Essays on the Effects of Upstream Intergenerational Support: from Adult Children to Parents

by

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Abstract

This thesis presents three novel chapters that aim to provide causal evidence on the impact of intergenerational ties through care, education, and support from adult children on parental wellbeing and how work-related policies affect the provision of informal caregiving. The main innovations of the chapters address a common empirical challenge: drawing robust causal inferences by controlling for endogeneity concerns within observational data.

Chapter Two examines the causal effect of flexible working arrangements in the workplace on parental informal care provision in the UK, using the UK Household Longitudinal Study (2010-2022) with both fixed effect and two-stage least squares estimation methods. The findings reveal a significant positive effect of flexible working arrangements on informal care provision. Access to such arrangements significantly increases the probability of children providing care to their parents. This effect varies according to the intensity of care provided and is heterogeneous according to family composition.

Chapter Three investigates the causal impact of children's college attainment on parental mental health in the US, using the US Health and Retirement Study (1998-2018). Employing nonparametric partial identification analysis that relies on weak and credible assumptions to produce bounds on the population average treatment effect, the findings show a noteworthy positive causal effect of children's college attainment on parental mental health status. The findings indicate that having a college graduate child improves parental mental health score, measured by the Center for Epidemiologic Studies Depression Scale.

Chapter Four examines the causal effect of receiving intergenerational support in the form of both financial and instrumental support from adult children on their parents' wellbeing, measured by self-reported health and activities of daily living. Using the Indonesia Family Life Survey and instrumental variable strategy, the findings reveal a significant positive impact of receiving support on parental wellbeing. This effect is driven primarily by financial transfers. The effect varies by parents' gender, age group, and region of residence. The mechanism analysis across the three chapters indicates that intergenerational support in its various forms and institutional and cultural settings is mostly mediated through time freedom and availability, financial relief through transfers and the exchange of knowledge-based and emotional support.

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Abbreviations

ADL	Activity of Daily Living
ATE	Average Treatment Effect
ATT	Average Treatment Effect on the Treated
CES-D	Center for Epidemiologic Studies Depression Scale
ETS	Exogenous Treatment Selection
FWAs	Flexible Working Arrangements
FWER	Familywise Error Rate
HRS	Health and Retirement Study
IADL	Instrumental Activity of Daily Living
IFLS	Indonesia Family Life Survey
LATE	Local Average Treatment Effect
MIV	Monotone Instrumental Variable
MTR	Monotone Treatment Response
MTS	Monotone Treatment Selection
PI	Partial Identification
SRH	Self-Reported Health
UKHLS	United Kingdom Household Longitudinal Study

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Author's Declaration

"I declare that, except where explicit reference is made to the contribution of others, that this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution."

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CHAPTER 1

Introduction

This thesis consists of three independent yet related chapters which explore how intergenerational ties, through care, education, and support, affect the wellbeing of the older generation and working-age adults. Specifically, two chapters address how different types of upward support from children to parents influence parental health across diverse institutional, economic and cultural contexts. One chapter addresses how work-related policies influence the provision of support to parents. While each chapter stands as an independent study, they are interrelated by establishing causal inferences using various rigorous methods. This thesis aims to provide causal evidence on the impact of intergenerational support on parental wellbeing and how work-related policies affect parental informal caregiving, enabling researchers to draw robust inferences that are significant to the fields of health and family economics.

Intergenerational support is generally defined as the transfers of resources such as financial, instrumental (i.e., caring), emotional and knowledge-based support between two or more members from different generations (Bengtson & Roberts, 1991). The dynamics of intergenerational support are based on various theoretical frameworks. Exchange theory identifies familial support as a reciprocal system of mutual advantage (Edwards, 1969). This theory implies that support given throughout the life course is anticipated to be returned. For example, adult children may provide support for their parents in expectation of a future inheritance or grandchild care provision. This is consistent with economic rational choice models, where people intentionally invest in relationships to maximize long-term gains. In contrast, altruism models suggest that support is motivated by family members who act in one another's best interests without anticipation of reciprocity. These altruistic behaviours aim to optimize household utility (Becker, 1974). This theory is particularly true in low- and middle-income nations, where adult children often give money to their ageing parents out of cultural duty rather than due to expectation of future benefits. Social roles, cultural responsibilities, and emotional connections are emphasized by alternative theoretical frameworks, including intergenerational solidarity and reciprocity norms (Silverstein & Bengtson, 1997).

With rising life expectancies, falling fertility rates, and rapid ageing of populations, the global demographics are changing in ways never seen before (United Nations, 2024). As a result of these changes, families, labour markets, and social welfare systems are experiencing significant transformations. Thus, countries now face the challenging responsibilities of caring for ageing populations, particularly due to the rise in healthcare costs. Simultaneously, they must maintain the productivity and wellbeing of younger generations. For these reasons, existing studies, as presented in this thesis, have highlighted the importance of the various forms of intergenerational support as a means to mitigate the related economic implications of the ageing population challenges by playing an important role in improving parental wellbeing.

In low and middle-income countries, comprehensive official care and state-sponsored support systems are often limited. As a result, families serve as the primary source of financial and instrumental support. This support directly and indirectly reduces the deterioration of health outcomes associated with older parents. In high-income countries, where informal care is still an important component of long-term care systems, many ageing individuals rely on their employed children for caregiving responsibilities. This leads to adult children juggling between work and caring responsibilities. Several empirical studies in high-income countries have proposed that knowledge-based support through educational spillovers from children can have various beneficial influences on parental health outcomes. This is particularly relevant where formal long-term care and social care expenses are escalating. Thus, the impact of intergenerational support varies significantly based on the cultural and economic settings and the kind of support provided. Despite the evidence on intergenerational support, existing literature suffers from several methodological limitations, mainly endogeneity concerns and limitations in measuring key variables of interest.

This thesis addresses these limitations through the implementation of multiple methodological strategies. Chapter two employs precise measurements of key treatment variable of interest and applies IV strategy complemented by fixed effects models. This approach accounts for both unobserved time variant and invariant heterogeneity, as well as reverse causality. Chapter three addresses all potential endogeneity concerns through nonparametric bounds analyses and estimates the population average treatment effect. Chapter four utilises IV approach to control for potential endogeneity issues often encountered in the literature. This thesis provides more robust causal evidence on intergenerational support than has previously been available.

Given the importance and various impacts of intergenerational ties through caregiving, educational spillovers and support across various contexts, this thesis investigates such relationships in three distinct settings. Chapter two investigates how workplace policies, flexible working arrangements (FWAs), influence informal care provision for parents in the United Kingdom. Chapter three investigates whether the academic performance of children, assessed by college attainment, affects their parents' mental health in the United States. Chapter four turns its attention to examine the effect of both financial and instrumental support received from children on parents' wellbeing in Indonesia.

The second chapter, entitled "*Balancing Work and Care: Flexible Employment and Parental Informal Caregiving in the UK*" examines the relationship between FWAs and the provision of parental informal care in the UK, using data from the UK Household Longitudinal Study. This chapter specifically investigates whether access to FWAs increases the likelihood that working-age children provide care for their parents. Additionally, this chapter explores how this effect varies depending on several measures of care intensity. Moreover, it explores the driving mechanism behind the relationship between FWAs and caregiving as well as the heterogeneous effect among several groups of carers. Endogeneity concerns stemming from reverse causality and time-varying heterogeneity effects are addressed in this chapter using both instrumental variable (IV) strategy and fixed effects models. The results indicate that access to flexible work arrangements significantly enhances the probability of children providing care to their parents. In particular, individuals providing high intensity care benefited most significantly from using FWAs at their workplace. These findings suggest that FWAs are an essential instrument for maintaining informal care systems in the face of growing demand for caring, especially in economies where labour forces are dwindling, and populations are ageing. They emphasise how institutional policies can enhance intergenerational support through caregiving.

The third chapter, "*The Educational Return to Mental Health: Parental Wellbeing and Children's College Attainment in the US*", shifts from instrumental support like informal care to knowledge-based support through educational spillovers. This chapter examines the causal association between children's college attainment and parental mental health, using panel data from the Health and Retirement Study (HRS). To overcome endogeneity concerns, this study applies nonparametric partial identification methods to estimate the bounds of the population average treatment effect using credible and weak assumptions. Specifically, this chapter examines whether children's education has beneficial effects on parents’ mental health and identifies the pathways through which this effect is transmitted. The findings reveal a statistically significant positive impact of children's college attainment on parental mental health. Additional analyses show patterns consistent with mechanisms operating through financial transfers, contact frequency, and health-related communication. These findings support the intergenerational human capital mobility theory and suggest that children’s education yields long-term intergenerational benefits that expand beyond individuals across generations. These findings highlight the potential of further educational investments as an indirect public health strategy for the older generations.

The fourth chapter, “*Family Support as Welfare: Intergenerational Transfers and Elderly Health in Indonesia*”, shifts to a low- and middle-income settings, where formal assistance for the elderly is scarce. This chapter investigates the causal effect of receiving both financial and instrumental support from children on parental wellbeing, using panel data from the Indonesia Family Life Survey (IFLS). Additionally, this study explores the mechanisms by which support provided by children enhances parental wellbeing and examines various heterogeneous effect among different demographics and socioeconomic status of parents. This study applies IV strategy to address potential endogeneity concerns, specifically those arising from unobserved heterogeneity and reverse causality bias. The findings provide evidence of a positive causal effect of receiving support on parental wellbeing, measured by self-reported health and functional health status. This effect varies among different demographics groups of parents and is mediated by an increase in household medical, food, and total expenditure. These findings emphasize the importance of intergenerational support in enhancing the wellbeing and the welfare of the elderly population.

Table 1.1
Summary of Research Questions, Data Sources, and Identification Strategies by Chapter

Chapter	Research Question	Data Source	Identification Strategy
Two	How do flexible working arrangements affect informal care provision for dependent adults?	UK Household Longitudinal Study	IV Strategy & Fixed Effects Models
Three	Does children’s college attainment affect parental mental health?	US Health and Retirement Study	Nonparametric Partial Identification
Four	Does intergenerational support received from offspring affect parental health outcomes?	Indonesia Family Life Survey	IV Strategy

Table 1.1 summarises the research questions, data source and identification strategies across the three chapters of this thesis. Overall, the results of the three chapters illustrate how various forms of upward intergenerational support and ties aid individuals across different institutional and cultural contexts. The thesis examines different types of support including caregiving, educational spillover and both direct financial and instrumental support. It employs various rigorous methods to establish causality such as fixed effects, IVs and nonparametric analysis. This thesis contributes to the understanding how intergenerational support affects the wellbeing of ageing individuals and how workplace policies can facilitate them. The findings highlight the benefits of such support and how policymakers should consider the unique institutional, cultural, and economic structure of various nations when aiming to establish supportive environments for the wellbeing of an ageing society.

CHAPTER 2

Balancing Work and Care: Flexible Employment and Parental Informal Caregiving in the UK

Abstract

This study investigates the relationship between flexible working arrangements and parental informal care provision among a sample of 36,100 individuals across six waves of the UK Household Longitudinal Study, covering the period 2010 to 2022. This study examines the impact of flexible working arrangements on informal care provision by controlling for potential endogeneity issues via both fixed effects and two-stage least squares regression models, using geographic variation in flexible work adoption across occupational classifications as a valid instrumental variable. The results demonstrate that failing to account for such endogeneity results in biased and inconsistent estimates. The overall findings show that access to flexible working arrangements exerts a significant positive effect on individuals providing informal care. Access to flexible working arrangements raises the likelihood of an individual providing care by 2.9 percentage points. This effect varies according to the intensity of care provided, measured by hours spent on caring. The impact is heterogeneous by family composition, with significantly larger effects for childless individuals, but largely homogeneous across gender and occupation types. Causal mediation analysis demonstrates that time freedom is the primary mechanism through which flexible working arrangements influence informal caregiving. These findings are robust across various alternative specifications and sensitivity tests.

2.1 Introduction

A growing number of studies stemming from multiple disciplines are interested in understanding the impact of informal care and its spillover effects on both carers and receivers. Informal care is generally defined by scholars as unpaid care provided to family members, neighbours, and friends needing support because of age, illness, or any other reason (Urwin et al., 2023). The phenomenon of the ageing population and the escalating expenses associated with long-term care and social care systems have posed serious challenges to governments across the world. One way to reduce the costs and fulfil the increasing demand for formal care is through the provision of informal care, mainly delivered by employed family members and friends. Across the European Union, it is estimated that 80% of care is provided by informal carers (Zigante, 2018). Informal care has long been acknowledged as a significant and substantive substitute for formal and long-term care systems (Bolin et al., 2008; Bonsang, 2009; Bremer et al., 2017). Informal care reduces medical expenditure and the likelihood of using formal home care, as well as having beneficial health effects on recipients (Barnay & Juin, 2016; Byrne et al., 2009; Urwin et al., 2019; Van Houtven & Norton, 2008). However, the general upward trend in life expectancy will result in a rise in demand for both informal and formal care in the forthcoming decades. Therefore, it is crucial to address the policy issues relating to whether the working environment for employed carers and the supply of providing informal care are suitable to effectively fulfil the growing demand of care.

This study examines the relationship between flexible working arrangements (FWAs) and informal care provision. Specifically, this research attempts to address the following questions: (a) How do flexible working arrangements affect informal care provision for dependent adults? (b) Does the impact of flexible working arrangements vary according to the level of care intensity? (c) What are the heterogonous effects of flexible working arrangements on informal care across different subgroups of individuals? (d) What factors mediate the relationship between FWAs and informal caregiving? The limited studies examining the relationship between FWAs and informal care failed to distinguish between care provided to dependent adults and childcare. Childcare and adult care differ significantly in terms of amount cared for and physical/emotional difficulty. This study attempts to fill this gap in the empirical literature by quantifying a robust causal relationship between FWAs and informal care provision for dependent adults using a panel dataset from the UK Household Longitudinal Study (UKHLS).

This study makes five important contributions to the literature. First, to the researcher's knowledge, this study is the first to provide robust causal evidence on the effects of FWAs on informal care provision for dependent adults using both fixed effects and instrumental variable (IV) strategy. Second, in contrast to existing literature this study is the first that combines robust causal analysis with actual data on FWAs and not perceived or availability data measures. Third, this study provides evidence of how the effect of FWAs varies according to low intensity and intensive care giving measured weekly hours spent on caring. Fourth, the detailed individual-level data enables an analysis of the heterogeneity of FWAs effects across the population in ways that are economically informative. Fifth, this study explores the causal mechanisms that drives the relationship between FWAs and informal caregiving via casual mediation analysis.

This study employs longitudinal data from six waves of the UKHLS, covering 36,100 individuals. To address potential endogeneity arising from unobserved individual characteristics and reverse causality, the analysis applies both individual fixed-effects and two-stage least squares (2SLS) estimation methods. The fixed-effects specification accounts for time-invariant unobserved individual characteristics that may simultaneously influence the use of FWAs and caregiving behaviour. The instrumental-variable approach exploits geographic variation in the adoption of FWAs across Standard Industrial Classification (SIC) codes and regions to instrument individual use of flexible work. This identification strategy captures variation in workplace flexibility policies that is plausibly exogenous to individual caregiving preferences while remaining strongly correlated with FWA availability. In addition, a causal mediation analysis is conducted to explore the mechanisms underlying this relationship, focusing on time availability and freedom as key mediating channels.

The empirical findings of this study shed light upon the positive effect of FWAs on informal care provision. Individuals with FWAs are more likely to provide informal care by at least 20% relative to the baseline mean probability of 8.89%, compared to individuals without FWAs. However, this effect varies significantly by care intensity. For high intensity care (defined as caring for more than 20 hours per week), FWAs increase the probability of providing care by 43% relative to the baseline mean. For low intensity care (less than 20 hours per week), the increase is smaller but still significant at 29% relative to the baseline mean. The general results indicate that failing to account for endogeneity concerns like unobserved individual heterogeneity and reverse causality results in biased and inconsistent estimates. The overall findings are robust across various alternative specifications and measures for informal care. They reveal that the impact of FWAs is heterogeneous by family composition, with significantly larger effects for childless individuals, but largely homogeneous across gender and occupation types. Causal mediation analysis results indicate that having more time freedom mediates 145% of the total effect of FWAs. These findings provide policymakers with a basis for the development of long-term care policies and programmes aimed to support carers. Policymakers are advised to use a comprehensive approach when formatting policies, considering the uniqueness of individuals caring responsibilities and socioeconomic characteristics.

The findings are important for policymakers and activists that are interested in promoting, improving and providing a stable environment for informal carers to continue with their caring responsibilities. Since formal care is expected to be relatively more expensive and impose pressures on public budget spending more than informal care. Specific laws and regulations have been enacted to promote workplace policies to encourage and support carers to reconcile their caring responsibilities and employment. For example, since the introduction of Work and Families Act 2006 in the UK, certain employed carers had the right to request FWAs from their employers (James, 2006).[1] At the same time, governments are promoting longer labour market participation through the rise of the state pension age. Extending working lives leads to an increase of workers juggling between employment and caring demands. More than 50% of informal carers across the EU are estimated to combine work with caring responsibilities (Eurofound, 2015). Whilst it is well documented that labour market participation and employment reduces informal care provision and vice versa (Bauer & Sousa-Poza, 2015; Kolodziej et al., 2018). The issue of juggling work and caregiving is often addressed with the suggestion that flexible work environments are an appropriate tool for the challenges of combining care and employment activities (Clancy et el., 2020; Heger & Korfhage, 2020). Such flexible arrangements can grant individuals the opportunity to adjust their working hours and how they wish to carry out their personal and professional duties and responsibilities, including caring and other obligations.

Previous studies have indirectly or directly promoted the role of flexible working arrangements for reconciling labour participation and employment with caring or reducing

[1] In June 2014, the right to request flexible working arrangements was extended to include all employees who have worked for their employer for at least 26 weeks (Golynker, 2015). Currently, there is a proposal suggesting that employees should be qualified for flexible working from day 1. The reason behind this proposal is that activists believe that some employees are reluctant to change their jobs in order to not lose the flexibility benefits.

family-work conflicts (Bryan, 2012; Russell et al., 2009; Vecchio, 2015). However, they have not specifically examined the effect of FWAs for working individuals on informal care for dependent adults and the context of such effect. Rather, they have mainly focused on family life-balance and caregiving broadly (including children and adults), with little attention given to dependent adults or the elderly. It is reasonable to assume that FWAs play a significant role when it comes to childcare and domestic labour. However, it is crucial to bear in mind that the context of adult care is quite different from childcare or housework (Larsen, 2010). Childcare is to some degree predictable and has a specific time frame, mostly during early childhood and preschool. On the other hand, adult care is more unpredictable, demanding and might be over a long period of time (Cheng et al., 2020). Depending on the circumstances of care receivers and their general health, they might require daily personal care and high intensity of caring until passing away or improvement in their health (Clancy et el., 2020).

Given these claims over FWAs, the future of informal care is extremely important in the context of long-term care systems reform planning, given the large economic implications of informal care. Therefore, it is important to investigate FWAs as a mechanism for carers within the labour market to combine participation in employment and caring responsibilities. Yet surprisingly, there is limited empirical evidence examining related policies. Specifically, it is important to understand whether the impact of FWAs on informal care provision truly affects the ability of employees to participate in caring responsibilities or not. Therefore, investigating the relationship between informal care provision and flexible working arrangements is crucial for the development of policies aimed at controlling the costs and expenses of the healthcare system. It is equally important to understand the effects and benefits of such workplace policies on promoting informal care for individuals.

The remainder of this study is structured as follows: Section 2.2 presents the background and literature review. Section 2.3 introduces and describes the data. Outlines of model specification and analysis are presented in Section 2.4. The main empirical results, robustness checks, mechanisms analysis, and the heterogenous effects results are presented in Section 2.5. Finally, the conclusion and discussion of this study are presented in Section 2.6.

2.2 Background and Literature

2.2.1 Informal Care in the United Kingdom

The UK provides an interesting setting to examine the relationship between informal care and FWAs. The UK is home to one of the largest populations of informal carers. Informal care is a crucial component within the social care system in the UK for meeting the demands of caring. *Figure 2.1* in the appendix displays the number of informal carers during the past two decades. Despite fluctuations, the number of carers has increased by approximately 12%, and averaged 4.9 million throughout this period. According to Carers UK (2022), recent estimates show that around 10% of the population provides informal care (approximately 5.7 million people), and this is expected to increase by 3.4 million (to over 9 million) by the year 2030 (Carers Trust, 2019). Around 1.7 million carers are providing more than 50 hours of care weekly. Currently, more than 40% of carers are in employment, out of which more than half are fully employed. The majority of them are worried about the likelihood and demands of continuing with their caring responsibilities during full employment. There is evidence that businesses are losing over £3.5 billion a year due to absences and stress from employees combining work and care (Carers UK, 2022).

In terms of socio-economic impacts, it was reported that a loss of £2.9 billion in earnings had been eliminated from the economy due to individuals leaving the labour market to focus solely on caring, which is equivalent to a loss of £1.2 billion in forgone taxes (Pickard, 2018). Current estimates reveal that informal care in England and Wales saves public expenditure £18.6 million per hour, equivalent to £162 billion per year (Petrillo & Bennett, 2023).[2] These figures are much larger than adult social care spending, and highlight the importance of informal care in the overall economy (Foster et al., 2020). Specifically, the figures highlight the burden that will be imposed on public spending and the loss of economic value of carers if carers choose their careers. Conversely, they themselves will suffer from the burden of choosing their caring responsibilities and forsaking their professional roles. Therefore, the ideal solution seems to be to allow carers the maximum flexibility at their workplace, to manage both caring and employment activities. The UK also provides an interesting case for investigating carers flexibility at the workplace. The UK has

[2] In 2017, the value of informal care in the UK was estimated to be £56.9 billion a year (Office for National Statistics, 2017).

a handful of different types of flexible working for all employees, including non-carers. Despite this, there is limited evidence of the association between workplace flexibility and informal care.

2.2.2 Literature Review

Due to the importance of the informal care sector and its various impacts across multiple disciplines, there has been increased research interest associated with this sector. Despite the general consensus on the desirability and *de facto* reliance on informal care discussed previously, it is not without disadvantages. Literature on the relationship between informal care provision and its diverse effects on caregivers and those cared for is rich and growing. Scholars have attempted to investigate this relationship through the use of both theoretical and empirical evidence. Exploring and understanding the existing literature is essential for identifying gaps that this study attempts to fill. From a theoretical perspective, scholars have for decades attempted to address and rationalise the determinants of individuals providing informal care.

One strand of the literature has focused on theories of intergenerational relationships such as altruism, solidarity and exchange theory (Alessie et al., 2014; Kalmijn & Saraceno, 2008; Mazzotta & Parisi, 2020; Tisch & Gutfleisch, 2023; Železná, 2018). The main principle of the solidarity theory is focused on family cohesion and the norms or expectations of individuals to support their family members (Broese van Groenou & De Boer, 2016). Studies conducted in Europe and the US have shown a strong association between solidarity and informal care (Batur et al., 2022; Haberkern et al., 2015; Klimaviciute et al., 2017; Mazzotta et al., 2020; Mulder & Van der Meer, 2009; Silverstein et al., 2006; Stuifbergen et al., 2008). They concluded that familial responsibility and family structure are strong determinants of care provision. Other studies have reported evidence supporting the conceptualisation of care as per the altruism and exchange theories (Evandrou et al., 2018; Grundy, 2005; Norton & Houtven, 2006; Norton et al., 2013; Steele & Grundy, 2021). Such researchers concluded that children are more likely to provide care for their parents who have helped them earlier in life than those who perceived that they did not receive sufficient support from their parents.

From an empirical perspective, studies have examined different socio-demographic factors associated with informal care provision, such as the health, wealth, and age of caregivers and care receivers. For instance, studies have shown that the deterioration of health and the loss of financial and social benefits of care receivers are strongly associated with adult children care provision (Haberkern & Szydlik, 2010; Mentzakis et al., 2009; Pope et al., 2012; Vlachantoni et al., 2020). The age and geographical proximity of care receivers were also found to be an important determinant of care provision (Carmichael & Ercolani, 2014; Dahlberg et al., 2007). In support of this notion, Leopold et al. (2014) used six waves from a "Health and Retirement Study" in the US to investigate the transition into parental care. Their results showed that children living closer to parents had almost double the odds of providing care compared to those living farther away. Similarly, Pillemer and Suitor (2014) found that living closer to the parent is likely to increase the likelihood of providing care by more than 6 times.

The second strand of the empirical literature has focused on different casual relationships between informal care and carers and care receivers (De Zwart et al., 2017; Longobardo et al., 2023). This group of studies concentrate mainly on issues such as health and employment. Studies that have examined the effect of informal care on caregivers' health investigated multiple dimensions of the construct. Studies that focused on the physical health of caregivers examined the proxies of self-reported health, activities of daily living, and healthcare use/costs (Coe & Van Houtven, 2009; Do et al., 2015; Lacey et al., 2018; Mentzakis et al., 2009). Others have examined mental and psychological health measures, such as life satisfaction (Bom & Stöckel, 2021; Chen, 2019; Stöckel & Bom, 2022; Van den Berg et al., 2014), depression (Schmitz & Westphal, 2015), antidepressant drug intake (Schmitz & Stroka, 2013) and self-reported happiness (Niimi, 2016). Most scholars have shown a strong negative effect on mental health among carers, but some found that the effect of informal care is small or insignificant (Eibich, 2023; Rafnsson et al., 2017). The inconsistency of the findings in previous studies might be driven by different empirical methodologies and outcomes employed to address potential endogeneity concerns.

A substantial body of literature has attempted to investigate whether employment and retirement reduces or increases informal care provision. The economic literature mainly focused on ways to solve for the endogeneity of informal care and employment status of children, using IV and panel regression methods. These methods allow for establishing a causal effect between informal care and employment by accounting for possible reverse causality and the effect of unobserved heterogeneity. Most studies have found a mixed causal effect, depending on the regions studied, samples, and variable definitions (Bergeot & Fontaine, 2020; Ciani, 2012; Crespo & Mira, 2014; Leigh, 2010; Meng, 2013; Schmitz & Westphal, 2017; Simard-Duplain, 2022; Viitanen, 2010). For instance, Mazzotta et al. (2020)

used two-stage and three-stage ordinary least square (OLS) regressions from the "Survey of Health, Ageing and Retirement in Europe", and found that a 10% increase in working hours reduced the time spent on caring by 26 minutes. On the other hand, Meng (2013) and Viitanen (2010) showed that the association between working and caring hours was not significant.

For the UK, however, there seems to be consensus on the relatively negative causal effect, with studies finding that providing informal care reduces employment participation and wages for caregivers (Carmichael et al., 2008; Harris et al., 2020; Heitmueller & Inglis, 2007; Van Houtven et al., 2013).[3] For instance, Carmichael et al. (2010) provided evidence that the likelihood of providing care is significantly and negatively associated with employment participation and wages. They showed that being employed reduces the odds of providing care by around 0.84 for both men and women. At the same time, an increase in wages reduces the probability of caring by a factor of 0.86 and 0.84 for men and women, respectively. Likewise, Michaud et al. (2010) used 6 waves from the "British Household Panel Survey" (BHPS) dataset to show that employment and care provision are negatively associated. These findings are in line with earlier work by Heitmueller (2007), which indicated that caring significantly reduces employment participation via estimates from cross-sectional and panel data from BHPS data.

The third strand of the literature has examined ways to reconcile employment and caring responsibilities. A substantial number of such studies recommended and promoted workplace policies such as flexible working arrangements and family leaves as a mechanism for carers to remain in employment and to reduce family-work conflicts as well as enhance their mental health (Hancioglu & Hartmann, 2014; Heger & Korfhage, 2020; Grünwald et al., 2021; Li & Wang, 2022; Niimi, 2021; Pavalko & Henderson, 2006; Schneider et al.,2013; Zuba & Schneider, 2013). Prior research in this area has shown that access to such arrangements for carers made it more likely that carers would remain employed, and reduced absenteeism compared to conditions with carers having no special arrangements.

However, despite the growing literature on the health and employment effects of providing informal care and the indirect policy recommendations to promote flexible working arrangements to aid carers with caring responsibilities. Little is known about the

[3] "Caregivers" and "carers" are used interchangeably in this study.

effect of FWAs on informal care provision for dependent adults. A thorough literature search undertaken by the researcher only identified three empirical studies that attempted to investigate the relationship between informal care and FWAs in the workplace for any care receiver (including children), as described below.

Using seven waves from the "Household, Income and Labour Dynamics in Australia" (HILDA) Survey, Nguyen and Connelly (2017) documented that carers perceptions of flexible work have no impact on their decision to provide care. In this context, flexible work perceptions did not capture the actual use of FWAs at the workplace, but rather captured work characteristics measured by employees' satisfaction with the flexibility to balance work with non-work commitments.[4] Similarly, Henz (2006) used cross-sectional data derived from the "British Family and Working Lives" survey to investigate the relationship between flexible working and care provision. She concluded that flexible working measures did not affect the probability of caring. However, the measure of job flexibility employed does not capture the actual usage of FWAs as it was derived based on an aggregated occupational group (work characteristics) of employees. Since there is no direct measure of job flexibility within the data, the author notes that the measure of flexibility in her study makes it difficult to capture the true effect of flexibility on caring provision.

Bryan (2012) differed from the two abovementioned studies in controlling for the potential endogeneity concerns of FWAs by estimating using a bivariate probit model. He considered realistic and accurate way to measure the availability of FWAs as defined by the UK government and legislations.[5] Using cross-sectional employer-employee matched data from the UK, the author concluded that carers with access to FWAs are more likely to participate in caring responsibilities, FWAs increase the likelihood of care provision by 13%. However, the main limitation of this study is that it did not capture the actual usage of FWAs for employees; it captures the availability of such arrangements for only 25 employees within each workplace. The author noted discrepancies between the reported availability of FWAs between employees and employers' responses. For example, few employees reported that such arrangements are available within the workplace, while employers routinely stated that

[4] Typically, respondents were asked: "I want you to pick a number between 0 and 10 to indicate how satisfied or dissatisfied you are with the flexibility to balance work and non-work commitments?".
[5] For more information, please see https://www.gov.uk/flexible-working/types-of-flexible-working.

such arrangements do not exist within the company. This variation raises several doubts about the validity and reliability of the data employed, which can affect the overall findings. Also, another limitation is related to the credibility of instruments employed in the estimated model. The instruments employed were based on workplace characteristics for employees like working a 24-hour schedule, which can directly affect the probability of providing informal care. Therefore, it does not satisfy the exclusion restriction assumption.

In summary, existing theoretical and empirical literature highlights some key elements of informal care across multiple disciplines and its various effects on both carers and care receivers. Despite the extensive literature in this area of research, the findings on the association between informal care and flexible working remain inconclusive. Results have been mixed and mismeasured FWAs, with important distinctions identified concerning having access to FWAs and the perception of availability not implying actual usage. Also, studies often ignored the potential endogeneity concerns of FWAs and informal care, which limits the ability to draw vigorous policy-relevant conclusions. Furthermore, studies have failed to distinguish between adults and childcare when attempting to examine the effect of FWAs on informal care provision. Therefore, there is a need for further research to fully comprehend and document robust causal inferences regarding FWAs and informal care provision for dependent adults.

Against the background described above, this study expands upon the limited existing literature and examines the relationship between informal care providing and FWAs by controlling for potential endogeneity concerns, using both fixed effects and IV regression models. This approach can provide important insights for policymakers seeking to support informal caregivers.

2.3 Data

This research utilises national representative panel data from the UKHLS, also known as "Understanding Society" (University of Essex, Institute for Social and Economic Research et al., 2022). The UKHLS is the largest nationally representative longitudinal survey in the UK, covering around 40,000 households and about 100,000 individuals in the initial wave during the period of 2009/2010 (Giaquinto et al., 2022). The survey contains a comprehensive annual multidisciplinary questionnaire that covers detailed information on respondents' demographic and socioeconomic characteristics (e.g., education, employment, family network and caring). Each survey wave is conducted over two overlapping years, using a stratified and clustered sampling design.

The UKHLS collects data from all household members aged 16 or above, and provides numerous measures of FWAs and time spent in informal care for dependent adults. This feature makes it well-suited to the research questions addressed in this study. The data used for this study were extracted from waves 2, 4, 6, 8, 10 and 12, covering the period 2010 to 2022, which collects data from all household members aged 16 or above. The reason for the selection of these waves of data is that they include specific questions that identify an individual's usage of FWAs at their workplace.

The analysis focuses on the extent to which FWA is associated with providing informal adult care. For this reason, this study focuses on employed adult individuals over 16 and excludes those not in paid employment and economically inactive (including those currently on any kind of leave) or who are self-employed. As their behaviour and freedom to access flexible work arrangements differ significantly by default. The final sample consists of 36,100 individuals, of whom only 2,758 were interviewed in all six waves, providing 95,295 person-wave observations.[6] Only 10,035 (27.7%) respondents had access to FWAs during the sample period, and 32,948 did not use any FWAs at their workplace.

The primary outcome variable in this study is informal care, measured through individual responses to survey questions. In the survey, individuals were asked: "Do you provide some regular service or help for any sick, disabled or elderly person not living with you?" and "Who is the first person that you look after or help?". Based on responses, a binary variable was constructed for informal care, taking the value of 1 if the individual helps parents, parents-in-law, step-parents and grandparents (henceforth "parents") living outside the respondent household, and 0 otherwise. Focusing on the provision of care for parents reduces the likelihood of including children's care receipts as well as other relatives, since the exact identification of care receipts cannot be determined within the data as the age of care receipts is not available in the data.[7]

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[6] 38,836 individuals were dropped due to missing values and exclusion restriction.

[7] The nature of the data prevents us from identifying the exact person who received informal care as categories were identified by: parent/parent-in-law, grandparent, aunt/uncle, other relative, friend or neighbour, voluntary organisation and others.

The main analysis was based on this binary variable, even though the survey provides information on the number of weekly caring hours, as respondents are much more likely to remember the provision of care than the exact number of hours in a given week, which reduces measurement error (Schmitz & Westphal, 2017).[8] Another reason is that hours spent on caring is defined in some overlapping brackets, and it is impossible to verify the precise distribution without the loss of number of observations.[9] Also, due to the imbalance of observations (as hours spent on caring is highly skewed), a binary specification was employed.

Informal care was limited to those who provide non-residential care for their parents living in a separate household, as they constitute a significant share of informal care receipts in the UK (Burchardt et al., 2021; Ciccarelli & Van Soest, 2018; Heitmueller, 2007; Hollingsworth et al., 2022). This helped to avoid potential endogeneity bias and measurement error from co-residential care and living arrangements. This pertains to co-residential carers exhibiting different behavioural patterns and altruism/solidarity characteristics in family relations. These characteristics are likely to be dependent on the supply and demand of care provision (Carmichael & Charles, 2003; De Koker, 2009; Mentzakis et al., 2009; Michaud et al., 2010). Furthermore, the definition of "care" can be ambiguous in the context of co-residential care, as individuals helping with daily or routine household chores may consider themselves carers, and vice versa (Diederich et al., 2021). Therefore, this research focuses on non-residential informal care, given the important distinctions between co-residential and non-residential care.

A key limitation of the UKHLS is that it does not adequately capture co-residential parental care. In the analytical sample, around 5% of respondents reported providing care to a co-resident household member; however, the survey does not clearly identify whether the recipient is a parent, child, spouse, or other relative. This ambiguity makes it difficult to construct a reliable measure of co-residential parental care. The survey also suffers from overlapping categories of reported caring hours, which makes it impossible to verify the precise distribution of time spent across different levels of care intensity.

[8] For robustness, the model is re-estimated using the number of weekly caring hours as an alternative dependent variable.

[9] Hours spent on caring are reported in following brackets: 0–4 h, 5–9 h,10–19 h, 20–34 h, 35–49 h, 50–99 h, 100+ h, varies between 0–20 h, varies between 20+ h and others. Reported brackets can be re-defined as 0 h (91%), <20 h (8%) and >20 h (1%).

The primary independent variable is employees' access to and usage of FWAs at their workplace. This measure differs from earlier work, as it measures the *actual* use of FWAs (not just their availability or related perceptions). The survey questions of interest concerning FWAs were: "I would like to ask about working arrangements at the place where you work. Which of the following arrangements listed on the card are available at your workplace?" and "Do you currently work in any of these ways?". The arrangements listed included various types and definitions of FWAs, which can be grouped mainly into three categories: (a) reduced hours arrangements (part-time, job-sharing and working term-time), (b) flexitime arrangements (flexitime, annualised hours and compressed hours), and (c) other arrangements (working from home and other informal working arrangements) (Cook et al., 2021). Using formal flexitime arrangements rather than the reduction of working hours or informal work arrangements in this study is consistent with the literature on FWAs (Atkinson & Hall, 2009; Chung et al., 2020; Bryan & Sevilla, 2017; Wheatley, 2017).

The individual responses were then used to construct a binary variable, with 1 denoting an individual's usage of at least one of the flexitime arrangements (flexitime, annualised hours and compressed hours) or working from home and 0 otherwise. Earlier studies have adopted a similar measure (Chandola, 2019; Chung et al., 2020). Flexitime can be defined as flexible start and end times, typically focusing on agreed hours, such as between 10 a.m. and 4 p.m. (Lee & DeVoe, 2012; Saxena, 2018). Annualised hours are when employees are required to work a certain number of hours within a year but are given some degree of flexibility in scheduling their work hours. Compressed hours represent a reduction in the number of working days, with a corresponding increase in the duration of each working day (e.g., a nine-day fortnight).[10]

Based on earlier literature, several control variables are included as essential determinants of the demand and supply of informal care provision (Carmichael et al., 2010; Koreshi, & Alpass, 2022; Mazzotta & Parisi, 2020). This study controls for a set of individuals' demographic and socioeconomic characteristics as well as household characteristics. These variables include gender, age, marital status, number of children, educational attainment, and working hours. Gender is a binary variable, with 1 denoting male and 0, otherwise. Age is categorised into seven groups: 16-19, 20-29, 30-39, 40-49, 50-59,

[10] For the definitions of flexitime arrangements according to UK government and legislation, see https://www.gov.uk/flexible-working/types-of-flexible-working.

60-69, and 70+ (years). Marital status is a categorical variable, with categories denoting the respondent is married or in a civil partnership, cohabiting, widowed/divorced/separated, and single/never married. Educational attainment is also a categorical variable that captures the respondent's highest education qualification, grouped as no education, degree or higher, school diploma/ other qualifications (A-level), GCSE or below, and others. The number of children represents the total number of children aged 15 or under currently living in the household. Working hours measures the total number of hours per week, excluding overtime and breaks.

Furthermore, homeownership is included to control for any wealth effect on informal care provision. Homeownership is a binary variable that represents whether the respondent owns the house they're currently living in or not. The individual's occupation class is also controlled using the National Statistics Socioeconomic Classification (NE-SEC), which classifies occupations as professional, managerial and technical, skilled non-manual, skilled manual, partly skilled, and unskilled. Other control variables included government office regions and year dummies to control for geographical differences and macroeconomic effects on providing informal care.[11] Further control variables like respondent health status and income are excluded from the main specification, as they are likely to be endogenous with informal care provision (Brenna & Di Novi, 2016; Carrino et al., 2023; Zwart et al., 2017).[12]

For example, the health of individuals is highly associated with their ability to provide care; if individuals are in significantly poor health, their ability to provide care will not be sustainable. Furthermore, studies have also shown that informal care has a deteriorating effect on caregivers' physical and mental health (Bobinac et al., 2010; Heger, 2017). High income levels can reflect an increased capability to purchase formal care services, rather than providing informal care personally (Bom et al., 2019). Another rationale for omitting these variables is reporting bias, as both variables are self-reported (Drexler et al., 2014). It is well known within the literature that individuals are reluctant to reveal their

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[11] The government office regions include North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, South East, South West, Wales, Scotland and Northern Ireland.

[12] For robustness, the model is re-estimated with the inclusion of the omitted variables (see Appendix *Table 2.A7.2*).

true income levels in addition to having a diverse interpretation regarding the subjective assessment of one's health status (Arni et al., 2021; Michael & Urban, 2020).

Table 2.1 provides descriptive statistics for the pooled sample (years 2010-2022) of all variables used in this study, using weighted analysis to correct for complex survey design and non-response. The sample consisted of 95,295 observations were split into two groups: those who had FWAs, and those who did not. This enabled direct comparison between the two studied groups. As the table shows, the two groups differ considerably in terms of their demographic and socioeconomic characteristics. Around 9% of the pooled sample provide informal care which consist of about 14% of individuals, greater than the 9.6% reported by the Office of National Statistics (ONS, 2021), and consistent with the general consensus among concerned organisations concerning informal caregivers across the UK (Carers UK, 2022).

Amongst those who provide informal care, about 18% have FWAs agreements at their workplace. A basic mean comparison across the two groups (FWAs vs. no-FWAs) reveals that individuals who utilise FWAs have a higher likelihood to provide a more significant amount of informal care than those without FWAs (9.7% vs. 8.71%). Over 54% of the individuals with FWAs are males and fall under the age of 60. They are also, on average, more likely to be highly educated, married and working longer hours. Individuals with FWAs tend to have a higher percentage of homeownership (80.28% vs. 70.9%). Also, they are more likely to have a higher socioeconomic status, measured by the number of individuals in professional occupations (11.06% vs. 4.67%) and managerial/technical occupations (52.81% vs. 33.81%). In comparison, individuals without FWAs (no-FWAs) tend to be more in manual and unskilled occupations (14.67% and 4.92% vs. 6.28% and 1.34%). It is notable that there is a clear pattern whereby the proportion of individuals with FWAs is higher for those in the middle age group (aged 30–50 years), but the opposite is the case for the young and old age groups (< 30 or > 50 years).

Overall, the descriptive statistics from *Table 2.1* indicate that individuals with FWAs and those without differ significantly in terms of providing informal care and socioeconomic characteristics. FWAs are associated with a higher likelihood of providing informal care, being male, having more children, being younger, being highly educated, working in professional and management fields, and owning their homes. The opposite is also true: those who lack access to FWAs are more likely to be unmarried, less educated, and work in skilled manual, somewhat skilled, and unskilled jobs (Broese van Groenou & De Boer, 2016; Van Houtven et al., 2013).

