Technology in the Aging World: The Role of Broadband and Green Revolution

by

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Declaration

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Contents

Introduction

The world is aging, and mental health-related issues like social isolation and loneliness are at a record high. Older ages also come with a decline in certain cognitive abilities and limitations to access to social benefits programs. At the same time, older adults are increasingly exposed to various technologies. For instance, broadband (high-speed internet technology) availability and use among older adults has increased substantially in the last decades in the US. Similarly, developing countries have seen the expansion of a massive agricultural technology (known as the *Green Revolution*) in the latter half of the twentieth century to cope with hunger and food scarcity. However, the role of these technologies in aging-related outcomes is understudied. This dissertation evaluates how some of these different technologies affect key aging-related outcomes, including mental health, cognitive function, chronic conditions, and access to social security programs among older adults in the US and India. To put the conclusion in a nutshell, in most cases, I find that these technologies play a positive role in the lives of older adults worldwide.

In the first chapter, I study how the expansion of broadband affects mental health among older adults (50+ years of age) in the US. In contrast to the literature that finds harmful effects of the internet among younger populations, my results show that broadband rollout significantly reduces depression symptoms by 5.7% among older adults, which is comparable with other major life events. The primary mechanisms driving these positive effects include increased virtual social connections with family and friends and decreased feelings of social isolation and loneliness. A back-of-the-envelope calculation suggests that broadband expansion may reduce the cost of excess Medicare spending by about $5 billion due to major depressive symptoms and social isolation among older adults.

In the second chapter, I and coauthors study how early life exposure to the Green Revolution affects later-life cognitive function and chronic conditions in India and what the potential pathways are. We find that exposure to the Green Revolution during the critical period (in-utero to age 2) significantly improved later-life cognitive function, especially among the socially disadvantaged groups and people born in rural areas. Improving schooling and financial conditions while growing up explains some positive gains in cognitive health. On the other hand, we also find men and individuals in urban areas are more likely to experience an increase in chronic conditions. Estimates from this paper are crucial for policies in developing countries adopting the Green Revolution, given their significantly higher share of the aging population than the rest of the world.

Finally, in the third chapter, I extend the broadband research to understand whether the broadband expansion affects the likelihood of older adults applying, appealing, or receiving the Supplemental Security Income (SSI) and Social Security Disability Insurance (SSDI) benefits. I find that broadband rollout significantly increased the probability of SSDI application, appeal, or receipt and did not affect the SSI process. However, there remain notable racial and regional disparities in access and the benefits of broadband. The estimates in this paper bear considerable importance for several reasons. Given a young entrant into the workforce has a one-in-three probability of mortality or meeting the eligibility criteria for SSDI before attaining Social Security's full retirement age and massive investments of over $65 Billion in the broadband expansion, the estimates from this study are relevant for the policymakers.

Chapter 1

Does High-Speed Internet Access Affect the Mental Health of Older Adults?

1.1 Introduction

The aging US population faces increasing mental health challenges that have substantial economic costs but partially effective available treatments. About 54 million individuals aged 65 and above represent 16% of the US population as of 2019; by 2060, 1 in 4 people (about 94.7 million individuals) will be 65 or older (ACL Report, Vespa *et al.* (2018)). As people live longer, they are more likely to experience significant mental health deterioration.[1] One in four older adults experiences depression, anxiety, or dementia.[2] Aged 60+ people in the US are more likely to live alone than elsewhere in the world (Ausubel, 2020).[3] Loneliness and social isolation have a similar impact on premature mortality as 15 cigarettes and six drinks a day.[4] Mental health-related issues were exacerbated during

[1]For example, Alzheimer's is quickly becoming one of the most pressing challenges facing public health officials.

[2]National Academies of Sciences, Engineering, and Medicine. 2020

[3]27% of US older adults live alone, compared to 16% in 130 other countries.

[4]The U.S. Surgeon General's Advisory on the Healing Effects of Social Connection and Community (2023).

COVID-19, as isolation among older adults compounded their risks of death.[5] Depression is often associated with suicide.[6] People aged 85 and above have the highest suicide rates among all age groups.[7] These mental health problems among older adults are a public health issue that can have enormous economic costs, both in direct medical expenses and indirect costs, such as caregiver burdens and lost productivity. The cost of major depressive disorders was over \$42 billion for the 50+ population in 2010 (Greenberg *et al.*, 2015), and social isolation accounts for excess Medicare spending of about \$6.7 billion annually (Flowers *et al.*, 2017).[8] However, the available treatments for mental health are only about 50% effective in achieving quality of life improvements (Reynolds III *et al.*, 2012).

The geographic distribution of older adults reveals a notable concentration in remote regions characterized by restricted availability of mental health services. Approximately one-fifth of the older American population lives in rural areas; in certain states, more than half of the elderly residents live in rural locations (Census report).[9] Rural residents are more likely to be older and poorer, to have lower levels of education and worse mental health, and to lack private health insurance.[10] Consequently, these areas are characterized by limited access to mental health services and a scarcity of trained mental health providers. More than half of all the locations with shortages of mental health professionals are located in rural areas.[11] Furthermore, regions with inadequate mental health services exhibit higher suicide rates (Henning-Smith, 2020).

Broadband (high-speed internet) has the potential to address some of the above-mentioned market failures; however, there remains a significant disparity in access to broadband, and its causal impact on older adults' mental health has not been studied well.[12] Broadband access may lower costs of communication and sharing information

[5] Scott Simon report in NPR Feb 19, 2022.

[6] (Pompili *et al.*, 2010, Reynolds III *et al.*, 2012)

[7] American Foundation for Suicide Prevention.

[8] In a recent study, researchers show that the

[9] The share of the older population is higher in rural areas than in urban areas; about 17.5% of the rural population was 65 years and older. For urban areas, the share is 13.8% (Smith and Trevelyan, 2019).

[10] (Foutz *et al.*, 2017, Mueller *et al.*, 2018, Moy *et al.*, 2017, Pender *et al.*, 2019).

[11] Medicaid and CHIP Payment and Access Commission, Issue April 202 and (Morales *et al.*, 2020).

[12] Broadband is an umbrella term for reliable and high-speed internet connection. Refer AARP ILSR Report.

with others, enabling services such as WhatsApp video calls with friends and families, entertainment through platforms like Netflix, video calls for telehealth, online learning or meditation through YouTube to stay mentally active, health information, and other social media use. Some of these uses are crucial for older adults who live alone, feel lonely or isolated, have limitations on mobility, and are in remote areas with limited access to mental health services. As a recent study suggests, lowering the cost of access to mental health care does not necessarily improve the economic impact since many people with mental health issues do not seek treatment due to various reasons, including a taboo associated with it (Abramson *et al.*, 2024). So, broadband could be an even more important channel for addressing some of the mental health issues. On the other hand, recent evidence in economics suggests that social media has adverse effects on the mental health of college students, especially due to 'unfavorable comparison' among girls (Braghieri *et al.*, 2022). With this background, the net effect of the internet on older adults' mental health is unclear. Secondly, a significant geographic and demographic disparity – the 'digital divide' – exists in access to reliable high-speed internet.[13] This disparity in internet access was further exacerbated by the COVID-19 pandemic, prompting policymakers to invest over $65 billion in broadband infrastructure policies, such as Internet for All.[14] Researchers are increasingly focusing on understanding the causal effects of broadband on various economic outcomes (Dettling *et al.*, 2018, Conroy and Low, 2022, Campbell, 2022, Amaral-Garcia *et al.*, 2022,). It is, however, unclear whether and to what extent the tools enabled by high-speed internet affect the worrying trends in mental health, social isolation, and loneliness among older adults.

This paper investigates the impact of high-speed internet (broadband) technology on the mental health of older adults in the US. The paper employs a quasi-experimental design, using the staggered introduction of high-speed 'fiber broadband' in census tracts from 2010 to 2018.[15] I use the biennial waves from nationally representative data from

[13](Conroy and Low, 2022, Low *et al.*, 2021). For example, internet speed is slower in Black-majority neighborhoods than the speed enjoyed in other neighborhoods, despite paying the same price. The Markup.

[14]"Internet For All" allocated $42.45 billion for Broadband Equity, Access, and Deployment (BEAD) in June 2023.

[15]Refer to section 3 on why this paper focuses on Fiber Broadband. Campbell (2022) also uses this

the Health and Retirement Study (HRS), which is an individual panel of individuals aged 51+.[16] The key dependent variable in my regressions is the commonly used CES-D score or 'symptoms of depression' to measure the mental health of older adults.[17] I focus on depression symptoms as a primary outcome since it is the key predictor of poor well-being and low life satisfaction (Kahneman and Krueger, 2006). I use census tract-level broadband data, observing the fiber broadband rollout each year.Merging individual panel data with the broadband data at the census tract and year level allows me to exploit the spatial, temporal, and individual level variation of the broadband to estimate the intent to treat (ITT) effect.[18] I employ new difference-in-differences (DID) estimators that are useful for the binary and staggered treatment and account for the dynamic treatment effects.The estimations conclude with robustness checks, heterogeneity analysis, and tests of underexplored potential mechanisms.

I find that the rollout of high-speed fiber broadband technology positively affected mental health among older adults, shown by a decline in depressive symptoms using the CES-D score. The most conservative DID estimate with individual fixed effects is remarkably similar in magnitude but exactly opposite in direction to the effects observed in a recent study by (Braghieri *et al.*, 2022), which found that the expansion of social media (such as Facebook) increased mental health problems among college students. This contrast in the effects highlights one of the key findings of this paper, indicating that the impact of a similar technology on mental health outcomes can vary substantially based on age cohorts and potentially on how individuals engage with the technology. I find that the average gain in mental health for older adults is equivalent to about 20% of the adverse effects of job loss, 41% of recession, and 14% due to an unexpected loss of a spouse. I find heterogeneous treatment effects based on race, gender, and geography, with positive and significant effects for Whites, women, and respondents from rural areas. I find that

definition.

[16]HRS data is most useful in this setting due to its richness in detailed measures of mental health, social isolation, social connectedness, and the use of internet technology among older adults.

[17](Cutler and Sportiche, 2022). The score is calculated by the Center for Epidemiology Studies Depression (CESD). I also complement the CES-D measure by using a binary version of the CES-D score, which roughly matches the symptoms of clinical depression.

[18]HRS has restricted data on the census-tract of residence of respondents.

an increase in 'social connectedness' and a decline in 'feeling of social isolation' primarily drive the positive effects. Further, improving health literacy and the likelihood of nearby hospitals offering telehealth services partially drive the results. I do not, however, find evidence of any improvement in cognitive function.

This paper contributes to the following strands of literature: economic analysis of mental health, economic impacts of technology, identification methods, and mechanisms that connect mental health and technology.

Current evidence suggests the adverse effect on mental health due to negative income shocks such as job loss and the positive gain in mental health due to cash transfers or antipoverty programs (Ridley *et al.*, 2020). However, this literature is primarily focused on younger populations. Most of the evidence on the social determinants of the mental health of the older population comes from other disciplines (Allen *et al.*, 2014, Lund *et al.*, 2018). I contribute to the limited economics literature by studying vulnerable age cohorts that are often overlooked.

The next strand of literature involves technologies as determinants of economic outcomes. The emerging literature suggests that broadband can have positive effects on education, entrepreneurship, and labor market outcomes (Dettling *et al.*, 2018, Conroy and Low, 2022, Campbell, 2022, Amaral-Garcia *et al.*, 2022).[19] A small number of studies evaluate the causal effects of broadband on health and suggest mixed evidence (Guldi and Herbst, 2017, DiNardi *et al.*, 2019, Johnson and Persico, 2021, Donati *et al.*, 2022, Amaral-Garcia *et al.*, 2022, Golin, 2022, Van Parys and Brown, 2023). For instance, some evidence suggests that an increase in broadband coverage increases body weight among white women (DiNardi *et al.*, 2019), or, on the other hand, leads to declines in teen pregnancies (Guldi and Herbst, 2017). However, most of the literature on mental health is focused on relatively younger populations and suggests an adverse effect of broadband and social media (Braghieri *et al.*, 2022, Golin, 2022, Allcott *et al.*, 2022, Donati *et al.*, 2022). This paper is among the first to evaluate the effect of broadband on the mental health of

[19] Bakiskan and El Kaissi (2023) provides a summary of 55 quantitative studies that examine the effects of broadband on various economic outcomes across multiple countries.

older adults.

My third set of contributions is methodological. While earlier studies on technology may suffer from the challenges of two-way fixed effects (TWFE), I use recent advances in DID for better identification. I also use data that overcomes some of the limitations in the literature. My measurement of broadband treatment is more precise than most studies, which define treatment at a broad geographic level, such as counties or zip codes.[20] Defining treatment by a broad area can make it challenging to control for confounding variables and may also create heterogeneity bias if one overlooks variations within that area. I define the treatment at a finer scale (census tracts) for more accurate treatment assessment and to reduce bias in the estimation.[21] Further, the individual panel nature of the data allows me to observe the same individuals for ten years (five survey waves), including detailed changes in social and health behavior and take-up of the internet, as opposed to most of the other studies, which are at the macro-level. As discussed below, this lets me analyze potential mechanisms that some other studies could not explore. Finally, the data also helps with locational accuracy. Typically, the current literature fixes the location at the first year of the panel and assumes no migration because migration could be endogenous to the treatment. This assumption may inaccurately measure exposure to the treatment. I do not have to make that assumption because I observe the location of the individual for every survey year and accurately measure exposure to the treatment.

My next key contribution involves a novel study of mechanisms. To my knowledge, this is one of the first papers to provide causal empirical evidence on how broadband may affect social isolation, loneliness, cognitive function, and technology in nearby hospitals, which in turn may affect mental health among older adults. The social isolation hypothesis suggests that social connections and networks are important for mental health.[22] Similarly, loneliness is a strong predictor of social isolation (Banerjee *et al.*, 2023). However, causal evidence on the social isolation hypothesis remains exceedingly scarce. Most of the

[20] One reason was that the broadband data was available at the zip/county level before 2010.

[21] Campbell (2022) uses treatment at the census block level. I use codes generously provided by Dr. Campbell.

[22] This insight is also motivated by the work by (Waldinger, 2015).

evidence on the social isolation hypothesis is from other fields, such as psychology and sociology, and suggests inconclusive correlations between internet use and older adults' mental health.[23] In addition, I provide some of the first evidence on the effect of broadband on cognitive function among older adults. Broadband access may induce the use of various technologies such as mobile phones, tablets, and computers, and these activities may improve some cognitive functions among older adults. Finally, I provide some of the first evidence on whether greater access to broadband may correlate with technological improvement in nearby hospitals. For instance, a major obstacle to the implementation of telehealth services is the lack of enough internet bandwidth, mostly in rural areas (Gajarawala and Pelkowski, 2021). I find an increase in the likelihood of nearby hospitals offering telehealth services when fiber broadband is available.

Information asymmetry is another mechanism through which broadband technology can affect mental health. A recent study suggests that internet access increased C-sections, potentially due to online information (Amaral-Garcia *et al.*, 2022). Another study finds a positive effect on the health of Medicare patients seeking hip or knee replacements, primarily due to better information about providers Van Parys and Brown (2023). In a developing country, a study in an experimental setting suggests that staying connected through mobile calling improves mental well-being among low-income adults (Annan and Archibong, 2023). I complement the evidence on the potential channels through which broadband may reduce information asymmetry and thereby affecting the mental health of older adults.

Social media is a potential mechanism suggested by studies of college students' mental health. Most of these studies are limited to self-reported well-being or digital addiction (Allcott *et al.*, 2022). Similarly, some observational studies also focus on a younger population than I study (Golin, 2022). I complement this literature in at least two critical dimensions. First, I studied mental health in detail using the CES-D score from the

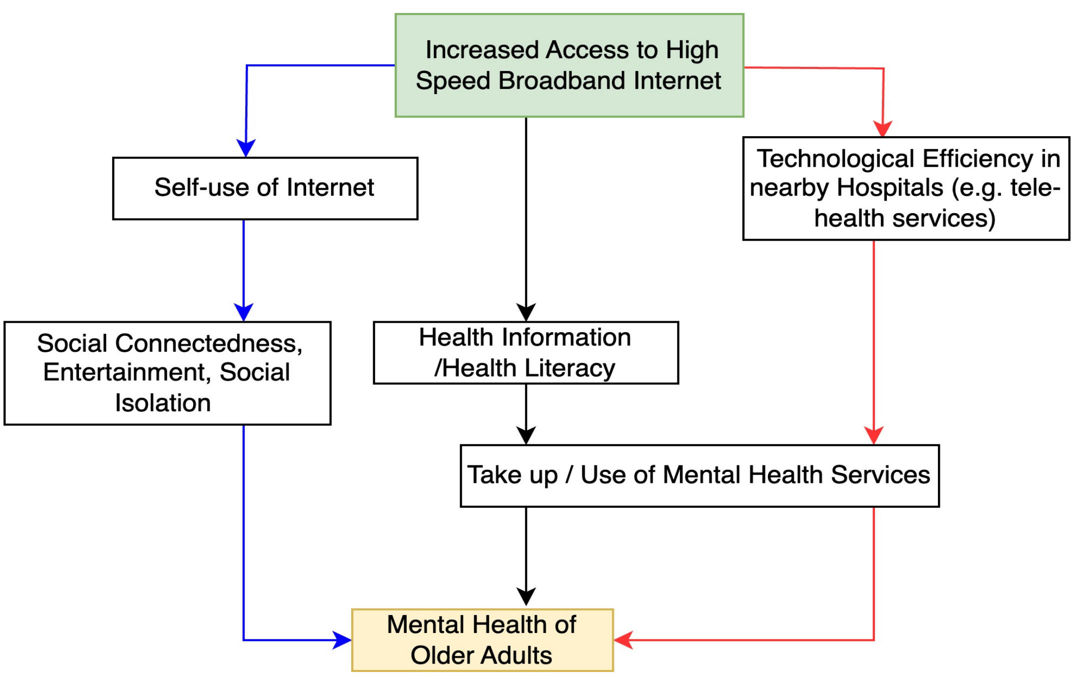
[23]For instance, some studies suggest a positive association between internet use and mental health, with a decrease in loneliness and increased social contact among older adults (Yu *et al.*, 2021, Lu and Kandilov, 2021, Cotten *et al.*, 2013). In contrast, one study suggests a negative association between internet use and mental health depending on the context of the life transition (separated, divorced, or widowed) and the type, level, and purpose of use (Yu *et al.*, 2019).

HRS data. Secondly, the cited studies are limited to the partial equilibrium effects of studying self-isolated respondents. In contrast, I study the general equilibrium effect of having exposure to high-speed fiber broadband, estimating the intent-to-treat (ITT) effects. Such general equilibrium effects are important for technologies like broadband that exhibit strong network externalities.

I study intent to treat (ITT) because the introduction of fiber broadband may improve the speed of the internet in homes, and people also may access high-speed internet through local public libraries or coffee shops. Unlike other studies, I observe an individual's use of the internet, which gives me confidence in the first-stage effect of the use of the internet. Fiber broadband availability may also give individuals access to adequate internet speed required for virtual medical visits (telehealth), video calls to friends and families, or online entertainment, which requires an immense amount of internet speed.

1.2 Conceptual Framework

Figure 1.1: Potential Mechanisms



The impact of high-speed broadband on the mental health of older adults encompasses various potential pathways (Figure 1.1). One such mechanism pertains to social connectedness. While increased virtual connectedness could theoretically mitigate social isolation, it is important to consider a possible counteractive effect. Specifically, a higher reliance on virtual interactions may diminish opportunities for in-person social engagements, potentially exacerbating symptoms of depression. Consequently, the impact of high-speed broadband on the mental health of older adults through social connectedness is an empirical question.

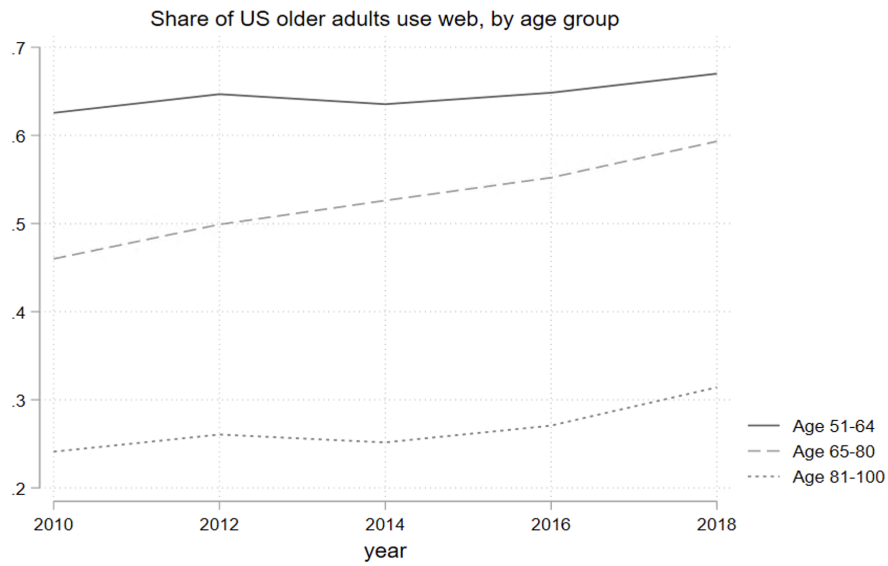
The second potential mechanism through which high-speed broadband may impact the mental health of older adults relates to the availability of online (mis)information. Evidence suggests that internet usage for information purposes enhances health literacy among older adults by approximately 12% (Bavafa *et al.*, 2019).[24] Moreover, the Internet's accessibility plays a pivotal role in facilitating enrollment in various federal and state programs, such as the Social Security program, where participants often rely on online platforms to access and submit necessary forms. This increased internet utilization has the potential to improve health-related information, enhance health literacy, and facilitate enrollment in safety net programs, ultimately influencing the mental well-being of older adults. Nevertheless, it is important to acknowledge the potential drawbacks stemming from misinformation. Notably, research suggests that older adults are among the demographic groups most prone to engaging with online fake news, which can undermine the intended benefits of internet usage (Swire-Thompson *et al.*, 2020).[25]

The third potential mechanism relates to improvements in technological and operational efficiencies within medical facilities. Telehealth services have been identified as efficient and effective tools for healthcare delivery, resulting in improved outcomes. Emerging evidence suggests that access to telemedicine during the COVID-19 lockdowns led to increased primary care visits without adverse effects on health (Zeltzer *et al.*, 2023). En-

[24]Studies also suggest that providing access and support on the use of technology has an enormous potential to facilitate technology adoption among older adults (Pruchno, 2019). This support may come from anyone in the household who knows how to use technology, e.g., children, relatives, neighbors, or friends.

[25]The study documents two other groups of people who engage in online fake news- individuals who are conservative-leaning and who are highly engaged in political news.

Figure 1.2: Internet Users



Note: Author's calculation using biennial waves from 2010 to 2018 of a nationally representative survey from the Health and Retirement Study (HRS). The sample is the balanced panel of HRS respondents.

hanced broadband services hold the potential to improve medical services, particularly in terms of consumer-facing digital technologies such as virtual visits, online bill payment and scheduling, virtual triage, and registration. Notably, a report based on the American Hospital Association's (AHA) IT survey indicates that hospitals experienced an increase in the adoption of digital tools for patient-generated data submissions (23%), appointment scheduling (24%), prescription refill requests (25%), and bill payments (8%) between 2015 and 2019. A major obstacle to the widespread implementation of telehealth is the lack of adequate high-speed internet bandwidth, particularly in rural and underserved areas (Gajarawala and Pelkowski, 2021). However, it is important to consider the potential ramifications of viewing telehealth services as substitutes for essential in-person visits with specialists, as this may translate into worse mental health outcomes. To the best of my knowledge, no prior studies have examined the empirical question of whether broadband technology affects the technology at healthcare facilities that may play a role in the mental health of older adults. Consequently, this paper aims to fill this research gap and shed light on this important empirical inquiry.

1.3 Background

1.3.1 Broadband Technology

Significant progress has been made in expanding broadband technology in recent years; however, there exists regional and racial disparities in the coverage of reliable high-speed internet. In 2021, about 4.9 billion people were using the internet worldwide, with about 89.5 percent of individuals from Europe and Northern America using the internet (SDG report 2022). In 2008, a mere 16% of Americans had access to internet service with a speed of 10 Mbps. Now, approximately 95% of Americans have access to a 10 Mbps connection, and around 80% have access to speeds of up to 1 Gbps.[26] FCC established a definition of broadband in 2015 as an internet connection with a minimum of 25 megabits per second (Mbps) of download speed and a minimum of 3 Mbps of upload speed (Conroy *et al.*, 2021). However, persistent disparities in access (digital divide) remain, primarily affecting rural areas and low socioeconomic households, leaving more than 42 million Americans without internet connectivity.[27] About 81% of rural households have broadband access, compared to 86% in urban areas.[28] Similarly, in Black-majority neighborhoods, the internet speed is slower than in other areas, even though residents are paying the same prices. (The Markup).

The COVID-19 pandemic has highlighted and exacerbated this digital divide, prompting policymakers to place significant emphasis on broadband connectivity. More recently, in June 2023, the Biden-Harris administration announced a $42.45 billion allocation for high-speed internet across states ("Investing in America"). Figure 1.2 illustrates the growing internet use among older adults in the United States over the past decade.[29]

[26] Refer to the Internet & Television Association report. Approximately 81% of households in the US had broadband connections in 2016 (Ryan and Lewis, 2017).

[27] For additional information on broadband access and solutions, see (Conroy and Low, 2022, Low *et al.*, 2021). Low *et al.* (2021) provides a detailed primer on broadband and summarises the benefits, challenges, and potential solutions of broadband access in the US.

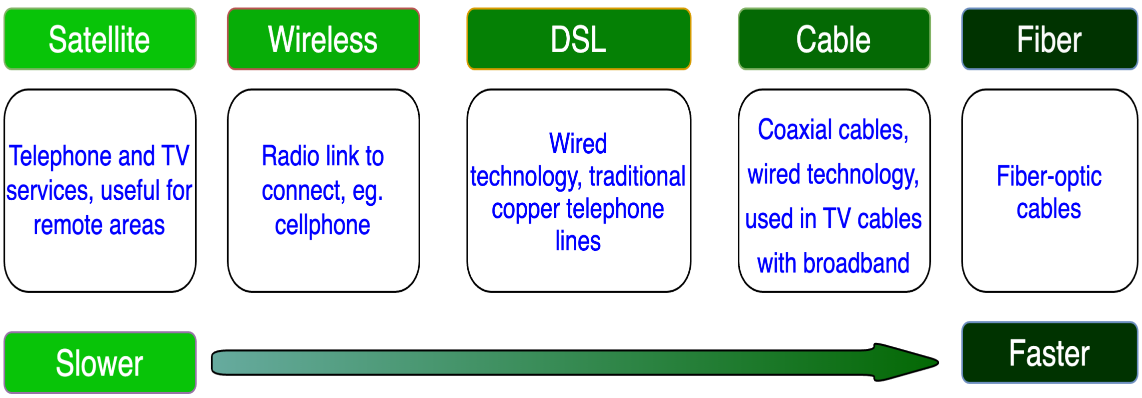
[28] The number of urban households lacking a connection is substantially higher, at 13.6 million, compared to 4.6 million rural households (Porter, 2021).

[29] (Hunsaker and Hargittai, 2018) shows a detailed review of who uses the internet and how it is used among older adults.

1.3.2 Types of Broadband Connections

There are five main categories of broadband that homes and businesses use to connect: fiber, cable, digital subscriber line DSL, fixed or mobile wireless, and satellite (Conroy *et al.*, 2021). The speed of the internet of each type can be categorized in the following way as shown in Figure 1.3.

Figure 1.3: Types of Broadband



Source: (Conroy *et al.*, 2021)

1.3.3 Fiber Broadband

There are two main reasons for this paper's focus on fiber broadband. First, the substantial increase in internet availability and speed in recent years can be attributed, in part, to the growing diffusion of broadband through fiber optic cables. Fiber broadband has emerged as a preferred choice, replacing older alternatives such as cable and DSL, owing to its superior speed, reliability, consistency, and reduced susceptibility to signal loss or damage; it has the potential to transmit large amounts of data.[30] Fiber broadband can transmit data at speeds reaching approximately 70% of the speed of light, equivalent to 124,274 miles per second. Commercial fiber connections typically offer signals above 10 Gbps, while residential fiber internet connections can reach speeds of up to 940 Mbps.[31] Using

[30] Most of the information in this section is from Century Link and Conroy *et al.* (2021).

[31] The use of fiber optic technology involves converting electrical signals into light, which is then transmitted through transparent glass fibers with a diameter comparable to that of a human hair. This approach

Fiber broadband, users can effortlessly download a 6.5 GB file within a mere minute, a stark comparison to the 1-14 hours DSL typically requires or the up to 14 hours cable may take. Moreover, high upload speeds under fiber broadband cater to the demands of modern activities like Zoom calls, ensuring seamless communication experiences, even when multiple individuals and devices concurrently connect to the network, without the bandwidth competition common during peak hours with other technologies like cable.

The second reason is that the availability of fiber broadband for older adults in the US over the past decade has increased exponentially while the availability of other technologies remains stable. Analyzing data from the Health and Retirement Study (HRS), Figure 1.4 illustrates the significant upward trend in the share of the 50+ population residing in census tracts with fiber technology accessibility. The proportion has grown from approximately 22% to 75% from 2010 to 2018. In contrast, the availability of other technologies has remained relatively consistent throughout this period. This notable expansion in fiber broadband availability highlights its increasing potential relevance for older individuals.

