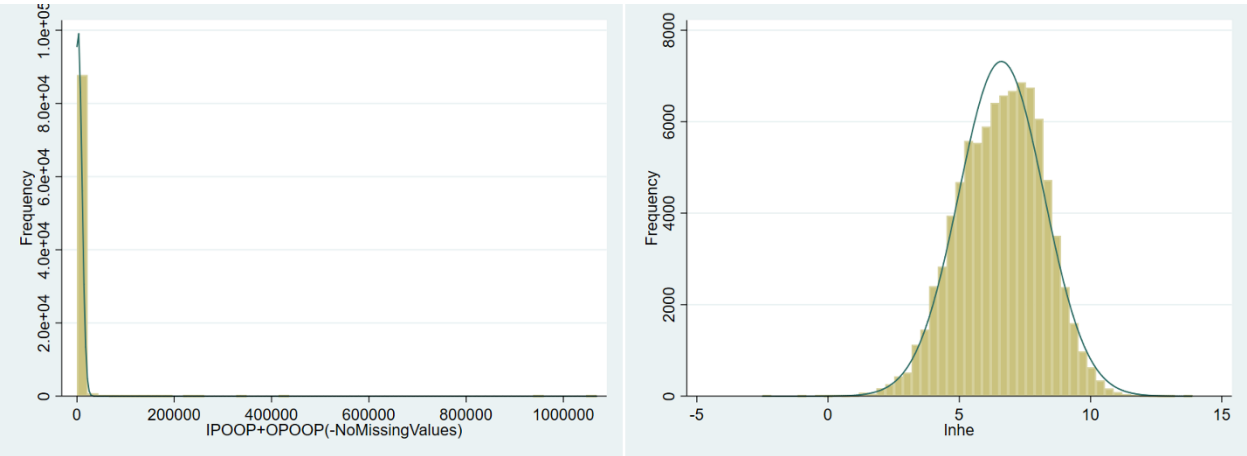

Figure 3.4. Histogram of non-transformed and Log-transformed Out-of-Pocket Health Expenditures

Table 3.29: 2PM-Part 1: Logistic Regression

Part 1	Logistic									
	NSS 52			NSS 60			NSS 71			NSS 75	
	Odds Ratio	95% Conf Interval		Odds Ratio	95% Conf Interval		Odds Ratio	95% Conf Interval		Odds Ratio	95% Conf Interval
Sector (Rural)											
Urban	1.247***	1.177-1.320		1.232***	1.153-1.316		1.176***	1.083-1.276		1.121**	1.047-1.201
Religion (Hindu)											
Islam				1.258***	1.164-1.359		1.024	0.919-1.140		1.197***	1.094-1.309
Christianity				1.492***	1.271-1.751		1.560***	1.284-1.894		1.252**	1.083-1.447
Others				1.148*	1.002-1.316		1.135	0.932-1.383		1.364***	1.162-1.600
SocialGroup (Other)											
ST	0.746***	0.670-0.829		0.615***	0.553-0.683		0.658***	0.575-0.754		0.646***	0.576-0.723
SC	1.029	0.963-1.099		0.979	0.908-1.055		1.005	0.898-1.126		0.937	0.855-1.025
OBC				0.957	0.902-1.014		0.974	0.893-1.062		0.865***	0.805-0.928
Income Class (Middle)											
Poorest	0.672***	0.616-0.733		0.722***	0.669-0.780		0.743***	0.665-0.831		0.830***	0.760-0.908
Poor	0.861***	0.797-0.929		0.845***	0.785-0.910		0.912	0.815-1.021		0.911*	0.832-0.997
Rich	1.287***	1.192-1.388		1.070	0.991-1.155		1.055	0.944-1.179		1.006	0.920-1.100
Richest	1.757***	1.622-1.903		1.424***	1.317-1.540		1.169**	1.041-1.313		1.144**	1.042-1.257
Household Type (Self-Employed)											
Regular Wage/Salaried	0.915**	0.856-0.978		0.943	0.856-1.038		1.007	0.911-1.113		0.984	0.905-1.069
Labour	1.155***	1.084-1.231		1.103**	1.039-1.171		1.042	0.950-1.143		0.961	0.893-1.035
Others	1.027	0.930-1.133		1.084	0.995-1.181		1.489***	1.276-1.737		1.043	0.927-1.173
Household Size	1.132***	1.120-1.145		1.144***	1.130-1.158		1.134***	1.111-1.158		1.096***	1.078-1.114
Child (No Child)	1.218***	1.150-1.289		1.119***	1.060-1.182		1.711***	1.577-1.856		2.248***	2.100-2.407

Old (No Old)	1.382***	1.311-1.456		1.579***	1.500-1.662		1.732***	1.605-1.868		1.763***	1.658-1.874
Gender of Head (Male)											
Female	0.955	0.872-1.046		1.071	0.989-1.161		1.127	0.999-1.273		1.051	0.953-1.158
Transgender										0.380	0.061-2.384
Education of Head (Illiterate)											
Upto Primary	1.193***	1.121-1.270		1.187***	1.115-1.264		1.272***	1.153-1.403		1.159***	1.067-1.259
Secondary	1.175***	1.096-1.260		1.243***	1.163-1.328		1.115*	1.013-1.227		1.036	0.957-1.120
Graduation and Above	0.883*	0.782-0.998		0.882*	0.782-0.995		0.851*	0.732-0.988		0.834**	0.736-0.946
Medical Insurance (No)	1.052	0.818-1.354		2.142***	1.635-2.808		1.528***	1.328-1.759		1.404***	1.243-1.584
Constant	0.072***	0.063-0.081		0.126***	0.111-0.144		0.187***	0.153-0.228		0.198***	0.169-0.232

Source: Author's Calculations from NSSO microdata.

Notes: The parenthesis next to each variable contain the base criteria used for the regression.

Notes: p-values : <0.5 = * ; <0.01 = ** ; <0.001 = ***

Table 3.30: 2PM-Part 2: Log-Linear Regression

Part 2	Log-linear									
	NSS 52			NSS 60			NSS 71			NSS 75	
	Odds Ratio	95% Conf Interval		Odds Ratio	95% Conf Interval		Odds Ratio	95% Conf Interval		Odds Ratio	95% Conf Interval
Sector (Rural)											
Urban	0.158***	0.098-0.218		0.119***	0.059-0.179		0.235***	0.159-0.311		0.289***	0.229-0.349
Religion (Hindu)											
Islam				0.033	-0.039-0.105		0.131**	0.044-0.218		0.012	-0.065-0.088
Christianity				0.019	-0.110-0.149		0.195*	0.019-0.372		0.043	-0.090-0.175
Others				0.059	-0.049-0.167		0.275***	0.129-0.422		0.147*	0.005-0.290
SocialGroup (Other)											
ST	-0.282***	-0.422--0.143		-0.378***	-0.487--0.268		-0.433***	-0.555--0.311		-0.394***	-0.504--0.283
SC	0.018	-0.057-0.092		-0.182***	-0.256--0.109		-0.251***	-0.347--0.154		-0.177***	-0.264--0.089
OBC				-0.075**	-0.128--0.023		-0.154***	-0.229--0.080		-0.068*	-0.131--0.006
Income Class (Middle)											
Poorest	-0.350***	-0.433--0.267		-0.336***	-0.408--0.264		-0.278***	-0.378--0.178		-0.305***	-0.387--0.223
Poor	-0.087*	-0.169--0.005		-0.156***	-0.226--0.086		-0.152**	-0.251--0.052		-0.118*	-0.208--0.029
Rich	0.247***	0.164-0.330		0.157***	0.088-0.226		0.165**	0.063-0.267		0.018	-0.063-0.098
Richest	0.692***	0.605-0.779		0.419***	0.348-0.490		0.497***	0.392-0.601		0.254***	0.168-0.339
Household Type (Self-Employed)											
Regular Wage/Salaried	-0.118**	-0.190--0.047		-0.083	-0.171-0.004		0.060	-0.029-0.149		0.050	-0.020-0.121
Labour	-0.111**	-0.176--0.047		-0.115***	-0.173--0.057		-0.049	-0.135-0.037		-0.057	-0.125-0.011
Others	-0.084	-0.206-0.039		0.089*	0.013-0.166		0.191*	0.045-0.338		0.094	-0.023-0.211
Household Size	0.082***	0.070-0.094		0.084***	0.075-0.094		0.108***	0.092-0.124		0.079***	0.066-0.093
Child (No Child)	0.034	-0.023-0.092		0.099***	0.049-0.149		-0.137***	-0.208--0.066		-0.338***	-0.395--0.282

Old (No Old)	0.112***	0.056-0.168		0.153***	0.104-0.203		0.184***	0.114-0.254		0.329***	0.271-0.387
Gender of Head (Male)											
Female	-0.171***	-0.263--0.078		-0.063	-0.139-0.013		-0.112	-0.227-0.003		-0.074	-0.163-0.016
Transgender										-0.085	-1.929-1.759
Education of Head (Illiterate)											
Upto Primary	-0.089**	-0.152--0.026		-0.013	-0.073-0.046		0.036	-0.049-0.121		0.055	-0.020-0.130
Secondary	-0.012	-0.085-0.061		0.107**	0.047-0.167		0.105*	0.017-0.192		0.190***	0.119-0.261
Graduation and Above	0.048	-0.121-0.216		0.221***	0.110-0.332		0.195**	0.062-0.327		0.338***	0.230-0.446
Medical Insurance (No)	0.164	-0.118-0.447		0.171	-0.008-0.350		-0.096	-0.212-0.019		0.040	-0.056-0.137
Constant	4.497***	4.361-4.633		5.255***	5.134-5.377		5.765***	5.591-5.939		5.772***	5.628-5.915

Source: Author's Calculations from NSSO microdata.

Notes: The parenthesis next to each variable contain the base criteria used for the regression.

Notes: p-values : <0.5 = * ; <0.01 = ** ; <0.001 = ***

3.7. DISCUSSION

The Table 3.29 and Table 3.30 show the results of Part 1 and Part 2 of the two part model respectively. The part 1 is a logistic regression that show the odds ratios of likelihood of facing OOPHE while part 2 shows the magnitude of that OOPHE, among different household attributes. The results suggest that households in urban areas are more likely to face OOPHE that the households in rural with ORs >1 in all rounds. Also, the households in urban spend more than the rural counterparts with statistically significant coefficients of 0.158, 0.119, 0.235, 0.289 across the four rounds.

Religious minorities were also more likely to face OOPHE than the majority Hindus, but the expenditure differences are statistically insignificant, except for the NSS71 where the minorities are found to be spending more than the majority Hindus. Social category was a weak predictor of OOPHE likelihood. Only STs were significantly less likely to face OOPHE in all rounds (ORs NSS52:0.746; NSS60:0.615; NSS71:0.658; NSS75:0.646). This could be indication underutilisation among the scheduled tribes generally. However, the part 2 shows that vulnerable social groups have less expenditures compared to the non-vulnerable OCs across all rounds. This trend could be indicative of lesser utilisation in general.

Economic class is a strong predictor of likelihood. The odds are in correspondence with the class. When compared to the median income class, the richer households are more likely to incur OOPHE and poorer households are less likely to incur OOPHE. Additionally, the spending on healthcare is also proportional to their standing in wealth quintiles. The poorer households have negative coefficients indicating lesser expenditures and richer households have positive coefficients indication higher expenditures, compared to the median category in all rounds.

Household type is a weak indicator of likelihood with insignificant ORs across rounds. It also is a weak predictor of the expenditure magnitude in the households. The ORs are indicate that the households of higher size are more likely to face OOPHE and also more likely to spend than the smaller households (coefficients NSS52:0.082; NSS60:0.084; NSS71:0.108; NSS75:0.079). Households with children under 6 years of age are also more likely to face OOPHE (ORs NSS52:1.218; NSS60:1.119; NSS71:1.711; NSS75:2.248) but spend significantly less money on OOPHE than those without children. This could be indicative of more services for children, but the services could be of less expensive (low levels of healthcare) in nature. Similarly, households

with people aged above 60 are also more likely face OOPHE (ORs NSS52:1.382; NSS60:1.579; NSS71:1.732; NSS75:1.763) and also likely to spend more (Coefficients NSS52:0.112; NSS60:0.153; NSS71:0.184; NSS75:0.329)

Gender of the household head has no significant impact on wither the OOPHE likelihood or the magnitude of expenditure. Education level of the head is a strong indicator. Compared to the illiterate category, the higher levels of education have higher likelihoods (ORS >1) except for the households with heads having graduation and above education. However, the education levels above secondary are found to increase the OOPHE expenditures in Indian households suggesting higher utilisation of healthcare services. Households with medical insurances are also found to be more likely to face OOPHE signifying more utilisation of healthcare services, but the presence of insurance has no significant effect on the OOPHE magnitude in Indian households. This signifies that insurance might offer no relief on the OOPHE burdens in Indian households.

3.8. CONCLUSION

The demographic trends found significant correlations between the social group, employment (Household type) and economic class. The distribution of classes by mode of subsistence reveals that non-vulnerable social groups (OCs) have higher levels of stable incomes, particularly in the form of regular salaries/wages, while the vulnerable social groups (ST/SC/OBC) have significantly higher shares of the population relying on less stable incomes based on casual labour. The wealthy households have higher percentages of people who depend on regular wage/salaried income, whereas a big section of the poor classes rely on incomes from labour that are significantly less constant in nature. Vulnerable social groups tend to remain in the lower income quintiles because they rely more heavily on livelihoods with less consistent payoffs. In India, the penetration of medical insurance is quite low. In both 2014 and 2018, about 85% of the general population lacked any type of insurance. Only 1% of people are covered by private insurance and non-government employer schemes. The burden of OOPHE health expenditures on Indian households may also result from this.

A transitional shift in utilisation from private to public healthcare facilities is seen both inpatient and outpatient episodes. Inpatient hospitalizations occurred in public hospitals at a rate of well than 50% in 2018 compared to just 40% in 2004. The bulk of people still use private facilities for outpatient episodes, which was around 70% in 2018. However, during the study

period, the public usage rate increased from 19.41% to 30.16%. Rural locations, households from weak social classes, lower economic quintiles, and those with less consistent earnings are found to have faster transitions. Additionally, it has been found that households reliant on government insurance programmes use public facilities more frequently than the national average.

This transitional trend could be a result of improvements in public healthcare market (proxied by increased investments in healthcare by government in past decade), and a disproportionate increase in average expenditures at private facilities. The data shows the rising expenses in public and private facilities for inpatient care. However, the rate of growth in private institutions is much higher than the public institutions. The average inpatient expenditure at public institutes has gone up from 2,117 to 4,489 in the period under study. In the same period the private bills went up from 4,653 to 32,158. This rising gap between public and private facility bills might be pushing households, especially of vulnerable sections towards public facilities.

Findings of the current study reveal that the demand for healthcare services has increased gradually during the period 1995-2014 but this demand is primarily financed from out-of-pocket expenditures and hence leading to an increasing risk of financial catastrophe. But in the latest round, 75th round of the survey, the OOPHE share in HHCE has reduced drastically. During this period, a reduction in OOPHE is witnessed, which could not be attributed to reimbursements either. Table 3.1 shows a substantial reduction in total health expenditure per households. This sudden reduction in the share of health expenditure in consumption expenditure suggests a contraction in demand for healthcare services.

The results show that the households in Urban India are far more likely to face OOP than the rural households and spend more. Economic vulnerability has a higher impact than social vulnerability on OOP incidence and intensity. The Religious minorities have a higher likelihood of facing OOPHE but no significant differences in amount spent. Social vulnerability has no impact on likelihood of OOPHE but has a negative impact on the amount of OOP. Compared to the Median economic group the lower groups are substantially less likely to face OOPHE and spend less; vice versa for the richer groups. Larger households are more likely to spend and are likely to spend more. Household age composition is a significant indicator given the households with children and aged persons are more likely to face OOPHE. The education level of household head has a positive impact on the healthcare demand of the household. Medically insured

households are more likely to face OOPHE but has no significant impact on OOPHE possibly signifying the ineffectiveness of medical insurance in alleviating OOPHE burden in Indian households. With the current understanding of OOPHE scenario in Indian households, the upcoming chapter estimates the burden of OOPHE in Indian households.

CHAPTER IV

BURDEN OF OUT-OF-POCKET EXPENDITURES ON INDIAN HOUSEHOLDS

4.1. INTRODUCTION

The global average share of total health expenditure in GDP for 2018 was 9.85 percent (World Bank) while Indian health expenditure is less than half of it at 3.8 percent in 2017 (National Health Accounts, 2016-17). Also, public health spending accounts for only 32 percent of total health expenditure, which is 1.2 percent of GDP.

Due to this low level of governmental funding, 63.2 percent of India's total healthcare spending in 2017 was made up of household out-of-pocket expenses. Such out-of-pocket expenses have the ability to hurt a person's life and their home. When a medical expense threatens the family's capacity to maintain their level of living, it becomes financially catastrophic (Berki 1986). With this understanding, this study tries to find the incidence of Catastrophic Health Expenditure (CHE) and assess the household socio-economic indicators that determine the incidence of CHE due to out-of-pocket (OOP) payments for healthcare services in India. Also, these high OOP expenditures have hampering effect on household consumption and welfare (Sangar et al. 2019; Wagstaff and Doorslaer 2003). In this regard research on catastrophic effects of health expenditures has been well documented. However, the impoverishment effect of the health expenditures is less emphasized upon (Kumar, 2015). The current study bridges this gap by undertaking a detailed analysis of the socio-economic differentials that impact the impoverishment arising out of OOPHE.