Table 2.1
Summary Statistics of Main Variables

	Pooled sample	FWAs	No-FWAs	Difference	t-test
No. observations	*95,295*	*17,990*	*77,305*		
No. individuals	*36,100*	*10,035*	*32,948*		
Outcome Variable					
Informal Care	8.89%	9.7%	8.71%	0.99%	***
Independent Variable					
Flexible Working Arrangements (FWAs)	18.27%	-	-	-	
Male	51.23%	54.67%	50.45%	4.22%	***
No. children	0.66	0.72	0.64	0.08	***
Working hrs.	3.44	3.5	3.42	0.08	***
Age bracket					
16-19	2.49%	0.89%	2.85%	1.96%	***
20-29	19.67%	15.49%	20.6%	5.11%	***
30-39	23.35%	26.4%	22.67%	3.73%	***
40-49	25.47%	28.63%	24.76%	3.87%	***
50-59	21.64%	22.53%	21.44%	1.09%	**
60-69	6.78%	5.76%	7.01%	1.25%	***
70+	0.6%	0.31%	0.67%	0.36%	***
No education	0.11%	0.01%	0.13%	0.12%	***
Degree or higher	43.38%	58.85%	39.92%	18.93%	***
School diploma/other qualification A-level	13.01%	13.29%	12.95%	0.34%	
GCSE and below	32.33%	22.99%	34.42%	11.34%	***
Other	11.17%	4.86%	12.58%	7.72%	***
Married	51.78%	57.49%	50.5%	6.99%	***
Cohabiting	15.35%	15.08%	15.41%	0.33%	
Widowed/divorced/separated	8.17%	7.55%	8.3%	0.75%	**
Single/never married	24.71%	19.88%	25.79%	5.91%	***
Professional occupation	5.83%	11.06%	4.67%	6.39%	***
Managerial & technical	37.28%	52.81%	33.81%	19%	***
Skilled non-manual	24%	22.59%	24.32%	1.73%	***
Skilled manual	13.14%	6.28%	14.67%	8.39%	***
Partly skilled occupation	15.48%	5.93%	17.62%	11.69%	***
Unskilled occupation	4.27%	1.34%	4.92%	3.58%	***
Homeownership	72.61%	80.28%	70.9%	9.38%	***

Notes: The last column indicates t-test for two-group means. The asterisks denote the following levels of significant: ***<1%, **<5%, * <10%.

2.4 Empirical Strategy

2.4.1 Endogeneity of Flexible Working Arrangement (FWAs)

The primary objective of this study is to investigate the relationship between FWAs and informal care provision. Achieving this adequately requires taking explicit account of the possible endogeneity bias within the empirical model. Economic theory and intuition suggest that the decision to work in FWAs is likely to be endogenous with informal care provision (Carmichael et al., 2010). Unobserved individual characteristics like preferences, personality traits, expectations about future gains (e.g., gifts/transfer) and work/family attitudes/attachments are likely to be simultaneously associated with both FWAs and informal care. For example, an individual with strong work attachments may have less preference for using FWAs and providing care than those with relatively weak work attachments. On the other hand, an individual with a strong sense of altruism may demonstrate a strong preference for jobs that offer FWAs to accommodate caregiving responsibilities, while simultaneously being more likely to provide care. Failure to consider such factors can lead to omitted variable bias, leading to inconsistent estimates (Wooldridge, 2010).

Previous studies demonstrated that unobservable characteristics like personality traits are associated with the provision of informal care (Schmitz & Westphal, 2017). To address this endogenous concern and to obtain consistent estimates, this study exploited the panel structure of the data by controlling for unobserved heterogeneity within individuals over time, using the fixed effects model (Cameron & Trivedi, 2005; Greene, 2003). By relying on within individual variation across time from individuals experiencing changes in FWAs status, the FE specification eliminates all time-invariant unobserved individual characteristics that are likely to simultaneously influence occupational sorting into FWAs and the likelihood of providing care.

Although fixed effects account only for time-invariant unobserved individual heterogeneity, the potential for time-varying heterogeneity and reverse causality remains a concern. For example, individuals with parents with caring needs decide to use FWAs only to be able to provide care for their parents; hence, the causality between FWAs and caring is reversed. Therefore, reverse causality and unobserved heterogeneity are significant challenges when attempting to establish causal inferences within any given model.

Consequently, the IV method is used to obtain unbiased estimates and check for potential endogeneity driven by reverse causality (Angrist & Pischke, 2009).

For the IV method, a variable measuring the aggregate geographical variation in the use of FWAs according to employees' Standard Industrial Classification 2007 (SIC) is used as a valid time-varying instrument for an individual's use of FWAs. The SIC classifies organisations and businesses according to the nature of the economic activity they are involved in. More specifically, this study uses the proportion of individuals in each SIC with access to FWAs in each governmental region as an instrument. The rationale for this instrument is that the share of employees with FWAs in a particular industry and region may influence the working conditions and arrangements for employees to utilise such arrangements. For example, the proportion of employees with FWAs in education sector will determine and require individuals to be working with FWAs in this particular region and sector, and not the other way around.

Previous studies have adopted a similar instrument in different contexts. These studies recognise that specific industries and jobs require more flexibility than others. They demonstrated that a higher share of FWAs provides a good indicator that there is a general trend for individuals to use FWAs according to exogenous geographical variation and specific industry characteristics (Bryan & Sevilla, 2017; Lamb et al., 2020). This study assumes that industry and regional variation in FWAs prevalence is highly correlated with the decision to work in FWAs, but should not directly affect informal care provision. The validity of this instrument relies on the underlying assumption that, conditional on all covariates, the share of FWAs affects informal care only through the channel of FWAs (Angrist et al., 1996; Stock & Watson, 2003).

The underlying assumption appears plausible unless individuals relocate to governmental regions and industries with a high FWAs to provide informal care. Due to the fact that informal care is provided daily and requires physical proximity, such a move would require that both the caregiver and receiver move simultaneously to the same region. According to Bryan (2012), the decision to participate in FWAs and informal caregiving is not primarily influenced by individuals joining workplaces as a result of their care obligations and responsibilities.

The exclusion restriction underlying the instrumental variable approach is plausible but cannot be verified directly. As with most instruments, complete exogeneity can never be guaranteed. The instrument captures exogenous variation in workplace flexibility arising from differences in industrial conditions, shared work practices, and sectoral labour market policies and factors that are plausibly exogenous to individual caregiving preferences or local social norms. Because the instrument is defined at the aggregation across SIC and regional level and is determined by organizational and market forces rather than by individual caregiving responsibilities, it is conceptually uncorrelated with individual unobserved characteristics. Therefore, the instrument is unlikely to be correlated with traits such as personality, family culture, or caregiving attitudes. Moreover, the inclusion of region and year fixed effects controls for time-invariant local characteristics (e.g. social norms, caregiving infrastructure, or regional regulations) as well as for national time trends in FWAs and caregiving that might be correlated with both FWAs prevalence and caregiving patterns.

A potential remaining concern is that sector or region specific characteristics, such as workplace culture or local availability of formal care services, might directly influence informal care independent of FWAs. For example, individuals who anticipate future caregiving responsibilities may systematically select into industries or regions with higher flexible work prevalence. This possibility cannot be fully ruled out, since it is not feasible to include both sector and regional dummies simultaneously without inducing collinearity, as their interaction defines the instrument itself. Nevertheless, any such bias would require that sectoral or regional conditions jointly affect both the use of FWAs and caregiving provision. The most plausible pathway for such bias is through systematic selection into flexible sectors based on anticipated caregiving needs. However, such selection would require individuals to anticipate caregiving needs years in advance when making career and location decisions, which is implausible given that caregiving responsibilities often arise unexpectedly due to parent illness, accidents, or sudden health deterioration. Moreover, most individuals establish their career paths well before caregiving needs emerge, and career choices are primarily driven by wages, job characteristics, and career prospects rather than anticipated family obligations. Together, these considerations make it unlikely that the instrument affects informal care through any channel other than individual use of FWAs, while acknowledging that the instrument exogeneity cannot be demonstrated with absolute certainty.

Suggestive evidence within the data shows no direct association between the instrument and informal care provision. Therefore, the instrument is unlikely to directly affect informal care. The annual mean of the instrument varies only gradually over the sample period, indicating that the prevalence of FWAs across SIC and regions evolves smoothly.[13] This pattern suggests that the instrument captures stable workplace and regional characteristics, rather than being influenced by individuals' caregiving behaviour. These findings, together with the strong first-stage diagnostics reported in *Table 2.2b*, support the validity of the instrument for identifying the causal effect of FWAs on informal caregiving.

2.4.2 Empirical specification

To study the effect of FWAs on informal care provision, the following fixed-effect empirical model is estimated:

$$y_{it} = \beta_1 FWA_{it} + \beta_2 X_{it} + u_i + \varepsilon_{it} \tag{2.1}$$

where the outcome variable of interest y_{it}, is a binary variable of informal care, which equals 1 if individuals *i* at time *t* provided informal care; FWA_{it} is the primary binary independent variable representing individuals using FWAs at their workplace; X_{it} is a vector of a range of control variables capturing individual's demographic and socioeconomic characteristics (gender, age, marital status, number of children, education, working hours, occupation class, homeownership, time and region fixed effects); u_i is individual time-invariant unobservable factors (individual fixed effects), which are likely to be correlated with the independent variables; and ε_{it} is a time-varying error term. All time-invariant controls, both observed (e.g., gender) and unobserved (e.g., personality traits), are eliminated by the fixed effect model.

As discussed in section 2.4.1, endogeneity is an alarming concern for obtaining consistent estimates of Eq. (2.1), as the assumption of a simple OLS estimation, $u_i = 0$, is violated (i.e., $u_i \neq 0$), hence it does not control for individuals' fixed effects (e.g., personality traits). Neglecting individuals' fixed effects will likely lead to bias and inconsistent estimates driven by omitted variables bias. Therefore, an FE specification is specified as its uses within individual variation across time to control for unobservable individual heterogeneity that may be associated with the independent variable, leading to a

[13] The annual means were computed by averaging the share of flexible workers across all SIC and regions for each year. The results, reported in Appendix *Table 2.A1*.

more valid estimate of the causal relationship between informal care and FWAs (Allison, 2009).

Nevertheless, there may still be potential endogeneity concerns related to reverse causality and unobserved time-varying heterogeneity that would bias the results, thus two-stage least squares (2SLS) specification is applied to provide robust causal evidence on the effects. Formally, the first-stage equation of the 2SLS specification is expressed as:

$$FWA_{it} = \pi_1 Z_{it} + \pi_2 X_{it} + u_i + v_{it} \tag{2.2}$$

Where FWA_{it} is the endogenous variable representing individuals using FWAs at their workplace; Z_{it} is the instrumental variable denoting the proportion of employees using FWAs across regions and SIC codes, while X_{it} and u_i are as specified in Eq. (2.1); and v_{it} is a time-varying error term. The instrument provides exogenous variation in using FWAs across industries and regions over time. Specifically, this variation shifts an individual's probability of using FWAs but is plausibly unrelated to their caregiving decisions, except through its effect on the use of FWAs. This instrument satisfies the relevance condition (correlated with the likelihood of individual use of FWAs) while plausibly meeting the exclusion restriction, as regional variation in industry-level FWAs adoption is unlikely to directly affect an individual's informal care provision.

To ensure a comprehensive analysis, both pooled 2SLS (pooled-2SLS) and fixed effect 2SLS (FE-2SLS) specifications are estimated. For robustness, an IV-Probit model and an IV-Probit with correlated random effects (CRE) specifications are also estimated.[14] To estimate the causal effect of using FWAs on informal care, Eq. (2.1) is estimated as a binary outcome with fixed effects using a Linear Probability Model (LPM) with robust standard errors. This method is widely applied for binary outcomes with fixed effects within the economic literature (Giovanis, 2017; Jacobs, 2017; Stock & Watson, 2008; Van den Berg et al., 2014).

[14] The CRE procedure adds individual-specific time averages for all time-varying covariates into the equation to control for individual fixed effects for nonlinear models, please see Papke and Wooldridge (2008) and Wooldridge (2019) for more details on CRE. This procedure is also known as Mundlak's correction model (1978).

Although a logit specification of the model seems to be more suitable for binary outcome variables, as it restricts the predicted probability to lie between 0 and 1 (Meng, 2013). Estimating a fixed effect logit (conditional logit) model is quite problematic, as it only provides estimates of the model coefficients or odds ratios and is unsuitable for computing average partial effects or marginal effects, making interpreting the results challenging (Greene, 2003; Wooldridge, 2010). [15] Also, the fixed effect conditional logit model will exclude observations that do not vary within the panel leading to significantly reducing the sample size.

Therefore, the LPM is the preferred specification in this study, as it provides results that are easier to interpret by means of computing marginal effects as well as it can be easily extended to IV models with 2SLS and fixed effects. For the sake of comparability, a CRE Probit model proposed by Wooldridge (2019) is also estimated. Nevertheless, estimates from the logit and fixed effect conditional logit model are still presented for comparison purposes.[16] As a baseline model, a pooled LPM and logit model are estimated with clustered robust standard errors to enable comparison with prior literature that do not account for unobserved individual fixed effects (Cameron & Trivedi, 2010).

2.5 Empirical Results

2.5.1 Main Results

Table 2.2a reports the results of various model specifications carried out to investigate the association between FWAs usage and informal care provision. For comparison purposes, Column 1 reports the pooled baseline models (LPM, Logit and Probit), Column 2 reports the fixed-effect models (FE-LPM, FE-Logit, and CRE Probit). A full set of the results for all regression models can be found in *Table 2.A3 – A6*.

Column 1 presents the pooled baseline estimates, which do not account for unobserved individual fixed effects. To aid the interpretation of results, the marginal effects of regressors

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[15] For robustness, the model is re-estimated using a user-written command developed by Kemp and Silva (2016), which computes the average elasticities for conditional logit model. They can be interpreted as the percentage change in informal care probability for a given change in treatment level.

[16] Estimates from the fixed effect conditional logit model demonstrate similar conclusions to the FE-LPM. See *Table 2.2a*.

were computed. Given that the logit, probit and LPM model estimates are very similar in terms of sign, magnitude and significance level, the LPM model will be considered the main results. These estimates capture the association between FWAs usage and informal care provision. The marginal effect of employees using FWAs is positive and is statistically associated with the probability of informal care provision at the 1% level. This suggests that people who use FWAs are more likely to offer regular services or assistance to their non-resident parents than those who do not. Holding all other factors constant, being in FWAs increases the likelihood of individuals providing informal care from 8.89% to 10.39% (1.5 percentage points), representing a 16.4% increase on average compared to those who do not use FWAs. Generally, the estimates are consistent with patterns observed in the summary statistics as well as with earlier cross-sectional studies for the UK (e.g., Bryan, 2012). This consistently shows that employees using FWAs are more likely to find a better balance between employment and caring responsibility, leading to a higher probability of providing informal care to adult dependents.

Column 2 in *Table 2.2a* shows the results for the FE-LPM, FE-logit and CRE Probit models which considers the panel aspect of the data to enable the control for unobserved heterogeneity. Column 2 presents the marginal effects for the FE-LPM and CRE Probit. In Panel B the conditional FE logit odds ratios are reported.[17] All models show that using FWAs is positively associated with care, and the effect is statistically significant at the 1% level. A high degree of agreement is observed in terms of the sign of the estimated coefficients and the level of statistical significance in the models. The difference in the number of observations in the FE-Logit model is due to the exclusion of individuals who do not vary their caregiving activity over time. To aid the interpretation of the results, the focus is on the estimates from FE-LPM as the marginal effects of regressors can be computed, whereas the FE-logit cannot (Van Houtven et al., 2013; Vangen, 2021).[18] For comparability and robustness, the marginal effects for CRE Probit model are presented, which enables the estimation of fixed effects estimators for nonlinear models.

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[17] The average elasticities estimate from the method developed by Kemp and Silva (2016) showed very similar findings as the FE-LPM and CRE-Probit estimates. Individuals who use FWAs are, on average, 12.6% more likely to provide informal care. There are no significant differences (see Appendix *Table 2.A5*, Column 1).

[18] See *Table 2.A5* (Column 2) for the odds ratio of the conditional logit model. The odds ratio of 1.2 indicates that individuals who use FWAs are, on average, 1.2 times more likely to provide informal care.

Panel B, Column 2, reports the marginal effect of using FWAs at individual workplaces increases the probability of caregiving by 12% (1.1 percentage points) on average compared to those who do not use FWAs. The estimates for the CRE Probit model in Panel C, Column 2 are consistent with FE-LPM and very similar, indicating that the LPM estimates are robust and can perform well in a nonlinear setting. In comparison with the pooled LPM estimates in Panel A, Column 1, the estimated association between FWAs and informal care provision is slightly smaller, which shows that unobserved individual effects that are omitted (e.g., personality traits) influence both the decision to work in FWAs and care provision. The change in coefficients confirms bias due to not controlling for unobserved individual heterogeneity.

The Breusch-Pagan Lagrange Multiplier (LM) test decides between a simple pooled OLS regression and a panel effect regression model (Breusch & Pagan, 1980). The LM test is significant, indicating that there are significant differences across individuals, thus a panel data analysis is needed, as a simple OLS would yield biased estimates. Also, the Hausman (1978) test is used to determine a more suitable estimation procedure between FE or random effects models. The test results indicate the existence of individual effects, therefore the FE model is the preferred estimation method.[19]

As discussed in section 2.4.1, the fixed effects estimation strategy accounts for time-invariant unobserved individual heterogeneity. The potential endogeneity bias for time-varying unobserved heterogeneity and reverse causality may still affect the results. Therefore, to control for the endogeneity of FWAs, the IV strategy is employed using the Pooled LPM-2SLS, FE-LPM-2SLS, IV-Probit and IV-Probit with CRE methods in *Table 2.2b*. The difference in the number of observations between the models is due to the exclusion of observations that do not vary within the panel. For robustness, all models are re-estimated on the FE-2SLS estimation sample to ensure that differences across estimators are not driven by differences in sample composition but solely by the choice of estimator. The results are consistent with the main findings indicating that the differences are not driven by sample composition (see Appendix *Table 2.A2*).

Table 2.2b reports the IV estimates of the causal effect of FWAs usage on informal care provision. The first-stage regression diagnostics confirm that the instrument is both

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[19] The test results are presented in Appendix 2.B2.

relevant and strong. The estimates show that the instrument (the share of employees using FWAs in the same industry and region) is strongly and positively associated with an individual's probability of using FWAs, with coefficients around 0.8–0.9 depending on specification. This indicates that the instrument is valid and informative, as it is highly associated with the endogenous variable (FWAs).

F-statistics diagnostic test is applied to assess the validity and relevance of the instrument employed based on the weakness of the excluded instrument. The F-statistics results for excluded instruments are far above 10, the commonly used rule of thumb threshold proposed by Stock et al. (2002), implying that the instrument is not weak. In comparison to the critical values for weak identification tests the F-statistics is well greater, confirming that the instrument is not weakly associated with FWAs (Stock & Yago, 2005). Given that the instrument is highly relevant and not weak, an endogeneity test is performed to determine whether FWAs is indeed endogenous using Durbin-Wu-Hausman endogeneity test for pooled 2SLS and Davidson-Mackinnon test for FE-2SLS (Davidson & MacKinnon, 1993). The results from the endogeneity test for the pooled-2SLS model strongly rejects the null hypothesis, implying that there is evidence of endogeneity and that failure of treating FWAs as an endogenous variable will lead to biased and inconsistent results. Whereas for FE-2SLS specification test failed to reject the null hypothesis, implying that FWAs could be treated as exogenous. Nevertheless, failure to reject the exogeneity of FWAs does not guarantee that endogeneity is not an issue in the context of this analysis. This is consistent with existing research in similar contexts of FWAs in the UK (Giovanis, 2019).

Despite the failure to reject the exogeneity of FWAs, the estimates of the marginal effects for Pooled-LPM-2SLS, FE-LPM-2SLS, IV-Probit and IV-Probit with CRE models are presented in *Table 2.2b*. Robust standard errors are clustered at regional and employees' SIC levels, as treatment assignment varies according to them. The IV estimates indicate a causal effect of FWAs usage on informal care provision at the 1% level for all models except for FE-LPM-2SLS. For the Pooled-LPM-2SLS specification, the estimates reveal that using FWAs increases the likelihood of providing care from 8.89% to 11.79% (2.9 percentage points), corresponding to a 32% increase relative to the baseline mean compared to those who do not use FWAs. The FE-LPM-2SLS specification, which relies on within individual variation, showed a 1.8 percentage points (20% on average) effect statistically significant at the 10% level.

The IV-Probit model and the IV-Probit with correlated random effects (CRE IV-Probit) approach are presented in Panel B, with Column (1) reporting pooled IV-Probit and Column (2) reporting CRE IV-Probit. The IV-Probit model shows very similar marginal effects to the Pooled-LPM-2SLS estimates. In contrast, the IV-Probit with CRE estimates in Column 2 showed a statistically significant effect at the 1% level for the increase in the likelihood of providing care by 2.3 percentage points (26% on average), slightly larger than the FE-LPM-2SLS estimate. The findings in Panel B demonstrate that the results confirm that the LPM does an acceptable degree of accuracy in many nonlinear contexts in estimating the marginal effects. The estimates in *Table 2.2b* can be interpreted as causal effects for the compliers, those individuals whose use of FWAs is influenced by industry and region rate.

Table 2.2b shows that the IV estimates after accounting for the endogeneity of FWAs are nearly double those from both the simple pooled LPM and fixed effects models in *Table 2.2a*. The fundamental reason for such differences in magnitude is that the OLS and IV models estimate distinct group effects. The OLS estimates the average effect over the entire population, whilst the IV provides estimates of the local average treatment effect (LATE) (Papke, 2005). The IV estimation strategy focuses on those individuals whose FWAs are responsive to the fluctuations of the instrument, usually called compliers (Angrist & Pischke, 2009). These are individuals who adopt FWAs because of higher prevalence of flexible working within their industry and region.

The IV estimates therefore represent the average effect of FWAs on informal caregiving among compliers. Specifically, those individuals whose likelihood of using FWAs is influenced by exogenous industry and regional variation in FWAs prevalence. These compliers typically work in sectors and regions where flexible work adoption changed exogenously, leading them to adjust their own FWA usage. As a result, the findings should be interpreted as a local causal effect, applying to individuals whose FWAs decisions are influenced by the instrument, rather than as a population wide average effect. The treatment effect of FWAs on care is therefore heterogeneous, differing across gender, occupation, and family composition. Section 2.5.4 further explores these subgroup differences, highlighting that the benefits of FWAs are not uniform across the population. This distinction is crucial for policy interpretation, as the findings reflect the effect of FWAs for those individuals whose adoption decisions are sensitive to workplace and institutional flexibility conditions, rather than for all individuals.

Regarding the marginal effects of other covariates, the estimates are generally in line with previous research and general expectations (Bryan, 2012; He & McHenry, 2016; Mentzakis et al., 2009). Column 1 of *Table 2.A6* presents a full set of the marginal effects of the remaining control variables. The results show that the provision of informal care is positively associated with age, education, homeownership and occupation class, and the effect is highly statistically significant for all these covariates. For instance, the results show that compared to the reference group (aged 16–19), the probability of providing care increases as individuals age to a certain degree and then declines as individuals age over 60 (Mentzakis et al., 2009). In particular, the estimates show the likelihood of providing care ranging from 11.1 percentage points (age group: 50-59) to 7.0 percentage points (age group: 60-69). These estimates are consistent with the explanation that as individuals age, their parents' health worsens, and they are much more likely to require care and assistance.

In terms of educational attainment, higher-educated individuals are more likely to provide care by 1.1, 2.4, and 2.7 percentage points for degree holders, school diploma and GCSE, respectively, compared to non-educated individuals. Owning a home increases the probability of providing informal care by around 1.0 percentage points. Regarding individuals' occupational class, in comparison with professionals, those not in managerial occupations are more likely to provide care, with the probabilities ranging from 1.4 to 1.8 percentage points. On the other hand, other observable characteristics like being male, having more children, and working longer hours are negatively associated with providing care. On average, being a male reduces the probability of providing informal care compared to women. Being a male also leads to a 4.2 percentage point reduction in the likelihood of providing care, while individuals with more children are less likely to provide care. The estimates show that having more children reduces the ability to provide care by 1.0 percentage points.

This is consistent with findings from Pesando (2019), who reported that childless individuals in 11 European nations are more likely to care for their parents. In terms of working hours, a 10% increase in working hours leads to a 0.15 percentage points reduction in the probability of providing care, which suggests that informal caregiving is less likely to be offered by individuals who work longer hours. Additionally, the probability of providing care varies significantly across governmental regions. The estimates indicate that individuals in most regions are less likely to offer care on average compared to the North East (the reference group).

Table 2.2a
The Effect of FWAs on Informal Care Provision: Baseline Models

Outcome Variable	(1) Pooled	(2) Fixed Effects
	Informal Care	
Panel A: LPM		
FWAs	0.015***	0.011***
	[0.003]	[0.003]
Observations	95,295	
Outcome Mean	0.089	
Panel B: Logit (Marginal Effect/Odds Ratio)		
FWAs	0.015***	1.230***
	[0.003]	[0.070]
Observations	95,295	16,134
Outcome Mean	0.089	0.382
Panel C: CRE-Probit		
FWAs	0.015***	0.010***
	[0.003]	[0.003]
Observations	95,295	
Outcome Mean	0.089	

Notes: The full set of the results are presented in *Table 2.A3 – A5*. All estimations include the full set of control variables listed in *Table 2.1*, as well as time and region fixed effects. In Panel B, pooled logit results are presented as marginal effects, while fixed-effects logit results are presented as odds ratios. The outcome mean differs in Panel B due to exclusion of non-varying individuals in the FE logit model. In Panel C, column (1) reports pooled probit estimates, while column (2) reports CRE-Probit estimates that account for correlated random effects using the Mundlak specification. Robust standard errors clustered at the individual level are reported in brackets. * p<0.10, **p<0.05, ***p<0.01.

Table 2.2b
The Effect of FWAs on Informal Care Provision: Instrumental Variable Models

Outcome Variable	(1) Pooled	(2) Fixed Effects
	Informal Care	
Panel A: LPM-2SLS (Second Stage)		
FWAs	0.029***	0.018*
	[0.008]	[0.010]
Observations	95,295	82,324
Outcome Mean	0.089	0.091
First Stage Diagnostics		
Instrument (SIC-Region FWAs rate)	0.928***	0.793***
	[0.005]	[0.011]
Kleibergen–Paap F-stat	9745	5099
Partial R-squared	0.167	0.100
Endogeneity Test	6.6***	0.65
Panel B: IV-Probit / CRE IV-Probit (Second Stage)		
FWAs	0.028***	0.023***
	[0.008]	[0.009]
Observations	95,295	
Outcome Mean	0.089	
First Stage Diagnostics		
Instrument (SIC-Region FWAs rate)	0.928***	0.791***
	[0.005]	[0.011]
Kleibergen–Paap F-stat	9745	4690
Partial R-squared	0.167	0.166
Endogeneity Test	6.6***	5.8***

Notes: The full set of the results are presented in *Table 2.A6*. All estimations include the full set of control variables listed in *Table 2.1*, as well as time and region fixed effects. The outcome mean differs in Panel A due to exclusion of non-varying individuals in the FE-LPM-2SLS model. In Panel B, column (1) reports pooled IV-Probit estimates, while column (2) reports CRE IV-Probit estimates with correlated random effects (Mundlak specification). Robust standard errors clustered at the regional and employees' Standard Industrial Classification (SIC) levels in brackets. * p<0.10, **p<0.05, ***p<0.01.

2.5.2 Robustness Checks

To ensure the validity of the main findings, several robustness checks were conducted. These checks include alternative model specifications, and measures for the primary dependent variable. Firstly, to assess the robustness of the informal care measure, the information on individuals self-reported weekly hours spent on caring is used as alternative measure for informal care to estimate Eq. (2.1). The dependent variable in this context is a binary variable, coded as 1 if the respondent spent weekly caring hours, and 0 otherwise. *Table 2.A7.1* in the Appendix shows the marginal casual effect of using FWAs on the alternative measure of informal care. Consistent with earlier findings, FWAs remains positive and statistically significant at the 1% level.

To further assess how sensitive the results, the estimates are reproduced for the original model controlling for additional control variables capturing respondent health and income that were initially omitted due to potential endogeneity to care provision.[20] *Table 2.A7.2* shows that the estimates for the coefficient of interest (FWAs) is robust and consistent across all specifications after controlling for individuals' health and income; there are no significant differences in the result.

Box 2.1: Robustness Summary	
Alternative Measure for Informal Care: • Pooled-LPM-2SLS: 0.029*** • IV-Probit: 0.028*** • FE-LPM-2SLS: 0.019* • CRE IV-Probit: 0.023**	Additional Control Variables: • Pooled-LPM-2SLS: 0.029*** • IV-Probit: 0.028*** • FE-LPM-2SLS: 0.018* • CRE IV-Probit: 0.022**
Key Findings: The positive effect of FWAs on informal care is robust across alternative outcome measure and additional control variables.	

Finally, to facilitate the assessment of whether the impact of FWAs varies according to intensity of care and to further check the robustness of the results. The dependent variable was constructed as an ordinal variable outcome banded into three weekly hours spent on caring categories: *0 h*, *<20 h* and *>20 h*. Based on prior studies and data availability, low intensity care is recognised as when individuals provide less than 20 hours per week, while high intensity or intensive care is defined as those providing more than 20 hours per week (Fernández et al., 2019; Young et al., 2005). Low intensity care is more common as around more than 90% of carers provide less than 20 hours.

Table 2.3 reports the results of the marginal causal effects across different care intensity levels using an ordered IV-Probit moel. The results show that the effect of FWAs is positive and statistically significant for low intensity care and high intensive care, however the effect for high intensive care is considerably larger. Compared to those who do not use FWAs, individuals with FWAs at the workplace increase the likelihood of providing care from 0.7% to 1% (0.3 percentage points), representing a 43% increase on average for high intensity caring. For low intensity care, the probability increases from 8.3% to 10.7% (2.4

[20] The health measure used is the General Health Questionnaire, which is an index ranging from 0–36. This variable is widely used in the economic health literature to capture the subjective wellbeing of respondents (Arulsamy & Delaney, 2022; Zhou & Kan, 2021).

percentage points), corresponding to a 29% increase. This likely reflects the high commitment and responsibility of intensive caregiving, individuals with highly intensive care are more able to gain more from reconciling work and caregiving responsibilities due to having access to FWAs (i.e., gaining some benefits or advantages from having access to FWAs while combining caring roles with employment).

However, individuals providing low intensity care is less beneficial for combining caring roles and employment. Therefore, individuals with low intensity care responsibilities require more attention and detailed policy initiatives to aid them with combining work and caregiving responsibilities, as FWAs have minimal effect on their decision to supply informal care. Overall, the results from IV ordered Probit show that individuals with FWAs significantly increases the probability of reporting *<20 h* and *>20 h* caring and reduces the probability of reporting *0 h* caring spent.

Table 2.3
The Effects of FWAs on the Intensity of Care: Instrumental Variable Model

Weekly Hours Spent on Caring	**Outcome Mean**	**Marginal Effects**
0	0.908	-0.027***
		[0.008]
< 20	0.083	0.024***
		[0.007]
> 20	0.007	0.003***
		[0.001]

Notes: Estimates are from an ordered IV-Probit regression. The full set of the results are presented in *Table 2.A8*. All estimations include control variables listed in *Table 2.1*, as well as time and region fixed effects. Robust standard errors are clustered at regional and employees' Standard Industrial Classification (SIC) levels in brackets. * p<0.10, ** p<0.05, *** p<0.01

Overall, the findings provide an indication of the importance of accounting for possible sources of bias associated with endogeneity issues, such as reverse causality and time-varying unobserved individual effects in the estimated models. The estimates from the baseline and FE models demonstrate that not accounting for such bias may lead to a slightly upward bias. This confirms that failure to control for unobserved characteristics along the lines of personality traits and ability as well as reverse causality leads to biased and inconsistent estimates. In general, the findings are robust and credible to several alternative specifications and measures. They verify the positive effect of FWAs on informal care provision.

2.5.3 Heterogeneity Analysis

Next, heterogeneous effects analysis is carried out using the Pooled-LPM-2SLS specification to investigate whether the effect of FWAs differs across various groups of caregivers. The sample is disaggregated by gender, occupation types and family composition. *Table 2.4* provides the results of the analysis of these subgroups, which is quite interesting but also enables a more straightforward comparison with earlier studies that frequently concentrated on subgroup analysis. The subgroups analysis is adjusted for familywise error rate (FWER), using the procedure proposed by Romano and Wolf (2016) and developed by Clarke et al. (2020).[21] This procedure jointly corrects p-values across the specific subgroups (within each panel), using 500 bootstraps replications to control for multiple hypothesis testing. Both unadjusted and adjusted *p*-values are reported for transparency. Additionally, formal heterogeneity tests are conducted using interaction terms between FWAs and subgroup indicators.

Panel A shows the results from examining whether the effect of FWAs is heterogeneous across gender. The findings show that FWAs significantly increase informal care provision for both females and males, 3.2 and 2.6 percentage points, respectively. While the estimate for females is slightly larger, the formal interaction test reveals that this difference is not statistically significant. Therefore, there are no heterogeneous effects across gender, suggesting that FWAs are effective in facilitating informal care provision regardless of gender.

Women constitute approximately 67% of informal carers in the sample, reflecting the well documented gender disparities in caregiving responsibilities across Europe (Ciccarelli & Van Soest, 2018). Despite these substantial differences in gender roles and social norms towards caring responsibilities, the results imply that FWAs enable both genders to increase their caregiving participation to a similar degree. This indicates that workplace flexibility operates as a gender neutral mechanism. It helps individuals reconcile employment and caring responsibilities without disproportionately benefiting one gender over the other, even though women experience these conflicts more frequently due to their large share of caring responsibilities. This finding indicates that policies promoting workplace flexibility can

[21] The "familywise error" (FWER) rate refers to the likelihood of rejecting one or more true null hypothesis (List et al., 2019).

expand participation in informal care across the workforce without exacerbating existing gender inequalities in care or the work environment.

Panel B shows the impact of FWAs on different occupational types. Using three classes of NE-SEC, the respondents were divided into three occupation groups: managerial occupations (including administrative and professionals), intermediate occupations, and routine/manual occupations. The estimates indicate that FWAs have positive and statistically significant effects across all occupational types. Specifically, the findings show an effect of 1.9 percentage points for managerial workers, 3.5 percentage points for intermediate occupations and 4.5 percentage points for routine workers. However, the joint F-test examining whether these effects differ significantly across occupation types yields a p-value of 0.476, indicating no statistically significant heterogeneity is present.

The lack of significant heterogeneity is somewhat surprising, as occupational types broadly reflect socioeconomic status and resource availability, with certain types being more privileged than others in many aspects. Individuals in managerial and professional occupations ("white-collar" workers) typically have greater financial resources that might enable them to purchase alternative formal care services such as nursing or home care (Cheng et al., 2020). Therefore, one might expect FWAs to be more beneficial for lower paid intermediate and routine workers ("blue-collar" workers) who lack financial alternatives and must rely more heavily on informal care arrangements. While the estimates align with this rationale, showing larger marginal effects for routine workers than managerial workers, these differences are not statistically significant. The homogeneity observed suggests that FWAs address a fundamental constraint that affects workers across all occupational categories, namely time constraints and freedom. Even higher income workers who could purchase formal care services still benefit from workplace flexibility to a similar degree as lower income workers. Therefore, the findings indicate that workplace flexibility policies have broad applicability and benefit all types of workers. FWAs appear to be a general mechanism that facilitates the balance between work and care responsibilities regardless of individuals' positions in the occupational hierarchy.

Panel C presents the results of the heterogeneous effect of FWAs on informal care by family composition. The sample is disaggregated into two groups: individuals living with children and individuals living without children. Around 40% of individuals in the sample live with at least one child. The results show that the effect of FWAs on care is greater for childless employees than employees with children (3.8 vs. 1.7 percentage points). This difference is statistically significant, as shown in Column 4 by the interaction test.

This finding is important, as the number of individuals caring simultaneously for parents and children has been growing. These individuals are often referred to as the “club sandwich generation” (Vlachantoni et al., 2020). Individuals living with children face fundamentally different time constraints than their childless counterparts. Parents must allocate their available time, including time made available through FWAs, across multiple demands such as childcare, household management, and parental care. The relatively smaller marginal effect for those with children suggests that FWAs may be insufficient to enable these individuals to substantially increase informal care provision beyond their existing commitments. On the other hand, childless individuals can more fully direct workplace flexibility towards parental care. These findings indicate that while FWAs are effective tools to facilitate the balance between work and care responsibilities, their impact depends heavily on individuals’ existing care commitments.

Overall, the heterogeneity analysis reveals that the effect of FWAs on informal care provision exerts a consistent effect across groups. The findings show no statistically significant differences by gender or occupation type, while family composition shows a statistically significant heterogeneous effect. Childless individuals show larger effects than those with children. This pattern indicates that while workplace flexibility addresses time constraints for all employees, its effectiveness depends on existing care commitments. Those managing multiple care responsibilities such as the sandwich generation may require additional supportive policies.

Table 2.4
Heterogeneous Effects of FWAs on Informal Care

Outcome Variable: **Informal Care**	(1) FWAs	(2) p-value (unadjusted)	(3) p-value (adjusted)	(4) Interaction Test (p-value)	(5) Outcome Mean
Panel A: Gender					
(a) Female	0.032*** [0.013]	0.012	0.009		0.112
Obs. 52,298				0.529	
(b) Male	0.026*** [0.010]	0.008	0.009		0.067
Obs. 42,997					
Panel B: Occupation Types					
(a) Managerial	0.019*** [0.009]	0.012	0.009		0.089
Obs. 43,850					
(b) Intermediate	0.035** [0.019]	0.066	0.029	0.476	0.099
Obs. 15,304					
(c) Routine	0.045** [0.029]	0.072	0.039		0.085
Obs. 36,141					
Panel C: Family Composition					
(a) Childless	0.038*** [0.014]	0.001	0.009		0.098
Obs. 57,201				0.008***	
(b) Child	0.017** [0.010]	0.086	0.019		0.073
Obs. 38,094					

Notes: All estimations include control variables listed in *Table 2.1*, as well as time and region fixed effects. Column (1) reports IV estimates of FWAs effects on informal care for each subgroup. Columns (2) and (3) show unadjusted and Romano-Wolf adjusted p-values correcting for multiple hypothesis testing, using 500 bootstrap replications. Column (4) reports interaction test p-values: for gender and family composition, the interaction term coefficient tests whether effects differ between the two groups; for occupation types, the joint F-test examines whether effects differ across all three categories. Robust standard errors are clustered at regional and employees' Standard Industrial Classification (SIC) levels in brackets. * p<0.10, ** p<0.05, *** p<0.01

2.5.4 Mechanisms Analysis

According to previous estimates, there is a positive causal relationship between the use of FWAs and informal care provision. In light of this, it is crucial to further understand the mechanisms (mediating factors) that drive this observed relationship. To examine such an effect, all previous regressions are employed to test whether FWAs affects the mediating factor. A significant effect of FWAs on the mediating factor provides suggestive evidence that informal care is indirectly affected through changes in the mediating factor. Understanding the factors mediating the relationship between FWAs and informal caregiving can inform policy making process to support informal caregivers and assess the effectiveness of flexible work regulations.

A possible mechanism that may mediate the effect of FWAs is increased time freedom. The idea is that individuals using FWAs have the ability to control their own time and schedule, thereby allowing more free time to perform any non-work-related activities, such as caring for their loved ones. A potential candidate variable that can be derived from the UKHLS is "Autonomy Over Work Hours". Autonomy over work hours can lead to improved work-life balance and less stress between work and family responsibility or conflicts. The UKHLS contains only one specific question that indicates an individual's ability to manage their own working hours. Respondents were asked to rate how much control they had over the hours they worked, ranging from "a lot" to "none". For the analysis, a dummy variable was used as a proxy for individual time freedom, where 1 denotes a lot and some freedom and 0, otherwise. This measure can help determine the level of freedom an individual has during their workday and how does that freedom contribute to performing caring activities.[22]

Table 2.5a presents the results of baseline model specifications carried out to estimate the effect of FWAs on the mediating variable (*Autonomy Over Work Hours)*. Column 1 Panel A and B shows both LPM and Logit estimates have a positive and statistically significant marginal effects at the 1% level. Both estimates reveal that FWAs increase the likelihood of having more freedom by 35.6 and 36.6 percentage points, respectively. The FE models (Column 2), which account for time-invariant unobserved individual heterogeneity, shows still a positive and significant effect with a slightly smaller magnitude.

Table 2.5b shows the IV estimates of the causal effect of autonomy on informal care provision. The first-stage regression diagnostics confirm that the instrument is both relevant and strong. The estimates show that the instrument (the share of employees using FWAs in the same industry and region) is strongly and positively associated with an individual's probability of using FWAs, with coefficients around 0.7–0.9 depending on specification. This indicates that the instrument is valid and informative, as it is highly associated with the endogenous variable (FWAs). The marginal effects range from 22.4 to 53.2 percentage points, depending on the model specification. These estimates provide evidence that individuals using FWAs are more likely to have greater freedom over their work hours. This

[22] Previous studies have used "feeling of satisfaction with amount of leisure time" as a proxy for subjective work-family and work-life balance in UKHLS (Melo et al., 2018; Ocean & Meyer, 2023).

increased time freedom may transmit to enhance individuals ability to provide informal care for their parents.

Table 2.5a
The Effect of FWAs on Autonomy Over Work Hours: Baseline Models

Outcome Variable	(1) Pooled	(2) Fixed Effects
	Autonomy Over Work Hours	
Panel A: LPM		
FWAs	0.356***	0.151***
	[0.004]	[0.005]
Observations	95,181	
Outcome Mean	0.450	
Panel B: Logit (Marginal Effect/Odds Ratio)		
FWAs	0.366***	2.875***
	[0.005]	[0.108]
Observations	95,181	40,453
Outcome Mean	0.450	0.475
Panel C: CRE-Probit		
FWAs	0.366***	0.156***
	[0.005]	[0.006]
Observations	95,181	
Outcome Mean	0.450	

Notes: The full set of the results are presented in *Table 2.A9 - A10*. All estimations include the full set of control variables listed in *Table 2.1*, as well as time and region fixed effects. In Panel B, pooled logit results are presented as marginal effects, while fixed-effects logit results are presented as odds ratios. The outcome mean differs in Panel B due to exclusion of non-varying individuals in the FE logit model. In Panel C, column (1) reports pooled probit estimates, while column (2) reports CRE-Probit estimates that account for correlated random effects using the Mundlak specification. Robust standard errors clustered at the individual level are reported in brackets. * p<0.10, **p<0.05, ***p<0.01.

Table 2.5b
The Effect of FWAs on Autonomy Over Work Hours: Instrumental Variable Models

Outcome Variable	(1) Pooled	(2) Fixed Effects
	Autonomy Over Work Hours	
Panel A: LPM-2SLS (Second Stage)		
FWAs	0.532***	0.224***
	[0.022]	[0.016]
Observations	95,181	82,222
Outcome Mean	0.450	0.457
First Stage Diagnostics		
Instrument (SIC-Region FWAs rate)	0.928***	0.793***
	[0.005]	[0.011]
Kleibergen–Paap F-stat	9748	5103
Partial R-squared	0.167	0.100
Endogeneity Test	413***	23.5***
Panel B: IV-Probit / CRE IV-Probit (Second Stage)		
FWAs	0.532***	0.302***
	[0.021]	[0.017]
Observations	95,181	
Outcome Mean	0.089	
First Stage Diagnostics		
Instrument (SIC-Region FWAs rate)	0.928***	0.791***
	[0.005]	[0.011]
Kleibergen–Paap F-stat	9748	4694
Partial R-squared	0.167	0.166
Endogeneity Test	413***	255***

Notes: The full set of the results are presented in *Table 2.A11*. All estimations include the full set of control variables listed in *Table 2.1*, as well as time and region fixed effects. The outcome mean differs in Panel A due to exclusion of non-varying individuals in the FE-LPM-2SLS model. In Panel B, column (1) reports pooled IV-Probit estimates, while column (2) reports CRE IV-Probit estimates with correlated random effects (Mundlak specification). Robust standard errors clustered at the regional and employees' Standard Industrial Classification (SIC) levels in brackets. * p<0.10, ** p<0.05, *** p<0.01.