1.4 Data

1.4.1 HRS

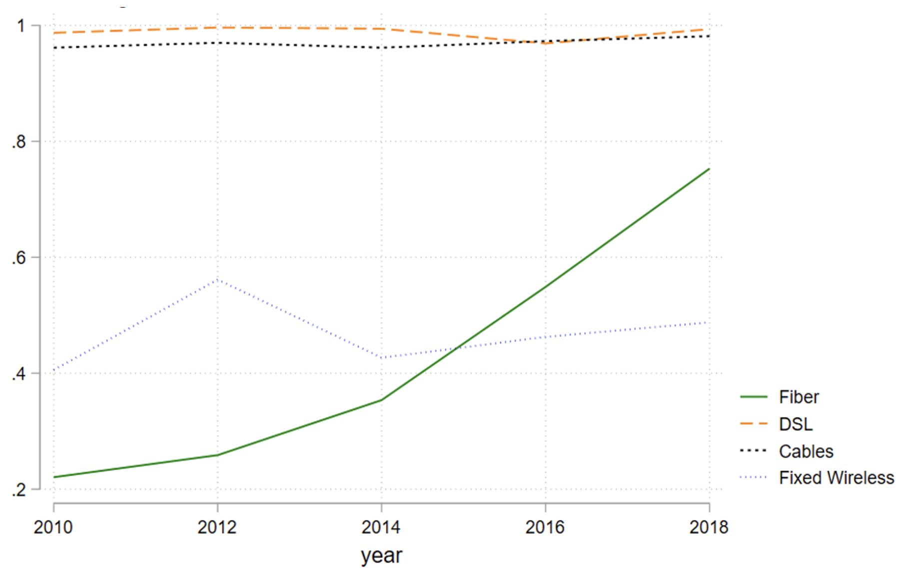
The HRS is a nationally representative panel study surveying approximately 20,000 individuals aged 51 and older ([DATASET], 2010-2018).[32] The core HRS has been conducted annually since 1992, transitioning to a biennial format in 1996. This survey collects extensive demographic, physical and mental health, relationship, income, and occupation-related information. Importantly, HRS also captures data on internet use, social connections and isolation, and the use of electronic technologies such as health apps. Restricted files of HRS have information on the respondents' geographic residence locations.[33]

enables significantly faster data transmission when compared to DSL or cable technologies. However, the actual speed experienced by users may vary based on factors such as proximity to the fiber provider and service configuration.

[32]The Health and Retirement Study data is sponsored by the National Institute on Aging (grant numbers U01AG009740 and is conducted by the University of Michigan.

[33]I obtained IRB approval from the University of Wisconsin-Madison. I use the RAND-HRS longitudinal version of HRS for most of the variables and borrow other variables from the raw HRS files whenever

Figure 1.4: Availability of Broadband Technologies for Older Adults



Note: The figure shows the share of older adults with the availability of various broadband technologies in their census tract of residence. The author's calculation uses HRS data merged with FCC data for 2010 to 2018. The sample is the balanced panel of HRS respondents.

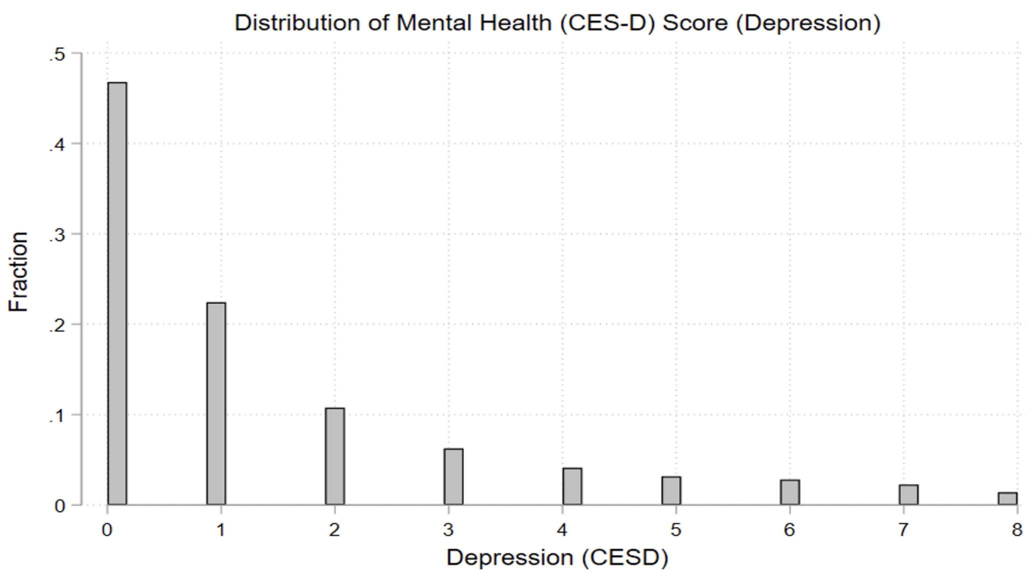
Outcome Variable- Mental health CES-D score

To mitigate potential selection bias arising from examining multiple outcome variables separately and to address concerns related to multiple hypothesis testing, I employ a composite measure of mental health known as the Center for Epidemiology Studies Depression (CES-D) score. The CES-D score is widely utilized across various social sciences and academic disciplines (Zivin *et al.*, 2010, Cutler and Sportiche, 2022). The score is derived from eight questions encompassing domains such as depression, sleep quality, and feelings of loneliness and sadness. It is computed by summing the responses to six negative indicators while subtracting the responses to two positive indicators (Appendix Table A.1). The negative indicators gauge the frequency with which respondents experience sentiments such as depression, difficulty in accomplishing tasks, restless sleep, feelings of sadness, loneliness, and lack of motivation. Conversely, the positive indicators assess the extent to which individuals report feelings of happiness and enjoyment in life. The resulting CES-D mental health score ranges from 0 (best mental health) to 8 (worst mental health).

required.

Recognizing that the manifestation of depressive symptoms may differ by gender, race, geography, or age, I conduct heterogeneity analyses to explore potential differences in the effects of broadband expansion on mental health outcomes.

Figure 1.5: Primary Outcome Variable



Note: Sample is the balanced panel of HRS respondents in survey waves 2010, 12, 14, 16, and 18. N=87,872

1.4.2 Broadband Data

The empirical analysis draws upon panel data from two sources. The first is from the Federal Communications Commission (FCC) Form 477, which spans 2014 to 2018. The second is from the National Telecommunications and Information Association's National Broadband Map (NBM) covering the years 2010 to 2013. This dataset encompasses the number of broadband providers, transmission technology (such as DSL, fiber, cable, or satellite), maximum download and upload speeds measured in Mbps, and whether the provider offers residential service at the census tract level.[34] To ensure comprehensive coverage, broadband providers are required to submit data biannually at the census-block

[34]The data is at the census block level (smaller than census tract); since we do not observe the census block of the HRS respondents, we aggregate the data at the census tract level.

level, demonstrating their ability to deliver internet service with speeds surpassing 200 Kbps in at least one direction. I aggregate the census-block level data at the census tract level by defining the census tract as treated if at least one census block had fiber in a particular year. The census tract, comprising smaller geographic units compared to counties, offers a finer granularity of analysis. There are a total of 84,414 census tracts in the United States, each ideally accommodating approximately 4,000 residents (Census Report). The census tract provides precise geographic treatment of the broadband, as opposed to aggregating at the county level, which has been done in the related literature. To ensure the most recent and reliable broadband data, the analysis primarily relies on the December dataset for each year.

The key treatment variable employed in this study pertains to the introduction of fiber broadband within a given census tract during a specific year. This binary variable takes the value of 1 in the year of introduction and persists as such in subsequent years. Conversely, for census tracts where fiber broadband has not been extended, the variable remains at 0 throughout the observation period, thus constituting the never-treated group. This research design effectively captures the staggered implementation of the treatment. The inclusion of FCC data starting in 2014 is primarily motivated by the need to address measurement issues present in earlier years. Finally, (Grubesic *et al.*, 2019) document some of the limitations of FCC data. Nevertheless, FCC data are the best publicly available records of the broadband providers in the US (Mack *et al.*, 2021).

1.4.3 Sample Selection

The primary analyses focus on the balanced panel of HRS respondents observed in the waves from 2010 to 2018, observing the same person over five survey waves. However, I also provide main estimates utilizing an unbalanced panel of HRS respondents to capture a broader sample and show that the estimates do not change. This research design includes outcomes that are measured less frequently than the treatment. This is because the HRS survey takes place every two years (2010, 12, 14, 16, and 18), and we know the treatment year for each survey respondent (2010, 11, 12, 13,....,18). So, the HRS sample can be categorized into two batches. The first batch receives the treatment in the years when the outcome is measured, and the second batch receives the treatment in the non-HRS wave year.[35] The main analysis is focused on the first batch, i.e., the respondents who were treated in the same year as the survey year, since 73% of the HRS sample belongs to this batch. I conduct a separate analysis for the second batch, as suggested by De Chaisemartin *et al.* (2019). I also show estimates that combine these two batches by estimating the 'length of the fiber treatment' as a treatment. In both of these cases, the results do not change.

In recent studies employing the difference-in-differences (DID) methodology, a common assumption involves carrying forward the initial geographic location of each individual for the subsequent years. This assumption is primarily driven by the lack of individual-level data and precise geographic information over time. However, it poses a notable limitation as it fails to account for potential variations in broadband exposure due to migration. For example, an individual resides during the first period t_0 in a census tract where fiber broadband was rolled out in 2010. Subsequently, the individual relocates to another census tract in t_1 that did not have broadband access and stayed there until the last survey wave t_3. To control for this kind of migration, researchers usually assume that the census tract of that individual in t_1 to t_3 is the same as that of t_0, which is a strong assumption. I depart from this assumption and examine whether individuals migrate following the introduction of broadband. Leveraging the advantages of the HRS data, I observe the census tract of residence for each respondent across all survey waves from 2010 to 2018. This allows me to identify whether respondents move out of their initial census tracts over the course of the study period. It is worth considering the possibility of endogenous migration within different treatment groups of census tracts, potentially induced by broadband expansion. Such migration patterns could introduce bias into the

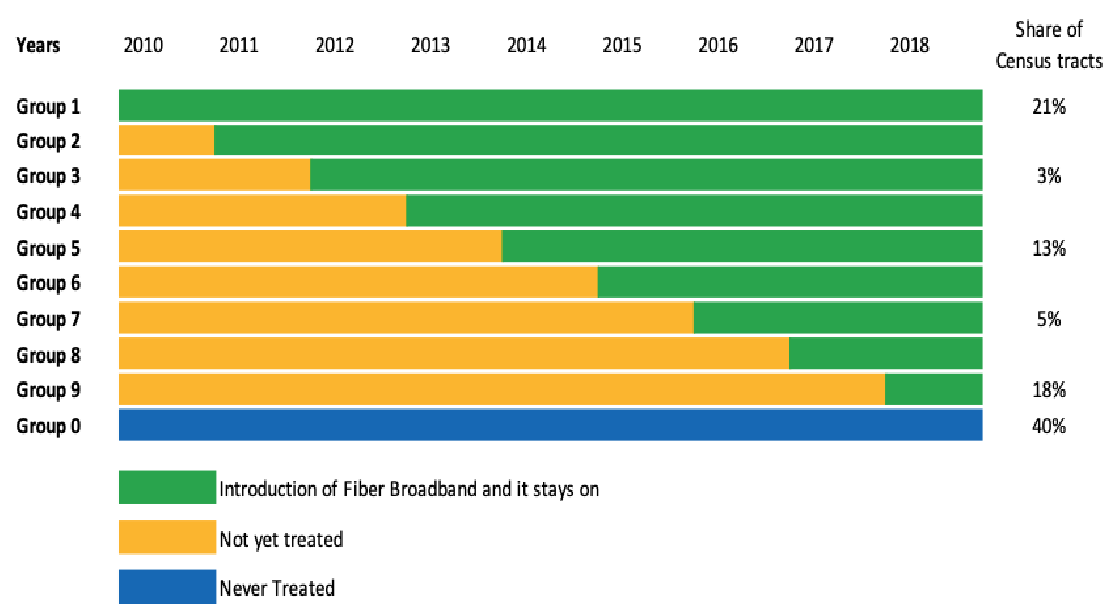
[35] The key reason is that, for the first batch, the first period ('instantaneous' or 'period 0') outcome is recorded. For instance, for the respondents treated in 2012, we have their first post-treatment outcome available for the wave of 2012. For the second batch, who were treated in non-HRS wave years, the first post-treatment outcome available is for the next year of treatment. For instance, for the HRS respondents treated in 2011, we have their first post-treatment outcome recorded in 2012.

estimated effects. To address this, I restrict the sample to non-migrants, encompassing individuals who remained in their census tracts throughout the study period. This non-migrant sample constitutes approximately 91% of the overall sample. Moreover, I present additional estimates that include both movers and non-movers in the 'robustness' section, ensuring a comprehensive analysis of the potential effects of migration on the results.

1.4.4 Introduction of Fiber

Figure 1.6 presents the categorization of the HRS sample into different cohorts based on their exposure to fiber broadband expansion. Nine distinct groups of census tracts are identified; eight correspond to each year of introduction of fiber broadband from 2010 to 2018, and a ninth group represents census tracts that never received fiber broadband during the study period. The primary sample of analysis is the group of census tracts that received the fiber in the survey year of HRS data, i.e., groups 1, 3, 5, 7, and 9. I also show the estimates, including the other groups, by redefining the treatment.

Figure 1.6: Transition from no-Fiber to Fiber Broadband



Note: The figure shows the introduction of fiber broadband in various groups of census tracts in different years. Group 1 received the fiber in 2010, Group 2 in 2011, Cohort 3 in 2012, and so on. Group 0 does not receive any fiber.

1.4.5 Summary Statistics

Table 1.1 presents the summary statistics for the merged dataset, combining the HRS with the broadband data at the census tract level, spanning the period from 2010 to 2018. The statistics provide insights into the baseline characteristics of HRS respondents across various groups, including both the fiber-expansion and no-expansion cohorts of census tracts. Additional demographic characteristics of the respondents are provided in Table A.2 in the Appendix. Table A.2 shows that demographic characteristics within all the groups are similar in age, gender, health, and social security benefits. One key difference that we observe is that the download speed of the internet is substantially higher in the fiber expansion groups (groups 1 to 5) than in the no-fiber expansion group (group 0). This suggests that treated groups are exposed to internet speeds that are very high compared to the control groups. Only the rural variable seems to have differences in means in some of the groups. This makes sense because the urban areas might drive the expansion of fiber. I conduct an analysis of rural and urban areas separately.

1.5 Empirical Strategy

1.5.1 Identification Strategy

To address concerns of endogeneity, it is crucial to account for potential omitted variable bias and unobserved demand factors associated with the rollout of fiber broadband. To ensure the credibility of the causal findings, I adopt a methodology similar to Campbell (2022), leveraging the staggered nature of the fiber broadband rollout across the United States from 2010 to 2018. Moreover, in line with existing literature, I consider the evidence suggesting that access to broadband was subject to significant lag due to supply-side constraints (Dettling *et al.*, 2018, Campbell, 2022).

The introduction of fiber technology presents a quasi-experimental variation that enables the estimation of the causal impact of fiber broadband access on the mental health of older adults using a differences-in-differences (DID) approach. This identification strat-

Table 1.1: Summary Statistics

Expansion in Year	Group 1 2010	Group 2 2012	Group 3 2014	Group 4 2016	Group 5 2018	Group 0 No Fiber
CES-D Depression Score (0-8)	1.34	1.23	1.25	1.45	1.50	1.38
	(1.91)	(1.82)	(1.81)	(1.97)	(2.01)	(1.94)
Clinical Depression (0-1)	0.09	0.08	0.08	0.10	0.11	0.10
	(0.28)	(0.27)	(0.27)	(0.31)	(0.31)	(0.29)
Feel Isolated (y/n)	0.30	0.26	0.34	0.32	0.34	0.32
	(0.46)	(0.44)	(0.47)	(0.47)	(0.47)	(0.47)
Use Web (y/n)	0.55	0.57	0.53	0.53	0.51	0.51
	(0.50)	(0.49)	(0.50)	(0.50)	(0.50)	(0.50)
Email Friends/Family (y/n)	0.31	0.32	0.33	0.32	0.33	0.33
	(0.46)	(0.47)	(0.47)	(0.47)	(0.47)	(0.47)
Number of Broadband Providers	8.87	9.30	8.78	9.13	8.78	7.99
	(3.75)	(3.73)	(3.07)	(3.38)	(3.28)	(2.92)
Max Download speed (Mbps)	399.91	446.57	505.04	431.71	301.35	279.31
	(437.18)	(454.85)	(475.86)	(458.37)	(393.35)	(375.57)
N Respondents-Group year	11728	1713	4353	10438	9332	18421
Number of Census Tracts	1085	174	696	258	922	2070

Note: Mean and (SD) are shown. The data are from a balanced panel of HRS that merged with FCC for the periods 2010 to 2018 every two years, using the geographical unit as a census tract. 'Depression' is the CES-D score equal to 0 if there is no depression and 8 with the highest depression.

egy leverages the comparison of changes in mental health outcomes between the pre-and post-treatment periods among older adults residing in census tracts that introduced fiber broadband and those residing in census tracts that did not experience such introduction. The most conservative model includes individual fixed effects and the treatment year fixed effect, which account for differences between individuals whose access to fiber changes over time and individuals whose access does not change.

I first estimate a difference-in-differences (DID) regression using the following equation.

$$Y_{icgt} = \beta_0 + \beta Fiber_{ct} + \delta_i + \gamma_{gt} + \epsilon_{igct}. \tag{1.1}$$

Here, Y_{igct} is the outcome for individual i, living in census-tract c, belonging to the fiber expansion group g of census tracts, and surveyed in HRS survey year t. $Fiber_{ct}$ is an indicator equal to 1 if the fiber was available at census tract c in survey year t, and 0 otherwise. δ_i is individual fixed effects that control for the time-invariant characteristics of individuals and allow identification to come from within-individual changes in fiber availability.[36] I also include the group-year fixed effects γ_{gt} to account for shocks that affect all the individuals in a given group of census tracts to which fiber was expanded in a given year. I cluster the standard errors at the census-tract level to allow for the correlation among individuals in the same census tract.

The DID model specified in Equation 1.1 estimates the average treatment effect of the introduction of high-speed fiber broadband on the mental health of older adults. In Equation 1.2, I show the event study version of the DID estimation to test for parallel trends and estimate the dynamic treatment effect. By incorporating time-varying treatment effects, this estimator provides valuable insights into the evolving impact of broadband expansion over time and allows for a more comprehensive analysis of the causal relationship between broadband access and mental health outcomes.

$$y_{igct} = \delta_i + \gamma_{gt} + \sum_{\tau=-3,\tau\neq-1}^{3} \beta_\tau Fiber_{\tau(ct)} + \epsilon_{igct}. \tag{1.2}$$

Here, $Fiber_{\tau(ct)}$ are indicator variables equal to 1 if the introduction of fiber was τ years away for fiber expansion group g in HRS survey wave t. I plot the estimates for three pre-periods of the treatment, out of which one year is omitted (-1), and four post-period estimates from 0 to 3 periods after the treatment, where 0 is the instantaneous treatment effect. For the main results, I show the estimates with a balanced and an unbalanced panel of HRS respondents. For all the subsequent analyses, I focus on the strictly balanced panel.

Recent advances in the DID literature suggest that the conventional two-way fixed effects (TWFE) estimator provides consistent estimates under the assumption of treat-

[36]Here, I cannot include both group and individual fixed effects at the same time. One of them must be dropped because there is no between-group movement for individuals. Therefore, I restrict the sample to individuals who did not migrate from their census tracts of residence during the study period of 2010-2018.

ment effect homogeneity (Sun and Abraham, 2021, De Chaisemartin and d'Haultfoeuille, 2022a). However, the introduction of fiber may result in heterogeneous treatment effects, given varying rates of adoption, potentially influencing the mental health of older adults differently. It is also conceivable that the treatment effects may vary across individuals, exhibiting heterogeneity based on various demographic characteristics. To capture this heterogeneity in treatment effects over time and across treated units, I employ the event study methodology proposed by new DID estimators, discussed below, that allow for the heterogeneous treatment effects of fiber broadband introduction on mental health outcomes among older adults.

As suggested by De Chaisemartin and d'Haultfoeuille (2022b), there are four main estimators that are relevant to this study. The estimators for the binary and staggered treatment that allow for dynamic treatment effects, i.e., outcomes that can be affected by past treatment, are provided by Sun and Abraham (2021), Callaway and Sant'Anna (2021), Borusyak *et al.* (2021) and De Chaisemartin and d'Haultfoeuille (2022a). Older adults are less likely to be tech-savvy than younger people. Also, on average, about 55% of the sample respondents have below a high school degree. If we think that the less-educated older people might take more time to learn new technology, we might see the treatment effect over time. So, I focus on estimators that account for the dynamic treatment effect.

I prefer the estimator provided by De Chaisemartin and d'Haultfoeuille (2022a) and De Chaisemartin and d'Haultfoeuille (2020) for various reasons. First, only De Chaisemartin and d'Haultfoeuille (2020) and Borusyak *et al.* (2021) readily provide the average treatment effects. Note that the Borusyak *et al.* (2021) estimator does not include the 'never-treated' group but considers the yet-to-treat group for comparison. Further, as suggested by De Chaisemartin and d'Haultfoeuille (2022b), the estimator provided by Borusyak *et al.* (2021) might not work well in the presence of a strong serial correlation. Here, I test the serial correlation between the outcome variable and its lag values and find that the serial correlation is strong (coefficient 0.59, sd(0.004)).

1.6 Results

1.6.1 Effect on the Speed of Internet

As explained in the theoretical model, in the first stage of the fiber expansion, one may speculate whether the quality of the internet improved or not. Following Campbell (2022), I measure the quality of the internet as the maximum advertised download speed in Mbps in a census tract in a given year. I show the estimate of the effect of fiber expansion on the maximum advertised download speed in Table 1.2. These estimates suggest a significant increase in the advertised maximum download speed after the fiber broadband expansion. There could be several reasons for this massive increase in the internet speed. First, fiber broadband comes with a massive internet speed. Secondly, due to the competition among the service providers, the introduction of fiber could drive this increase in speed Campbell (2022) has documented this competition in more detail.

Table 1.2: Average Treatment Effect of Fiber Broadband on the Internet Download Speed (Mbps)

	Max Advertised Download Speed (Mbps)		
	(1)	(2)	(3)
Post Fiber	344.5***	344.5***	344.3***
	[16.1]	[17.3]	[19.9]
Observations	55,606	55,606	54,234
Year Fixed Effects	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	
Controls		Yes	
Census-Tract Fixed Effects			Yes
Baseline Mean of Outcome	199.1	199.1	199.1

Note: This table shows the average intent-to-treat effects of the staggered introduction of fiber broadband on the availability of the average maximum download speed for older adults, using Equation 1.1 and the estimator provided by De Chaisemartin and d'Haultfoeuille (2022a). The sample is a balanced panel of HRS respondents for biennial waves from 2010 to 2018. The age group is 51 to 103. The treatment variable is equal to 1 if fiber is available in a census tract of residents in survey year t and 0 otherwise. The individual controls include age and whether the individual receives Medicaid, is currently married, and works for pay. I also include the HRS person weights in the estimation. Standard errors in square brackets are clustered at the census tract level. *** p<0.01, ** p<0.05, * p<0.10.

1.6.2 Main Results

Table 1.3 shows the estimates of the average treatment effect (intent-to-treat) of the introduction of fiber broadband on the mental health of older adults using the equation (Equation 1.1) and estimator provided by De Chaisemartin and d'Haultfoeuille (2022a) using the balanced panel of HRS respondents. The estimate in the first column with my preferred specification shows the key results of the DID specification. This specification incorporates the individual fixed effects and the fiber broadband expansion year fixed effects to ensure that identification stems from within-individual changes in fiber availability over time. Column 2 includes individual-level time-varying controls in addition to the specifications in column 1. In column 3, I replace individual fixed effects with the census-tract fixed effects. In column (4), I introduce expansion group-year fixed effects to account for the shocks that affect all individuals in an expansion group in a given year.

Table 1.3: Average Treatment Effect of Fiber Broadband on the Symptoms of Depression

	CES-D Depression Score			
	(1)	(2)	(3)	(4)
Post Fiber	-0.082^{**}	-0.073^{**}	-0.091^{**}	-0.128^{**}
	[0.032]	[0.035]	[0.039]	[0.061]
Observations	47,935	47,163	49,728	47,935
Year Fixed Effects	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes		Yes
Controls		Yes		
Census-Tract Fixed Effects			Yes	
Expansion Group-year Fixed Effects				Yes
Baseline Mean of Outcome	1.42	1.42	1.42	1.42

Note: This table shows the average intent-to-treat effects of the staggered introduction of fiber broadband on depression symptoms among older adults, using Equation 1.1 and the estimator provided by De Chaisemartin and d'Haultfoeuille (2022a). The outcome variable 'depression' is the CES-D mental health categorical score from 0 to 8. The sample is a balanced panel of HRS respondents for biennial waves from 2010 to 2018. The age group is 51 to 103. The treatment variable is equal to 1 if fiber is available in a census tract of residents in survey year t and 0 otherwise. The individual controls include age and whether the individual receives Medicaid, is currently married, and works for pay. I also include the HRS person weights in the estimation. Standard errors in square brackets are clustered at the census tract level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 1.3 suggests that the introduction of fiber broadband decreases depression symptoms among older adults, with estimates consistently supporting these findings across the various specifications. The point estimates are statistically significant in all the specifications. For example, column 1 shows that fiber expansion reduces depression symptoms among older adults by 0.082 units. After accounting for the individual-level time-varying controls and other fixed effects, the estimates are still statistically significant and increase in some cases. This robustness in the results strengthens the evidence for the beneficial impact of fiber broadband on mental health outcomes.[37] Apart from the main analysis, I will focus on De Chaisemartin and d'Haultfoeuille (2022b) for the reasons explained in Section 5.[38]

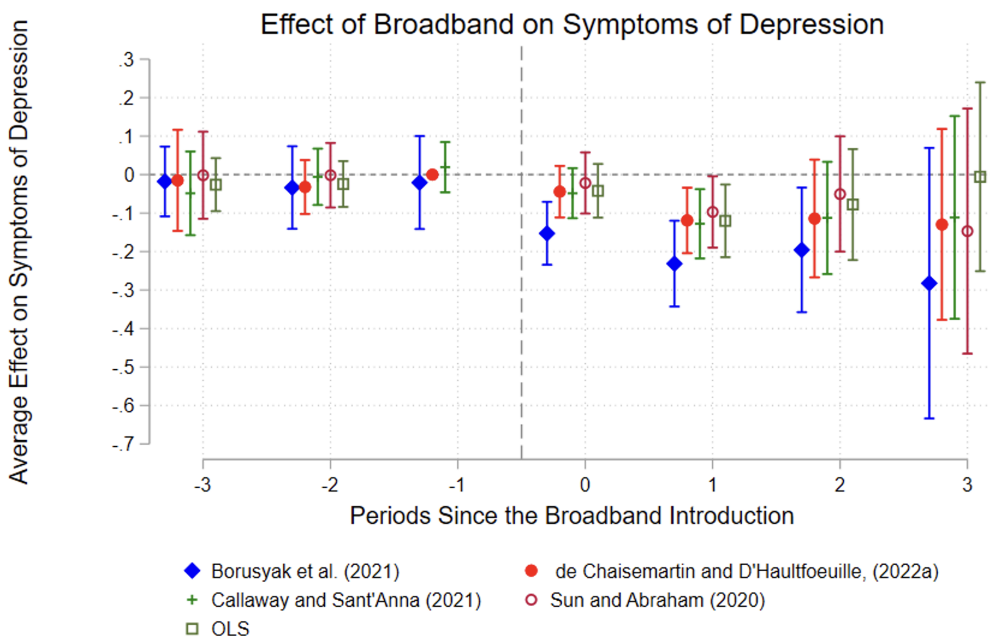
I use additional measures to illustrate the magnitude of the results. The preferred estimate from column 1 in Table 1.3 shows that fiber expansion reduces depression symptoms among older adults by 0.082 units on a scale of 0 to 8. This estimate is remarkably similar in magnitude (0.085) but opposite in direction to the effect observed in a study by Braghieri *et al.* (2022), which suggests that the expansion of Facebook increased mental health problems among college students in the US. These contrasting findings highlight a key result of this paper, indicating that the impact of a similar technology on mental health outcomes can vary based on age cohorts and potentially on how individuals engage with the technology. Section 8 provides further insights into the underlying reasons for this divergence. Additionally, I compare the estimates with a closely related meta-analysis conducted by Paul and Moser (2009). The results suggest that the positive effect of broadband expansion on depression symptoms is approximately 20% of the negative effect of job loss. Another comparison can be made with the study by McInerney *et al.* (2013), which examines the effect of the 2008 recession on the mental health of older adults. The estimates from my paper indicate that the benefit of broadband expansion is roughly 41%

[37] Appendix Table A.3 shows the estimates of the average effects of the introduction of fiber broadband on the mental health of older adults using an alternate DID estimator provided by Borusyak *et al.* (2021) and replicates similar positive effects of fiber broadband expansion.

[38] Because the Borusyak *et al.* (2021) estimator does not include the 'never-treated' group but considers the yet-to-treat group for comparison, the sample size in Appendix Table A.3 is smaller than in Table 1.3. Secondly, Borusyak *et al.* (2021) may not work well in the presence of a strong serial correlation.

of the negative effect of the recession. These comparisons provide a context for understanding the relative importance of broadband expansion in affecting mental health as compared to the effects of other factors.

Figure 1.7: Dynamic Treatment Effects of Broadband Expansion on the Symptoms of Depression



Note: This figure shows the dynamic effects plots using Equation 1.2 with the estimator provided by De Chaisemartin and d'Haultfoeuille (2022a), Borusyak *et al.* (2021), Sun and Abraham (2021), Callaway and Sant'Anna (2021), and the traditional TWFE. The sample is from the HRS respondents for biennial waves from 2010 to 2018. The age group is 51 to 103. The outcome variable 'depression' is a CES-D mental health categorical score from 0 to 8, 0 being no depression and 8 being the highest depression. For Borusyak *et al.* (2021) and De Chaisemartin and d'Haultfoeuille (2022a), I include a fiber broadband expansion year and HRS respondents' individual fixed effects. For Callaway and Sant'Anna (2021), I include expansion group fixed effects in addition to the above two FEs. Standard errors are clustered at the census tract level. The bars show the 95 percent confidence interval. Sample size for DCDH estimator: N= 47,935 (switchers =6,726); N_{t0} = 23,694 (switchers =3,655), N_{t1} = 14,668 (switchers =2,155), N_{t2}= 7079 (switchers =735), N_{t3} = 2,494 (switchers =181).

Further, I show the results with the dynamic treatment effects in Figure 1.7 using Equation 1.2 and the DID estimators proposed by De Chaisemartin and d'Haultfoeuille (2022a), Borusyak *et al.* (2021), Sun and Abraham (2021), Callaway and Sant'Anna (2021), and the traditional TWFE. Figure 1.7 suggests that depression symptoms are declining after the introduction of high-speed fiber broadband and are statistically significant, no matter which estimator I use, providing confidence in the main results. Figure 1.7 also suggests that the estimates prior to the introduction of the fiber broadband (period -2 and -3) are closer to 0 and insignificant, providing evidence for no pre-trends and consistent with the parallel trend assumption.