4.2. LITERATURE REVIEW

Health-care financing in many LMICs including India is heavily relied upon OOP payments of the individuals. Estimates from consumer expenditures survey (CES) of 1999-2000 show that OOP expenditures in India amounts to 5 percent of total household consumption expenditure, ranging from 2 percent in Assam to 7 percent in Kerala (Garg & Karan, 2008). Low levels of utilisation of public health facilities, only 45 percent in inpatient care and 20 percent in outpatient care, leads to seeking health services from private facilities which is another driving factor behind the high OOP expenditures in India (Ramani & Mavalankar, 2006). An analysis of 75th round of NSSO Survey also supports the notion of private facilities increasing OOP burden

with ill episode affected households spending 30.4 percent of consumption expenditure on health when visiting public facilities against spending 74.1 percent when visiting private facilities (Yadav et al., 2021). When OOP health spending reaches a particular percentage of overall consumption spending, it becomes catastrophic for the population and imposes a major financial burden (Sangar et al., 2019; Wagstaff & Doorslaer, 2003).

A comparison between the 52nd and 60th round of National Sample Survey Office (NSSO) surveys has shown that the average OOP share in consumption expenditure rose in richer households than the poorer signifying a over medicalisation among the richer quintiles, while the poorer quintiles were facing more impoverishment than the richer quintiles (Ghosh, 2011). Ghosh (2011) explored the changes in CHE and impoverishment due to OOP expenditure in India between 1990s and 2000s using the secondary data from 2 rounds of NSSO on consumption expenditure (1993-94 and 2004-05) for 16 major Indian states. The analysis for CHE was done using fixed thresholds and the incidence of CHE was compared among the rounds. The study found that the share of Inpatient care expenditure in OOP has more than doubled for all the states during this period. The authors explained this as a result of decreasing public health expenditure. According to the quantile analysis of health expenditure as a share of household expenditure, except for the state of Kerala, the richest quantile in all the states had the highest share while the poorest had the smallest share, in both the periods under comparison. For the CHE incidence, when the threshold was set at 5%, 10%, 15% and 25%, the percentage of households incurring CHE increased from 26.66%, 12.97%, 7.45% and 2.77% in 1993-94, to 29.98%, 15.37%, 9.24% and 4.15% in 2004-05. Except for the states of Bihar and Karnataka, all the remaining states experienced an increase in the incidence of CHE. The number of people experiencing impoverishment due to OOP expenditures was calculated using the poverty head count before and after the payment of such OOP expenses. According to the study, OOP payments raised the poverty ratio by 4% in 1993–1994 and 4.4 % in 2004–2005. In other words, the requirement to pay for healthcare services forced 47 million people into poverty in 2004–05 and 35 million people into poverty in 1993–94. OOP increased the poverty gap by Rs. 3.1 in 1993–1994 and Rs. 7.2 in 2004–2005.

Analysis of 3 CESs (2000, 2005, 2012) showed that the poorest quintile of India saw a relative decline in the OOP spending on inpatient care, likely a result of foregoing care rather than benefitting from cashless publicly financed insurance schemes (Karan et al., 2014).

Studies comparing between 60th and 71st round of NSSO surveys found significant rural-urban differences exist in the economic impact of OOP expenditure. The burden is higher on poor in urban areas and rich in the rural areas. The rural households were also more likely to resort to financial coping mechanisms like borrowing and sale of assets to meet the OOP expenses (Sangar et al., 2018). Also, nationally, the incidence of CHE was disproportionately concentrated among rich in 2004, but in 2014 it was equally distributed among income classes due to rise in CHE among poor over time (Pandey et al., 2018). The mean OOP expenditure has also shot up in this decade. Richer households are found to be spending more on inpatient care while the poor were spending more in outpatient care. The CHE incidence decreased for outpatient care and increased for inpatient care (Akhtar et al., 2020). A study in Urban India showed a similar result with poor households bearing high OOP spending burden ratio (0.57) compared to the rich (0.15) (Misra et al., 2013). In order to assess the healthcare spending burden in an Urban setting in India, Misra et.al. (2013) used a community based cross-sectional survey. The survey was conducted for 3 months (Dec'2011-Mar'2012) period in the city of Lucknow in India to assess the proportion of families incurring OOP HCE across household expenditure quintiles. The survey sample was 400 households with a total population of 2,343 members. Out of the 200 families 115(28.75%) had at least one sick person in the 3 months and were taken for outpatient care, while 10 families had to resort an inpatient care. The mean total expenditure on a health shock was 6.590.75 INR. The inpatient care cost on average was 19,975 INR while the average outpatient care (both direct and indirect costs) totalled to 3,382 INR. Also, the study found that OOP HCE burden is higher on the low-income groups with spending burden ratio going up from 15% for families in Q5 of the income quintile to 57% for the families in Q1.

Similar results were also seen in another survey in the district of Haryana, where the aggregate incidence was 30 percent, but it was 37.7 percent in poorest quintile and 27.1 percent in richest quintile (Prinja et al., 2016). Prinja et.al. (2016) developed a methodology to quantify the coverage of UHI at district level by creating a composite index for UHC based on the WHO framework for UHC. The data for the study was collected in a multi-stage stratified random sample survey in rural and urban Haryana over a period of 15 months (Sep'2012-Dec'2013). For service coverage, ANC care and immunization was taken. For financial risk assessment, prevalence of CHE (>40% of monthly percapita household expenditure) and impoverishment due to OOP was taken (poverty estimation at $2 percapita per day). For distributional aspect, a concentration index

was calculated with +1 to -1 range with +1 meaning pro-rich and -1 meaning pro-poor distribution. The study found that although 68% pregnant women had 3 ANC visits, only 28% completed the full ANC. 71% of the children were immunized properly. Service utilization is more among the rich (quintiles based on monthly percapita household expenditure) in full ANC and Immunization. At $2 poverty line, the prepayment headcount was 28.6% while the post-payment count was 44.8% implying that impoverishment due to OOP is significant. Overall CHE was found to be 30.3% with poorest quintile at 37.7% and richest at 27.1%. Concentration index results show a positive sign for all indices suggesting a pro-rich distribution of services. The UHC index for each district was calculated as a geometric mean of the 3 indices. The results show huge variation in UHC between different districts.

Prinja et.al. (2012) made a model to estimate the percapita cost of making a UHC package available to the Indian population based on a study of the case of Chandigarh city in India. The necessary quality of services required as per the Indian Public Health Standards was used as the guideline for creating a care package. The necessary disease burden and overall morbidity data was collected from NNSO 60th round (2004-05); and the data for morbidity and cost of services were collected from 2 secondary and 2 tertiary care facilities in the city. The morbidity figures from NSS were raised to a factor of 1.5 (to compensate for the possible increase in demand for services with a UHC plan introduction). According to IPHS, to provide quality care for the city (with a population of 100,000) there would a need for recruiting more staff and the overall salaries for the total staff would end up being 53 lakh INR per month. Additionally, the IPD and OPD patient care would cost 1.16 crore INR (with branded medicine) or 83 lakh INR (with generic medicine). Even Generic medicine would cost INR 6,852 per household per month. Similar care for entire India would cost INR 4290 billion for preventive and curative care alone. The study revealed that INR 6,852 (USD 152) would need to be invested each home (INR 1,713 per capita per year) in India in order to universalize health care services using generic medications after accounting for the cost of maintaining infrastructure. 3.8 percent of India's GDP, or $1,176 per person, would be spent on this.

The percentage of households experiencing CHE because of OOP expenditures differed greatly between nations, according to a study of household surveys from 59 LMIC countries. Some transitional and Latin American nations have the highest CHE levels. The availability of medical

services that required money, a limited ability to pay, and the absence of prepayment or health insurance were the three main causes of CHE incidence. So, moving the health system reliance off OOP Health expenditure would be the most efficient solution to reducing CHE (Xu et al., 2003). Xu et al. (2003) studied the determinants of CHE in 59 countries using the data of national household surveys from the respective countries. WHO standard of 40% threshold of CTP was used for the study. The cross-country analysis used the data ranging from 1991 to 2000 (depending on the most recent survey available for any country). The study found that incidence of CHE was very geographically volatile from less than 0·01% in Czech Republic and Slovakia to 10·5% in Vietnam. CHE due to OOP was especially high the transitioning economies (such as Azerbaijan, Ukraine, Vietnam, and Cambodia) and the Latin American nations (Argentina, Brazil, Colombia, Paraguay, and Peru). A simple Multivariate OLS found that OOP share of HCE is the biggest determinant of CHE incidence (coefficient = 2.161) followed by Total HCE as a share of GDP (1.645). Proportion of poor in total population also had a positive relationship with CHE (0.173). The authors suggest that moving the health system reliance off OOP Health expenditure would be the most efficient solution to reducing CHE.

Other studies from LMIC countries revealed that Socio-economic factors like education level, age composition, and geographical location impact the risk of incurring CHE among households (Su et al., 2006; Minh et al., 2013; Aregbeshola & Khan, 2017). Su, Phokrel, et.al. (2006) conducted a primary survey to find the determinants of household expenditure on western medical care in the country of Burkina Faso. The western institutional medical care was highlighted because, contrary to the western care, payment in kind can be made to other types of providers in the context of rural and semi-urban areas in developing countries. And the authors also assumed that patients treated with western institutional health care tend to be diagnosed correctly and receive appropriate treatment. The survey was conducted in the Nouna health district during 2000-2001. 800 (320 urban, 480 rural) households were selected using two-stage cluster sampling method. The survey consisted of morbidity data and complementary socio-economic data. The morbidity data was collected 4 times during 4 different seasons of the year. Socio-economic data was twice in the year, once in the rainy season and once in the dry season. Logit models were used to find the determinants of illness reporting and provider choice. OLS estimators were used to estimate the magnitude of household health expenditure on western institutional care. 1,549 out of 6,853 respondents said they were sick; 1,019 (66%) said they were only sick once,

and 372 (24%) said they had been sick twice. The remaining 10% reported three times or more. Adulthood, being a woman, being married, and having a disability were all associated with a higher risk of reporting illness. There were 1,176 acute and 1,140 chronic disease occurrences found over the course of the four rounds of data collection. 56 percent of chronic illnesses were not spread by other people. Of the 2,316 illness events, 1,403 (60.6 percent) involved seeking some sort of therapy, while the remaining 913 (39.5 percent) did not. 1,235 of the 1,403 episodes received only one treatment, while 92 received a second treatment and 76 received a third. For all disease episodes, the following provider selection patterns were observed: 275 (11.7%) for western institutional care, 74 (3.2%) for western private care, 117 (5.1%) for traditional healer, 937 (40.5%) for self-medication, and 913 (39.4%) for no care. are. It was more probable to use western institutional care if you had a serious disease, were a member of a home with a female head of household, were literate, and had a greater household income. All other illnesses had a higher likelihood of being treated in a western facility than malaria did, although using western care was connected negatively with chronic illness. The average cost of institutional care in the west was 5,923 CFA (7.67 USD). Being an adult, being married, and contracting an illness during the rainy season all greatly increased health costs. On the other hand, chronic illnesses like malaria were less likely to have an influence on household spending.

Out-of-pocket (OOP) HCE has been known to eat into the household consumption expenditure and push the family into poverty. Minh et.al. (2013) tried to quantify the catastrophic impact of OOP HCE and find various determinants of CHE in Vietnam. They approach this objective using the data from Viet Nam Living Standard Survey (VLSS) rounds in 2002, 2004, 2006, 2008 and 2010 giving a total household of sample of 66,498 spread across the 5 rounds. Apart from the OOP expenditure and the total household expenditure, the family composition and the locality (urban/rural) of the family were considered for the Logistic Regression to find the determinants of CHE. The study set the CHE threshold at 40% of Capacity-to-pay . The regression found that across the five surveys, the households with elderly population and the households situated in rural areas had the higher risk of incurring CHE. Also, the study found that larger households have a lesser risk of incurring CHE, possibly due to the home-care provided by the family members. Moreover, being enrolled in a health insurance plan only seemed to have a modest impact on reducing CHE risk signifying the failure of health insurance promotion and adoption.

Aregbeshola and Khan (2017) assessed the determinants of CHE among households in Nigeria. Data from Harmonized Nigeria Living Standard Survey (HNLSS) of 2009-10 was used for the study. The survey covered a total of 1,16,100 households. In order to assess the factors associated with CHE, a Multivariate Logistic Regression method was implemented with CHE as the dependent variable and several household properties, geo-political, and socio-economic indicators were taken as independent variables. According to the findings, households in the north central region are more likely to have members of the household who are between the ages of 6 and 14 years, 15 to 24 years, 25 to 54 years, lack health insurance, have primary or secondary education, visit a private health facility, and consume between 10 percent, 25 percent, and 40 percent of both total consumption and non-food consumption.

In India, a study of CES 2004-05 data using 'ability-to-pay approach' found that the incidence of CHE decreases as the income increases. higher education levels were found to be reducing the probability of facing CHE and social and economic vulnerability increased CHE incidence (Pal, 2012). Studies on catastrophic health expenditure (CHE) have often used an arbitrary threshold of the monthly household (or non-food) expenditures as a measure for the incidence of CHE. But Pal (2012) has empirically shown that such an arbitrary threshold analysis will result in higher incidence of CHE among the richer classes (34.9% rural and 23.29% urban richest; compared to 14.68% rural and 14.71% urban poorest), especially in a private expenditure driven health system like India. This is due to the richer classes being able to pay for the health services more than the poorer classes. In order to circumvent this issue, the author used a new measure to evaluate incidence of CHE: a particular OOP health expenditure is catastrophic if the total household consumption remaining after such an expense is not enough to purchase the necessities. For this purpose, the data from 61st NSSO Round (2004-05) was used. Engel curve analysis was used to identify the necessities: cereal, sugar, salt, egg/fish, vegetables, pulses, clothing, pulses, clothing, rent, and cooking oil. After deducting the saturation amount of consumption expenditure required for necessities from the total household consumption expenditure, the study found that almost all the households in poorest two quantiles are incurring CHE, across rural and urban areas in all 15 major states considered for the study (99.90% rural and 99.95% urban in poorest quantile; 99.53% rural and 99.40% urban in 2nd poorest quantile). The third quantile too has high CHE incidence (92.13% rural and 78.47% urban). The 2nd richest quantile has some significant CHE especially in rural, but the richest quantile has low CHE

incidence (57.94% rural and 29.83% urban in 2nd richest quantile; 9.99% rural and 1.70% urban in richest quantile). Using a probit method, the study also found that education (especially female education) and social factors (being from SC/ST classes) has an impact on the incidence of CHE among households.

Onoka, Onwujekwe, et.al. (2011) examined the incidence of CHE in different socio-economic groups of south-east Nigeria. The study used fixed and variable thresholds of CHE for the descriptive statistical analysis. The data was collected using Health and expenditure pictorial diaries the were kept at the households for a period of 4 months in 2008. The diaries were replaced every week and the entries were monitored twice a week. The diary consisted of details on the illness, expenditures on health, transportation, entertainment, food, education, clothing, cooking fuel. The field study covered 1,128 household consisting of 4,988 individuals. The authors used fixed threshold levels of 40%,20%, and 10% of the total consumption expenditure. And used two variable thresholds: (i) with poorest quantile as the 'index' quantile, set the Q1 threshold at 5% and calculated the rest of the quantiles' thresholds by multiplying 5, with the share of the respective quantile's food expenditure with that of the index quantile; (ii) using Q5 as the 'index' quantile and setting the threshold at 40%, and calculating the remaining threshold with the same previous method. The study found that out of all the illnesses reported during the period, malaria was the most repetitive with 585 (47.1%) of the total households affected. At fixed thresholds of 40%,20%, and 10%, 167(14.8%), 314 (27.8%), and 453 (40.2%) households were found to be incurring CHE. In terms of variable thresholds, when Q1 is taken as the index quantile, the thresholds ranged from 5% to 29.6% for Q1 through Q5, and when Q5 is taken as the index, the thresholds ranged from 6.8% to 40%. In the first case, CHE was incurred in 412 (36.5%) households, and in the second, 361 (32%) households. So the authors opined that variable thresholds technique is better for CHE evaluation as they take into account the variations in incomes and expenditures across the different socio-economic groups.

Having a National Health System (NHS) is usually considered a good sign of UHC in a country. However, Kronenberg and Barros (2013) showed that CHE can still be seen in such a setting with the case scenario of Portugal. Portuguese Household Budget Surveys of 2000 and 2005 data was used for CHE calculation and Logistic Regression was used for determinants of CHE. 1/3rd of the Portuguese health system is financed by OOP expenditure. At a CHE threshold

of 10% (share of CTP) CHE incidence was 29% in 2000 and 33 % in 2005. At the WHO standard of 40% threshold, the incidence of CHE was 7.85% and 5.03% in 2000 and 2005 respectively. According to the regression analysis, income had little effect on the CHE, and the gender of the household head, age and employment had a significant effect on the incidence of CHE. So the authors calculated CHE incidence for the vulnerable groups separately. The vulnerable groups as found in the study were children age ≤ 9 (% CHE in this subgroup = 62.3%), children age ≤ 14 (58.21%), Unemployed (63.37%), Low Pensioned (53.88%) and Disabled (Incapacity to work – 63.51%; Retired due to disability – 71.74%). The authors note that drug purchase is a major part of OOP in Portugal and a policy to reduce the prices might hopefully alleviate the problem.