Next, the novel IV mediation procedure proposed by Dippel et al. (2022) was used to examine the causal mechanism of the effect of FWAs on informal care provision.[23] Unlike traditional mediation approaches that rely on sequential ignorability and explicit temporal ordering, this method identifies causal pathways through exclusion and exogeneity restrictions (Celli, 2022). The IV mediation approach allows for the identification of direct and indirect effects even when both the treatment and the mediator may be endogenous. This method relies on three underlying assumptions that extend the standard IV framework: (i) the instrument affects the treatment but not the mediator or the outcome directly (relevance and exclusion restrictions); (ii) unobserved factors may jointly influence both the

[23] For detailed procedure of the causal mediation analysis, see Appendix 2.B2.3.

treatment and the mediator, as well as the mediator and the outcome; and (iii) conditional on observed covariates and the mediator, unobserved factors affecting the treatment do not directly affect the outcome (conditional independence).

The conditional independence assumption requires that unobserved factors affecting FWA adoption do not directly influence informal caregiving once autonomy and observed characteristics are controlled. This assumption is plausible because the mechanism through which unobserved factors affect both FWA adoption and caregiving operates primarily through the autonomy channel. Specifically, individuals anticipating caregiving responsibilities may seek FWAs to gain schedule control; in this case, unobserved caregiving needs influence care provision through autonomy, not via an independent pathway. Similarly, if work–family conflicts drive FWA requests, they affect caregiving behaviour through the autonomy FWAs provide.

Moreover, unobserved characteristics such as organisational culture, management practices, or sectoral norms that jointly influence FWAs usage and autonomy are unlikely to independently affect caregiving decisions once autonomy is accounted for. These unobserved factors shape whether and how much autonomy employees gain, but conditional on that autonomy, they have no direct effect on care provision, which is driven by individual preferences and caregiving behaviours.

The instrument, which captures aggregate FWA usage patterns across sectors and regions, satisfies the exclusion restriction by capturing exogenous variation arising from structural and institutional factors rather than individual caregiving attitudes, family culture, or local norms. It reflects sectoral practices and regional labour-market conditions that determine workplace FWA availability, influencing individual adoption likelihood without directly affecting either the degree of autonomy employees experience (shaped by firm-specific practices) or their caregiving behaviour (driven by caregiving needs).

Nonetheless, these assumptions cannot be verified empirically. The exclusion restriction could be violated if the instrument directly affects autonomy or caregiving. The conditional independence assumption could be violated if FWAs influence care provision through mechanisms beyond autonomy (e.g., reduced commute time, or selection on care needs). The results should be interpreted as identifying effects through the autonomy pathway specifically.

Table 2.6 reports the marginal effects of the causal mediation analysis FWAs after controlling for the effect of the mediator. The results reveal that *Autonomy Over Work Hours* exerts mediating effect on informal care provision. The estimate shows that having more freedom increases the probability of providing care by 4.2 percentage points, which explains 145% of the total effect of FWAs on care. The statistically significant mediating effects indicates that there is casual evidence for time freedom affecting the ability to provide care through the use of FWAs. They verify the earlier conclusion that individuals with access to FWAs are more likely to provide care due to having more time freedom and feeling less time-squeezed with work and non-work-related activities.

Overall, the findings show autonomy over work hours (as a proxy for time freedom) is an important channel through which FWAs affects informal care provision. They underscore the importance of promoting FWAs to support individuals in managing their caregiving responsibilities effectively. These findings are in line with prior literature, which established that more time availability or feeling less stressed from work (work-life balance) was positively associated with informal caregiving (Angst et al., 2019; Fredriksen-Goldsen & Scharlach, 2006).

Table 2.6
Causal Mediation Analysis: The Effect of FWAs on Informal Care Provision through Autonomy Over Work Hours

Mediating variable	**Autonomy Over Work Hours**
Mediator (M)	0.078*
	[0.044]
Direct Effect (DE)	-0.013
	[0.044]
β_{FWAs} (est. in *Table 2.5b*)	0.532***
Indirect Effect (IE)	0.042
Total Effect (TE) (est. in *Table 2.2b*)	0.029
Mediation Effect	1.45

Notes: The M represents the second-stage estimates from the mediation model; it is the causal effect of the mediating variable on informal care (see *Table 2.A12* for full results). The DE represents the direct effect of FWAs on informal care obtained from *Table 2.A12*. β_{FWAs} represents the effect of FWAs on the mediating variables obtained from *Table 2.5b*. The IE represents the effect of the mediating outcome caused by FWAs on informal care (IE = TE – DE), which can be also calculated as the product of M and β_{FWAs}. Standard errors are clustered at the individual level in brackets. * p<0.10, ** p<0.05, *** p<0.01.

2.6 Conclusion

Demand for informal care has consistently increased in recent years, largely due to the increasing number and proportion of older people living longer lives, increasing healthcare costs and the expenses of formal care. This, in turn, is leading to significant long-term care policy and systems reforms in many countries. While informal care is highly effective at reducing the macroeconomic costs of care, it has been hampered by other state policies increasing the retirement age, and limited scope for people to undertake informal caring responsibilities while performing their normal professional employment roles. Put simply, there has been an increase in the number of workers juggling between employment and caring demands. FWAs have been suggested as an appropriate tool to address the challenges of combining care and employment activities. Due to the vital role of informal care in fulfilling the caring demands in society, this study has examined the informal care provision in the context of FWAs.

This examination of the relationship between FWAs and informal care provision used panel data from the UKHLS, also known as "Understanding Society" (University of Essex, Institute for Social and Economic Research et al., 2022). The central question was whether informal care provision increases with more FWAs amongst workforce participants, thereby providing robust causal empirical evidence to support the use of FWAs to facilitate such care services. Addressing this question, however, requires considering the potential endogeneity issues like unobserved heterogeneity and reverse causality that may influence individual intention to provide informal care. For instance, individuals with parents with caring needs might decide to use FWAs only to be able to provide care for their parents. Additionally, such outcomes are affected by general attitudes and individual preferences, personality traits, normative beliefs, and perceived barriers that influence the decision of caregiving. To consistently address such concerns, and other potential sources of bias that may lead to misleading conclusions, this study made use of both fixed effects and IV strategy.

The findings show that, when controlling for other factors and sources of potential bias, employees having access to FWAs were significantly more likely (by at approximately 20-32% on average) to provide informal care. Informal caregiving tends to vary significantly with the intensity of care as measured by self-reported care hours. Higher intensity of care tends to reflect greater commitment and responsibility, which potentially lower substitutability between care and work than for low intensity care (He & McHenry, 2016). The findings indicate that FWAs is more beneficial for intensive carers with minimal effect for low intensity carers. Mediation analysis showed that time freedom exerts mediating effects on informal caregiving. Putting the results in perspective, the findings appear to suggest that having access to FWAs provides an opportunity for employees to find a better balance between employment and caring responsibility through the ability to have more freedom of time. This in turn leads to greater motivation to provide informal care to adult dependents. These findings are robust and consistent across various model specifications and sensitivity tests.

Furthermore, the findings also show that there are no statistically significant differences by gender or occupation type, while family composition shows a statistically significant heterogeneous effect. These findings reflect that FWAs are effective in facilitating informal care provision and balance between work and caring responsibilities regardless of gender and occupational type. However, the effect differs by family composition, with childless individuals showing substantially larger effects than those with children. This indicates that FWAs effectiveness depends on existing care commitments such as childcare and household management.

While the findings offer robust causal evidence, it is essential to clarify the interpretation of the estimated parameter. The IV estimates identify a LATE, reflecting the average causal effect among compliers, that is, those employees whose likelihood of adopting FWAs is influenced by exogenous variation in industry and regional prevalence. Therefore, the estimated effects should be interpreted as local effects rather than representing population wide average treatment effects. From a policy standpoint, this implies that interventions aimed at expanding FWAs are likely to be most effective for workers in comparable institutional contexts, specifically for those whose access to or uptake of flexible working is responsive to industry and regional conditions. As a result, the findings should not be generalised to all individuals but rather understood as providing policy relevant evidence for those groups whose adoption decisions are influenced by exogenous industry and regional variation in FWA prevalence.

In terms of policy implications, this study is timely against the background on the recent increase in demand for informal care, leading to policy reforms in long-term care policy and systems in many countries. Specifically, the findings provide evidence supporting the context in which current policy reforms such as greater FWAs are used as a tool to enhance the provision of informal care for workforce participants. The findings provide a more precise understanding of how FWAs might affect informal care provision. The relationship between FWAs and informal care provision is much more evident. For carers, the findings highlight the beneficial consequences of using FWAs, suggesting that carers can be optimistic about the outcomes of taking on future caring responsibilities when combining care and employment.

Additionally, the findings can reassure managers and employers who currently have the right to refuse a FWAs request for an employee that granting them this privilege is effective and beneficial for participating in a caring role in society, which might encourage employers to adopt all FWAs requests, especially for primary carers, as ways to promote and showcase the corporate social responsibility of the organisation. Therefore, workplace policies should reduce barriers to requesting FWAs as they effectively assist carers to meet the higher demands for informal care. Policies should further strengthen and protect the rights of requesting FWAs. Targeted measures should carefully consider the intensity of care provided and the significant impact it has on high intensity carers as highlighted in the findings. Governments may encourage companies to adopt such measures by offering tax incentives for those that implement caregiving friendly practices.

Overall, this study makes important contributions to the emerging literature on the relationship between FWAs and informal care provision and offers policymakers a better understanding of the role of FWAs. The study provides robust and consistent evidence of the influences on the supply of informal care provision in the context of FWAs. The empirical modelling and analysis of data employed rigorous approaches and statistical tests to ensure consistent and robust estimates. This analysis took into account potential sources of endogeneity bias associated with unobserved heterogeneity and reverse causality. Also, the analysis extended the understanding of how the findings might vary by intensity of care as well as other social and work dimensions aspects.

Further research should examine the effect of different forms of FWAs measures. A disaggregated measure of FWAs would provide a better understanding of which exact measure or policy is more or less effective. Limited information regarding care receivers prevented this study from identifying and including care receivers' socioeconomic characteristics. Further work should utilise more detailed data on care receivers, and should include additional considerations, such as the duration of care, which could provide greater insight into the supply and demand of care. Such research would be more likely to reflect the complex relationships of modern care. These involve multiple determinants in various contexts that are instrumental in care, which were beyond the scope of the present study.

Also, analysing a more precise and detailed caring hours measure will aid an understanding of the effect of different care intensities. Lastly, future work may explore further potential mechanisms that drives the mediating effect of FWAs on informal care. This could provide an in depth understanding of what factors help to drive the relationship between FWAs and informal care.

Appendix 2.A

Appendix 2.A provides the complete set of regression results and robustness checks supporting the empirical analysis in this study. The tables present the full estimation results for the baseline, fixed-effects, and instrumental variable specifications discussed in the main text, along with alternative definitions of the dependent variable and models including extended control variables. These supplementary tables complement the main findings, confirming the robustness and consistency of the estimated effects across alternative model specifications and variable definitions.

Table 2.A1
Annual Mean and Standard Deviation of the Instrument (Share of Flexible Workers by SIC × Region)

Year	Mean	Standard deviation
2010	0.182	0.157
2011	0.166	0.150
2012	0.183	0.162
2013	0.160	0.159
2014	0.188	0.185
2015	0.186	0.176
2016	0.175	0.164
2017	0.168	0.167
2018	0.188	0.176
2019	0.199	0.184
2020	0.239	0.198
2021	0.267	0.233
2022	0.251	0.374

Notes: Values represent the annual mean and standard deviation of the proportion of individuals using flexible working arrangements (FWAs) within each SIC × regional cell.

Table 2.A2
Robustness of Main Results Using the FE-2SLS Estimation Sample

Outcome Variable	(1) Pooled		(2) Fixed Effects
		Informal Care	
Panel A: LPM-2SLS (Second Stage)			
FWAs	0.027***		0.018*
	[0.009]		[0.010]
Observations		82,324	
Outcome Mean		0.091	
First Stage Diagnostics			
Instrument (SIC-Region FWAs rate)	0.943***		0.793***
	[0.006]		[0.011]
Kleibergen–Paap F-stat	8323		5099
Partial R-squared	0.172		0.100
Endogeneity Test	4.5**		0.65
Panel B: IV-Probit / CRE IV-Probit (Second Stage)			
FWAs	0.026***		0.022***
	[0.009]		[0.007]
Observations		82,324	
Outcome Mean		0.091	
First Stage Diagnostics			
Instrument (SIC-Region FWAs rate)	0.943***		0.790***
	[0.006]		[0.011]
Kleibergen–Paap F-stat	8323		4633
Partial R-squared	0.172		0.232
Endogeneity Test	4.5**		3.6*

Notes: All estimations include the full set of control variables listed in *Table 2.1*, as well as time and region fixed effects. In Panel B, column (1) reports pooled IV-Probit estimates, while column (2) reports CRE IV-Probit estimates with correlated random effects (Mundlak specification). Robust standard errors clustered at the regional and employees' Standard Industrial Classification (SIC) levels in brackets. * p<0.10, **p<0.05, ***p<0.01.

Table 2.A3
The Effect of FWAs on Informal Care Provision: Logit and Linear Probability Model Estimates

Outcome Variables	(1) Logit	(2) LPM
	Informal Care	**Informal Care**
FWAs	0.015***	0.015***
	[0.003]	[0.004]
Age (ref: 16-19 years old)		
20-29	0.002	0.007
	[0.005]	[0.005]
30-39	0.024***	0.028***
	[0.005]	[0.006]
40-49	0.063***	0.066***
	[0.005]	[0.006]
50-59	0.105***	0.112***
	[0.006]	[0.006]
60-69	0.068***	0.071***
	[0.006]	[0.007]
70+	-0.021***	-0.023***
	[0.007]	[0.008]
Male	-0.043***	-0.042***
	[0.003]	[0.003]
Marital status (ref: Married)		
Cohabiting	-0.010***	-0.012***
	[0.004]	[0.004]
Widowed/divorced/separated	-0.017***	-0.021***
	[0.004]	[0.005]
Single/never married	-0.018***	-0.019***
	[0.004]	[0.004]
No. children	-0.010***	-0.010***
	[0.002]	[0.001]
Education (ref: No education)		
Degree or higher	0.010***	0.011***
	[0.004]	[0.004]
School diploma	0.025***	0.024***
	[0.006]	[0.005]
GCSE and below	0.025***	0.026***
	[0.004]	[0.005]
Other	0.002	0.002
	[0.004]	[0.005]
Working hrs.	-0.013***	-0.015***
	[0.003]	[0.003]
Occupation (ref: professional occupation)		
Managerial & technical	0.007	0.007
	[0.005]	[0.005]
Skilled non-manual	0.010*	0.012**
	[0.006]	[0.006]
Skilled manual	0.017***	0.015**
	[0.007]	[0.006]
Partly skilled	0.005	0.005
	[0.006]	[0.006]
Unskilled	-0.008	-0.007
	[0.008]	[0.007]
Homeownership	0.011***	0.010***
	[0.003]	[0.003]
Region (ref: North East)		
North West	-0.030***	-0.031***
	[0.009]	[0.009]
Yorkshire and the Humber	-0.030***	-0.031***
	[0.009]	[0.009]
East Midlands	-0.014	-0.014
	[0.009]	[0.009]

Table 2.A3
The Effect of FWAs on Informal Care Provision: Logit and Linear Probability Model Estimates

Outcome Variables	(1) Logit	(2) LPM
	Informal Care	**Informal Care**
West Midlands	-0.01	-0.01
	[0.009]	[0.009]
East of England	-0.024***	-0.024***
	[0.009]	[0.009]
London	-0.049***	-0.048***
	[0.008]	[0.008]
South East	-0.037***	-0.038***
	[0.008]	[0.009]
South West	-0.027***	-0.027***
	[0.009]	[0.009]
Wales	-0.013	-0.014
	[0.009]	[0.010]
Scotland	-0.01	-0.011
	[0.009]	[0.009]
Northern Ireland	0.008	0.007
	[0.010]	[0.010]
Year (ref: 2010)		
2011	0.003	0.003
	[0.004]	[0.004]
2012	0	0
	[0.003]	[0.003]
2013	-0.007*	-0.007*
	[0.004]	[0.004]
2014	0.005	0.004
	[0.005]	[0.004]
2015	0.006	0.006
	[0.005]	[0.005]
2016	-0.003	-0.003
	[0.004]	[0.004]
2017	-0.011***	-0.011***
	[0.004]	[0.004]
2018	-0.013***	-0.014***
	[0.004]	[0.004]
2019	-0.009**	-0.009**
	[0.005]	[0.005]
2020	-0.011***	-0.012***
	[0.004]	[0.004]
2021	-0.021***	-0.022***
	[0.005]	[0.005]
2022	-0.02	-0.021
	[0.019]	[0.019]
_cons		0.115***
		[0.015]
No. Obs.	95,295	95,295

Notes: Robust standard errors are clustered at individual level in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 2.A4
The Effect of FWAs on Informal Care Provision: Fixed Effects and Correlated Random Effects Estimates

Outcome Variables	(1) FE-LPM	(2) FE-Logit	(3) CRE-Probit
	Informal Care	**Informal Care**	**Informal Care**
FWAs	0.011***	0.207***	0.010***
	[0.003]	[0.057]	[0.003]
Age (ref: 16-19 years old)			
20-29	-0.014*	-0.399	-0.012
	[0.008]	[0.293]	[0.009]
30-39	-0.013	-0.285	-0.001
	[0.010]	[0.329]	[0.010]
40-49	-0.008	-0.133	0.018
	[0.011]	[0.353]	[0.012]
50-59	0.003	-0.03	0.034**
	[0.014]	[0.374]	[0.014]
60-69	-0.028*	-0.484	-0.016
	[0.016]	[0.402]	[0.015]
70+	-0.076***	-2.393***	-0.075***
	[0.023]	[0.724]	[0.013]
Marital status (ref: Married)			
Cohabiting	-0.003	-0.045	-0.008*
	[0.005]	[0.106]	[0.005]
Widowed/divorced/separated	-0.019**	-0.311**	-0.015***
	[0.007]	[0.127]	[0.006]
Single/never married	-0.01	-0.271*	-0.013*
	[0.006]	[0.151]	[0.007]
No. children	-0.004*	-0.051	-0.002
	[0.002]	[0.040]	[0.002]
Education (ref: No education)			
Degree or higher	0.002	0.068	0.009**
	[0.013]	[0.263]	[0.004]
School diploma	-0.001	0.014	0.021***
	[0.020]	[0.355]	[0.006]
GCSE and below	-0.01	-0.095	0.019***
	[0.020]	[0.334]	[0.007]
Other	-0.003	-0.059	-0.006
	[0.008]	[0.144]	[0.007]
Working hrs.	-0.008*	-0.144**	-0.009***
	[0.004]	[0.063]	[0.003]
Occupation (ref: professional occupation)			
Managerial & technical	0.002	0.057	0.007
	[0.008]	[0.181]	[0.006]
Skilled non-manual	0.004	0.091	0.011*
	[0.009]	[0.193]	[0.007]
Skilled manual	0.018*	0.368*	0.018**
	[0.010]	[0.210]	[0.008]
Partly skilled	0.005	0.119	0.007
	[0.010]	[0.202]	[0.009]
Unskilled	-0.011	-0.228	-0.007
	[0.013]	[0.263]	[0.011]
Homeownership	-0.010**	-0.231**	-0.015**
	[0.005]	[0.112]	[0.007]
Region (ref: North East)			
North West	-0.073*	-1.849**	-0.034***
	[0.039]	[0.922]	[0.011]
Yorkshire and the Humber	-0.044	-0.641	-0.034***
	[0.034]	[0.934]	[0.012]
East Midlands	-0.024	0.095	-0.02
	[0.036]	[0.994]	[0.014]
West Midlands	-0.031	0.061	-0.017
	[0.035]	[1.145]	[0.016]

Table 2.A4
The Effect of FWAs on Informal Care Provision: Fixed Effects and Correlated Random Effects Estimates

Outcome Variables	(1) FE-LPM	(2) FE-Logit	(3) CRE-Probit
	Informal Care	**Informal Care**	**Informal Care**
East of England	-0.045	-0.867	-0.033*
	[0.035]	[0.970]	[0.018]
London	-0.039	-0.619	-0.058***
	[0.035]	[0.943]	[0.020]
South East	-0.061*	-1.39	-0.048**
	[0.035]	[0.947]	[0.021]
South West	-0.054	-1.218	-0.040*
	[0.037]	[0.988]	[0.024]
Wales	-0.033	-0.654	-0.026
	[0.039]	[1.136]	[0.027]
Scotland	-0.037	-0.677	-0.027
	[0.037]	[1.253]	[0.029]
Northern Ireland	-0.05	-1.394	-0.011
	[0.058]	[1.577]	[0.034]
Year (ref: 2010)			
2011	0.015**	0.280**	0.005
	[0.006]	[0.110]	[0.004]
2012	0.007**	0.108*	0.005*
	[0.003]	[0.064]	[0.003]
2013	0.014**	0.234**	0.001
	[0.006]	[0.112]	[0.004]
2014	0.018***	0.291***	0.015***
	[0.005]	[0.086]	[0.005]
2015	0.031***	0.569***	0.020***
	[0.006]	[0.113]	[0.005]
2016	0.013***	0.222***	0.014***
	[0.005]	[0.079]	[0.004]
2017	0.020***	0.372***	0.008
	[0.006]	[0.119]	[0.005]
2018	0.013**	0.208**	0.008*
	[0.005]	[0.089]	[0.005]
2019	0.026***	0.467***	0.017***
	[0.007]	[0.127]	[0.006]
2020	0.019***	0.342***	0.017***
	[0.006]	[0.099]	[0.005]
2021	0.022***	0.409***	0.009
	[0.008]	[0.139]	[0.006]
2022	0.025	0.518	0.011
	[0.023]	[0.425]	[0.023]
_cons	0.168***		
	[0.038]		
No. Obs.	95,295	16,134	95,295
Hausman test (p-value)	0.000		
LM test (p-value)	0.000		

Notes: In Column 2 the estimated coefficient from the conditional logit model with FE are shown. Column 3 individual-specific time averages of all time-varying covariates are included as additional controls. Robust standard errors are clustered at individual level in brackets. * p<0.10, ** p<0.05, *** p<0.01.

Table 2.A5
The Effect of FWAs on Informal Care Provision: Average Elasticities and Odds Ratio

Outcome Variables	(1) FE-logit **Informal Care**	(2) Odds Ratio **Informal Care**
FWA	0.126***	1.230***
	[0.036]	
Age (ref: 16-19 years old)		
20-29	-0.243	0.671
	[0.182]	[0.197]
30-39	-0.173	0.752
	[0.206]	[0.248]
40-49	-0.081	0.876
	[0.220]	[0.309]
50-59	-0.018	0.97
	[0.232]	[0.363]
60-69	-0.295	0.616
	[0.248]	[0.248]
70+	-1.458***	0.091***
	[0.451]	[0.066]
Marital Status (ref: Married)		
Cohabiting	-0.027	0.956
	[0.069]	[0.101]
Widowed/divorced/separated	-0.189**	0.733**
	[0.083]	[0.093]
Single/never married	-0.165*	0.762*
	[0.096]	[0.115]
No. children	-0.031	0.95
	[0.027]	[0.038]
Education (ref: No education)		
Degree or higher	0.042	1.071
	[0.158]	[0.281]
School diploma	0.008	1.014
	[0.239]	[0.360]
GCSE and below	-0.058	0.909
	[0.216]	[0.304]
Other	-0.036	0.943
	[0.093]	[0.136]
Working hrs.	-0.088**	0.865**
	[0.041]	[0.055]
Occupation (ref: professional occupation)		
Managerial & technical	0.035	1.059
	[0.115]	[0.191]
Skilled non-manual	0.055	1.095
	[0.123]	[0.212]
Skilled manual	0.224*	1.444*
	[0.135]	[0.304]
Partly skilled	0.073	1.127
	[0.129]	[0.228]
Unskilled	-0.139	0.796
	[0.171]	[0.210]
Homeownership	-0.141**	0.794**
	[0.072]	[0.089]
Region (ref: North East)		
North West	-1.127**	0.157**
	[0.531]	[0.145]
Yorkshire and the Humber	-0.391	0.527
	[0.576]	[0.492]
East Midlands	0.058	1.1
	[0.629]	[1.093]

Table 2.A5
The Effect of FWAs on Informal Care Provision: Average Elasticities and Odds Ratio

Outcome Variables	(1) FE-logit **Informal Care**	(2) Odds Ratio **Informal Care**
West Midlands	0.037	1.063
	[0.795]	[1.218]
East of England	-0.528	0.42
	[0.634]	[0.407]
London	-0.377	0.538
	[0.588]	[0.508]
South East	-0.847	0.249
	[0.599]	[0.236]
South West	-0.742	0.296
	[0.638]	[0.292]
Wales	-0.399	0.52
	[0.707]	[0.591]
Scotland	-0.412	0.508
	[0.705]	[0.637]
Northern Ireland	-0.849	0.248
	[1.062]	[0.391]
Year (ref: 2010)		
2011	0.170**	1.323**
	[0.069]	[0.145]
2012	0.066*	1.114*
	[0.037]	[0.072]
2013	0.143**	1.264**
	[0.069]	[0.141]
2014	0.177***	1.338***
	[0.053]	[0.114]
2015	0.347***	1.767***
	[0.070]	[0.200]
2016	0.135***	1.249***
	[0.050]	[0.098]
2017	0.226***	1.450***
	[0.074]	[0.173]
2018	0.127**	1.231**
	[0.057]	[0.109]
2019	0.285***	1.596***
	[0.080]	[0.202]
2020	0.208***	1.408***
	[0.065]	[0.139]
2021	0.249***	1.506***
	[0.090]	[0.209]
2022	0.315	1.678
	[0.292]	[0.714]
No. Obs.	16,134	16,134

Notes: Robust standard errors in brackets. * p<0.10, ** p<0.05, *** p<0.01.

Table 2.A6
The Effect of FWAs on Informal Care Provision: Instrumental Variable Estimates

Outcome Variables	(1) Pooled-LPM-2SLS	(2) FE-LPM-2SLS	(3) IV-Probit	(4) CRE IV-Probit
	Informal Care	**Informal Care**	**Informal Care**	**Informal care**
FWAs	0.029***	0.018*	0.028***	0.023**
	[0.008]	[0.010]	[0.008]	[0.009]
Age (ref: 16-19 years old)				
20-29	0.007	-0.014*	0.003	-0.013
	[0.005]	[0.008]	[0.005]	[0.009]
30-39	0.027***	-0.013	0.024***	-0.002
	[0.006]	[0.009]	[0.005]	[0.011]
40-49	0.065***	-0.008	0.062***	0.017
	[0.006]	[0.011]	[0.006]	[0.012]
50-59	0.111***	0.002	0.106***	0.033**
	[0.007]	[0.013]	[0.006]	[0.014]
60-69	0.070***	-0.028*	0.068***	-0.016
	[0.007]	[0.016]	[0.006]	[0.015]
70+	-0.023***	-0.076***	-0.021***	-0.076***
	[0.008]	[0.023]	[0.007]	[0.013]
Male	-0.042***	-	-0.042***	-0.042***
	[0.003]	-	[0.003]	[0.003]
Marital status (ref: Married)				
Cohabiting	-0.012***	-0.003	-0.010**	-0.008
	[0.004]	[0.005]	[0.004]	[0.005]
Widowed/divorced/separated	-0.021***	-0.019***	-0.017***	-0.015**
	[0.006]	[0.007]	[0.004]	[0.006]
Single/never married	-0.019***	-0.01	-0.017***	-0.013*
	[0.003]	[0.006]	[0.004]	[0.007]
No. children	-0.010***	-0.004*	-0.009***	0.009**
	[0.001]	[0.002]	[0.001]	[0.004]
Education (ref: No education)				
Degree or higher	0.011**	0.002	0.010**	0.009**
	[0.004]	[0.013]	[0.004]	[0.004]
School diploma	0.024***	-0.001	0.025***	0.021***
	[0.005]	[0.019]	[0.005]	[0.006]
GCSE and below	0.027***	-0.01	0.026***	0.019**
	[0.004]	[0.020]	[0.004]	[0.008]
Other	0.002	-0.003	0.003	-0.006
	[0.005]	[0.008]	[0.004]	[0.009]
Working hrs.	-0.015***	-0.008**	-0.014***	-0.009**
	[0.003]	[0.004]	[0.002]	[0.004]
Occupation (ref: professional occupation)				
Managerial & technical	0.008	0.003	0.007	0.007
	[0.005]	[0.008]	[0.005]	[0.005]
Skilled non-manual	0.014**	0.004	0.012**	0.012*
	[0.005]	[0.008]	[0.006]	[0.007]
Skilled manual	0.018***	0.018*	0.020***	0.020**
	[0.006]	[0.010]	[0.007]	[0.009]
Partly skilled	0.008	0.005	0.009	0.009
	[0.006]	[0.009]	[0.006]	[0.010]
Unskilled	-0.004	-0.011	-0.005	-0.005
	[0.007]	[0.013]	[0.007]	[0.011]
Homeownership	0.009***	-0.010**	0.010***	-0.015**
	[0.002]	[0.005]	[0.003]	[0.007]
Region (ref: North East)				
North West	-0.031***	-0.074*	-0.030***	-0.034***
	[0.011]	[0.041]	[0.010]	[0.013]
Yorkshire and the Humber	-0.030***	-0.044	-0.030***	-0.034***
	[0.010]	[0.036]	[0.010]	[0.013]
East Midlands	-0.014	-0.025	-0.014	-0.02
	[0.010]	[0.038]	[0.010]	[0.015]

Table 2.A6
The Effect of FWAs on Informal Care Provision: Instrumental Variable Estimates

Outcome Variables	(1) Pooled-LPM-2SLS	(2) FE-LPM-2SLS	(3) IV-Probit	(4) CRE IV-Probit
	Informal Care	**Informal Care**	**Informal Care**	**Informal care**
West Midlands	-0.01	-0.031	-0.009	-0.016
	[0.011]	[0.036]	[0.011]	[0.018]
East of England	-0.024**	-0.045	-0.024**	-0.033*
	[0.011]	[0.038]	[0.010]	[0.019]
London	-0.048***	-0.039	-0.048***	-0.058***
	[0.010]	[0.037]	[0.009]	[0.021]
South East	-0.038***	-0.061*	-0.037***	-0.048**
	[0.010]	[0.037]	[0.009]	[0.024]
South West	-0.027***	-0.055	-0.027***	-0.04
	[0.010]	[0.039]	[0.009]	[0.026]
Wales	-0.014	-0.074*	-0.012	-0.026
	[0.010]	[0.041]	[0.010]	[0.029]
Scotland	-0.011	-0.044	-0.01	-0.027
	[0.011]	[0.036]	[0.010]	[0.032]
Northern Ireland	0.007	-0.025	0.009	-0.01
	[0.011]	[0.038]	[0.011]	[0.037]
Year (ref: 2010)				
2011	0.003	-0.034	0.002	0.005
	[0.004]	[0.041]	[0.004]	[0.004]
2012	0	-0.037	-0.001	0.005*
	[0.003]	[0.037]	[0.003]	[0.003]
2013	-0.007	-0.049	-0.008*	0.001
	[0.004]	[0.061]	[0.005]	[0.004]
2014	0.004	0.015**	0.004	0.015***
	[0.004]	[0.006]	[0.004]	[0.005]
2015	0.006	0.007*	0.005	0.020***
	[0.005]	[0.004]	[0.005]	[0.005]
2016	-0.003	0.014**	-0.003	0.014***
	[0.004]	[0.006]	[0.004]	[0.005]
2017	-0.011**	0.018***	-0.012**	0.008
	[0.005]	[0.005]	[0.005]	[0.005]
2018	-0.014***	0.031***	-0.014***	0.008*
	[0.004]	[0.006]	[0.004]	[0.005]
2019	-0.010**	0.013***	-0.010**	0.016***
	[0.005]	[0.004]	[0.005]	[0.006]
2020	-0.013***	0.021***	-0.012***	0.016***
	[0.004]	[0.006]	[0.004]	[0.006]
2021	-0.023***	0.013**	-0.022***	0.008
	[0.005]	[0.005]	[0.005]	[0.007]
2022	-0.022	0.026***	-0.023	0.01
	[0.019]	[0.007]	[0.019]	[0.022]
_cons	0.113***			
	[0.016]			
No. Obs.	95,295	82,324	95,295	95,295

Notes: Column 4 individual-specific time averages of all time-varying covariates are included as additional controls. Robust standard errors are clustered at regional and employees' Standard Industrial Classification (SIC) levels in brackets. Time-invariant variables are omitted from the FE model. * p<0.10, ** p<0.05, *** p<0.01.

Table 2.A7.1
The Effect of FWAs on Informal Care Provision using an Alternative Measure: Instrumental Variable Models

Outcome Variable	(1) Pooled	(2) Fixed Effects
	Informal Care	
Panel A: LPM-2SLS (Second Stage)		
FWAs	0.029***	0.019*
	[0.008]	[0.010]
Observations	95,283	82,316
Outcome Mean	0.089	0.091
First Stage Diagnostics		
Instrument (SIC-Region FWAs rate)	0.928***	0.793***
	[0.005]	[0.011]
Kleibergen–Paap F-stat	9746	5095
Partial R-squared	0.167	0.100
Endogeneity Test	6.6***	0.73
Panel B: IV-Probit / CRE IV-Probit (Second Stage)		
FWAs	0.028***	0.023***
	[0.008]	[0.009]
Observations	95,283	
Outcome Mean	0.089	
First Stage Diagnostics		
Instrument (SIC-Region FWAs rate)	0.928***	0.791***
	[0.005]	[0.011]
Kleibergen–Paap F-stat	9746	4690
Partial R-squared	0.167	0.166
Endogeneity Test	6.6***	5.8***

Notes: All estimations include the full set of control variables listed in *Table 2.1*, as well as time and region fixed effects. The outcome mean differs in Panel A due to exclusion of non-varying individuals in the FE-LPM-2SLS model. In Panel B, column (1) reports pooled IV-Probit estimates, while column (2) reports CRE IV-Probit estimates with correlated random effects (Mundlak specification). Robust standard errors clustered at the regional and employees' Standard Industrial Classification (SIC) levels in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 2.A7.2
The Effect of FWAs on Informal Care Provision with Extended Controls: Instrumental Variable Models

Outcome Variable	(1) Pooled	(2) Fixed Effects
	Informal Care	
Panel A: LPM-2SLS (Second Stage)		
FWAs	0.029***	0.018*
	[0.008]	[0.010]
Observations	89,693	77,272
Outcome Mean	0.090	0.092
First Stage Diagnostics		
Instrument (SIC-Region FWAs rate)	0.931***	0.798***
	[0.005]	[0.011]
Kleibergen–Paap F-stat	9382	4876
Partial R-squared	0.169	0.101
Endogeneity Test	6.8***	0.72
Panel B: IV-Probit / CRE IV-Probit (Second Stage)		
FWAs	0.028***	0.022**
	[0.009]	[0.009]
Observations	89,693	
Outcome Mean	0.090	
First Stage Diagnostics		
Instrument (SIC-Region FWAs rate)	0.931***	0.975***
	[0.005]	[0.012]
Kleibergen–Paap F-stat	9382	4727
Partial R-squared	0.169	0.167
Endogeneity Test	6.8***	5.3***

Notes: All estimations include the full set of control variables listed in *Table 2.1*, as well as time and region fixed effects and health and income as additional controls. The outcome mean differs in Panel A due to exclusion of non-varying individuals in the FE-LPM-2SLS model. In Panel B, column (1) reports pooled IV-Probit estimates, while column (2) reports CRE IV-Probit estimates with correlated random effects (Mundlak specification). Robust standard errors clustered at the regional and employees' Standard Industrial Classification (SIC) levels in brackets. * p<0.10, ** p<0.05, *** p<0.01.

Table 2.A8
The Effects of FWAs on the Intensity of Care: Instrumental Variable Ordered Probit Estimates

	(1)	(2)	(3)
Outcome Variables	**Weekly Hours Spent**	**Weekly Hours Spent**	**Weekly Hours Spent**
	0	**<20**	**>20**
FWAs	-0.027***	0.024***	0.003***
	[0.008]	[0.007]	[0.001]
Age (ref: 16-19 years old)			
20-29	-0.004	0.004	0
	[0.005]	[0.004]	[0.000]
30-39	-0.026***	0.024***	0.002***
	[0.005]	[0.005]	[0.000]
40-49	-0.064***	0.058***	0.006***
	[0.005]	[0.005]	[0.001]
50-59	-0.106***	0.094***	0.012***
	[0.005]	[0.005]	[0.001]
60-69	-0.070***	0.063***	0.007***
	[0.006]	[0.006]	[0.001]
70+	0.019***	-0.018***	-0.001***
	[0.007]	[0.007]	[0.000]
Male	0.042***	-0.037***	-0.005***
	[0.003]	[0.002]	[0.000]
Marital status (ref: Married)			
Cohabiting	0.009**	-0.008**	-0.001**
	[0.004]	[0.003]	[0.000]
Widowed/divorced/separated	0.014***	-0.013***	-0.002***
	[0.004]	[0.004]	[0.001]
Single/never married	0.015***	-0.013***	-0.002***
	[0.004]	[0.003]	[0.000]
No. children	0.009***	-0.008***	-0.001***
	[0.001]	[0.001]	[0.000]
Education (ref: No education)			
Degree or higher	-0.010**	0.009**	0.001**
	[0.004]	[0.003]	[0.000]
School diploma	-0.025***	0.022***	0.003***
	[0.005]	[0.004]	[0.001]
GCSE and below	-0.026***	0.023***	0.003***
	[0.004]	[0.004]	[0.001]
Other	-0.003	0.003	0
	[0.004]	[0.004]	[0.000]
Working hrs.	0.016***	-0.014***	-0.002***
	[0.002]	[0.002]	[0.000]
Occupation (ref: professional occupation)			
Managerial & technical	-0.008*	0.007*	0.001*
	[0.005]	[0.004]	[0.001]
Skilled non-manual	-0.014**	0.012**	0.002**
	[0.005]	[0.005]	[0.001]
Skilled manual	-0.020***	0.017***	0.002***
	[0.006]	[0.005]	[0.001]
Partly skilled	-0.011*	0.010*	0.001*
	[0.006]	[0.005]	[0.001]
Unskilled	0.005	-0.004	-0.001
	[0.007]	[0.006]	[0.001]
Homeownership	-0.008***	0.007***	0.001***
	[0.003]	[0.003]	[0.000]
Region (ref: North East)			
North West	0.029***	-0.025***	-0.004***
	[0.010]	[0.009]	[0.001]

Table 2.A8
The Effects of FWAs on the Intensity of Care: Instrumental Variable Ordered Probit Estimates

	(1)	(2)	(3)
Outcome Variables	**Weekly Hours Spent**	**Weekly Hours Spent**	**Weekly Hours Spent**
	0	**<20**	**>20**
Yorkshire and the Humber	0.028***	-0.024***	-0.004***
	[0.010]	[0.008]	[0.001]
East Midlands	0.015	-0.013	-0.002
	[0.009]	[0.008]	[0.001]
West Midlands	0.009	-0.008	-0.001
	[0.010]	[0.009]	[0.001]
East of England	0.025***	-0.022***	-0.003**
	[0.010]	[0.008]	[0.001]
London	0.049***	-0.043***	-0.006***
	[0.009]	[0.008]	[0.001]
South East	0.036***	-0.032***	-0.005***
	[0.009]	[0.008]	[0.001]
South West	0.026***	-0.023***	-0.003***
	[0.009]	[0.008]	[0.001]
Wales	0.011	-0.009	-0.001
	[0.010]	[0.008]	[0.001]
Scotland	0.011	-0.009	-0.001
	[0.010]	[0.008]	[0.001]
Northern Ireland	-0.012	0.011	0.002
	[0.011]	[0.009]	[0.002]
Year (ref: 2010)			
2011	-0.002	0.002	0
	[0.004]	[0.003]	[0.001]
2012	0	0	0
	[0.003]	[0.003]	[0.000]
2013	0.007	-0.006	-0.001
	[0.004]	[0.004]	[0.001]
2014	-0.003	0.003	0
	[0.004]	[0.004]	[0.001]
2015	-0.004	0.003	0.001
	[0.005]	[0.004]	[0.001]
2016	0.003	-0.002	0
	[0.004]	[0.003]	[0.001]
2017	0.013***	-0.011***	-0.002***
	[0.005]	[0.004]	[0.001]
2018	0.014***	-0.012***	-0.002***
	[0.004]	[0.003]	[0.000]
2019	0.011**	-0.009**	-0.001**
	[0.005]	[0.004]	[0.001]
2020	0.012***	-0.010***	-0.001***
	[0.004]	[0.004]	[0.000]
2021	0.022***	-0.019***	-0.003***
	[0.005]	[0.004]	[0.001]
2022	0.021	-0.019	-0.003
	[0.019]	[0.016]	[0.002]
Predicted probability	0.9087	0.0839	0.0074
No. Obs.	95,333	95,333	95,333

Notes: Robust standard errors are clustered at regional and employees' Standard Industrial Classification (SIC) levels in brackets. * p<0.10, ** p<0.05, *** p<0.01.