Further, Appendix Table A.4 shows the effect of fiber broadband rollout on a relatively extreme measure of symptoms of depression – 'clinical depression.' In the HRS, a CES-D score above three is considered indicative of clinically relevant symptoms of depression or 'caseness' (Schane *et al.*, 2008, McInerney *et al.*, 2013). Appendix Table A.4 supports the main conclusion of the paper, that the clinical symptoms of depression decline after the introduction of fiber broadband technology. To put these findings into context, I compare them with research that examines the effect of unexpected widowhood on depression. The results from my study suggest that the benefit of broadband expansion is about 14% of the negative effects associated with the unexpected loss of a spouse (Siflinger, 2017).[39] This comparison sheds light on the relative impact of broadband expansion in mitigating depression symptoms compared to other significant life events. Similarly, I provide evidence of whether the fiber broadband rollout has any effect on the likelihood of an individual taking medications for anxiety or depression. The estimates in Appendix Table A.5 suggest no evidence that the broadband expansion affects individuals regularly taking medications for anxiety or depression.

1.6.3 Self-use of Internet

The estimates presented in Table 1.3 reflect the ITT effect, which captures the overall effect of the availability of fiber broadband. This effect encompasses both the direct impact on individuals who actively use the internet and the potential indirect effects arising from others in the household or network using the internet. However, a significant contribution of this study lies in leveraging the rich data provided by the HRS to disentangle the direct and indirect effects. This is a departure from similar research.[40]

[39] I compare my DID estimate that has individual fixed effects.

[40] For instance, (Braghieri *et al.*, 2022) documents that they cannot observe whether or not college students use Facebook, and their estimates are a combination of direct and indirect treatment effects.

To distinguish between the direct and indirect effects, I incorporate variables from the HRS survey that capture respondents' use of the internet. Specifically, I consider measures such as regular web use and whether respondents engage in email communication with their children, family, or friends. By including these variables, I aim to provide a more nuanced understanding of the mechanisms through which broadband availability affects mental health outcomes among older adults.

The survey question is–[41]

"Do you regularly use the Internet (or the World Wide Web) for sending and receiving e-mail or for any other purpose, such as making purchases, searching for information, or making travel reservations?"

To assess the impact of broadband expansion on older adults' use of the internet, I transform positive responses to the above survey questions into a binary variable, assigning a value of 1 if the respondent answers affirmatively and 0 otherwise. Figure A.1 presents the dynamic effects, using estimators provided by De Chaisemartin and d'Haultfoeuille (2022a) and Borusyak *et al.* (2021). Importantly, the pre-trend estimates are close to zero and mostly statistically insignificant, providing support for the validity of the parallel trend assumption in our analysis. Figure A.1 shows mixed evidence on the effect of the rollout of fiber broadband on the use of the internet. The estimates are statistically significant under the Borusyak *et al.* (2021) estimation. However, under the De Chaisemartin and d'Haultfoeuille (2022a) estimation, the effect is not significant. One explanation is that the Borusyak *et al.* (2021) estimation, unlike De Chaisemartin and d'Haultfoeuille (2022a), does not include the 'never-treated' group; this is because the estimator provided by Borusyak *et al.* (2021) works well when there is not much serial correlation. Here, the serial correlation in the outcome variable is very small, so I prefer the Borusyak *et al.* (2021) estimator.

Note that I do not observe whether the respondent has access to fiber broadband at home.

[41] For the missing values, I impute the value =1 if the respondents report that they send emails to friends or families.

1.6.4 Heterogeneous Effects

In this section, I explore the heterogeneity of the effects of broadband expansion based on various characteristics. To begin, I examine whether the effects vary between urban and rural areas. Rural regions may be less likely to adopt fiber broadband and maybe less likely to experience an improvement in mental health. Then, I investigate whether the effects differ based on gender, taking into account the well-documented differences in baseline depression levels between men and women, in that women tend to experience higher levels of depression across countries and age groups. If women are less likely to be exposed to fiber broadband, then one may expect even lesser benefits for women. Additionally, I examine the differential impact of broadband expansion based on race, considering the higher prevalence of mental health issues among African Americans and disparities in access to the Internet based on race. Moreover, I analyze whether the estimates vary across age groups, separating out people who might still be below the retirement age (below 65) and may have access to broadband through their workplace. I expect higher access to the internet and potentially higher benefits for working people. Finally, I study the effect based on marital status. Married couples often rely on each other for social interaction and support. Recent evidence suggests the existence of such spousal spillover of mental health among older English couples (Jain and Ma, 2024). Broadband access may affect their mental health differently depending on how they utilize it for social engagement. Importantly, instead of using the traditional two-way fixed effects (TWFE) estimator commonly used to explore these heterogeneities, I estimate the effects using the latest DID estimator proposed by De Chaisemartin and d'Haultfoeuille (2022a).[42]

Rural vs. Urban

Appendix Table A.2 provides evidence that fiber broadband expansion was slower in rural areas during the initial years. As noted above, rural residents tend to be older and poorer, with lower levels of education, worse mental health, and lower levels of private health

[42] As mentioned in the previous sections, this estimator allows for treatment effect heterogeneity across groups and over time, providing a more robust analysis of the differential impacts of broadband expansion.

insurance; they also have less access to mental health professionals because of shortages of such services in rural areas(Foutz *et al.*, 2017, Mueller *et al.*, 2018, Moy *et al.*, 2017, Pender *et al.*, 2019). [43] To assess whether the positive effects of fiber broadband are concentrated in a specific region, I analyze the effects separately for urban and rural areas based on the HRS respondents' residential locations. Table 1.8 shows the average treatment effects, and Figure 1.8 shows the dynamic treatment effects of fiber broadband on depression symptoms separately for urban and rural areas.

The estimates in Table 1.8 and Figure 1.8 indicate that the introduction of fiber broadband reduced depression symptoms among older adults in both urban and rural areas; however, there was a statistically significant decline in rural areas. One potential reason could be that the baseline mental health is already better in urban areas, so the gain is not much. The second reason could be that the frequency of monthly and yearly internet use for health information by older rural residents is significantly higher than that of urban areas (MCBS, 2022). These findings suggest that fiber broadband expansion has the potential to deliver significant benefits for the rural community in terms of mental health outcomes.

Age Groups

The effect of broadband expansion on mental health outcomes may vary based on the age of the respondents. To investigate this, I analyze the effects separately for different age groups: below 65, above 65, below 85, and above 85 years old. Figure 1.9 shows the estimates for these age groups. The findings indicate a decline in depression symptoms over time for the age groups below 85 and above 65, with the effects becoming statistically significant as time progresses. However, I do not find evidence of a decline in mental health among individuals below 65 and those above 85. This suggests that the expansion of fiber broadband may have potential benefits for the mid-age group cohort, specifically individuals aged 65 to 85, suggesting an inverted U-shaped effect based on the age groups.

These results align with the idea that the impact of broadband technology on mental

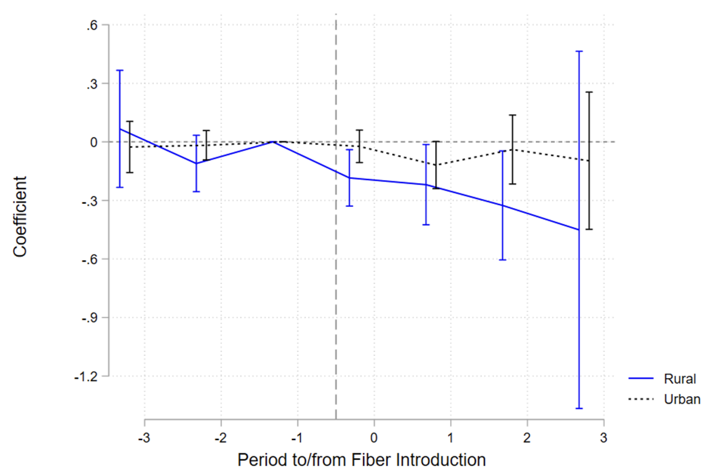
[43]Medicaid and CHIP Payment and Access Commission, Issue April 2021.

Table 1.4: Average Treatment Effect of Fiber Broadband on the Depression Symptoms-By Region

	Rural	Urban
Post Fiber	-0.229^{***}	-0.057
	[0.087]	[0.044]
Observations	9,930	37,779
Year Fixed Effects	Yes	Yes
Individual Fixed Effects	Yes	Yes
Mean of Outcome Variable	1.37	1.43

Note: This table shows the average treatment effects of the staggered introduction of the fiber broadband on the depression symptoms (CES-D) among older adults using Equation 1.1 and estimating with the estimator provided by De Chaisemartin and d'Haultfoeuille (2022a). The sample is a balanced panel of HRS respondents for biennial waves from 2010 to 2018, aged 51+. The treatment variable is equal to 1 if fiber is available in a census tract of residents in survey year t and 0 otherwise. Standard errors in square brackets are clustered at the census tract level. *** p<0.01, ** p<0.05, * p<0.10.

Figure 1.8: Dynamic Treatment Effect of Fiber Broadband on the Depression Symptoms-By Region



Note: This figure shows the dynamic effects plots using Equation 1.2 with the estimator provided by De Chaisemartin and d'Haultfoeuille (2022a). The sample is a balanced panel of HRS respondents for biennial waves from 2010 to 2018. The age group is 51 to 103. The time variable is the survey wave, and the fiber group variable is the group of census tracts in which fiber was introduced in different years. The outcome variable 'depression' is a CES-D mental health categorical score from 0 to 8, 0 being no depression and 8 being the highest depression. I include individual and treatment-year fixed effects. Standard errors are clustered at the census tract level. The bars show the 95 percent confidence interval. Sample size: N (Rural)= 9,930. N(Urban)= 37,779.

Table 1.5: Average Treatment Effect on Depression Symptoms: By Age Groups

	Below 65	65 to 85	Above 85
	(1)	(2)	(3)
Post Fiber	−0.068	−0.084*	0.041
	[0.066]	[0.043]	[0.101]
Observations	12,190	31,226	7,681
Year Fixed Effects	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes
Mean of Outcome Var	1.58	1.30	1.42

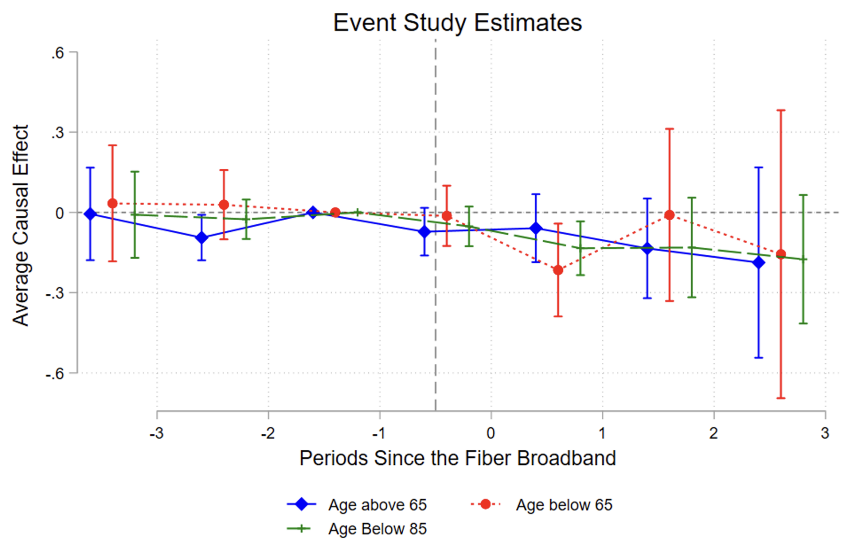
Note: This table shows the average treatment effects of the staggered introduction of the fiber broadband on the depression symptoms among older adults using Equation 1.1 and estimating with the estimator provided by De Chaisemartin and d'Haultfoeuille (2022a). The outcome variable 'depression' is a CES-D mental health categorical score from 0 to 8, 0 being no depression and 8 being the highest depression. The sample is a balanced panel of HRS respondents for biennial waves from 2010 to 2018. The treatment variable is equal to 1 if the fiber is available in a census tract of residents in survey year t and 0 otherwise. Standard errors in square brackets are clustered at the census tract level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

health might operate differently at the intensive and extensive margins, depending on the age group. For individuals below 65, who are likely to still be working, broadband may have some effect at the intensive margin if they have access to the internet at their workplace. In contrast, individuals above 65 may have limited access to broadband, making the effect more pronounced at the extensive margin. Overall, these findings shed light on the potential benefits of fiber broadband expansion on mental health outcomes for the mid-age group cohort.

By Gender

The mean depression (CES-D) score for women (1.52 (sd 2.07)) is higher than that of men (1.19 (sd 1.76)). Across nations and age groups, women have higher levels of depressive symptoms (Nolen-Hoeksema and Hilt, 2008, Salk *et al.*, 2017, Banerjee *et al.*, 2023). However, women may be more likely to use the internet for purposes such as emails, accessing health-related information, and seeking support for personal and health-related issues (Pew Research). This suggests important potential benefits of broadband for women.

Figure 1.9: Dynamic Treatment Effects: By Age Groups



Note: This figure shows the dynamic effects plots, using the estimator provided by De Chaisemartin and d'Haultfoeuille (2022a) for various age groups. The sample is a balanced panel of HRS respondents for biennial waves from 2010 to 2018. The outcome variable 'depression' is a CES-D mental health categorical score from 0 to 8, 0 being no depression and 8 being the highest depression. I include individual fixed effects and treatment year fixed effects. Standard errors are clustered at the census tract level. The bars show the 95 percent confidence interval. Sample sizes: $N_{Above65}$ = 25,663; $N_{Below65}$ = 16,749; $N_{Below85}$ = 42,795.

The estimates presented in Figure 1.10 indicate a declining trend in depression symptoms among men compared to women following the introduction of fiber broadband. Neither of these estimates is statistically significant. However, on average, women experience a greater decline in depression symptoms (estimates -0.031, SE 0.046) compared to men (estimates -0.028, SE 0.094). The difference between the two is -0.003 (p-value 0.07) and is statistically significant at the 10% level. This suggests potentially greater benefits of broadband expansion for women.

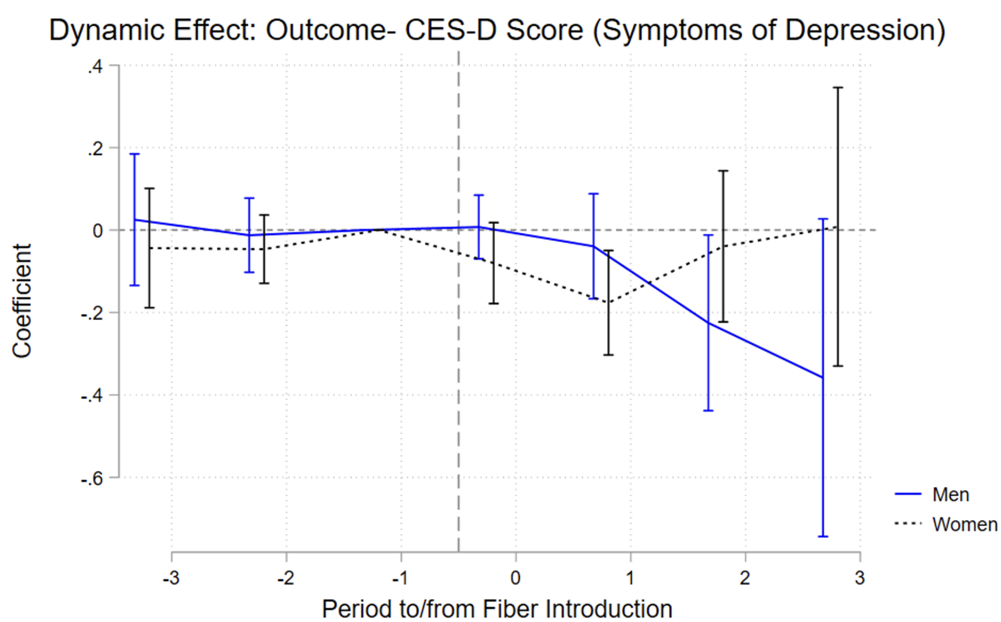
These estimates contrast to the findings of Braghieri *et al.* (2022), who observed the adverse effects of social media (Facebook) on the mental health of female college students. This suggests that the impact of technology can vary across gender and age groups. It is worth mentioning that while the trend of CES-D depression score estimates is increasing for women over time and declining among men, these trends are statistically insignificant. Nonetheless, these estimates contribute valuable insights into the potential differential effects of broadband expansion on mental health outcomes between men and women.

Table 1.6: Average Treatment Effect– By Gender

	Men	Women
Post Fiber	−0.041	−0.103**
	[0.037]	[0.049]
Observations	19,453	28,482
Year Fixed Effects	Yes	Yes
Individual Fixed Effects	Yes	Yes

Note: This table shows the average treatment effects of the staggered introduction of the fiber broadband on the depression symptoms (CES-D) among older adults using Equation 1.1 and estimating with the estimator provided by De Chaisemartin and d'Haultfoeuille (2022a), estimated by gender. The sample is a balanced panel of HRS respondents for biennial waves from 2010 to 2018. The age group is 51 to 103. The treatment variable is equal to 1 if the fiber is available in a census tract of residents in survey year t and 0 otherwise. Standard errors in square brackets are clustered at the census tract level. *** p<0.01, ** p<0.05, * p<0.10.

Figure 1.10: Dynamic Treatment Effects by Gender



Note: This figure shows the dynamic effects plots, using the estimator provided by De Chaisemartin and d'Haultfoeuille (2022a) for men and women separately. The sample is a balanced panel of HRS respondents for biennial waves from 2010 to 2018. The age group is 51 to 103. The outcome variable 'depression' is a CES-D mental health categorical score from 0 to 8, 0 being no depression and 8 being the highest depression. I include the group and expansion year fixed effects. Standard errors are clustered at the census tract level. The bars show the 95 percent confidence interval.

Race

In order to examine the potential heterogeneity of the effects, I estimate the model separately for Whites and non-Whites, considering the higher prevalence of mental health problems among African Americans. The mean CES-D depression score for Whites is 1.27 (sd 1.88), while for African Americans, it is 1.69 (sd 2.00). Recent reports also suggest disparities in internet access and speed, with non-White and economically disadvantaged areas experiencing slower internet speeds for the same price (Wisconsin State Journal Report, 2022). The estimates in Table 1.7 present the treatment effects for Whites and African Americans. The results indicate a decline in depression symptoms among older Whites. Conversely, for African Americans, they are not statistically significant. One potential reason for the noisy estimates might be the sample size for the African Americans, who represent about 19% of the HRS sample. These findings suggest that fiber broadband expansion may not yield significant benefits for African Americans in terms of reducing depression symptoms. These estimates highlight the need for further research to understand the factors that may contribute to the lack of significant effects among African Americans. Examining other socio-economic and contextual factors could provide valuable insights into the underlying mechanisms and help address disparities in the impact of broadband expansion on mental health outcomes.

1.6.5 Effect Based on the Length of Exposure

To capture the potential effects of the length of exposure to fiber broadband at the individual level, I extend the analysis by examining the effects at the census-tract-survey-year level. In the main sample, I include HRS respondents who were exposed to broadband during odd years: 2011, 2013, 2015, and 2017. For instance, in the year 2014, individuals who received broadband in 2011 would have been exposed for three years, while those who received broadband in 2012 would have been exposed for only two years. By incorporating the length of exposure in the analysis, I aim to capture the potential cumulative effects of broadband technology on mental health over time. This provides a more comprehen-

Table 1.7: Average Treatment Effect – By Race

	White	Non-White
Post Fiber	-0.096^{***}	-0.021
	[0.035]	[0.080]
Observations	36,403	11,396
Year Fixed Effects	Yes	Yes
Individual Fixed Effects	Yes	Yes

Note: This table shows the average treatment effects of the staggered introduction of the fiber broadband on the depression symptoms (CES-D) among older adults using Equation 1.1 and estimating with the estimator provided by De Chaisemartin and d'Haultfoeuille (2022a), estimated by race. The sample is a balanced panel of HRS respondents for biennial waves from 2010 to 2018. The age group is 51 to 103. The treatment variable is equal to 1 if the fiber is available in a census tract of residents in survey year t and 0 otherwise. Standard errors in square brackets are clustered at the census tract level. *** p<0.01, ** p<0.05, * p<0.10.

Table 1.8: Average Treatment Effect of Fiber Broadband on the Depression Symptoms-By Marital Status

	Married	non-Married
Post Fiber	-0.088^{***}	-0.040
	[0.033]	[0.060]
Observations	25,487	15,969
Year Fixed Effects	Yes	Yes
Individual Fixed Effects	Yes	Yes
Mean of Outcome Variable	1.07	1.78

Note: This table shows the average treatment effects of the staggered introduction of the fiber broadband on the depression symptoms (CES-D) among older adults using Equation 1.1 and estimating with the estimator provided by De Chaisemartin and d'Haultfoeuille (2022a). The estimates are separated for the marital status, i.e., married and non-married (divorced, separated, widowed, never married, and partnered). I include the individuals whose marital status does not change over time. The sample is a balanced panel of HRS respondents for biennial waves from 2010 to 2018, aged 51+. The treatment variable is equal to 1 if the fiber is available in a census tract of residents in survey year t and 0 otherwise. Standard errors in square brackets are clustered at the census tract level. *** p<0.01, ** p<0.05, * p<0.10.

sive perspective on the relationship between broadband expansion and mental well-being among older adults.

To study the effect of length of exposure, I follow Braghieri *et al.* (2022) and estimate the following equation-

$$Y_{icgt} = \alpha_c + \gamma_t + \sum_{\tau=0}^{8} \beta_\tau \times YearsinFiber_{\tau(ict)} + \mathbf{X}'_i \times \lambda + \epsilon_{icgt}, \tag{1.3}$$

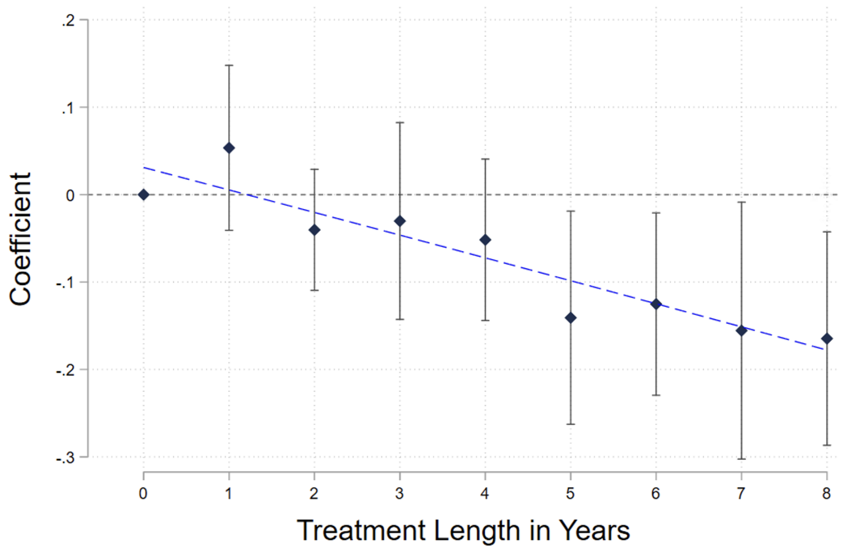
where 'Years in Fiber$_{\tau(ict)}$' are indicators equal to 1 if HRS respondent i at census-tract c in survey-wave t had access to fiber for τ years. The number of treated years is calculated as $\tau = Fiber_{gt} \times (t - Yearoftreatment)$ where t is the survey year. α_c is the census-tract fixed effects and γ_t is the survey year fixed effects. I also include a vector of individual-level controls X_i'. Figure 1.11 shows the β_τ estimates and suggests a decline in mental health CES-D depression score over time. The figure shows that the number of treated years has a significant effect over time on the decline in depression symptoms. These estimates provide evidence that excluding HRS sample respondents who were exposed to fiber broadband in odd years and interviewed in even survey years does not bias the results.

1.7 Robustness

I report several sensitivity analyses. I show estimates with different specifications in Table 1.3 using the estimator provided by De Chaisemartin and d'Haultfoeuille (2022b) and another DID estimator by Borusyak *et al.* (2021) in Table A.3. Because we cannot readily obtain the standard errors of the average treatment effects from the commands used in Callaway and Sant'Anna (2021) and Sun and Abraham (2021), I show the average treatment effects without those estimators. Further, in Table 1.10, I show the estimates, including the 'movers,' since the main estimation is focused on the 'stayers,' i.e., individuals who do not move out of their census tract for the study period.

In Table 1.3, I show the robustness of the estimates, including controls, the census-tract fixed effects, and group-year fixed effects. Column 2 of Table 1.3 suggests that the estimates with controls demonstrate robustness, indicating a consistent decline in depression symptoms and providing evidence of the positive impact of broadband expansion on the

Figure 1.11: Effect on Mental Health CES-D score by Length of Exposure



Note: This figure shows the estimates of the effect of the length of exposure to fiber broadband on the CES-D depression score. The dashed curve is the quadratic curve of best fit. The coefficients are estimated using the Equation 1.3 and the TWFE estimation. The sample is a balanced panel of Health and Retirement Study (HRS) respondents for biennial waves from 2010 to 2018. The age group is from 51 to 103. The outcome variable 'depression' is a CES-D mental health categorical score from 0 to 8, 0 being no depression and 8 being the highest depression. Individual controls include binary indicators if the respondent is male, enrolled in Medicaid, rural, White, has education more than high school, receives social security disability insurance (SSDI), and is currently married. Also, individual controls include age-fixed effects. I included the missing dummies for the covariates which are missing and replaced them with a value of 1. Standard errors are clustered at the census tract level. The bars show the 95 percent confidence interval.

mental well-being of older adults. The estimates are statistically significant, with standard errors almost the same. This analysis strengthens the validity of the findings, suggesting that omitted variables or confounding factors do not drive the observed effects that can be attributed to the introduction of broadband technology.

Another concern could be mortality selection. Even though the main estimates are focused on the individual balance panel sample from HRS if more depressed individuals are dropping out of the sample and only the mentally healthier individuals are surviving, then the estimates shown in Table 1.3 could have upward biased. I show the estimates in Table 1.9 where the outcome is whether the individual has died or not. The estimates suggest that the rollout of fiber broadband declines individual-level mortality, suggesting other positive benefits of the broadband rollout. Secondly, I include a control variable for baseline (year 2010) health status (indicator =1 if self-reported health is excellent, very good, or good, and 0 if fair or poor) that may affect both mortality risk and mental health outcomes. Controlling for this variable may reduce the bias due to unobserved heterogeneity. The estimate of this regression is (-0.070, p¡0.1), which replicates the estimates in column 2 of Table 1.3.

Table 1.9: Average Treatment Effect of Fiber Broadband on Mortality

	Using DCDH Estimator	Using Borusyak Estimator
Post Fiber	-0.004^{*}	-0.006^{**}
	[0.002]	[0.003]
Observations	60,123	41,935
Year Fixed Effects	Yes	Yes
Individual Fixed Effects	Yes	Yes
Mean of Outcome Variable	0.016	0.016

Note: This table shows the average treatment effects of the staggered introduction of the fiber broadband on individual mortality among older adults using Equation 1.1 and estimating with the estimator provided by De Chaisemartin and d'Haultfoeuille (2022a) in Column 1 and by Borusyak *et al.* (2021) in Column 2. Note that the estimator in column 1 includes the never-treated units in the estimation, while the estimator in column 2 does not, and that's why there is a difference in the sample sizes. The sample is a balanced panel of HRS respondents for biennial waves from 2010 to 2018, aged 51+. The treatment variable is equal to 1 if the fiber is available in a census tract of residents in survey year t and 0 otherwise. Standard errors in square brackets are clustered at the census tract level. *** p<0.01, ** p<0.05, * p<0.10.

1.7.1 Stayers and Movers

Among the balanced panel of HRS respondents, approximately 91% of the sample, referred to as "stayers," did not move out of their census tracts of residence during the period of 2010-2018. On the other hand, around 9% of the respondents, referred to as "movers," relocated at least once from their census tract of residence during the same period. In the primary analysis, I focus exclusively on the stayers to mitigate the potential endogeneity issues associated with migration and its relationship with broadband treatment. To test the robustness of the estimates, I also include the movers in the main sample. Table 1.10 shows the estimates for the stayers and movers. The dynamic effect persists, with evidence supporting the parallel trend assumption and a slightly lower estimate in the third period. The estimates suggest that the movers are not driving the estimates. This analysis provides reassurance that mobility patterns do not drive the observed effects, which are consistent even when considering the impact of migration on the estimates.

Table 1.10: Average Treatment Effect of Fiber Broadband on the Symptoms of Depression for both stayers and movers

	CES-D Score		
	(1)	(2)	(3)
Post Fiber	-0.076^{***}	-0.072^{**}	-0.071
	[0.026]	[0.033]	[0.045]
Observations	71,323	70,129	53,459
Year Fixed Effects	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	
Controls		Yes	
Census-Tract Fixed Effects			Yes

Note: Estimates are using Equation 1.1 and estimating with the estimator provided by De Chaisemartin and d'Haultfoeuille (2022a). The individual controls include whether the individual receives Medicaid, is married, and works for the pay. I also included the HRS person weights in the estimation. *** p<0.01, ** p<0.05, * p<0.10.

1.7.2 Spatial Spillover

There could be a bias in the estimates if spatial spillover effects exist. For instance, an individual living in a census tract does not receive the treatment (fiber broadband), but the nearby census tracts receive the treatment. This gives an individual access to the resources in the areas with fiber broadband, such as medical facilities (for in-person or virtual visits) or a public library for health-related information, telehealth, or connecting with friends and families through the web. The health of this person might get better with the introduction of fiber internet in the nearby census tract. In this case, the estimates are biased downward. Previous literature often neglects bias due to spatial spillover.

I follow Butts (2021) to address some of these concerns, mainly by excluding the units closer to the treatment areas. First, I use the DID estimator by Borusyak *et al.* (2021) in

Figure 1.7 and Table A.3, which does not include the 'always control group.' The estimates shown in Table A.3 are higher than if I include the 'always control group' and the main effects in Table 1.3 are potentially the lower bounds of the actual effects. This increase suggests evidence of the presence of spatial spillover from the 'always control group', and after correcting for the potential bias, the treatment effect persists. Secondly, I randomly choose a census tract from each county to reduce the bias in the estimation due to spillover effects. The estimates are shown in Table 1.11, which shows that the estimates are almost doubled. This also provides evidence that there may exist a spatial spillover effect, and the main effects shown Table 1.3 are lower bounds of the actual effects.