The Turkish healthcare system has undergone a series of reforms post the year 2003 to improve the quality of the healthcare delivered and to strengthen healthcare finance system. So, Erus and Aktakke (2012) tried to check the impacts of the reforms on out-of-pocket (OOP) health expenditure on the public insurees. They used the data from the Household Budget Surveys of 2003 and 2006 years. They considered the families that have all the members insured under some form of premium-based public insurance for this purpose. The dependent variable was Health expenditure, and several socio-economic indicators like Household size, total monthly expenditure, age of the members, etc., were taken as the independent variables. A Probit Regression model was used for the analysis. The study found that the OOP monthly expenditure has risen from 15 lira in 2003 to 23 lira in 2006, but the average share of health expenditure in total expenditure reduced from 3.8% to 3.5%. the probability of having a OOP health expenditure in a month has gone up by 6% during this period. This increase could be seen as increase in the demand for healthcare services. Additionally, households with low levels of monthly expenses—those with less than 200 lira—which represent the poorest 10% of the income distribution—seem to have seen a rise in the ratio of health expenditures in income. There is a decline in the percentage of OOP expenditures connected to health for those who spend more than 200 lira per month, indicating that wealthier sectors have benefited more from the reforms.

Hajizadeh and Nghiem (2011) attempted to find the determinants of OOP expenditure and CHE in the Iranian healthcare system using a nation-wide 2003 Utilisation of Health Services Survey data. A concentration curve inequality study yielded a result of -0.135, indicating that the CHE is concentrated among households with lower socioeconomic status. According to the

Heckman selection model's findings, a longer hospital stay, admittance to a hospital run by the private sector or the Ministry of Health and Medical Education, and living in a rural place are all positively correlated with greater out-of-pocket expenses. The Ordered-Probit Selection Model's findings show that admittance to a private hospital, a shorter length of stay, and a lower household wealth index all significantly increase the likelihood of developing CHE. Also, geographical location of the household impacts the CHE. The authors conclude that a single universal health insurance programme that covers health services for every Iranian—regardless of their work status—can better protect households against catastrophic health spending than the current employer-sponsored health insurance system.

In the Asian countries a substantial portion of OOP health expenditure is financed by borrowings and sale of assets, leading to a reduced CHE shock on consumption in the short-run. However, these coping mechanisms may lead to much greater impact in the long-run (Flores & Donnell, 2016). Flores and Donnell (2016) studied the risk of incurring catastrophic medical expenditure (CME) in the Asian countries. They though that the existing CHE studies did not take into consideration the 'informal insurance' (savings and borrowings) in paying for health expenditure. For the study they used the socio-economic data from World Health Survey 2002-03 by WHO conducted in the 7 Asian countries of Bangladesh, India, Pakistan, China, Laos, Malaysia, and Philippines. Probit method was used to check the probability of positive expenditure, and a quantile regression was used to find the density of CME. According to the study, OOP expenses have a favourable correlation with the prevalence of health conditions and an even stronger correlation with the method used to pay for medical expenses. Households reporting using savings, asset sales, transfers, and borrowing to pay for medical care and medications typically report significantly higher median medical expenditures. The study also discovered that this type of financing tends to raise total household consumption spending, indicating that people may utilise informal insurance to pay for medical expenses while partially shielding non-medical consumption, leading to a rise in overall household spending. When CME threshold was set at 40%, Laos had the highest probability (9.16%) of health expenditure crossing 40% of total consumption, and Malaysia had the least probability (1.2%). With the exception of Laos and to a lesser extent China, a sizable portion of OOP costs that are commonly classified as catastrophic are covered by informal insurance, not by renouncing consumption of other goods and services, despite what is frequently asserted. So, the risk of incurring CME is the highest in

Laos, and least in Malaysia. In India, such coping mechanisms account for as much as three-quarters of inpatient expenses (Flores et al., 2008).

Coping mechanisms are more popular among the economically and socially vulnerable (belonging to SC/ST/OBC) in India (Gupta & Joe, 2013). Empirical studies on health expenditure are often based on household consumption expenditure, so Gupta and Joe (2013) opined that this disregards the 'ability to pay' of the different socio-economic classes and as such they tried to create a multidimensional approach to estimating CHE. The authors primarily distinguished low economic class as people without pucca houses and no sanitation facilities, and SC/ST and OBC were taken into the social class variable. NSSO's Morbidity and Health Survey (MHS, 2004) was used for the data. The study found that, average health expenditure on hospitalization is Rs. 6,752 for those with low economic status and Rs. 13,159 for others. Although the expenditure of non-vulnerable houses was high, they were able to pay for with savings/income (59% of total expenditure) while vulnerable economic classes had to pay for by borrowing (44% of total expenditure). Similar picture is seen from the social vulnerability point-of-view, with non-vulnerable houses pay most of the expenses with savings/income (55%) while vulnerable social classes (SC/ST/OBC) had to pay substantially from borrowing (40%). Similar expenditure patterns are also observed in out-patient care. The authors then created 5 criteria to classify catastrophic households: (i) over 2/3rd of mean health expenditure; (ii) ½ of health expenditure financed by borrowings and sale of assets; (iii) education level of household head is primary or below; (iv) Socially deprived SC/ST/OBC; (v) economic status. These criteria are stacked upon one another to find the share of catastrophic households. In the case of inpatient care expenditure, the percentage of households incurring CHE increases as more criteria are stacked on one another; leading to 37.3% CHE households at criteria 1 and 5.2% when all the criteria are stacked. Similar trend is seen in outpatient expenses; 41.58% at criteria 1 to 2.78% when all criteria are stacked. The authors conclude that such a multidimensional approach to estimating catastrophic households can improve targeting households for future healthcare policy interventions.

The economic impact of OOP expenditure differs significantly across rural and urban areas, according to studies comparing the 60th and 71st round of NSSO surveys. In urban settings, the burden is heavier on the poor, while in rural areas burden is higher on rich. To cover OOP expenses, rural households were also more prone to adopt financial coping techniques such as

borrowing and asset sales (Sangar et al. 2018). The mean OOP expenditure has also shot up in this decade (2004-2014). It was shown that wealthier households spent more on inpatient care, whilst the poor spent more on outpatient care (Akhtar et al. 2020). In a study conducted in urban India, impoverished households had a higher OOP spending burden ratio (0.57) than the wealthy (0.15) (Misra et al. 2013). Using $1 per day as absolute poverty threshold, Doorslaer et.al. (2007) found that in 11 LMICs in Asia, after paying for health care, an additional 2.7 percent of the study's population (78 million people) lived on less than $1 per day. Estimates of poverty in countries where households pay more than 60% of health-care costs out of pocket, such as Bangladesh, China, India, Nepal, and Vietnam, were significantly higher than traditional estimates. These countries include Vietnam, where an additional 1.2 percent of the population lives in poverty, Bangladesh, where 3.8 percent of the population does, and India, where 3.7 percent does.

In rural areas, OOP expenditure is concentrated among the wealthy, whereas in urban centres, it is fairly distributed according to the ATP of demographic groups. In 1999–2000, approximately 32.5 million people slipped into poverty due to OOP payments, indicating a 3.2 percent increase in overall poverty after accounting for OOP spending (Garg and Karan 2008). Due to rising health-related costs, more than half of Indian households experience poverty, which affects over 39 million Indians annually (Balarajan et.al., 2011). At the national level, impoverishment estimates are higher for the rural than in the urban areas (Berman et.al., 2010; Ladusingh and Pandey, 2013). OOP payment typically rises when there is a state-level physician shortage and income inequality (Ladusingh and Pandey, 2013).

Healthcare utilisation is pro-rich and the OOP burden is higher on the poorest population, meaning the OOP expenditure rises with ability to pay but the share of OOP expenditure reduces with increasing ATP (Chaudhury & Roy, 2008; Khan et al., 2017). Khan et al. (2017) tried to estimate the financial risk protection in Bangladesh with the main objective of finding the incidence of CHE and the impoverishment magnitude of the OOP HCE. Data were obtained from the latest Household Income and Expenditure Survey 2010 (HIES). Two criteria were used for CHE threshold: 10% of total household expenditure and 20% of non-food expenditure. The per household monthly OOP HCE is higher in the rural areas (709.1) than the urban (468.5). Also, the OOP distribution is pro-rich with the richest paying significantly higher (966.3) OOP for healthcare than poorest (416.7). However, at variable threshold levels of 5%, 10%, and 15% of

total expenditure, the poorest quantile had the highest incidence of CHE. Similar result was found with 15%, 25%, and 40% thresholds of non-food expenditure. Also, the study finds that presence of elderly people, or reproductive-age women in the household increases the risk of CHE and higher literacy significantly reduces the risk of incurring CHE. Additionally, the poverty headcount increased by 3.5% due to OOP HCE from 37.8% pre-payment to 41.3% post-payment. Thus the study found that annually 3.5% of the population i.e. 5 million people are pushed into poverty due to OOP HCE.

However, introduction of a UHI scheme is found to improve the utilisation of healthcare services among the low-income classes. Introduction of UHI has resulted in doubling the amount of outpatient visits and more than doubles the hospital admissions in the newly insured population (Cheng & Chiang, 1997). On 1st March 1995, Taiwanese government introduced a Universal Health Insurance scheme for all the citizens. During this period, Cheng and Chiang (1997) conducted two surveys, one in Oct-Dec'1994 with 11,925 respondents and a follow-up telephone interview survey in Dec'1995. The inquiry is related the utilization, spending and health status of the respondents. With this study they tried to check if the health care utilization has grown with the introduction of UHI scheme. The major indicator under study was the number of physician visits before and after the inception of the scheme, especially in the people who are newly insured (wealthier classes were already enrolled in some form of insurance scheme). The study found the previously insured saw only a 2% rise (from 27.3% to 29.5%) in utilization, while the newly insured had 10% rise (from 14.7% to 24.9%). Hospital admissions have also gone up for the newly insured (from 4.0% to 9.8%). The OOP expenditure for OP visits have gone down significantly from USD 15.8 for (uninsured) in 1994 to a co-payment of USD 4.9 in 1995. However, the perceived health of individuals hasn't changed significantly. So, the authors conclude that the UHI scheme has been a success in increasing utilization and reducing OOP HCE.

Health insurance schemes targeted at the poor help reduce the incidence of CHE. Seguro Popular (SP) was introduced in Mexico to provide financial protection for the uninsured. The scheme is found to reduce the catastrophic expenses at national level by 54 percent (Gala´rraga et al., 2010). Gala´rraga, Sosa-Rubı´, et.al. (2010) estimated the impact of health insurance targeted at poor on the OOP and Catastrophic Health Expenditure (CHE) of the poor in Mexico. They used the Seguro Popular (SP) program which was intended to protect the poor from excess health

expenditure burden, for this study. In order to evaluate the impact, they used the data collected from SP Impact Evaluation Survey (2005-06) and ENSANAUT-2006 (National Health and Nutritional Survey). Out of the total households, only those with all its members insured under SP were selected for the sample. The data on OOP health expenditure, CHE, outpatient, inpatient, and medical expenditures were used, along with several other characteristics of the households like the size, age composition, gender, education, medical conditions, etc. were taken into account for the empirical analysis. Instrumental Variables Estimation techniques were used including two-stage least squares (2SLS), bivariate probit, and two-stage residual inclusion (2SRI) models. The study found that SP has a positive impact on the target group and reduces the probability of incurring CHE by 49%. Also, the findings suggest that a potential adaption of such universal health coverage scheme at the national level might reduce Catastrophic Health Expenditure by up to 54%.

Introduction of Catastrophic Medical Insurance in China has reduced CHE incidence from 4.8 percent to 0.1 percent in covered expenses and from 15.5 percent to 7.9 percent for the total health expenditure (Zhao et al., 2019). Studies on health insurance in India have found that health insurance has a positive impact on the illness reporting as well as reducing OOP and CHE. But in order to increase health insurance participation in the poor, improvements on the supply side of health care are also needed (SK Hooda, 2015; Ahuja & De, 2004). SK Hooda (2015), in his study evaluated the impact of different insurance schemes on access, costs, and financial risk protection. For this study he used the data from the 60th and 68th NSSO surveys (Morbidity and Health Care 2004-05; and Consumer Expenditure Survey 2011-12). He categorized the insurance schemes as Government Financed Health Insurance (GFHI), Social Health Insurance (SHI), and Voluntary Health Insurance (VHI). And districts which were covered under any of the GFHI were termed Intervention Districts (ID) and the others, Non-Intervention Districts (NID). Districts with insurance coverage less than the national average were termed Low Insurance Coverage Districts (LICD) and those with higher coverage, High Insurance Coverage Districts (HICD). The study used t-test and Case Control Approach (CCA) to check for the differences in access and costs between the different insurance schemes. The t-test results indicate that the insured persons have significantly higher (19.7%) rate of reporting for inpatient care than the inpatient care rate (IPR) reporting of uninsured persons at the aggregate level. Social and voluntary health insurance (SVHI) schemes play a significant role in improving the healthcare utilization across rural–urban residents and economic stratum groups of India. GFHI schemes improve the utilization rate. Illness

reporting in HICDs is 11% better than LICDs. Also, the study found that insured seek more hospitalization care from private facilities than public, possibly due to the non-availability of services and inadequate quality. Importantly, SVHI schemes rather than reducing cost of care, increased the cost per inpatient episode by 11.3%, compared to uninsured, with variation in such increase between low economic strata incurring 16-18% more, and high economic strata incurring 35% additional cost per inpatient episode. So, SVHIs might be cost effective for poor and provide costlier alternatives for the rich. Also, the study found that reimbursements of health expenditures were high in government employees, accounting for % of total reimbursements.

Ahuja and De (2004) used the Universal Health Insurance (UHI) policy to empirically test if the demand for healthcare is limited by the weak supply of healthcare services. They used the data from the 55th round of NSSO survey, General Insurance Public Sector Association, and India Health Report 2003. Data was collected for 16 states, which account for 95% of all the UHI policies sold. The dependent variable was the number of families covered under UHI per 1 lakh population. The independent variables were incidence of infrastructure (beds per 1 lakh population), and incidence of poverty (% of population below poverty line). Regression analysis was undertaken. The study found that at 10% significance level, there is a positive relation between infrastructure and the UHI figures, and a negative relation exists between below poverty line population and UHI figures. Thus the study suggests that improving the supply side is required to increase the number of insured poor.

Gupta (2002) surveyed the attitude of general public in a case study to see whether the individuals and households would be willing to participate in private health insurance schemes. The longitudinal survey was conducted in Delhi over a course of 6 months. The survey was conducted in 3 rounds to cover 504 households across low, middle, and high income groups. The survey found that the low income group had the highest share of food expenses (46% of total monthly expenses), highest acute and chronic diseases (52.5% in the income group, and 48% of all respondents), lowest insurance rate (23% in the income group, and 17.4% of all respondents), and highest acute and chronic health expenditure (2.8% and 7.2% of total consumption). Survey also found high incidence of uninsured and underinsured and welcomes a health insurance policy that covers these. People with existing insurance policies are least willing to opt for a private insurance, especially those in middle and high income group. Middle income group was the least

willing to participate in the private health insurance, while the high income groups were indifferent towards the idea, probably since they can afford the usual medical expenses and have a savings fund to use during a health shock. The group of people that were interested in the private health insurance had the perceived benefits of refund of unused funds and better health facilities.

The goal of Siskou, Kaitelidou, et al. (2009) was to study the function of private health insurance in Greece, to pinpoint the variables influencing its growth, and to offer some recommendations for future trends and policies. The authors point out that approximately equal amounts of public and private funding go toward Greece's healthcare system. Private spending is primarily made up of cash payments and payments made under the table. Also, the establishment of National Health System in 1983 had no positive effect on the public sector as the public HCE share of GDP has risen only from 4.4% to 5.3%, from 1987 to 2004. Private health insurance is still scarce despite substantial private health spending (about 50% of total health spending) and discontent with the public system (just 10 percent of the population are covered by PHI). The authors also point out that most PHI firms only offer coverage for the hospital sector, and insurers have not yet built core benefit packages to enable comparisons and give customers a choice that is well-informed. The HAIC study found that younger people (aged 25 to 34) who were not already covered by PHI expressed a desire to do so in the future (12 percent of the study sample). In Greece, PHI is anticipated to increase during the coming several years. Because of this, scholars advise that significant efforts should be made by policymakers to curb either the phenomenon of moral hazard or adverse selection (cream skimming).

In Ethiopia's rural areas, Asfaw and Braun (2005) investigated the potential of community health insurance programmes. The Center for Development Research at Bonn University conducted a survey of 550 families in 2000–2001 to gather the data for the study. The willingness to pay for a CBHIS policy was calculated using the Double Bounded Contingent Valuation (CV) approach. The responders were offered an initial offer at the first stage; if they accepted it, they were given a higher offer; if they rejected it, they were given a lesser offer. The first offer was accepted by 43.27 percent (Birr 7.53), while the second offer was approved by 38.94 percent (Birr 6.73). Only the initial proposal was accepted by 20%, the lower bid by 15.6 percent, and both bids were accepted by 23 percent of respondents. A CBHIS was something that 60 percent of respondents were willing to pay for. The study discovered a potential for CBHIS since households

in the selected locations are willing to pay Birr 4.75 per month (3.75 percent of the respondents' mean income) to be a part of a hypothetical CBHIS that would pay for all family members' outpatient and inpatient costs. The cost is comparable to the monthly fee for the Ethiopian Teachers' Association Health Insurance, according to the authors (Birr 5 per month). The findings also indicate that if UHC is assumed and even if urban and rural areas pay the same, implementing this programme at the national level will yield approximately Birr 630 million ($75 million).