Table 2.A9
The Effect of FWAs on Autonomy Over Work Hours: Logit and Linear Probability Model Estimates

Outcome Variables	(1) Logit	(2) LPM
	Autonomy Over Work Hours	**Autonomy Over Work Hours**
FWAs	0.366***	0.356***
	[0.005]	[0.004]
Age (ref: 16-19 years old)		
20-29	0.008	0.005
	[0.012]	[0.011]
30-39	0.049***	0.047***
	[0.013]	[0.012]
40-49	0.079***	0.077***
	[0.013]	[0.012]
50-59	0.063***	0.061***
	[0.013]	[0.012]
60-69	0.085***	0.084***
	[0.014]	[0.013]
70+	0.154***	0.154***
	[0.025]	[0.025]
Male	0.059***	0.058***
	[0.004]	[0.004]
Marital status (ref: Married)		
Cohabiting	-0.015***	-0.015***
	[0.006]	[0.006]
Widowed/divorced/separated	-0.044***	-0.045***
	[0.007]	[0.007]
Single/never married	-0.030***	-0.030***
	[0.006]	[0.006]
No. children	0.006**	0.006**
	[0.002]	[0.002]
Education (ref: No education)		
Degree or higher	-0.019***	-0.019***
	[0.007]	[0.007]
School diploma	-0.021**	-0.020**
	[0.009]	[0.008]
GCSE and below	-0.016**	-0.016**
	[0.007]	[0.007]
Other	-0.019**	-0.020**
	[0.008]	[0.008]
Working hrs.	0.007	0.008*
	[0.004]	[0.004]
Occupation (ref: professional occupation)		
Managerial & technical	-0.073***	-0.065***
	[0.009]	[0.008]
Skilled non-manual	-0.205***	-0.197***
	[0.010]	[0.009]
Skilled manual	-0.257***	-0.252***
	[0.011]	[0.010]
Partly skilled	-0.297***	-0.290***
	[0.010]	[0.009]
Unskilled	-0.279***	-0.274***
	[0.013]	[0.012]
Homeownership	0.014***	0.015***
	[0.005]	[0.005]
Region (ref: North East)		
North West	0.028**	0.028**
	[0.012]	[0.012]
Yorkshire and the Humber	0.013	0.012
	[0.013]	[0.013]

Table 2.A9
The Effect of FWAs on Autonomy Over Work Hours: Logit and Linear Probability Model Estimates

	(1)	(2)
	Logit	LPM
Outcome Variables	**Autonomy Over Work Hours**	**Autonomy Over Work Hours**
East Midlands	0.026**	0.025**
	[0.013]	[0.013]
West Midlands	0.033***	0.032**
	[0.013]	[0.013]
East of England	0.044***	0.044***
	[0.013]	[0.013]
London	0.086***	0.085***
	[0.012]	[0.012]
South East	0.042***	0.042***
	[0.012]	[0.012]
South West	0.039***	0.039***
	[0.013]	[0.013]
Wales	0.007	0.006
	[0.013]	[0.013]
Scotland	-0.011	-0.011
	[0.013]	[0.013]
Northern Ireland	-0.034**	-0.034**
	[0.013]	[0.013]
Year (ref: 2010)		
2011	-0.009	-0.01
	[0.006]	[0.006]
2012	-0.016***	-0.016***
	[0.005]	[0.005]
2013	-0.020***	-0.021***
	[0.007]	[0.007]
2014	0.01	0.009
	[0.007]	[0.007]
2015	0.015**	0.015**
	[0.007]	[0.007]
2016	0.002	0.001
	[0.006]	[0.006]
2017	0.01	0.01
	[0.007]	[0.007]
2018	0.015**	0.015**
	[0.006]	[0.006]
2019	0.015**	0.014*
	[0.007]	[0.007]
2020	0.007	0.006
	[0.006]	[0.006]
2021	0.022***	0.020**
	[0.008]	[0.008]
2022	-0.060*	-0.060*
	[0.032]	[0.033]
_cons		0.425***
		[0.024]
No. Obs.	95,181	95,181

Notes: Robust standard errors are clustered at individual level in brackets. * p<0.10, ** p<0.05, *** p<0.01.

Table 2.A10
The Effect of FWA on Autonomy Over Work Hours: Fixed Effects and Correlated Random Effects Estimates

Outcome Variables	(1) FE-LPM **Autonomy Over Work Hours**	(2) FE-Logit **Autonomy Over Work Hours**	(3) CRE-Probit **Autonomy Over Work Hours**
FWAs	0.151***	1.056***	0.156***
	[0.005]	[0.038]	[0.006]
Age (ref: 16-19 years old)			
20-29	0.066***	0.367***	-0.01
	[0.019]	[0.123]	[0.013]
30-39	0.088***	0.464***	0.013
	[0.022]	[0.143]	[0.016]
40-49	0.098***	0.561***	0.03
	[0.024]	[0.161]	[0.019]
50-59	0.078***	0.437**	0.002
	[0.027]	[0.181]	[0.023]
60-69	0.069**	0.373*	0.012
	[0.030]	[0.206]	[0.027]
70+	0.107**	0.665**	0.071*
	[0.043]	[0.313]	[0.038]
Marital status (ref: Married)			
Cohabiting	-0.003	-0.028	-0.004
	[0.009]	[0.061]	[0.006]
Widowed/divorced/separated	-0.002	-0.014	-0.026***
	[0.012]	[0.080]	[0.009]
Single/never married	-0.001	0.007	0.003
	[0.012]	[0.077]	[0.011]
No. children	0.005	0.038	0.004
	[0.003]	[0.024]	[0.003]
Education (ref: No education)			
Degree or higher	0.017	0.089	-0.021***
	[0.024]	[0.155]	[0.007]
School diploma	-0.034	-0.16	-0.016*
	[0.033]	[0.210]	[0.010]
GCSE and below	0.019	0.12	-0.003
	[0.030]	[0.208]	[0.011]
Other	0	0.005	-0.004
	[0.013]	[0.092]	[0.013]
Working hrs.	-0.003	-0.033	0
	[0.006]	[0.039]	[0.006]
Occupation (ref: professional occupation)			
Managerial & technical	-0.014	-0.051	-0.042***
	[0.015]	[0.101]	[0.010]
Skilled non-manual	-0.116***	-0.629***	-0.145***
	[0.017]	[0.106]	[0.011]
Skilled manual	-0.112***	-0.608***	-0.161***
	[0.019]	[0.116]	[0.014]
Partly skilled	-0.160***	-0.917***	-0.183***
	[0.018]	[0.113]	[0.015]
Unskilled	-0.145***	-0.802***	-0.142***
	[0.024]	[0.147]	[0.020]
Homeownership	0.016*	0.111*	0.014
	[0.009]	[0.058]	[0.009]
Region (ref: North East)			
North West	0.084	0.469	0.029**
	[0.083]	[0.441]	[0.013]
Yorkshire and the Humber	0.066	0.396	0.017
	[0.082]	[0.439]	[0.015]
East Midlands	0.036	0.24	0.033*
	[0.083]	[0.447]	[0.018]
West Midlands	0.024	0.148	0.040*

Table 2.A10
The Effect of FWA on Autonomy Over Work Hours: Fixed Effects and Correlated Random Effects Estimates

Outcome Variables	(1) FE-LPM	(2) FE-Logit	(3) CRE-Probit
	Autonomy Over Work Hours	**Autonomy Over Work Hours**	**Autonomy Over Work Hours**
	[0.085]	[0.464]	[0.021]
East of England	0.053	0.44	0.054**
	[0.081]	[0.444]	[0.024]
London	0.082	0.541	0.093***
	[0.080]	[0.435]	[0.028]
South East	0.05	0.311	0.051
	[0.081]	[0.425]	[0.032]
South West	0.058	0.462	0.048
	[0.084]	[0.456]	[0.036]
Wales	0.117	0.634	0.019
	[0.094]	[0.500]	[0.040]
Scotland	0.018	0.274	0.003
	[0.086]	[0.491]	[0.044]
Northern Ireland	0.027	0.259	-0.015
	[0.103]	[0.922]	[0.048]
Year (ref: 2010)			
2011	0	0.004	-0.006
	[0.010]	[0.068]	[0.006]
2012	-0.015***	-0.106**	-0.010**
	[0.005]	[0.041]	[0.005]
2013	-0.004	-0.027	-0.01
	[0.010]	[0.068]	[0.007]
2014	0.014*	0.105*	0.024***
	[0.008]	[0.056]	[0.007]
2015	0.027***	0.198***	0.034***
	[0.010]	[0.070]	[0.008]
2016	0.015**	0.113**	0.019***
	[0.007]	[0.050]	[0.007]
2017	0.033***	0.236***	0.037***
	[0.010]	[0.072]	[0.008]
2018	0.040***	0.290***	0.041***
	[0.008]	[0.057]	[0.008]
2019	0.049***	0.333***	0.049***
	[0.011]	[0.077]	[0.009]
2020	0.040***	0.288***	0.045***
	[0.009]	[0.063]	[0.009]
2021	0.076***	0.510***	0.066***
	[0.012]	[0.085]	[0.010]
2022	0.029	0.184	-0.007
	[0.033]	[0.248]	[0.033]
_cons	0.339***		
	[0.084]		
No. Obs.	95,181	40,453	95,181
Hausman test (p-value)	0.000		
LM test (p-value)	0.000		

Notes: In Column 2 the estimated coefficient from the conditional logit model with FE are shown. Column 3 individual-specific time averages of all time-varying covariates are included as additional controls. Robust standard errors are clustered at individual level in brackets. * p<0.10, ** p<0.05, *** p<0.01.

Table 2.A11
The Effect of FWA on Autonomy Over Work Hours: Instrumental Variable Estimates

Outcome Variables	(1) Pooled-LPM-2SLS	(2) FE-LPM-2SLS	(3) IV-Probit	(4) CRE IV-Probit
	Autonomy Over Work Hours	**Autonomy Over Work Hours**	**Autonomy Over Work Hours**	**Autonomy Over Work Hours**
FWAs	0.532***	0.224***	0.532***	0.294***
	[0.022]	[0.016]	[0.021]	[0.017]
Age (ref: 16-19 years old)				
20-29	0.002	0.065***	0.002	-0.012
	[0.013]	[0.018]	[0.013]	[0.015]
30-39	0.038***	0.087***	0.036**	0.006
	[0.014]	[0.021]	[0.015]	[0.018]
40-49	0.066***	0.097***	0.065***	0.022
	[0.013]	[0.023]	[0.014]	[0.020]
50-59	0.050***	0.078***	0.049***	-0.005
	[0.013]	[0.026]	[0.014]	[0.024]
60-69	0.076***	0.070**	0.075***	0.008
	[0.014]	[0.029]	[0.015]	[0.027]
70+	0.155***	0.112***	0.150***	0.072**
	[0.024]	[0.043]	[0.024]	[0.037]
Male	0.054***	-	0.054***	0.050***
	[0.006]	-	[0.006]	[0.006]
Marital status (ref: Married)				
Cohabiting	-0.015***	-0.002	-0.015**	-0.004
	[0.006]	[0.009]	[0.006]	[0.006]
Widowed/divorced/separated	-0.045***	-0.001	-0.044***	-0.026***
	[0.007]	[0.012]	[0.007]	[0.009]
Single/never married	-0.027***	0.001	-0.026***	0.005
	[0.006]	[0.012]	[0.006]	[0.010]
No. children	0.005*	0.004	0.005*	0.003
	[0.003]	[0.003]	[0.003]	[0.004]
Education (ref: No education)				
Degree or higher	-0.022***	0.018	-0.022***	-0.023***
	[0.007]	[0.023]	[0.007]	[0.007]
School diploma	-0.021**	-0.03	-0.022**	-0.017
	[0.009]	[0.032]	[0.009]	[0.011]
GCSE and below	-0.011	0.019	-0.011	0.001
	[0.008]	[0.030]	[0.008]	[0.012]
Other	-0.014	0	-0.013	0
	[0.009]	[0.013]	[0.009]	[0.015]
Working hrs.	0.003	-0.004	0.001	-0.003
	[0.006]	[0.006]	[0.006]	[0.007]
Occupation (ref: professional occupation)				
Managerial & technical	-0.052***	-0.013	-0.058***	-0.032*
	[0.014]	[0.015]	[0.016]	[0.017]
Skilled non-manual	-0.174***	-0.112***	-0.179***	-0.128***
	[0.014]	[0.016]	[0.015]	[0.016]
Skilled manual	-0.211***	-0.107***	-0.212***	-0.130***
	[0.014]	[0.018]	[0.016]	[0.018]
Partly skilled	-0.249***	-0.155***	-0.252***	-0.153***
	[0.016]	[0.017]	[0.017]	[0.020]
Unskilled	-0.232***	-0.139***	-0.233***	-0.112***
	[0.017]	[0.023]	[0.018]	[0.022]
Homeownership	0.010*	0.015*	0.009	0.012
	[0.006]	[0.009]	[0.006]	[0.010]
Region (ref: North East)				
North West	0.028	0.077	0.027	0.029
	[0.023]	[0.078]	[0.023]	[0.022]
Yorkshire and the Humber	0.016	0.064	0.015	0.019
	[0.020]	[0.075]	[0.020]	[0.021]

Table 2.A11
The Effect of FWA on Autonomy Over Work Hours: Instrumental Variable Estimates

Outcome Variables	(1) Pooled-LPM-2SLS	(2) FE-LPM-2SLS	(3) IV-Probit	(4) CRE IV-Probit
	Autonomy Over Work Hours	**Autonomy Over Work Hours**	**Autonomy Over Work Hours**	**Autonomy Over Work Hours**
East Midlands	0.029	0.031	0.029	0.035
	[0.024]	[0.077]	[0.023]	[0.028]
West Midlands	0.036	0.019	0.035	0.042
	[0.023]	[0.077]	[0.023]	[0.028]
East of England	0.050**	0.052	0.049**	0.058*
	[0.024]	[0.075]	[0.023]	[0.034]
London	0.088***	0.081	0.086***	0.094**
	[0.023]	[0.074]	[0.023]	[0.038]
South East	0.044*	0.049	0.043*	0.052
	[0.026]	[0.075]	[0.026]	[0.039]
South West	0.037	0.054	0.037	0.047
	[0.027]	[0.078]	[0.027]	[0.046]
Wales	0.006	0.111	0.006	0.019
	[0.028]	[0.086]	[0.027]	[0.050]
Scotland	-0.009	0.025	-0.009	0.005
	[0.025]	[0.083]	[0.024]	[0.053]
Northern Ireland	-0.027	0.037	-0.028	-0.01
	[0.028]	[0.102]	[0.028]	[0.060]
Year (ref: 2010)				
2011	-0.008	0.002	-0.008	-0.005
	[0.006]	[0.010]	[0.006]	[0.006]
2012	-0.016***	-0.014***	-0.016***	-0.010**
	[0.005]	[0.005]	[0.005]	[0.005]
2013	-0.017***	-0.002	-0.017***	-0.007
	[0.006]	[0.010]	[0.006]	[0.007]
2014	0.008	0.014*	0.009	0.023***
	[0.007]	[0.008]	[0.007]	[0.008]
2015	0.014**	0.028***	0.015**	0.033***
	[0.007]	[0.010]	[0.007]	[0.008]
2016	0.004	0.016**	0.004	0.021***
	[0.006]	[0.007]	[0.006]	[0.007]
2017	0.013*	0.033***	0.013*	0.038***
	[0.007]	[0.010]	[0.007]	[0.009]
2018	0.015**	0.040***	0.015**	0.041***
	[0.007]	[0.008]	[0.007]	[0.009]
2019	0.012	0.048***	0.013*	0.047***
	[0.007]	[0.011]	[0.007]	[0.010]
2020	-0.002	0.037***	-0.001	0.038***
	[0.006]	[0.009]	[0.006]	[0.008]
2021	0.007	0.071***	0.008	0.056***
	[0.008]	[0.012]	[0.008]	[0.011]
2022	-0.070*	0.023	-0.067*	-0.014
	[0.036]	[0.034]	[0.037]	[0.036]
_cons	0.398***			
	[0.034]			
No. Obs.	95,181	82,222	95,181	95,181

Notes: Column 4 individual-specific time averages of all time-varying covariates are included as additional controls. Robust standard errors are clustered at regional and employees' Standard Industrial Classification (SIC) levels in brackets. Time-invariant variables are omitted from the FE model. * p<0.10, ** p<0.05, *** p<0.01.

Table 2.A12
Causal Mediation Analysis

Outcome Variables	(1) **Informal Care**
FWA	-0.013
	[0.016]
Autonomy Over Work Hours	0.078*
	[0.044]
Age (ref: 16-19 years old)	
20-29	0.007
	[0.005]
30-39	0.025***
	[0.006]
40-49	0.061***
	[0.007]
50-59	0.108***
	[0.007]
60-69	0.065***
	[0.008]
70+	-0.034***
	[0.011]
Male	-0.047***
	[0.004]
Marital Status (ref: Married)	
Cohabiting	-0.011***
	[0.004]
Widowed/divorced/separated	-0.018***
	[0.007]
Single/never married	-0.017***
	[0.004]
No. children	-0.010***
	[0.001]
Education (ref: No education)	
Degree or higher	0.012***
	[0.004]
School diploma	0.026***
	[0.005]
GCSE and below	0.028***
	[0.004]
Other	0.003
	[0.005]
Working hrs.	-0.015***
	[0.003]
Occupation (ref: professional occupation)	
Managerial & technical	0.012**
	[0.006]
Skilled non-manual	0.027***
	[0.010]
Skilled manual	0.035***
	[0.012]
Partly skilled	0.028*
	[0.014]
Unskilled	0.015
	[0.014]
Homeownership	0.009***
	[0.003]
Region (ref: North East)	
North West	-0.033***
	[0.012]
Yorkshire and the Humber	-0.032***
	[0.011]
East Midlands	-0.016
	[0.011]
West Midlands	-0.012

Table 2.A12
Causal Mediation Analysis

Outcome Variables	(1) **Informal Care**
	[0.013]
East of England	-0.028**
	[0.012]
London	-0.054***
	[0.011]
South East	-0.041***
	[0.011]
South West	-0.030***
	[0.011]
Wales	-0.014
	[0.011]
Scotland	-0.01
	[0.012]
Northern Ireland	0.01
	[0.013]
Year (ref: 2010)	
2011	0.003
	[0.004]
2012	0.001
	[0.003]
2013	-0.005
	[0.005]
2014	0.004
	[0.004]
2015	0.004
	[0.005]
2016	-0.003
	[0.004]
2017	-0.012**
	[0.005]
2018	-0.015***
	[0.004]
2019	-0.010**
	[0.005]
2020	-0.012***
	[0.004]
2021	-0.023***
	[0.005]
2022	-0.016
	[0.019]
_cons	0.081***
	[0.026]
No. Obs.	95,144

Notes: Robust standard errors are clustered at regional and employees' Standard Industrial Classification (SIC) levels in brackets. * p<0.10, ** p<0.05, *** p<0.01.

Appendix 2.B

Appendix 2.B presents supplementary figures and diagnostic analyses supporting the empirical results in this study. It includes a graphical overview of informal care trends in the United Kingdom, a description of the mediation analysis framework used in Section 2.5.4, and a set of panel-data specification tests and correlation matrices. These materials provide additional context for the main findings in this study.

Table 2.B1
Pairwise Correlations

	Informal Care	Instrumental Variable	FWAs	Age	Male	Marital Status	No. Children	Education	Working Hours	Occupation	Homeownership
Informal Care	1.000										
Instrumental Variable	0.006	1.000									
FWAs	0.016*	0.456*	1.000								
Age	0.195*	0.052*	0.056*	1.000							
Male	-0.091*	0.052*	0.027*	-0.006	1.000						
Marital Status	-0.059*	-0.064*	-0.073*	-0.386*	-0.056*	1.000					
No. Children	-0.073*	-0.003	0.017*	-0.112*	0.026*	-0.284*	1.000				
Education	0.030*	-0.099*	-0.108*	0.047*	0.058*	0.041*	-0.017*	1.000			
Working Hours	-0.051*	0.099*	0.075*	0.009*	0.315*	-0.022*	-0.113*	-0.049*	1.000		
Occupation	0.011*	-0.222*	-0.222*	-0.044*	0.009*	0.113*	0.009*	0.310*	-0.171*	1.000	
Homeownership	0.056*	0.085*	0.082*	0.199*	0.013*	-0.224*	0.004	-0.093*	0.030*	-0.190*	1.000

Notes: * shows significance at the 0.05 level

2.B2 Tests of panel data

2.B2.1 Breusch-Pagan Lagrange Multiplier (LM) Test for OLS

Informal care[id,t] = Xb + u[id] + e[id,t]

Table 2.B2
Breusch-Pagan Lagrange Multiplier Test for OLS

	Var	SD = sqrt(Var)
Informal care	0.0952347	0.3086011
e	0.0600714	0.2450946
u	0.024445	0.1563491

Test: Var(u) = 0 $\bar{\chi}^2$ (01) = 13612.88 [$Prob >\ \bar{\chi}^2$] = 0.0000

2.B2.2 Hausman Test

A Hausman test was carried out to identify whether fixed or random effects should be employed. The null hypothesis is that the difference in the coefficients is not systematic. Based on results below, the null hypothesis was rejected, indicating that the fixed effect is an appropriate model to estimate.

χ^2 = (b-B)'[(V_b-V_B)^(-1)](b-B) = 344.74

[$Prob > \chi^2$] = 0.000

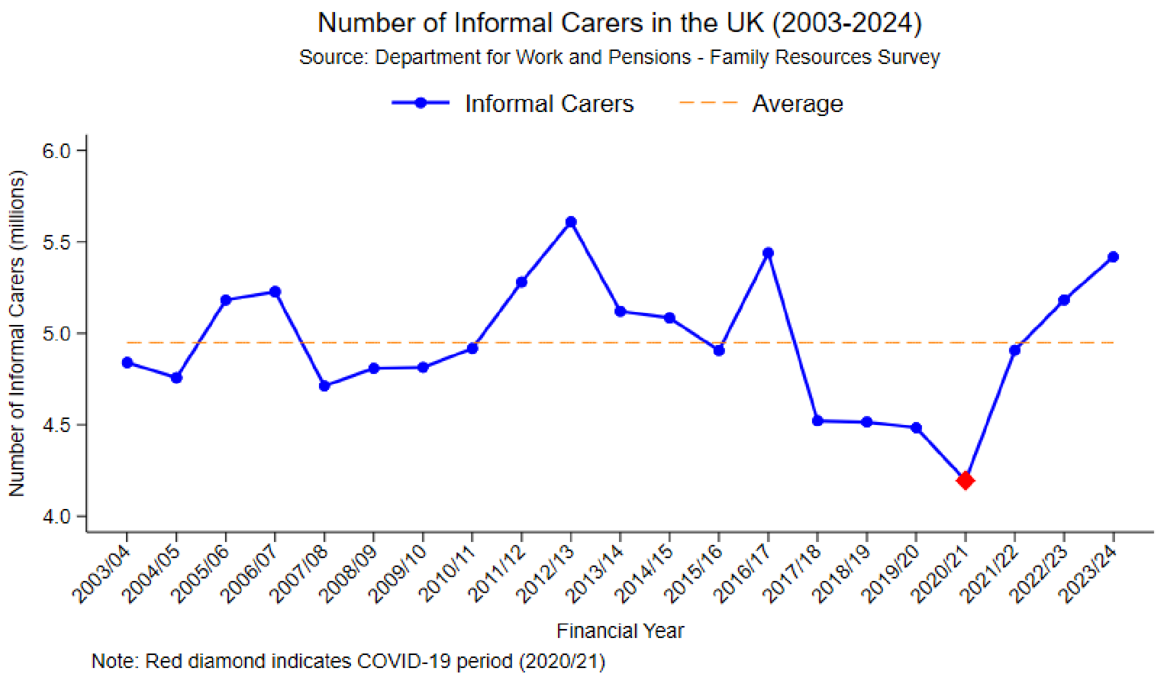


Figure 2.1 Number of Informal Carers in the UK, 2003-204

2.B2.3 Causal Mediation Analysis

Causal mediation analysis purpose is to separate the total treatment effect (TE) into the indirect effect (IE) caused by the mediating variables (M), known as the mediators, and the direct effect (DE) of the treatment on the outcome of interest. Dipple et al. (2020) proposed the following three step procedures, all of which are based on a standard IV specification. First, estimate the TE of FWA on informal care, instrumented by the variable Z, represented by β_1 in Eq. (2.3). Second, estimate the effect of FWA on the mediating variable, instrumented by the variable Z, represented by β_1 in Eq. (2.4). Third, estimate the DE of FWA on informal care by estimating the mediating variable on the informal care, instrumented by the variable Z and conditioning on the treatment (FWA), represented by DE_1 in Eq. (2.5). To calculate the indirect effect, simply take the difference between the TE and DE (*IE = TE – DE*) or alternatively by multiplying the coefficients of M_1 and ${B_1}^{y_m}$ (β_1 in Eq. (2.4)).

$$y = \beta_0 + \beta_1 FWA + \ \beta_2 X + u_1 \tag{2.3}$$

$$y_m = \beta_0 + \beta_1 FWA + \ \beta_2 X + u_2 \tag{2.4}$$

$$y = \beta_0 + M_1 mediator + \ \beta_1 X + DE_1 FWA + \ u_3 \tag{2.5}$$

Where y denotes the informal care outcome; y_m is the different mediating outcomes; $mediator$ is the mediating variable tested; FWA represents individuals using FWAs at their workplace; X is a vector of control variables capturing household and individual characteristics and u is an error term.

CHAPTER 3

The Educational Return to Mental Health: Parental Wellbeing and Children's College Attainment in the US

Abstract

The association between children's education and parental health has attracted increasing research attention, yet little known about the causality of this association. This study examines the causal effect of children's college attainment on parental mental health using longitudinal data from the United States Health and Retirement Study covering, waves 4 (1998) through 14 (2018), and including 33,942 individuals. Unlike previous research, this study applies nonparametric partial identification analysis that relies on weak and credible assumptions to produce bounds on the population average treatment effect, while controlling for any potential sources of endogeneity bias. The estimated bounds show that, under the MTR + MTS + MIV assumptions, the average treatment effect ranges from 0.017 to 0.421, indicating a positive causal impact of children's college attainment on parental mental health. Specifically, having college graduates improves parental mental health scores by at least 0.017 points and at most by 0.421 points, representing 0.87-21% of one standard deviation. The findings of the mechanism analysis are consistent with mechanisms via communicative and health monitoring behaviours, such as frequency of contact and preventive care. Importantly, the results provide evidence that methods which fail to adequately address endogeneity concerns tend to overestimate the true causal effects.

3.1 Introduction

The relationship between human capital and health has received considerable academic attention from many researchers in economics, epidemiology, and related fields. In the context of education, a large body of literature has documented the benefits of education on individuals' various dimensions of health and financial wellbeing (Doyle & Skinner, 2016; Eide & Showalter 2011; Silles, 2009). Additionally, the benefits of education can also be transmitted intergenerationally, across different generations within the family networks (Becker, 1994; Dodin et. al, 2024). Most studies exploring this dimension of educational impacts have highlighted a downward spillover effect of the impact of intergenerational human capital mobility on their children's health and education; for instance, the education of grandparents and parents have significant positive causal impacts on the wellbeing of their offspring (Cui et al., 2019; Lundborg et al., 2014). However, there has been much less attention to the converse relationship, exploring the upward generational flow of spillover effects from children's education attainments (i.e., to their parents' health). While some studies, as presented in this study, have noted the association between children's education and parental health outcomes, they have failed to establish vigorous causal inferences. Only a limited number of studies have attempted to estimate a causal association, and they have primarily applied quasi-experimental designs. While these approaches attempt to control for potential endogeneity concerns of mental health and education, their assumptions might be violated, and the underlying causal association continues to be unclear. Establishing causal associations between education and health is crucial to enhance the understanding of the theoretical framework of intergenerational human capital mobility and for the development of effective health interventions and educational policies.

This research examines the causal effect of children's education attainment on parents' mental health in the United States. Specifically, this study utilises 11 waves of the Health and Retirement Study (HRS) for individuals aged over 50 to address the following research questions: (a) Does children's college attainment affect parental mental health? (b) What are the potential mechanisms through which children's education improves parental mental health? The limited literature that has attempted to establish causal inferences, as discussed below, has mostly concentrated on lower and secondary education, particularly with regard to exploring whether increasing the schooling age has a causal effect on parental wellbeing. Their findings were mixed, ranging from no causal association to moderate effects depending on the geographical region of study and the methodological approaches applied. This study attempts to add to the existing literature by obtaining robust causal estimates of the effect of children's college attainment on parental mental health. Estimating the causal effect of having children who are college graduates is more desirable as recent debates are focused on the merits of higher education due to the rising cost of student loans and tuition fees.

This study makes four valuable contributions to the literature. First, to the researcher's knowledge, this study is the first to apply a novel nonparametric bound analysis to estimate the causal effect of children's education on parental health via partial identification (PI) methods. Second, in contrast to the existing literature, this study is the first that provides a causal association for children's college attainment. Third, this study estimates the bounds of the population average treatment effect of children's education contrary to a subpopulation treatment effect in the existing literature. Fourth, this study is the first to provide evidence consistent with the potential mechanisms that drive the relationship between children's education and parental mental health, using PI methods.

This study utilises eleven waves of longitudinal data from the U.S. Health and Retirement Study (HRS) covering the period 1998–2018. Parental mental health is measured using the eight-item "Center for Epidemiologic Studies Depression Scale" (CES-D) score, which is reverse-coded so that higher values indicate better mental health (fewer depressive symptoms). To overcome potential endogeneity concerns including reverse causality, omitted variable bias, and measurement error the analysis applies a nonparametric PI framework based on weak yet credible assumptions: Monotone Treatment Response (MTR), Monotone Treatment Selection (MTS), and Monotone Instrumental Variable (MIV). This approach allows estimation of informative bounds on the causal effect without imposing strong and untestable assumptions. The analysis also explores channels consistent with mechanisms via financial transfers and communicative behaviours such as frequency of contact, through which children's education may influence parental wellbeing.

The empirical findings of this study demonstrate that children's college attainment has a statistically significant positive effect on parental mental health. The bounds estimates reveal that having college graduates improves mental health scores by at least 0.017 points and at most improves scores by 0.421 points, which translates to at least 0.25% and 6.4% increase on average compared to their counterparts and 0.87-21% of one standard deviation (SD). The analysis showed that failing to control for potential endogeneity concerns and relying on strong assumptions, the OLS point estimates will result in upward biased and inconsistent estimates. These results are robust to an alternative treatment measure and are not sensitive to imputed mental health measures. The findings of the mechanism analysis are consistent with mechanisms via communicative and health monitoring behaviours, such as frequency of contact and preventive care. The bounds estimates showed that having a college graduate child increases the frequency of contact with children and preventive care by at most 13% and 16% SDs, respectively. Overall, the general findings reveal evidence of a positive causal effect of children's college attainment on parental mental health in the United States.

The findings are particularly interesting since policymakers state that education is an important and beneficial factor for the wellbeing of individuals as well as for promoting social cohesion (World Bank, 2018). Mental health challenges, such as depression and anxiety, are a growing global health problem particularly for the older population (Rong et al., 2024). Aside from intrinsically reducing quality of life, they are the one most common health conditions that increase individuals' mortality risks (Kondirolli & Sunder, 2022; Layard, 2017). Governments around the world allocate a substantial amount of their total health expenditure to mental health issues, particularly in high-income economies, where they spend around 3.4% of the health expenditure (Ridley et al., 2020). With rising life expectancy and ageing populations, it has been well-documented that ageing and social isolation are predominant factors associated with declining mental health and increased healthcare costs (Banerjee et al., 2023; Bhattacharyya, 2021; Smith & Victor, 2019). The proportion of Americans aged 65 and above is estimated to exceed 21% by 2030 (Jones & Dolsten, 2024). This will have significant implications for the future healthcare systems in the United States, particularly in meeting the healthcare needs of the growing numbers and proportions of older populations.

According to the World Health Organization (2023), around 14% of worldwide individuals aged above 60 live with severe mental health conditions. The increasing number of mental health problems poses several challenges for public health, economies and societies. For instance, in Europe, the cost of annual depression alone was estimated at EUR 120 billion (Ekman et al., 2013). In the United States, estimates reached as high as USD 114 billion, with individuals aged above 50 being the most affected (Greenberg et al., 2021). The true economic burden of mental health costs is undoubtedly much higher, even if hard to quantify, when considering the indirect costs of loss of productivity at individual and workplace levels resulting from absenteeism, unemployment, and income losses due to mental health issues (Knapp & Wong, 2020; Razzouk, 2017). Therefore, understanding the beneficial spillover effects of children's college attainment on parental mental status can inform public policies targeted at improving parental wellbeing and reducing the prevalence of mental disorders for the elderly within an economy.

Furthermore, the findings provide empirical evidence for the benefits of contributing to children's college education. It is particularly important to understand the broader benefits and returns of college education in the United States, given the fact that there is a generally rising trend for people to obtain college degrees (Korhonen, 2023). However, college attendance is highly expensive, and costs continue to rise dramatically. Tuition fees and other related living expenses of students are usually financed by parents, including direct subsidies and in terms of loans (Fomby & Kravitz-Wirtz 2019; Hotz et al., 2023). A recent study has shown that 51% of college students received financial assistance for tuition fees from their families (Kuperberg, 2023).

With the ever-rising costs of tuition fees and associated expenses, exacerbated by inflation in recent years, parents are faced with difficult choices of whether to contribute to their offspring's education or hold onto their finances for financial stability for retirement and unexpected medical expenditures and shocks later in their ageing years, particularly as healthcare costs generally increase. Parents' financial burdens from their contribution to their children's education can have detrimental impacts on their health and financial wellbeing, including delaying their own retirement to be able to afford to send their children to college (Rauscher, 2016; Walsemann et al., 2020). Also, the financial burden can affect parents' selections regarding deciding on a comprehensive health plan or medical provider. Given the rise in both children's college attainments and associated costs, understanding the relationship between children's education and parental health outcomes can reveal important insights about the long-term intergenerational benefits and social returns of investing in college education within the family networks.

There are several pathways through which educational attainment may affect parental mental wellbeing beneficially. First, higher educational attainment may lead children to be in better highly paid jobs and therefore economically secure. Leading them to have more financial resources to support their ageing parents for any potential health-related expenses in later years (Smith-Greenaway et al., 2018). Second, parents of better-educated children are less likely to be stressed and anxious about their children's future financial stability and independence (Greenfield & Marks, 2006). In particular, parents commonly experience a pervasive sense of pride and relief from their children's educational accomplishments (Igarashi et al., 2013; Pai et al., 2024). Third, highly educated children are equipped with better health-based knowledge, which may improve parental health through making better health-related decisions like taking preventive care measures and treatments, promoting healthy lifestyles and discouraging unhealthy habits (Thoits, 2011). Some of these pathways can be summarised into two main classes of intergenerational transfers and support: financial transfers and knowledge-based support. Intergenerational support could serve as the primary leading channel that drives the relationship between children's education and parental mental health. Therefore, it is important to explore such channels as they will provide a comprehensive understanding of the observed relationship.

The remainder of this study is structured as follows: Section 3.2 presents the background and literature review. Section 3.3 introduces and describes the data. Outlines of the underlying assumptions of PI strategy and the potential endogeneity concerns are addressed in Section 3.4. The main nonparametric results, robustness checks, and the mechanisms analysis are presented in Section 3.5. These are followed by the conclusion and discussion in section 3.6.

3.2 Background and Literature

The literature on the intergenerational impact of children's education attainment on parental wellbeing is a growing academic topic across multiple fields, stretching from gerontology to health economics and intergenerational human capital mobility. Human capital theory provides the theoretical framework for understanding how investment in education yields returns to family members across different generations (Becker, 1994; Dustmann & Glitz, 2011). The human capital model suggests that accumulating human capital through education generates various spillover health and living conditions benefits across different generations (Ahlburg, 1998; De Neve & Harling, 2017; Jiang & Kaushal, 2020; Mirowsky, 2003; Wolfe et al., 2018). This led to an emerging body of work across Western and non-Western nations that explored the relationship between children's educational attainment and how it may affect various dimensions of parental wellbeing including mental health, physical health, economic security, and mortality (De Neve & Kawachi, 2017; Lee, 2018; Lee et al., 2017; Yahirun et al., 2017; Wang et al., 2022).

Previous studies in the United States have documented that children's education attainment was positively associated with parental wellbeing. For instance, Yahirun et al. (2020b) investigated the association between offspring education and parental cognitive health using logit models on HRS data and found that parents with college graduate children were 41% less likely to experience cognitive impairment. In a similar context, Pai et al. (2023) employed a mixed-effect model to examine parental cognitive health. Their results confirmed the earlier findings that parents with highly educated children report better cognitive health over time relative to parents with children who were less educated. Another study by Yahirun et al. (2020a) employed OLS method to examine 12 years of panel data from HRS and concluded that educated offsprings were positively associated with reducing parental stress and depression. Building on this evidence, Dennison and Lee (2021) employed propensity to score methods to account for selection, using Add Health Parent Study data, which is a nationally representative sample of individuals in the United States and comparable with HRS data. They examined the relationship between children's college educational attainment and parental health, measured by self-rated health (SRH) and depression symptoms. Their findings demonstrated that having no children who attained college degrees was negatively associated with reporting better SRH and positively associated with reporting more depression symptoms.

Another recent study by Yahirun et al. (2022) further expanded on the association between offspring education and parental health by examining how the effect of education on mental health differs according to black and white parents. Using a multilevel growth model, their analysis revealed that respondents with college graduate children had significantly better mental health, with a greater effect for black respondents than white. In a similar context, Peng et al. (2019) focused on the association of mental and physical health of mothers. By applying OLS and logit model, their results revealed that mothers with children with a college degree had better physical and mental health. More recently, Zhang et al. (2024) further expanded this research by examining the relationship between college timing completion on mothers' SRH. Their general analysis was in line with the earlier work, which revealed that children's completion of college on time or late was positively associated with better maternal health relative to mothers with children without college degrees.

Moreover, beyond physical and behavioural health measures, several studies have extended the relationship between college education and parental health by investigating the association with regard to parental mortality risk using hazard models. For example, Friedman and Mare (2014) investigated the association between offspring education and parents' mortality on data derived from HRS. Their analysis established that having a college graduate child would increase life expectancy for parents by 2 years, compared to those whose children were only high school graduates. Similarly, Wolfe et al. (2018) provided evidence that fathers with children with a college degree lived almost 2 years longer than those without college graduates. These studies highlight the potential long-term benefits of having a highly educated child on parents' longevity.

In the context of developing nations, the association between children's education and parental wellbeing is well established. A growing literature from Asia documented similar findings to the United States. In Taiwan, Lee et al. (2017) applied a multilevel mixed-effect model from five waves of Taiwanese Longitudinal Study of Aging to examine the relationship between children's education and parental depression symptoms. Their analysis concluded that parents with highly educated children are predicted to score lower depression symptoms. Another study by Lee (2018) investigated the relationship between children's education and parent's biological health and found that having highly educated children was associated with lower inflammation in parents as well as overall physiological dysregulation. Earlier studies in Taiwan have shown that having highly educated children significantly reduces the probability of parents reporting functional limitations by 31% and lowered mortality risk by 16% (Zimmer et al., 2002; Zimmer et al., 2007). In India, it was found that parents with college graduates had 41% higher odds of reporting better SRH than those with less than primary education children (Thoma et al., 2021). Beyond parental SRH, two studies have established that children's education significantly lowered the odds of depression and increased the life satisfaction of parents (Mustafa et al., 2024; Mustafa & Shekhar, 2024).

A recent study in Mexico has established that less educated children were associated with lower parental cognition function (Torres et al., 2021). While in China, empirical evidence concluded that children's education attainment was positively associated with parental cognition function (Xu & Luo, 2022). Expanding to other mental health outcomes, Pei et al. (2020) used six waves from a national longitudinal study in China to examine the effect of children's education on parental depression symptoms. Using a random effect model, the results highlighted that having a highly educated child reduces the number of depression symptoms even after controlling for various types of intergenerational support. Furthermore, Yang et al. (2016) concluded that parents who had children who completed at least 10 years of schooling had 15% and 17% lower mortality risk for men and women, respectively, compared to those who had lower years of schooling. While in Mexico it was established that parents with college-graduate children had 10% and 19% lower mortality risk for men and women, respectively (Yahirun et al., 2017). In parallel research, De Neve and Kawachi (2017) reported that in South Africa, one year of child schooling was associated with 6% and 5% lower mortality risk for men and women, respectively.

` In addition, an emerging body of research in several European countries explored the relationship between parental health and children's education. For example, Torssander, (2013) applied fixed effects Cox regression models on Swedish data and reported that parents who have children with tertiary education of three years or more (that is equivalent to a college degree in the United States) had around 21% lower mortality than those with children who completed compulsory schooling. In a subsequent study, Torssander (2014) expanded her earlier work by investigating the relationship between children's education and parental causes of death. The results showed that having highly educated children was significantly associated with lower circulatory diseases and various forms of cancer.

In Finland, Elo et al. (2018) established that children's education was associated with 30-36% lower mortality for parents. Using five waves from 11 countries from the Survey of Health, Ageing and Retirement in Europe (SHARE), Sabater et al. (2020) arrived at a similar finding. Parents with highly educated children are associated with lower mortality, particularly for those aged between 50 and 74. They concluded that this association is partially explained through improvement in parental health behaviours like physical health and SRH. Tosi and Uccheddu (2023) extended earlier studies by examining the association between children's education and parental frailty index. This index measures the number of difficulties a respondent faces ranging from physical to psychological health domains (Fuertes-Guiró & Viteri Velasco, 2020). By applying a mixed effect model on 29 countries from SHARE data, the general results supported the hypothesis that children's education was positively associated with better parental wellbeing.

While prior literature has documented a positive association between children's educational attainment and various dimensions of parental health outcomes, using various methods, the establishment of a robust causal relationship has been challenging. A growing number of empirical studies have attempted to identify rigorous causal inferences through a variety of econometric methods specifically designed to address potential endogeneity concerns arising from education and health outcomes. However, these investigations have yielded mixed results, ranging from minimal causal effects to no statistically significant association depending on the methodological approaches employed, health outcomes and regions of study. The majority of these studies have mainly applied Regression Discontinuity Design (RDD) and Instrumental Variable (IV) approach, as described below.

For instance, two recent studies in the UK have examined the causal relationship between children's education and parental longevity using RDD. Madia et al. (2022) applied fuzzy RDD to analyse both the 1947 and 1973 educational reforms using English Longitudinal Study of Aging data. They concluded that both reforms significantly reduced mortality risk. Specifically, one-year increase in child schooling-leaving age reduced mortality by 13% and 16.5% for fathers and mothers, respectively. However, Potente et al. (2023) applied a similar approach using the 1958 National Child Development Study cohort data and found no statistically causal association between the reform and parental mortality. Similar findings were observed in Swedish data by Lundborg and Majlesi (2018). In their study, they utilised Swedish compulsory schooling reforms as instruments and found no causal effect on parents' mortality. Conversely, in the low-income setting of Tanzia, schooling reforms were found to have significantly reduced parental mortality (De Neve & Fink, 2018). In China, Cui et al. (2021) exploited the geographical variations of compulsory schooling reforms as instruments and concluded that children's education increased parents' survival rate for fathers, but it had a minimal and insignificant effect on mothers.

Other scholars have explored the causality of children's education on several subjective and objective parental health measures (Liu et al., 2022). For instance, Ma (2019) examined the effect of children's schooling years on parental cognitive function, SRH, depression and physical health. By adopting IV strategy with data from the China Health and Retirement Longitudinal Study (CHARLS), the results were heterogeneous, depending on the health outcome of interest. The findings revealed a significant causal effect for physical and cognitive health outcomes only. These findings are consistent with a later study that applied a similar methodological approach to data derived from the China Health and Nutrition Survey by Wei et al. (2022). Their IV estimation results revealed that offspring with higher education had a positive and significant effect on parental physical health through the adoption of healthy behaviours such as exercise activities. Zhang et al. (2022) expanded earlier studies in China by applying IV quantile regression to explore the heterogeneity in the effects of children's education on parental health measured by frailty index. Their results confirmed that education has a beneficial effect on parent's frailty index, with unhealthy parents benefiting significantly more than their counterparts.