Table 1.11: Average Treatment Effect of Fiber Broadband on the Symptoms of Depression for one random census tract from each county

	CES-D Score		
	(1)	(2)	(3)
Post Fiber	-0.199^{**}	-0.186^{***}	-0.198^{**}
	[0.079]	[0.065]	[0.085]
Observations	9,372	9,372	9,710
Year Fixed Effects	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	
Controls		Yes	
Census-Tract Fixed Effects			Yes

Note: Estimates are using Equation 1.1 and estimating with the estimator provided by De Chaisemartin and d'Haultfoeuille (2022a). The individual controls include whether the individual receives Medicaid, is married, and works for the pay. I also included the HRS person weights in the estimation. *** p<0.01, ** p<0.05, * p<0.10.

Finally, I control whether the individual takes regular medicine for anxiety or depression, which may provide additional evidence of the mental health of an individual. Specifically, I added an additional control in the specification in Column 2 of Table 1.3. I find the magnitude of the estimates is consistent (-0.073, SD 0.043), but the statistical significance is at the 10% level. Further, I find a strong correlation (0.328, significant at 1% level) between the variable of medication for anxiety or depression and the primary measure of depression symptoms (CES-D score). I still provide the estimates with the medication as an outcome in Table A.5, which suggests a null effect on the use of the medications for anxiety and depression. This also provides evidence that the primary channels through which broadband may affect the mental health of older adults could be through social channels, explained in the next section.

1.8 Mechanisms

In this section, I present empirical evidence regarding the potential mechanisms underlying the positive effect of high-speed broadband on the mental health of older adults. Specifically, I test whether broadband affects social connectedness, social isolation, health literacy, cognitive score, and technological efficiency in nearby hospitals. This study is among the first to empirically test the causal relationship between high-speed broadband technology and most of these key channels.

1.8.1 Social Isolation and Loneliness

To further explore the impact of broadband expansion on social isolation among older adults, I utilize specific questions from the HRS survey that assess feelings of being isolated from others. I estimate the Equation 1.2 and the estimator provided by De Chaisemartin and d'Haultfoeuille (2022a) to evaluate whether broadband expansion affects the incidence of social isolation. Table 1.12 indicate a substantial decrease in social isolation among older adults following the expansion of broadband technology. These findings provide further support for the social isolation hypothesis, suggesting that broadband expansion has been instrumental in mitigating feelings of social isolation among older individuals. This causal evidence also supports the claim from the correlational studies in medical research Cotten *et al.* (2013). The results underscore the significance of technological advances in promoting social connectedness and well-being among older adults.

Table 1.12: Average Treatment Effect of Fiber Broadband on the Feelings of Social Isolation and Loneliness

	(1) Felt Isolated	(2) Felt Lonely
Post Fiber	-0.050^{***}	-0.014^{**}
	[0.019]	[0.007]
Observations	6,006	47,830
Year Fixed Effects	Yes	Yes
Individual Fixed Effects	Yes	Yes
Mean of Dependent Var	0.319	0.154

Note: This table shows the average treatment effects of the staggered introduction of the fiber broadband on the 'feeling of social isolation' and the 'feeling of loneliness' among older adults using Equation 1.1 and estimating with the estimator provided by De Chaisemartin and d'Haultfoeuille (2022a). The 'feeling of loneliness' question is used to calculate the CES-D score and is asked to everyone. However, the 'feeling of social isolation' question is asked to a subset, and that's why the sample size is smaller. The sample is a balanced panel of Health and Retirement Study (HRS) respondents for biennial waves from 2010 to 2018, aged 51+. The treatment variable is equal to 1 if the fiber is available in a census tract of residents in survey year t and 0 otherwise. Standard errors in square brackets are clustered at the census tract level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

1.8.2 Social Connectedness

Because the internet can serve as a source of social support Pescosolido (2011), a plausible pathway through which broadband technology may influence mental well-being is by facilitating virtual connectedness with family members and friends. To examine this, I construct a proxy for social connectedness using relevant survey questions from the HRS. These questions inquire about the frequency of sending emails to family, friends, and children, as well as the use of social media platforms such as Facebook or Skype to connect with loved ones. Additionally, the HRS survey captures regular web usage. Combining these scores, I create an index that I convert into an indicator variable, taking a value of 0 to indicate low or negligible social connectedness and a value of 1 for positive values signifying high social connectedness.

Moreover, in Table 1.13, I conduct separate estimations for individuals categorized as low and high in terms of social connectedness. This analysis explores whether the effects of broadband expansion on mental health differ for these two groups. The results reveal a significant decline in depression symptoms for highly socially connected individuals while indicating no significant change in depression symptoms for those with low levels of social connectedness. These findings align with the social isolation hypothesis, which posits that limited social connections can have detrimental effects on mental health. Overall, these empirical findings shed light on the unexplored potential mechanisms through which broadband expansion influences the mental well-being of older adults, emphasizing the role of virtual connectedness and the consequences of social isolation on mental health outcomes.

Table 1.13: Average Treatment Effects of Broadband on Depression Symptoms Based on Social Connectedness

	Outcome: CES-D Depression Score	
	Social Connectedness Index	
	Below 25 pct	Above 75 pct
	(1)	(2)
Post Fiber	-0.060	-0.163^{**}
	[0.068]	[0.065]
Observations	7,857	7,852
Year Fixed Effects	Yes	Yes
Individual Fixed Effects	Yes	Yes

Note: The estimator is by Borusyak *et al.* (2021) since the . The sample is a balanced panel of Health and Retirement Study (HRS) respondents for biennial waves from 2010 to 2018. The age group is from 51 to 103. The outcome variable 'depression' is a CES-D mental health categorical score from 0 to 8, 0 being no depression and 8 being the highest depression. The treatment variable is equal to 1 if the fiber is available in a census tract of residents in survey year t and 0 otherwise. The social-connectedness index is calculated based on the frequency with which the respondent reported that they send emails to either family, friends, or children and use social media like Facebook to connect with friends and family and regular web use for "sending and receiving e-mail or for any other purpose, such as making purchases, searching for information, or making travel reservations." The time variable is the survey wave, and the fiber group variable is the group of census tracts in which fiber was introduced in various years. Standard errors are clustered at the census tract level. *** p<0.01, ** p<0.05, * p<0.10.

1.8.3 Health Literacy

Another potential mechanism through which the introduction of high-speed fiber broadband may positively impact the mental health of older adults is through improvements in health literacy. It is possible that within-household spillovers or social circles contribute to enhanced health literacy among individuals. Additionally, the self-use of health apps may also play a role in improving mental health outcomes.

I follow the literature to define health literacy from the 2010 wave of HRS, where the respondents were asked:

How confident are you filling out medical forms by yourself – extremely confident, quite confident, somewhat confident, a little confident, not at all confident?.

I use a scoring system that takes the value 0 if the response is 'not at all' and the value 1 if 'extremely' and 0.25, 0.5, and 0.75 in between (Bavafa *et al.*, 2019). Table 1.14 columns (1) and (2) suggest that the introduction of fiber is strongly and significantly correlated with health literacy.

Secondly, I use two survey questions from the 2014 HRS survey to test the likelihood of using health-related applications or websites. The questions in HRS are

In the past month, have you used any downloaded health-related mobile applications or "apps" on a smartphone or tablet computer such as an iPad, Android, or Kindle Fire?

And,

In the past month, have you used any online health-management tools or websites, including those connected with your doctor's office, health care agency, insurance company, pharmacy, or other health-related sites such as Patient Portals or Weight Watchers Online?

Columns (3) and (4) in Table 3 indicate a positive relationship between the introduction of fiber broadband and the use of health-related apps. While none of the estimates reach statistical significance, the magnitudes of the coefficients are more than double the mean of the outcome variable. These findings suggest a strong correlation between the availability of fiber broadband and the utilization of medical apps, even though the lack of statistical significance indicates the need for further research to explore these mechanisms more comprehensively.

Table 1.14: Mechanisms: Effect on Health Literacy, Use of Health Apps and Health Websites

	Health Literacy		Use of Health Apps		Use Health Management Sites	
	(1)	(2)	(3)	(4)	(5)	(6)
Fiber X Post	0.341**	0.408***	0.519	0.625	0.211	0.340
	[0.141]	[0.149]	[0.374]	[0.392]	[0.215]	[0.226]
Observations	896	893	820	804	820	804
Individual Controls		Yes		Yes		Yes
Mean of Outcome Var	0.672	0.673	0.036	0.037	0.133	0.136
HRS Survey Year	2010		2014		2014	

Note: The sample is the cross-section data of HRS for the specified periods. Refer to the text for the definition of the outcome variables. I use the logit model for the estimations in columns 3 to 6. Individual controls include gender, binary indicators if the respondent is enrolled in Medicare or Medicaid, age-fixed effects, rural, White, an indicator for more than high school, an indicator if the respondent receives social security disability insurance, whether receives a pension, and whether the respondent is currently married. I also include the missing dummies for the covariates. Standard errors are clustered at the census tract level. *** p<0.01, ** p<0.05, * p<0.10.

It is, however, important to exercise caution when interpreting the findings presented in Table 1.14. The mechanisms analyzed in this table are based on survey questions that were administered to a limited number of HRS respondents in either one or two waves. Consequently, the small sample size may limit the statistical power to detect significant effects accurately. Another concern could be reverse causation. For instance, internet use may affect health literacy, and health literacy may affect internet use.[44] Since the primary treatment here is the 'introduction of fiber broadband in a census tract', I think reverse causation may not be a concern.

[44] The presence of such reverse causation is evident in studies (Levy *et al.*, 2015, Bavafa *et al.*, 2019).

1.8.4 Technological Efficiency for Telehealth

In this subsection, I examine whether the introduction of broadband improves the technological efficiency of nearby hospitals by investigating the availability of telehealth services. Telehealth has been recognized as an efficient and effective tool in healthcare, but its widespread implementation has been hindered by the lack of high-speed internet access, particularly in rural and underserved areas(Gajarawala and Pelkowski, 2021). Recent evidence suggests that access to telemedicine during the COVID-19 pandemic increased primary care visits without adverse effects on health outcomes (Zeltzer *et al.*, 2023). To explore this hypothesis, I utilize data from the 2018 Annual Survey Database administered by the American Hospital Association (AHA).[45] This voluntary survey collects information on hospital organizational structure, utilization, finances, facilities, and staffing. I analyzed 24 survey questions related to the availability of telehealth services for various types of care and hospital networks. (See Appendix Table A.6 for the list of the questions). Since the AHA data is at the county level, I calculate the average number of broadband providers and speed at the county level. Using a logit model, Table 1.15 presents estimates that demonstrate a strong and statistically significant relationship between the number of broadband providers and the likelihood of hospitals offering telehealth services. Similarly, a strong relationship is observed when considering download speed instead of the number of providers. However, it is important to note that these estimates represent correlation rather than causal evidence due to the limited availability of AHA survey data for multiple years. [46]

[45] The primary reason that I use the AHA survey for only 2018 is that the surveys are paid data, and UW-Madison had access to only the 2018 wave. In my other work in progress, I collaborate with other researchers who have access to more waves of data, and we are answering this question in more detail.

[46] One may use the number of broadband providers as an instrument for whether or not a hospital offers telehealth services and then look into the mental health outcomes. This instrument, however, may not satisfy the exclusion restrictions.

Table 1.15: Mechanisms: Hospitals offer Telehealth Services

	(1)	(2)
VARIABLES	Offer Telehealth Services	Offer Telehealth Services
# Broadband Providers	0.136***	
	[0.013]	
Log (Download Speed +1)		0.131***
		[0.021]
Observations	6,941	6,941
Mean of Outcome Var	0.446	0.446

Note: The data is the American Hospital Association (AHA) survey 2018 merged with the broadband data for the year 2018 at the County level. The outcome variable is an indicator equal to 1 if the hospital or its network offers telehealth services and 0 if not. Standard errors are clustered at the county level. *** p<0.01, ** p<0.05, * p<0.10.

1.9 Conclusion

This study contributes to the existing literature by examining the causal relationship between the rollout of high-speed broadband technology and the mental health outcomes of older adults. Furthermore, this research explores the unexplored pathways through which these effects may manifest. The findings demonstrate that the expansion of broadband significantly reduces symptoms of depression among individuals aged 50 and above, providing robust statistical evidence of sustained improvements in mental health over time. Heterogeneity analysis reveals that older adults residing in rural areas experience greater benefits compared to their urban counterparts, emphasizing the importance of geographic context. Moreover, the study identifies an inverted U-shaped effect based on age groups, indicating that individuals aged 65 and above but below 85 derive the most significant and substantial benefits. Conversely, the average treatment effects for individuals below the age of 65, who are more likely to be employed, are positive but not statistically significant. Additionally, the study uncovers racial disparities, as Whites drive the positive effects of broadband expansion, while no significant effects are observed for Blacks. Further investigation is needed to address this gap. Furthermore, the results indicate that women experience slightly larger average treatment effects compared to men. Exploring potential mechanisms, the study highlights the role of higher social connectedness, lower social isolation, improved health literacy, enhanced cognitive function, and technological advancements in nearby hospitals as potential pathways through which the effects of broadband technology may translate into better mental health outcomes for older adults. These findings contribute important insights to the literature, informing policymakers and stakeholders about the implications of broadband expansion for the mental well-being of older adults.

Recent research has highlighted the adverse mental health effects of social media, particularly on college students, with young women being more susceptible due to *social comparisons*. Concerns arise regarding whether the internet may impact older individuals in a similar manner, raising public health implications. Surprisingly, this study finds that internet availability is beneficial for older adults, with the mental health benefits approximately equal in magnitude to the costs observed among youth. The primary driver of these benefits is *social connectedness*, which stands in contrast to the costs experienced by teenagers due to social comparison. This finding emphasizes that the impact of similar technologies can differ significantly based on the user and individual patterns of technology use. It underscores the importance of investing in broadband technology and implementing policies that foster social connections, telehealth, and other mechanisms.

One important limitation of this study is that the data does not provide information on whether the survey respondents have fiber broadband at their homes. Internet use could occur at various locations such as home, work, coffee shops, or public libraries. As a result, the estimates presented in this study represent intent-to-treat effects. Nonetheless, the findings are important for policymakers seeking to understand the potential health benefits of broadband expansion for older adults, understand the potential mechanisms underlying these effects, and assess whether there are specific benefits for rural communities.

1.10 Discussion

The estimates presented in this paper hold significant relevance for several reasons. Firstly, the global population is aging, leading to an increase in issues such as mental health and social isolation. Concurrently, there has been substantial growth in internet usage, with approximately 63% of the world's population utilizing the internet in 2021, compared to just 7% in 2000. Moreover, there are around 1.33 billion fixed broadband subscriptions worldwide (World Bank 2021). High-speed internet has become a necessity regardless of age or occupation, as it plays a crucial role in various daily activities. The usage of the internet and social media technologies has also seen a significant increase among older adults, making it imperative to focus on this vulnerable age group. The findings of this paper underscore the benefits of high-speed broadband for the well-being of older adults, emphasizing the importance of internet access for maintaining social connections with family and friends.

Secondly, broadband has demonstrated its positive influence on these technological advances, such as telehealth, which can have significant implications for the well-being of older adults. As telehealth services become increasingly important, reliable and high-speed internet access becomes a critical component for enabling effective healthcare delivery and remote consultations.

Thirdly, it is essential to recognize that not everyone has equal access to high-speed internet. Disparities in internet availability based on geographical location, race, and income have been documented, and the COVID-19 pandemic has further highlighted these disparities. To address these inequities, substantial government investments using public funds have been allocated to initiatives such as the Internet for All and Affordable Connectivity Program (ACP), which have dedicated over $65 billion USD to expand internet access. Understanding the potential effects of such substantial investments on the health of one of a vulnerable age group is of utmost importance in ensuring equitable outcomes and maximizing the benefits of these initiatives.

This paper's findings shed light on the significant implications of broadband expansion for the mental health and well-being of older adults, highlighting the importance of internet access for staying socially connected. Moreover, it underscores the role of broadband in facilitating technological advancements like telehealth. Finally, the study emphasizes the need to address disparities in internet access, particularly for vulnerable populations, as substantial investments are made to bridge the digital divide and promote equitable outcomes.

Chapter 2

Effect of Early Life Exposure to the Green Revolution on Aging Outcomes in India

2.1 Introduction

The Green Revolution is arguably the most significant shock to agricultural productivity gains in developing countries and one of the most significant technological innovations of the 20th century (Gollin *et al.*, 2021). The Green Revolution started with the development of the high-yield crop variants (HYV) in the 1960s, dramatically increasing the yield of major crops like wheat and rice.[1] Due to its success, it was adopted worldwide to produce more food for a growing population.

A significant body of research suggests mixed effects of the Green Revolution; however, its long-term effects are still understudied. On the one hand, the Green Revolution technologies improved development indicators (yields, food security, GDP per capita) while reducing negative externalities (food prices, poverty, fertility, child mortality) in developing regions (Foster and Rosenzweig, 1996, Evenson and Gollin, 2003, Goltz *et al.*, 2020,

[1] Norman Borlaug, who led the initiative to develop high-yield crops, received a Nobel Prize in 1970. Various reports referred to Borlaug as "The Man Who Saved a Billion Lives" (MacAray, 2015).

Bharadwaj *et al.*, 2020, Gollin *et al.*, 2021, Carter *et al.*, 2021). On the other hand, the Green Revolution had adverse effects of increased infant mortality due to exposure to agrochemicals use and an increase in mid-life chronic conditions primarily due to dietary changes during gestation and infancy (Brainerd and Menon, 2014, Sekhri and Shastry, Forthcoming). With more food availability (nutrition) and higher family income due to the Green Revolution, one may expect persistent positive effects on long-term (aging-related) outcomes.[2] On the other hand, exposure to excess agrochemicals and changes in nutrition intake due to changes in dietary habits may adversely affect later-life outcomes, and the net long-term effect is ambiguous. Research, however, has not yet explored whether early life exposure to this massive shock impacted later life aging-related outcomes.

This paper evaluates whether early-life exposure to the Green Revolution affects long-term aging-related outcomes in India. To measure the exposure to the Green Revolution, we use district panel data of crops from 1966 to 1974. Our primary treatment is the *share of the area planted under the HYV crops* in a district in a given year. Further, we use the newly available first wave of the nationally representative aging data of individuals aged 45+ collected during 2017-18. We match these two data using the respondents' birth district and birth year, with the primary sample being between 45 and 54 years old. Our key outcome variable to measure physical health is the *total number of chronic conditions*, and to measure cognitive health is the *general cognition score*. We exploit the temporal and spatial variation in the HYV crops across districts over time in the empirical specification. Further, we explore the heterogeneous treatment effects based on gender, caste, and region, given the stronger gender, caste, and regional diversity in India. Finally, we explore potential mechanisms through which early life exposure to the Green Revolution may affect later life outcomes, including early life nutritional investment, education, and school construction.

We find that early-life exposure to the Green Revolution positively affects later-life

[2] This hypothesis is based on the growing literature that documents the link between early childhood conditions and long-term outcomes, which is mainly focused on the developed countries (Barker, 1990, Almond, 2006, Currie and Almond, 2011, Hoynes *et al.*, 2016, Aizer *et al.*, 2016, Duque and Schmitz, 2023).

cognitive function (statistically significant at 10% level). Specifically, one SD exposure to the Green Revolution at early life (in-utero to age two) increases the cognitive ability of 0.054 SDs among the 45-54 age group.[3] We find stronger treatment effects for the socially disadvantaged groups (lower castes) and people born in rural areas, with the strongest impact for low castes individuals born in rural areas. Specifically, we find that one standard deviation increase in the Green Revolution in-utero to age two improved later-life cognitive function between 0.083 to 0.123 standard deviation for these subgroups, and the results are statistically significant. However, we find an increase in chronic conditions among men and individuals born in urban areas, providing evidence for the 'double burden of malnutrition,' which suggests that the high rate of undernutrition and growing chronic conditions due to overconsumption exist simultaneously.[4] To explore the potential channels, we find that early life exposure to the Green Revolution significantly improves schooling and financial conditions while growing, especially among the beneficiary groups, explaining positive gains in cognitive health. Using the universe of the schooling data, we rule out that the school construction was increasing, which might have improved gains in schooling and, eventually, cognition. Finally, we also rule out that improvement in height, which is one of the key measures of nutrition and human capital development, is driving the benefits in cognitive function.[5] Our findings suggest that early-life exposure to the Green Revolution improved later-life cognition, primarily through income channels.

This paper makes several contributions to the economics literature. First, we contribute to the literature by providing one of the first evidence focusing on long-term (aging-related) outcomes for the population from low- and middle-income countries (LMIC) using the largest aging data.[6] Very little is known about the early-life investments and later-life aging-related outcomes in developing countries, where accelerated aging and limited

[3]These effects can (loosely) be comparable with a recent study which finds a one SD improvement in weather conditions during age two leads to an improvement in cognition during adulthood (aged 16-37) by 0.063 SDs in a comparable developing country (Webb, 2024).

[4]These effects are consistent with a recent study which finds that the Green Revolution increases the likelihood of diabetes among men in India (Sekhri and Shastry, Forthcoming).

[5]These effects also echo the literature that does not find the early life exposure to a shock on the height. E.g., (Bharadwaj *et al.*, 2020, Webb, 2024).

[6]Only 17 out of 528 studies referred by Global Burden of Disease were designed to study the older population from the LMICs (Banerjee *et al.*, 2023).

clinical care have led to poorly understood aging and ADRD risk trajectories.[7] There is very small and growing literature on aging from the LMICs, however, most of which is descriptive, associative, limited in the sample size or scope, and focused on other non-health outcomes (Dias *et al.*, 2008, Srivastava *et al.*, 2021, Huangfu and Nobles, 2022, Banerjee *et al.*, 2023, Alzua *et al.*, 2023).[8] One of the primary reasons for the lack of evidence from developing countries is that detailed aging data was not available until recently. We use the newly available aging data from India, considered the largest aging data in the world, with over 72,000 respondents in the 45+ age group, including detailed health, economic, and social well-being of India's elderly population, to answer the empirical question we study.[9]

Secondly, to our knowledge, this is the first study to explore the linkages between the Green Revolution and long-term cognitive health and one of the first studies to investigate the novel potential mechanisms at the individual level. Cognitive health outcomes are a relatively newer area of research in Economics.[10] Research on the Green Revolution focuses on several other health aspects and suggests mixed evidence. For instance, studies suggest that Green Revolution technologies contributed to mixed evidence on child mortality and had adverse effects on increasing metabolic syndrome (Brainerd and Menon, 2014, Sekhri and Shastry, Forthcoming, Bharadwaj *et al.*, 2020, Gollin *et al.*, 2021, Carter *et al.*, 2021).[11] We contribute by providing empirical evidence on whether the short-term benefits and costs of the Green Revolution on health translate to the two key long-term aspects of aging, i.e., the number of chronic conditions and cognitive health. Most evidence on the impact of the Green Revolution on key mechanisms like education is at the aggregate level, focusing on relatively short-term effects and including small-scale studies (Foster and Rosenzweig, 1996). We contribute by exploring novel mechanisms at the individual

[7] That's why the NIA has emphasized the urgent need to study aging in developing countries.

[8] There is also a small literature focusing on old-age pension from the LMICs (Bando *et al.*, 2020, 2022).

[9] The data is from the Longitudinal Aging Study in India (LASI) (Bloom *et al.*, 2021). The LASI data are comparable to the Health and Retirement Study (HRS) in the United States.

[10] Notable studies on cognitive function, primarily from the LMICs include (Barker *et al.*, 2022, McKelway *et al.*, 2022).

[11] We could find only one study that explores the impact of the Green Revolution over several decades of exposure focusing on the chronic condition (Sekhri and Shastry, Forthcoming).

level, like educational attainment, financial condition, and height, as a proxy for early-life nutritional investment. Also, we use the universe of schooling data to evaluate whether the impact of the Green Revolution translates through school construction.

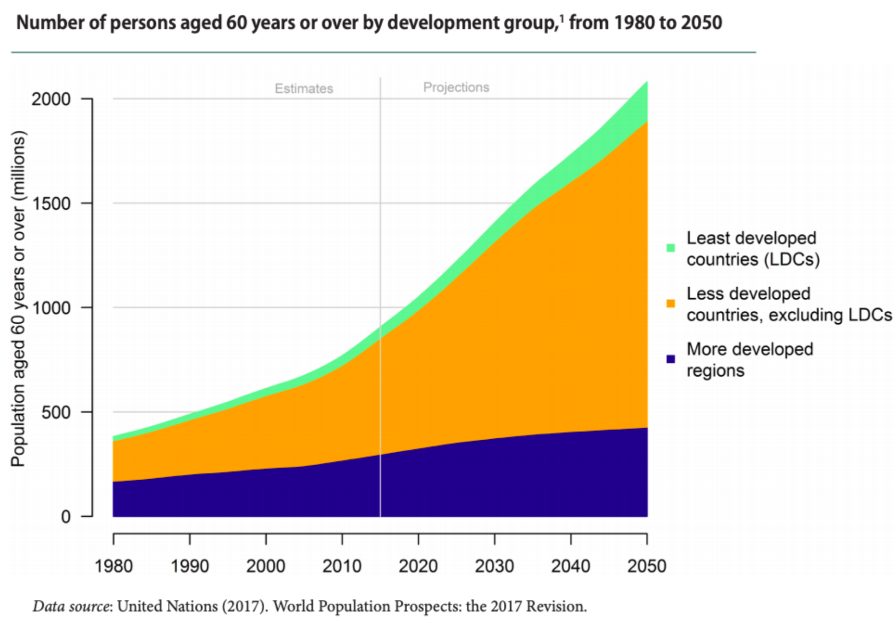
Third, we contribute to the literature on fetal origin by exploring the extent to which exposure to agriculture investment in the first years of life influences later life health and identifying the critical period of development. Fetal origins research is a relatively newer area in Economics and has shown that changes in nutrition, stress, income, and the disease environment during pregnancy increase the risk for Type II diabetes, hypertension, coronary and artery disease (Almond, 2006, Hoynes *et al.*, 2016, Aizer *et al.*, 2016). Research suggests the importance of the prenatal and early childhood years in setting the foundations for life-long success (Barker, 1990, Currie and Almond, 2011). However, there exists very little causal work on how much the timing of the shocks matters for later life cognitive development, and research highlighting the critical period of development from the LMICs is virtually absent.[12] A few studies document the shocks across ages, and usually, in-utero to age 5 is considered a critical period for later life outcomes (Hoynes *et al.*, 2016, Almond *et al.*, 2018, Webb, 2024, Duque and Schmitz, 2023). This paper fills the gap in the literature by studying the impacts of one of the largest agricultural shocks in the world's history on later-life aging-related outcomes and specifying the critical period of cognitive development.

Finally, we improve on existing literature by precisely identifying individuals' birth districts, allowing for a more accurate estimation of their exposure to the Green Revolution. Due to the lack of birth location data, this dimension has been largely overlooked in observational studies from developing nations, including studies focused on the Green Revolution. Without precise birth locations, other studies have to rely on assumptions of no or little migration, i.e., the individuals did not move from their birth districts to their current districts.[13] However, we do not have to make such an assumption, which helps us minimize the measurement error and maximize the precision.

There are at least four reasons to study the effects of the Green Revolution on long-

[12]We found only one study that focuses on the critical period of development from the LMICs (Webb,

Figure 2.1: Share of older people across the world



Source: United Nations Report, 2017

term (aging-related) outcomes, such as chronic conditions and cognitive function. First, the aging population is growing in the world and is (and will be) much higher in developing countries, with a major share of the people with Alzheimer's Disease and Related Dementias (ADRD) living in low and middle-income countries (Figure 2.1). By 2050, one in five people in low-income countries will be over 60 years old. Falling fertility rates and increased life expectancy from improvements in health care, especially in Asia, have led to a rapidly aging population and, with it, a higher prevalence of age-related health problems.[14] However, much of the evidence from the fetal origin literature focuses on high-income countries, yet there is an urgent need to understand how the long reach of childhood shocks affects long-term well-being in developing nations, given diverse cultural and demographic factors.[16] Secondly, the relationship between early life shock and later

2024).

[13]Notable studies include Sekhri and Shastry (Forthcoming), Webb (2024).

[14]For example, a rapid increase in older populations is projected to also rise in ADRD, from about 47 million people worldwide in 2015 to more than 152 million in 2050, with over three-quarters of the people with ADRD from low- and middle-income countries.[15]

[16]Indeed, National Institute of Aging (NIA) has emphasized the urgent need to study aging and ADRD risk in developing countries because well-known patterns of aging documented in high-income countries (HICs) may not be generalizable in LMICs, where contexts differ dramatically from those experienced in

life health could be complex in LMICs since individuals are subject to repeated shocks throughout their childhood, and it will be essential to understand the critical period of early life for the development of the later life outcomes. Furthermore, investigating the underlying relationships in the contexts of developing countries was challenging primarily due to the lack of detailed long-term empirical data until recently. Finally, the Green Revolution is an ongoing policy yet to be adopted in several parts of other developing countries.[18] From a policy perspective, it's crucial to understand if the short-term benefits and costs of the Green Revolution continue in the long term. In the context of India, another important reason is that currently, 70% of rural households in India (~ 630 million people) still depend on agriculture for their livelihood.[19]

Our empirical specification follows Bharadwaj *et al.* (2020) and may suffer from similar limitations of lack of random adoptions of HYVs in different parts of India.[20] Different prevalences of adopting the Green Revolution in different regions primarily depended on various input factors. For instance, northern states adopted the HYVs earlier due to the canal irrigation network that had developed during the colonial era. We addressed some of these challenges in various ways. First, to address the temporal and spatial factors associated with adopting the HYV, which might also affect health later in life, we include the fixed effects of birth district and birth year. We also include birth state-specific linear time trends or birth state-by-year fixed effects.[21] Similarly, we control for the various characteristics at the individual level like parental education, gender, castes, regional characteristics like rainfall and temperature, and other district-level characteristics from the Census like literacy rate, gender ratio, and share of rural population. Finally, we also show tests for the robustness checks that strengthen our confidence in estimates.