A review of data from the World Health Survey from 63 nations revealed that the health system is also better able to serve the poor due to an increase in the share of public health spending in overall health spending. The likelihood of receiving a "very good" response from the poorest person increases more than it does from the richest person across the six responsiveness dimensions of outpatient services (prompt attention, dignity, choice, clarity of information, confidentiality, and quality of basic amenities) with every 10% increase in the proportion of public spending in total health expenditure (Malhotra & Do, 2016).

With the help of NSSO surveys specific to ‘health and morbidity’, the current study tries to ascertain a picture of incidence and determinants of out-of-pocket health expenditure burden (in terms of health expenditure catastrophe and illness induced impoverishment) at national level over a wider time period compared to the previous literature and also analyses the significance of various socio-economic covariates that might determine the said incidence in Indian households.

4.3. DATA DESCRIPTION

The current study used the unit level data collected by the NSSO to achieve the aforementioned objectives. The data collected in 4 consecutive surveys of NSSO on ‘Healthcare Consumption and Morbidity’ spread across a period of 23 years (from 1995-2018). The data sets used for analysis of OOPHE determinants in Chapter 3 are used for this chapter as well.

All four surveys included in the study use the same recall period for consumption and healthcare expenditures. A recall period of one month was used for consumption expenditure, while the recall periods for health expenditures was 365 days for the inpatient care and 15 days for the outpatient care. For the purpose of the study, the expenditure and reimbursements on inpatient and outpatient cases are adjusted to a 30-day reference period. The data contains individual cases of hospitalisation, which are cumulated at the household level to gather a total healthcare

expenditure estimate for the households in the survey sample. Similarly, the reimbursements are also aggregated at households and deducted from the total health expenditure to arrive at out-of-pocket health expenditure (OOPHE). Since the survey data also lacks information on income of the households, monthly household consumption expenditure (HHCE) is used as a proxy.

Table 4.1: Survey Description and Household Average Expenses

	NSS52	NSS60	NSS71	NSS75
Sample Estimates				
Villages/Blocks	12231	7423	8269	14258
Sample Households	120942	73868	65932	113823
Sample Persons	629888	383339	333104	555115
Average Household Size	4.92	4.82	4.51	4.35
Population Estimates				
Estimated Population	840,392,489 (840 million)	958,922,889 (959 million)	1,121,101,609 (1.12 billion)	1,140,187,554 (1.14 billion)
Average HHCE (INR per household)	1,801.11	2,887.42	7,333.01	9,404.56
Average Health Expenditure	106.63	296.92	886.03	747.64
Average Reimbursement	1.66	6.49	19.31	25.57
Average OOPHE	104.97	290.43	866.72	722.07
Average % Reimbursed	**1.55**	**2.19**	**2.18**	**3.42**

Source: Author's Estimations from NSSO microdata.

Notes: Population Estimations calculated using population weights provided in the data.

Table 4.1 depicts the sample sizes and populations estimates for the 4 rounds of data. Additionally, average consumption expenditures and health expenditures per household are also estimated. Both the consumption and healthcare expenditures have seen a substantial rise from 60th to 71st round. The HHCE has risen further in the 75th round, however the average health expenditure has gone down in the same period.

Section I: Incidence, Inequality and Determinants of Catastrophic Health Expenditure in India

4.4. METHODOLOGY

In this study, a fixed threshold approach was followed to determine the incidence of household catastrophe (Pradhan and Prescott, 2002; Ranson, 2002; Wagstaff and Van Doorslaer, 2003 and Sangar et al. 2018). The present study has used 10 percent of 'household monthly consumption expenditure' as the threshold at which households expose themselves to significant health expenditure catastrophe. The current study measures the incidence, intensity and inequality of such catastrophic payments.

A household is marked as incurring CHE if $H/E > Z$, where 'H' is OOP health expenditure of the household and 'E' is monthly consumption expenditure. The 'Z' is the predetermined CHE threshold, which is set at 10 percent. We measure the incidence of CHE by estimating the share of households facing CHE the total population.

$$Catastrophic\ Payment\ Headcount\ (CHC)\ =\ \frac{1}{N}\sum_{i=1}^{n} Ci$$

where N is the number of households, Ci=1 if $H/E > 10$ and 0 otherwise.

The intensity of catastrophe is measured by measuring the average degree by which the share of expenditure exceeds the threshold level.

$$Catastrophic\ Payment\ Gap\ (CPG) = \frac{1}{N}\sum_{i=1}^{n} Gi$$

where N is the number of households and $Gi = C_i\left[\left(\frac{H_i}{E_i}\right) - 10\right]$ is the overshoot or excess by which the share of expenditure exceeds the threshold level.

An additional measure of $Mean\ Positive\ Gap\ (MPG)\ =\ CPG/CHC$ is used to relate the incidence and intensity of CHE payments. It measures the average intensity of payments over the households facing CHE incidence.

In order to measure the inequality of catastrophe, *Concentration Indexes* (CIs) are calculated. For this purpose, the households were divided into 5 quintiles based on the per capita monthly consumption expenditure (MPCE). These quintiles form the income classes needed to estimate CIs. A positive value of CI indicates a pro-rich distribution of CHE incidence i.e., the richer households are facing more CHE incidence compared to the poor. Similarly, a negative CI indicates a pro-poor distribution of HE incidence. A zero value indicates perfect equality while a value of 'one' indicated perfect inequality. Wagstaff and Doorslaer (2003) suggested weighted indices in order to understand whether the catastrophic payment burden is concentrated among the poor or the better off. The rank weighted index is simply the estimated measure multiplied by the complement of its CI. This means,

$$Rank\ Weighted\ Headcount\ (CHC^{W}) = CHC(1 - CI_{H}) \quad \text{and}$$
$$Rank\ Weighted\ Payment\ Gap\ (CPG^{W}) = CPG(1 - CI_{G}).$$

In order to find the household characteristics that determine the incidence of CHE. The dependent variable is the incidence of household CHE and is classified into two categories: household facing CHE or not facing CHE. Since the dependent variable is a binary variable, a binary logistic model can be applied.

Let the probability distribution of Y_i be:

$$P_i = Prob(Y_i = 1) = \text{Household facing CHE}$$
$$1 - P_i = Prob(Y_i = 0) = \text{Household not facing CHE}$$

The logistic probability distribution function can be:

$$Pi = \frac{1}{1+e^{-(\beta_0+\beta_i X_i)}} \quad \text{---------- (1)}$$

$$Pi = \frac{1}{1+e^{-zi}} = \frac{e^{z}}{1+e^{z}} \quad \text{----------(2)}$$

Where

$$Zi = \beta_0 + \beta_i Xi$$

Equation (3) represents what is known as the (cumulative) logistic distribution function.

$$1 - Pi = \frac{1}{1+e^{zi}} \quad \text{----------(3)}$$

Therefore, we can write

$$\frac{\mathbf{Pi}}{\mathbf{1-Pi}} = \frac{\mathbf{1+e^{Zi}}}{\mathbf{1+e^{-Zi}}} = \mathbf{e^{Zi}} \qquad \text{----------(4)}$$

Now $P_i/(1-P_i)$ is simply the odds ratio in favour of household facing CHE or the ratio of probability that the household will face CHE due to health payments to the probability that the household will not face CHE. The current study reports the Odds Ratios for the independent variables. An odds ratio of 1 means the 'odds' of the household belonging to the category are the same as that of the reference category. An odds ratio less than 1 indicates lower odds, while more than 1 indicates higher odds of respective category compared to the reference category.

The independent variables used in this study include socio economic characteristics of the households like the sector, religion, social class, type of employment, household size and economic class (5 MPCE quintiles). Demographic burden (people aged 60 and above) is also considered along with the medical insurance status of the household. In addition, the gender and education level of the head of the household are used as predictor variables.

The current study has a few limitations. the loss of income due to ill health episodes was not included in the analysis possibly underestimating the catastrophe. Also, in adjusting the inpatient and outpatient expenditures over a uniform period of 30days, the study might have overestimated the burden of outpatient expenses. Also, survey of the literature has identified two different approaches in the analysis of CHE. They are fixed threshold approach and ability to pay approach. The 'capacity to pay' approach has not been used in the current study, due to the limitations of NSS health surveys data, where in food and non-food expenditures are not a part of the questionnaire.

4.5. RESULTS

4.5.1. INCIDENCE, INTENSITY AND INEQUALITY OF CHE

Table 4.2 depicts the incidence, intensity and inequality of CHE among indian households disintegrated among rural and urban areas in the 4 rounds of NSSO surveys.

Incidence:

The incidence of CHE has risen in Indian households with each passing round of Health survey from 1995-96 to 2014. 52nd round saw the least incidence with 11.15 percent of Indian households facing CHE with 11.47 percent incidence in Rural and 10.27 percent in Urban. This period also witnessed the least share of OOPHE in consumption expenditure of 5.83 percent. The average share of OOPHE is also significantly higher in the rural areas at 6.32 percent than urban at 4.9 percent. In the 60^{th} round, the incidence has risen drastically to 19.69 percent nationally, with higher incidence in rural areas at 20.38 percent compared to the urban areas at 17.92 percent. The average share of OOPHE has also almost doubled during thiss time to 10.06 percent, with 11.11 percent in Rural and 8.46 percent in urban settings. This sudden rise signifies a rise in demand for healthcare services during the decade between 1995-2004.

This increasing demand for healthcare services has lingered to the 2010s with 71^{st} round witnessing the highest incidence at 23.45 percent. The difference between rural and urban has also comedown markedly with 23.61 percent and 23.12 percent in rural and urban areas respectively. The average share of OOPHE has also crept up to 11.82 but the rural urban disparity shrinked with 12.46 percent in rural and 11.82 percent in urban settings. However, the latest round witnessed a contraction in CHE incidence to 16.69 percent , with rural and urban incidence fairly similar to the national aggreagte at 16.97 percent and 16.12 percent respectively. This contraction in demand for healthcare services can be witnessed in the average share of OOPHE as well. The consumption expenditures have risen in both urban and rural settings from the previous rounds, but the OOPHE has gone down from the rpevious rounds, resulting in an average share of 8.47 percent in rural, 6.77 percent in urban areas amounting a national aggreagate of 7.68 percent of household consumption expenditure which is much less than the previous round's 11.82 percent.

Table 4.2: Incidence, Intensity and Inequality of Catastrophic Health Expenditure in India.

	NSS52			NSS60			NSS71			NSS75		
	Rural	Urban	India	Rural	Urban	India	Rural	Urban	India	Rural	Urban	India
Catastrophic Headcount (%)	11.47	10.27	11.15	20.38	17.92	19.69	23.61	23.12	23.45	16.97	16.12	16.69
Concentration Index	0.1270	0.0230	0.0894	0.0683	-0.0375	0.0249	0.0292	-0.0518	0.0036	0.0178	-0.0758	-0.0147
(Standard Error)	(0.0058)	(0.0072)	(0.0046)	(0.0051)	(0.0071)	(0.0042)	(0.0053)	(0.0058)	(0.0040)	(0.0049)	(0.0055)	(0.0037)
(P-Values)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.37)	(0.00)	(0.00)	(0.00)
Rank Weighted Index	10.01	10.03	10.16	18.99	18.59	19.20	22.92	24.31	23.37	16.67	17.35	16.94
Catastrophic Payment Gap (%)	3.82	2.93	3.59	13.83	6.22	11.70	9.76	8.49	9.35	6.42	5.16	6.01
Concentration Index	0.1284	-0.0059	0.0771	-0.2850	-0.1441	-0.3086	-0.0574	-0.1167	-0.0833	-0.0312	-0.1601	-0.0830
(Standard Error)	(0.0165)	(0.0270)	(0.0139)	(1.0229)	(0.2876)	(0.8283)	(0.0147)	(0.0166)	(0.0111)	(0.0128)	(0.0197)	(0.0109)
(P-Values)	(0.00)	(0.83)	(0.00)	(0.78)	(0.62)	(0.71)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)
Rank Weighted Index	3.33	2.94	3.31	17.77	7.11	15.31	10.32	9.48	10.12	6.62	5.99	6.51
Mean Positive Gap (%)	33.32	28.51	32.17	67.90	34.74	59.47	41.33	36.76	39.86	37.84	32.03	36.00
Concentration Index	0.0044	-0.0294	-0.0114	-0.3413	-0.1101	-0.3332	-0.0840	-0.0677	-0.0866	-0.0469	-0.0850	-0.0687
(Standard Error)	(0.0135)	(0.0216)	(0.0113)	(0.8057)	(0.2309)	(0.6560)	(0.0100)	(0.0112)	(0.0075)	(0.0084)	(0.0131)	(0.0071)
(P-Values)	(0.74)	(0.17)	(0.31)	(0.67)	(0.63)	(0.61)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Rank Weighted Index	33.17	29.35	32.53	91.08	38.56	79.29	44.80	39.25	43.31	39.62	34.75	38.47
Average HHCE (INR)	1,598.20	2,377.80	1,801.11	2,413.58	4,108.80	2,887.42	6,031.05	10,029.85	7,333.01	7,498.69	13,315.61	9,404.56
Average OOPHE (INR)	100.93	116.47	104.97	268.21	347.71	290.43	751.20	1,105.97	866.72	634.85	901.05	722.07
Avg Share (%)	6.32	4.90	5.83	11.11	8.46	10.06	12.46	11.03	11.82	8.47	6.77	7.68

Source: Author's Calculations from NSSO microdata. Notes: Standard Errors and P-Values in Parentheses; INR-Indian Rupee

Intensity:

Intensity of health OOP health expenditure catastrophe is measured using the Catastrophic Payent Gap (or overshoot) and Mean Positive Gap. CPG measures the average overshoot across all households while MPG measures the average over the households with CHE incidence.

Like with incidence, intensity is also lowest in the 52nd round with national CPG of 3.59 percent and MPG of 32.17 percent. The rural-urban disparity have also carried from the incidence section with CHE intensity higher among rural areas than the urban. The intesnity of catastrophe has risen drastically across next decade and reached a peak in 60th round with CPG of 11.70 percent and MPG of 59.47 percent. The rural-urban disparity was also drastic in this time period with rural areas facing much higher intesity of 13.83 percent CPG and 67.90 percent MPG compared to the urban intensity of 6.22 percent CPG and 33.74 percent MPG. This shows that during this round the rural households had to spend higher share of consumption expenditure on health service and the households facing CHE are also crossing the threshold by huge margins.

Compared to the 60th round, the next two rounds saw a significant drop in intensity of catastrophic payments. During the 71st round, the CPG and MPG has come down to 9.35 percent and 39.86 percent respectively. Since the last round, the difference between rural and urban intenities have also reduced. This intensity has further come down in the 75th round to 6.01 percent CPG and 36 percent MPG. This reduction in intensity during the last two rounds could be attributed th the drastic rise of household consumption expenditures in the years since the 60th round.

Inequality:

The inequality in distribution of CHE incidence and intensity is measured using concentration indexes (CIs). The CIs show a pro-rich distribution of CHE incidence during the 52nd round (CI=0.0894). The richer households were more likely to cross the 10 percent threshold level of consumption. This pro rich distribution is seen both in Rural (CI=0.1270) and Urban (CI=0.0230) settings. In 60th round, a similar pro rich distribution was seen at national level (CI=0.0249) as well as in rural areas (CI=0.0683), but here the urban areas witnessed a pro-poor distribution (CI=-0.0375), meaning poorer households were more likely to face CHE than richer households in urban areas, indicationg higher demand for health services among poor in urban compared to the poor in rural areas.

The rural-urban difference in inequality carried to the 2010s with both 71st and 75th round witnessing pro-rich distribution in the rural households (CIs: NSS71: 0.0292 ; NSS75: 0.0178) and pro-poor distribution in the urban households (CIs: NSS71: -0.0518 ; NSS75: -0.0758). During the 71st round, the CI was pro rich, but insignificant ($p>0.05$) but in the 75th round, the CI has turned pro-poor (CI=-0.014). The insignificant CI at national level in 71st round indicates an equal distribution of CHE incidence across income classes, as a result of rising OOP expenditures and CHE incidence among poor poor households in both the rural and urban areas. This suggests that at national level, the CHE incidence has transformed from pro-rich in 1995-96 to pro-poor in 2017-18. This means that poor households are increasingly more likely to face CHE than the rich.

In terms of inequlaity in intensity of catastrophic payments, the CPG was significantly pro-rich distributed in the 52nd round (CI=0.1284) but the MPG was insignificant. The CPG and MPG for 60th round were insignificant ($p>0.05$). In the last two round however, the intensity is significantly pro-poor distributed suggesting that the poor households are more likely to cross the thresahold by higher margins than the rich.

Table 4.3: Determinants of CHE incidence in Indian Households.