Furthermore, a recent study conducted in Mexico examined the causal effect of education on parental depression symptoms and life satisfaction using compulsory schooling reform as an instrument for children's years of schooling (Gutierrez et al., 2024). The study established that one year of schooling was associated with lower parental depression symptoms and not associated with parental life satisfaction, providing some causal evidence of the beneficial spillover effects of children's education on parental mental health status.

Additionally, Ma et al. (2021) exploited Mexican educational reforms to identify the causal effect of children's education on parental cognitive health. Their analysis displayed evidence of a positive effect on the overall cognitive score measure, specifically one year of schooling was associated with a 7.4% increase in the standard deviation of cognitive score. However, across different domains, it was found to be significant for only verbal fluency, verbal learning and orientation but not for recall, visual scanning, memory and ability scores.

However, in high-income European contexts, Torres et al. (2022a) used variation of children's exposure to compulsory educational reforms derived from SHARE and established that offspring education was not associated with the overall cognitive score. Their analysis revealed that the causal effect was found to be related to only improving verbal fluency scores. Also, Torres et al. (2022a) extended their analysis by examining other psychosocial health outcomes, mainly quality of life and depression symptoms. They concluded that increased schooling for children was associated with lower depression symptoms and higher quality of life for parents. A parallel study conducted by Torres et al. (2022b) examined the effects of education on several health behaviours such as physical activity, smoking, BMI, and alcohol consumption using an identical dataset and methodological approaches. The authors identified a beneficial causal effect across most health behaviour measures except for father's alcohol consumption, it was found to be positively associated with children's education but insignificant. For mothers, the relationship was reversed and statistically significant establishing a notable heterogenous effect.

In summary, the existing empirical literature emphasises the beneficial effects of offspring education on various parental health outcomes. However, most of the aforementioned studies have mainly concentrated on the association between education and health outcomes. They have often failed to address the potential endogeneity concerns arising from children's education and health outcomes, which limits the robustness of such findings. Only a limited number of studies have attempted to establish a causal association with mainly quasi-experimental designs like RDD and IV methods. However, most of these studies utilised schooling reforms as instruments that primarily focus on lower educational attainment groups, and yielded local average treatment effects for a one-year increase in children's schooling. Such estimates would not represent the effect across the whole population due to the possibility of a heterogeneous treatment effect.

These diverse methodological approaches highlight the complexity of identifying the average treatment effect of education on health. Further research is needed to fully comprehend and document rigorous causal inferences. This study expands on the growing causal literature on the effect of children's education on parental wellbeing to identify the average treatment effect by applying nonparametric bounds analyses, mainly on college graduate attainment and mental health. This approach can provide robust causal inferences regarding the effect and mechanisms through which college graduates affect parental health.

3.3 Data

This study used waves 4 (1998) through 14 (2018) of the HRS (Health and Retirement Study, 2024). The HRS is one of the most comprehensive national representative longitudinal surveys of individuals in the US over the age of 50. The HRS is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and is conducted by the University of Michigan. The survey consists of more than 37,000 respondents from 23,000 households throughout the US (Fisher & Ryan, 2018; Sonnega et al., 2014). The dataset contains extensive information on respondents demographic and socioeconomic characteristics (e.g., employment history, income, health, education and family relationships). In particular, it includes a rich set of variables recording respondents' various health indicators and their children's educational attainment. Initially, the first wave started in 1992, covering 12,652 individuals across 7,608 households and has been collected biennially ever since (Van der Klaauw & Wolpin, 2008), establishing a rich longitudinal database particularly valuable for intergenerational research.

The empirical analysis utilised the HRS data extracted from the RAND HRS Longitudinal file (RAND HRS Longitudinal File 2020 (V2), 2024), merged with the RAND Family Data file (RAND HRS Family Data 2018 (V2), 2023). These integrated datasets offer a unique advantage by synchronising HRS core interviews and children files across waves. The Family Data file contains detailed information about the characteristics of all living children and children-in-law of each respondent, including their age, education attainment and whether they provided any kind of support. Such features make it ideal for the research questions addressed in this study for two key reasons. First, the data contains refined and efficient information for each child's educational level as well as the parent's mental and physical health status. Second, it includes specific measures of each child's different types of support, like help with financial transfers and medical costs assistance, and the frequency of contact a child has had with their parents. This information allows this research to investigate potential mechanisms through which children's education may influence parental mental health.

This research focuses on data from waves 4 -14, covering the period 1998 to 2018, as the survey questions were inconsistent prior to wave 4 and from wave 15 onwards, especially for responses to children's education level (Lee et al., 2024; Yahirun et al., 2020a; Yahirun et al.,2020b). Also, crucial health variables like ADL and IADL were recorded inconsistency in early waves (Kabuche et al., 2024; Li, 2023; Wu et al., 2024). Several scholars have stated similar assumptions (Fong et al., 2015; Fu et el., 2022; Sherris & Wei, 2021). Lastly, this study time frame aligns with the earlier cited research, which facilitates a meaningful comparison of the new causal evidence in this study with prior findings. This time frame also ensures that children's education data and parents' CES-D mental health measures are drawn from the same observation waves, ensuring consistency across measurements.

The empirical analysis was restricted to living respondents aged 50 and above who provided sufficient responses to key variables of interest across the eleven waves. The reason for this restriction is that the HRS is not designed to be a representative sample of respondents under 50. The final weighted sample consisted of 33,942 individuals from 22,764 households comprising 183,492 person-waves observations. Of the total respondents, 16,506 (48.6%) had at least one child who had attained a college degree, while around 17,436 (51.4%) had children who had not completed a college-level education.

The primary outcome variable in this study is parental mental health, measured by using the eight-item "Center for Epidemiologic Studies Depression Scale" (CES-D), developed by (Radloff, 1997). This is a widely used and valid measure of mental health mainly, the accuracy of depression symptoms, among older adults compared to the full-scale CES-D (Andresen, 1994; Siflinger, 2017; Van de Velde, 2010). The survey asks respondents eight yes/no questions whether they experienced most of the time during the past week any of the following depression symptoms: (1) felt depressed, (2) felt everything they did was an effort, (3) felt sleep was restless, (4) felt happy, (5) felt lonely, (6) felt sad, (7) felt they could not get going, and (8) felt they enjoyed life. The positive items are coded as ones (e.g., felt happy and enjoyed life), while negative items are coded as zeros. The negative items were reverse-coded to generate a total score of 8. The total number of symptoms was summed to create a CES-D score ranging from 0 to 8, with a higher score indicating fewer depressive symptoms corresponding to better mental health and a lower score indicating more depressive symptoms and worse mental health. A similar approach has been undertaken by previous studies (Ohrnberger et al., 2017a; Ohrnberger et al., 2017b; Yang & Zikos, 2022). For robustness, the analysis is re-estimated excluding imputed values of the CES-D score variable.

Furthermore, this study investigates additional outcomes that may operate as mechanisms through which children's education may influence parental mental health. These variables include financial transfers from children to parents, frequency of contacts with children, number of serious illnesses, and preventive care measures.

The main treatment variable of interest in this study is the respondent's children's college education attainment at the time of the survey. The HRS reports offspring education as years of education (0 – 17 years maximum) and does not routinely ask about educational degrees attained, for all living children. There are several ways that have been adopted in prior studies that examined children's education and parental health. Some studies have used the average years of education for all children (Friedman & Mare, 2014; Pai et al., 2023; Yahirun et al., 2017), or the education of the oldest son (Torres et al., 2022b; Torssander, 2013; Zimmer et al., 2007). Others have examined the most educated child (De Neve & Fink, 2018; Ma, 2019; Zimmer et al., 2002). In this study, children who have completed 16 or more years of schooling were assumed to have attained a college degree or higher (Hayward et al., 2015; Yahirun et al., 2022); for robustness, the use of mean years of education will be employed as an alternative treatment variable.

Respondents' children's college attainment was coded as a binary variable, with 1 denoting having at least one child who has completed a college education degree or higher and 0 indicating otherwise (no children with college degrees). The binary specification is methodologically necessary because the partial identification framework relies on discrete treatment levels to apply its key identifying assumptions. Although years of schooling could be discretised into multiple bins, the binary specification maximises statistical power and simplifies interpretation. Focusing on college attainment also aligns with the motivation outlined in the introduction to this chapter, reflecting the growing importance of higher education and its intergenerational implications for parental wellbeing. Prior research using HRS and other US data has adopted a similar measure (Bunkley et al, 2023; Friedman & Mare, 2014; Yahirun et el., 2020b; Peng et al., 2019). For robustness and sensitivity analysis, this study examined the mean years of education for all children as an alternative specification of children's educational attainment. The findings were generally consistent across the different measures, supporting the robustness of the primary specification.

The HRS data also includes measures of respondents' household income, limitations in Activity of Daily Living (ADL), limitations in Instrumental Activity of Daily Living (IADL) and Self-Reported Health (SRH). Additionally, the survey reports whether respondents received assistance from their children with either ADL or IADL tasks (Instrumental support). These health indicators are widely used measures for assessing the physical health and functional status of respondents (Eibich & Zai, 2024; Li & Sunder, 2024; Li et al., 2024; Wei et al., 2022). These variables are used in this study as a monotone instrument variable, to tighten the nonparametric bounds (as clarified in more detail in the next section).

The ADL score variable captures the respondent's limitations or difficulties with performing the following activities: getting in and out of bed, walking across a room, bathing, dressing and eating. The ADL was coded as a score variable ranging from 0 to 4, representing how many of the activities the respondent indicated difficulties with, whereby a higher score reflects greater functional dependence. Similarly, the IADL captures more complex activities like grocery shopping, preparing meals, managing money, using the phone and taking medications. The IADL was constructed in a similar manner, with scores ranging from 0 to 4, whereby a higher IADL score reflects an individual's inability to make daily decisions and live independently. Both ADL and IADL scores were reversed coded for ease of estimation purposes (i.e., lower scores represent worse physical and greater functional limitations). The measure of assistance received from children (Instrumental support) was coded as a score ranging from 0 to 2, representing whether help was provided for ADL or IADL exclusively or mutually.

Household income represents the sum of respondent and spouse earnings, pensions and annuities, supplement security income and social security disability, social security retirement, unemployment and worker's compensation, other government transfers, household capital income, and other income. Income was adjusted for inflation via the annual Consumer Price Index (CPI) obtained from the U.S Bureau of Labor Statistics (2024). The SRH variable is defined in the HRS based on responses to the question "Next, we have some questions about your health. Would you say your health is excellent, very good, good, fair, or poor?", with responses ranging from "1" for Excellent to "5" for poor.

Table 3.1 provides weighted summary statistics for the estimation sample of the main outcome variable and various demographic characteristics. The overall sample contained 183,492 observations from 33,942 individuals separated by treatment status: respondents with college grad children and those without. Around 54% of the sample have offspring with a college grad education (treated) and 46% did not. These statistics are generally consistent with previous studies that investigated parent and children's education in the US (Bunkley et al, 2023; Friedman & Mare, 2014; Yahirun et al., 2022). A simple mean difference between treated and untreated respondents shows that the two groups differ in terms of the main outcome and demographic characteristics. As the table shows, individuals with college grad children report better mental health, as measured by CES-D score (6.81 vs. 6.27). Also, physical health indicators show that individuals with college grad children demonstrate better physical health status, ADL score (3.79 vs. 3.67) and IADL (3.83 vs. 3.74). Furthermore, they are less likely to receive assistance from children (0.04 vs. 0.06) compared to non-graduates and more likely to report better SRH. These differences are all statistically significant at the 1% level. Suggesting that on average individuals with college grad children are associated with greater psychological and physical wellbeing.

Overall, summary statistics from *Table 3.1* show that the sample consists of 55.7% of females, which tends to be similar in both groups. The average age is 65 years, and individuals with college grad children are likely to be older (66.7 vs. 64.6). White individuals make up 84% of the sample and higher for college grads. The average annual income is USD 367, but the figure is more than double for college graduates compared to non-grads (USD 435.9 vs. 286.9). On average, respondents across the sample have completed 13 years of education, and individuals with college grad offspring are more likely to have had 1.5 more years of schooling compared to non-grads (13.7 vs. 12.3). These statistics reveal systematic differences between individuals with college graduates and non-graduate offspring across different dimensions of observed characteristics.

Table 3.1
Summary Statistics of Main Variables

	Pooled sample	College-Grad	Non-College-Grad	Difference	t-test
No. observations	*183,492*	*98,488*	*85,004*		
No. individuals	*33,942*	*16,506*	*17,436*		
CES-D score	6.57	6.81	6.28	0.54	***
	(1.96)	(1.77)	(2.12)		
Offspring College attainment (College-Grad)	54.0%	-	-		
	(0.498)				
Female	55.7%	55.6%	55.8%	-0.22%	
	(0.497)	(0.497)	(0.497)		
Age	65.8	66.7	64.6	2.06	***
	(10.0)	(10.1)	(9.7)		
ADL	3.74	3.79	3.67	0.12	***
	(0.751)	(0.661)	(0.841)		
IADL	3.79	3.83	3.74	0.09	***
	(0.644)	(0.577)	(0.711)		
Income	367.33	435.98	286.9	149.08	***
	(1172.29)	(1221.05)	(1106.10)		
Instrumental support	0.05	0.04	0.06	-0.02	***
	(0.265)	(0 235)	(0.296)		
Self-Reported Health (SRH)					
Excellent	11.5%	13.7%	8.9%	4.80%	***
	(0.319)	(0.344)	(0.285)		
Very Good	31.6%	35.2%	27.4%	7.80%	***
	(0.465)	(0.478)	(0.446)		
Good	31.7%	31.3%	32.0%	-0.70%	***
	(0.465)	(0.464)	(0.467)		
Fair	18.3%	14.9%	22.4%	-7.50%	***
	(0.387)	(0.356)	(0.417)		
Poor	6.8%	4.8%	9.2%	-4.40%	***
	(0.252)	(0.214)	(0.289)		
White	84.1%	86.8%	80.9%	5.90%	***
	(0.365)	(0.338)	(0.392)		
Years of Education	13.0	13.7	12.3	1.4	***
	(3.02)	(2.768)	(3.150)		

Notes: Observations are weighted using RAND sampling weights. Standard deviations are in parentheses. Due to missing responses, the numbers of observations for the following values are as listed: SRH (183,356), Race (183,299), Instrumental support (182,135) and Years of education (183,039). The last column indicates t-test for treated and untreated means. The asterisks denote the following levels of significance: ***<1%, **<5%, * <10%.

3.4 Empirical Strategy[24]

3.4.1 Endogeneity of Children's Education

The primary objective of this study is to estimate the causal effect of children's educational attainment on parental mental health. However, identifying the causal effect without explicitly considering the possible endogeneity of children's educational attainment may lead to less credible and inconsistent results. The potential endogeneity bias of education may stem from unobserved heterogeneity (both time-invariant and time-varying) and reverse causality, as well as simultaneity bias. Unobserved individual characteristics like parental and individuals' educational preferences or intrinsic abilities (e.g., learning aptitude and traits), can influence both the educational attainment of children and parental health. Time-varying unobservable factors, such as household economic and health shocks or family crises, may simultaneously affect children's education and parental psychological outcomes. Reverse causality bias can arise from parental health status, as it can influence children's education through parents' ability to provide educational support or investment as well as children's academic performance. Empirical evidence suggests that such endogeneity concerns are present in studying children's education and parental health outcomes (De Neve & Kawachi, 2017; Ma et al., 2021; Wei et al., 2022). Thus, failure to address these factors may result in inconsistent and biased estimates of the true causal impact of education on parental health.

Quasi-experimental designs are appropriate to address such biases, but they come with costs. In general, the IV is vulnerable to criticisms due to weak instruments and the exogeneity exclusion assumption, which requires that the instrument affects the outcome solely through its impact on the endogenous variable. Moreover, the IV estimates only the Local Average Treatment Effect (LATE), which focuses on those individuals (usually called compliers) whose treatment (education) is responsive to the change of the instrument (Angrist & Pischke, 2009). Therefore, such estimates would not represent the effect across the whole population due to the possibility of a heterogeneous treatment effect.

[24] This section draws from Brunello et el. (2024) and Christelis and Dobrescu (2020) to present the empirical strategy undertaken in this research.

To address the potential endogeneity concerns noted above, this study makes use of PI methods introduced by Manski (1989,1990,1997) and further developed by Manski and Pepper (2000, 2009). This approach relies on a nonparametric bounds analysis to estimate the upper and lower bounds of the average treatment effect (ATE) using fewer weaker and more plausible assumptions. Specifically, the bounds locate the ATE in an identification region instead of a point estimate. The advantage of the PI strategy over other commonly used methods like OLS, IV and panel data is that it estimates ATE rather than LATE, using straightforward mean calculations of the outcome and treatment. Another main advantage, researchers do not need to worry about any control variables selection and their functional form in the model as PI bounds unconditional expectation. Furthermore, PI relies on relatively weak and in some part testable transparent assumptions to narrow the bounds. Lastly, PI does not require panel data and sample unit dependencies can be controlled for through bootstrapping procedures. However, the main disadvantage of PI is that it may produce identification regions that are too wide leading to less precise and informative estimates than point estimates. On the other hand, point estimates use strong and untestable assumptions which according to the law of decreasing credibility may lead to greater uncertainty in the results (Manski, 2003).

Due to its advantages, the PI method has received great academic attention across various fields in economics. Recent empirical applications include health (Brunello et al., 2024; Christelis & Dobrescu, 2020), crime (Fé, 2024; Richey, 2015), labour (Germinario et al., 2022; Xu & Liu, 2023), welfare and poverty (Aizawa, 2022; Jensen et al., 2023), education (De Haan & Leuven, 2020; Hof, 2014; McDonough & Tra, 2017) and many others.

3.4.2 Empirical Specification

This study employs non-parametric methods mainly PI to examine the causal relationship between offspring's college education and parental mental health. The aim of PI is to bound the ATE within an identification region. This method relies on three key assumptions to effectively tighten the bounds and produce more informative regions: Monotone Treatment Response (MTR), Monotone Treatment Selection (MTS), and Monotone Instrumental

Variables (MIVs). This section briefly discusses the theoretical foundations and the empirical evidence supporting these assumptions.[25]

The objective of this analysis is to bound the ATE of children's education on parental mental health. Following Manski's (1997) standard terminology let every individual i have a response function $Y_i(\cdot) : T \rightarrow Y$, which maps treatments into $\mathrm{t} \in T$ into potential outcomes $Y_i(t) \in Y$. Due to heterogeneity, individuals respond differently to identical treatments. In this context, the treatment t is children's education and the outcome Y is parental mental health measured by CES-D score. For each individual in the sample the realised treatment z_i and the realised outcome $y_i \equiv Y_i(z_i)$ can be observed. However, one cannot observe the counterfactual outcome $Y_i(t)$ with $t \neq z_i$. To simplify the notation the subscript i will be dropped as well as conditioning expectations of outcomes and probabilities of treatments on observables X.

Empirically, the aim is to identify and estimate the ATE of children's education $t_2 \in T$ and $t_1 \in T$ s.t. $t_2 > t_1$, which can be expressed as follows:

$$ATE = E[Y(t_2)] - E[Y(t_1)] \tag{3.1}$$

Where Y is an individual mental health outcome measured by CES-D score. While t_2 is having a college graduate child and t_1 is otherwise (as defined in section 3.3). Specifically, $Y(t_2)$ denotes individuals mental health when having a college grad offspring and $Y(t_1)$ otherwise. Due to the binary nature of the treatment the ATE can be alternatively simplified to the familiar:

$$ATE = E[Y(1)] - E[Y(0)] \tag{3.2}$$

The ATE is the difference between two potential outcomes, both of which are assessed using the whole population, accounting for every other characteristic (either observable or unobservable) as given (Manski, 1997). Therefore, this examines the causal effect of the treatment on the outcome while keeping everything else constant. Specifically, the ATE represent the difference between the mean CES-D score if all individuals had a college graduate child $E[Y(t_2)]$ and the mean CES-D score if all individuals had not

[25] For full derivations, please refer to Manski (1989; 1997) and Manski and Pepper (2000).

$E[Y(t_1)]$. However, the estimation of the ATE using observational data is quite problematic, due to the fundamental problem of causal inference. Since the potential outcome $E[Y(t_2)]$ is observable only for respondents with college graduate children and remains as a counterfactual for respondents with children that did not graduate college (untreated individuals). On the other hand, $E[Y(t_1)]$ is observable for respondents with children who did not graduate college and remains as a counterfactual for respondents with college graduate children (treated individuals). In other words, these potential outcomes are latent one can only observe one potential outcome for an individual but never both.

To see this more clearly, the law of iterated expectations (also known as the law of total expectations) can be used to express the mean potential outcome $E[Y(t)]$ as follows, for any generic value of t:

$$E[Y(t)] = E[Y|z = t] * P(z = t) + E[Y(t)|z \neq t] * P(z \neq t) \tag{3.3}$$

Where $P(z = t)$ and $P(z \neq t)$ are the probabilities of individuals receiving or not receiving the treatment. Note that each of the above terms can be identified by the observed data except for the counterfactual outcome $E[Y(t)|z \neq t]$ (that untreated individuals would have experienced if they were treated). This counterfactual outcome cannot be observed in the data since an individual can only be observed in either the treated (t_2) or untreated (t_1) state at any given time, but never both simultaneously. Therefore, the ATE is unidentifiable without imposing further assumptions about the missing counterfactual.

A widely used assumption in the literature is the Exogenous Treatment Selection (ETS), which is generally implemented within an OLS framework. Under the ETS assumption, treatment is randomly assigned and statistically independent of potential outcomes. When this condition holds, the treatment effect can be consistently point estimated as the difference in mean outcomes between treated and untreated groups, or equivalently, as the OLS coefficient from regressing the outcome on the binary treatment variable. In that case, the OLS estimate identifies the population ATE, even when treatment effects are heterogeneous (Angrist & Pischke, 2009). However, in observational data, treatment assignment is typically not random, as individuals receiving treatment may differ systematically in unobserved characteristics related to both treatment and potential outcomes. Such endogeneity violates the ETS assumption and leads to biased and inconsistent estimates. The ETS estimate in this study is therefore presented only as a benchmark for comparison with the PI analysis derived below. The ETS is estimated by taking the mean difference between treated and untreated groups, following Eq. (3.2).

Instead of imposing strong assumptions on the counterfactual outcomes to point identify the ATE, Manski (1989) introduced a bounding analysis that identifies the unobserved counterfactual outcomes through PI, which caters for all types of endogeneity concerns by imposing relatively weak and plausible assumptions. Specifically, he proposed bounding the counterfactual potential outcomes from above and below via the minimum (Y_{min}) and maximum (Y_{max}) of the outcome variable, given that the outcome variable can be bounded. This assumption seems more credible since the outcome variable of interest is the CES-D score which has a minimum score of zero and a maximum score equal to 8. These maximum and minimum values can be substituted for the unobserved outcomes, i.e., $E[Y(t)|z \neq t]$, yielding the no-assumption bounds (also known as the worst-case bounds). Therefore, the $E[Y(t)]$ can be expressed as follows, where $LB(t)$ and $UB(t)$ denote lower and upper bounds of $E[Y(\mathrm{t})]$:

$$LB(t) = E[Y|z = t] * P(z = t) + (Y_{min}) * P(z \neq t)$$

$$\leq E[Y(t)] \leq$$

$$E[Y|z = t] * P(z = t) + (Y_{max}) * P(z \neq t) = UB(t) \tag{3.4}$$

Manski (1990) illustrated that the average treatment effect can be identified by the following expression:

$$LB(t_2) - UB(t_1) \leq ATE \leq UB(t_2) - LB(t_1) \tag{3.5}$$

The causal effect must lie between the lower and upper bounds; hence the identification region is an interval and therefore the ATE is partially identified. However, the no-assumption bounds are typically too wide and uninformative in practice. To tighten the bounds some further assumptions are needed to be able to make meaningful inferences.

The first assumption this study imposes is MTR introduced by Manski (1997). This assumption states that potential outcomes on average are weakly increasing function of the treatment. Implying a restriction on the direction of the treatment and assuming no negative effect, there can only be positive or zero effect by construction. Hence, the MTR identification region on its own includes zero and never below zero. Formally, the MTR can be expressed as, for any treatment value $t \in T$, and any two values $t_1 \in T$ and $t_2 \in T$ such that:

$$t_2 \geq t_1 : E[Y(t_2)|z = t] \geq E[Y(t_1)|z = t] \tag{3.6}$$

In this study, MTR assumes that individuals having a college graduate child weakly increases parental health (higher CES-D scores) on average. This is a reasonable assumption, as there are many reasons to expect that more educated children will exert a positive effect on parental health. Children who are more educated are generally healthier and equipped with greater health knowledge that might lead to providing better care or informative exchange of preventive health-related issues to parents, like exercises, nutrition and regular health tests (e.g., blood tests, flu shots, monthly checks for cancer etc.). This improves the parent's health literacy and therefore it may improve the overall health through engaging in a healthier lifestyle and habits.

Another possible effect is positive psychological effects. For example, parents feel pride or relief that a child is doing well with typically high income and socioeconomic status due to completing a college education, leading parents to feel less stressed and anxious about their children's future. It is well-known in the US that children who are not economically secure rely extensively on their parents for assistance (Caputo, 2019; Caputo & Cagney, 2023; Fingerman et al., 2012; Greenfield & Marks, 2006; Kahn et al., 2013; Maroto, 2017; McGarry, 2016; Newman, 2012). Also, as parents age and their health worsens, they rely on their offspring for financial assistance for healthcare services and insurance coverage, as college-educated children are better positioned to provide such services and ancillary support. Evidence from the US showed that children's education is positively associated with financial assistance and knowledge-based support to parents (Jiang & Kaushal, 2020; Kaushal, 2014; Silverstein et al., 2006). Therefore, children's education attainment tends to be positively associated with their parents' mental and overall health.

The MTR assumption is consistent with theoretical and empirical studies of the positive spillover association between college graduate offspring and parental health outcomes (Friedman & Mare, 2014; Pai et al., 2023; Peng et al., 2019; Wolfe et al., 2018; Yahirun et al., 2022; Yahirun et al., 2020a). There is no empirical evidence of a negative association between offspring education and parental health in the context of the US. As shown by Manski (1997) however, the MTR assumption does not rule out the no-association assumption. Therefore, the MTR assumption can be justified given the above arguments.

The MTR bounds for $E[Y(\mathrm{t})]$ can be expressed as:

$$LB(t) = (Y_{min}) * P(z > t) + E[Y|z = t] * P(z = t) + E[Y|z < t] * P(z < t)$$

$$\leq E[Y(t)] \leq$$

$$(Y_{max}) * P(z < t) + E[Y|z = t] * P(z = t) + E[Y|z > t] * P(z > t) = UB(t) \quad (3.7)$$

The MTR indicates that for any treatment levels $t < t_2$, the conditional mean $E[Y(t_2)|z = t]$ is no less than $E[Y(t)|z = t]$; i.e., the observed mean outcome at t, that is $E[Y|z = t]$. This increases the lower bound of $E[Y(t)]$, as it replaces the no-assumption bound Y_{min}. Under the MTR assumption, the potential outcome for individuals with lower treatment levels, their potential outcomes under higher treatment cannot be lower than their observed outcomes at current treatment levels. Similarly, for any treatment levels $t > t_2$ the potential outcomes cannot be higher than their observed mean outcome. This reduces the upper bound on the unconditional mean $E[Y(t_2)]$, as it replaces the no-assumption bound Y_{max}. The ATE bounds are computed by the same subtractions as shown earlier in Eq. (3.5). In positive MTR assumption, the lower bound of the ATE is always equal to zero by construction, as MTR ensures that mean outcomes cannot decrease with increased treatment levels.

The second assumption that will be used is MTS, under which treatment assignment is not exogenous, but demonstrates a monotone relationship with the potential outcomes, such that individuals who select into treatment tend to have systematically higher or lower potential outcomes than those who do not select, regardless of the realised treatment status (Manski & Pepper, 2000). Formally this can be expressed as follows, for each $t \in T$ and two treatment levels t_1 and t_2 such that:

$$t_2 \geq t_1 : E[Y(t)|z = t_2] \geq E[Y(t)|z = t_1] \quad (3.8)$$

In this study, MTS assumes individuals with college graduate offspring have on average weakly better potential health outcomes (i.e., higher CES-D score) than those without college graduate offspring. The MTS assumption could be justified given the vast literature documenting that healthier adults are highly associated with other characteristics and traits like higher education, intelligence and socioeconomic status (Assari, 2019; Benos et al., 2019; Hummer & Hernandez, 2013; Lundborg, 2013; Zajacova & Lawrence, 2018). Research on intergenerational human capital mobility in Western countries showed that individuals with higher-educated offspring are usually well-educated themselves (Black & Devereux, 2011; Holmlund et al., 2011; Ishitani, 2006; Mogstad & Torsvik, 2023). As such, they are more privileged, with greater resources like higher income and socioeconomic status than their counterparts, making health care services more available and accessible. Thus, more educated (privileged) individuals are more likely to have pre-treatment characteristics that make them more likely to have better potential health outcomes (on average). These arguments are consistent with the MTS assumption, supporting the theory that on average individuals with college graduate offspring realise better overall health.

The MTS bounds for $E[Y(t)]$ can be expressed as:

$$LB(t) = (Y_{min}) * P(z < t) + E[Y|z = t] * P(z = t) + E[Y|z = t] * P(z > t)$$

$$\leq E[Y(t)] \leq$$

$$(Y_{max}) * P(z > t) + E[Y|z = t] * P(z = t) + E[Y|z = t] * P(z < t) = UB(t) \quad (3.9)$$

The MTS implies that the conditional mean potential outcome cannot be more than the observed outcome $E[Y|z = \mathrm{t}]$. This observed outcome can be used as an upper bound for the mean potential outcome for treatment level $z <$ t. Similarly, for treatment level $z >$ t, the mean potential outcome cannot be less than the observed mean. This observed outcome can be used as a lower bound for the mean potential outcome when treatment level $z > t$.

The MTR and MTS assumptions alone are untestable, and can only be validated through economic theory, since they are imposed on unobserved potential outcomes. However, the combination of both MTR and MTS simultaneously is testable (Masnki & Pepper, 2000). Combining both assumptions simultaneously imposes monotonicity on the response function and that selection into treatment to be positive. Therefore, it is assumed that the mean health outcome (i.e., CES-D score) of individuals in the sample should be weakly increasing with the realised level of treatment. In other words, the mean score of individuals is weakly positively associated with having a college graduate child. If this is not the case, the assumption is rejected, and MTR+MTS cannot be applied. *Table 3.1* shows that the assumption is not rejected since the average score for individuals with college graduates is statistically higher than their counterparts (6.81 vs 6.28).

The third assumption that will be imposed is MIV one (Masnki & Pepper, 2000). This assumption states that potential outcomes on average must have a weakly increasing or decreasing monotone relationship with the instrument. The MIV assumption is more realistic and weaker than the traditional IV exogeneity exclusion assumption, which requires that the instrument affects the outcome solely through its impact on the endogenous variable. Also, the MIV assumption does not require the relationship of the instrument to have a causal effect on the outcome of interest nor any restrictions between the instrument and the treatment variable. Hence, the instrument is not vulnerable to being weak. The MIV assumption cannot be tested using observed data, as it is imposed on unobserved mean potential outcomes. however, it is more credible and can be justified theoretically. The MIV assumption can be expressed as follows, let S be an instrument for any treatment level $\mathrm{t} \in T$, such that:

$$m_1 \leq m \leq m_2 \rightarrow E[Y(t)|S = m_1] \leq E[Y(t)|S = m] \leq E[Y(t)|S = m_2] \qquad (3.10)$$

The MIV assumption implies that lower values of the instrument (m) are associated with lower potential health outcomes, and higher instrument values are associated with higher potential outcomes, on average. With a valid instrument satisfying the above expression, one can divide the sample into subsamples defined by the value of the instrument (i.e., the instrument must be categorical) and obtain bounds for each subsample. One can obtain bounds by taking the maximum lower bound where $S \leq m$ and the minimum upper bound where $S \geq m$ of all subsamples. Following this procedure for all values of S (subsamples), the bounds are then obtained by taking the weighted average of each of them. The $E[Y(t)]$ under the MIV assumption can be expressed as:

$$\sum_m \max_{m_1 \leq m} LB^M(E[Y(t)|S = m_1)] * P(S = m)$$

$$\leq E[Y(t)] \leq$$

$$\sum_m \min_{m_2 \geq m} UB^M(E[Y(t)|S = m_2)] * P(S = m) \qquad (3.11)$$

Where $LB^M(E[Y(t)|S = m_1)]$ denotes the lower bound of $E[Y(t)|S = m_1]$ under the set of assumptions M. Similarly, $UB^M(E[Y(t)|S = m_2)]$ denotes the upper bound of $E[Y(t)|S = m_2]$ under the same set of assumptions.

This study employs ADL and IADL scores as two MIVs simultaneously to further tighten the bounds. Both scores are categorised into five levels ranging from zero to four, where lower values indicate greater functional limitations and worse physical health. The MIV assumption assumes that under either treatment level individuals with lower ADL or IADL scores (indicating greater functional limitations) would have a weakly lower potential CES-D score (indicating worse mental health), on average. This assumption is based on the belief that these limitations and difficulties scores are associated directly or indirectly with mental health outcomes through increased dependence on others and loss of personal autonomy. *Table 3.A9* demonstrates the positive association between the two MIVs (ADL and IADL scores) and CES-D score, which directly supports and validates the underlying assumption of MIV.

To further assess the validity of the proposed MIVs, the relationships between the outcome and the instruments are illustrated in *Figure 3.A3.3*, which shows that mean CES-D scores gradually increase with higher levels of physical functioning and rise sharply at the highest category. This pattern provides a clear visual indication of a weakly increasing relationship between mental health and both ADL and IADL categories, consistent with the monotonicity assumption. In addition, a stochastic dominance test in mean CES-D scores across ADL and IADL categories was formally conducted following Drukker et al. (2024), which implements joint one-sided tests for multiple inequality restrictions. The null hypothesis states that the conditional mean of the outcome is weakly increasing in the MIVs, against the alternative that at least one mean difference is negative. The test provides no statistical evidence of monotonicity violations, supporting the use of ADL and IADL scores as valid MIVs (see Appendix *Table 3.A1*). Overall, the graphical evidence, correlation patterns, and formal test results jointly support the plausibility of the MIV monotonicity assumption and the use of ADL and IADL as valid monotone instrumental variables in the partial identification analysis.

The validity of these instruments is theoretically justified through several pathways in health studies, mainly that physical limitations increase the risk of depression (Gayman et al., 2008; Ng & Yang, 2023). Empirical evidence across various cultures showed that individuals with greater functional limitations measured by ADL or IADL scores often experience depression, stress and anxiety disorders due to their struggle to perform basic activities and ability to live independently (Brewster et al., 2017; Ohrnberger et al., 2017b; Yang, 2006; Yang & George, 2005). There is suggestive evidence from the HRS data used in this study that verifies the instruments to be positively associated with mental health status (Li et al., 2024; Luo et al., 2020). Furthermore, other studies have illustrated that improvement in mental health can be driven by physical health (Das et al., 2009; Kesavayuth et al., 2022; Li & Sunder, 2024). Therefore, the use of ADL and IADL scores as monotone instruments is theoretically and empirically supported.

3.5 Empirical Results

3.5.1 Main Results

Table 3.2 reports the results for the effect of having a college graduate child on mental health derived from different identifying assumptions. To estimate the bounds, this study follows the intersection-bounds procedure developed by Chernozhukov, Lee, and Rosen (2013) (CLR), which applies a half-median unbiased correction. The CLR method constructs bias-corrected 95% confidence intervals using 500 weighted bootstrap replications clustered at the household level, with 100,000 simulation draws for the half-median unbiased adjustment.[26] All estimations incorporate HRS survey sampling weights, which are applied in both the partial identification (PI) estimation and the bootstrap resampling procedures.

The first assumption ETS estimate indicate that having a college graduate child is associated with a 0.527 points improvement in CES-D score (approximately 8%) on average compared to individuals without a graduate child. This effect magnitude corresponds to 26.9% of one SD. This implies that parents of college graduate children are more likely to be in a better mental health state relative to their counterparts. This estimate is consistent with earlier studies in similar contexts in the US (Dennison & Lee, 2021; Yahirun et al., 2020a). However, as noted in section 3.4, the ETS assumption is likely to overestimate the true causal effect due to its strong assumption that fails to account for potential endogeneity

[26] For bounds estimated under the MTR or MTS assumptions (without MIVs), bias-corrected percentile (BC) 95% confidence intervals are constructed using 500 weighted bootstrap replications clustered at the household level.

arising from various unobservable variables that affect both treatment selection and potential outcomes.

This study addresses the potential endogeneity concerns by imposing relatively weak assumptions, using PI to bound the causal effect. The first assumption to introduce is the no-assumption, which is the most conservative identification strategy that relies solely on the extrema of the outcome variable. As expected, the ATE is quite wide and uninformative, ranging from -3.534 to 4.466 points in CES-D score. These bounds suggest that having a college graduate can lower CES-D score by at least 3.534 points, and at most improve scores by 4.466 points. This identification region is relatively wide and includes zero, hence one cannot conclude that college graduates have a positive or negative effect on their parents.

By imposing the MTR assumption, the lower bound is significantly reduced to zero by construction. Note, this is due to the MTR assumption, which rules out the negative effect of college graduates on mental health (i.e., allowing to identify the sign of the ATE), leading to a narrower identification region than before. The MTR bounds indicate that the ATE of graduates on the CES-D score can have no effect or improve scores by at most 4.466 points. On the other hand, the MTS assumption, which implies that individuals with a college graduate have on average higher potential CES-D scores than those without college graduate children, significantly lowers the upper bound to 0.527 points compared to the other bounds. The MTS bounds indicate that the effect of graduates is to improve CES-D by at most 0.527 points. Nevertheless, under MTS the bounds remain uninformative, as one cannot conclude the direction of the effect, as it includes a negative lower bound.

The individual bounds derived under the no-assumption, MTR, and MTS assumptions are relatively wide, and are not very informative. However, when imposed together they produce more narrow and meaningful bounds. The combination of MTR+MTS in *Table 3.2* illustrates significantly narrow bounds compared to the earlier bounds. The combination of both assumptions yields an ATE that ranges from 0 to 0.527 points in the CES-D score, suggesting that college graduates at worst have no effect and at most improve CES-D score by 0.527 points.

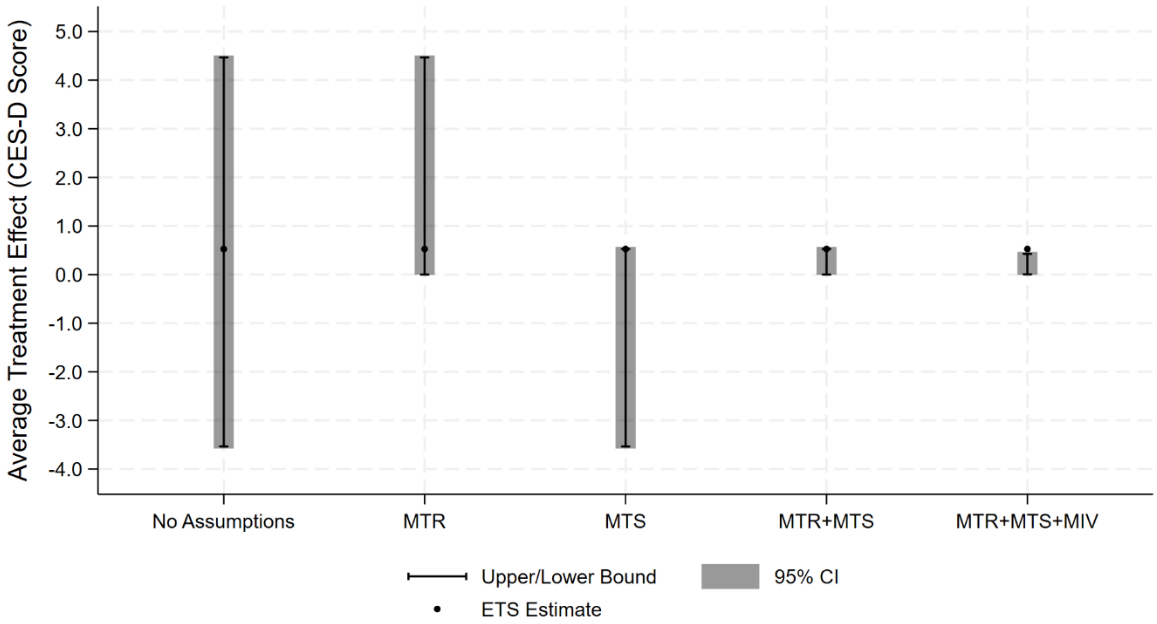
Combining the MTR+MTS with the MIV assumption further tightens the identification region by producing higher lower bounds and smaller upper bounds, as the lower bound excludes zero, yielding a more informative region of the true causal ATE ranging from 0.017 to 0.421. The finding suggests that having college graduates children improves CES-D scores by at least 0.017 points, and at most improve scores by 0.421 points, which translates to at least 0.25% and 6.4% increase on average compared to their counterparts and 0.87-21% of one SD. The 95% CIs excludes zero, implying that the true effect lies between 0.006 and 0.461 points improvement, which corresponds to 0.09-7% relative to the baseline mean and 0.31-24% of one SD. Also, the CIs around the bounds are narrow, demonstrating that there is little uncertainty about the treatment effects derived from the PI strategy.

Table 3.2
ETS Estimate and PI Bounds of the Effect of Having College Graduate Children on Mental Health

Assumptions	***Estimates***		***Lower Bound 95% CI***	***Upper Bound 95% CI***
	Lower Bound	***Upper Bound***		
Exogenous Treatment Selection (ETS)	0.527		0.484	0.570
No Assumptions	-3.534	4.466	-3.576	4.509
MTR	0	4.466	0	4.509
MTS	-3.534	0.527	-3.576	0.570
MTR+MTS	0	0.527	0	0.570
MTR + MTS + MIV	0.017	0.421	0.006	0.461
observations	183,492			
Mean	6.57			
Standard Deviation	1.96			

Notes: MTR: Monotone Treatment Response, MTS: Monotone Treatment Selection, MIV: Monotone Instrumental Variable. Bias-corrected 95% bootstrap confidence intervals use 500 weighted, household-clustered replications.

Although there is little uncertainty about the identification regions, the estimated ATE under the MTR + MTS + MIV assumptions ranges from 0.017 to 0.421, representing the most informative and preferred region derived from the PI strategy. The identification region demonstrates evidence of a positive causal effect of offspring education attainment on mental health outcomes. The results show that by imposing relatively weak and credible assumptions one can establish informative bounds on the true causal effect without the need to impose strong assumptions that produce biased point estimates. This can be visually illustrated in *Figure 3.1*, which shows how imposing each assumption helps to tighten the ATE identification region. Furthermore, the findings showcase that ETS point estimate is upwardly biased relative to the true causal effect and inconsistent. As seen in *Figure 3.1*, the MTR+MTS+MIV upper bound and 95% CI illustrated by the grey area excludes the ETS point estimate.