HICs.[17]

[18]For instance, Sub-Saharan African countries started investing in these technologies in much later decades compared to Asia and Latin America, primarily due to differences in the type of the crop consumption. While rice and wheat were prominent in Asia and Latin America, the advancements in Maize (a dominant staple in African countries) started after several decades (Carter *et al.*, 2021).

[19]Refer summary provided by The Food and Agricultural Organization of the United Nations (FAO).

[20]Our specification is also similar to a study on the effect of weather shock on cognition in a similar context (Webb, 2024).

[21]The first takes into account any unobserved trending variables that may vary by state-specific cohorts, and the second accounts for any annual pattern in later life outcomes that may differ across states.

2.2 Background

In the second half of the twentieth century, the economic development policies were on high after the end of colonial regimes. Global concerns regarding low levels of agricultural productivity and the increasing issue of food insecurity prompted donor agencies to allocate resources towards agricultural research.[22] The investments made in the early 1960s were the cornerstone for the successes at the International Maize and Wheat Improvement Centre (CIMMYT) in Mexico and the International Rice Research Institute (IRRI) in the Philippines and can be credited to the inception of the Green Revolution. (Pingali, 2012, Gollin *et al.*, 2021).[23] The success of this development of high-yielding crop varieties (HYV) is typically referred to as a "Green Revolution" (Evenson and Gollin, 2003).[24] Further, the Consultative Group on International Agricultural Research (CGIAR) was established to help other developing countries adopt these technologies.

The adoption of the Green Revolution technologies has led to substantial improvement in crop production and economic growth in the developing world. Vast research suggests that Green Revolution technologies contributed to a massive increase in crop production, food security, gross domestic product (GDP), real income per capita, demand for goods and services, new income and employment opportunities, stimulating the rural non-farm economy, and a decline in food prices, poverty, fertility, and child mortality across developing nations (Foster and Rosenzweig, 1996, Evenson and Gollin, 2003, Goltz *et al.*, 2020, Bharadwaj *et al.*, 2020, Gollin *et al.*, 2021, Carter *et al.*, 2021). For instance, in Asia, a 1% increase in the per hectare agricultural production led to a 0.48% reduction in poverty (Pingali, 2012). A 10-year delay of the Green Revolution in 2010 would have cost 17% of GDP per capita to the developing-world population, and the cumulative GDP loss would

[22] The donor agencies include the Ford Foundation and the Rockefeller Foundation.

[23] Crop scientist Norman Borlaug began work on crop development in the 1940s, and for his efforts, he received the Nobel Peace Prize in 1970.

[24] Green Revolution is a series of complex innovations to make new crop varieties. One such innovation includes the fact that these high-yield varieties (HYV) were designed to be semi-dwarf so that they do not lodge (fall) when they grow tall enough like the traditional crops. Similarly, crops with other characteristics like disease resistance were developed. The HYVs of rice and wheat were more successful earlier due to vast preexisting scientific knowledge compared to other crops (Gollin *et al.*, 2021). However, these HYVs did not do better compared with the traditional varieties in the absence of enough fertilizers and water. Traditional varieties of rice and wheat were not 'tolerant' to fertilizers and water as the HYVs.

have been 83 trillion US dollars (Gollin *et al.*, 2021).

India was among the early adopters of the HYV crops around the mid-1960s, and the adoption had significant variations based on factors like agro-climatic conditions, infrastructure, education, and other socioeconomic factors.[25] Climatic and environmental conditions, rain, networks of canal irrigation systems, and groundwater access significantly affected the adoption of the Green Revolution (D'Agostino, 2017, Bharadwaj *et al.*, 2020, Sekhri and Shastry, Forthcoming, Asher *et al.*, 2022).[26] As discussed in Bharadwaj *et al.* (2020) in detail, due to the heavy canal irrigation networks during the colonial era in the northern states and favorable conditions, HYVs were adopted earlier in the northern states, while the rest of the country relied primarily on rain, which have enormous variation based on agro-climatic conditions. Similarly, socio-economic factors like castes and wealth also played a major role in unequal access to the HYVs, with wealthy or large-scale landowners (typically belonging to higher castes) having higher access to the Green Revolution technologies than landless farmers and agricultural workers (typically belonging to lower castes) (Hurt, 2020).[27] Gender also played a part in the distribution of the HYVs and the benefits of the Green Revolution, with women farmers and female-headed households gaining proportionately less than men counterparts (Pingali, 2012).

India saw a massive improvement in various economic factors within the first few years of the Green Revolution. For instance, the adoption of HYV crops played a vital part in India's agriculture sector, which accounts for 23% of its GDP. From 1961 to 1970, cereal production increased by over 30% from 70 million tons to 93 million tons, and by 1999, it reached 186 million tons (Borlaug, 2002). Wheat and rice yields and cereal production

[25] Stagnation of agriculture during the colonial era, favoring industrial sectors over agricultural sectors post-independence, disastrous draughts, and sluggish land reforms were key reasons that India was on the verge of famine and set a stage for policymakers and donor agencies to invest in new technologies through the Green Revolution (Parayil, 1992).

[26] Several other factors also contributed to the diffusion of the HYVs. For instance, a study found that radio broadcasts led to an increase in the adoption of the HYVs (Vasudevan, 2023). Similarly, crops' susceptibility to diseases and pests and the skills of farm workers also affected the adoption of the HYVs (Pingali *et al.*, 1996).

[27] Hurt (2020) describes that the education also played a role in adoption, since well-educated, usually large-scale farmers made better use of the supportive environment and multiple cropping. Even though the uniform benefits were not guaranteed, studies document that the Green Revolution also benefitted the poor through channels like a reduction in food prices and employment opportunities (International Food Policy Research Institute (IFPRI) Report 2002-03).

doubled from 1970 to 1995, and cereal and calorie availability per person increased by 30%. Also, it is estimated that the 1% increase in the adoption of HYVs per hectare reduced poverty by 0.4% in the short run and 1.9% in the long run (Pingali, 2012). Child and infant mortality was considerably higher in India. The increase in HYV crop diffusion under the Green Revolution declined child mortality by about 15 deaths per 1,000 children and succeeded in improving the health status of about 32 to 42 million preschool children (Evenson and Gollin, 2003, Bharadwaj *et al.*, 2020).

A small literature also documents the adverse effects of the Green Revolution on the use of agrochemicals, health, ecology, and social equity in India. For instance, during the first two years of the Green Revolution in India, the consumption of nitrogenous fertilizer increased from about 658,000 metric tons to 1,196,000 metric tons (Chakravarti, 1973). A study suggests that exposure to such fertilizer agrochemicals in water increased infant and neonatal mortality and height-for-age and weight-for-age for children below age five, and the effects are most pronounced for poor women in rural areas (Brainerd and Menon, 2014). Similarly, a recent study suggests that exposure to the Green Revolution increases the likelihood of diabetes during mid-life for boys, primarily due to changes in dietary habits (Sekhri and Shastry, Forthcoming). Other critics of the Green Revolution highlight the overuse and mismanagement of agrochemicals, loss of distinct indigenous crops, land infertility due to lack of crop rotation, loss of groundwater, and troubles of small farmers who sold their lands to large farmers due to increasing farm expenses and debt, creating a social inequity (Eliazer Nelson *et al.*, 2019).

2.3 Data

We evaluate whether early-life exposure to the adoption of Green Revolution technology affects long-term aging-related outcomes in India. To answer this question, we use data primarily from two sources, as mentioned below. We also use additional data from other sources described in this section.

2.3.1 Village Dynamics of South Asia (VDSA)

VDSA has the annual information on the area in hectares planted under high yield variant (HYV) for 281 districts and 19 states in India from 1966 to 2017.[28] The data on HYVs are for six major crops- rice, wheat, maize, finger millet, pearl millet, and sorghum. The data also includes annual information on the area and the production of 25 major and minor crops. We sum the area planted under the HYV crops in each district in the year of birth. We then divide this sum by the total area cultivated under all crops in each district in a year, which is our main treatment variable. This ratio gives us a share of the cultivated area planted under the HYV.[29]

Figure 2.2 shows the share of the total cultivated area planted under HYV for India from 1966 to 1989. As shown in the figure, the adoption of rice and wheat was rapid compared to that of the other HYV crops. Figure 2.3 describes the district-wise share of the high-yield crops from 1966 to 1989. This figure shows a substantial variation in the adoption of high-yield crops by various districts. As mentioned in detail in the previous section, the adoption was rapid in the northern states compared to the other parts of India. In our identification strategy, we explore these temporal and spatial variations in the adoption of the Green Revolution.

2.3.2 Longitudinal Aging Study in India (LASI)

The LASI is the world's largest and India's first longitudinal aging study.[30] It is a nationally representative survey of over 72,000 older adults aged 45+ and their spouses (irrespective of age) above in 28 out of 29 States (except Sikkim) and 7 union territories in India. A survey for the first wave was conducted in 2017-19; the data was released in 2021. LASI is the first detailed scientific investigation of the health, social determinants, and economic well-being of older adults in India. More importantly, the data includes the

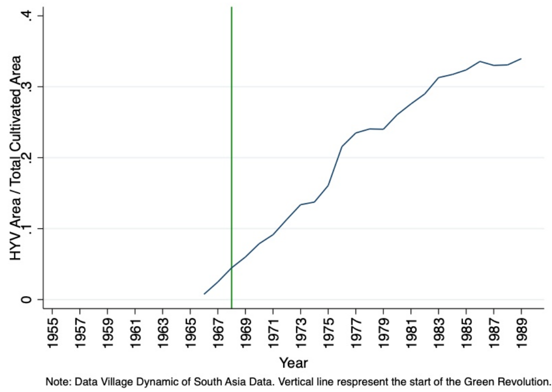
[28] These data are commonly used in the literature on the Green Revolution in India (e.g., Bharadwaj *et al.* (2020)).

[29] We remove a small number of observations if the total HYV area is greater than the total cultivated area.

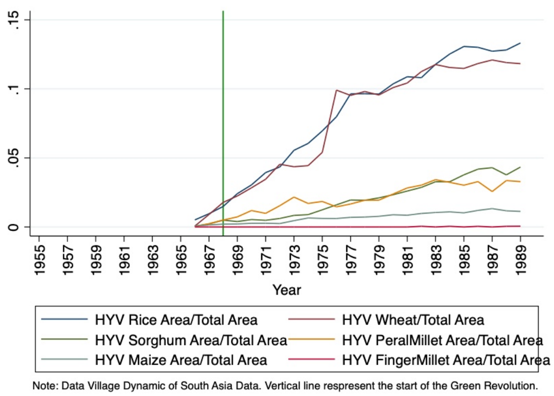
[30] Details on LASI's first wave can be found in (Bloom *et al.*, 2021).

Figure 2.2: Share of Total Area Under High Yield Crops (by Year)

(a) High Yield Area Share- Combined



(b) High Yield Area Share- Separated



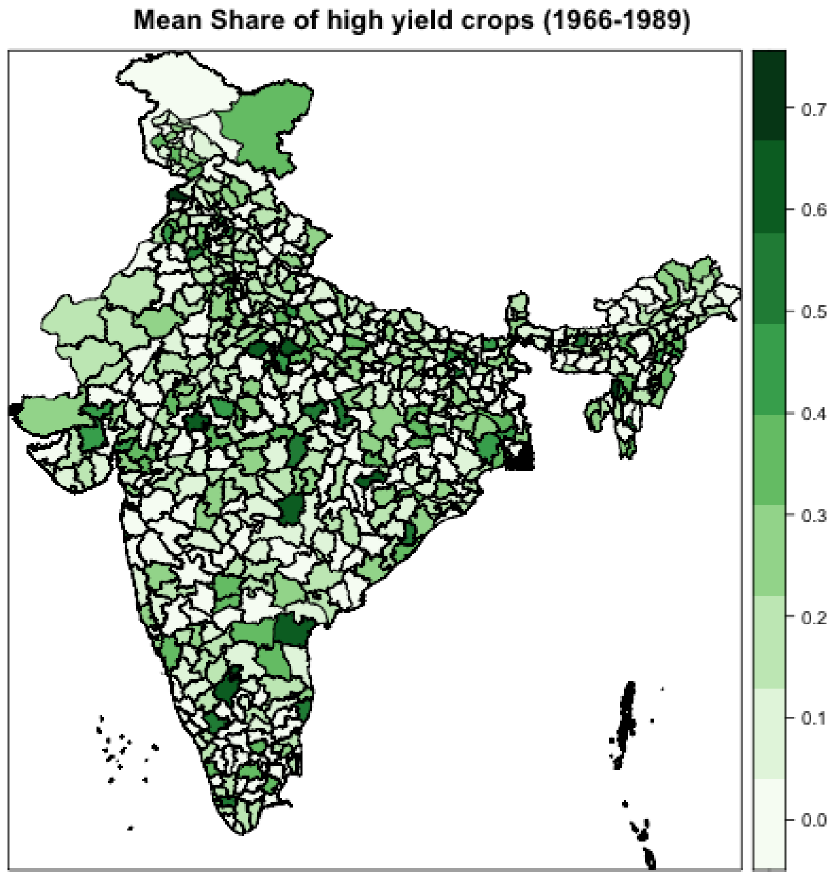
Note: This figure shows the trend in adopting HYV crops using VDSA data. The share of the total area under green evolution (high-yield crops) is the ratio of area planted to high-yield crops to the total cultivated area (both in hectares) in an individual's birth district. Panel A shows the trend combined with all the HYV crops, and panel b shows the trend separately for each HYV crop.

respondents' birth district, which was virtually absent from any household surveys from the developing countries. We merge LASI and VDSA using the birth district and birth year.

Our primary sample includes respondents who were born from 1966 through 1974. We focus on this cohort since the Green Revolution started in India in 1966, and the youngest cohort of the LASI survey was born in 1974.[31] When we merge LASI data with the VDSA data using the birth district and birth year, we match almost all the districts in the VDSA

[31] LASI is a nationally representative data of 45+ age group. And that's why our main sample is the 45+ age group. LASI also includes detailed data of the respondents' spouses irrespective of age, meaning some spouses could be below the 45+ age group (or born after 1974). However, we do not include them since the LASI data does not represent the population below 45.

Figure 2.3: Mean Share of High Yield Crops



Note: We merge LASI and VDSA data for the mean district share of HYV across all the birth cohorts from 1966 to 1989. We cross-walked the contemporary districts in LASI data, i.e., the 2011 Census with the 1961, 1971, and 1981 census.

data.[32] We have 281 districts that have experienced the Green Revolution since 1966, and the remaining 61 districts have not experienced it during our analysis period.

2.3.3 Other Data

In addition to the primary data, we use the following data. First, we use the 1961 Census for the pre-treatment census variables of sex ratio, the share of the rural population, and literacy rate. Secondly, we use the universe of the schooling data from the District

[32]LASI data have the birth districts coded as per the 2011 Census. India had 640 districts in the 2011 Census and 397 districts in the 1961 Census. As the district boundaries changed over time from 1961 to 2011, we created a district crosswalk file from various sources, including Google Search, Census of India, and a crosswalk file generously provided by Aaditya Dar. Finally, We obtained the restricted data on the district of birth from the University of Southern California.

Information System for Education (DISE) dataset, which is the 'most comprehensive information system in the education sector in India' (Ward, 2007). DISE is a school-level panel data of over 1.5 million schools in India. Each school is observed over time, starting from the year 2005. We use the 2015-16 wave of the DISE data. More importantly, DISE includes the school establishment year of each school, which we use to calculate the total number of schools in each district over time.[33]

2.3.4 Outcome Variables

Cognitive Health

Summary

Our primary outcome variable, the 'general cognitive score,' is a general cognitive factor score representing the latent trait of the respondent's cognitive function (Flood *et al.*, 2022). The 'general cognition score' measures the respondent's overall cognitive ability, including latent factors of general cognitive function, memory, executive function, orientation, and language (Gross *et al.*, 2023, Livingston *et al.*, 2020). The score is harmonized with the Health and Retirement Study–Harmonized Cognitive Assessment Protocol (HRS-HCAP) from the United States, empirically reflects comparable domains of cognitive function among older adults across six countries, has high reliability, and is useful for population-based research (Gross *et al.*, 2023).[34] HRS is an ongoing national study of over 20,000 U.S. adults aged 51 and older. HRS-HCAP, a sub-study within HRS, specifically targets cognitive impairment and dementia in a representative sample of U.S. adults aged 65 and older. HCAP employs cognitive tests to assess various cognitive domains affected

[33]DISE data covers school characteristics under different captions like school location, school management (public/ private), school categories (Primary, middle schools, secondary, high school), school facilities (building condition, availability of drinking water, library, toilets, playgrounds, computers, etc.), enrollment of boys and girls, teachers' information (number of teachers, teachers' qualification), etc. DISE covers enrollment from grades 1 to 8.

[34]The HCAP network represents the largest coordinated global initiative to date for conducting harmonized large-scale, population-representative studies on cognitive aging and dementia. The primary goal of the HCAP network is to offer standardized estimates of dementia and mild cognitive impairment prevalence on a global scale. By leveraging cross-national differences in essential risk and protective factors, the network aims to enhance our comprehension of the determinants of cognitive aging and dementia. The score is harmonized across aging studies from China, England, India, Mexico, South Africa, and the USA.

by aging, facilitating comparisons with other global studies (Langa *et al.*, 2020). This score is derived from latent variable modeling and using rich cognitive testing information from the population-representative LASI. One notable characteristic of this score is its insensitivity to including items that rely on literacy and numeracy. This aspect ensures that the score accurately reflects cognitive performance across individuals with varying literacy levels.

Construction

The score is calculated in the following way, which includes LASI– Diagnostic Assessment of Dementia (LASI-DAD), which is a subset of the LASI data designed to offer a more precise estimation of dementia at the national level and to investigate key risk factors associated with cognitive decline and dementia in India (Hu *et al.*, 2020).[35] LASI-DAD adopted the HCAP, with necessary modifications to suit the Indian context based on the higher illiteracy and innumeracy rates in India, as well as considering cultural nuances.[36] For instance, LASI-DAD was divided into literate (43·4%) and illiterate (56·6%) subgroups, and some tests were delivered as verbal instructions or cues instead of writing instructions for the illiterate individuals (Gross *et al.*, 2023). The 'general cognition score' is derived using a graded response item response theory (IRT) / confirmatory factor analysis (CFA) model outlined by (Muthén and Muthén, 2017), a well-established standard practice in the field of cognitive aging.[37] First, a CFA model for the general cognitive function was estimated in LASI-DAD (Gross *et al.*, 2020). The tests in the battery in-

[35] LASI-DAD study uses stratified, random sampling design for recruiting participants from the main LASI study and also oversamples participants with low cognitive function for the adequate sample size of the participant with dementia. Refer Gross *et al.* (2023), Flood *et al.* (2022) for more details.

[36] One example of such modification is that the tests were conducted in 19 different languages, given the vast diversity of the languages in India, which usually varies by the States. Another example of modification includes changing the names of persons and places from the original logical memory story recall test so that the Indian population can relate to it.

[37] IRT is a statistical framework used to analyze and interpret data from tests and questionnaires (Embretson and Reise, 2013). It is widely used in the field of psychology to measure various constructs such as intelligence, personality, and attitudes. IRT provides a more sophisticated approach to test analysis than classical test theory, as it takes into account the difficulty of individual test items and the ability of test-takers. This allows for more accurate and precise measurement of the construct being assessed. IRT has practical applications in education, clinical psychology, and market research, among other fields. It is a valuable tool for researchers and practitioners seeking to improve the quality and validity of their assessments.

clude broad domains of orientation, executive functioning, language/fluency, memory, and visuospatial, and five narrow domains of reasoning, attention/speed, immediate memory, delayed memory, and recognition memory. Appendix Figure A.2 shows these domains and the correlations between each domain and the observed cognitive test items. Secondly, a CFA model for general cognitive functioning was estimated for the entire LASI sample. In this CFA, the model parameters of 11 comparable items between LASI-DAD and LASI were included, while the parameters of 42 unique items in LASI were freely estimated.[38] A statistical approach is shown in Vonk *et al.* (2022) for the cross-national harmonization of this cognition score in HRS-HCAP and LASI-DAD. Importantly, the score is scaled to have a mean of 0 and a variance of 1 within the LASI-DAD population because no natural scaling in latent variable space exists, ensuring comparability and consistency in measurement (Gross *et al.*, 2023).

Validity

The general cognitive score is a validated and widely accepted method for evaluating cognitive health in observational and clinical research settings. The HCAP battery from the HRS has been successfully adapted in various countries, including the United States, England, Mexico, China, and South Africa (Gross *et al.*, 2020). A validated general cognitive score obtained from a neuropsychological test battery holds credibility in clinical samples and proves its relevance for clinically significant endpoints. Factor scores are increasingly being adopted as endpoints in clinical trials. The methodologies employed in test construction serve as the foundation for initiatives like the National Institute of Health (NIH) PROMIS and NIH Toolbox.

Cognitive Impairment

We use mild cognitive impairment (MCI) as another outcome, defined as the symptomatic pre-dementia stage defined by the U.S. National Institute on Aging guidelines (Langa and

[38] This approach of estimating parameters in one sample and fixing shared parameters to be equal in the second sample to create a link is referred to as 'item banking' (Gross *et al.*, 2023).

Levine, 2014). We follow the literature to define MCI as an indicator equal to 1 if the general cognition score is 1.5 standard deviations or below the education and age-matched mean for the main sample (Flood *et al.*, 2022, Kobayashi *et al.*, 2019). Since the sample in our study is relatively young (mean age is 49), MCI is the key outcome for measuring dementia.

Physical Health

We measure physical health outcomes by using the total number of chronic conditions as our key outcome variable. This measure is calculated by adding the positive responses to eight questions on 'ever had the following conditions: blood pressure, diabetes, cancer, lung disease, psych problems, arthritis, stroke, heart problems.'

2.3.5 Descriptive Statistics

We begin with descriptive evidence of the Green Revolution and the LASI cohort. Table 3.1 shows the characteristics of the 15,759 respondents in our sample. The mean age of the respondent is 49. The general cognitive score has a mean of 0.51 (SD 0.87), and about 7% of the sample had cognitive impairment. On average, the number of total chronic conditions is lower than 1; however, about 32% have some form of chronic conditions. About 58% of our sample is Women, and about half of the respondents were born in rural areas. On Average, one-third of the respondents have education above the primary level, and 42% never attended school. The fathers of the respondents are more than twice as likely to attend school than their mothers, given the social stigma about women's education in India. Almost 72% belong to lower castes.[39] The average exposure to the Green Revolution from in-utero to age 2 was 12 %.

[39]We define 'lower castes' if the respondent belongs to either Scheduled Castes (SC), Scheduled Tribes (ST), or Other Backward Classes (OBC). The share of the SC, ST, and OBC population closely matches with the share from different sources, including the Census 2011 (Pew Research Center, 2021).

Table 2.1: Descriptive Statistics for Individuals Born from 1966 to 1974

	Mean	SD	Min	Max	Obs
Green Revolution					
Avg. Treatment during					
Pre-conception	0.06	0.09	0.00	0.73	15758
In-utero to age 2	0.12	0.13	0.00	0.72	15759
Age 3 to 5	0.18	0.15	0.00	0.81	15759
Age 6 to 8	0.23	0.17	0.00	0.85	15759
Age 9 to 11	0.27	0.19	0.00	0.90	15759
Age 12 to 14	0.30	0.20	0.00	0.92	15759
Age 15 to 17	0.32	0.20	0.00	0.93	15759
Avg. Rain(mm) VDSA	105.05	63.34	0.00	388.23	15759
Avg.Max Temp(c)	31.14	2.69	0.00	35.40	15759
Avg.Min Temp(c)	19.62	2.48	-1.60	24.80	15759
Individual Characteristics					
Cognition Score	0.51	0.87	-3.50	3.25	15706
Cognition>25 pct	0.75	0.43	0.00	1.00	15706
Cognitive Impair	0.07	0.26	0.00	1.00	15706
Height (Stdz.)	0.05	0.99	-4.45	4.47	14242
BMI	23.47	4.75	10.52	63.41	14248
Total Chronic Conditions	0.42	0.70	0.00	6.00	15759
Any Chronic Condition	0.32	0.47	0.00	1.00	15759
Ever had Diabetes	0.08	0.28	0.00	1.00	15703
Ever had High BP	0.20	0.40	0.00	1.00	15705
Ever had Heart Problems	0.02	0.13	0.00	1.00	15709
Birth Year	1969.78	2.36	1966.00	1974.00	15759
Male	0.42	0.49	0.00	1.00	15759
Attended School	0.58	0.49	0.00	1.00	15759
Above Primary Edu	0.35	0.48	0.00	1.00	15759
Birth Rural	0.51	0.50	0.00	1.00	15759
Father Went School	0.33	0.47	0.00	1.00	15759
Mother Went School	0.14	0.35	0.00	1.00	15759
Low Caste	0.72	0.45	0.00	1.00	15759
1961 Census					
Share Literate(age10 above)	0.30	0.14	0.00	0.72	15759
Share Rural Population	0.79	0.23	0.00	1.00	15759
Sex Ratio M/F	1.05	0.20	0.00	1.63	15759
Observations	15759				

Note: The table shows the summary statistics of the respondents from the first wave of the Longitudinal Aging Study in India (LASI) for the 45+ age group (born from 1966 to 1974). We merged Village Dynamics in South Asia (VDSA) data with LASI data using the birth district and birth year of the LASI respondents with 314 districts at that time. Refer to the text for the variable definitions.

2.4 Estimation Strategy

We study the long-term effect of early-life exposure to the Green Revolution. We follow (Bharadwaj *et al.*, 2020) to use a proxy for the Green Revolution as the share of the total area planted under high-yield crops.[40] In the basic specification, we use the ordinary least square (OLS) to estimate the following equation.

$$Y_{isdt} = \sum_{\tau=-4,\tau\neq-1}^{17} \beta_\tau HYV_{\tau(d,t)} + X'_{isdt}\gamma + \delta_t + \mu_d + \tau_{st} + \varepsilon_{isdt} \tag{2.1}$$

where Y_{idt} is the health outcomes of individual i, born in district d of state s at year t. The measure of exposure to the Green Revolution is $HYV_{d,t}$, which is the share of the total area planted under high-yield crops in the birth district d at the birth year t. We include the exposure to the treatment over the early life cycle from pre-birth (4 years before the birth to 2 years before), around the birth (in-utero to age 2), and early childhood life period (age 3 to 5, age 6 to 8, age 9 to 11, age 12 to 14, and age 15 to 17). We average the treatment in these categories primarily to account for the potential measurement error in reporting the birth year. We include birth district fixed effects μ_d that control for all the time-invariant characteristics of the district. We also include birth year fixed effects δ_b that control for the time-specific shocks affecting all the districts in the year of birth. We add a vector of controls, X', that includes average rainfall, temperature, gender, castes, an indicator if the respondent was born in a rural area, and an indicator if the father and mother went to school. We also control for the pre-treatment 1960 census variables- sex ratio, the share of the rural population, and literacy rate. Additionally, we also include birth state-specific linear time trends ($\tau_s.t$) or birth state-by-year fixed effects (τ_{st}). The first takes into account any unobserved trending variables that may vary by state-specific cohorts and the second accounts for any annual pattern in later life outcomes that may differ across states. Standard errors are clustered at the district of birth level.

For identification, we compare individuals from the same district who were exposed

[40] Our specification is also similar to a study on the effect of weather shock on cognition in a similar context (Webb, 2024).

to varying levels of high-yield crops based on their years of birth, over and above any unobserved shocks to the cognition scores that vary by year of birth and any long-run trends (or annual pattern) in that individual's state (or region) of birth. The estimate β is the consistent estimate of exposure to the Green Revolution if, conditional on the district and birth-year fixed effects and controls, changes in the district-level yield of HYV crops are not correlated with other factors that also affect long-term health. Our study's primary analysis period is from 1966 to 1974, since the Green Revolution period is considered to have begun in about 1966, and the youngest cohort of the LASI respondents was born in 1974.

2.5 Results

2.5.1 Main Results

In this section, we present our main findings. Panel (A) and Panel (B) of Table 2.2 show the effect of in-utero to age 2 exposure to the high yield varieties (HYV) on later life cognitive function and the number of chronic conditions, respectively. The first columns in each panel show estimates for the specification with birth-district and birth-year fixed effects. In the second column of both panels, we include four types of control variables- individual-level time-invariant, parental education, weather, and the 1961 Census characteristics. For individual controls, we include gender and caste; for weather controls, we include average rainfall and temperature; for parental controls, we include indicators that the father and mother went to school; and for the pre-treatment census variables, we include sex ratio, the share of the rural population, and literacy rate from the 1960 Census. In the third column, we add state-specific linear time trends to account for possible unobserved trending variables that may vary by state-specific cohort. In our preferred specification, in the fourth column, we replace state-specific linear time trends with state-by-birth-year fixed effects to control for the annual variation in health outcomes that may vary across states. Our preferred specification controls for unobserved heterogeneity across different states, given the massive heterogeneity in states in India in terms of language, culture, education level, and agricultural practices. By including fixed effects for each state, we account for any unobserved factors that might vary across states but remain constant over time. Similarly, state-by-birth-year fixed effects capture the nonlinear patterns in the data, while linear trends might not be able to capture the underlying dynamics in the data.

Table 2.2: Effect of early life exposure to the HYV on cognitive and physical health

	Panel (A) Outcome: General Cognition Score				Panel (B) Outcome: Total Chronic Conditions			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Pre-Conception	0.221	0.171	0.218	0.026	0.285**	0.268*	0.327*	0.426*
	[0.167]	[0.171]	[0.186]	[0.250]	[0.142]	[0.159]	[0.194]	[0.239]
In-utero to Age 2	0.109	0.058	0.089	0.416*	-0.006	0.065	0.214	0.211
	[0.192]	[0.158]	[0.171]	[0.234]	[0.199]	[0.198]	[0.236]	[0.274]
Observations	15,695	15,695	15,695	15,705	15,748	15,748	15,748	15,758
R-squared	0.14180	0.33291	0.33395	0.34351	0.06771	0.08104	0.08237	0.09240
Birth year FE	Y	Y	Y	Y	Y	Y	Y	Y
Birth District FE	Y	Y	Y	Y	Y	Y	Y	Y
Weights	Y	Y	Y	Y	Y	Y	Y	Y
Controls		Y	Y	Y		Y	Y	Y
State-Birth Y Trend			Y				Y	
State-Birth Y FE				Y				Y
Mean of Y	0.518	0.518	0.518	0.519	0.400	0.400	0.400	0.400

Note: This table shows the effect of in-utero to age 2 exposure to the Green Revolution on later life cognitive function (panel A) and the total number of chronic conditions (panel B) using Equation 2.1. The data are from Village Dynamics of South Asia (VDSA), which merged with the first wave of the Longitudinal Aging Study in India (LASI). Controls include weather conditions (temperature and rainfall), parental education, gender, castes, Census level literacy rate, gender ratio, and share of the rural population. We include person weights in the estimation. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.