	NSS52				NSS60				NSS71				NSS75			
CHE@10%	OR	R.S.E.	P	95% C.I.	OR	R.S.E.	P	95% C.I.	OR	R.S.E.	P	95% C.I.	OR	R.S.E.	P	95% C.I.
Sector (Rural)																
Urban	0.76	0.028	0.00	0.7-0.81	0.79	0.032	0.00	0.73-0.85	0.94	0.041	0.15	0.86-1.02	0.96	0.039	0.27	0.88-1.04
Religion (Hindu)																
Islam					1.27	0.056	0.00	1.16-1.38	1.16	0.066	0.01	1.04-1.30	1.19	0.061	0.00	1.08-1.31
Christianity		-NA-			1.37	0.134	0.00	1.13-1.66	1.49	0.163	0.00	1.20-1.85	1.20	0.098	0.03	1.02-1.41
Others					1.02	0.079	0.78	0.88-1.19	1.27	0.127	0.02	1.04-1.54	1.27	0.117	0.01	1.06-1.52
Social Group (General)																
Scheduled Tribes	0.64	0.042	0.00	0.56-0.73	0.56	0.036	0.00	0.49-0.63	0.56	0.046	0.00	0.48-0.66	0.60	0.044	0.00	0.52-0.70
Scheduled Castes	1.04	0.046	0.33	0.96-1.14	0.91	0.040	0.03	0.83-0.99	0.89	0.055	0.06	0.79-1.00	0.84	0.046	0.00	0.76-0.94
Other Backward Classes		-NA-			0.95	0.032	0.13	0.89-1.01	0.90	0.041	0.03	0.83-0.99	0.86	0.035	0.00	0.79-0.93
Income Class (Poorest)																
Poorer	1.15	0.068	0.02	1.02-1.29	1.11	0.050	0.03	1.01-1.21	0.93	0.056	0.25	0.83-1.05	0.86	0.048	0.01	0.77-0.96
Middle	1.24	0.073	0.00	1.11-1.39	1.17	0.051	0.00	1.07-1.27	0.94	0.060	0.35	0.83-1.07	0.90	0.050	0.07	0.81-1.01
Richer	1.72	0.103	0.00	1.53-1.94	1.34	0.064	0.00	1.22-1.47	1.10	0.070	0.15	0.97-1.24	0.94	0.054	0.31	0.84-1.06
Richest	2.40	0.156	0.00	2.11-2.73	1.30	0.074	0.00	1.16-1.46	0.93	0.068	0.35	0.81-1.08	0.71	0.048	0.00	0.62-0.81
Type of Household (Self Employed)																
Regular Wage/Salaried	0.85	0.038	0.00	0.78-0.93	0.86	0.051	0.01	0.77-0.97	1.03	0.057	0.61	0.92-1.15	1.03	0.051	0.51	0.94-1.14
Labour	1.07	0.044	0.11	0.99-1.16	1.00	0.034	0.94	0.93-1.07	0.99	0.049	0.78	0.90-1.09	0.94	0.042	0.14	0.86-1.02
Others	0.93	0.053	0.17	0.83-1.03	1.09	0.053	0.08	0.99-1.20	1.33	0.106	0.00	1.13-1.55	1.03	0.067	0.66	0.91-1.17
HHSize>4 (No)																
Yes	1.35	0.048	0.00	1.26-1.45	1.38	0.041	0.00	1.30-1.46	1.24	0.051	0.00	1.14-1.34	1.01	0.038	0.85	0.94-1.08
Demographic Burden (No)																
Yes	1.77	0.061	0.00	1.66-1.90	1.73	0.047	0.00	1.64-1.82	1.95	0.083	0.00	1.79-2.12	2.44	0.091	0.00	2.27-2.63
Gender of Head (Male)																

Female	0.84	0.046	0.00	0.76-0.94	1.06	0.049	0.18	0.97-1.16	1.09	0.068	0.16	0.97-1.23	1.06	0.059	0.27	0.95-1.19
Transgender			-NA-				-NA-				-NA-		0.52	0.490	0.49	0.08-3.29
Education of Head (Illiterate)																
Informal literate	1.17	0.115	0.11	0.97-1.42	1.10	0.117	0.35	0.90-1.36	1.31	0.192	0.06	0.99-1.75	0.76	0.124	0.09	0.55-1.04
Below primary	0.98	0.052	0.65	0.88-1.08	1.05	0.051	0.34	0.95-1.15	1.28	0.088	0.00	1.12-1.47	1.12	0.073	0.09	0.98-1.27
Primary	1.15	0.060	0.01	1.03-1.27	1.21	0.052	0.00	1.11-1.31	1.17	0.072	0.01	1.03-1.32	1.05	0.059	0.35	0.94-1.18
Middle	1.12	0.057	0.02	1.02-1.24	1.29	0.056	0.00	1.18-1.40	1.19	0.073	0.01	1.05-1.34	1.07	0.061	0.21	0.96-1.20
Secondary	1.02	0.061	0.78	0.90-1.14	1.28	0.072	0.00	1.15-1.43	1.07	0.074	0.30	0.94-1.23	0.99	0.057	0.85	0.88-1.11
Higher secondary	0.87	0.073	0.10	0.74-1.03	1.18	0.090	0.03	1.02-1.37	0.96	0.081	0.65	0.82-1.13	1.01	0.072	0.86	0.88-1.16
Graduate & above	0.73	0.064	0.00	0.62-0.87	0.95	0.064	0.49	0.84-1.09	0.87	0.071	0.09	0.74-1.02	0.93	0.068	0.32	0.80-1.07
Medical Insurance (No)																
Yes	1.06	0.164	0.71	0.78-1.43	2.14	0.303	0.00	1.62-2.82	1.25	0.090	0.00	1.08-1.44	1.29	0.082	0.00	1.13-1.46
constant	0.09	0.007	0.00	0.08-0.11	0.19	0.013	0.00	0.17-0.21	0.24	0.022	0.00	0.20-0.29	0.20	0.016	0.00	0.17-0.24

Source: Author's Calculations from NSSO microdata.

Notes: OR: Odds Ratio; R.S.E.: Robust Standard Errors; P: P-value; 95%CI: 95% Confidence Interval.

Notes: -NA-: Not Applicable/Data Unavailable.

Notes: The parenthesis next to each variable contain the base criteria used for the regression.

4.5.2. DETERMINANTS OF CHE INCIDENCE IN INDIAN HOUSEHOLDS

The results of the logistic regression, depicted in Table 4.3, show that many of the socio-economic aspects have a significant impact on the CHE of the households. The results show that the households in urban areas were less likely to face CHE than the ones in rural India during the 52nd Round (Odds Ratio:0.76; 95%CI: 0.70-0.81) and 60th Round (Odds Ratio:0.77; 95%CI: 0.73-0.85). However, the later two rounds, 71st and 75th found an insignificant impact of Sector on the incidence

Unlike Sector, religion is found to have a significant impact on the incidence of CHE across all four rounds. People practicing minority religions (Islam, Christianity and others) face significantly high odds facing CHE due to OOP expenditure compared to the majority Hindus. Households belonging to Christianity were the most likely to face CHE during 60th Round (Odds Ratio:1.37; 95%CI: 1.13-1.66) and 71st Round (Odds Ratio:1.49; 95%CI: 1.20-1.85). The other religious minorities (viz., Sikhism, Jainism, Buddhism, Zoroastrianism etc.,) were the most likely to face CHE in 75th round (Odds Ratio:1.27; 95%CI:1.06-1.52).

However, households pertaining to socially vulnerable classes (castes) were significantly less likely to face CHE compared to the non-vulnerable 'Other Castes'. Scheduled tribes are the least likely to face CHE across all rounds with odds of 0.64, 0.56, 0.56 and 0.60 across the four rounds. Scheduled Castes were also significantly less likely to face CHE during 60th, 71st and 75th rounds with Odds of 0.91, 0.89 and 0.84 respectively. Other Backward Classes are also facing higher odds in the last two rounds (ORs: 0.90 and 0.86). This phenomenon of non-vulnerable classes facing less CHE likelihood could be a hinting at underutilisation of healthcare utilisation and low out-of-pocket payments for the health services.

The results also indicate that the economically vulnerability is an impact factor for CHE incidence. When compared among the five quintiles of household consumption expenditure, the quintiles Q2 through Q5 were more likely to face CHE than the Q1 i.e., poorest quintile in 52nd Round (Odds Ratios: Q2-1.15, Q3-1.24, Q4-1.72, and Q5-2.40) and 60th Round (Odds Ratios: Q2-1.11, Q3-1.17, Q4-1.34, and Q5-1.30). During the 70th round, the income class was an insignificant factor but the relationship reversed in the 75th round with richer households much less likely to face the CHE than the poor (Odds Ratios: Q2-0.86, Q3-0.90, Q4-0.94, and Q5-0.71). This is consistent with the Concentration Indexes of the respective rounds. The first 2 rounds have the

burden of OOP concentrated in richer households while the burden has slowly shifted to the poorer households in the latest round.

Type of household i.e., type of employment is an insignificant factor in assessing the likelihood of CHE incidence in a household. Household size, however is a significant factor with larger households (with 5 or above members) are more likely to face CHE than the small households during the first 3 rounds (Odds Ratios: NSS52- 1.35; NSS60- 1.38; NSS71- 1.24). The size of the household is an insignificant factor during the latest 75th round. Demographic Burden is another major factor impacting the CHE incidence in Indian households. Households with members above 60 years of age are significantly more likely to face CHE, more than twice as likely in the latest 75th round (Odds Ratio: 2.44; 95%CI: 2.27-2.63).

Households with female heads were less likely to face CHE during the 52nd round (Odds Ratio: 0.84; 95%CI: 0.76-0.94) compared to the households with male heads, but the gender of head has been an insignificant factor in the remaining rounds. Education level of the head of the household is also fairly insignificant across the rounds. Only the households with heads literate at primary to secondary level having any significant Odds at facing CHE. These households were more likely to face CHE compared to the households with illiterate heads during the first 3 rounds. Level of education is an insignificant factor in the 75the round. Medical Insurance was an insignificant factor in the first round but the later, the households with medical insurance were more likely to face CHE than the households without medical insurance (Odds Ratios: NSS60- 2.14; NSS71- 1.25, NSS75- 1.29), suggesting a better utilisation or more demand for medical insurance in these households.

Section II: Out-Of-Pocket Health Expenditures and their Impoverishment Effects in Indian Households

4.6. METHODOLOGY

The current study adapts the methodology of Wagstaff and Doorslaer (2003) to estimate the incidence of illness induced poverty, which was further popularized by Flores (2008) and Berman et.al., (2010). The impoverishment impact of health expenditures is measured as the difference between the pre-payment and post-payment poverty estimates of headcounts and their poverty gaps.

The first step is to identify the poverty line for the population and for the current study the poverty line suggested by the SR Tendulkar Committee in 2004, which was accepted by the Planning Commission of India, is used. The poverty line for Rural and Urban areas are defined separately for the year 2004-05. Using the Consumer Price Index (CPI) data, the poverty lines were inflated and deflated to arrive at the poverty lines for the years of the four surveys in the study. CPI-Agricultural Labour and CPI-Industrial Workers were used for Rural and Urban poverty line estimations respectively.

Impoverishment Headcount

Impoverishment headcount is the difference between headcounts of pre-payment and post-payment poverty headcounts. Denoting S_i for size of the household, E_i for percapita consumption expenditure, HE_i as health expenditure of the household and PL as poverty line. Poverty headcount before payments of healthcare is denoted HC^{pre}, and poverty headcount after the payment of healthcare is denoted HC^{post}.

$$HC^{pre} = \frac{\sum_{i=1}^{n}(S_i P_i^{pre})}{\sum_{i=1}^{n}(S_i)}$$

Where P_i^{pre}=1 if $E_i < PL$ and 0 otherwise.

$$HC^{post} = \frac{\sum_{i=1}^{n}(S_i P_i^{post})}{\sum_{i=1}^{n}(S_i)}$$

Where P_i^{post} =1 if $(E_i - HE_i) < PL$ and 0 otherwise.

Using HC^{pre} and HC^{post} the impoverishment headcount $ImpHC$ is derived as follows:

$$ImpHC = HC^{post} - HC^{pre}$$

Poverty Gap

Poverty Gap also known as overshoot is used to measure the intensity of impoverishment. It measures the extent by which the households are falling below the poverty line. G_i^{pre} and G_i^{post} measure the overshoot before and after healthcare payments for the households.

$$PG^{pre} = \frac{\sum_{i=1}^{n}(S_i G_i^{pre})}{\sum_{i=1}^{n}(S_i)}$$

Where G_i^{pre}=P_i^{pre} $(PL - E_i)$.

$$PG^{post} = \frac{\sum_{i=1}^{n}(S_i G_i^{post})}{\sum_{i=1}^{n}(S_i)}$$

Where G_i^{post}=P_i^{post} $(PL - (E_i - HE_i))$.

The study also uses Mean Positive Gap (MPG), which measures the average overshoot for the impoverishment induced households. A MPG ratio is calculated to compare the overshoot intensity across rural and urban sectors and across the four survey rounds.

$$MPG^{pre} = \frac{\sum_{i=1}^{n}(S_i G_i^{pre})}{HC^{pre}}$$

$$MPG^{post} = \frac{\sum_{i=1}^{n}(S_i G_i^{post})}{HC^{post}}$$

Socio-economic Determinants of Impoverishment

The current study also tries to identify the socio-economic features of the households that may be exposing the household to a greater risk of illness induced impoverishment. The estimation approach used for impoverishment incidence results in an impoverishment variable with two outcomes, household not facing impoverishment and households facing impoverishment. Owing to the binary nature of the variable the study chose to execute a multiple binary logistic regression model to estimate the determinants.

Let the probability distribution of Y_i be:

$P_i = Prob(Y_i = 1)$= Household facing impoverishment

$1 - P_i = Prob(Y_i = 0)$= Household not facing impoverishment

The logistic probability distribution function can be:

$$Pi = \frac{1}{1+e^{-(\beta_0+\beta_i X_i)}} \quad \text{---------- (1)}$$

$$Pi = \frac{1}{1+e^{-zi}} = \frac{e^z}{1+e^z} \quad \text{----------(2)}$$

Where

$$Zi = \beta_0 + \beta_i Xi$$

Equation (3) represents what is known as the (cumulative) logistic distribution function.

$$1 - Pi = \frac{1}{1+e^{zi}} \quad \text{----------(3)}$$

Therefore, we can write

$$\frac{\mathbf{Pi}}{\mathbf{1-Pi}} = \frac{\mathbf{1+e^{Zi}}}{\mathbf{1+e^{-Zi}}} = \mathbf{e^{Zi}} \quad \text{----------(4)}$$

Now $P_i/(1-P_i)$ is simply the odds ratio in favour of household facing impoverishment due to OOPHE or the ratio of probability that the household will face impoverishment due to health payments to the probability that the household will not face impoverishment. The current study reports the Odds Ratios for the independent variables. An odds ratio of 1 means the 'odds' of the household belonging to the category are the same as that of the reference category. An odds ratio less than 1 indicates lower odds, while more than 1 indicates higher odds of respective category compared to the reference category.

The independent variables used in this study include socio economic characteristics of the households like the sector, religion, social class, type of employment, household size and economic class. Monthly percapita consumption expenditure is used as a proxy of wealth due to the lack of an income variable in the survey questionnaire and subsequently 5 wealth quintiles were generated based on the same. Demographic burden (people aged 60 and above) is also considered along with the medical insurance status of the household. In addition, the gender and education level of the head of the household are used as predictor variables.

Table 4.4: Headcounts of Impoverishment due to OOP Payments

		NSS52		NSS60		NSS71		NSS75	
		Households	Headcount	Households	Headcount	Households	Headcount	Households	Headcount
Rural	Population Count	12,62,95,434	63,70,15,034	14,32,06,617	71,50,76,540	16,75,54,984	78,49,54,357	17,62,34,124	80,42,73,325
	Poverty Counts								
	Prepayment	7,65,23,334	42,61,52,898	7,07,27,019	39,61,21,843	6,61,53,484	34,75,17,985	4,85,51,189	25,37,11,634
	(% of population)	60.59	66.90	49.39	55.40	39.48	44.27	27.55	31.55
	PostPayment	8,09,64,055	44,81,20,592	8,07,89,002	44,54,76,285	7,94,48,052	41,07,59,065	5,92,28,846	30,22,93,814
	(% of population)	64.11	70.35	56.41	62.30	47.42	52.33	33.61	37.59
	Impoverished	44,40,721	2,19,67,693	1,00,61,983	4,93,54,443	1,32,94,568	6,32,41,080	1,06,77,657	4,85,82,180
	(% of population)	3.52	3.45	7.03	6.90	7.93	8.06	6.06	6.04
Urban	Population Count	4,44,36,920	20,33,77,456	5,55,64,052	24,38,46,348	8,09,02,797	33,61,47,252	8,58,79,615	33,59,14,229
	Poverty Counts								
	Prepayment	1,36,76,216	7,85,79,785	1,34,60,205	7,53,18,170	1,54,68,613	8,57,99,558	84,25,141	4,49,66,186
	(% of population)	30.78	38.64	24.22	30.89	19.12	25.52	9.81	13.39
	PostPayment	1,50,89,008	8,55,44,105	1,64,65,955	8,99,09,581	2,13,86,765	11,25,94,998	1,21,42,082	6,14,48,044
	(% of population)	33.96	42.06	29.63	36.87	26.44	33.50	14.14	18.29
	Impoverished	14,12,792	69,64,320	30,05,750	1,45,91,411	59,18,152	2,67,95,440	37,16,941	1,64,81,859
	(% of population)	3.18	3.42	5.41	5.98	7.32	7.97	4.33	4.91
Total	Population Count	17,07,32,353	84,03,92,489	19,87,70,669	95,89,22,889	24,84,57,782	1,12,11,01,609	26,21,13,740	1,14,01,87,554
	Poverty Counts								
	Prepayment	9,01,99,550	50,47,32,684	8,41,87,224	47,14,40,012	8,16,22,097	43,33,17,543	5,69,76,330	29,86,77,819
	(% of population)	52.83	60.06	42.35	49.16	32.85	38.65	21.74	26.20
	PostPayment	9,60,53,063	53,36,64,697	9,72,54,958	53,53,85,866	10,08,34,817	52,33,54,063	7,13,70,929	36,37,41,858
	(% of population)	56.26	63.50	48.93	55.83	40.58	46.68	27.23	31.90
	Impoverished	58,53,513	2,89,32,014	1,30,67,734	6,39,45,854	1,92,12,720	9,00,36,520	1,43,94,599	6,50,64,039
	(% of population)	3.43	3.44	6.57	6.67	7.73	8.03	5.49	5.71

Source: Author's Estimations from NSSO microdata.