Notes: MTR: Monotone Treatment Response, MTS: Monotone Treatment Selection, MIV: Monotone Instrumental Variable. ETS: Exogenous Treatment Selection. Higher CES-D scores indicate better mental health.

Figure 3.1 Partial Identification Bounds for the Effect of College Graduate Children on Mental Health

The findings in this study derived from using the partial identification PI strategy cannot be directly compared to previous point estimates research for several reasons, the most significant of which is that the differences between estimation methods, data sets, and measures of both outcome and treatment variables preclude comparison. Nevertheless, the findings can be compared with two earlier works that employed similar measures and datasets. The first of these, by Yahirun et al. (2020a), employed the OLS method to investigate how children's education and characteristics affect the level of parental depression. Their OLS estimations yielded a much larger ATE that corresponds to about a 10% improvement in CES-D score on average. This point estimate lies outside 95% CI of the MTR+MTS+MIV upper bound obtained from using PI method, suggesting that the upward bias arising from potential endogeneity may have driven such a larger estimate.

Furthermore, Dennison and Lee (2021), using propensity score method (PSM), found that having a college graduate child is associated with 0.447 points improvement in CES-D score. The estimate falls within the 95% CI of the upper bound, indicating that the ATE is consistent with the plausible effect for the entire population. It should be noted, in this context, that PSM identifies the average treatment effect on the treated (ATT) and therefore cannot be directly compared with the estimated bounds (i.e., in *Table 3.2*), which estimate the ATE. However, when the ATT estimate from this study is compared with the ATT derived in Section 3.5.1.1, it falls within the 95% CI of the upper bound, indicating that the ATT is consistent with the plausible effect for the treated population.

3.5.1.1 Average Treatment Effect on the Treated

The main analysis in this study focuses on the ATE, which captures the population wide causal impact of children's college attainment on parental mental health. This estimand aligns with the broader research objective of assessing the overall intergenerational spillover of education across all parents. The ATE is most appropriate for evaluating population level intergenerational effects and understanding the broader social implications of educational attainment. However, from a policy perspective, it is also informative to consider the Average Treatment Effect on the Treated (ATT), which measures the causal effect among parents whose children actually attained a college degree, thereby focusing on the treated subgroup. The ATT provides a useful complementary measure that reflects the impact of children's education on parents directly affected by their children's college attainment. This parameter is particularly relevant for policy interventions that primarily influence a subset of individuals at the margin of college completion, rather than shifting educational attainment for the entire population.

Following the terminology in Section 3.4.2, the ATT can be expressed as follows:

$$ATT = E[Y(t_2)|\, z = t_2] - E[Y(t_1)|\, z = t_2] \tag{3.12}$$

Where $Y(t_2)$ and $Y(t_1)$ denote potential parental mental health outcomes under treatment and non-treatment, respectively, conditional on the realised treatment status t_2. While the

ATE averages the effect across all parents (Eq. (3.1)), the ATT conditions on the treated group, providing insight into potential outcomes for those directly exposed to the treatment.

This study extends the PI framework to bound the ATT under the same assumptions employed for the ATE analysis, namely MTR, MTS and MIV. Following, the same approach and logic to bound ATE but focusing on the treated subpopulation, bounds on the ATT are derived conditional on treatment status with ADL and IADL scores again serving as monotone instruments to tighten the bounds. The derivations of the assumptions are presented in Appendix B.

Table 3.3 reports the results for the ATT of having a college graduate child on mental health derived from different identifying assumptions. The bounds are estimated following the CLR procedure described in Section 3.5.1. Under the benchmark ETS assumption, the point estimate indicates that parents of college educated children have, on average, a 0.527 points higher CES-D score compared to those whose children did not complete college. Under ETS, where treatment assignment is random and independent of potential outcomes, the ATT is identical to the ATE reported in *Table 3.2*, as both represent the same population parameter under exogeneity. This magnitude corresponds to an improvement of approximately 8% of the mean CES-D score and 30% of one SD, implying better mental health among treated parents.

When no assumptions are imposed, the identification region is wide and uninformative (–1.187 to 6.813), reflecting limited information about the treatment effect as it includes zero. Imposing MTR substantially narrows the region, while adding MTS reduces the upper bound to 0.527 and eliminates negative values under the joint MTR + MTS assumptions. This combination yields an informative identification region ranging from 0 to 0.527, suggesting a non-negative effect on parental mental health among treated parents. Combining the MTR+MTS with the MIV assumption using ADL and IADL further tightens the identification region by producing higher lower bounds and smaller upper bounds, yielding a more informative region of the true causal ATT ranging from 0.002 to 0.521. These findings correspond to at least 0.03% and 7.7% increase of the mean CES-S score and 0.11% to 29% of one SD.

Table 3.3
ETS Estimate and PI Bounds of the ATT of Having College Graduate Children on Mental Health

Assumptions	*Estimates*		*Lower Bound 95% CI*	*Upper Bound 95% CI*
	Lower Bound	*Upper Bound*		
Exogenous Treatment Selection (ETS)	0.527		0.484	0.570
No Assumptions	-1.187	6.813	-1.212	6.840
MTR	0	6.813	0	6.840
MTS	-1.187	0.527	-1.212	0.570
MTR+MTS	0	0.527	0	0.570
MTR + MTS + MIV	0.002	0.521	0.0005	0.573
observations	98,488			
Mean	6.81			
Standard Deviation	1.77			

Notes: MTR: Monotone Treatment Response, MTS: Monotone Treatment Selection, MIV: Monotone Instrumental Variable. Bias-corrected 95% bootstrap confidence intervals use 500 weighted, household-clustered replications.

Figure 3.2 shows how imposing each assumption helps to tighten the ATT identification region. Similar to the ATE results, the figure demonstrates that each additional assumption (MTR, MTS, and MIV) progressively narrows the bounds toward a more informative and positive region. The figure also indicates that under strong identifying assumptions, the ETS point estimate provides a reasonable approximation of the ATT within an acceptable degree of accuracy in this context, as it falls within the MTR + MTS + MIV upper bound and the 95 percent confidence interval.

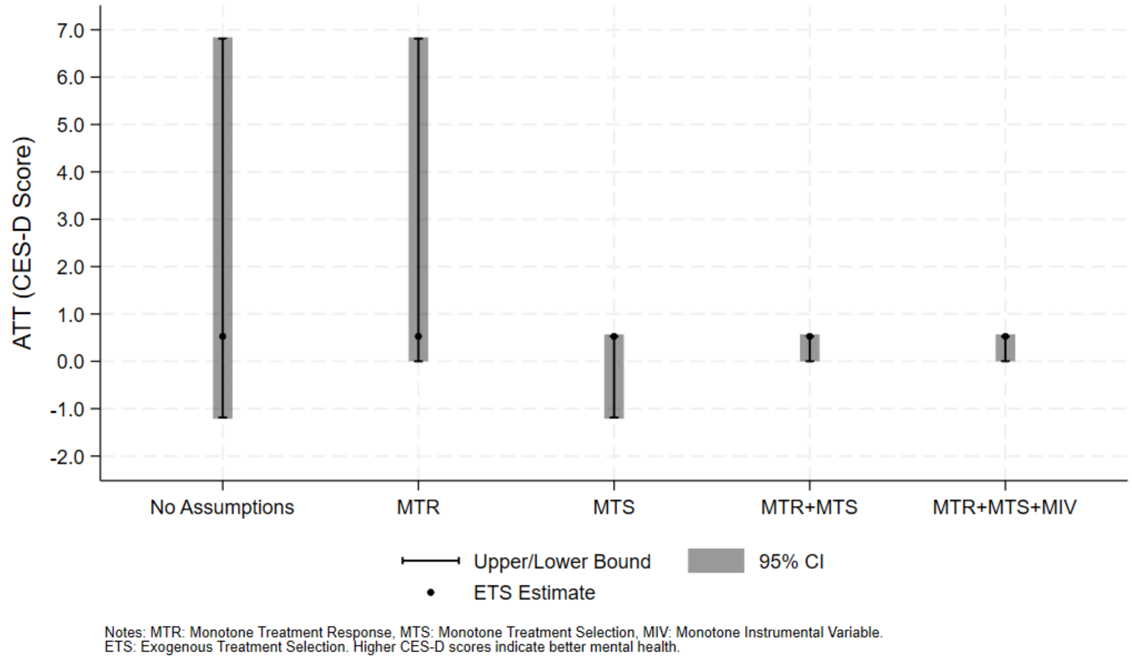


Figure 3.2 Partial Identification Bounds for the ATT of College Graduate Children on Mental Health

Overall, the ATT estimates support the main ATE findings, reinforcing evidence of a positive intergenerational spillover from children's college attainment. Importantly, the results demonstrate that while the ATE captures the population level effect, the realised benefit among treated parents is of comparable or slightly greater magnitude. This extension strengthens the policy interpretation of the results, illustrating that the mental health advantages associated with children's college attainment are both broad and meaningful for those directly affected, offering valuable insight for targeted educational policy design.

3.5.2 Robustness Checks

To assess the sensitivity and the validity of the main results several robustness checks were conducted. Firstly, PI bounds were re-estimated using an alternative measure for the treatment variable. The treatment variable in this context is the average years of education for all children. Respondent's children's college attainment was coded as a binary variable, with 1 denoting having average years of schooling for all children equal to 16 or more years (which is equivalent to completing college) and 0 otherwise. *Table 3.A2* in the appendix shows the ETS estimates and PI bounds under the alternative treatment measure. The findings are similar and consistent with the main findings, as the estimated bounds show evidence of a positive causal effect of offspring education attainment on mental health outcome. Secondly, the PI bounds were re-estimated excluding imputed values of the outcome variable, which reduced the original sample by 1,622 observations. *Table 3.A3* presents the bounds after excluding imputed measures. The estimated bounds are similar and consistent with the main findings, there are no significant changes with respect to the main results.

To enhance the clinical relevance of the findings, an additional robustness check redefines the outcome as a binary indicator of being non-depressed. Consistent with prior studies, respondents with CES-D scores of 6 or above are classified as non-depressed and depressed otherwise (Dang et al., 2020; Schlechter et al., 2023).[27] *Table 3.A4* shows that having a college educated child increases the probability of being non-depressed by approximately 0.36 to 7 percentage points, representing approximately 0.46-9% relative to the baseline mean and 0.88-17% of one SD. The estimated bounds are consistent in the direction with the main findings, supporting the robustness and clinical significance of the estimated bounds.

Box 3.1: Robustness Summary Results
Alternative Treatment Measure: • MTR+MTS+MIV: Lower Bound 0.004 Upper Bound 0.421 Excluding Imputed Measures: • MTR+MTS+MIV: Lower Bound 0.003 Upper Bound 0.427 Alternative Outcome Measure (Non-Depressed Indicator): • MTR+MTS+MIV: Lower Bound 0.036 Upper Bound 0.070 Key Findings: The bounds are robust across alternative treatment and outcome measures, as well as after excluding imputed observations.

Overall, the findings provide evidence of a positive causal effect of children's college attainment on parental mental health status, measured by CES-D score. Through the implantation of PI strategy and by imposing relatively weak and credible assumptions this study was able to provide informative bounds on the ATE with minimal uncertainty. The

[27] Individuals in prior studies are classified as depressed if their CES-D score corresponds to the conventional screening threshold of 3 or above on the original CES-D scale. Given that the CES-D measure in this study is reverse-coded so that higher values indicate better mental health, this threshold translates to a score of 6 or above.

findings show that traditional OLS estimates are likely to be upward biased from the true causal effect, which may be driven by endogeneity concerns. In general, the robustness checks confirm that the findings are consistent across alternative treatment and outcome measures and are not sensitive to the exclusion of imputed mental health observations. The additional analysis based on the non-depressed indicator further supports the robustness and clinical relevance of the estimated effects.

3.5.3 Mechanisms Analysis

Based on the earlier findings, this study identifies a positive causal effect of having a graduate child on parental mental health status. This section explores potential mechanisms through which college graduate children may affect parental mental health, as understanding such channels provides insight into the processes consistent with the observed relationship. According to earlier work, researchers concluded that intergenerational support like financial assistance and knowledge-based support to parents are the main channels through which children's education may affect parental health (Jiang & Kaushal, 2020; Kaushal, 2014; Silverstein et al., 2006; Torssander, 2013). Furthermore, it is well evident that social interaction with children plays an important role that leads to the reduction of parental stress, anxiety, and depression (Lee, 2018; Teo et al., 2015).

With the available dataset, the following potential mechanisms are examined: financial transfers from children to parents, frequency of contacts with children, number of serious illnesses and preventive care measures. The definitions of these mechanism variables are presented in *Table 3.4*.

Table 3.4
Definitions of Mechanisms

Mechanism	Definition
Financial Transfer	A binary variable indicating whether a child provided financial assistance to parents.
Frequency of contacts with children	Total number of contacts a child has had with parents over the course of the last 12 months. Contacts may be made via letter, phone, or in person.
Number of serious illnesses	A score variable that ranges from 0 to 7 indicating whether the respondent has ever been informed by a doctor that they have any of the following illnesses: High blood pressure, diabetes, cancer, lung disease, heart disease, stroke, and arthritis. For analysis purposes the score has been reversed i.e. low values indicate high number of illnesses and high values indicate otherwise.
Preventive care measures	A score variable that ranges from 0 to 2 indicating whether the respondent has any of the following preventative health tests and procedures: flu shots and blood test for cholesterol.

These channels are expected to improve mental health in various ways (De Neve & Kawachi, 2017). For example, well-educated children are more likely to be in higher paid jobs, leading them to have greater financial resources, which translates into providing more monetary and ancillary support to parents, which buttresses parents' socioeconomic status and can offset any medical expenses (Lee et al., 2017; Ma, 2019; Torres et al., 2022b). Therefore, parents of more educated children tend to have greater access to long-term care, as well as being more likely to adopt healthier habits like buying healthy food and doing regular medical checkups. Also, due to children's education and interaction with people of a higher socioeconomic status and greater health, they are equipped with more health-related knowledge. Highly educated children are more likely to exchange preventive health-related issues that helps to improve their parents' health literacy, access to health and reduce the number of serious illnesses they incur via the frequency of contacts (Berniell et al., 2023; Ram et el., 2022; Thoma et al., 2021).

Table 3.5 reports the PI bounds for college graduate children across the various potential mechanisms, under MTR+MTS+MIV assumptions, as this is the most informative and tightest bound.[28] In this context, the MTR assumption implies that parents having a college graduate children weakly increases financial transfers, frequency of contacts, and preventive care measures; and weakly decreases number of serious illnesses on average. Under the MTS assumption, individuals, on average, with college graduates have weakly better potential outcomes. These assumptions are credible and justified given the above arguments.

The instruments used for the MIV assumption differ according to each mechanism. For financial transfers, bounds are estimated using seven quantiles of household income and SRH simultaneously. There is evidence to show that parents who are worse of financially and medically are positively associated with receiving monetary transfers from their children (Iacovou & Davia, 2019; Patterson, 2023; Schaller & Eck, 2023). For frequency of contacts, the assistance received from children and SRH are used as a valid MIVs. Previous studies have shown that frequency of contacts with children is positively correlated with parent's health and the type of support they received (Batur et al., 2024; Haberkern & Szydlik, 2010; Teo et al., 2015).

When examining the number of serious illnesses, ADL and IADL scores are used as MIVs. Empirical work has confirmed that these functional limitation scores are highly associated with individuals' overall health and the number of chronic conditions (Bowling et al., 2019; Gondek et al., 2019; Ryan et al., 2015). For preventive care measures, eighteen quantiles of income were used as an MIV. The validity of this instrument stems from a theoretical and empirical perspective demonstrating that richer individuals are more privileged with greater access to health care services, making the utilisation of routine preventive care measures like regular blood tests and flu shots more accessible (Devaux, 2015; Gaskin et al., 2023).

[28] For full set of results, please refer to *Table 3.A5-A8*.

Table 3.5
PI bounds of the effect of having College Graduate Offspring on Mechanisms

Mechanisms	*Mean*	*Std. Dev.*	*Estimates* *Lower Bound*	*Upper Bound*	*Lower Bound 95% CI*	*Upper Bound 95% CI*
Financial Transfers	0.042	0.199	0.001	0.006	0.0007	0.010
Frequency of Contact	149	241	1.05	31.5	0.208	36.0
Number of Serious Illnesses	5.26	1.34	0.00003	0.12	0.0002	0.16
Preventive Care	1.43	0.69	0.006	0.104	0.0006	0.125

Notes: Bounds reported here are derived from MTR+MTS+MIV assumption only, for full set of results see Table 3.A5-A8.

As shown in *Table 3.5*, the ATE bounds of college graduates on providing financial transfers to parents increase the probability of providing such transfers by 0.1 to 0.6 percentage points, which corresponds to 2.3% and 14.3% increase on average compared to their counterparts, and 0.5-3% of one SD. For frequency of contacts, the results suggest that college graduates increase the frequency of contact with parents by 1.05 to 31.5 contacts, corresponding to 0.7% and 21% increase in contact points on average (0.4-13% SD). The findings further indicate that having college graduate offspring improves the score of reporting number of illnesses by 0.00003 to 0.125 points (0.0006-2.3% increase relative to the baseline mean and 0.002-9% SD). Lastly, the ATE for preventive care ranged from 0.006 to 0.104 points, which translates to 0.4-7% increase on average and 0.9-16% of one SD.

These results provide evidence consistent with several mechanisms via which offspring with college degrees may influence parental mental health. The results indicate variation in magnitude depending on each mechanism. Although the ATE appears modest across the different transmission channels, the most prominent effects are consistent with mechanisms via communicative and health monitoring behaviours, such as frequency of contact and preventive care, rather than direct economic transfers. These measures suggest that emotional support and knowledge exchange through interaction with children play a significant role in shaping parental mental health, indicating that familial relationships and closeness to children are significant determinants of parental wellbeing. The results also suggest that general financial transfers not focused on medical costs have some additional importance.

Overall, the findings are consistent with mechanisms via a combination of contact, knowledge exchange, and financial assistance that may contribute to improved parental mental health. The results are aligned with earlier work that demonstrated that knowledge, and financial support from highly educated children have beneficial effect on parental mental status (Applegate & Yahirun, 2023; Friedman & Mare, 2014; Jiang & Kaushal, 2020).

3.6 Conclusion

The economic and social burden of the wellbeing of the aging population presents several challenges for healthcare systems and public policy, reflecting the increase in both life expectancy and healthcare expenditures associated with ageing populations and older generations. A number of recent studies have investigated the potential benefits of children's education on parental wellbeing as opposed to traditional healthcare interventions aimed at addressing such challenges directly among older patients themselves. While reviewed studies generally found a positive association between children's education and various parental health outcomes. However, the complex and interconnected relationship between children education attainment and parental health makes it difficult to establish causal associations. Potential sources of endogeneity bias resulting from unobserved heterogeneity and reverse causality are likely to produce biased and inconsistent estimates. Thus, there is a need to address such challenges in empirical research to obtain robust causal inferences.

This study addresses the gap in existing literature on the association between children educational attainment and parental wellbeing by providing causal evidence on parental mental health, measured by CES-D score. Using a nationally representative longitudinal data from HRS and employing a nonparametric PI analysis, based on credible and plausible assumptions to control for any potential sources of endogeneity bias. This study produced bounds of the population average treatment effect of education on parental health using partially testable weak monotonicity assumptions: Monotone Treatment Response (MTR), Monotone Treatment Selection (MTS), and Monotone Instrumental Variables (MIVs). The MTR assumptions states that potential outcomes on average are weakly increasing function of the treatment. The MTS assumes that individuals who select into treatment tend to have systematically higher potential outcomes than those who do not select, regardless of the realised treatment status. The MIV assumption states that potential outcomes on average must have a weakly increasing or decreasing monotone relationship with the instrument. The validity of these assumptions and choice of the instruments is consistent and theoretically justified within the related literature documenting the relationship between children education and parental wellbeing.

The findings provide evidence of a robust positive causal effect of children's college attainment on parental mental health status. Specifically, by combining all three assumptions, the estimated MTR+MTS+MIV bounds produced the most informative region of the average treatment effect with minimal uncertainty and statistically significant non-zero effect. The findings suggest that having college graduates improves CES-D scores by between 0.017 and 0.421 points, which corresponds to at least 0.25% and 6.4% increase on average compared to their counterparts and 0.87-21% of one SD. The findings also demonstrate that failing to account for the endogeneity of children's education and parental mental health will result in upward biased estimates of the true causal effect. These findings are robust and consistent across various specifications and sensitivity tests. The mechanism analysis results indicate that the effects of children's education are consistent with mechanisms via communicative and health monitoring behaviours, such as frequency of contact and preventive care. These findings confirm that children human capital acquired through college degree attainment provides health benefits that expands beyond the individuals themselves and can be transmitted intergenerationally to their parents. Specifically, the findings support the intergenerational human capital mobility theory.

Several policy implications can be derived from the positive effect of children's education on parental health. The general findings stress that the full impact of returns of education can go beyond individual gains and could generates a broader social return through intergenerational health benefits. They specifically support policies that would increase children's education attainment as means to improve parental health outcomes. The findings deliver justifications for policymakers to increase spending and reduce barriers to higher education, as such investment not only yields benefits for one generation but also have positive externalities that extend to benefit the older generations. As tuition fees continue to increase, such expanding education spending will benefit both generations particularly those in low-income households as they are most vulnerable to limited access to health and education institutions.

Also, given the findings on the channels through which education influences parental health, policymakers and healthcare institutions should develop specific programs to incorporate adult children into their parents' medical treatment plans. These programs should boost health communication between adult children and their parents, while also promoting adult children's engagement in overseeing and assisting the implementation of treatment plans. This is advisable, as such involvements will aid adult children with parental health management, particularly regarding complex treatment plans, medical appointments and preventive health measures. Children involvement potentially improves treatment outcomes for their parents while reducing healthcare utilization costs.

Overall, this study significantly contributes to the existing literature on the association between children educational attainment and parental wellbeing and offers insights into the role of children's education. This study provides robust causal evidence of the impact of children college attainment on parental mental health. The nonparametric bounds analysis and statistical tests employed in this study ensure that the findings are not driven by any potential sources of bias associated with the endogeneity of education and health. Also, this study extended the understanding of the complex relationship of children's education and parental health, highlighting how this relationship is likely to operate through various channels of intergenerational support.

Future work on the causal association between children college attainment and parental health should explore different domains of subjective and objective parental health outcomes such as physical activity and cognitive function. Examining different health measures would provide a comprehensive understanding of which aspects of parental wellbeing are most affected by children's education. Additionally, researchers should investigate the possible heterogeneity effects of children's education across different parental socioeconomic status, race, gender and family structure. These heterogeneity effects would highlight the reasons and means of how different parents are affected. Future research should consider applying a formal mediation analysis to assess the extent to which factors such as knowledge-based support, financial transfers, and parent–child relationship quality account for the observed effects. Understanding these channels would provide a deeper understanding of the causal pathways connecting children's education and parental health. Lastly, future research should utilise more rigorous methodological strategies to obtain point estimates of the average treatment effect of education, as estimates from nonparametric analysis produces identification regions of the effect and not point estimates. This would allow more targeted and precise policies of the spillover benefits.

Appendix 3.A

Appendix 3.A provides the full set of supplementary results and robustness analyses supporting the empirical findings presented in Chapter 3. The tables report the Exogenous Treatment Selection (ETS) estimates and Partial Identification (PI) bounds under alternative assumptions and specifications, including different definitions of the treatment variable, the exclusion of imputed measures, and analyses of potential mechanisms. The appendix also presents figures illustrating the PI bounds under various specifications, as well as tests and correlation matrices that validate the use of the monotone instrumental variables (ADL and IADL). These extended results support the main conclusions, demonstrating that the positive effect of children's college attainment on parental mental health is robust across alternative samples, model specifications, and outcome definitions.

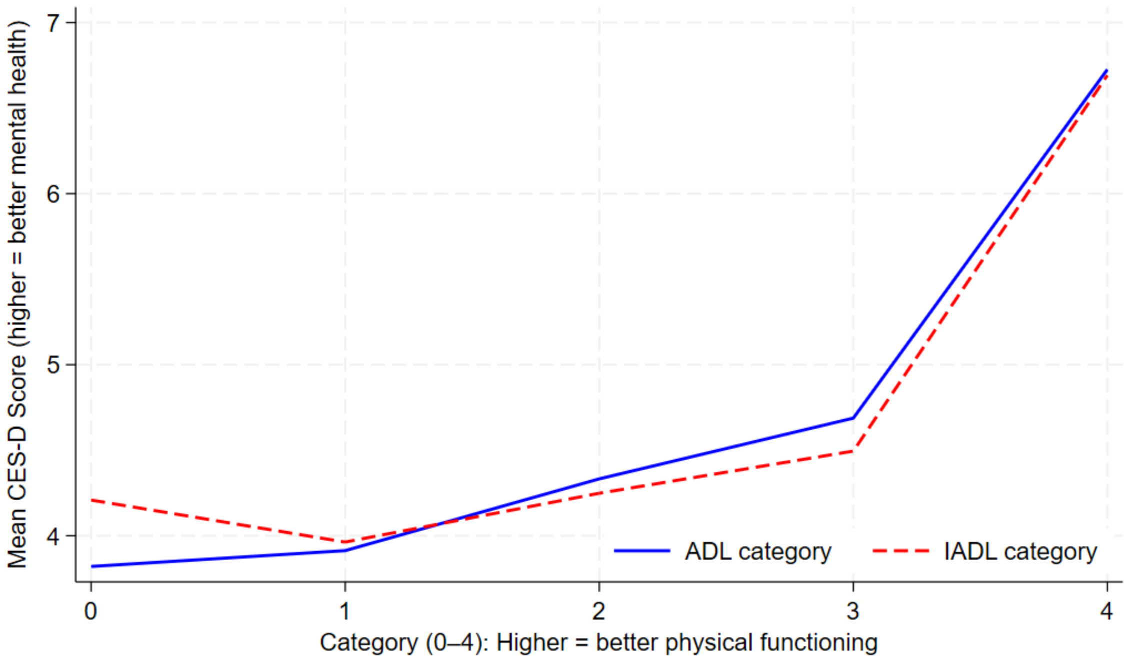


Figure 3.A3.3 Mean CES-D Score by ADL and IADL category

Table 3.A1
Stochastic dominance test for mean CES-D Score across ADL and IADL categories

Comparison (ADL, IADL)	Difference in mean CES-D	Adjusted p-value
(0, 1) – (0, 0)	0.176	1.000
(1, 1) – (0, 1)	-0.431	0.806
(1, 2) – (1, 1)	0.415	1.000
(2, 2) – (1, 2)	0.327	1.000
(2, 3) – (2, 2)	0.351	1.000
(3, 3) – (2, 3)	-0.026	1.000
(3, 4) – (3, 3)	0.694	1.000
(4, 4) – (3, 4)	1.840	1.000
(1, 0) – (0, 0)	0.055	1.000
(2, 0) – (1, 0)	0.722	1.000
(3, 0) – (2, 0)	0.345	1.000
(4, 0) – (3, 0)	1.165	1.000
(2, 1) – (1, 1)	0.986	1.000
(3, 1) – (2, 1)	-0.505	0.617
(4, 1) – (3, 1)	1.096	1.000
(3, 2) – (2, 2)	0.025	1.000
(4, 2) – (3, 2)	0.970	1.000
(4, 3) – (3, 3)	0.592	1.000
Overall max-t p-value	0.617	
Critical value (max-t test)	-2.981	

Notes: The table reports one-sided stochastic dominance tests in mean CES-D across ordered categories of Activities of Daily Living (ADL) and Instrumental Activities of Daily Living (IADL). Each row presents the difference in conditional means of CES-D between adjacent values of the MIVs ADL and IADL. The test uses max-t–adjusted p-values that control the familywise error rate (FWER = 0.05). The null hypothesis states that the conditional mean of CES-D is weakly increasing in the MIVs (i.e., no decrease across higher ADL/IADL levels). The overall joint test yields p = 0.617, indicating no statistical evidence of monotonicity violations.

Table 3.A2
ETS Estimate and PI Bounds Under Alternative Treatment Measure

Assumptions	***Estimates***		***Lower Bound 95% CI***	***Upper Bound 95% CI***
	Lower Bound	***Upper Bound***		
Exogenous Treatment Selection (ETS)	0.516		0.467	0.560
No Assumptions	-5.476	2.523	-5.515	2.562
MTR	0	2.523	0	2.562
MTS	-5.476	0.516	-5.515	0.560
MTR+MTS	0	0.516	0	0.560
MTR + MTS + MIV	0.0004	0.429	0.000004	0.476
observations	183,492			
Mean	6.57			
Standard Deviation	1.96			

Notes: MTR: Monotone Treatment Response, MTS: Monotone Treatment Selection, MIV: Monotone Instrumental Variable. Bias-corrected 95% bootstrap confidence intervals use 500 weighted, household-clustered replications.

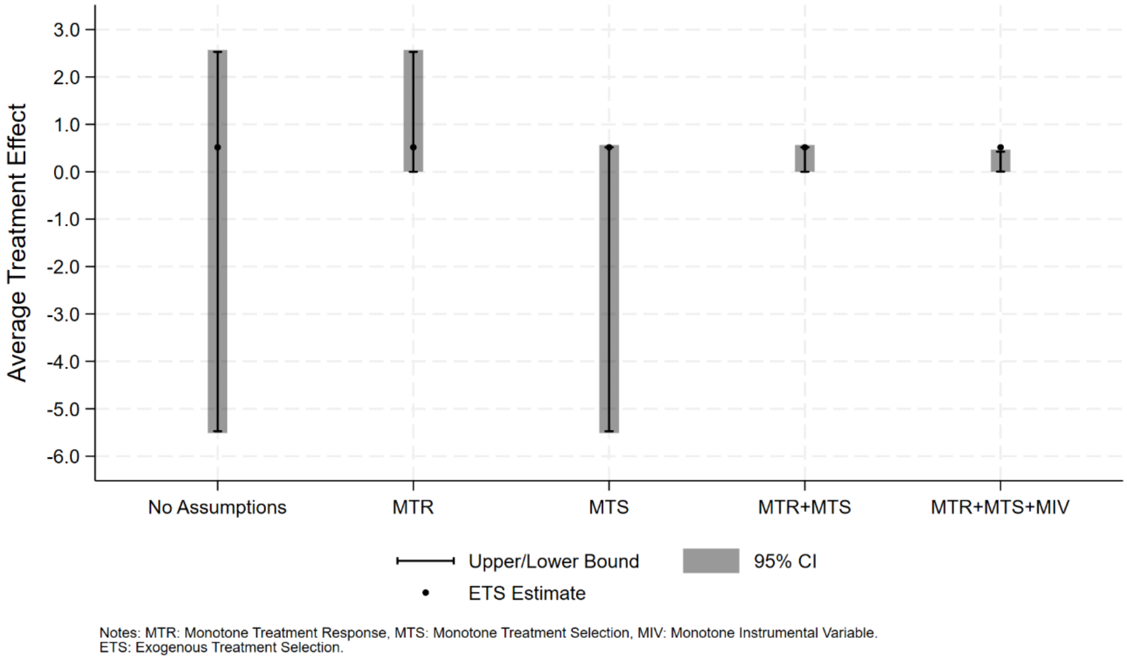
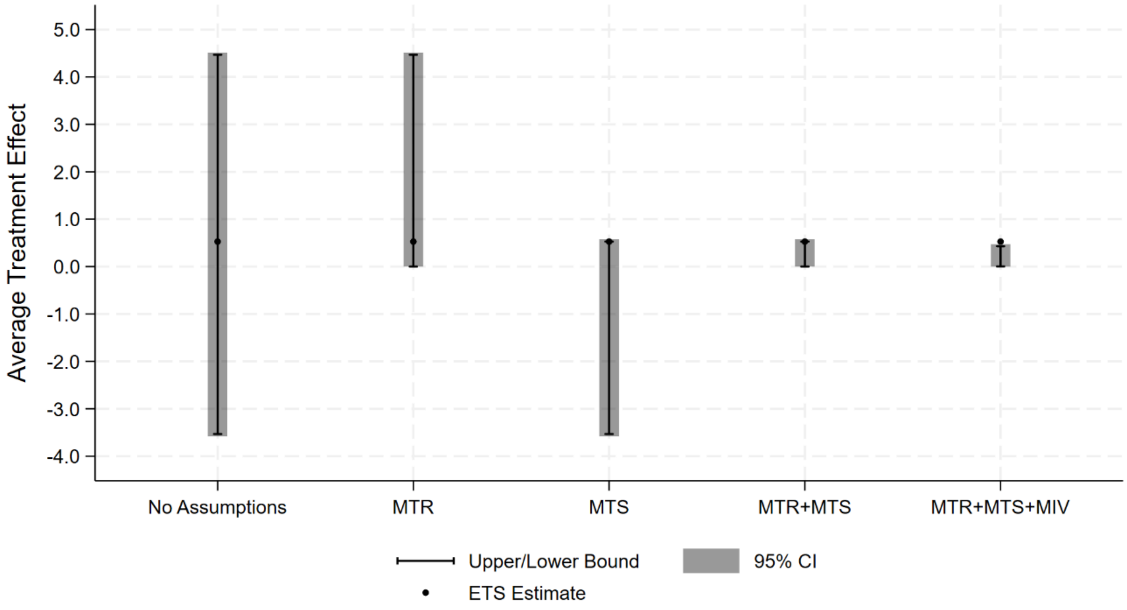


Figure 3.A3.4 Partial Identification Bounds Under Alternative Treatment Measure

Table 3.A3
ETS Estimate and PI Bounds After Excluding Imputed Measures

Assumptions	*Estimates*		*Lower Bound 95% CI*	*Upper Bound 95% CI*
	Lower Bound	*Upper Bound*		
Exogenous Treatment Selection (ETS)	0.528		0.483	0.573
No Assumptions	-3.531	4.469	-3.580	4.519
MTR	0	4.469	0	4.519
MTS	-3.531	0.528	-3.580	0.573
MTR+MTS	0	0.528	0	0.573
MTR + MTS + MIV	0.015	0.427	0.004	0.471
observations	181,870			
Mean	6.57			
Standard Deviation	1.95			

Notes: MTR: Monotone Treatment Response, MTS: Monotone Treatment Selection, MIV: Monotone Instrumental Variable. Bias-corrected 95% bootstrap confidence intervals use 500 weighted, household-clustered replications.



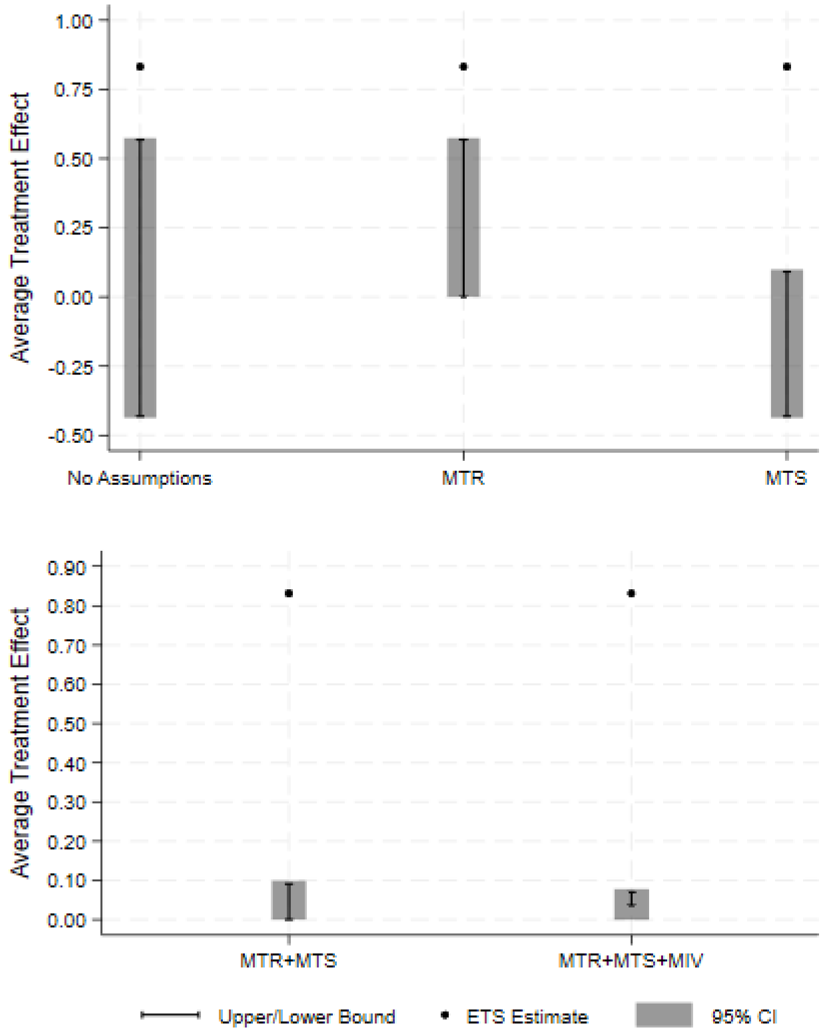
Notes: MTR: Monotone Treatment Response, MTS: Monotone Treatment Selection, MIV: Monotone Instrumental Variable.
ETS: Exogenous Treatment Selection.

Figure 3.A3.5 Partial Identification Bounds Excluding Imputed Measures

Table 3.A4
ETS Estimate and PI Bounds of the Effect of Having College Graduate Children on the Probability of Being Non-Depressed (Alternative Outcome Measure)

Assumptions	***Estimates***		***Lower Bound 95% CI***	***Upper Bound 95% CI***
	Lower Bound	***Upper Bound***		
Exogenous Treatment Selection (ETS)	0.832		0.827	0.836
No Assumptions	-0.431	0.568	-0.437	0.574
MTR	0	0.568	0	0.574
MTS	-0.431	0.091	-0.437	0.099
MTR+MTS	0	0.091	0	0.099
MTR + MTS + MIV	0.036	0.070	0.001	0.078
observations		183,492		
Mean		0.790		
Standard Deviation		0.407		

Notes: MTR: Monotone Treatment Response, MTS: Monotone Treatment Selection, MIV: Monotone Instrumental Variable. Bias-corrected 95% bootstrap confidence intervals use 500 weighted, household-clustered replications.



Notes: MTR: Monotone Treatment Response, MTS: Monotone Treatment Selection,
MIV: Monotone Instrumental Variable. ETS: Exogenous Treatment Selection.
Upper panel: Wider bounds (No Assumptions, MTR, MTS);
Lower panel: Narrower bounds (MTR+MTS, MTR+MTS+MIV).

Figure 3.A3.6 Partial Identification Bounds for the Effect of Having College Graduate Children on the Probability of Being Non-Depressed (Alternative Outcome Measure)

Table 3.A5
ETS Estimate and PI Bounds of the Effect of Having College Graduate Offspring on Financial Transfers

Assumptions	***Estimates***		***Lower Bound 95% CI***	***Upper Bound 95% CI***
	Lower Bound	***Upper Bound***		
Exogenous Treatment Selection (ETS)	0.006		0.003	0.010
No Assumptions	-0.534	0.466	-0.540	0.473
MTR	0	0.466	0	0.473
MTS	-0.534	0.006	-0.540	0.010
MTR+MTS	0	0.006	0	0.010
MTR + MTS + MIV	0.001	0.006	0.0007	0.010
observations			180.172	
Mean			0.042	
Standard Deviation			0.199	

Notes: MTR: Monotone Treatment Response, MTS: Monotone Treatment Selection, MIV: Monotone Instrumental Variable. Bias-corrected 95% bootstrap confidence intervals use 500 weighted, household-clustered replications.

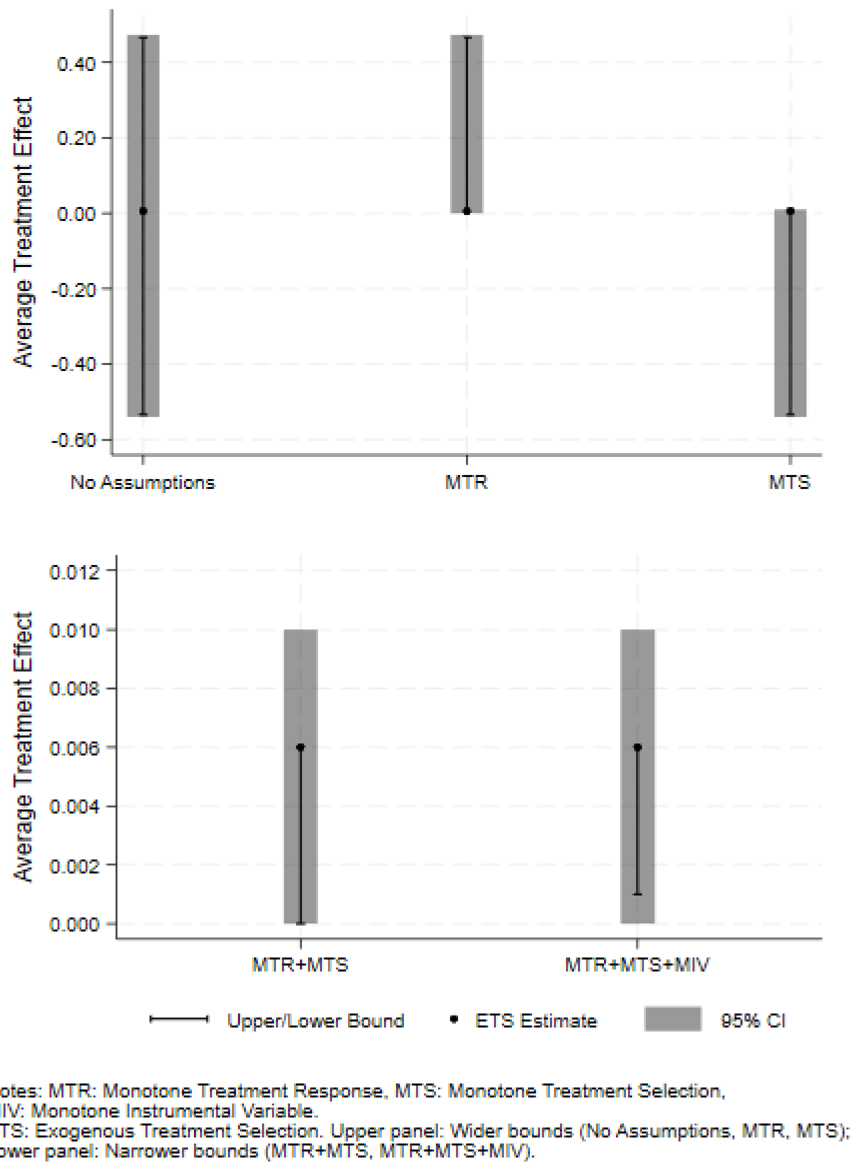


Figure 3.A3.7 Partial Identification Bounds for the Effect of College Graduate Children on Financial Transfers

Table 3.A6
ETS Estimate and PI Bounds of the Effect of Having College Graduate Offspring on Frequency of Contact

Assumptions	***Estimates*** ***Lower Bound***	***Upper Bound***	***Lower Bound 95% CI***	***Upper Bound 95% CI***
Exogenous Treatment Selection (ETS)	31.5		26.6	36.0
No Assumptions	-6376	6033	-6465	6127
MTR	0	6033	0	6127
MTS	-6376	31.5	-6465	36.0
MTR+MTS	0	31.5	0	36.0
MTR + MTS + MIV	1.05	31.5	0.208	36.0
observations		114,135		
Mean		149		
Standard Deviation		241		

Notes: MTR: Monotone Treatment Response, MTS: Monotone Treatment Selection, MIV: Monotone Instrumental Variable. Bias-corrected 95% bootstrap confidence intervals use 500 weighted, household-clustered replications.