Column 1 in Table 2.2 shows that early-life exposure to the Green Revolution affects later-life cognitive function positively; however, the estimates are statistically insignificant. The estimates on the pre-conception are also statistically insignificant, suggesting evidence of the fulfillment of the parallel trend assumption. In column 2, we introduce controls, and the estimates decline by half; however, they are still insignificant. In column 3, with the state-by-birth-year trends, we also do not find a significant effect. Finally, column 4 of Table 2.2, which is our preferred specification with state-by-birth-year fixed effects, suggests that one standard deviation (SD) increase in the average HYV share during in-utero to age 2 improves the cognitive score by 0.054 and are statistically significant at 10% level.[41] These effects can (loosely) be comparable with a recent study which finds a one SD improvement in weather conditions during age two leads to an improvement in cognition during adulthood (aged 16-37) by 0.063 SDs in a comparable developing country (Webb, 2024). In Appendix Table A.7, we also show the estimates with the full age profile from pre-conception to age 17.[42] We also show results with the results on 'cognition impairment' in Appendix Table A.8, which shows that the direction of the effect is as expected. However, the effect is not statistically significant.

In panel (B), we show the effects on later life physical health, using the total number of chronic conditions as an outcome. In our preferred estimates in column 8, we find that early life exposure (in-utero to age 2) to the Green Revolution increases the total number of chronic conditions; however, the estimates are not statistically significant. To explore further, we provide evidence of the effects of heterogeneous treatment in the next section.

2.5.2 Heterogeneity Analysis

We explore various heterogeneity in the effect of early life exposure to the Green Revolution on later-life cognitive function in Table 2.3. We mainly explore the treatment effects based on gender, caste, and region for various reasons. First, stronger gender norms exist in India, with usually higher intra-household resources such as food, nutrition, and education investments in early life allocated for males than females. Research also suggests that the Green Revolution reduced infant mortality among males more than females, suggesting potentially other biological factors that may differ by gender (Goltz *et al.*, 2020, Bharadwaj *et al.*, 2020). Such stark gender disparities are also evident in the cognition score, with men having significantly higher scores (0.739) than women (0.204). Secondly, caste-based disparities are deeply entrenched in Indian society and have significant implications for access to societal resources and health outcomes. Examining how the Green Revolution influenced health outcomes across caste groups helps identify and address in-

[41]The estimate = 0.416 X SD of the treatment variable.

[42]We find that in-utero to age 2 exposure to the Green Revolution positively affects later-life cognitive function; however, the estimates are not statistically significant.

equalities in agricultural development and healthcare provision. Finally, rural areas often bear the brunt of agricultural changes, yet they may also benefit from increased agricultural productivity since agriculture is usually saturated around rural areas. Understanding how the Green Revolution affected health outcomes in rural versus urban areas provides insights into the broader implications of agricultural transformations on public health and informs policies to improve rural healthcare infrastructure and services.

First, we do not find any statistically significant effects on cognitive function among men and women (columns 1 and 2), even though the coefficients are positive and large. Secondly, we find a statistically significant increase in cognitive function among the low-caste respondents (column 3).[43] Specifically, one SD increase in the average HYV share during in-utero to age 2 improves the cognitive score by 0.083 SD among lower castes. There are two possible explanations for the positive effects on lower castes. First, the lower caste households are more likely to be poorer and usually lack the financial and nutritional resources to invest in a child's development. Generally, low castes are significantly less likely to attend school, have less educated parents, are less likely to stay in literate population areas, and are more likely to reside in rural areas. With access to some of the resources through the Green Revolution, one might expect improvement in the financial and nutritional resources for the low castes.[44] This evidence is consistent with the literature suggesting better outcomes of the Green Revolution for low castes, like reduced child mortality and increased access to health facilities (Bharadwaj *et al.*, 2020, Munshi and Rosenzweig, 2009). The second explanation is about an increase in education among low castes, which we explore more the mechanism section 2.6.

Further, we find a statistically significant increase in cognitive function among responders born in rural areas (column 5). Specifically, one SD increase in the HYV share during

[43]The data do not include the castes categories for the high castes, so we cannot say anything about the results on high castes.

[44]The increased production resulting from the Green Revolution (GR) has effectively reduced food prices (Evenson and Gollin, 2003). Since the poor (more likely from the lower castes) spend a greater share of their income on food than the rich (more likely from the higher castes), the price reduction might expand the budget constraints for the lower castes. This shift in budgetary dynamics could potentially allow them to allocate a higher share of their income than before to invest in their children's human capital development, which may affect later life cognitive health.

Table 2.3: Heterogenous Treatment Effect

	Outcome Variable: General Cognition Score					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Men	Women	Low Castes	Urban	Rural	Rural Low Caste
Pre-conception	-0.273	0.188	-0.066	0.097	-0.142	0.100
	[0.388]	[0.278]	[0.277]	[0.466]	[0.249]	[0.363]
In-utero to Age 2	0.577	0.319	0.639**	0.335	0.803***	0.947***
	[0.360]	[0.285]	[0.272]	[0.451]	[0.284]	[0.358]
Observations	6,556	9,117	11,323	7,640	8,023	5,813
R-squared	0.287	0.325	0.342	0.323	0.369	0.373
Birth year FE	Y	Y	Y	Y	Y	Y
Birth District FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
State-Birth year FE	Y	Y	Y	Y	Y	Y
Weights	Y	Y	Y	Y	Y	Y
Mean of Y	0.739	0.204	0.434	0.663	0.322	0.244

Note: This table shows the effect of in-utero to age 2 exposure to the Green Revolution on later life cognitive function using Equation 2.1, separately estimated for each group. Controls include weather conditions (temperature and rainfall), parental education, gender, castes, Census level literacy rate, gender ratio, and share of the rural population. We include person weights in the estimation. Standard errors are clustered at the birth district level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

in-utero to age 2 improves the cognitive score among rural born by 0.104 SD. The positive benefits of the Green Revolution for rural areas may imply that the benefits of the Green Revolution were mediated through agricultural income and rural development. This evidence is also consistent with the literature suggesting the benefit of the Green Revolution in reducing child mortality in rural areas (Bharadwaj *et al.*, 2020). Finally, the positive effects on the cognitive function of the Green Revolution are strongest for the low castes born in rural areas (column 6), i.e., an increase in general cognitive function by 0.123 SD. In section 2.6, we show some of the potential channels for these positive gains in cognitive function.

We also show the results of heterogeneous treatment effects on another measure of cognition, i.e., cognition impairment. Table 2.4 shows that the men and respondents born in rural areas have significantly less likelihood of cognitive impairment. We find the direction of effect for the low castes as expected, but the effect is not statistically significant. These results provide evidence that early life exposure to the Green Revolution also benefitted men and rural areas by decreasing the occurrence of cognitive impairments. Finally, in Appendix subsection A.3.4, we show and explain in detail the heterogeneous treatment effects of the Green Revolution on the physical outcomes of any chronic conditions, diabetes, and Body Mass India (BMI).[45]

Table 2.4: Heterogenous Treatment Effect

	Outcome Variable: Cognitive Impairment					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Men	Women	Low Castes	Urban	Rural	Rural Low Caste
Pre-conception	0.082	-0.049	0.126	0.023	0.129	0.055
	[0.087]	[0.176]	[0.090]	[0.127]	[0.126]	[0.161]
In-utero to Age 2	-0.258***	0.043	-0.104	-0.074	-0.246**	-0.079
	[0.089]	[0.127]	[0.083]	[0.112]	[0.104]	[0.121]
Observations	6,556	9,117	11,323	7,640	8,023	5,813
R-squared	0.105	0.096	0.101	0.102	0.108	0.138
Birth year FE	Y	Y	Y	Y	Y	Y
Birth District FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
State-Birth year FE	Y	Y	Y	Y	Y	Y
Weights	Y	Y	Y	Y	Y	Y
Mean of Y	0.044	0.090	0.067	0.048	0.083	0.087

Note: This table shows the effect of in-utero to age 2 exposure to the Green Revolution on later-life cognitive impairment using Equation 2.1, separately estimated for each group. Controls include weather conditions (temperature and rainfall), parental education, gender, castes, Census level literacy rate, gender ratio, and share of the rural population. We include person weights in the estimation. Standard errors are clustered at the birth district level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

2.6 Mechanism

In subsection 2.5.2, we find the heterogeneous treatment effect of the early life exposure to the Green Revolution on the later life cognitive function, mainly for the low-castes and rural areas. We unpack some of the channels through which this effect may exist. First, we test whether better cognition mediates through better nutrition by using 'height' as a proxy, which is one of the predictors for better early life investments. Secondly, we study whether education contributes to better cognitive function. Finally, we study school construction as one of the mediators to rule out if the construction of schools was driving some of the positive effects.

[45] We are also working on including the overweight and obesity as outcomes.

2.6.1 Height

We test whether early life exposure to the Green Revolution also affects other later life health outcomes that may explain the benefits in the positive cognitive function. We study height as one of the outcomes. We standardized the height based on gender. The estimates are documented in Table 2.5.

Table 2.5: Heterogenous Treatment Effect on Height

	Outcome Variable: Standardized Height					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Men	Women	Low Castes	Urban	Rural	Rural Low Caste
Pre-conception	-0.016	-0.147	0.033	0.300	-0.522	-0.209
	[0.635]	[0.376]	[0.471]	[0.574]	[0.465]	[0.584]
In-utero to Age 2	0.854	-0.333	0.421	0.185	0.274	-0.341
	[0.639]	[0.487]	[0.416]	[0.641]	[0.516]	[0.642]
Observations	5,880	8,325	10,376	6,861	7,332	5,360
R-squared	0.165	0.140	0.117	0.150	0.154	0.160
Birth year FE	Y	Y	Y	Y	Y	Y
Birth District FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
State-Birth year FE	Y	Y	Y	Y	Y	Y
Weights	Y	Y	Y	Y	Y	Y
Mean of Y	0.030	0.009	-0.027	0.025	0.016	-0.025

Note: This table shows the effect of in-utero to age 2 exposure to the Green Revolution on height using Equation 2.1, separately estimated for each group. The outcome variable is the standardized height based on gender. Controls include weather conditions (temperature and rainfall), parental education, gender, castes, Census level literacy rate, gender ratio, and share of the rural population. We include person weights in the estimation. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.

If the Green Revolution helped the weakest survive, one would expect those people to have worse health outcomes. We do not find evidence that early-life exposure to the Green Revolution affects later-life height for any group. This evidence is also consistent in the literature that suggests the Green Revolution does not affect heights among children (Bharadwaj *et al.*, 2020).[46]

2.6.2 Education

Since education is profoundly related to later-life cognition[47], we test whether the subgroups' cognitive function improvement is attributed to education. We use outcome on

[46] This evidence is also consistent with a study with similar context from other developing country (Webb, 2024).

[47] Angel *et al.* (2010)

education as an indicator that takes the value of 1 if the respondent attended any school and 0 otherwise. Table 2.6 shows the estimates of early life exposure to the Green Revolution on education. The magnitudes in columns 3 and 8 show significant improvement in the likelihood of attending school for low-castes (10% level) and low-castes born in rural areas (1% level). Further, in Appendix Figure A.4, we show the results with the full age profile for the different groups. We find that early life exposure to the Green Revolution significantly improved the likelihood of attending school among these groups. Importantly, the effect is higher and more significant during the Green Revolution exposure around birth and during the age of 9-11. Using another nationally representative data from India, we provide distributions in Figure A.5 of the education levels in low-caste people born during the pre and post-Green revolution period, which provides some evidence that the share of the sample who completed primary education among lower castes was higher in post-Green revolution period. [48]

Table 2.6: Heterogenous Treatment Effect on Schooling

	Outcome Variable: Attended School					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Men	Women	Low Castes	Urban	Rural	Rural Low Caste
Pre-conception	-0.045	-0.257*	-0.087	0.016	-0.259	-0.382*
	[0.235]	[0.148]	[0.137]	[0.206]	[0.173]	[0.197]
In-utero to Age 2	0.078	0.263	0.316*	0.018	0.317	0.678***
	[0.256]	[0.182]	[0.176]	[0.235]	[0.206]	[0.226]
Observations	6,582	9,144	11,363	7,676	8,040	5,827
R-squared	0.250	0.380	0.328	0.297	0.386	0.393
Birth year FE	Y	Y	Y	Y	Y	Y
Birth District FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
State-Birth year FE	Y	Y	Y	Y	Y	Y
Weights	Y	Y	Y	Y	Y	Y
Mean of Y	0.677	0.403	0.506	0.630	0.475	0.412

Note: This table shows the effect of in-utero to age 2 exposure to the Green Revolution on schooling using Equation 2.1, separately estimated for each group. The outcome variable is whether the respondent went to school or not. Controls include weather conditions (temperature and rainfall), parental education, gender, castes, Census level literacy rate, gender ratio, and share of the rural population. We include person weights in the estimation. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.

[48] We use the India Human Development Survey (IHDS) wave 2011-12.

2.6.3 Construction of Schools

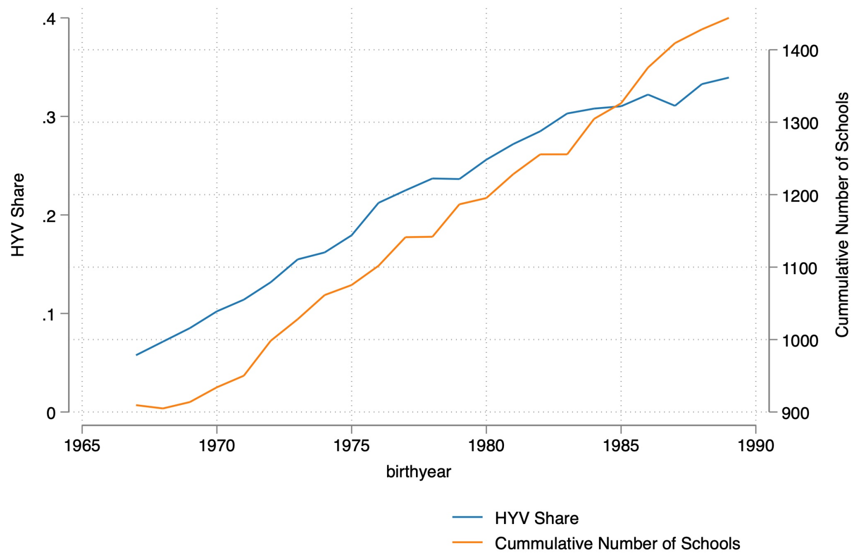
We further explore one of the first pieces of evidence on whether the Green Revolution also affected the building of more schools to explain whether the positive gain in cognitive functions was driven by the construction of schools. We use the universe of the school administration data for the year 2015-16, which has information on over 1.5 million schools in India in 2015-16, including the school construction years.[49] We merged VDSA data with DISE data using the district and year of construction. We cross-walked the districts from DISE data in 2015-16 to the 1960s districts to match with the VDSA data. Figure 2.4 shows the adoption of the HYVs and the cumulative number of schools in India.

For the analysis, we restrict the sample period to 1966-1989. The primary treatment is the same as before, i.e., the share of HYV crops. The outcome variables are the total number of schools in a district in a given year in all the above categories. We also calculate the rural and urban schools in each of these categories. We control for the 1961 census district-level share of literate aged 5+ population, share of the rural population, and male-female ratio; for each, we include the linear time trend.

The results are shown in Table 2.7 for school constructions in rural areas. Our preferred specification in column 3 with birth-state-by-year fixed effects suggests that the increase in the adoption of HYVs did not significantly affect the construction of the school. This evidence rule out that the school construction did not drive the gain in education and cognitive function, especially among the rural population.

[49] The data goes back to schools constructed in the 1850s.

Figure 2.4: Green Revolution and Number of Available Schools



Note: We merge DISE and VDSA data using the district and year. The cumulative number of schools is the average of the cumulative number of schools in each district in India.

Table 2.7: Effect of the Green Revolution on Rural School Construction

VARIABLES	(1) Rural Schools	(2) Rural Schools	(3) Rural Schools
HYV Area / Cultivated Area	-14.74***	-4.58	-0.88
	[5.08]	[4.41]	[4.78]
Observations	6,968	6,968	6,968
R-squared	0.29	0.32	0.53
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Census Controls	Yes	Yes	Yes
Mean of dependent variable	21.79	21.79	21.79
State-Year Trend		Yes	
State-Year FE			Yes

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

Note: The table shows the effect of the Green Revolution on the cumulative number of schools constructed. We merged Village Dynamics in South Asia (VDSA) data with DISE data using district and year from 1966 to 1989. We control for the 1961 census district-level share of literate aged 5+ population, share of the rural population, and male-female ratio; for each, we include the linear time trend.

2.6.4 Financial Condition as Growing Up

Further, we find evidence on whether early life exposure to the HYVs under the Green Revolution affects the financial conditions while growing up. LASI survey asks questions about the self-rated family financial situation before age 16 in three categories: pretty well off, average, and poor. We create an indicator variable equal to 1 if the financial condition was poor and 0 if it was either pretty well off or average. The results are shown in Appendix Table A.9, showing the statistically significant improvement in financial conditions (decline in the 'poor financial condition') for the lower castes respondents (Column 3). We find improvement in financial condition for other beneficiary groups like respondents born in rural areas (column 6) and lower castes born in rural areas (column 8). However, the estimates are not statistically significant.

2.7 Robustness

To examine the robustness of main estimates, we perform several robustness checks. First, we include different specifications in our main results in Table 2.2. For instance, we control for observable characteristics like weather conditions, parental education, gender, and castes, as well as district-level characteristics from the Census, such as literacy rate, gender ratio, and share of rural population. We include the fixed effects of birth district and birth year to address the temporal and spatial factors associated with adopting the HYV, which might also affect health later in life. Alternatively, we include birth state-specific linear time trends or birth state-by-year fixed effects.[50] In these specifications, the direction of the effects remains the same.

Secondly, in Appendix Table A.7, we show the estimates on the full age profile from in-utero to age 17. In this table, we show the effect of the Green Revolution on later-life cognitive function at different stages of childhood. In column 4, the estimate of exposure to the treatment in utero to age 2 (0.375) is similar in magnitude to the estimate (0.416)

[50]The first takes into account any unobserved trending variables that may vary by state-specific cohorts, and the second accounts for any annual pattern in later life outcomes that may differ across states.

in Table 2.2. Similarly, for our key heterogeneous treatment effects based on castes and regions, our estimates in Table 2.3 replicate the significant positive effect on cognitive function when we include a full age profile in Appendix Figure A.3.

Further, our estimates might suffer from differential survival bias if only the weakest kids survived after the Green Revolution. To account for the survival bias, we drop the bottom 5 percentile sample in the distribution of the gender-adjusted height.[51] We show the results in Table A.13 for our preferred specification using Equation 2.1. We observe a reduction in the coefficients related to our primary treatment variables compared to the main results presented in Table 2.2. Nevertheless, the standard errors remain largely unchanged, suggesting our estimates' precision has not been affected after excluding the bottom 5th percentile of the sample.

Similarly, our results could be driven by the composition effects due to increased survival in the older age group. To address this, we will use the Census 2011 data, which has the 5-year age groups.[52] We will compare if the number of people born after the Green Revolution is higher than those born before in districts that experienced the Green Revolution.

2.8 Conclusion & Discussion

We contribute to the vast literature on the Green Revolution by studying its unexplored long-term impacts on aging-related cognitive and physical health outcomes, focusing on cognitive function, cognitive impairments, and chronic conditions, using the largest aging data in the world from India. We find that in-utero to age 2 exposure to the Green Revolution among 45 to 54 age groups improves the later-life general cognitive function, with stronger effects for the socially disadvantaged group (lower caste) and individuals born in rural areas, with the highest effects for the lower castes born in rural areas. For men, rural-born, and the higher castes individuals, we also find a significant decline in the

[51] This cut-off is motivated by a study that finds that the Green Revolution reduces child mortality by 5.1% (Bharadwaj *et al.*, 2020).

[52] We will follow Sekhri and Shastry (Forthcoming) who conduct a similar analysis.

likelihood of mild cognitive impairment, which is considered the pre-dementia stage. On the other hand, we also find evidence of an increase in chronic conditions, primarily for men and people born in urban areas.

Our findings suggest that the demand side factors primarily drive the positive gains in cognition. We find that the significant improvement in attending schools explains the cognitive gains for low-caste and rural-born individuals. We do not find evidence that supply-side factors like school construction were driving these positive gains in the general cognitive function. Our results also rule out that the improvement in early-life nutrition drove these factors since we did not find any improvement in age-adjusted height, suggesting other evidence that the income effects play a significant role.

Regarding policy, our estimates suggest that the Green Revolution has the potential for long-term benefits in aging-related outcomes like cognition and ADRD; however, it has some negative effects in chronic conditions. These findings are important from a policy perspective since the Green Revolution is an ongoing policy in developing countries, especially in the African regions, and we need to understand whether to keep investing in these policies. In particular, the Alliance for a Green Revolution in Africa (AGRA) was established in 2006 by former UN Secretary-General Kofi Annan to promote Green Revolution technologies in African countries (Carter *et al.*, 2021). Our findings highlight the potential benefits and costs of adopting the HYVs. We hope future research will focus on understanding whether these benefits and costs of the Green Revolution for India also translate to African countries and other under-adopted countries.

Chapter 3

Does Broadband Technology Affect Social Security Applications?

3.1 Introduction

There are extensive administrative burdens for applying for Social Security benefits, including understanding eligibility and submitting paperwork and medical records. There could be an ambiguous effect of increasing these administrative burdens — only the people in dire need will apply for the benefits or opt-out due to the high costs. Such administrative burdens are distributive, i.e., they affect some groups more than others, creating structural barriers (Herd and Moynihan, 2019). Studies in behavioral economics suggest that these costs may discourage needy applicants (Bertrand *et al.*, 2004). Especially for older adults (50+), these frictions could be a cornerstone for individuals deciding whether to apply for Social Security benefits.

We have made enormous technological progress in recent decades, providing access to computers, the Internet, and smartphones; however, significant disparities still remain in access to these technologies. In 2000, about half (52%) of U.S. adults were using the

Internet, and 1% of adults had home broadband, but by 2023, 95% of U.S. adults use the Internet, with 80% of adults reporting that they have broadband at home.[1] Importantly, broadband availability for older adults is also increasing. For instance, the availability of high-speed broadband for the 65+ population in 2010 was about 45 percent, but by 2018, it had become about 60 percent (Gawai, 2023). However, more than 42 million Americans still lack access to broadband services, and significant geographical and socioeconomic disparities remain in broadband access (Busby *et al.*, 2021). Federal agencies like the Social Security Administration (SSA) encourage applicants to use the Internet to apply for benefits (Kauff *et al.*, 2011).[2] One key reason for the focus on older adults is that the likelihood of individuals receiving SSDI increases by over two-fold between the ages of 40 and 50 and similarly doubles between ages 50 and 60 (CBPP). Figure 3.1 suggests that the percentage of people filling out online SSDI applications has been relatively consistent from 2014 onward, even after the increase in broadband technology. The COVID-19 period highlighted the urgent need for internet connectivity for employment, business, and other essential activities. Recent policies to expand broadband access, mainly in rural areas and low-income households, suggest stark disparities in technology access based on geography and income. More importantly, SSA applications on the internet have expanded from minimal internet speed sufficient for sending emails, web browsing, and online shopping to the requirement of higher speeds and larger bandwidths used in streaming video, online gaming, and, lately, video conferencing, telehealth, and remote learning (Butrica and Schwabish, 2022). However, it is unclear in the literature whether high-speed broadband availability increases the SSI or SSDI application rate, especially among older adults.

This study provides causal evidence on whether better broadband expansion affects the process of applying, appealing, or receiving SSI and SSDI benefits among older adults in the US.[3] Specifically, I study whether broadband improves production efficiency and reduces the friction of applying SSI and SSDI benefits at an extensive margin. The paper

[1] Refer to the Pew Research Center report.

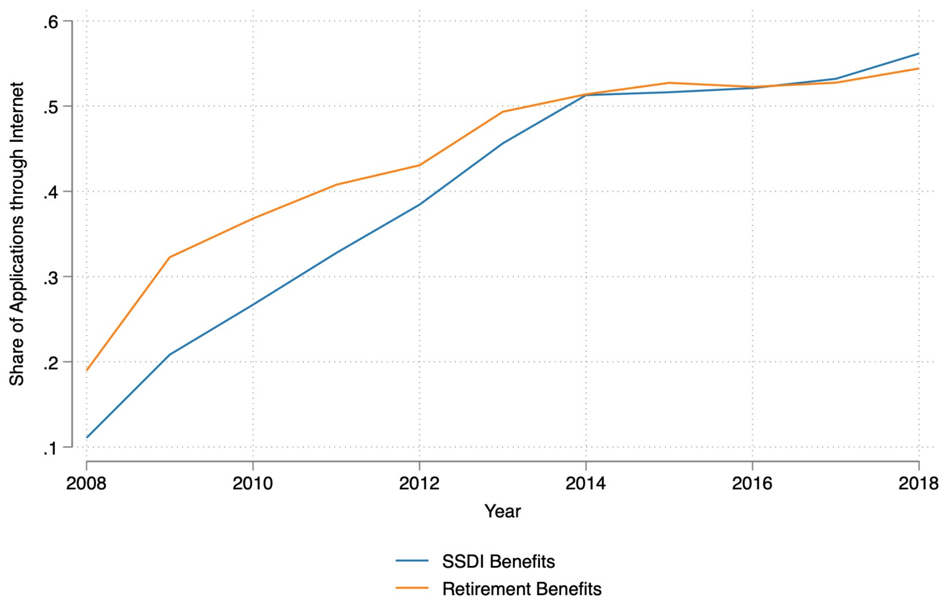
[2] See SSA official website.

[3] This paper is the extension of (Gawai, 2023), which studies the effect of broadband on mental health among older adults.

employs a quasi-experimental design, using the staggered introduction of high-speed 'fiber broadband' in census tracts. I use the biennial waves from individual panel data of the Health and Retirement Study (HRS), a nationally representative study of individuals aged 51+. The analysis period is from 2010 to 2018, with over 39,000 person-year observations. The key dependent variable in my regressions is an indicator equal to one if the HRS respondent reports that they applied, appealed, or received the SSI or SSDI benefits (separately) during the survey year. I use two yearly data sets on broadband at the census tract level from 2010 to 2018. Merging individual panel HRS data with the broadband data at the census tract and year level allows me to exploit the spatial, temporal, and, importantly, individual-level variation in the staggered introduction of high-speed fiber broadband to estimate the intent to treat (ITT) effect. The new staggered difference-in-differences (DID) treatment estimator developed by Borusyak *et al.* (2021) forms the basis for my primary estimations because it addresses the negative weighting problems and does not rely on the strict assumption of homogeneity as commonly found in two-way-fixed-effects (TWFE) estimators.

The net effect of Broadband expansion on the SSI or SSDI application rates could be ambiguous. On the one hand, one may expect a reduction in the application costs, including the distance and time to visit SSA offices in person. For remote areas, these costs might be higher. So, the benefits of better internet might be saturated in rural areas. Broadband access may be even more critical to reduce distance and time when SSA offices are not nearby. These costs might differ based on broadband availability and the ability to use those technologies. Studies document that broadband technology does not help 40 percent of older adults, and about 60 percent of individuals with less than a high school education or residents of rural areas do not use the internet (Herd and Moynihan, 2019). This is important to address the technological divide between urban and rural areas. On the other hand, the digital divide may exacerbate structural barriers among geographic locations with poor broadband connectivity and households with low socioeconomic status who might need access to these technologies, including training in internet literacy. Studies

Figure 3.1: Share of Applications through Internet



Note: This figure shows the share of total applications that are filled online using the publicly available data from the Social Security Administration.

document that in-person assistance matters for low-income and low-education levels, even in online applications (Deshpande and Li, 2019).

This study finds that introducing high-speed fiber broadband technology positively affects the likelihood of applying, appealing, or receiving SSDI benefits among older adults; however, it does not affect the SSI process. On average, I find a 21% increase in the likelihood of applying, appealing, or receiving SSDI benefits. I, however, find the existence of the racial and regional barriers, with no effect for the non-White and rural dwellers. These findings emphasize the need for policies that promote broadband expansion and more investments to understand other structural barriers involved in online applications for SSI and SSDI benefits.

This paper contributes to the growing literature on evaluating the effect of broadband by applying the latest methodological advances and improving precision by more accurately measuring the treatment exposure. One of SSA's primary goals is to deliver services to the public effectively and efficiently and understand the role of technology like broadband and internet on the social security benefit application rates. The causal evidence of whether broadband technology helps in this goal is unclear in the economics literature. Butrica and Schwabish (2022) document the correlation between broadband and disability insurance awards, suggesting that counties with a high proportion of DI beneficiaries have less access to broadband and the internet. The only recent study I could find suggests that better internet access increases SSDI applications by about 1.6 percent and benefits rural areas more after the introduction of iClaim, an innovation in the online applications process (Foote *et al.*, 2019). Most of these studies, however, are either correlational or suffer from challenges due to two-way-fixed-effects (TWFE), lack individual panel data, and conduct analysis at the broader geographic level (e.g., county). I improve the literature by using the latest DID estimator developed by Borusyak *et al.* (2021), which accounts for the treatment-effect heterogeneity. Similarly, I use the individual panel of HRS data to observe the same individuals over time and their precise geographic locations at the census tract level. This panel nature of the data allows for the identification to come from the within-individual changes in the access to high-speed broadband. Similarly, the precision of measuring the treatment at the census tract level helps reduce bias in the estimation.