Table 4.5: Payment Gaps due to OOP Payments

	INR. (₹)	NSS 52	NSS60	NSS71	NSS75
Rural	Overshoot Pre OOP	41,12,53,01,204	47,05,41,25,882	97,72,20,07,012	64,07,44,94,494
	Overshoot Post OOP	49,37,16,97,968	71,63,85,41,938	1,69,14,05,03,712	1,21,94,96,63,584
	PG Pre OOP	64.559	65.803	124.494	79.668
	PG Post OOP	77.505	100.183	215.478	151.627
	Poverty Induced Gap	12.945	34.380	90.984	71.960
	MPG Pre OOP	96.504	118.787	281.200	252.549
	MPG Pos OOP	110.175	160.813	411.775	403.414
	MPG Ratio	1.142	1.354	1.464	1.597
Urban	Overshoot Pre OOP	7,45,67,76,224	10,73,02,15,316	27,38,75,09,754	14,63,91,54,811
	Overshoot Post OOP	9,70,36,77,960	19,14,35,97,082	63,60,37,94,985	38,63,66,15,228
	PG Pre OOP	36.665	44.004	81.475	43.580
	PG Post OOP	47.713	78.507	189.214	115.019
	Poverty Induced Gap	11.048	34.503	107.739	71.439
	MPG Pre OOP	94.894	142.465	319.203	325.559
	MPG Pos OOP	113.435	212.921	564.890	628.769
	MPG Ratio	1.195	1.495	1.770	1.931
Total	Overshoot Pre OOP	48,58,20,77,428	57,78,43,41,198	1,25,10,95,16,766	78,71,36,49,305
	Overshoot Post OOP	59,07,53,75,928	90,78,21,39,020	2,32,74,42,98,697	1,60,58,62,78,812
	PG Pre OOP	57.809	60.260	111.595	69.036
	PG Post OOP	70.295	94.671	207.603	140.842
	Poverty Induced Gap	12.486	34.411	96.008	71.806
	MPG Pre OOP	96.253	122.570	288.725	263.540
	MPG Pos OOP	110.698	169.564	444.717	441.484
	MPG Ratio	1.150	1.383	1.540	1.675

Source: Author's Estimations from NSSO microdata.

4.7. FINDINGS

4.7.1. Impoverishment Estimates

Incidence of impoverishment is shown in Table 4.4. The poverty levels have come down at the national level from 52.83% of households to 21.74% in the period under consideration, before the payment of any OOP expenditures. Similarly, post OOP payment poverty levels also dropped from 56.26% to 27.23% in the same period. The resulting illness induced impoverishment estimate follows a similar trend to the average share of OOP expenditures, increasing from 3.43% of the households in 1995-96 to 7.73% in 2014 and dropping to 5.49% in 2017-18. The rural and urban households have major difference in poverty levels. The poverty headcounts are twice as high for the rural areas compared to the urban. The illness induced poverty incidence is also higher among the rural households.

Intensity of impoverishment is depicted in Table 4.5. Like the incidence of impoverishment, intensity also gradually increased between 1995-96 and 2014 with illness induced poverty gap growing from 12.49/- to 96.01/- and had a significant drop in 2018 to 71.81/- . Although the poverty gap has reduced, the Mean Positive Gap has continued to widen post 2014. The MPG ratio has gone up from 1.15 in 1995-96 to 1.54 in 2014. This ratio further rose to 1.675 in 2018, suggesting that the intensity of poverty gap is much deeper among the population impoverished due to OOP payments.

Table 4.6: Logistic Regression of Socio-economic Determinants of Impoverishment Incidence in Indian Households

	NSS 52		NSS 60		NSS 71		NSS 75	
	Odds Ratio	95% Conf.Interval	Odds Ratio	95% Conf.Interval	Odds Ratio	95% Conf.Interval	Odds Ratio	95% Conf.Interval
Sector (Rural)								
Urban	0.677*	0.601-0.762	0.600***	0.538-0.670	1.005	0.889-1.136	1.072	0.949-1.211
Religion (Hindu)								
Islam			1.172*	1.021-1.346	1.083	0.915-1.283	1.033	0.883-1.208
Christianity			1.472	0.960-2.258	1.436*	1.001-2.059	1.138	0.863-1.500
Others			0.893	0.708-1.126	1.046	0.766-1.429	1.413*	1.052-1.899
SocialGroup (Other)								
ST	0.637***	0.488-0.832	0.406***	0.316-0.522	0.595***	0.457-0.776	0.587***	0.456-0.756
SC	1.042	0.900-1.205	0.933	0.813-1.071	0.880	0.729-1.063	0.916	0.775-1.083
OBC			0.964	0.870-1.068	0.891	0.774-1.025	0.825**	0.728-0.936
Income Class (Richest)								
Poorest							0.122***	0.065-0.232
Poor			0.602***	0.467-0.776	3.363***	2.718-4.161	10.415***	8.389-12.930
Middle	1.332***	1.118-1.588	4.096***	3.543-4.736	4.883***	3.970-6.006	5.127***	4.137-6.356
Richer	2.262***	1.939-2.638	2.448***	2.109-2.842	2.509***	2.043-3.082	2.661***	2.138-3.313
Household Type (Self-Employed)								
Regular Wage/Salaried	0.966	0.828-1.126	1.151	0.957-1.385	0.972	0.817-1.158	1.012	0.865-1.185
Labour	1.385***	1.202-1.595	0.986	0.885-1.098	0.954	0.818-1.113	0.847*	0.737-0.974
Others	1.108	0.927-1.324	1.286**	1.099-1.505	1.267*	1.002-1.602	1.355*	1.095-1.678
Household Size	1.058***	1.036-1.080	1.025**	1.007-1.044	1.029*	1.000-1.059	0.971*	0.944-0.999
Child (No Child)	1.223***	1.084-1.379	1.084	0.977-1.203	1.140*	1.003-1.297	1.222***	1.083-1.379
Old (No Old)	1.358***	1.211-1.523	1.604***	1.448-1.776	1.587***	1.395-1.805	1.887***	1.678-2.122
Gender of Head (Male)								
Female	0.774**	0.649-0.925	0.965	0.834-1.118	1.010	0.834-1.224	1.050	0.881-1.251
Transgender							2.702	0.475-15.377

Education of Head (Illiterate)								
Upto Primary	1.010	0.883-1.155	1.073	0.957-1.202	1.127	0.962-1.320	1.139	0.981-1.323
Secondary	1.012	0.871-1.176	1.177**	1.046-1.325	1.078	0.927-1.255	1.136	0.984-1.312
Graduation and Above	0.701**	0.537-0.915	1.016	0.825-1.250	0.932	0.720-1.205	1.154	0.910-1.463
Medical Insurance (No)	0.939	0.543-1.626	1.512	0.952-2.403	1.128	0.905-1.405	1.370**	1.093-1.718
Constant	0.039***	0.030-0.051	0.054***	0.043-0.069	0.025***	0.019-0.035	0.011***	0.008-0.016

Source: Author's Calculations from NSSO microdata.

Notes: The parenthesis next to each variable contain the base criteria used for the regression.

Notes: p-values : <0.5 = * ; <0.01 = ** ; <0.001 = ***

4.7.2. Socio-Economic Determinants of Impoverishment Incidence

The results of the logistic regression, depicted in Table 4.6, show that many of the socio-economic aspects have a significant impact on the CHE of the households. The results show that the households in urban areas were less likely to face CHE than the ones in rural India during the 52nd Round (Odds Ratio:0.677) and 60th Round (Odds Ratio:0.600). However, the latter two rounds, 71st and 75th found an insignificant impact of Sector on the incidence.

Religion is found to be a weakly significant with the groups of Islamic, Christian, and other minor religious faiths facing higher odds of impoverishment incidence in the 60th, 71st and 75th round respectively. And among social groups, only Scheduled Tribes (ST) were significantly less likely to face to face impoverishment than the non-vulnerable castes with odds ratios of 0.637, 0.406, 0.595, and 0.587 across the four rounds. This lower likelihood coupled with low OOPHE shares in consumption expenditure suggest a significant underutilization of health services among this group.

The results also indicate that the economically vulnerability has the most impact on impoverishment incidence. During the 52nd round, the two bottom quintiles do not have an estimated odds ratio since they are facing poverty even without the inclusion of OOPHE. In the subsequent two rounds this scenario is restricted to the bottom quintile. In the remaining quintiles, when compared against the richest quintile the remaining groups tend to have higher odds of facing impoverishment. In the 52ns round, Q3 and Q4 were facing higher odds of 1.332 and 2.262 respectively. In the 60th round, Q3 were 4 times more likely of facing impoverishment than the Q5 while Q4 were more than twice as likely. Similarly, the poorer quintiles in 71st round were more than twice as likely to face impoverishment (Odds Ratios: Q2-3.363, Q3-4.883, and Q4-2.509). In the latest round, the households of Q2 were 10 times as likely to face expenditure induced impoverishment than the richest Q5. Even the relatively richer Q3 and Q4 face significantly higher odds of 5.127 and 2.661 respectively. However, Q2 in 60th round and Q1 in 75th round have significantly low odds which could be due to the few households that managed to escape poverty classification being wary of health payments.

Type of household i.e., type of employment the household relies primarily on for consumption expenditure is an insignificant factor in assessing the likelihood of impoverishment incidence with only households relying on other menial jobs facing higher odds than the self-

employed households. Household size, however, is a significant factor with larger households having slightly higher odds of facing impoverishment in the first three rounds but the odds have revered in the recent round suggesting lower incidence for higher household sizes. Demographic Burden is another major factor impacting the impoverishment incidence in Indian households. Households with at least one kid aged 6 or under have higher odds than the households with no children (Odds Ratios: 52nd-1.223; 60th-1.084; 71st-1.140; 75th-1.222). Similarly, households with members above 60 years of age are significantly more likely to face CHE across all rounds (Odds Ratios: 52nd-1.358; 60th-1.604; 71st-1.587; 75th-1.887).

Gender of the household head is an insignificant estimator across the rounds. Similarly, education level of the household head has no significance especially in the latest two rounds. Medical Insurance too was an insignificant factor in the first in the first three rounds. However, in the latest round, the households with medical insurance have higher odds (OR: 1.370) of facing impoverishment than the ones without suggesting a better utilization or more demand for medical services in medically insured households.

4.8. CONCLUSIONS

In order to design appropriate health policy, it is important to identify households who are more vulnerable to OOP health expenditure. Findings of the current study reveal that the demand for healthcare services has increased gradually during the period 1995-2014 but this demand is primarily financed from out-of-pocket expenditures and hence leading to an increasing risk of financial catastrophe. But in the latest round, 75th round of the survey, the incidence of CHE has reduced drastically. During this period, a reduction in OOPHE is witnessed, which could not be attributed to reimbursements either. Table 4.1 shows a substantial reduction in total health expenditure per households. This sudden reduction in the share of health expenditure in consumption expenditure suggests a contraction in demand for healthcare services.

The present paper has managed to identify a few household characteristics that influence the chances of household catastrophe due to out-of-pocket healthcare payments. The results show that economic and social vulnerability (religion and social group) have a significant impact on the likelihood of CHE incidence of the households. The results also show that a household can face CHE irrespective of the type of employment they rely on or the gender and education endowments

of the household head, and having a medical insurance might result in better utilisation of health services.

More alarmingly, the catastrophic burden is moving from the rich to the poor. During the earlier rounds, the richer households were bearing the burden of CHE more but the latest round witnessed a shift to poorer households both in rural and urban areas. The results of the study suggest that a targeted approach is required to alleviate the socially and economically vulnerable households from health expenditure catastrophe.

The poverty levels witness a linear downward trend through the rounds which is to be expected since the same poverty line from 2004-05 was used in the estimation, albeit adjusted for inflation. Rapidly growing economy provides increasing opportunities and presents new expenses that households would want to spend on. In this new reality, poverty should be defined as a lack of income to pay for these opportunities, rather than living on the edge of hunger (Gaur & Rao 2020).

The present paper has managed to identify a few household characteristics that influence the chances of household facing poverty due to out-of-pocket healthcare payments. The place of residence influences the risk of impoverishment. Economical vulnerability is the most important determinant of medical expenditure induced impoverishment. Social vulnerability and primary employment type of the household has little to no effect on the impoverishment incidence. The demographic composition of the households also has an impact on the risk. Households with higher size, and presence of children or aged have higher odds of impoverishment. However, gender and education level of household head have little to no effect. The results also show that medical insurance is ineffective against protection from impoverishment due to medical expenses.

During the time between 71st and 75th round, India's percapita government health spending has gone up from INR 913 in 20113-14 to an estimated INR 1,657 in 2017-18 (NHP, 2019). This monetary increase in public spending could have helped alleviate the burden of OOPHE in the Indian households. However, the share of public spending is only 32 percent of total health expenditure in India. 68.1 percent of health spending is private, with 63.2 percent coming out-ot-pocket (NHA, 2016-17). Another reason for the high OOP expenditure is the lack of insurance coverage. Only 14 percent of rural and 19 percent of urban population have medical insurance. of these, only 13 percent rural and 9 percent urban population are covered by

government healthcare schemes (NSS, 2019). Table 1 also shows that only 3.4 percent of total household health expenditure is reimbursed in 2018, indicating a low insurance penetration in India.

The governments at state and central level have health insurance schemes like, Rajiv Aarogyasri Health Insurance Scheme (RAS), Rashtriya Swasthya Bima Yojana (RSBY) and Chief Minister's Comprehensive Health Insurance Scheme (CMCHIS), to alleviate the poor from financial catastrophe due to healthcare spending but they have not been able to reduce OOP burden (Karan et al., 2017). This could be due to limited outpatient cover and low insurance caps, like in the case of flagship program RSBY where outpatient episodes are not included, and the inpatient cover is capped at 30,000/- (~$400) for a family of five on a floater basis. However, the central government has a new scheme, Ayushman Bharat Pradhan Mantri Jan Arogya Yojana (PM-JAY) to achieve the vision of Universal Health Care. This scheme is an improvement over the RSBY due to an increased coverage of up to INR 5,00,000/- (~$6,700) and no limitation of family size and age. This scheme is set to apply for 21.24 crore (212 million) households belonging to poor and vulnerable population (PM-JAY Report, 2022). This could be a crucial step in the right direction to alleviate catastrophic payment burdens in Indian households.

CHAPTER V

FINDINGS AND SUGGESTIONS

5.1. INTRODUCTION

Investment in human capital in the form of education, health, and on-job-training are considered to be important for individual wellbeing and economic development. Michael Grossman developed his model of demand for health. According to Grossman, the individual makes investment or demand health because health is both consumption and investment good. The demand model developed by Grossman (1972a) in his paper comprised one individual who planned investments in health over the lifecycle. Illness calls for a measure (curative health care) to restore the level of health. Good health is crucial for the wellbeing of the individuals as well as for the nation.

Improved health promotes economic growth in four ways, according to the World Development Report (1993): (1) it reduces productivity losses brought on by worker illness; (2) it allows the use of natural resources that were previously completely or nearly inaccessible due to disease; (3) it increases the enrolment of children in school and improves their academic performance; and (4) it frees up resources that would otherwise have to be used for treating illness. Illness on the other hand is a factor of social and economic stagnation and considered to be a key determinant of poverty. In a developing country like India, health expenditure accounts for under 5 percent of GDP out of which public health expenditure constitutes about 1 percent of GDP. Hence health expenditure is dominated by private spending with household out of pocket (OOP) health payments constituting the single largest component of total health expenditure. The absence of proper health protection mechanisms like health insurance and high health payments leads to catastrophe and a major cause of debt and poverty in India (Van Doorslaer 2007 and Garg and Karan 2009).

Keeping the points mentioned above in mind, the present study proceeded to examine the following five objectives:

- Testing the long-term relationship between growth and health (health-led growth hypothesis) in India.
- Finding the determinants of Out-of-Pocket Healthcare Expenditure in India.

- ❖ Estimating the incidence and determinants of Catastrophic Health Expenditure (CHE).
- ❖ Estimate the level and determinants of impoverishment due to Out-of-Pocket Healthcare Expenditures.

The objectives were examined using secondary data. The data for the healthcare expenditures and GDP will be acquired from various government publications. And the data for household expenditures, and other social indicators like income, age composition and social status will be acquired from the NSS 75th Round, 71st Round, NSS 60th Round and 52nd Round.

5.2. FINDINGS FROM THE STUDY

Findings from current study are listed as follows. The findings from secondary data on healthcare financing in India are:

- Health expenditure has seen a favorable shift towards the public side since 2008. The share of public expenditure in total health expenditure has gone up from 23 percent in 2008 to 37 percent in 2020.
- This increase in public health expenditure share also helped reduce the OOPHE share from 69 percent to 51 percent in the same time period.
- However, the overall health expenditure percapita has remained stagnant around ~55-60 USD since 2013. This stagnant expenditure resulted in a reduction of health expenditure share in GDP from 3.75 percent in 2013 to 2.96 percent in 2020. This shows a contraction in demand for healthcare services in India.