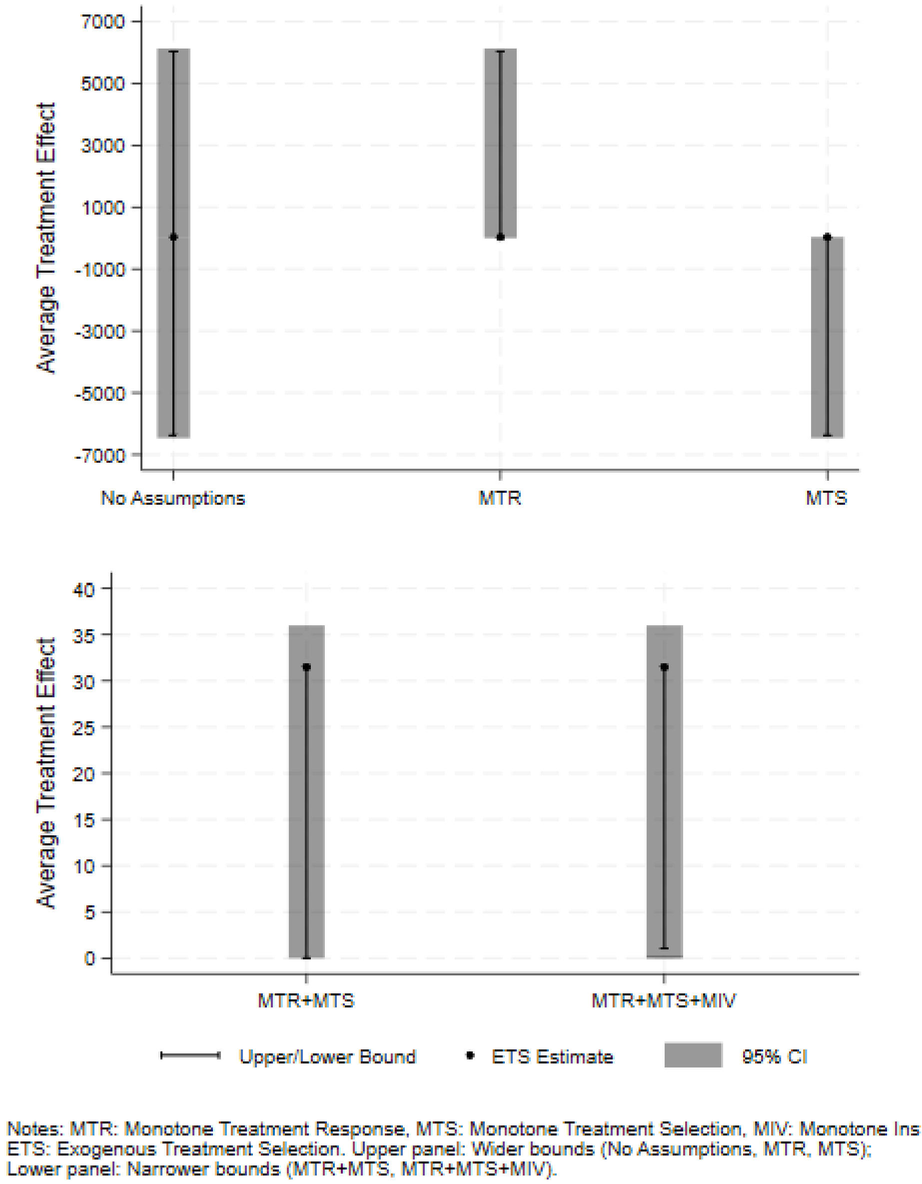


Figure 3.A3.8 Partial Identification Bounds for the Effect of College Graduate Children on Frequency of Contact

Table 3.A7
ETS Estimate and PI Bounds of the Effect of Having College Graduate Offspring on Number of Serious Illnesses

Assumptions	***Estimates***		***Lower Bound 95% CI***	***Upper Bound 95% CI***
	Lower Bound	***Upper Bound***		
Exogenous Treatment Selection (ETS)	0.18		0.14	0.21
No Assumptions	-3.27	3.73	-3.30	3.76
MTR	0	3.73	0	3.76
MTS	-3.27	0.18	-3.30	0.21
MTR+MTS	0	0.18	0	0.21
MTR + MTS + MIV	0.00003	0.12	0.0002	0.16
observations			183,492	
Mean			5.26	
Standard Deviation			1.34	

Notes: MTR: Monotone Treatment Response, MTS: Monotone Treatment Selection, MIV: Monotone Instrumental Variable. Bias-corrected 95% bootstrap confidence intervals use 500 weighted, household-clustered replications.

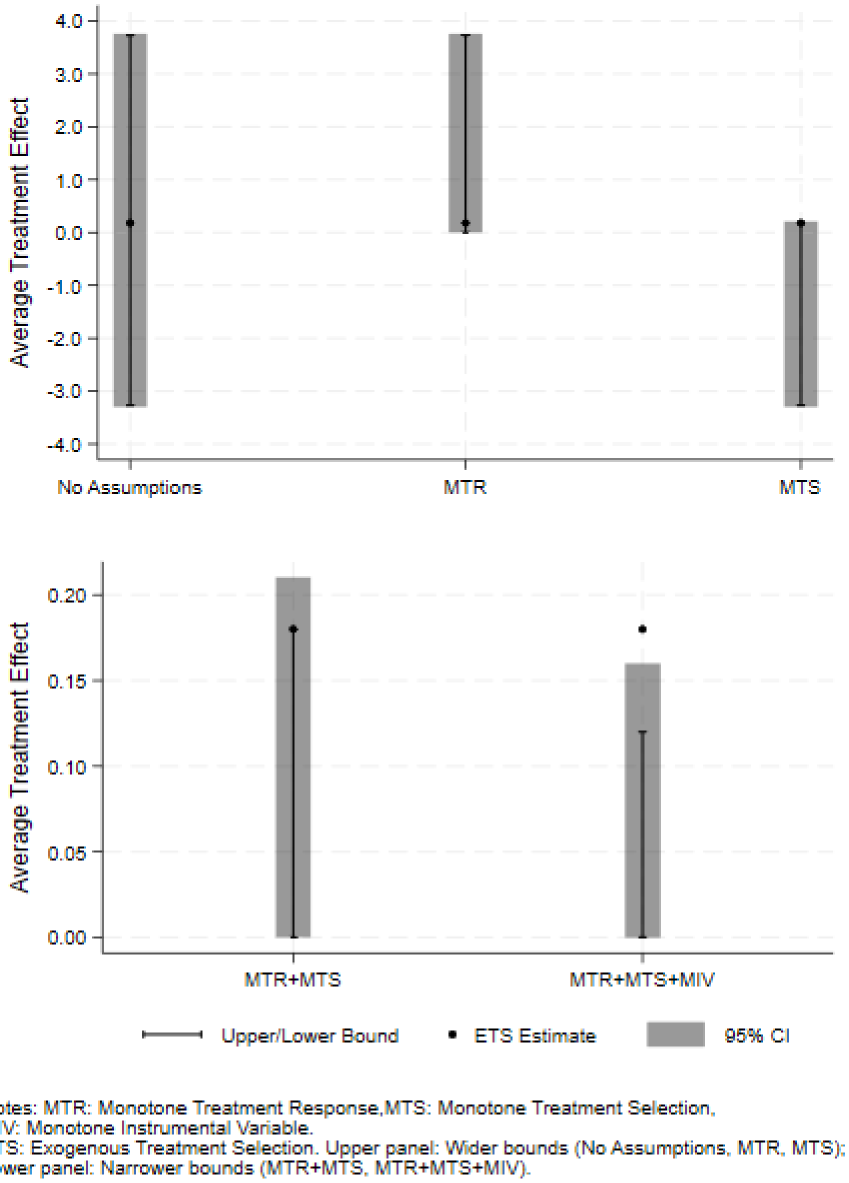


Figure 3.A3.9 Partial Identification Bounds for the Effect of College Graduate Children on Number of Serious Illnesses

Table 3.A8
ETS estimate and PI bounds of the effect of having College Graduate Offspring on Preventive Care

Assumptions	***Estimates*** ***Lower Bound***	***Upper Bound***	***Lower Bound 95% CI***	***Upper Bound 95% CI***
Exogenous Treatment Selection (ETS)	0.134		0.118	0.150
No Assumptions	-0.899	1.101	-0.908	1.111
MTR	0	1.101	0	1.111
MTS	-0.899	0.134	-0.908	0.150
MTR+MTS	0	0.134	0	0.150
MTR + MTS + MIV	0.006	0.104	0.0006	0.125
observations		180,092		
Mean		1.43		
Standard Deviation		0.69		

Notes: MTR: Monotone Treatment Response, MTS: Monotone Treatment Selection, MIV: Monotone Instrumental Variable. Bias-corrected 95% bootstrap confidence intervals use 500 weighted, household-clustered replications.

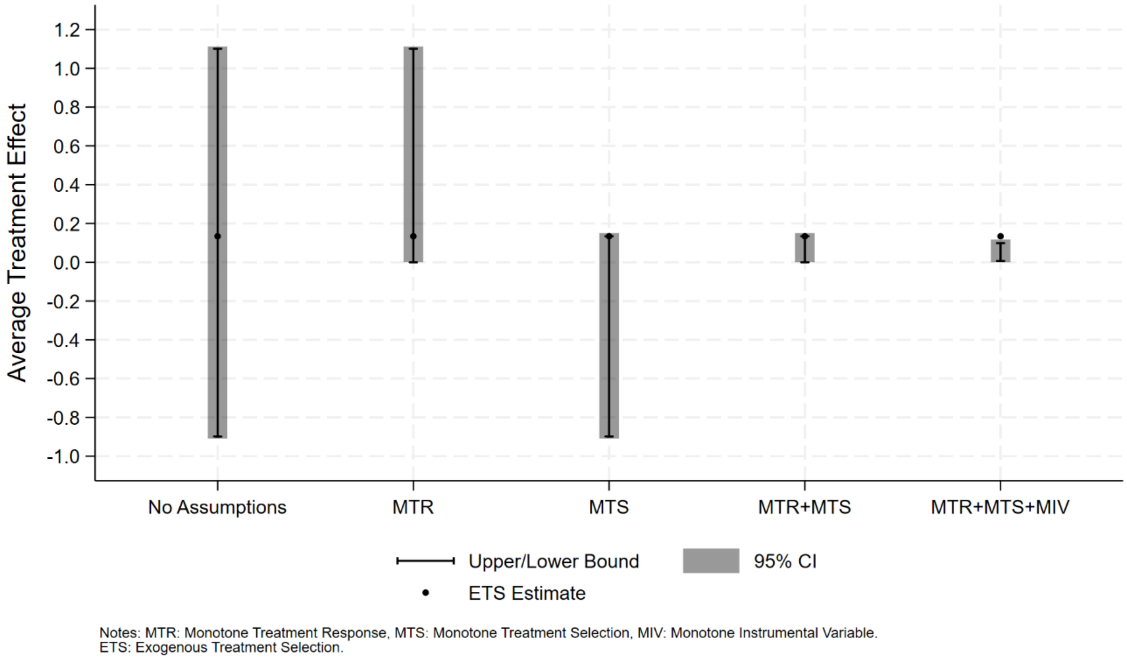


Figure 3.A3.10 Partial Identification Bounds for the Effect of College Graduate Children on Preventive Care

Table 3.A9
Correlation between MIVs and outcome variables

MIVs	Outcome Variables				
	CES-D score	Financial Transfer	Frequency of Contact	No. Serious Illnesses	Preventive Care
ADL	0.287***			0.217***	
IADL	0.246***			0.187***	
SRH		0.066***	0.021***		
Income		-0.122***			0.061***
Instrumental support			0.052***		

Notes: *** shows significance at the 0.01 level

Appendix 3.B

This appendix describes how the Average Treatment Effect on the Treated (ATT) is bounded under different identifying assumptions.

Let Y denote the outcome variable, and t_1, t_2 represent the two treatment states with $t_2 > t_1$. The parameter of interest is the average treatment effect among the treated population (ATT):

$$ATT = E[Y(t_2)|\, z = t_2] - E[Y(t_1)|\, z = t_2] \tag{3.12}$$

The ATT is the difference between two potential outcomes, both of which are assessed using the treated population. The observed potential outcome for the treated group is directly observed by $E[Y(t_2)|\, z = t_2] = E[Y|\, z = t_2]$, while the counterfactual potential outcome $E[Y(t_1)|\, z = t_2]$ cannot be observed in the data since an individual can only be observed as receiving treatment (t_2). Therefore, the ATT is unidentifiable without imposing further assumptions about the missing counterfactual.

This study extends the PI assumptions used in Section 3.4.2 to bound the missing counterfactual. Under the no-assumption, the counterfactual potential outcomes for the treated group can be bounded from above and below via the minimum (Y_{min}) and maximum (Y_{max}) of the outcome variable. Hence, the ATT can be expressed as:

$$LB_{ATT} = E[Y(t_2)|\, z = t_2] - Y_{max} \leq ATT \leq E[Y(t_2)|\, z = t_2] - Y_{min} = UB_{ATT} \tag{3.13}$$

Under the MTR assumption, potential outcomes are weakly increasing in the treatment level, $t_2 \geq t_1$ for all individuals. The MTR implies that the maximum potential outcome for the missing counterfactual cannot exceed the realised observed outcome, while the minimum remains the smallest possible outcome (Y_{min}). Thus, the ATT can be expressed as:

$$LB_{ATT} = E[Y(t_2)|\, z = t_2] - E[Y(t_2)|\, z = t_2] = 0$$

$$\leq ATT \leq$$

$$E[Y(t_2)|\, z = t_2] - Y_{min} = UB_{ATT} \tag{3.14}$$

The MTS assumption implies that individuals who select into treatment tend to have systematically higher potential outcomes than those who do not select, regardless of the realised treatment status. Formally, as:

$$E[Y(t_1)|\, z = t_2] \geq E[Y(t_1)|\, z = t_1] \quad (3.15)$$

The MTS assumption implies that individuals who select into treatment tend to have systematically higher potential outcomes than those who do not select. Therefore, the minimum feasible counterfactual for the treated cannot be lower than the realised outcome of the lower treatment group, i.e. $E[Y(t_1)|\, z = t_1]$, while the upper bound remains the maximum possible outcome (Y_{max}). Accordingly, the ATT is bounded as:

$$LB_{ATT} = E[Y|\, z = t_2] - Y_{max}$$

$$\leq ATT \leq$$

$$E[Y|\, z = t_2] - E[Y|\, z = t_1] = UB_{ATT} \quad (3.16)$$

Under the MIV assumption, the bounds are obtained as in Eq. (3.11), conditional on the treated group $z = t_2$. The ATT bounds under MIV are:

$$LB_{ATT} = E[Y|\, z = t_2] - \sum_{m} \min_{m_2 \geq m} UB^M(E[Y(t_1)|z = t_2, S = m_2)] * P(S = m|z = t_2)$$

$$\leq ATT \leq$$

$$UB_{ATT} = E[Y|\, z = t_2] - \sum_{m} \max_{m_1 \leq m} LB^M(E[Y(t_1)|z = t_{2,}S = m_1)] * P(S = m|z = t_2) \quad (3.17)$$

where LB^M and UB^M denote the lower and upper bounds of the counterfactual $E[Y(t_1) \mid z = t_2, S]$ under the set of assumptions M.

CHAPTER 4

Family Support as Welfare: Intergenerational Transfers and Elderly Health in Indonesia

Abstract

This study investigates the impact of intergenerational support from adult children on their elderly parents' wellbeing, focusing on the causal effects of such support as measured by self-reported health and activities of daily living. An instrumental variable strategy is used to control for potential endogeneity issues often encountered in the literature. The analysis is based on a sample of 6,433 individuals from the 1993, 1997, and 2000 waves of the Indonesia Family Life Survey. The results show that receiving support from children has a significant positive effect on parents' health outcomes, including better self-reported health and fewer difficulties in undertaking activities of daily living. Compared to individuals who do not receive support, receiving support improves activities of daily living by 0.4 activities and increases the probability of being healthy by 4.2 percentage points. These findings are robust to alternative model specifications with alternative measures of health outcomes. Causal mediation analysis shows that support affects parents' health outcomes through an increase in household medical, food and total expenditure. Furthermore, an analysis of subsamples of parents shows important heterogeneous effects. Specifically, the effects of support from adult children on elderly parents' wellbeing vary by gender, age group, and region.

4.1 Introduction

Recent studies have focused on providing support to the elderly population. The proportion and numbers of elderly people are increasing in the global population. In developing countries, rural-urban migration and emigration for work purposes leads to many older people being left in isolation in dwindling communities. The increasing life expectancy and high dependency ratios of the elderly make them a vulnerable group, whose wellbeing should be a priority for any effective social protection system. With insufficient state-sponsored support systems, especially in low- to middle-income countries, family support systems remain the primary source of relief to elderly parents, in line with traditional universal cultural norms (Kendall & Anglewicz, 2018; Palloni & Pinto, 2014). Adult children are seen as primary caretakers of their parents by means of intergenerational support, which often becomes the only source of material support as well as daily life assistance for elderly parents (Chen et al., 2017; Ruggles & Heggeness, 2008). Such support may include financial transfers, as well as non-economic instrumental like informal care and emotional support. Therefore, investigating the impact of support from children on elderly parents' wellbeing is crucial for the development of policies aimed at improving their welfare in developing nations.

This study examines the effect of support received from children on parents' wellbeing in Indonesia. Specifically, this study utilises three waves of the Indonesian Family Life Survey (IFLS) to explore the following questions: (a) Does intergenerational support received from offspring affect parental health outcomes? (b) What are the mechanisms through which support received from offspring improves parental health? (c) What are the heterogenous effects of support across different subgroups of parents? Previous studies on the effects of support on parents' wellbeing are largely inconclusive. This is partly due to methodological concerns relating to potential endogeneity bias, which constrains the ability to adequately examine the causal impacts of children's support on parents' wellbeing. This study attempts to add to the existing literature by estimating a robust causal effect of support received from children on parents' wellbeing.

This study contributes to the literature by addressing the endogeneity concerns in the relationship between children's support decisions and parents' health outcomes, specifically those arising from unobserved heterogeneity and reverse causality. The potential endogeneity issues are addressed through instrumental variable (IV) regression models, which provide consistent estimates of the causal effects of children's support on parents' health outcomes. To the researcher's knowledge, this is the first study to examine this relationship using an IV approach in the Indonesian context. Moreover, this study makes a further contribution to the literature by exploring a set of potential causal mechanisms by which support provided by children enhances the parents' health and wellbeing using causal mediation analysis. Finally, this study advances the understanding of intergenerational support by examining the heterogeneity of support effects across different subgroups of the population.

This study employs longitudinal data from three waves of the IFLS, covering over 6,433 individuals aged 50 and above. To address potential endogeneity arising from unobserved parental characteristics and reverse causality between children's support and parents' health, the analysis applies a two-stage least squares (2SLS) framework. The instrument (number of male children) captures exogenous variation in parents' likelihood of receiving support, reflecting cultural norms that sons bear greater financial responsibility for ageing parents, while being plausibly unrelated to parents' health status. This identification strategy isolates the causal effect of receiving support on parents' wellbeing, measured by self-reported health (SRH) and activities of daily living (ADL). In addition, causal mediation analysis is conducted to examine the mechanisms linking children's support to parental wellbeing through household medical, food, and total expenditure.

The empirical findings of this study reveal that receiving support from children can positively impact parents' health outcomes, as measured by SRH and ADL. Parents that received support from their children had an improvement in ADL scores by 0.4 activities compared to parents that did not receive any support, representing 37% improvement relative to the baseline mean of 1.12. For SRH outcome, receiving support increased the probability of parents being healthy by 4.2 percentage points, representing 5% increase relative to the baseline mean of 79%. These findings are robust to several alternative specifications and measures for parental health outcomes. Decomposition analysis distinguishing financial from instrumental support shows that estimated effects are driven by financial support, as instrumental help is rare and weakly identified. Furthermore, the findings reveal that the effect is heterogeneous and differs according to region, gender and age group. Based on casual mediating analysis, the results show that most of the causal effects of support on parental health outcomes are mediated through household food, medical and total expenditure. These findings establish the efficacy of children's support in influencing parents' wellbeing to either strengthen current norms on parent support or develop other supporting policies. The findings provide policymakers with a basis for the development of policies and programs to promote intergenerational support, which continues to be important in influencing the wellbeing of the elderly.

The findings are particularly timely and relevant considering the rapidly ageing global population. In recent decades, a substantial body of research has established the significant economic implications of the ageing populations, including increased healthcare costs, labour market participation and economic growth (Bloom et al., 2010; Harper, 2014; Howse, 2012; Lobo & da Piedade Falleiro, 2024). Several studies have concentrated on the role of adult children in promoting the wellbeing of their elderly parents (Bui et al., 2022; Cai et al., 2021; Teerawichitchainan et al., 2015; Polenick et al., 2017). Such studies, focusing on both developed and developing countries, reflect the increased interest that stems partly from the rapid social and economic transformations of contemporary society. Such developments may jeopardise existing social welfare arrangements for the elderly within family structures. For instance, social changes like a shift away from traditional extended families toward nuclear families, with commensurate changes in living arrangements, pose alarming implications for many elderly people, considering the critical role of familial support systems in their lives. These developments have raised concerns about the reliability of support received from children, especially in regions like East and Southeast Asia where they depend heavily on such support.

Examining the effect of support on parents' wellbeing is of great importance in the Indonesian context. Indonesia is home to one of the largest elderly populations in the world, with an increasing cohort of people aged over 65 who account for about 10% of the total population (about 26 million) (TNP2K, 2020). Indonesia is expected to become one of the ten countries with the greatest proportion of elderly people, with a predicted 20% increase in this population by 2050 (United Nations, 2015). This situation has emerged due to a dramatic increase in life expectancy coupled with a declining birth rate. According to the World Bank (2020), Indonesian average life expectancy has increased from 58 to 72 years from 1980 to 2020, while the birth rate decreased from 4.4 to 2.3 births per woman during the same period. This demographic change has resulted in a significant increase in elderly dependency ratio over the years (World Bank, 2024).

Most elderly Indonesians receive financial support from their adult children (Cameron & Cobb-Clark, 2008). Only 12% of elderly Indonesians have access to formal pension benefits, making intergenerational family support even more essential for their wellbeing (TNP2K, 2020). These statistics highlight the significant burden that will be imposed on the overall economy in terms of supporting the larger numbers and proportions of elderly people in future. This burden is further aggravated as the reliance on support from children is challenged due to dramatic social and economic transformations that can be anticipated in the emerging digital economy, aside from general economic fluctuation and instability worldwide. Therefore, investigating the impact of support from children on elderly parents' wellbeing is of critical importance.

The remainder of this study is organised as follows: Section 2 presents the related literature review and background. Section 3 introduces and describes the data. Outlines of model specification and analysis are presented in Section 4. The main empirical results, robustness checks, mechanisms analysis and the heterogeneous effects analysis are presented in Section 5. Section 6 concludes by discussing the findings and identifies opportunities for future research.

4.2 Background and Literature

The empirical literature on the relationship between intergenerational support and parental outcomes is large and growing, as it has continued to generate research interest. The empirical literature examined in this study relates to the methodological approaches adopted, particularly the different definitions and measurements of children's support and parental wellbeing and the associated results from such methods. Understanding this particular aspect of the literature is important for identifying some knowledge gaps that this study attempted to address. Several definitions have been adopted to measure children's support in the empirical literature. One strand of the studies has focused on migration studies in which the migration status of the children is considered a proxy for remittances children provide to their parents (Kumar, 2021; Li et al., 2020; Lu, 2012; Tang & Xie, 2021).

Studies conducted in the Indonesian context adopted various measures of parental wellbeing, such as body mass index (BMI) and mental health indicators like depression symptoms, reporting a negative association between children's migration and elderly parents' mental health outcomes (Kumar, 2021; Lu, 2012). They concluded that elderly parents experienced negative health outcomes due to the loss of emotional and instrumental support received from children. Parents with children who have emigrated are more likely to experience depressive symptoms. However, evidence of the impact of offspring supports on parental wellbeing is largely inconclusive, as these findings contradict the findings of Kuhn et al. (2011) and Lu (2013).

For example, Kuhn et al. (2011) found a positive association between remittances from migrated children and parental health outcomes. Also, Lu (2013) concluded that migrated children were associated with higher parental BMI, which the author attributed to improved nutritional intake of parents (compared to parents with no migrated children) due to the remittances sent home from their children working abroad. However, while improved nutrition intake is obviously beneficial for health, increased BMI does not necessarily indicate improved *nutrition*; higher BMI increases the risk of developing various health conditions such as type 2 diabetes, high blood pressure, and several types of cancer, particularly when it is linked to the adoption of Western dietary and lifestyle characteristics in developing country contexts (Barlin & Mercan, 2016).

The second strand of the empirical studies examined different measures of support on parental wellbeing (Chen et al., 2020; Choi et al., 2020; Cong & Silverstein, 2008; Guo et al., 2017; Luo et al., 2017; Shu et al., 2021; Silverstein et al., 2006; Yue-pin, 2014; Wu et al., 2018; Wu, 2022; Xiang & Yao, 2016; Zeng et al., 2016). These studies have examined the effect of financial and non-financial support (e.g., emotional support) on parental wellbeing, and considered instrumental support related to in-kind support provided by children, such as helping with household chores (Choi et al., 2020; Cong & Silverstein, 2008; Luo et al., 2017; Shu et al., 2021; Silverstein et al., 2006). The measures of parental wellbeing varied across the literature. Studies have investigated self-rated health or self-reported health (Yue-pin, 2014; Yang & Yao, 2016), ADL in which individuals experience difficulties, BMI (Yang & Yao, 2020), and changes in cognitive function and mortality risk (Zeng et al., 2016), in addition to mental health measures like depression symptoms such as loneliness (Chen et al., 2020; Luo et al., 2017; Wu at al., 2018) and life satisfaction (Wu, 2022; Xiang & Yao, 2016).

Relatively more recent studies on Asian contexts based on data derived from the China Health and Retirement Longitudinal Study (Chen et al., 2020; Gruijters, 2018; Guo et al., 2017; Shu et al., 2021; Wu, 2022; Zeng et al., 2016) and the Korean Living Profiles of Older People Survey (Choi et al., 2020; Hong & Kwak, 2014) adopted various statistical methods to examine the association between children's support and parental health outcomes, mainly fixed-effect and binary logistic models. As in migration-based studies, their findings on the impacts of children's support on parental wellbeing were far from conclusive and varied considerably according to the measures or types of support considered and different indicators of parental wellbeing. For example, studies examining the impact of financial support on mental health measured by the level of depression and parents' life satisfaction found mixed results.

Several studies found a positive effect, suggesting that financial support from children improved mental health by reducing parents' depression symptoms and increased life satisfaction measures (Chen & Jordan, 2018; Shu et al., 2021; Silverstein et al., 2006; Wu et al., 2018; Wu, 2022). On the other hand, other studies reported a negative association between financial support and parental mental health (Choi et al., 2020; Guo et al., 2017), or reported no statistically significant association (Yue-pin, 2014; Xiang & Yao, 2016). Moreover, prior studies investigated the relationship between emotional support and parental health outcomes also found mixed results. Most of the studies found a positive impact, suggesting that emotional support from children improved parents' mental health by reducing depression symptoms (Guo et al., 2017; Luo et al., 2017; Silverstein et al., 2006). However, in Korea, Choi et al. (2020) reported a negative association between emotional support and parental mental health. Additionally, studies assessing emotional support's impact on parental physical health measured by ADL found conflicting results. For example, in China, Wu (2022) found a positive effect of ADL by reducing the activities in which individual parents experience difficulties. In contrast, Bai et al. (2020) found that receiving emotional support from adult children had no statistically significant association with parents' physical health.

In summary, existing studies have shown that parents who receive support from their children experience different health outcomes than those who do not. However, the evidence on the association between children's support and parental health outcomes is inconsistent. The lack of consistent findings is mainly explained by the potential endogeneity issues arising from mainly unobserved heterogeneity and reverse causality, as discussed below. Therefore, there is a need for a better understanding of the direction of the casual impact of support, which has remained largely a matter of conjecture. This study addresses an important knowledge gap within the empirical literature by controlling for the potential endogeneity concerns.

4.3 Data

This research pools the 1993, 1997, and 2000 waves of the IFLS, a nationally representative survey conducted by the RAND Corporation.[29] The IFLS is a continuing longitudinal survey that collects broad information at the community, household, and individual levels. The first wave was conducted in 13 provinces in 1993, and the sample was representative of 83% of the Indonesian population (Frankenberg & Karoly, 1995). Detailed individual-level information on demographic and socioeconomic characteristics (e.g., marital status, age, education, ethnicity, employment, and income) was collected from over 33,000 individuals and 7,224 households. During the second wave in 1997, around 94.4% of respondents from the first wave were re-interviewed (about 7,619 households and more than 38,200 individuals (Frankenberg & Thomas, 2000). The third wave was conducted in 2000, with an attrition rate of 4.6% from the second wave (Strauss et al., 2004). The IFLS contains detailed information on receiving economic and instrumental support from children during the 12 months prior to the interview. Also, the survey asks specific questions on respondent's health, including SRH, and contains additional information on individuals' physical and functional health status (e.g., the number of ADLs in which individuals experience difficulties with performing certain activities).

The final sample used for this study comprised those individuals aged 50 and above at the time of the survey who provided adequate responses to main variables of interest throughout the three waves. The final sample used comprises of 6,433 respondents, out of which only 2,626 were interviewed in all three waves, providing 13,416 person-year observations. Only, 2,638 respondents have received support during the sample period and 4,904 did not receive support. Approximately 11% of respondents dropped out between interview waves, around 6% between 1993 and 1997, and 5% between 1997 and 2000. Such attrition may induce bias if dropouts are non-random. To address potential attrition bias, all analysis in this study descriptive statistics and regression analyses apply longitudinal weights provided by the IFLS, which adjust for both complex sampling design and non-random attrition across waves.

[29] This study excludes the latest waves of IFLS (2007 and 2014) due to changes of measurements of key variables. Specifically, changes to the wording and categories of the support and ADL variables.

The primary treatment variable is a binary variable denoting that the parent receives support from their children, taking the value 1 if the respondent reported receiving economic support (financial transfers) or instrumental support (helping parents with household chores) during the preceding 12 months (prior to the interview) from at least one non-coresident child aged over 15 years old; and 0 otherwise. Non-coresident children are defined as biological and non-biological children who reside outside the respondents' household. To assess the relative contribution of the two forms of support, Section 4.5.1.1 later decomposes the combined measure into financial and instrumental support.

The analysis employs the number of male children as an instrumental variable to address potential endogeneity concerns in the relationship between support and parental health. The rationale is that in Indonesia cultural norms place stronger expectations of receiving support from non-resident male children than on daughters. The identification strategy is outlined in detail in Section 4.4. The instrumental variable is defined as the total number of coresident and non-coresident male children of each respondent, regardless of their age.

This analysis focuses on health status as an indicator of parental wellbeing, as measured by the SRH, which is considered a reliable self-reported (or self-assessed) indicator of individual health status, which is widely used to assess overall health (Currie & Stabile, 2003; Dong et al., 2017; Södergren et al., 2008). The SRH is a complex multidimensional indicator, representing more than just objective health *per se*. It embeds rich data reflecting individuals' assessments of their past, current, and future health status (Balaj, 2022). The SRH status outcome variable was constructed based on responses to the question: "*In general, how is your health?*" Responses ranged from 1 to 4 (1 = *very healthy*, 2 = *somewhat healthy*, 3 = *somewhat unhealthy*, and 4 = *unhealthy*). However, reported SRH may differ from the actual health status. In other words, an objectively identical clinical health condition might be observed and experienced differently by different individuals, reflecting individual characteristics and experiences, and socio-cultural factors (Baron-Epel et al., 2005). Individuals' ability to adapt to health tends to vary the reported SRH (Bailis et al., 2003; Goldberg et al., 2001). To reduce potential measurement errors in SRH, variables were converted into binary outcomes (1 = *healthy*, and 0 = *unhealthy*).[30] However, for robustness, the ordinal nature of the variable is used.[31]

The second outcome variable of interest in this study is ADL, particularly activities oriented toward taking care of one's own body. These activities are fundamental to living one's daily life, and functioning in a social world. They enable basic survival and wellbeing such as bathing, toileting, dressing, and eating. The ADL is used as an indicator of an individual's functional status, and the inability to accomplish essential ADL *ipso facto* indicates poor quality of physical health (and poor quality of life). This variable has been commonly used in earlier empirical work as a proxy for physical health (Davin et al., 2009; Tabassum et al., 2009). In this study, the ADL captures respondents' difficulties with performing nine functional activities, namely: (i) standing up from a chair without help; (ii) carrying a heavy load; (iii) walking for 5 km; (iv) sweeping the house; (v) squatting or kneeling; (vi) going to the bathroom without help; (vii) dressing without help; (viii) drawing water from a well; and (ix) standing up from sitting on the floor. Respondents were asked if they could perform these tasks easily, with difficulty, or were unable to do them. An ADL score variable was constructed with values ranging from 0 to 9, denoting the number of activities that respondents cannot perform or can only perform with difficulty. Higher response values for the variable indicate worse health.

Several control variables are used in this study, all of which were consistently identified by previous studies as essential determinants of individuals' health outcomes (Dunga, 2018; Lordan et al., 2012; Thompson et al., 2021). These variables include marital status, gender, age and emigration status of at least one child. Marital status is a binary variable, with 1 denoting the respondent is married and 0 indicating otherwise (i.e., single, divorced, or widowed). Gender is also a binary variable, with respondents' gender being indicated by 1 for males and 0 for females. Age is a categorical variable, with categories denoting age below 60, 60-69 and 70^{+}. Other control variables included household size, province fixed effects (to account for regional differences in health outcomes), and an

[30] The ordered category SRH question exhibited minimal variation among respondents. Observations were concentrated mainly around two categories: somewhat healthy (71%) and somewhat unhealthy (22%). Therefore, I follow the approach adopted by many studies by grouping the categories into two (Clarke & Van Ourti, 2010; Hongbin & Yi, 2006).

[31] To check the robustness of results, I employ the IV ordered Probit regression model (Roodman, 2011) to estimate the parameters by considering the SRH variable as an ordinal variable rather than a binary variable, following Cullinan and Gillespie (2016) and Fang et al. (2021).

indicator for living in a rural area. Due to endogeneity concerns, certain variables possibly associated with parental health status were not included in the specifications, such as income, expenditure, education, and work status.[32]

Table 4.1 presents descriptive statistics of 13,416 observations evaluated by using sample weights variables used in the study. Around 6,433 parents aged 50 to 70 were included in the study. Half of them are males and below 60 years old. About 35.2% of parents received support from their children. A simple comparison of means between the two groups indicates that parents that receive support have worse health outcomes than their counterparts. Specifically, those receiving support are more likely to report a worse SRH status (80.74% versus 76.9%) as well as a higher mean ADL score (1.45 versus 0.94). They are also more likely to be older, live in urban areas, and to be married. Most parents that receive support are females.

The average number of household members among the sample is four, with minimal difference between the two subsamples defined by receipt of support. Parents receiving support are more likely to have migrated children, and to have a higher number of male children (the IV) than those who do not. Overall, the descriptive statistics from *Table 4.1* show that there are significant disparities in terms of both health outcomes and confounding variables between respondents who receive support from their children and those who do not.

[32] For robustness, I re-estimate the models with the inclusion of the omitted variables (see Appendix *Table 4.A4.1*).

Table 4.1
Summary Statistics of Main Variables

	Pooled sample	With support	Without support	Difference	t-test
No. observations	*13,416*	*4,857*	*8,559*		
No. individuals	*6,433*	*2,638*	*4,904*		
Outcome Variables					
SRH	79.39%	76.90%	80.74%	3.84%	***
ADL score	1.12	1.45	0.94	-0.50	***
Independent Variables					
Support	35.20%	-	-		
Age bracket					
<60	51.94%	42.41%	57.12%	14.71%	***
60-69	32.64%	38.98%	29.20%	-9.78%	***
70^{+}	15.42%	18.61%	13.68%	-4.93%	***
Gender	50.05%	20.62%	66.03%	45.41%	***
Marital status	75.79%	59.64%	84.56%	24.92%	***
Urban	35.15%	32.46%	36.60%	4.14%	***
Child migration status	31.33%	53.61%	19.23%	-34.38%	***
Household size	4.35	3.99	4.55	0.56	***
No. male children	2.07	2.96	1.58	-1.38	***

Notes: Due to incomplete information, the number of observations for ADL score is 13,395. The last column indicates t-test for two-group means. ***Significant at 1%.

4.4 Empirical Strategy

4.4.1 Endogeneity of Support

The primary objective of this study is to estimate the causal impact of children's support on their parents' health outcomes. However, estimating the causal effect of receiving support from children on parents' health is challenging because the decision to provide support is self-selected and not random. Two main sources of potential endogeneity arise, namely reverse causality and omitted variable bias. Parents in poorer health may be more likely to receive financial or instrumental support from their children, which leads to reverse causality and potentially biased OLS estimates. Unobserved factors such as emotional attachment from children and the ability to receive or provide support may jointly influence both the outcomes of interest (parental health) and the likelihood of receiving support, which leads to omitted variable bias and inconsistent estimates. Therefore, a standard OLS regression would lead to biased and inconsistent estimates of the true causal effect.

To address the potential endogeneity concerns, this study employs an IV approach using the number of male children as an instrument for receiving support. The fundamental reason for the instrument is that in developing countries, including in Indonesia, non-coresident women are expected to take care of their children, their husbands' families, and household chores, leading them to be relatively isolated from their own parents (Aisyah & Parker, 2014; Damar & du Plessis, 2010; Khoo et al., 2017). On the other hand, men are expected to be the sole providers and carer for their elderly parents, and they are more likely to have employment opportunities and earn income (Tambunan, 2008; Utomo, 2012). Also, men are more likely to support their parents with difficult household chores, like farming activities and other kinds of instrumental help (Keasberry, 2001).[33] Therefore, the number of male children is expected to be a strong predictor of whether parents receive support from their children.[34] The instrument is defined as the total number of male children, including both coresident and non-coresident children, regardless of age, reflecting the broader family composition that shapes cultural expectations and the potential for future intergenerational support.

Descriptive evidence of the relationship between the number of male children and support is shown in Appendix *Table 4.A1*, which reports the distribution of male children and the proportion of parents receiving support. The likelihood of receiving support increases steadily with the number of male children. The rate of receiving support increases from 12.31% (no sons) to 23.97% (one son), 36.11% (two sons), 46.54% (three sons), and 63.93% (four or more sons).

It is assumed that while the number of male children is likely to be strongly correlated with the decision to support parents, it has no direct effect on parental health outcomes. The validity of the IV in this study relies on the assumption that conditional on all covariates, the number of male children affects parental health outcomes only through the support channel. Suggestive evidence within the literature indicated that the number of children has no association with parents' health outcomes (e.g., Chen & Silverstein, 2000; Kuhn et al., 2011).

[33] Keasberry (2001) reported that male non-coresident children in Indonesia provided more support to their parents than women.

[34] Children's characteristics were widely used as valid IVs in many contexts (Mansuri, 2016). Coe and Van Houtven (2009) made use of the number of male children to account for selection into caregiving. Ku et al. (2012) employed the number of grandchildren as an instrument for grandparents' caregiving. Also, Ao et al. (2022) demonstrated that the number of siblings was a valid instrument to address the endogeneity of family care choice.

Hence, the number of male children should not directly affect parental health outcomes. *Fig. 4.1* presents a Directed Acyclic Graph (DAG) that summarises the identification strategy. The IV (number of male children) influences the treatment (support received from children) but has no direct path to the health outcomes. Unobserved factors (U) such as emotional attachment, ability and family norms may influence both support and health, but are assumed to be independent of the instrument.

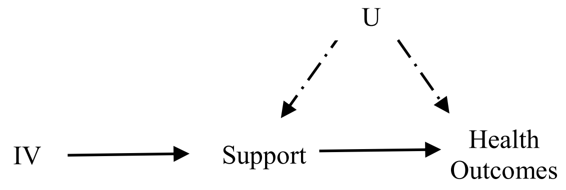


Figure 4.1 Directed Acyclic Graph (DAG) of the Causal Effect of Support on Parental Health

Under the standard IV framework, the two-stage least squares (2SLS) estimator identifies a Local Average Treatment Effect (LATE) rather than a population average effect. Specifically, the LATE pertains to individuals whose likelihood of receiving support from children is influenced by the number of male children (compliers). Therefore, the estimated causal effect reflects the impact of receiving support on parental health among compliers, those for whom the probability of receiving support is influenced by the number of male children. These compliers may represent a selected subpopulation that differs systematically from the broader population in terms of cultural norms and preferences surrounding gender roles and attitudes towards intergenerational support. As a result, the estimated effects should be interpreted as local to this complier group and may not necessarily generalise to all Indonesian households, particularly those whose support arrangements are less affected by the number of male children.

4.4.2 Empirical Specification

The primary objective of this study is to examine the causal impact of receiving support from children on parents' health. To that effect, I use the following empirical model:

$$y_{it} = \beta_0 + \beta_1 Support_{it} + \beta_2 X_{it} + u_{it} \tag{4.1}$$

where the dependent variable of interest y_{it} denotes the two different health outcomes (SRH and ADL score) of individuals i and time t; X is a vector of control variables capturing household and individual characteristics (gender, age, marital status, household size, urban residence, migration status of children, time and province fixed effects); $Support$ is a binary indicator of whether parents receive support from their children; and u_{it} is an error term.

Obtaining consistent estimates using Eq. (4.1) is challenging due to potential endogeneity concerns arising from unobserved characteristics and reversed causality. Therefore, a simple OLS regression of Eq. (4.1) will likely lead to biased and inconsistent estimates of the impact of $Support$ on the health outcomes. A panel data estimation procedure is preferable to control for time-invariant unobserved individual characteristics. However, due to the lack of variation of the independent variable of interest ($Support$) for individuals within the sample, it is not possible to control for individual fixed effects.

To address the potential endogeneity concerns, an IV specification is specified, using the number of male children as a valid IV. The first-stage equation of the 2SLS specification is expressed as:

$$Support_{it} = \pi_0 + \pi_1 Z_{it} + \pi_2 X_{it} + v_{it} \tag{4.2}$$

Where $Support_{it}$ is the endogenous variable representing whether parent receives support from their children; Z_{it} is the instrumental variable denoting the number of all male children for each respondent, while X_{it} is as specified in Eq. (4.1); and v_{it} is an error term.