Secondly, this paper contributes to the growing literature on information and the take-up of social benefits by evaluating a staggered introduction of high-speed internet through fiber technology. Research documents low enrollment rates among eligible recipients across various programs due to the need to be more aware of program availability and rules, which are barriers to taking up (Chetty *et al.*, 2013). The information could be translated through peers (Dahl *et al.*, 2014). The internet is a valuable tool for information, and evidence suggests that providing information increases the likelihood of enrollment in various welfare programs (Barr and Turner, 2018). Several recent studies suggest that informing likely-eligible individuals increases program enrollment (Armour, 2018, Barr and Turner, 2018, Bhargava and Manoli, 2015, Finkelstein and Notowidigdo, 2019). On the other hand, the complexity involved in using the internet or the lack of cognitive ability required to process online applications may discourage some applicants and create friction in the take-up of social benefit programs (Bhargava and Manoli, 2015).

3.2 Background

3.2.1 Eligibility for SSI and SSDI

Supplemental Security Income (SSI) is a federal initiative that is accessible to individuals who have disabilities, are visually impaired, or are 65 years and older. SSI benefits are determined not by work history but by income and assets within specified limits.[4] One can also get SSI if a medical condition prevents employment and is anticipated to persist for at least one year or result in death. For instance, the standard monthly SSI payment remains consistent nationwide in 2024 at $943 for an individual and $1,415 for a couple. However, payment amounts can vary. Residents of states supplementing the federal SSI payment may receive more, while those with additional household income may receive less. Moreover, the amount of your SSI payment is influenced by factors such as one's living arrangements and household composition. Total federal spending for disbursements within the SSI program during the calendar year 2022 amounted to $57.1 billion.

Eligibility for SSDI is stringent. The applicant must have worked for at least one-fourth of their adult life and five of the last ten years to be insured for disability benefits; have severe, medically determinable physical or mental impairment expected to last at least 12 months or result in death, based on clinical findings; should be inability to engage in substantial gainful activity, defined as earning $1,550 per month ($2,590 for blind individuals) regardless of job availability or location. For older, severely impaired applicants unable to change careers, lack of education and skills are considered, unlike younger applicants. Most SSDI beneficiaries are older and contend with serious physical or mental impairments. The typical recipient is in their 50s, with over 75% falling into this age group, and more than 40% are aged 60 or above.[5] In October 2023, approximately 7.4

[4] All the information in this section is from the SSA official website.

[5] Disabilities among recipients are diverse; musculoskeletal conditions such as osteoarthritis and scoliosis are common among those over 50, while severe mental disorders like schizophrenia and bipolar disorder

million individuals received disabled worker benefits through Social Security. Additionally, payments extended to 89,000 spouses and 1.1 million children of beneficiaries. Funding for SSDI benefits mainly comes from a portion of the Social Security payroll tax, amounting to about $143 billion in 2022. This sum represents roughly 2 percent of the federal budget and less than 1 percent of GDP. However, only 1 in 3 SSDI applicants are awarded benefits at the end of the application and appeal process.

The process of applying for SSI and SSDI typically begins with the initial application, where the applicant submits their medical records and other relevant documentation to the Social Security Administration (SSA). In the case of SSI applications, applicants have to submit documents related to their financial situation. After submission, the application undergoes review by SSA staff to determine if the applicant meets the eligibility criteria for disability benefits or SSI benefits based on income, resources, disability status, or both. If the initial application is denied, which is common, the applicant can request reconsideration within a certain timeframe. During reconsideration, the application undergoes another review by different SSA staff. If denied again, the applicant can appeal the decision and request a hearing before an administrative law judge.

3.3 Data

3.3.1 Broadband Data

The empirical analysis draws upon panel data from two sources: the Federal Communications Commission (FCC) Form 477 spanning 2014 to 2018, and the National Telecommunications and Information Association's National Broadband Map (NBM) covering 2010 to 2013. This dataset encompasses crucial information, including the number of broadband providers, transmission technology (such as DSL, fiber, cable, or satellite), maximum download and upload speeds measured in Mbps, and whether the provider offers residential service at the census tract level. To ensure comprehensive coverage, broadband providers must submit data biannually, specifically in June and December, demonstrating

prevail among those under 50.

their ability to deliver internet service with speeds surpassing 200 Kbps in at least one direction. The census tract, comprising smaller geographic units compared to counties, offers a finer granularity of analysis. With 84,414 census tracts in the United States, each ideally accommodating approximately 4,000 residents (Census Report). The census tract provides precise geographic treatment of broadband instead of aggregating at the county level, which has been done in the related literature. To ensure the most recent and reliable broadband data, the analysis primarily relies on the December dataset for each year.

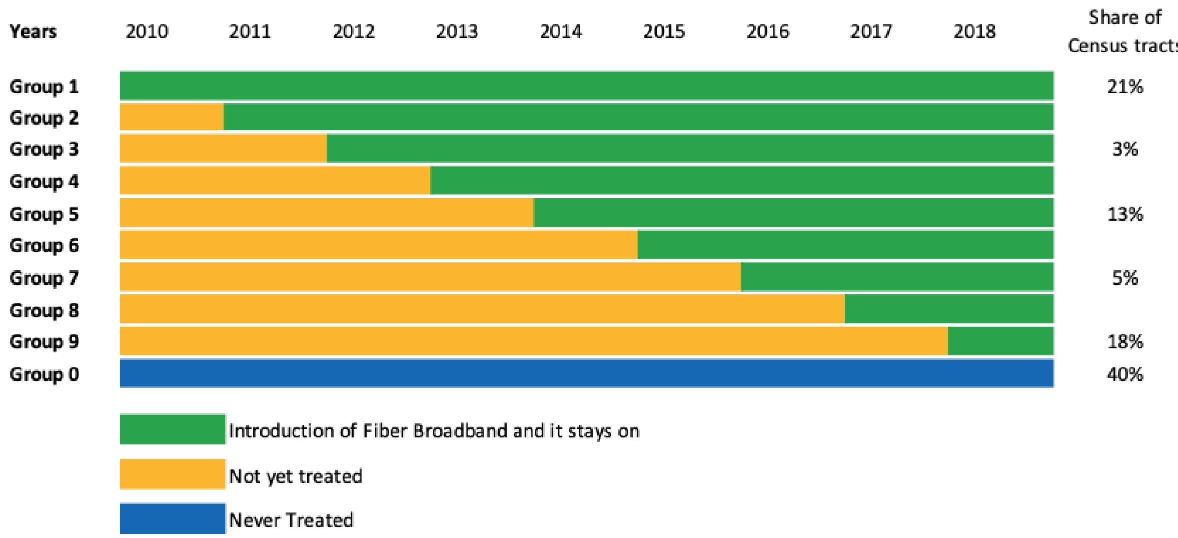
Definition of the Broadband Providers

The key treatment variable is an indicator of whether the fiber broadband had been introduced in a given census tract during a survey year. This binary variable takes the value of 1 in the year of introduction and persists as such in subsequent years. Conversely, for census tracts where fiber broadband has not been extended, the variable remains at 0 throughout the observation period, thus constituting the never-treated group. This research design effectively captures the staggered implementation of the treatment. The inclusion of FCC data from 2014 onwards is primarily motivated by the need to address measurement issues present in earlier years. Grubesic *et al.* (2019) documents some of the limitations of FCC data. Nevertheless, FCC data are the best publicly available records of broadband providers in the US (Mack *et al.*, 2021).

Expansion of Fiber Broadband

Figure 3.2 categorizes the Health and Retirement Study (HRS) sample into different cohorts based on their exposure to fiber broadband expansion. Six distinct cohorts are identified, five corresponding to each year of introduction of fiber broadband, namely 2010, 2012, 2014, 2016, and 2018, and a sixth cohort representing individuals who never received fiber broadband during the study period. The selection of these specific years aligns with the biannual nature of the HRS data, which serves as the primary source for outcome measurements. By focusing on these time points, the analysis captures the dy-

Figure 3.2: Fiber Broadband Expansion Groups



Note: This figure shows the fiber broadband expansion in different census tracts in the US, using the HRS data merged with the broadband data. For instance, cohort 1 received fiber broadband in 2010, and cohort 0 did not receive fiber broadband (never treated). The figure is adapted from Gawai (2023).

namics of broadband adoption and its potential effects on mental health within the HRS sample.

3.3.2 Health and Retirement Study

The Health and Retirement Study (HRS) is a nationally representative panel study surveying approximately 20,000 individuals aged 51 and older. The core HRS has been conducted annually since 1992, transitioning to a biennial format from 1996 onwards. This comprehensive survey collects demographic, health, relationship, income, and occupation-related information. Importantly, HRS also captures data on internet use, electronic devices within households, and the use of electronic technologies like health apps. Furthermore, the restricted HRS files contain information concerning respondents' geographic residence locations. I use five HRS waves from 2010 to 2018 (biennial) and merge them with the broadband data using the census tract of the resident and the survey year.

Key Outcome Variables

Since HRS does not include the respondents' SSI or SSDI eligibility, I calculate the potential eligible individuals in the following way. HRS includes several separate questions on whether the respondents applied, appealed, denied, or received SSI or SSDI benefits and the year they applied or appealed in the past. For SSDI benefits, an additional condition I use is the age of the respondent is below 62 since people will be more likely to enroll in the OASI program. Similarly, for SSI benefits, the age group should be 65+. I define an individual as eligible if they responded to the above questions based on their past and current activities related to SSI and SSDI benefits. Further, conditional on the eligibility, the primary outcome variables are whether the respondent applied, appealed, or received the SSI and SSDI benefits during the current survey year. The first key reason to combine these variables is that, with the exposure to broadband, we might expect the effects on several activities of the processes and not just on the applications of the benefits. Another key reason is that I do not have the administrative data from SSA. While HRS reports SSI and SSDI applications, receipt or appeals are lower than the administrative records, and individual misreports are common, even though both the sources have similar trends by survey wave, cohort, and age (Hyde and Harrati, 2023).[6]

3.3.3 Descriptive Statistics

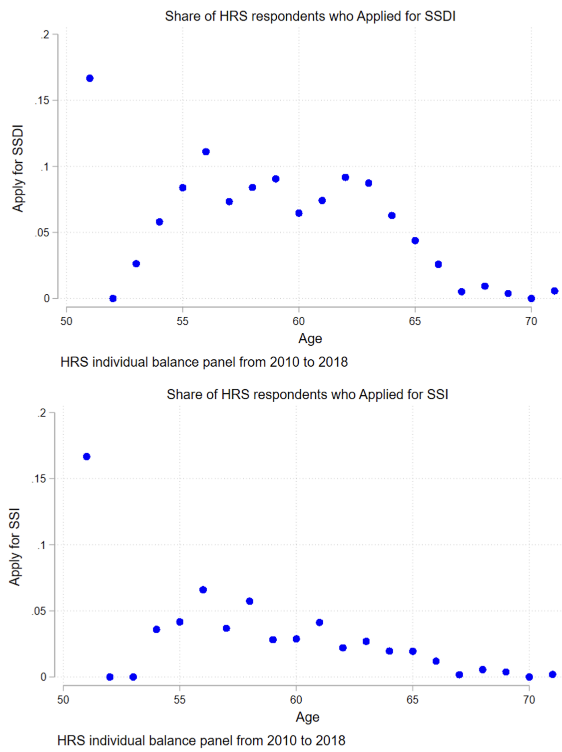
Table 1 shows the sample characteristics of the treated and never-treated groups. Most of the individual characteristics of the treated groups are similar to those of the never-treated group.[7] One may note that rural areas are less likely to receive fiber broadband than urban areas. Respondents who reported that they ever applied, appealed, or received the SSDI or SSI benefits are the same across these two groups. However, in some cases, a higher share of respondents received or appealed for SSI benefits in the treated groups compared

[6] I am in the process of obtaining the administrative data from the SSA office, which will be used for future research.

[7] Note that the identification is not merely through comparing these two groups since every treated group was treated at different periods, so the identification also accounts for the pre-and post-period of the treated groups.

to the never-treated group. Figure 3.3 shows the share of the nationally representative sample of older adults who applied for SSI and SSDI benefits from 2010 to 2018. The application for SSDI declines after around 63 years, potentially due to OASI (Old-Age and Survivors Insurance) enrollment.

Figure 3.3: Share of older people who apply for SSDI and SSI



Note: This figure shows the distribution of the HRS respondents who applied for the SSDI and SSI benefits using the HRS waves from 2010 to 2018.

3.4 Method

I first estimate a difference-in-differences (DID) regression using the following equation:

$$Y_{icgt} = \beta_0 + \beta Fiber_{gt} + \delta_i + \gamma_{gt} + \epsilon_{igct}. \quad (3.1)$$

Here, Y_{igct} is the outcome for individual i, living in census-tract c, belonging to the fiber expansion group g of census tracts, and surveyed in HRS survey year t. $Fiber_{ct}$ takes

Table 3.1: Descriptive Statistics

Variables	Treated	Never-Treated
Ever applied, appealed, received SSDI Benefits	0.91	0.91
Ever applied, appealed, received SSI Benefits	0.96	0.96
Applied, appealed, received SSDI this wave	0.08	0.08
Applied, appealed, received SSI this wave	0.04	0.03
Applied SSDI this wave	0.02	0.02
Applied SSI this wave	0.01	0.01
Received SSDI this wave	0.06	0.06
Received SSI this wave	0.03	0.02
Appealed SSDI this wave	0.54	0.54
Appealed SSI this wave	0.36	0.28
Self-Reported Good Health	0.73	0.73
Age	70	70
Male	0.42	0.42
Above High School	0.48	0.45
White	0.72	0.78
Rural	0.15	0.27
Medicare	0.52	0.54
Medicaid	0.08	0.08
Gets Pension	0.20	0.22
Working for Pay	0.33	0.31
Mortality	0.02	0.02
Income through SSI/SSDI	$686.19	$677.93
Currently Married	0.52	0.52
Maximum Download Speed (Mbps)	398.00	279.31
Maximum Upload Speed (Mbps)	291.94	48.95
N Respondents	37,564	18,421

Note: The data are the balanced panel of HRS respondents merged with broadband data using the geographical unit as census tracts and year and show the descriptive statistics of the treated groups (groups 1,3,5,7,9) and a never treated group (group 0). Self-reported good health is 1 if the reported health is either 'excellent,' 'very good,' or 'good.' and 0 if 'fair' or 'poor'.

the value 1 if the fiber was available at census tract c in survey year t, and 0 otherwise. δ_i is individual fixed effects that control for the time-invariant characteristics of individuals and allow identification to come from within-individual changes in fiber availability.[8] I also

[8] Here, I cannot include both group and individual fixed effects at the same time. One of them must be dropped because there is no between-group movement for individuals. Therefore, I restrict the sample to individuals who did not migrate from their census tracts of residence during the study period of 2010-2018.

include the group-year fixed effects γ_{gt}, to account for shocks that affect all the individuals in a given group of census tracts to which fiber was expanded in a given year. I estimate the equation using one of the recent DID estimators provided by Borusyak *et al.* (2021).

The DID model specified above estimates the static treatment effect. My preferred estimate is the dynamic version of the DID estimator, as suggested by Borusyak *et al.* (2021), to test for parallel trends and estimate the dynamic effect of the introduction of high-speed fiber broadband on SSI and SSDI benefits applications. By incorporating time-varying treatment effects, this estimator provides valuable insights into the evolving impact of broadband expansion over time and allows for a more comprehensive analysis of the causal relationship between broadband access and SSDI reception.

I use Equation 3.2 for the dynamic treatment effects as follows.

$$y_{igct} = \delta_i + \gamma_{gt} + \sum_{\tau=-3,\tau\neq-1}^{3} \beta_\tau Fiber_{\tau(gt)} + \epsilon_{igct}. \tag{3.2}$$

Recent advancements in the DID literature suggest that the conventional two-way fixed effects (TWFE) estimator provides consistent estimates under the assumption of treatment effect homogeneity (Sun and Abraham, 2021, De Chaisemartin and d'Haultfoeuille, 2022b). However, it is plausible to expect that introducing highspeed fiber broadband may result in a heterogeneous treatment effect, given the varying adoption rates among different economic agents, potentially influencing SSDI reception among older adults differently. Moreover, treatment effects may vary across individuals, exhibiting interesting heterogeneity based on various demographic characteristics. To capture this heterogeneity in treatment effects over time and across treated units, I employ the event study methodology proposed by Borusyak *et al.* (2021), which allows for the heterogeneous treatment effect of fiber broadband introduction. Finally, I include the person weights in the estimation and will replace them with the SSA weights after the data is available.

3.5 Results

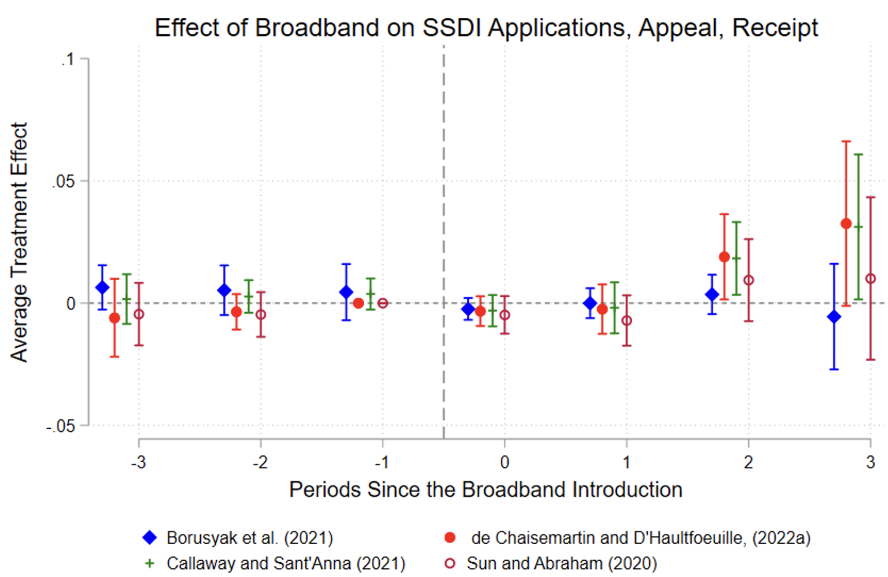
Table 3.2 shows the average treatment effect of the fiber broadband expansion using Eq. 1 and estimating with the estimator provided by Borusyak *et al.* (2021). Columns 1 to 3 show the effects of the outcome of the process of SSI benefits (applied, appealed, or receipt). Columns 4 to 6 show the effects of the outcome of the process of SSDI benefits (applied, appealed, or receipt). Columns 1 and 4 include the broadband expansion year fixed effects and the individual fixed effects. In Columns 2 and 5, I include the time-varying individual controls, and in Columns 3 and 6, I include the census tract fixed effects. Estimates from columns 1 to 3 suggest that the broadband expansion does not affect any process related to the SSI benefits. However, columns 4 to 6 suggest that the broadband expansion significantly improves the application, appeal, or receipt of the SSDI benefits among older adults. Specifically, the preferred specification in column 4 suggests that fiber broadband expansion increased the likelihood of the application, appeal, or receipt of the SSDI benefits by about 20% from the baseline. This result is also consistent with the literature (Foote *et al.*, 2019).

Table 3.2: Effect of Broadband on the Process of SSI and SSDI benefits

	Applied/Appealed/Received					
	SSI			SSDI		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Post Fiber	0.001	0.000	0.002	0.017***	0.013***	0.014**
	[0.002]	[0.002]	[0.003]	[0.004]	[0.004]	[0.005]
Observations	40,221	40,221	40,208	39,222	39,222	39,186
Expansion Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes		Yes	Yes	
Controls		Yes			Yes	
Census-Tract Fixed Effects			Yes			Yes
Mean of Outcome at baseline	0.035	0.035	0.035	0.078	0.078	0.078

Note: This table shows the average treatment effects of the staggered introduction of the fiber broadband on an indicator of whether the respondents applied, appealed, or received the SSI and SSDI benefits among older adults conditional on their eligibility using Eq. 1 and estimating with the estimator provided by Borusyak *et al.* (2021). The sample is a balanced panel of Health and Retirement Study (HRS) respondents for biennial waves from 2010 to 2018. The treatment variable is equal to one if fiber is available to census tract residents in survey year t and zero otherwise. The individual controls include whether the individual receives a pension, is currently married, and works for the pay. I also include the HRS person weights in the estimation. Standard errors in square brackets are clustered at the census tract level. *** p<0.01, ** p<0.05, * p<0.10.

Figure 3.4: Dynamic Effect of Broadband on the Application, Appealed, and Receipt of SSDI



Note: This figure shows the dynamic effects plots conditional on their eligibility using Equation 2, estimating with the estimator provided by De Chaisemartin and d'Haultfoeuille (2022a), Borusyak *et al.* (2021), Sun and Abraham (2021) and Callaway and Sant'Anna (2021). The sample is a balanced panel of Health and Retirement Study (HRS) respondents for biennial waves from 2010 to 2018. The treatment variable is equal to one if fiber is available to census tract residents in survey year t and is zero otherwise. The individual controls include whether the individual receives a pension, is currently married, and works for the pay. I also include the HRS person weights in the estimation. Standard errors in square brackets are clustered at the census tract level. The bars show the 95-percent confidence interval.

There could be several reasons that the effects are significant for the SSDI process but not for the SSI process. The eligibility criteria for SSDI and SSI differ significantly. SSDI primarily considers an individual's work history and earnings record, while SSI focuses on financial need and disability status, and the average SSDI applicant is in their 50s. On the other hand, there is a lack of effect on SSI since the majority of the applicants are in the 65+ age group, are blind, or disabled with stringent financial eligibility and lower access to broadband. It's possible that the expansion of broadband access disproportionately affected individuals who were more likely to qualify for SSDI based on work history, earnings, and higher-tech savviness, leading to an increase in SSDI applications and appeals.

Finally, Figure 3.4 shows the dynamic treatment effect using Equation 3.2 and estimated using various DID estimators proposed by De Chaisemartin and d'Haultfoeuille (2022a), Borusyak *et al.* (2021), Sun and Abraham (2021) and Callaway and Sant'Anna (2021). Figure 3.4 suggests that the likelihood of applying, appealing, or receiving SSDI benefits increases after introducing high-speed fiber broadband. The dynamic effect becomes statistically significant over time, suggesting that potential strategic complementarities, characterized by waiting for others to adopt, may play a role. Figure 3.4 also suggests that the estimates before introducing the fiber broadband (period -2 and -3) are closer to zero and insignificant. I consider this evidence to have no pre-trends and to be consistent with the parallel trend assumption.

3.6 Heterogeneity

In this section, I explore the effect of broadband differences based on gender, race, region, or education level. Firstly, understanding heterogeneity in the effect of broadband expansion based on gender can shed light on potential disparities in access to and utilization of technology among older individuals. Gender-specific differences in internet usage patterns and familiarity with online platforms may affect how individuals interact with SSDI application processes, affecting application, appeal, and receipt outcomes. Notably, women are more likely to use the internet for purposes such as emails and accessing information (Pew Research). Secondly, examining the effect of broadband expansion across racial groups is essential for identifying and addressing disparities in access to disability benefits. Historically marginalized communities face unique barriers, such as digital literacy gaps or structural inequalities in internet infrastructure, which could influence the effectiveness of broadband in facilitating SSDI applications and appeals. Thirdly, regional variations in broadband availability and quality can significantly impact older adults' access to online resources and support services related to SSDI. For instance, Table 3.1 suggests that the broadband expansion was slower in rural areas. Studying regional heterogeneity allows policymakers to target interventions and resources more effectively, ensuring equitable access to SSDI benefits across different geographic areas. Finally, educational attainment is crucial in shaping individuals' digital literacy skills and ability to navigate online platforms. Examining the effect of broadband expansion across education levels can provide insights into how educational disparities intersect with technological advancements, affecting older adults' engagement with SSDI application processes.

Table 3.3: Heterogenous Treatment Effect on SSDI Processes

	Outcome Variable: Applied, Appealed, Received SSDI benefits in this wave							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	Men	Women	White	non-White	Rural	Urban	High School and Above	Below High School
Post Fiber	0.015**	0.018***	0.017***	0.017	0.010	0.017***	0.014***	0.018**
	[0.006]	[0.005]	[0.004]	[0.012]	[0.011]	[0.004]	[0.004]	[0.007]
Observations	16,475	22,747	29,245	9,853	7,743	31,466	18,479	20,743
Expansion Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the average treatment effects of the staggered introduction of the fiber broadband on the SSDI benefit application, appeal, or receipt among older adults conditional on their eligibility using Eq. 1 and estimating with the estimator provided by Borusyak *et al.* (2021). The sample is a balanced panel of Health and Retirement Study (HRS) respondents for biennial waves from 2010 to 2018. The treatment variable is equal to one if fiber is available to census tract residents in survey year t and zero otherwise. I also include the HRS person weights in the estimation. Standard errors in square brackets are clustered at the census tract level. *** p<0.01, ** p<0.05, * p<0.10.

Estimates in Table 3.3 suggest that the broadband expansion increased the likelihood of application, appeal, or receipt of the SSDI benefits in almost all the subgroups, except for the non-Whites and rural dwellers. These estimates highlight the racial and regional disparities in the benefits of broadband expansion. The estimates on different subgroups are consistent between 0.14 to 0.18, which echos the main estimates in Table 3.2.

3.7 Robustness

I provide robustness of the main results of the SSDI processes. First, in Table 3.2, I provide the results with different specifications, including the individual fixed effects, controls, and census tract fixed effects. The magnitude and the significance are consistent across different specifications. Secondly, in Figure 3.4, I provide the results with different DID estimators relevant to the binary and staggered treatment. These estimates also suggest that the effect of broadband on the SSDI process is consistent across different DID estimators. Further, I include the migrants and show estimates in Table 3.4, which suggests similar estimates and significance as in Table 3.2.

Table 3.4: Effect of Broadband on the Process of SSI and SSDI benefits- Including Migrants

	SSDI
Variables	(1)
Post Fiber	0.013***
	[0.004]
Observations	44,824
Expansion Year Fixed Effects	Yes
Individual Fixed Effects	Yes

Note: This table shows the average treatment effects of the staggered introduction of the fiber broadband on the SSDI process among older adults (migrants and non-migrants) conditional on their eligibility using Eq. 1 and estimating with the estimator provided by Borusyak *et al.* (2021). The sample is a balanced panel of Health and Retirement Study (HRS) respondents for biennial waves from 2010 to 2018. The treatment variable is equal to one if fiber is available to census tract residents in survey year t and zero otherwise. I also include the HRS person weights in the estimation. Standard errors in square brackets are clustered at the census tract level. **** p<0.01, ** p<0.05, * p<0.10.

Further, mortality selection bias may exist if there is a differential likelihood of individuals with certain characteristics (in this case, possibly related to health status) being included in or dropping out of the sample due to death. For instance, individuals with poorer health who are more likely to apply, appeal, or receive SSDI benefits are also more likely to die before the broadband expansion can affect their application behavior. This could lead to an underestimation of the true effect of broadband expansion on application and benefit receipt, as the most vulnerable individuals are not included in the analysis due to mortality. Table 3.5 shows that the broadband expansion significantly declines individual-level mortality.

Table 3.5: Effect of Broadband on Mortality

Variables	SSDI (1)
Post Fiber	-0.011***
	[0.001]
Observations	39,183
Expansion Year Fixed Effects	Yes
Individual Fixed Effects	Yes
Mean of Outcome Var	0.02

Note: This table shows the average treatment effects of the staggered introduction of the fiber broadband on mortality among older adults conditional on their eligibility for SSDI using Eq. 1 and estimating with the estimator provided by Borusyak *et al.* (2021). The sample is a balanced panel of Health and Retirement Study (HRS) respondents for biennial waves from 2010 to 2018. The treatment variable is equal to one if fiber is available to census tract residents in survey year t and zero otherwise. I also include the HRS person weights in the estimation. Standard errors in square brackets are clustered at the census tract level. **** p<0.01, ** p<0.05, * p<0.10.

3.8 Conclusion

This study contributes to the existing literature by examining the causal relationship between the rollout of high-speed broadband technology and the likelihood of application, appeal, or receipt of benefits through SSI and SSDI among older adults. The findings demonstrate that expanding broadband significantly increases the chances of applying, appealing, or receiving SSDI benefits. Specifically, the fiber broadband expansion improved the SSDI likelihood of the SSDI process by over 21%. These effects are robust to alternative specifications and DID estimators for binary and staggered treatment, including migrants and mortality selection. The positive effects are consistent across different subgroups, including for men and women and applicants with more than a high school education or lower than a high school education. However, the effects are primarily driven by the Whites and dwellers from the urban areas, highlighting the significant racial and regional disparities.

An important caveat of this study is the absence of data delineating whether survey respondents have fiber broadband access at their residences. Given the possibility of internet utilization in diverse settings such as homes, workplaces, coffee shops, or public libraries, the estimates herein primarily capture intent-to-treat effects. Nonetheless, these findings hold significance for policymakers aiming to grasp the plausible access to the social security benefits from broadband expansion among older populations.

3.9 Policy Implications

The estimates in this paper bear considerable importance for several reasons. First, a young entrant into the workforce has a one-in-three probability of mortality or meeting the eligibility criteria for SSDI before attaining Social Security's full retirement age (CBPP). Secondly, the global population is aging, with an increase in challenges of awareness or dealing with the process of applications or receipt of social security benefits among older adults. At the same time, there has been a significant increase in the availability and adoption of the Internet adoption, with roughly 63% of the global population engaging with the Internet in 2021, a stark contrast to the mere 7% in 2000. More importantly, Internet access and use are also increasing among the older population. This paper finds that whether these technologies mitigate access issues has mixed evidence, with significant benefits for the SSDI-related process and no effect for the SSI-related processes with stark racial and regional disparities. These findings contribute important insights to the literature, informing policymakers and stakeholders about the implications of broadband expansion for the well-being of older adults. In future research, it will be crucial to understand what type of SSI/SSDI applications get affected. For instance, broadband services might not significantly impact the applications for issuing a new card since these applications may require in-person contact. On the other hand, the applications for benefits can be made entirely online and may have a significant impact. Similarly, I will extend this research by adding the distance to the SSA office to understand whether the broadband helped the SSDI process through the distance channel.