The analysis of long run relationship between health expenditures and GDP of India using ARDL cointegration yielded the following results.

- A look at the national accounts shows that the private expenditures on health had a significantly higher uptrend in India than the public health expenditures.
- GDP and health expenditures have a long-term cointegrating relationship in India, validating the existence of health led growth hypothesis in India
- The Government health expenditures are found to positively impact the national income of India, while the private expenditure is found to have no statistically significant impact

Demographic trends in India from the four rounds of NSSO surveys found the following.

- India is witnessing a demographic transition from rural to urban. But it is still largely a rural dominant country with more than 70 percent population living in Rural areas in 2018.
- India is largely a Hindu country, with more than 80% of the population being Hindu. From 12.3 percent in 1995 to 14.13 percent in 2018, the population percentage of Muslims has seen a small increase. Christians make up a minority of 2.5% of the population and Sikhs 2%, respectively.
- More than 25 percent of the population still rely on incomes from casual labour.
- The households with stable salaries/wages doubled in the 23-year period understudy, but they still form only under 20 percent of total population in 2018.
- India also has a large labour pool, with more than 50% of the population between the ages of 15 and 50 being considered productive. This group's percentage rose with time, rising from 51.33 percent in 1996 to 58.12 percent in 2018.
- During this time, the burden of the ageing population increased, rising from 11.88 percent in 1996 to 15.51 percent in 2018.
- In terms of social group (also known as caste), OBCs make up the largest portion of India's population with over 45 percent of the total, while the general category makes up 26.39 percent of the total. Scheduled caste and tribe populations make up 20% and 10% of the total population, respectively.
- Over the four rounds, India has seen some encouraging improvements in the field of education. By 2018, 74 percent of people were literate, up from 51 percent in 1996. Additionally, there have been noticeable gains in education levels above the primary level. However, as of 2018, there are still 26.07 percent of illiterate Indians.
- The demographic trends found significant correlations between the social group, employment (Household type) and economic class.
- While the vulnerable social groups (ST/SC/OBC) have significantly higher shares of the population relying on less stable incomes based on casual labour, the distribution of classes by type of livelihood shows that non-vulnerable social groups (OCs) have higher levels of stable incomes, particularly in the form of regular salaries/wages.

- While a large portion of the poor classes rely on incomes from labour that are significantly less steady in nature, the wealthy households have higher shares of people reliant on regular wage/salaried income.
- Vulnerable social groups rely more on livelihoods that have fewer stable pay-outs and hence tend to stay in poorer income quintiles.
- Medical Insurance penetration is very low in India. Nearly 85% of the overall population is not covered by any form of insurance in both 2014 and 2018. Coverage by non-govt. employers and private insurance schemes is only ~1 percent. This could also be leading to burdens of OOPHE health expenditures in Indian households.

The utilisation patterns in Indian households show the following trends.

- A transitional shift in utilisation from private to public healthcare facilities is seen in both inpatient and outpatient episodes.
- More than 50 percent of inpatient hospitalisations happened in public facilities in 2018 which is higher than the 40 percent utilisation in 2004.
- In terms of outpatient episodes, majority of population still rely on private facilities with ~70 percent in 2018. However, the public utilisation rate improved from 19.41 percent to 30.16 percent during the period under study.
- The transition is found to be faster in rural areas, households of vulnerable social classes, lower economic quintiles, and less stable incomes. Additionally, households relying on government insurance schemes are found to have higher public facility utilisation than the national average.
- This transitional trend could be a result of improvements in the public healthcare market (proxied by increased investments in healthcare by government in past decade), and a disproportionate increase in average expenditures at private facilities.
- The data shows the rising expenses in public and private facilities for inpatient care. However, the rate of growth in private institutions is much higher than the public institutions. The average inpatient expenditure at public institutes has gone up from 2,117 to 4,489 in the period under study. In the same period the private bills went up from 4,653 to 32,158. This rising gap between public and private facility bills might be pushing households, especially vulnerable sections towards public facilities.

The consumption expenditures and health spending in Indian households have seen the following patterns.

- At the national level, consumption spending increased over the rounds from 1,801 per month in 1995–1996 to 9,404 per month in 2017–18. The OOPHE, however, climbed from 105/- in 1995–1996 to 867/– in 2014 before suddenly declining to 722/– in 2017–2018. As a result, the average share of OOPHE in HHCE decreased significantly during these two decades, from 11.82 percent to 7.68 percent. This reduction in OOPHE share is in line with dropping OOP percapita at national level.
- The inpatient expenses rose from INR 282.42/- from 1995-96 to INR 3932.68/- in 2014. However, both inpatient and outpatient expenses have dropped significantly in the 2017-18 period hinting at a reduction in demand for healthcare services.
- Urban households spend significantly more on ill-episodes compared to the rural and the disparity has risen drastically during the period of study.

The results from two-part model show the socio-economic determinants of OOP expenditures in Indian households. The empirical analysis found the following:

- Households in urban India are far more likely to face OOP than the rural households and spend more signifying that Urban households are vulnerable to OOP payments.
- Economic vulnerability has a higher impact than social vulnerability on OOP incidence and intensity.
- The Religious minorities have a higher likelihood of facing OOPHE but no significant differences in amount spent.
- Social vulnerability has no impact on likelihood of OOPHE but has a negative impact on the amount of OOP possibly hinting at a lower utilisation in general. Additionally, this could be due to higher public facility utilisation in these groups.
- Compared to the Median economic group, richer households are more likely to incur OOPHE while poorer households are less likely. The spending on healthcare is also proportional to their standing in wealth quintiles. The poorer households have negative coefficients indicating lesser expenditures and richer households have positive coefficients indicating higher expenditures.
- Larger households are more likely to spend and are likely to spend more.

- Household age composition is a significant indicator given the households with children and aged persons are more likely to face OOPHE. This shows the prevalence of demographic burden in Indian households.
- The education level of household head has a positive impact on the healthcare demand of the household.
- Medically insured households are more likely to face OOPHE but has no significant impact on OOPHE possibly signifying the ineffectiveness of medical insurance in alleviating OOPHE burden in Indian households.

The burden of the OOP expenditures on households is analysed using logistic regressions. The burden is further decomposed into financial catastrophe and impoverishment due to OOP spending. The following findings are pertaining to the analysis of household catastrophe due to OOP health expenditures.

- The incidence of CHE has risen in Indian households along with the OOPHE shares from 11.15 percent in 1995 to 23.45 percent in 2014. Then there was a drop to 16.69 percent in 2018.
- The rural urban differences in CHE incidence have also gone down over the period of study. This signifies that the OOPHE burden is affecting households of all sectors.
- The intensity of catastrophic payments too has gone down in the last two rounds, possibly due to the drastic rise in household consumption expenditures over time across Indian households.
- However, the inequality estimates (Concentration Indexes) show that, more alarmingly, the catastrophic burden is moving from the rich to the poor.
- During the earlier rounds, the richer households were bearing the burden of CHE more, but the latest round witnessed a shift to poorer households both in rural and urban areas.
- The incidence started to turn pro poor in the recent 75th round while the intensity has been pro rich from 71st round.
- The incidence has been pro poor in urban areas for the past three rounds signifying the excess burden being faced by urban poor.
- The results of regression analysis show that the CHE incidence is not affected by the sector of the household

- The results also show that economic and social vulnerability (religion and social group) have a significant impact on the likelihood of CHE incidence of the households.
- The religious minorities were found to face more burdens than the majority Hindus.
- The socially vulnerable households face lower odds of facing CHE than the non-vulnerable OCs, hinting at underutilisation of health services in these classes and low OOP payments.
- The income class of the households is a significant factor with the richer households facing more CHE likelihood in the first two rounds. But the odds ratios were insignificant in 71st round and started to reverse in the 75th round. This reversal validates the shifting of CHE burden from pro rich to pro poor.
- The results also show that a household can face CHE irrespective of the type of employment they rely on or the gender and education endowments of the household head.
- The household composition, i.e., size of the household and the demographic burden are found to be significant factors. The households of size 5 and above and households with people aged 60 and above are found to face more CHE burden.
- The presence of medical insurance also does not help the CHE alleviation possibly due to low penetration in India.

Additionally, burden of OOPHE in terms of impoverishments was also analysed using logistic regressions for the study. The results indicate that:

- The poverty levels have come down at the national level from 52.83% of households to 21.74% in the period under consideration, before the payment of any OOP expenditures.
- Similarly, post OOP payment poverty levels also dropped from 56.26% to 27.23% in the same period.
- The resulting illness induced impoverishment estimate follows a similar trend to the average share of OOP expenditures, increasing from 3.43% of the households in 1995-96 to 7.73% in 2014 and dropping to 5.49% in 2017-18.
- The rural and urban households have major differences in poverty levels. The poverty headcounts are twice as high for the rural areas compared to the urban. The illness induced poverty incidence is also higher among the rural households.

- Like the incidence of impoverishment, intensity also gradually increased between 1995-96 and 2014 with illness induced poverty gap growing from 12.49/- to 96.01/- and had a significant drop in 2018 to 71.81/-.
- Although the poverty gap has reduced, the Mean Positive Gap has continued to widen post 2014.
- The MPG ratio has gone up from 1.15 in 1995-96 to 1.54 in 2014. This ratio further rose to 1.675 in 2018, suggesting that the intensity of poverty gap is much deeper among the population impoverished due to OOP payments.
- The results of the logistic regression indicate that impoverishment incidence is not impacted by the place of residence (sector) in the last two rounds.
- Religion of the household is found to be a weak predictor of impoverishment incidence.
- among social groups, only Scheduled Tribes (ST) were significantly less likely to face to face impoverishment than the non-vulnerable castes with odds ratios of 0.637, 0.406, 0.595, and 0.587 across the four rounds. This lower likelihood coupled with low OOPHE shares in consumption expenditure suggest a significant underutilization of health services among this group.
- The results also indicate that economic vulnerability has the most impact on impoverishment incidence. Compared to the richest households, the odds ratios increased for the subsequent lower quintiles of wealth class. In the latest round, the households of Q2 were 10 times as likely to face expenditure induced impoverishment than the richest Q5. Even the relatively richer Q3 and Q4 face significantly higher odds of 5.127 and 2.661 respectively. However, Q2 in 60th round and Q1 in 75th round have significantly low odds which could be due to the few households that managed to escape poverty classification being wary of health payments.
- Household type is an insignificant factor in assessing the likelihood of impoverishment incidence with only households relying on other menial jobs facing higher odds than the self-employed households.
- Household size, however, is a significant factor with larger households having slightly higher odds of facing impoverishment.
- Demographic Burden is another major factor impacting the impoverishment incidence in Indian households. Households with at least one kid aged 6 or under have higher odds than

the households with no children (Odds Ratios: 52nd-1.223; 60th-1.084; 71st-1.140; 75th-1.222).

- Similarly, households with members above 60 years of age are significantly more likely to face CHE across all rounds (Odds Ratios: 52nd-1.358; 60th-1.604; 71st-1.587; 75th-1.887)
- Gender of the household head is an insignificant estimator across the rounds. Similarly, the education level of the household head has no significance, especially in the latest two rounds.
- Medical Insurance too was an insignificant factor in the first in the first three rounds. However, in the latest round, the households with medical insurance have higher odds (OR: 1.370) of facing impoverishment reinforcing that insurance might increase utilisation but does not successfully alleviate burden of OOPHE in Indian households.

5.3. POLICY SUGGESTIONS

- Promote healthcare facilities to improve demand for healthcare since contraction in demand for healthcare might have far outreaching impact in subsequent years.
- Further enhance the public investments in healthcare since government health expenditure is shown to enhance national income. This could help reduce OOP burdens further since the less average expenses at public facilities would have direct impact on the overall OOPHE bills for the households.
- Given the rising gap between the public and private facility bills, the government could choose to regulate private facility bills to alleviate the burden.
- The correlation between social group, employments, income class and utilisation found in the study warrants for additional support to the socially vulnerable to uplift their livelihoods further and reduce the inequality in OOPHE burdens.
- Demographic burden is an important driver of OOPHE in Indian households and hence there is a need for burden alleviation in those households.
- There is a need for targeted insurance for rural population since most economically weaker live in rural. Also, urban poor should be targeted since they are facing more OOP and burden.

- Encourage insurers to bring awareness of insurance and its benefits to help improve the insurance penetration since at current levels, the insurance prevalence has no significant impact in alleviating OOPHE burdens in Indian households.

5.4. LIMITATION OF THE CURRENT STUDY

The methodology adopted in gathering information regarding morbidity and utilization of health care services in all the three rounds of National Sample Surveys used here was self-reported in nature. Self-reported morbidity is conceptually complex, and it is difficult to apply with high validity and reliability (Murray and Chen, 1992). Moreover, it is highly sensitive to many factors, viz., education, person's knowledge and perception about the diseases, willingness to report and others socioeconomic variables. Therefore, it possesses all the limitations of what a self-reported morbidity possesses.

While the current study analysed the healthcare expenditure and their burdens on the Indian households, the analysis on the insurance scenario is lacking due to the data limitation of NSSO surveys. Further study could ascertain the picture of Indian insurance market with an analysis of various schemes available, their financing mechanisms and their utilisation. Further, the improvements in public health expenditures could also be further investigated to find the improvements made to the healthcare industry (in terms of infrastructure/human resources/financing mechanisms).

Bibliography

Ahuja, R., & De, I. (2004). Health Insurance for the Poor: Need to Strengthen Healthcare Provision. *Economic And Political Weekly*, *39*(41), 4501-4503. http://www.jstor.org/stable/4415637

Akhtar, A., Ahmad, N., & Roy Chowdhury, I. (2020). Socio-economic inequality in catastrophic health expenditure among households in India: A decomposition analysis. *Indian Economic Review*, *55*(2), 339-369. https://doi.org/10.1007/s41775-020-00093-3

Apergis, N., & Padhi, P. (2013). Health expenses and economic growth: convergence dynamics across the Indian States. *International Journal of Health Care Finance and Economics*, *13*(3–4), 261–277. https://doi.org/10.1007/s10754-013-9130-9

Aregbeshola, B., & Khan, S. (2017). Determinants of catastrophic health expenditure in Nigeria. *The European Journal Of Health Economics*, *19*(4), 521-532. https://doi.org/10.1007/s10198-017-0899-1

Arrow, K. J. (1963). UNCERTAINTY AND THE WELFARE ECONOMICS OF MEDICAL CARE. *American Economic Review*, *53*(5), 941–973. https://doi.org/10.1257/aer.102.7.i

Atilgan, E., Kilic, D., & Ertugrul, H. M. (2017). The dynamic relationship between health expenditure and economic growth: is the health-led growth hypothesis valid for Turkey? *The European Journal of Health Economics*, *18*(5), 567–574. https://doi.org/10.1007/s10198-016-0810-5

Balarajan, Y., Selvaraj, S., & Subramanian, S. V. (2011). Health Care and equity in India. The Lancet, 377(9764), 505–515. https://doi.org/10.1016/s0140-6736(10)61894-6

Baltagi, B. H., & Moscone, F. (2010). Health care expenditure and income in the OECD reconsidered: Evidence from panel data. *Economic Modelling*, *27*(4), 804–811. https://doi.org/10.1016/j.econmod.2009.12.001

Becker, G. S. (1964). *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*. University of Illinois at Urbana-Champaign's Academy for Entrepreneurial Leadership Historical Research Reference in Entrepreneurship.

Becker, G. S. (1965). A Theory of the Allocation of Time. *The Economic Journal*, *75*(299), 493. https://doi.org/10.2307/2228949

Berki, S. (1986). A Look at Catastrophic Medical Expenses and the Poor. *Health Affairs*, *5*(4), 138-145. https://doi.org/10.1377/hlthaff.5.4.138

Bhat, R., & Jain, N. (2006). Analysis of Public and Private Healthcare Expenditures. *Economic and Political Weekly*, *41*(1), 57–68. https://doi.org/10.2307/4417643

Berman, P., Ahuja, R., & Bhandari, L. (2010). The Impoverishing Effect of Healthcare Payments in India: New Methodology and Findings. Economic and Political Weekly, 45(16), 65–71. http://www.jstor.org/stable/25664359

Bhattacharjee, A., Shin, J. K., Subramanian, C., & Swaminathan, S. (2017). Healthcare investment and income inequality. *Journal of Health Economics*, *56*, 163–177. https://doi.org/10.1016/j.jhealeco.2017.08.007

Central Bureau of Health Intelligence, India. (2019). *NATIONAL HEALTH PROFILE 2019*.

Chaudhuri, A., & Roy, K. (2008). Changes in out-of-pocket payments for healthcare in Vietnam and its impact on equity in payments, 1992–2002. Health Policy, 88(1), 38–48. https://doi.org/10.1016/j.healthpol.2008.02.014

Cheng, S. H., & Chiang, T. L. (1997). The effect of universal health insurance on Health Care Utilization in Taiwan. results from a natural experiment. JAMA: The Journal of the American Medical Association, 278(2), 89–93. https://doi.org/10.1001/jama.278.2.89

Danzon, P. M., Wang, Y. R., & Wang, L. (2005). The impact of price regulation on the launch delay of new drugs?evidence from twenty-five major markets in the 1990s. *Health Economics*, *14*(3), 269–292. https://doi.org/10.1002/hec.931

Dardanoni, V., & Wagstaff, A. (1990). Uncertainty and the demand for medical care. *Journal of Health Economics*, *9*(1), 23–38. https://doi.org/10.1016/0167-6296(90)90039-6

Deb, S., Strodl, E., & Sun, H. (2015). Academic stress, parental pressure, anxiety and mental health among Indian high school students. *International Journal of Psychology and Behavioral Science*, *5*(1), 26–34.