Appendix A

Appendix Title

Table A.1: HRS question for the CESD Score

CES-D depression indicators	"Much of the time during the past week, you..." (Y/N)
Negative (1: Yes, 0: No)	1. Felt depressed 2. Felt lonely 3. Felt sad 4. Could not get going 5. Felt that everything was an effort 6. Your sleep was restless
Positive (1: No, 0: Yes)	7. Felt happy 8. Enjoyed Life

A.1 Data

A.2 Results

Table A.2: Summary Statistics on Various Characteristics

Variables	Group 1	Group 3	Group 5	Group 7	Group 9	Group 0
Fiber Expansion Year	2010	2012	2014	2016	2018	No Fiber
Self Repo. Good Health	0.74	0.77	0.75	0.71	0.70	0.73
Normal BMI (18.5-24.9)	0.20	0.22	0.20	0.19	0.20	0.19
Age	70	70	70	69	70	70
Male	0.42	0.42	0.43	0.43	0.41	0.42
Above High School	0.50	0.57	0.48	0.48	0.45	0.45
White	0.70	0.71	0.76	0.71	0.74	0.78
Rural	0.14	0.05	0.37	0.13	0.10	0.27
Medicare	0.51	0.54	0.54	0.51	0.53	0.54
Medicaid	0.09	0.06	0.07	0.08	0.09	0.08
Gets SSDI	0.06	0.04	0.05	0.07	0.06	0.06
Gets Pension	0.21	0.23	0.22	0.19	0.20	0.22
Working for Pay	0.34	0.33	0.34	0.32	0.32	0.31
Currently Married	0.50	0.58	0.54	0.55	0.50	0.52
N Respondents-Group year	11728	1713	4353	10438	9332	18421
Number of Census Tracts	1085	174	696	258	922	2070

Note: The data are the balanced panel of HRS respondents merged with FCC for the periods 2010 to 2018 for every even year, using the geographical unit as census tracts.

Table A.3: Average Treatment Effect of Fiber Broadband on the Symptoms of Depression (Using Borusyak et al. (2021) Estimator)

	Borusyak et al. (2021)			
	(1)	(2)	(3)	(4)
Post Fiber	-0.096^{***}	-0.083^{**}	-0.113^{***}	-0.188^{***}
	[0.035]	[0.035]	[0.043]	[0.050]
Observations	36,206	36,206	36,230	36,772
Expansion Year Fixed Effects	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes		
Controls		Yes		
Census-Tract Fixed Effects			Yes	
Fiber Expansion group FE				Yes

Note: This table shows the average treatment effects of the staggered introduction of the fiber broadband on the depression symptoms among older adults using Equation 1.1 estimating with the estimator provided by Borusyak *et al.* (2021). The sample is a balanced panel of Health and Retirement Study (HRS) respondents for biennial waves from 2010 to 2018. The age group is from 51 to 103. The treatment variable is equal to 1 if the fiber is available in a census tract of residents in survey year t and 0 otherwise. The outcome variable 'depression' is a CES-D mental health categorical score from 0 to 8, 0 being no depression and 8 being the highest depression. The individual controls include whether the individual receives Medicaid, is currently married, and works for the pay. I also include the HRS person weights in the estimation. Standard errors in square brackets are clustered at the census tract level. *** p<0.01, ** p<0.05, * p<0.10.

Table A.4: Average Treatment Effect of Fiber Broadband on the Clinical Symptoms of Depression

	Dummy=1 if CES-D>3, 0 otherwise		
	(1)	(2)	(3)
Post Fiber	-0.014^{**}	-0.012^{*}	-0.015^{*}
	[0.007]	[0.007]	[0.008]
Observations	47,935	47,163	49,728
Year Fixed Effects	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	
Controls		Yes	
Census-Tract Fixed Effects			Yes
Baseline Mean of Outcome	0.14	0.14	0.14

Note: This table shows the average intent-to-treat effects of the staggered introduction of fiber broadband on depression symptoms among older adults, using Equation 1.1 and the estimator provided by De Chaisemartin and d'Haultfoeuille (2022a). The outcome variable 'depression' is the CES-D mental health categorical score from 0 to 8. The sample is a balanced panel of Health and Retirement Study (HRS) respondents for biennial waves from 2010 to 2018. The age group is 51 to 103. The treatment variable is equal to 1 if fiber is available in a census tract of residents in survey year t and 0 otherwise. The individual controls include age and whether the individual receives Medicaid, is currently married, and works for pay. I also include the HRS person weights in the estimation. Standard errors in square brackets are clustered at the census tract level. *** p<0.01, ** p<0.05, * p<0.10.

Table A.5: Average Treatment Effect of Fiber Broadband on Use of Medications for Anxiety or depression

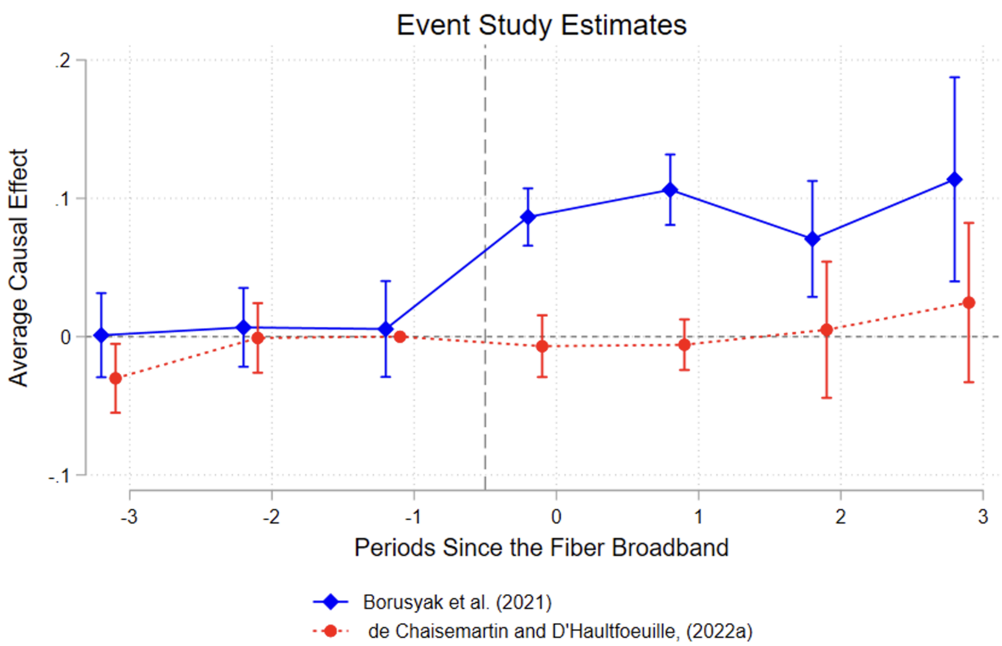
	Using DCDH Estimator	Using Borusyak Estimator
Post Fiber	0.003	0.001
	[0.006]	[0.006]
Observations	38,479	30,270
Year Fixed Effects	Yes	Yes
Individual Fixed Effects	Yes	Yes
Mean of Outcome Variable	0.208	0.208

Note: This table shows the average treatment effects of the staggered introduction of the fiber broadband on whether the respondents take drugs for anxiety or depression using Equation 1.1 and estimating with the estimator provided by De Chaisemartin and d'Haultfoeuille (2022a) in Column 1 and by Borusyak *et al.* (2021) in Column 2. Note that the estimator in column 1 includes the never-treated units in the estimation, while the estimator in column 2 does not, and that's why there is a difference in the sample sizes. The sample is a balanced panel of HRS respondents for biennial waves from 2010 to 2018, aged 51+. The treatment variable is equal to 1 if the fiber is available in a census tract of residents in survey year t and 0 otherwise. Standard errors in square brackets are clustered at the census tract level. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A.6: Questions in AHA data related to telehealth

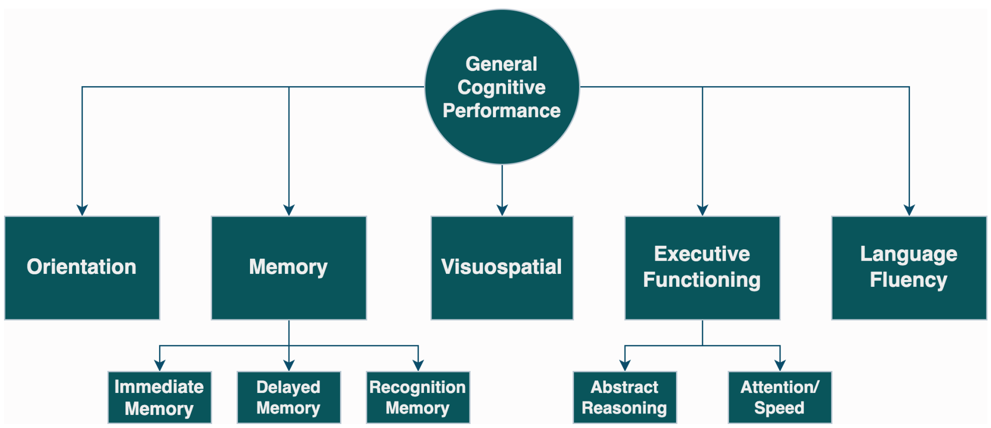
Telehealth consultation and office visits hospital
Telehealth consultation and office visits health system
Telehealth consultation and office visits joint venture
Telehealth eICU - hospital
Telehealth eICU - health system
Telehealth eICU - joint venture
Telehealth stroke care - hospital
Telehealth stroke care - health system
Telehealth stroke care - joint venture
Telehealth psychiatric and addiction treatment - hospital
Telehealth psychiatric and addiction treatment - health system
Telehealth psychiatric and addiction treatment - joint venture
Telehealth remote patient monitoring: post-discharge - hospital
Telehealth remote patient monitoring: post-discharge - health system
Telehealth remote patient monitoring: post-discharge - joint venture
Telehealth remote patient monitoring: ongoing chronic care management - hospital
Telehealth remote patient monitoring: ongoing chronic care management - health system
Telehealth remote patient monitoring: ongoing chronic care management - joint venture
Telehealth other remote patient monitoring - hospital
Telehealth other remote patient monitoring - health system
Telehealth other remote patient monitoring - joint venture
Other telehealth - hospital
Other telehealth - health system
Other telehealth - joint venture

Figure A.1: Dynamic Treatment Effects- Outcome: Self Use of Internet



Note: This figure shows the dynamic effects plots using Equation 1.2 estimating with the estimator provided by De Chaisemartin and d'Haultfoeuille (2022a) and Borusyak *et al.* (2021). Note here that Borusyak *et al.* (2021) does not use the 'never-treated' group while De Chaisemartin and d'Haultfoeuille (2022a) does. The outcome variable is an indicator equal to 1 if the respondent uses the regular web or sends emails to children, friends, or family and 0 otherwise. The sample is a balanced panel of Health and Retirement Study (HRS) respondents for biennial waves from 2010 to 2018. The age group is from 51 to 103. The time variable is the survey wave, and the fiber group variable is the group of census tracts in which fiber was introduced in different years. I include group and treatment year fixed effects. Standard errors are clustered at the census tract level. The bars show the 95 percent confidence interval.

Figure A.2: Components of the cognition score



Note: This framework shows the broad components of the cognition score, as documented in Gross *et al.* (2020). 'Orientation' includes assessing orientation to time (e.g., name the current month and year) and place (e.g., city or state). 'Memory' tests include tests such as recalling a 3-word and 10-word list and names and places from a short story. 'Visuospatial' tests include recall of the drawings like interlocking pentagons and constructional praxis. 'Executive function' tests include tests like Raven progressive matrices task, drawing of a clock, go/no-go tests, numeracy tasks, and backward day counting. Finally, 'language fluency' includes tests like animal naming, writing or saying a sentence, naming common objects by sight, and pointing to a window and a door.

Table A.7: Effect of early life exposure to the HYV on the cognition score

	Outcome Variable: General Cognition Score			
	(1)	(2)	(3)	(4)
Variables				
Pre-Conception	0.296*	0.221	0.224	-0.044
	[0.161]	[0.161]	[0.178]	[0.235]
In-utero to Age 2	-0.007	0.026	0.024	0.375
	[0.205]	[0.167]	[0.170]	[0.234]
Avg. Treatment Age 3 to 5	0.388	0.224	0.199	0.254
	[0.248]	[0.206]	[0.223]	[0.277]
Avg. Treatment Age 6 to 8	-0.266	-0.455**	-0.433**	-0.644**
	[0.212]	[0.191]	[0.199]	[0.252]
Avg. Treatment Age 9 to 11	0.019	-0.051	-0.060	0.159
	[0.309]	[0.271]	[0.286]	[0.307]
Avg. Treatment Age 12 to 14	-0.410	-0.438*	-0.314	-0.072
	[0.314]	[0.262]	[0.287]	[0.259]
Avg. Treatment Age 15 to 17	0.028	0.097	0.085	0.098
	[0.209]	[0.173]	[0.191]	[0.199]
Observations	15,695	15,695	15,695	15,705
R-squared	0.142	0.333	0.334	0.343
Birth year FE	Y	Y	Y	Y
Birth District FE	Y	Y	Y	Y
Weights	Y	Y	Y	Y
Mean of Y	0.518	0.518	0.518	0.519
Controls		Y	Y	Y
State-Birth year Trend			Y	
State-Birth year FE				Y

Note: This table shows the effect of early life exposure to the Green Revolution on later life cognitive function. The data are from Village Dynamics of South Asia (VDSA), which merged with the first wave (2018) of the Longitudinal Aging Study in India (LASI). The outcome variable is the general cognitive score. We include person weights. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.

Table A.8: Effect of early life exposure to the HYV on the cognitive impairment

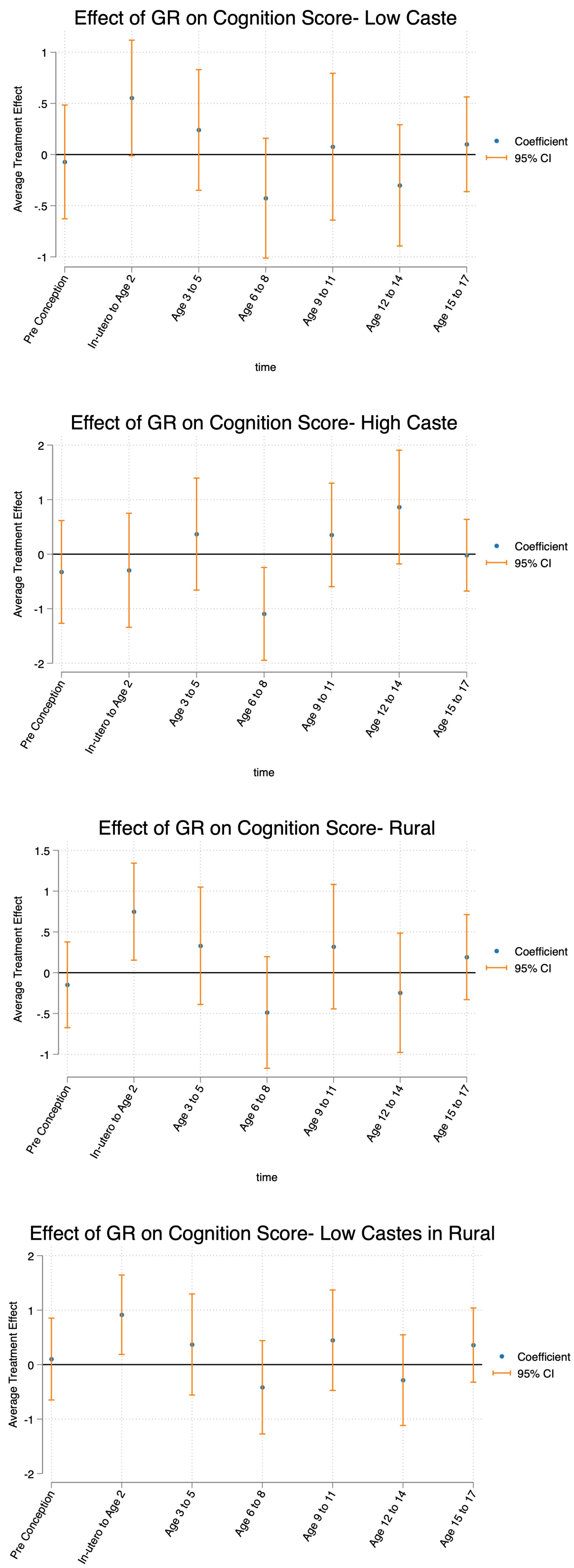
	Outcome Variable: Cognitive impairment			
	(1)	(2)	(3)	(4)
Variables				
Pre-Conception	0.017	0.016	0.049	0.015
	[0.064]	[0.066]	[0.077]	[0.101]
In-utero to Age 2	-0.004	0.002	-0.077	-0.114
	[0.048]	[0.051]	[0.058]	[0.075]
Observations	15,695	15,695	15,695	15,705
R-squared	0.054	0.067	0.068	0.079
Birth year FE	Y	Y	Y	Y
Birth District FE	Y	Y	Y	Y
Weights	Y	Y	Y	Y
Mean of Y	0.063	0.063	0.063	0.063
Controls		Y	Y	Y
State-Birth year Trend			Y	
State-Birth year FE				Y

Note: This table shows the effect of early life exposure to the Green Revolution on later life cognitive impairment, a dummy variable equal to 1 if the person has mild cognitive impairment (MCI). The data are Village Dynamics of South Asia (VDSA) merged with the first wave (2018) of the Longitudinal Aging Study in India (LASI). We include person weights. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.

A.3 Heterogeneity

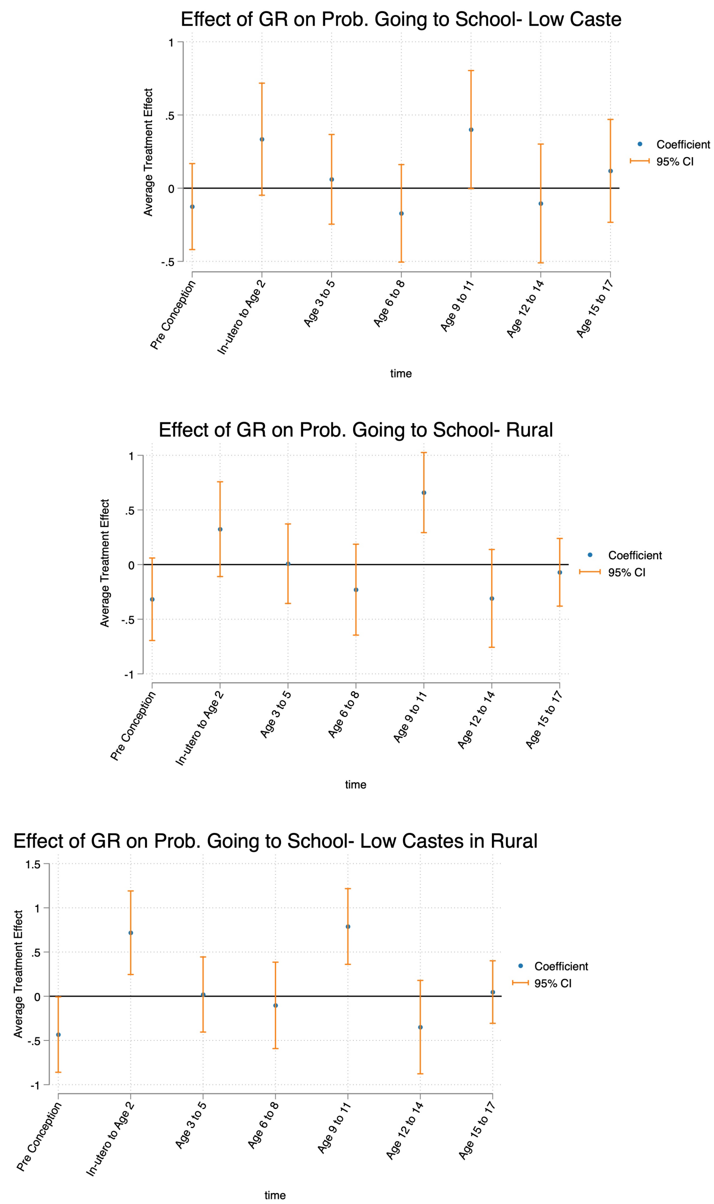
A.3.1 Effect on Cognition with Full Age Profile

Figure A.3: Effect on Cognition with Full Age Profile



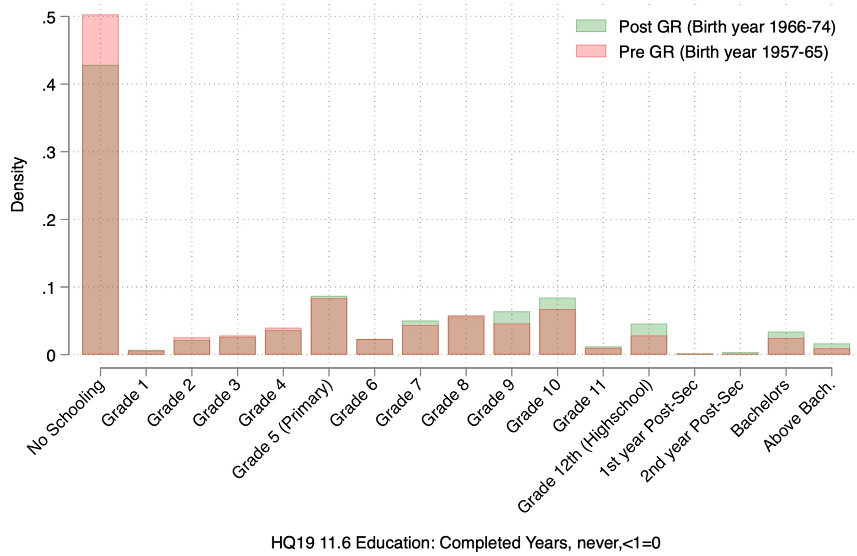
A.3.2 Effect on Education

Figure A.4: Effect on Education with Full Age Profile



Note: This figure shows the effect of the Green Revolution at different age groups on schooling for different groups. The coefficients and the 95% confidence intervals are shown.

Figure A.5: Distribution of Education Level for Low-Castes from the IHDS data



Note: This figure shows the distribution of the education level for the Low Castes (SC, ST, OBC) for the main sample in our data (born between 1957 and 1974) using another nationally representative data from India, India Human Development Survey (IHDS) using a wave of 2011-12. N=29,191.

A.3.3 Effects on Early-Life Economic Condition

Table A.9: Effect of Early Life Exposure to the HYV on Financial Condition while Growing Up

	Outcome Variable: Financial Condition was Poor					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Men	Women	Low Castes	Urban	Rural	Rural Low Caste
Pre-conception	0.097	0.224	0.173	0.110	0.138	-0.126
	[0.217]	[0.186]	[0.186]	[0.217]	[0.205]	[0.280]
In-utero to Age 2	-0.307	-0.046	-0.388**	-0.117	-0.088	-0.074
	[0.264]	[0.174]	[0.177]	[0.240]	[0.227]	[0.297]
Observations	6,510	9,055	11,248	7,591	7,964	5,772
R-squared	0.216	0.205	0.194	0.231	0.198	0.214
Birth year FE	Y	Y	Y	Y	Y	Y
Birth District FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
State-Birth year FE	Y	Y	Y	Y	Y	Y
Weights	Y	Y	Y	Y	Y	Y
Mean of Y	0.451	0.403	0.455	0.424	0.440	0.458

Note: This table shows the effect of early life exposure to the Green Revolution on whether the respondent had poor financial condition while growing up. The outcome variable is 1 if the financial condition was poor and 0 if the financial condition was either average or pretty well off. The data are from Village Dynamics of South Asia (VDSA), which merged with the first wave (2018) of the Longitudinal Aging Study in India (LASI). The outcome variable takes value 1 if the respondent reported of having any chronic condition and 0 otherwise. We include person weights. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.

A.3.4 Results on Any Chronic Condition, Diabetes, and BMI

Panel (B) of Table 2.2 of our main results shows the effect of early life exposure to the high-yield varieties (HYV) on the total number of chronic conditions, where we do not find a significant effect. We show results in Table A.10 to better understand the heterogeneous treatment effects. We use the outcome as whether an individual ever had at least one condition out of blood pressure, diabetes, cancer, lung disease, psych problems, arthritis, stroke, or heart problems. Columns 1 and 5 show that early life exposure to the Green Revolution increases the probability of any chronic condition for men and people living in urban areas. Similarly, in Table A.11 Column1, it shows that early life exposure to the Green Revolution increases the probability of ever having diabetes for men. These conclusions are consistent with the recent literature (Sekhri and Shastry, Forthcoming). We also provide evidence of the effect of the Green Revolution on BMI. One potential way to increase the likelihood of chronic conditions might be through dietary changes in early life through a high-fat, high-calorie, and lower-protein diet, which may also translate to higher BMI or obesity later in life.[1] We show these results in Table A.12, which shows that the effects on BMI are not statistically significant. We are working on including the measures of overweight and obesity, which could be better measurements than BMI, to understand the potential channels for the adverse effects on chronic conditions.

A.4 Robustness

[1]Various studies have documented such relation (Portella *et al.*, 2012, Sekhri and Shastry, Forthcoming).

Table A.10: Effect of Early Life Exposure to the HYV on Chronic Conditions

	Outcome Variable: Any Chronic Conditions					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Men	Women	Low Castes	Urban	Rural	Rural Low Caste
Pre-conception	0.052	0.464**	0.118	0.292	0.291	0.242
	[0.243]	[0.214]	[0.232]	[0.267]	[0.224]	[0.261]
In-utero to Age 2	0.526**	-0.103	0.124	0.442*	-0.024	-0.058
	[0.255]	[0.185]	[0.189]	[0.265]	[0.225]	[0.272]
Observations	6,582	9,144	11,363	7,676	8,040	5,827
R-squared	0.126	0.108	0.101	0.127	0.123	0.147s
Birth year FE	Y	Y	Y	Y	Y	Y
Birth District FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
State-Birth year FE	Y	Y	Y	Y	Y	Y
Weights	Y	Y	Y	Y	Y	Y
Mean of Y	0.269	0.354	0.286	0.283	0.334	0.314

Note: This table shows the effect of early life exposure to the Green Revolution on whether the respondent has any chronic condition. The data are from Village Dynamics of South Asia (VDSA), which merged with the first wave (2018) of the Longitudinal Aging Study in India (LASI). The outcome variable takes the value 1 if the respondent reported having any chronic condition and 0 otherwise. We include person weights. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.

Table A.11: Effect of early life exposure to the HYV on Diabetes

	Outcome Variable: Ever had Diabetes					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Men	Women	Low Castes	Urban	Rural	Rural Low Caste
Pre-conception	0.033	0.075	0.127	0.132	-0.013	0.026
	[0.111]	[0.122]	[0.090]	[0.134]	[0.121]	[0.115]
In-utero to Age 2	0.298*	-0.206	0.106	0.183	-0.063	0.051
	[0.168]	[0.131]	[0.113]	[0.157]	[0.121]	[0.111]
Observations	6,556	9,114	11,333	7,643	8,017	5,812
R-squared	0.113	0.094	0.089	0.098	0.107	0.129
Birth year FE	Y	Y	Y	Y	Y	Y
Birth District FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
State-Birth year FE	Y	Y	Y	Y	Y	Y
Weights	Y	Y	Y	Y	Y	Y
Mean of Y	0.081	0.076	0.072	0.083	0.074	0.065

Note: This table shows the effect of early life exposure to the Green Revolution on whether the respondent ever had diabetes. The data are from Village Dynamics of South Asia (VDSA), which merged with the first wave (2018) of the Longitudinal Aging Study in India (LASI). The outcome variable takes the value of 1 if the respondent reported ever having diabetes and 0 otherwise. We include person weights. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.

Table A.12: Effect of early life exposure to the HYV on Body Mass Index (BMI)

	Outcome Variable: BMI					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Men	Women	Low Castes	Urban	Rural	Rural Low Caste
Pre-conception	3.304	-0.765	1.319	4.901***	-0.913	-3.343
	[2.118]	[2.642]	[1.923]	[1.853]	[2.491]	[3.544]
In-utero to Age 2	-0.118	0.701	0.733	-0.636	1.162	2.228
	[2.570]	[2.094]	[1.657]	[2.230]	[2.271]	[2.385]
Observations	5,883	8,328	10,382	6,865	7,334	5,362
R-squared	0.217	0.218	0.195	0.250	0.196	0.213
Birth year FE	Y	Y	Y	Y	Y	Y
Birth District FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
State-Birth year FE	Y	Y	Y	Y	Y	Y
Weights	Y	Y	Y	Y	Y	Y
Mean of Y	22.63	23.72	22.68	22.99	23.20	22.84

Note: This table shows the effect of early life exposure to the Green Revolution on BMI. The data are from Village Dynamics of South Asia (VDSA), which merged with the first wave (2018) of the Longitudinal Aging Study in India (LASI). We include person weights. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.

Table A.13: Effect of early life exposure to the HYV on Cognition and Chronic Conditions (dropping bottom 5 percentile sample)

	(1)	(2)
VARIABLES	Cognition Score	Total Chronic Conditions
Pre-conception	0.15842	0.32587
	[0.25740]	[0.28862]
In-utero to Age 2	0.27438	0.12921
	[0.23345]	[0.30354]
Observations	13,579	13,580
R-squared	0.35060	0.10104
Birth year FE	Y	Y
Birth District FE	Y	Y
Controls	Y	Y
State-Birth year FE	Y	Y
Weights	Y	Y
Mean of Y	0.523	0.401

Note: This table shows the effect of early life exposure to the Green Revolution on cognition score and the number of chronic conditions. The data are from Village Dynamics of South Asia (VDSA), which merged with the first wave (2018) of the Longitudinal Aging Study in India (LASI). In this table, we restrict the analysis to the respondents in the top 95 percentile distribution of the height distribution. We include person weights. Standard errors are clustered at the birth district level. *** p<0.01, ** p<0.05, * p<0.10.

A.5 Heterogeneity

Table A.14: Heterogenous Treatment Effect on SSI Applications

	Outcome Variable: Applied for SSI since last wave							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	Men	Women	White	non-White	Rural	Urban	High School and Above	Below High School
Post Fiber	0.003	-0.000	0.002	-0.002	-0.006	0.002	0.000	0.002
	[0.003]	[0.003]	[0.002]	[0.008]	[0.008]	[0.002]	[0.002]	[0.004]
Observations	16,874	23,347	30,267	9,834	8,120	32,088	18,699	21,522
Expansion Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the average treatment effects of the staggered introduction of the fiber broadband on the SSI applications among older adults conditional on their eligibility using Eq. 1 and estimating with the estimator provided by Borusyak *et al.* (2021). The sample is a balanced panel of Health and Retirement Study (HRS) respondents for biennial waves from 2010 to 2018. The treatment variable is equal to one if fiber is available to census tract residents in survey year t and zero otherwise. The individual controls include whether the individual receives pension, is currently married, and works for the pay. I also include the HRS person weights in the estimation. Standard errors in square brackets are clustered at the census tract level. *** p<0.01, ** p<0.05, * p<0.10.

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