Deb, P., & Trivedi, P. K. (2002). The structure of demand for health care: latent class versus two-part models. *Journal of Health Economics*, *21*(4), 601–625. https://doi.org/10.1016/S0167-6296(02)00008-5

Di Matteo, L. (2010). The sustainability of public health expenditures: evidence from the Canadian federation. *The European Journal of Health Economics*, *11*(6), 569–584. https://doi.org/10.1007/s10198-009-0214-x

Diehr, P., Yanez, D., Ash, A., Hornbrook, M., & Lin, D. Y. (1999). METHODS FOR ANALYZING HEALTH CARE UTILIZATION AND COSTS. *Annual Review of Public Health*, *20*(1), 125–144. https://doi.org/10.1146/annurev.publhealth.20.1.125

Duan, N. (1983). Smearing Estimate: A Nonparametric Retransformation Method. *Journal of the American Statistical Association*, *78*(383), 605. https://doi.org/10.2307/2288126

Duan, N., Manning, W. G., Morris, C. N., & Newhouse, J. P. (1984). Choosing Between the Sample-Selection Model and the Multi-Part Model. *Journal of Business & Economic Statistics* .

Farag, M., NandaKumar, A. K., Wallack, S., Hodgkin, D., Gaumer, G., & Erbil, C. (2012). The income elasticity of health care spending in developing and developed countries. *International Journal of Health Care Finance and Economics*, *12*(2), 145–162. https://doi.org/10.1007/s10754-012-9108-z

Farag, M., Nandakumar, A. K., Wallack, S., Hodgkin, D., Gaumer, G., & Erbil, C. (2013). Health expenditures, health outcomes and the role of good governance. *International*

Journal of Health Care Finance and Economics, *13*(1), 33–52. https://doi.org/10.1007/s10754-012-9120-3

Flores, G., & O'Donnell, O. (2016). Catastrophic medical expenditure risk. Journal of Health Economics, 46, 1–15. https://doi.org/10.1016/j.jhealeco.2016.01.004

Flores, G., Krishnakumar, J., O'Donnell, O., & van Doorslaer, E. (2008). Coping with health-care costs: implications for the measurement of catastrophic expenditures and poverty. *Health Economics*, *17*(12), 1393-1412. https://doi.org/10.1002/hec.1338

Fogel, R. W. (2004). Health, Nutrition, and Economic Growth. *Economic Development and Cultural Change*, *52*(3), 643–658. https://doi.org/10.1086/383450

Galárraga, O., Sosa-Rubí, S. G., Salinas-Rodríguez, A., & Sesma-Vázquez, S. (2009). Health Insurance for the poor: Impact on catastrophic and out-of-pocket health expenditures in Mexico. The European Journal of Health Economics, 11(5), 437–447. https://doi.org/10.1007/s10198-009-0180-3

Garg, C. C., & Karan, A. K. (2008). Reducing out-of-pocket expenditures to reduce poverty: A disaggregated analysis at rural-urban and state level in India. Health Policy and Planning, 24(2), 116–128. https://doi.org/10.1093/heapol/czn046

Gaur, S., & Rao, S., Poverty Measurement in India: A Status Update, Working Paper No. 1/2020. Ministry of Rural Development

Gerdtham, U.-G., & Löthgren, M. (2000). On stationarity and cointegration of international health expenditure and GDP. *Journal of Health Economics*, *19*(4), 461–475. https://doi.org/10.1016/S0167-6296(99)00036-3

Ghosh, S. (2010). Catastrophic payments and impoverishment due to out-of-pocket health spending: The effects of recent health sector reforms in India. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.1658573

Grossman, M. (1972). On the Concept of Health Capital and the Demand for Health. *The Journal of Political Economy*, *80*(2), 223–255.

Grossman, M. (1972). *The Demand for Health: A Theoretical and Empirical Investigation*. National Bureau of Economic Research.

Gupta, I., & Joe, W. (2013). Refining estimates of Catastrophic Healthcare Expenditure: An application in the Indian context. International Journal of Health Care Finance and Economics, 13(2), 157–172. https://doi.org/10.1007/s10754-013-9125-6

Hansen, P., & King, A. (1996). The determinants of health care expenditure: A cointegration approach. *Journal of Health Economics*, *15*(1), 127–137. https://doi.org/10.1016/0167-6296(95)00017-8

Hartwig, J. (2008). What drives health care expenditure?—Baumol's model of 'unbalanced growth' revisited. *Journal of Health Economics*, *27*(3), 603–623. https://doi.org/10.1016/j.jhealeco.2007.05.006

Hartwig, J. (2010). Is health capital formation good for long-term economic growth? – Panel Granger-causality evidence for OECD countries. *Journal of Macroeconomics*, *32*(1), 314–325. https://doi.org/10.1016/j.jmacro.2009.06.003

Hitiris, T., & Posnett, J. (1992). The determinants and effects of health expenditure in developed countries. *Journal of Health Economics*, *11*(2), 173–181. https://doi.org/10.1016/0167-6296(92)90033-W

Hooda, S. (2015). Health Insurance, Health Access and Financial Risk Protection. *Economic And Political Weekly*, *50*(50), 63-72. https://www.jstor.org/stable/25664359

Kaiser Family Foundation (2021). *Employer Health Benefits*.

Karan, A., Selvaraj, S., & Mahal, A. (2014). Moving to universal coverage? trends in the burden of out-of-pocket payments for health care across social groups in India, 1999–2000 to 2011–12. PLoS ONE, 9(8). https://doi.org/10.1371/journal.pone.0105162

Karan, A., Yip, W., & Mahal, A. (2017). Extending health insurance to the poor in India: An impact evaluation of rashtriya swasthya bima yojana on out of pocket spending for

healthcare. Social Science & Medicine, 181, 83–92. https://doi.org/10.1016/j.socscimed.2017.03.053

Khan, J. A., Ahmed, S., & Evans, T. G. (2017). Catastrophic healthcare expenditure and poverty related to out-of-pocket payments for healthcare in Bangladesh—an estimation of financial risk protection of Universal Health Coverage. Health Policy and Planning, 32(8), 1102–1110. https://doi.org/10.1093/heapol/czx048

Kiymaz, H., Akbulut, Y., & Demir, A. (2006). Tests of stationarity and cointegration of health care expenditure and gross domestic product. *The European Journal of Health Economics*, *7*(4), 285–289. https://doi.org/10.1007/s10198-006-0375-9

Kumar, K., Singh, A., Kumar, S., Ram, F., Singh, A., Ram, U., Negin, J., & Kowal, P. R. (2015). Socio-economic differentials in impoverishment effects of out-of-pocket health expenditure in China and India: Evidence from who sage. PLOS ONE, 10(8). https://doi.org/10.1371/journal.pone.0135051

Ladusingh, L., & Pandey, A. (2013). Health expenditure and impoverishment in India. Journal of Health Management, 15(1), 57–74. https://doi.org/10.1177/0972063413486031

Lancaster, K. J. (1966). A New Approach to Consumer Theory. *Journal of Political Economy*, *74*(132). https://doi.org/10.1086/259131

Leiter, A. M., & Theurl, E. (2012). The convergence of health care financing structures: empirical evidence from OECD-countries. *The European Journal of Health Economics*, *13*(1), 7–18. https://doi.org/10.1007/s10198-010-0265-z

López-Casasnovas, G., & Saez, M. (2007). A multilevel analysis on the determinants of regional health care expenditure: a note. *The European Journal of Health Economics : HEPAC : Health Economics in Prevention and Care*, *8*(1), 59–65. https://doi.org/10.1007/S10198-006-0007-4

Malhotra, C., & Do, Y. K. (2016). Public health expenditure and health system responsiveness for low-income individuals: Results from 63 countries. Health Policy and Planning. https://doi.org/10.1093/heapol/czw127

Manning, W. G., Newhouse, J. P., Duan, N., Keeler, E. B., Leibowitz, A., & Marquis, M. S. (1987). Health insurance and the demand for medical care: evidence from a randomized experiment. *The American Economic Review*, *77*(3), 251–277.

Manning, W. G. (1998). The logged dependent variable, heteroscedasticity, and the retransformation problem. *Journal of Health Economics*, *17*(3), 283–295. https://doi.org/10.1016/S0167-6296(98)00025-3

Matsaganis, M., Mitrakos, T., & Tsakloglou, P. (2009). Modelling health expenditure at the household level in Greece. *The European Journal of Health Economics*, *10*(3), 329–336. https://doi.org/10.1007/s10198-008-0137-y

Ministry of Statistics and Programme Implementation. (2020). *Health in India - NSS 75th Round*.

Misra, S., Awasthi, S., Singh, J. V., Agarwal, M., & Kumar, V. (2013). Estimation of out of pocket direct and indirect medical expenditure and spending burden ratio across income quintiles in urban Lucknow, India. *Clinical Epidemiology and Global Health*, 1(1), 12–18. https://doi.org/10.1016/j.cegh.2013.01.001

Mocan, H. N., Tekin, E., & Zax, J. S. (2004). The Demand for Medical Care in Urban China. *World Development*, *32*(2), 289–304. https://doi.org/10.1016/j.worlddev.2003.07.006

Muurinen, J.-M. (1982). Demand for health: A generalised Grossman model. *Journal of Health Economics*, *1*(1), 5–28. https://doi.org/10.1016/0167-6296(82)90019-4

Narayan, S., Narayan, P. K., & Mishra, S. (2010). Investigating the relationship between health and economic growth: Empirical evidence from a panel of 5 Asian countries. *Journal of Asian Economics*, *21*(4), 404–411. https://doi.org/10.1016/j.asieco.2010.03.006

National Health Authority, India. (2020). *AYUSHMAN BHARAT PRADHAN MANTRI JAN AROGYA YOJANA.*

National Health Systems Resource Centre, India. (2019). *National Health Accounts Estimates for India FY 2016-17*.

Nixon, J., & Ulmann, P. (2006). The relationship between health care expenditure and health outcomes. *The European Journal of Health Economics*, *7*(1), 7–18. https://doi.org/10.1007/s10198-005-0336-8

Onoka, C., Onwujekwe, O., Hanson, K., & Uzochukwu, B. (2011). Examining catastrophic health expenditures at variable thresholds using household consumption expenditure diaries. *Tropical Medicine & International Health*, *16*(10), 1334-1341. https://doi.org/10.1111/j.1365-3156.2011.02836.x

Pal, R. (2012). Measuring incidence of catastrophic out-of-pocket health expenditure: with application to India. *International Journal Of Health Care Finance And Economics*, *12*(1), 63-85. https://doi.org/10.1007/s10754-012-9103-4

Pandey, A., Kumar, G., Dandona, R., & Dandona, L. (2018). Variations in catastrophic health expenditure across the states of India: 2004 to 2014. *PLOS ONE*, *13*(10), e0205510. https://doi.org/10.1371/journal.pone.0205510

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, *16*(3), 289–326. https://doi.org/10.1002/jae.616

Potrafke, N. (2010). The growth of public health expenditures in OECD countries: Do government ideology and electoral motives matter? *Journal of Health Economics*, *29*(6), 797–810. https://doi.org/10.1016/j.jhealeco.2010.07.008

Pradhan, M., & Prescott, N. (2002). Social risk management options for medical care in Indonesia. *Health Economics*, *11*(5), 431-446. https://doi.org/10.1002/hec.689

Prinja, S., Gupta, R., Bahuguna, P., Sharma, A., Kumar Aggarwal, A., Phogat, A., & Kumar, R. (2016). A composite indicator to measure universal health care coverage in India: way forward for post-2015 health system performance monitoring framework. *Health Policy And Planning*, *32*(1), 43-56. https://doi.org/10.1093/heapol/czw097

Raban, M., Dandona, R., & Dandona, L. (2013). Variations in catastrophic health expenditure estimates from household surveys in India. *Bulletin Of The World Health Organization*, *91*(10), 726-735. https://doi.org/10.2471/blt.12.113100

Ramani, K. V., & Mavalankar, D. (2006). Health System in India: Opportunities and challenges for improvements. Journal of Health Organization and Management, 20(6), 560–572. https://doi.org/10.1108/14777260610702307

Ranson, M. (2002). Reduction of catastrophic health care expenditures by a community-based health insurance scheme in Gujarat, India: current experiences and challenges. *Bulletin Of The World Health Organization*, *80*(8), 613-621.

Reddy, K. S., Patel, V., Jha, P., Paul, V. K., Kumar, A. K. S., & Dandona, L. (2011). Towards achievement of Universal Health Care in India by 2020: A call to action. The Lancet, 377(9767), 760–768. https://doi.org/10.1016/s0140-6736(10)61960-5

Sachs, J. D. (2001). Macroeconomics and Health : Investing in Health for Economic Development. In J. D. Sachs (Ed.), *Report of the Commission on Macroeconomics and Health* (Issue December). World Health Organisation.

Sangar, S., Dutt, V., & Thakur, R. (2018). Economic burden, impoverishment and coping mechanisms associated with out-of-pocket health expenditure: Analysis of rural-urban differentials in India. *Journal of Public Health*, 26(5), 485–494. https://doi.org/10.1007/s10389-018-0904-x

Sangar, S., Dutt, V., & Thakur, R. (2019). Burden of out-of-pocket health expenditure and its impoverishment impact in India: Evidence from National Sample Survey. *Journal of Asian Public Policy*, 15(1), 60–77. https://doi.org/10.1080/17516234.2019.1601065

Shahrawat, R., & Rao, K. (2011). Insured yet vulnerable: out-of-pocket payments and India's poor. *Health Policy And Planning*, *27*(3), 213-221. https://doi.org/10.1093/heapol/czr029

Shiu, Y.-M., & Chiu, M.-C. (2008). Re-estimating the Demographic Impact on Health Care Expenditure: Evidence from Taiwan. *The Geneva Papers on Risk and Insurance - Issues and Practice*, *33*(4), 728–743. https://doi.org/10.1057/gpp.2008.26

Su, T. (2006). Catastrophic household expenditure for health care in low-income society: a study from Nouna District, Burkina Faso. *Bulletin Of The World Health Organisation*, *84*(1), 21-27. https://doi.org/10.2471/blt.05.023739

Sülkü, S. N., & Caner, A. (2011). Health care expenditures and gross domestic product: the Turkish case. *The European Journal of Health Economics*, *12*(1), 29–38. https://doi.org/10.1007/s10198-010-0221-y

Thomson, S., Foubister, T., & Mossialos, E. (2009). *Financing health care in the European Union*. World Health Organization on behalf of the European Observatory on Health Systems and Policies.

Thorpe, H., Jayne, D. G., Guillou, P. J., Quirke, P., Copeland, J., & Brown, J. M. (2008). Patient factors influencing conversion from laparoscopically assisted to open surgery for colorectal cancer. *British Journal of Surgery*, *95*(2), 199–205. https://doi.org/10.1002/bjs.5907

U.S. Census Bureau. (2020). *Health Insurance Coverage in the United States: 2019* (pp. 60-271). Washington, DC: U.S. Government Publishing Office.

van Doorslaer, E., O'Donnell, O., Rannan-Eliya, R., Somanathan, A., Adhikari, S., & Garg, C. et al. (2007). Catastrophic payments for health care in Asia. *Health Economics*, *16*(11), 1159-1184. https://doi.org/10.1002/hec.1209

Van Minh, H., Kim Phuong, N., Saksena, P., James, C., & Xu, K. (2013). Financial burden of household out-of pocket health expenditure in Viet Nam: Findings from the National Living Standard Survey 2002–2010. *Social Science & Medicine*, *96*, 258-263. https://doi.org/10.1016/j.socscimed.2012.11.028

Wagstaff, A., & Doorslaer, E. van. (2003). Catastrophe and impoverishment in paying for health care: With applications to Vietnam 1993-1998. *Health Economics*, 12(11), 921–933. https://doi.org/10.1002/hec.776

World Development Report 1993. (1993, June). https://doi.org/10.1596/0-1952-0890-0

World Health Organization. (2010). *HEALTH SYSTEMS FINANCING The Path to Universal Coverage*. Retrieved from http://apps.who.int/iris/bitstream/handle/10665/44371/9789241564021_eng.pdf?sequence=1

Xu, K., Evans, D., Kawabata, K., Zeramdini, R., Klavus, J., & Murray, C. (2003). Household catastrophic health expenditure: a multicountry analysis. *The Lancet*, *362*(9378), 111-117. https://doi.org/10.1016/s0140-6736(03)13861-5

Yadav, J., Menon, G. R., & John, D. (2021). Disease-specific out-of-pocket payments, catastrophic health expenditure and impoverishment effects in India: An Analysis of National Health Survey Data. *Applied Health Economics and Health Policy*, 19(5), 769–782. https://doi.org/10.1007/s40258-021-00641-9

Yavuz, N. C., Yilanci, V., & Ozturk, Z. A. (2013). Is health care a luxury or a necessity or both? Evidence from Turkey. *The European Journal of Health Economics*, *14*(1), 5–10. https://doi.org/10.1007/s10198-011-0339-6

Zhao, S., Zhang, X., Dai, W., Ding, Y., Chen, J., & Fang, P. (2020). Effect of the catastrophic medical insurance on household catastrophic health expenditure: evidence from China. *Gaceta Sanitaria*, *34*(4), 370-376. https://doi.org/10.1016/j.gaceta.2018.10.005

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E-mail: rohingaddam@uohyd.ac.in

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