The hurdle in applying the IV strategy is determining a valid instrument, as a weak instrument leads to biased estimators (Baum et al., 2003). The IV must be highly correlated with the endogenous regressor, and should not directly affect the outcome variable (Hahn & Hausman, 2002). The effect of the IV on the outcome variable can be only through the endogenous regressor. The validity of the IV can be tested via a Wald test of the significance of the coefficient of the IV in the first-stage regression. An *F*-test higher than 10 implies that the instrument is strong and is thus a good predictor for the endogenous variable (Andrews et al., 2019).

To estimate the causal effect of interest, a pooled 2SLS estimator is used. Since the two main outcomes differ in nature, different estimation models are used. For the binary variable SRH, the analysis is based on a Probit model.[35] On the other hand, the ADL score is a count dependent variable ranging from 0-9, thus the Poisson regression method is utilised to model this outcome, as well as a standard linear regression model.

4.5 Empirical Results

4.5.1 Main Results

Table 4.2 presents the results of the estimated baseline models that do not consider the endogeneity of support. To aid the interpretation of the results, the marginal effects of regressors were calculated. As shown in Columns 1 and 2, the OLS and the Poisson regressions show no statistically significant relationship between children's support and the ADL scores of parents, indicating that receiving support from children did not affect the ability or inability of parents to perform ADL. The results for the SRH score in Column 3 show a statistically significant negative effect of children's support on parents' health. This indicates that receiving support causes a deterioration in health, contrary to intuitive expectations. Specifically, the results show that receiving support reduces the likelihood of parents being healthy by 2.4 percentage points. This is likely attributable to potential simultaneity bias, as parents with worse health conditions are more likely to require and receive more support from their children.

[35] As a robustness check, the same model was estimated separately using a linear probability model (LPM) (see Appendix *Table 4.A2*).

Table 4.2

The Effect of Children's Support on Parental Health Outcomes: Baseline Models

Outcome Variables	(1) OLS	(2) Poisson	(3) Probit
	ADL score	**ADL score**	**SRH**
Support	0.048	0.032	-0.022**
	[0.043]	[0.039]	[0.010]
Age: (Ref: <60)			
Age: 60-69	0.602***	0.616***	-0.070***
	[0.036]	[0.036]	[0.009]
Age: 70+	1.759***	1.754***	-0.145***
	[0.067]	[0.071]	[0.013]
Male	-0.563***	-0.592***	0.009
	[0.040]	[0.041]	[0.010]
Married	-0.349***	-0.220***	0.030***
	[0.051]	[0.043]	[0.011]
Urban	0.078**	0.084**	0.014
	[0.039]	[0.039]	[0.009]
Migrant	-0.103**	-0.098***	0.036***
	[0.040]	[0.037]	[0.009]
Household Size	-0.01	-0.016**	0.002
	[0.008]	[0.008]	[0.002]
Province of Residence: (Ref: South Sulawesi)			
North Sumatra	0.373***	0.258***	-0.054**
	[0.113]	[0.095]	[0.023]
West Sumatra	0.517***	0.387***	-0.130***
	[0.131]	[0.102]	[0.024]
South Sumatra	0.03	0.003	0.009
	[0.117]	[0.105]	[0.025]
Lampung	-0.031	-0.033	0.026
	[0.121]	[0.117]	[0.027]
Jakarta	-0.104	-0.11	-0.013
	[0.109]	[0.106]	[0.024]
West Java	-0.089	-0.091	-0.002
	[0.096]	[0.090]	[0.021]
Central Java	-0.273***	-0.291***	0.070***
	[0.096]	[0.093]	[0.021]
Yogyakarta	-0.593***	-0.604***	0.086***
	[0.102]	[0.105]	[0.024]
East Java	-0.382***	-0.403***	0.115***
	[0.095]	[0.092]	[0.021]
Bali	0.449***	0.323***	0.028
	[0.122]	[0.098]	[0.026]
West Nusa Tenggara	0.148	0.095	-0.059**
	[0.115]	[0.100]	[0.024]
South Kalimantan	-0.082	-0.085	-0.027
	[0.126]	[0.120]	[0.026]
Year: (Ref: 1993)			
1997	0.485***	0.495***	-0.015*
	[0.035]	[0.036]	[0.009]
2000	0.339***	0.354***	-0.025***
	[0.035]	[0.035]	[0.009]
Constant	1.114***		
	[0.110]		
Observations	13,395	13,395	13,416
Outcome Mean	1.12		0.79

Notes: All regressions are estimated using longitudinal person-level weights provided by the IFLS to adjust for sampling design and attrition. Standard errors are clustered at the household level in brackets. * p<0.10, ** p<0.05, *** p<0.01

Next, I employ the 2SLS estimation model. Table 4.3 presents the first-stage results, showing that the IV has a positive significant impact on support, indicating that the number of male children is associated with a higher likelihood of parents receiving support. Specifically, an additional male child increases the probability of parents receiving support by about 8.1 percentage points. In terms of diagnostic test, the Kleibergen-Paap F-statistics from the tests of joint significance is higher than the rule of thumb threshold of 10 proposed by Stock et al. (2002), enabling us to confirm that the instrument is not weak. Also, based on a factor analysis, the minimal eigenvalue statistics were estimated and compared to the critical values determined by Stock and Yogo (2005). As the minimum eigenvalue statistics values are greater, the IV is not weakly associated with the outcome (Sanderson & Windmeijer, 2016). Moreover, following Wooldridge (1995), the Durbin-Wu-Hausman endogeneity test was computed for all models using robust standard errors (Durbin, 1954; Hausman 1978; Wu, 1974). The statistically significant results of the test confirm the validity of treating support as an endogenous variable, which justified the ultimate choice of the IV regression.

Table 4.3 presents the marginal effects from the second stage of the 2SLS, IV-Poisson, and IV-Probit models after accounting for endogeneity of support. As shown in Column 1, the marginal effect of the receipt of support is negative and statistically significant at the 1% level. The result indicates that holding other factors constant, the ADL score of parents that received support from their children declined by about 0.41 activities compared to parents that did not receive any support. Since higher ADL score implies worse physical health, this reduction represents a 37% improvement in score on average. Column 2 presents the Poisson regression estimates, which is a better fit for working with count variables. The marginal effect of support on ADL score declined slightly further to approx. 0.42 activities, representing 38% improvement relative to the baseline mean score. This effect is statistically significant at the 1% level.

Column 3 presents the IV-Probit estimates for SRH, which show that the marginal effect of support on SRH is positive and statistically significant at the 10% level. This indicates that after correcting for endogeneity bias in the IV-Probit, the original Probit result (Table 4.2) did not estimate the true association between support and SRH (the sign of the support coefficient reversed). Specifically, the result reveals that receiving support increases the probability of individuals reporting being healthy by 4.2 percentage points compared to non-receiving individuals (i.e., since SRH is defined healthy vs unhealthy).

The substantial differences between the OLS and IV estimates across both health outcomes provide critical insights into the nature and direction of endogeneity bias. These differences manifest in two distinct patterns that highlight the severity of endogeneity concerns when estimating the health effects of intergenerational support. For ADL scores, the IV estimates are substantially larger in absolute magnitude than the OLS estimates, implying that OLS underestimates the true causal effect due to endogeneity. For SRH, the complete reversal in sign from negative in OLS to positive in IV provides strong evidence of severe endogeneity bias.

These differences are likely to arise from two primary sources, reverse causality and unobserved factors that simultaneously affect support and health. Reverse causality arises because parents in poor health are more likely to receive support from their children, creating a spurious negative association. In addition, unobserved factors such as family preferences for independence, emotional closeness, or children's ability and availability may also jointly influence both support provision and parental health. These biases create correlations between support and poor health that bias OLS estimates toward zero or reverse the sign. The Durbin-Wu-Hausman endogeneity tests formally confirm these concerns by rejecting the null hypothesis of exogeneity, providing statistical evidence that support receipt is endogenous and that OLS estimates are inconsistent. Overall, the comparison between OLS and IV estimates indicates that the OLS results are biased downward due to reverse causality and omitted variables, confirming that parental support is endogenous to health status

Beyond correcting for endogeneity bias, the magnitude of the IV estimates represents LATE for complier families, as discussed in Section 4.4.2. The larger IV estimates suggest that the health benefits of support may be particularly evident among families where sons play a distinct support role, potentially due to greater economic capacity of sons to provide meaningful support. Thus, the difference between OLS and IV estimates arises both from the correction of endogeneity bias and the focus on a specific complier subpopulation whose support arrangements are influenced by the number of male children.

Table 4.3
The Effect of Children's Support on Parental Health Outcomes: Instrumental Variable Models

Outcome Variable	(1) LPM-2SLS	(2) IV-Possion	(3) IV-Probit
	ADL score		**SRH**
Second Stage Results			
Support	-0.409***	-0.419***	0.042*
	[0.140]	[0.127]	[0.033]
Observations	13,395		13,416
Outcome Mean	1.12		0.79
First Stage Diagnostics			
Instrument (No. of male children)		0.081***	
		[0.003]	
Kleibergen–Paap F-stat		703	
Partial R-squared		0.092	
Endogeneity Test	12.9***		4.8**

Notes: All regressions are estimated using longitudinal person-level weights provided by the IFLS to adjust for sampling design and attrition. The full set of the results are presented in *Table 2.A2*. All estimations include the full set of control variables listed in *Table 4.2*. Standard errors are clustered at the household level in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

The estimated marginal effects for the control variables are presented in Appendix *Table 4.A2*. The marginal effects of control variables for the 2SLS model, show that compared to the reference group (those aged under 60 years), being 60-69 years old increases the ADL score by 0.7 activities. The ADL score for individuals aged 70 years and above increases by almost two activities compared to the reference group. These results suggest that parental health worsened with age, which is consistent with expectations. The results are comparable with the IV-Poisson regression model results.

Regarding gender, the ADL score is lower for males than for females. On average, males have better physical health than females. In terms of marital status, being married reduces the ADL score by approx. 0.4 activities, compared to unmarried, separated, divorced, or widowed individuals. In the Poisson regression model, the marginal effect of ADL score for married individuals dropped only by approx. 0.2 activities.

Additionally, on average, the ADL score amongst parents living in urban areas is higher than amongst parents living in rural areas. The marginal effect of living in an urban area is estimated at 0.058 in the 2SLS model and 0.07 in the IV Poisson model, with the latter being statistically significant at the 10% level. The migration status of children shows no significant association with parents' ADL scores in either specification. Household size is negatively associated with ADL scores across both specification and statistically significant. Consistent with Yue-pin (2014), the migration status of children exerts no significant influence across both specifications. Moreover, the ADL score varies significantly across regions; whereas some provinces have lower and statistically significant ADL scores compared to the reference group, other provinces show higher scores relative to the reference group.

The marginal effects of control variables for SRH show similar results. Being aged 60–69 reduces the probability of being healthy by about 7.8 percentage points compared to those under 60 years, while being aged 70 years and above reduces the probability by 14.3 percentage points. These findings confirm that SRH declines with age. Male respondents report better SRH than females, and married respondents report better SRH than unmarried individuals. Individuals living in urban areas have slightly higher probabilities of reporting good health, while household size and children's migration remain insignificant. Province differences persist across all models.

In general, the results show that receiving support improves parents' health outcomes as measured by both ADL score and SRH. The results from the 2SLS and IV-Poisson are less sensitive to model specification and are generally comparable, particularly in terms of the levels of statistical significance. All other control variables demonstrate similar effects between the two health outcomes, except for living in urban areas, which shows the opposite effect for ADL score and SRH. Most of the remaining control variables are generally consistent with the current literature for Indonesia and other global examples (Bai et al., 2020; Kumar, 2021).

4.5.1.1 Financial versus Instrumental Support

The support variable aggregates two types of intergenerational support, financial and instrumental support. Although these forms of support may operate through different channels, the main analysis treats them jointly to capture the overall effect of children's support on parental health. To understand which channel drives the results, this section decomposes the treatment and estimates effects separately by financial and instrumental support. Financial support is defined as parents receiving monetary transfers, payment of expenses (such as medical costs or household bills), and the provision of food, goods, or other economic items. Instrumental support is defined as receiving help with household chores and childcare, or assistance during periods of illness or recovery.

Table 4.4 presents results for three specifications. Column 1 shows the aggregated measure of support, column 2 shows financial support only, and column 3 shows instrumental support only. Financial support accounts for 33.2% of the sample, while instrumental support is rare at only 0.6%. The first stage estimates show that the instrument (number of male children) is positively associated with the probability of receiving both the aggregated measure of support and financial support, with coefficients of approximately 8.1 and 7.7 percentage points, respectively. These relationships are statistically significant as reflected by Kleibergen–Paap F-statistics, which are well above the conventional threshold. In contrast, the association of the instrument with instrumental support is negligible (0.2 percentage points), and the corresponding F-statistic is relatively low, indicating a weak instrument.

The second stage estimates in columns 1 and 2 show very similar magnitudes for the aggregated measure and financial support (-0.409 vs -0.432, respectively), confirming that financial support drives the overall effect. The estimated effect of instrumental support is implausibly large and unreliable due to weak identification. The weak instrument for instrumental support violates the relevance condition, and therefore the estimates should not be interpreted causally. These findings validate using the aggregated support measure, as it empirically captures financial transfers. This pattern holds for both ADL score and SRH health outcomes.[36]

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[36] See Appendix *Table 4.A3* for SRH decomposition results.

Table 4.4
Effect of Support on ADL Score: Decomposition by Support Type

Outcome Variable: ADL score	(1) Any Support	(2) Financial	(3) Instrumental
Second Stage Results			
Support	-0.409***	-0.432***	-14.732**
	[0.140]	[0.147]	[6.309]
Observations	13,395	13,328	13,328
Outcome Mean		1.12	
First Stage Diagnostics			
Instrument (No. of male children)	0.081***	0.077***	0.002***
	[0.003]	[0.003]	[0.001]
Kleibergen–Paap F-stat	703	661	14
Partial R-squared	0.092	0.084	0.002

Notes: All estimations include the full set of control variables listed in *Table 4.2*. Column (1) shows the aggregated measure of support, column (2) shows financial support only, and column (3) shows instrumental support only. The slight difference in observations across columns is due to missing responses for specific support types. Columns (2) and (3) include only those who provide exclusively financial or instrumental support, respectively. Standard errors are clustered at the household level in brackets. * p<0.10, ** p<0.05, *** p<0.01.

4.5.2 Robustness Checks

To verify and confirm the validity of the main findings, a series of robustness checks were carried out. These checks include several alternative model specifications and measures for parental health outcomes. Firstly, to assess the robustness of the role of support, I use Principal Component Analysis (PCA) to construct the ADL score index. The PCA method is widely used for creating a variable index from a set of binary responses (Klapper et al., 2013; Kolenikov & Angeles, 2009). *Table 4.A4* (Column 1) shows the estimated effects of support on the alternative measures for health outcomes. Consistent with earlier results, the marginal effect of the receipt of support is negative and statistically significant at the 1% level.

Secondly, to further check the robustness of the results, another alternative measure for ADL health outcome was constructed as a binary variable, taking the value of 1 if the respondent's ADL score is above a certain threshold within the full sample, indicating bad health, and 0 otherwise. Thus, I apply the IV-Probit specification to model this outcome. As shown in *Table 4.A4* (Column 2), the marginal effect of support on alternative measure of ADL is negative and statistically significant, indicating that receiving support reduces the probability of reporting an ADL score above the threshold (thereby indicating good health).

As a robustness check for the SRH estimates I estimate the same model in Eq. (4.1) using a 2SLS linear probability model (LPM), the results are generally similar with the estimates from the Probit model.[37] Also, to further check the robustness of the SRH results, I estimate an IV ordered Probit regression model by considering the SRH variable as an ordinal variable (SRH outcomes are ordered variables, taking values of *unhealthy*, *somewhat unhealthy*, *somewhat healthy*, and *healthy*). The results of the IV ordered Probit model in Table 4.A4 (Column 3) indicate that support has a significant positive effect on SRH of parents, confirming the findings shown in Table 4.2. The marginal effects of support on SRH, as shown in Table 4.A5, are as follows: *unhealthy* (-0.007), *somewhat unhealthy* (-0.067), *somewhat healthy* (0.039), and *healthy* (0.035). They are all significant at the 5% significance level (except for *somewhat healthy* at the 1% significance level), indicating that receiving support significantly reduces the probability of individuals reporting being unhealthy, and increases the probability of being healthy.

Lastly, I re-estimate the baseline models controlling for the earlier omitted variables: household total expenditure, parental education and work status. The findings of the inclusion of the additional controls are generally consistent with the original results, there are no significant differences (see Table 4.A6). Overall, the study's findings are robust and credible; they verify the beneficial effect of support on parental health outcomes, regardless of the alternative specifications and measures.

Box 4.1: Robustness Summary

Alternative Outcome Measure:

- ADL (PCA): -0.21***
- ADL (threshold): -0.07***

Alternative Specification:

- LPM: -0.023***
- LPM-2SLS: 0.044*
- IV-Oprobit: 0.271**

Additional Control Variables:

- ADL: -0.362***
- SRH: 0.042*

Key Findings: The beneficial effect of support on parental health is robust across alternative outcome measures, specifications and additional control variables.

[37] See Appendix Table 4.A2 Column 4 for full results.

4.5.3 Heterogeneous Effects

This section presents the investigation of whether there were any heterogeneous effects across different groups of parents, controlling for the familywise error rate (FWER) using methods developed by (Jones et al., 2019).[38] *Table 4.5* disaggregates the sample by age, gender, and regional differences, focusing on estimates from IV regression models. Panel A shows the results for male and female parents, indicating significant gender differences in the effect of support on the ADL score. The results shows significant differences by gender of parents. Fathers receiving support from their children are more affected than mothers. The results suggest that fathers benefit more from receiving support in terms of relatively lower ADL scores, which can be attributed to traditional norms and customs in Indonesia, in which most household chores are highly gendered. These gender differences align with Indonesian culture, where mothers often continue to perform household management and care for their husbands regardless of their age as part of their cultural identity (Schröder-Butterfill, 2004). This offsets the beneficial health impacts from receiving support from children compared to men. Therefore, this burden will damages mothers' physical health outcomes and leads them to report poorer ADL scores than men. Another possible explanation is that in the IFLS data, the majority (85%) of heads of households that received support are females, and heads of household bear more significant burdens in relation to household responsibilities, which could negatively affect their overall health. The results do not show any significant differences between male and female parents with respect to SRH outcomes.

In Panel B, I examine the effect of support on different age groups by dividing the sample into three age cohorts: <60, 60-69, and 70^{+}. The results for SRH estimates are insignificant for all age groups, showing no significant differences between the age groups. In contrast, the ADL score presents significant differences between the relatively younger and older parents. Receiving support significantly lowers the ADL score by 1.498 activities for parents aged above 70, and by 0.477 activities for parents aged 60-69 (although the latter effect is only marginally significant). For parents aged below 60, the effect is much smaller and insignificant. These findings appear reasonable since younger parents are likely to report better physical health and require little physical support, so they are less dependent on receiving support from their children. Therefore, receiving support from their children may

[38] The FWER is the probability of making one or more type 1 error when testing for multiple hypothesis (Anderson, 2008).

have little effect on their ADL score. However, support for older parents has a much larger impact, mainly because they need to be cared for by their children more extensively, and are commensurately more likely to be vulnerable, and to report poorer physical health.

Panel C examines the impact of support on regional differences for parents living in urban and rural areas, showing significant differences. Urban residents tend to benefit more from their children than rural residents. Urban residents receiving support reduces the ADL score by 0.593 activities, whereas support for rural residents reduces the ADL score by only 0.346 activities. However, the SRH estimates do not show statistically significant effects in either urban or rural areas. One possible explanation for these results is that rural regions are less developed and have higher poverty rates than urban areas. Also, adult children in urban areas are more likely to participate in job opportunities, which often results in receiving higher income. Access to health services remains challenging in rural regions due to fewer health facilities and inadequate workforce. Therefore, with the insufficient health services in rural areas and higher poverty rates, parents would not have the privilege to benefit as much from receiving support compared to urban areas.

Overall, the findings suggest considerable heterogonous effects of support across different subgroups of parents. Receiving support from children has a greater beneficial effect on parental health for elderly parents, typically for male cohorts and those living in urban regions.

Table 4.5
Heterogeneous Effects of Children's Support on Parental Health Across Subgroups

Outcome Variables	(1) 2SLS	(2) IV-Probit
	ADL score	**SRH**
Panel A: Gender		
(a) Female		
Support	-0.199*	0.057
	[0.193]	[0.042]
Observations	7,005	7,018
Outcome Mean	1.436	0.786
(b) Male		
Support	-0.849***	0.025
	[0.227]	[0.057]
Observations	6,390	6,390
Outcome Mean	0.804	0.801
Panel B: Age		
(c) Below 60		
Support	0.008	0.013
	[0.157]	[0.043]
Observations	6,610	6,621
Outcome Mean	0.629	0.841
(d) 60-69		
Support	-0.477*	0.083
	[0.270]	[0.056]
Observations	4,421	4,428
Outcome Mean	1.259	0.768
(c) 70^{+}		
Support	-1.498***	0.088
	[0.387]	[0.071]
Observations	2,364	2,367
Outcome Mean	2.455	0.689
Panel C: Regions		
(d) Urban		
Support	-0.593***	0.047
	[0.228]	[0.052]
Observations	5,715	5,724
Outcome Mean	1.165	0.801
(e) Rural		
Support	-0.346***	0.048
	[0.178]	[0.041]
Observations	7,680	7,692
Outcome Mean	1.095	0.790

Notes: All estimations include control variables listed in *Table 4.2*. Standard errors are clustered at the household level in brackets. * p<0.10, ** p<0.05, *** p<0.01.

4.5.4 Mechanisms Analysis

So far, the findings have confirmed a causal positive effect of receiving support from children on parental health outcomes. This raises an issue of what mechanisms are driving the relationship between support and parental health. This section explores the potential transmission mechanisms or channels through which support received from children affects parental health outcomes. The ultimate aim of the mechanisms is to provide an in-depth understanding of the earlier findings for policymakers to formulate policies to alleviate the adverse effects on parental health. Understanding the mechanisms is essential for explaining the pathways through which the observed impact of support on health outcomes, as manifest in ADL scores and SRH. The conceptual framework presented in *Fig. 1* provides a way to understand the mechanisms through which the findings can be explained and understood. In the framework, the mechanisms relate to the utility of the support received; the effect of the support received by individuals is mainly dependent on the use of the support.

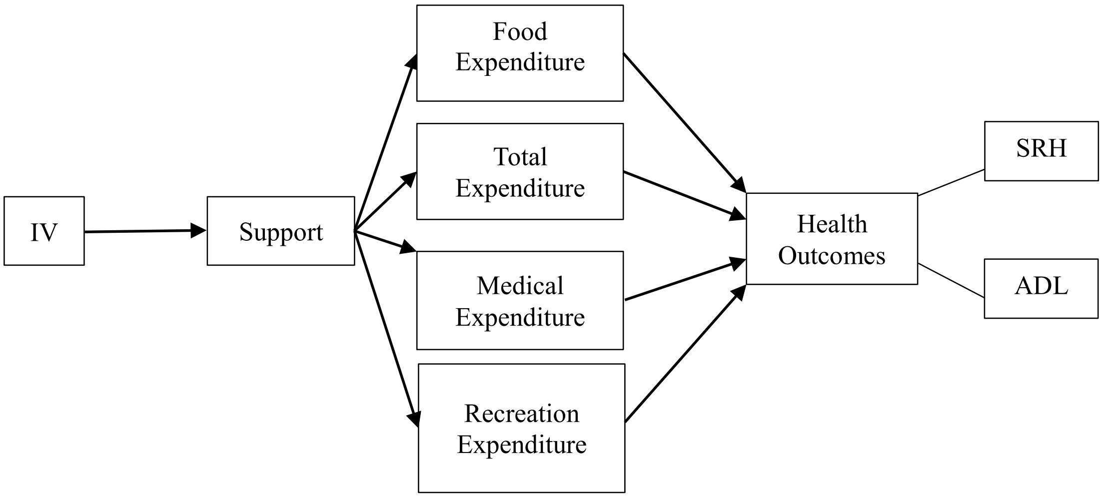

Figure 4.2 Conceptual Framework for Support Impacts on Parental Health Outcomes

To identify the mechanisms through which support can contribute to health, as shown in *Figure 4.2*, the effects of support are examined using mediation analysis on four key mediating variables. Due to data limitation, the four key variables that represent the use of the support are total household expenditure (as a proxy for wealth/income) (Jenkins et al., 2019), household medical expenditure (including hospitalization costs, clinic charges, physicians' fees, traditional healers' fees, and medicines), household food expenditure, and household recreation and entertainment expenditure.

Each of the proposed channels has a distinct effect. For instance, for total expenditure, support received from children may improve parents' overall standard of living and help buttress their expenditure, especially in the form of economic support, given that

Indonesians tend to incur expenses comprising about 29% of their monthly income in the event of health shocks (Gertler & Gruber, 2002). Increased medical expenditure may directly increase access to healthcare and treatment quality. Similarly, food expenditure is likely to represent nutritional status and physical strength. Recreation and entertainment expenditure can improve individuals mental health, potentially contributing to their overall wellbeing. Also, the interaction of adult children with parents through instrumental support and the ease of communication between them can lead to better health awareness for parents via exchanging helpful health-related knowledge and information with children (Amuedo-Dorantes & Pozo, 2009).

Table 4.6 reports the OLS and 2SLS estimates of the effects of support on the four various mediating variables. Column 1 shows the estimated impact of support on total household expenditure. The OLS estimate is negatively associated with total expenditure and is not statistically significant. However, the 2SLS estimate indicates that parents receiving support have a significantly higher total expenditure than their counterparts, specifically a 101% increase. Column 2 shows the estimated effects on medical expenditure. The OLS estimate indicates that receiving support significantly reduces medical spending by about 9.7%, while the 2SLS estimate shows that, after instrumenting for support, medical expenditure increases by 37.4%, and this effect is statistically significant at the 5% level.

Column 3 presents the effects on food expenditure. The OLS estimate is small and insignificant, but the 2SLS result indicates a large and statistically significant effect, suggesting that households receiving support spend roughly 104% more on food compared to those without support. The last column shows the estimated effects on recreation and entertainment expenditure. The OLS estimate in Column 4 reveals that receiving support reduces recreation spending by 22%. This indicates that parents receiving support spend more on essentials and less on leisure activities. However, the 2SLS results show that receiving support is not statistically associated with recreation and entertainment spending after instrumenting for support.

Overall, the results show that receiving support is positively associated with several potential mechanisms channels, mainly food, medical and total expenditure. This implies that receiving support increases the income/wealth of parents as a result of the increase in their expenditure levels, which leads to better health through the ability to afford essential medication, preventive care measures and access to better healthcare services. Also, the results illustrate that due to support, individuals increase their food expenditure, which implies they are more capable of buying more fresh and nutritious food to meet their dietary needs, which feeds into developing their immune systems and overall health and resilience to illness.

Based on the estimates shown in *Table 4.6*, I employ a casual mediation analysis to establish the causal mechanisms of the effect of support on parental health outcomes through the four mediating channels discussed earlier. Causal mediation analysis seeks to investigate the mechanisms that cause the treatment to affect the outcome variable (Kemp, 2003). The aim is to separate the total treatment effect into the indirect effect caused by the mediating variables, known as the mediators, and the direct effect of the treatment on the outcome of interest (Celli, 2022; Frölich & Huber, 2017). To determine support's direct and indirect effects on parental health outcomes in IV settings, I follow the framework to estimate casual mediation analysis developed by Dippel et al. (2020).[39]

Table 4.6
The Effect of Children's Support on Expenditure Mechanisms

		(1) **Total Expenditure**	(2) **Medical Expenditure**	(3) **Food Expenditure**	(4) **Recreation Expenditure**
	Coeff.	-0.027	-0.097**	-0.019	-0.220**
OLS	SE	[0.025]	[0.050]	[0.023]	[0.093]
2SLS	Coeff	1.012***	0.374**	1.037***	0.14
	SE	[0.094]	[0.151]	[0.087]	[0.250]
Observations		13,325	10,102	13,286	1,868
Outcome Mean		11.2	10.5	10.5	9.6
First Stage Diagnostics					
Instrument (No. of male children)		0.080***	0.082***	0.080***	0.080***
		[0.003]	[0.003]	[0.003]	[0.006]
Kleibergen–Paap F-stat		817	668	809	192
Partial R-squared		0.108	0.112	0.108	0.116

Notes: Due to incomplete information, the number of observations differs for each variable. The full set of results for the OLS and IV regressions are presented in *Table 4.A7.1* and *Table 4. A7.2*. Standard errors are clustered at the household level in brackets. * p<0.10, ** p<0.05, *** p<0.01.

[39] Appendix 4.B2 provides an overview of the causal mediation analysis procedure.

Table 4.7 reports the causal mediation analysis results, which illustrate that the direct effect of support is statistically insignificant for all mediator variables for both health outcomes. The indirect effect of household recreation and entertainment expenditure is also insignificant, indicating that spending on leisure and entertainment has no mediation effect on parental health outcomes. However, the indirect effect results for the other types of expenditure variables are statistically significant. Panel A shows the results of the casual mediation analysis for the ADL score. The indirect effect of total expenditure in Column 1 indicates that 0.423 of the decrease in the ADL score is caused by the increase in total expenditure through receiving support. It is evident that mediating effect of total expenditure explains 103% of the total effect of support on ADL score.[40] In comparison, household medical expenditure explains 80% of the mediating effect of support. The indirect effect of medical expenditure in Column 2 reveals that 0.326 of the decrease in the ADL score is mediated by medical expenditure through receiving support. In contrast, the indirect effect of food expenditure (Column 3) shows a 0.425 reduction in ADL score and explains around 103% of the mediating impact of support.

Furthermore, the indirect effect for the SRH outcome in Panel B (Column 7) indicates that 5.2 percentage points of the increase in the probability of reporting better SRH is mediated by total household expenditure, which explains 102% of the total effect of support on SRH. In Column 8, the results show that an increase in medical expenditure through support raises the likelihood of reporting better SRH by 4.0 percentage points and explains 95% of the total effect of support. In contrast, the indirect effect of food expenditure is likely to increase the likelihood of reporting better SRH by 5.4 percentage points, which is equivalent to explaining 102% of the total effect. These statistically significant mediating effects reveal that most of the causal effects of support on parental health outcomes are mediated almost entirely through household food, total expenditure and, to some extent, medical expenditure. The results affirm the earlier conclusion that parents receiving support have better access to health care due to the improvement of financial resources. These results align with the literature findings, which found that income is positively associated with better health outcomes (Contoyannis et al., 2004; Hasanah et al., 2021; Schmeiser, 2009).

[40]The mediation effect as a percentage of the total effect is the indirect effect divided by the total effect, multiplied by 100 (Johnsen et al., 2017).

Table 4.7
Causal Mediation Analysis: The Effect of Children's Support on Parental Health Through Expenditure Mechanisms

Mediating variables	**Total Expenditure**	**Medical Expenditure**	**Food Expenditure**	**Recreation Expenditure**
Panel A: ADL Score				
	(1)	(2)	(3)	(4)
Mediator (M)	-0.452***	-0.972**	-0.456***	-0.205
	[0.112]	[0.421]	[0.109]	[0.772]
Direct Effect (DE)	0.014	-0.083	0.016	-0.12
	[0.042]	[0.083]	[0.042]	[0.219]
β_{support} (est. in *Table 4.6*)	1.012***	0.374**	1.037***	0.14
Indirect Effect (IE)	-0.423	-0.326	-0.425	-0.289
Total Effect (TE) (est. in *Table 4.3*)	-0.409	-0.409	-0.409	-0.409
Mediation Effect	1.03	0.80	1.03	0.71
Panel B: SRH				
	(7)	(8)	(9)	(10)
Mediator (M)	0.080***	0.144*	0.079***	0.646
	[0.026]	[0.082]	[0.026]	[0.433]
Direct Effect (DE)	-0.012	0.002	-0.012	0.143
	[0.010]	[0.016]	[0.010]	[0.113]
β_{support} (est. in *Table 4.6*)	1.012***	0.374**	1.037***	0.14
Indirect Effect (IE)	0.052	0.040	0.054	-0.101
Total Effect (TE) (est. in *Table 4.3*)	0.042	0.042	0.042	0.042
Mediation Effect	1.2	0.95	1.2	2.4

Notes: The M represents the second-stage estimates from the mediation model; it is the causal effect of the mediating variable on the health outcomes (see *Table 4.A8.1* and *Table 4.A8.2* for full results). The DE represents the direct effect of support on health outcomes obtained from *Table 4.A8.1* and *Table 4.A8.2*. β_{support} represents the effect of support on the mediating variables obtained from *Table 4.6*. The IE represents the effect of the mediating outcomes caused by support on health outcomes (IE = TE – DE), which can be also calculated as the product of M and β_{support}. Standard errors are clustered at the household level in brackets. * p<0.10, ** p<0.05, *** p<0.01.

4.6 Conclusion

The elderly population is one of the most vulnerable groups in society, and one to which everyone ultimately aspires to belong. The holistic wellbeing and welfare of the elderly should be a core priority of any effective social protection system. For Indonesia, the range of social protection programmes for the elderly that central and local governments provide is grossly inadequate, thus parents rely heavily on adult children for support. Support is particularly important for the elderly parents' wellbeing as they pass their productive age and experience loss of income and poorer health. Changes in lifestyle and the migration of children lead to a rise in parents' vulnerability to poverty and isolation. Due to the vital role of support in altering parents' wellbeing, this study examined the impact of receiving support from children on parents' health outcomes and further explores several potential mechanisms by which support provided by children enhances parental health and wellbeing.

Using IFLS data, this study applied the IV approach to investigate the causal impact of children's support on parents' health outcomes. The study improved upon the outcomes of previous literature by introducing an instrumental variable approach to address potential endogeneity issue, like unobserved heterogeneity and reverse causality. The analysis showed that receiving support improved parents' health outcomes measured by activities of daily living and self-reported health. Precisely, parents that received support from their children had an improvement in ADL scores by 0.4 activities and increased their likelihood for being healthy by 4.2 percentage points. Decomposition analysis distinguishing financial from instrumental support shows that the estimated effects are primarily driven by financial support, whereas instrumental support is limited due to its low prevalence and weak empirical association with the instrument. Furthermore, the findings suggest that there are large heterogonous effects of support across different subgroups of parents. A causal mediation analysis was conducted based on four key variables: household medical, food, total expenditure, and recreation spending. The findings indicated that household medical, food and total expenditure mediate the effect of support on parental health. Thus, parents receiving support are more likely to have higher expenditure levels through the improvement of income level (financial relief), which leads to better health status by means of access to better healthcare services and the ability to acquire and adapt healthy habits like more nutritious food that meets their dietary needs.

From the perspective of policy-making, the findings suggest that as the population ages, the role of support provided by children on the health and wellbeing of elderly parents becomes increasingly important and should be accorded a top priority. Particularly in low and middle-income nations where insufficient state-sponsored support systems exist. Policies and programmes should encourage the current norms and familial responsibilities of providing support to parents. However, this strategy comes with a cost while the family-based support systems may reduce governmental financial burden of the ageing population. The reliance on support from children may potentially widen inequalities between individuals with children and childless individuals. Even those individuals with children whose resources and availability are limited would be vulnerable and disadvantaged.

The traditional family-based support is susceptible to be less reliable over time with the declining fertility rates and demographic shifts. Therefore, a balanced approach between formal and informal support mechanisms may benefit all. For example, community-based care programs could complement family-based support, particularly in rural areas where generally resources are limited. This would ensure support is received across all demographic groups and therefore reduce inequalities.

Furthermore, it is essential for the state to improve the institutional pension funds so that parents can be less dependent on receiving support from children. This could include expanding pension coverage and developing specific subsidies for healthcare costs, given that medical expenditure is a key channel in improving health outcomes. As confirmed by the mediation analysis which highlights the significance of parents' increased income levels in improving their health. In general, the analysis presented evidence for policymakers to focus on alleviating the welfare of the elderly as a health strategy. Focus should be particularly directed towards the most vulnerable groups, specifically those aged over 70 and those living in rural areas, as they are more likely to benefit from such policies (which in turn reduces total healthcare costs over the long term).

Overall, the empirical findings add to the body of literature on the causal relationship between support and health and offer policymakers a better understanding of the vital role of intergenerational support on parents' wellbeing to plan for future health needs. An essential contribution of this study is that, to the best of my knowledge, this is the first study to provide the causal effects of support on parental health outcomes using an IV regression model to account for endogeneity. The study also provided the first causal mediation analysis to examine how the support provided by children enhances parental health outcomes.

Further research should investigate the impact of the isolated types of support on various health outcomes through differentiating between economic and non-economic support. Also, to better understand the causal pathways through which support affects parental health outcomes, future research should explore different potential mechanisms to determine the importance of mediating factors of support on health. In particular, mechanisms that can show the mediation effect of receiving non-economic support such as mental and cognitive functions. Additionally, research should examine cross-cultural comparisons of benefit of support to assist with identifying universal or culturally specific benefits.

Appendix 4.A

Appendix 4.A provides descriptive statistics as well as the complete set of regression results and robustness checks supporting the empirical analysis in this study. The tables present the full estimation results for the instrumental variable specifications discussed in the main text, along with alternative definitions of the dependent variable and models including extended control variables. These supplementary tables complement the main findings, confirming the robustness and consistency of the estimated effects across alternative model specifications and variable definitions.

Table 4.A1
Distribution of Male Children and Cross-Tabulation with Parents Receiving Support

Number of Male Children	(1) Full Sample	(2) With Support	(3) Without Support	(4) Support Rate
0	20%	7%	27%	12%
1	25%	17%	29%	24%
2	22%	22%	22%	36%
3	15%	18%	12%	47%
4+	19%	34%	11%	64%
Observations	13,416	4,722	8,694	-

Notes: Sample weights applied. Columns (1) – (3) show percentages of the distribution of number of sons within each group. Column (4) shows percentage of parents with a given number of sons who receive support from at least one non-coresident child aged 15+). The 4+ category aggregates parents with four or more male children.

Table 4.A2
The Effect of Children's Support on Parental Health Outcomes: Instrumental Variable Estimates

Outcome Variables	(1) 2SLS **ADL score**	(2) IV-Poisson **ADL score**	(3) IV-Probit **SRH**	(4) 2SLS **SRH**
Support	-0.409***	-0.419***	0.042*	0.044*
	[0.140]	[0.127]	[0.033]	[0.033]
Age: (Ref: <60)				
Age: 60-69	0.652***	0.816***	-0.078***	-0.076***
	[0.040]	[0.048]	[0.010]	[0.010]
Age: 70^{+}	1.816***	1.540***	-0.143***	-0.154***
	[0.070]	[0.055]	[0.012]	[0.013]
Male	-0.709***	-0.747***	0.030**	0.031**
	[0.058]	[0.056]	[0.014]	[0.014]
Married	-0.389***	-0.244***	0.035***	0.036***
	[0.053]	[0.043]	[0.011]	[0.011]
Urban	0.058	0.070*	0.017*	0.018*
	[0.040]	[0.038]	[0.009]	[0.009]
Migrant	0.024	0.032	0.019	0.019
	[0.053]	[0.051]	[0.013]	[0.013]
Household Size	-0.014*	-0.022***	0.002	0.002
	[0.008]	[0.008]	[0.002]	[0.002]
Province of Residence: (Ref: South Sulawesi)				
North Sumatra	0.335***	0.210**	-0.048**	-0.059**
	[0.113]	[0.095]	[0.024]	[0.028]
West Sumatra	0.533***	0.398***	-0.133***	-0.170***
	[0.132]	[0.103]	[0.024]	[0.030]
South Sumatra	0.05	0.009	0.006	0.006
	[0.119]	[0.107]	[0.025]	[0.028]
Lampung	-0.016	-0.015	0.024	0.026
	[0.120]	[0.116]	[0.027]	[0.028]
Jakarta	-0.088	-0.099	-0.016	-0.016
	[0.109]	[0.106]	[0.024]	[0.026]
West Java	-0.014	-0.023	-0.012	-0.014
	[0.099]	[0.093]	[0.021]	[0.023]
Central Java	-0.246**	-0.260***	0.066***	0.067***
	[0.097]	[0.094]	[0.021]	[0.022]
Yogyakarta	-0.559***	-0.572***	0.081***	0.081***
	[0.103]	[0.105]	[0.024]	[0.024]
East Java	-0.357***	-0.388***	0.111***	0.105***
	[0.096]	[0.092]	[0.021]	[0.022]
Bali	0.449***	0.315***	0.028	0.029
	[0.123]	[0.099]	[0.026]	[0.028]
West Nusa Tenggara	0.233**	0.169*	-0.071***	-0.087***
	[0.119]	[0.102]	[0.025]	[0.029]
South Kalimantan	-0.024	-0.04	-0.035	-0.043
	[0.129]	[0.121]	[0.027]	[0.031]
Year: (Ref: 1993)	0.494***	0.546***	-0.017*	-0.015*
	[0.036]	[0.041]	[0.009]	[0.009]
1997	0.326***	0.403***	-0.023**	-0.021**
	[0.035]	[0.042]	[0.009]	[0.009]
2000	1.308***			0.744***
	[0.123]			[0.028]
Constant	0.335***	0.210**	-0.048**	-0.059**
	[0.113]	[0.095]	[0.024]	[0.028]
Observations	13,395	13,395	13,416	13,416

Notes: Standard errors are clustered at the household level in brackets. * p<0.10, ** p<0.05, *** p<0.01

Table 4.A3
Effect of Support Children's on SRH Score: Decomposition by Support Type

Outcome Variable: SRH	(1) Any Support	(2) Financial	(3) Instrumental
Second Stage Results			
Support from children	0.042* [0.033]	0.043* [0.034]	1.421* [1.222]
Observations	13,416	13,349	13,349
Outcome Mean		0.79	
First Stage Diagnostics			
Instrument (No. of male children)	0.081***	0.077***	0.002***
	[0.003]	[0.003]	[0.001]
Kleibergen–Paap F-stat	703	660	14
Partial R-squared	0.092	0.083	0.002

Notes: All estimations include the full set of control variables listed in Table 4.2. Column (1) shows the aggregated measure of support, column (2) shows financial support only, and column (3) shows instrumental support only. The slight difference in observations across columns is due to missing responses for specific support types. Columns (2) and (3) include only those who provide exclusively financial or instrumental support, respectively. Standard errors are clustered at the household level in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 4.A4
Robustness Checks: Effects of Children's Support on Parental Health using Alternative Specifications and Measures

Outcome Variables	(1) 2SLS **ADL score (PCA)**	(2) IV-Probit **ADL score (threshold)**	(3) IV-OProbit **Ordinal SRH**
Support	-0.212***	-0.077**	0.271**
	[0.065]	[0.033]	[0.107]
Age: (Ref: <60)	0.287***	0.159***	-0.283***
Age: 60-69	[0.018]	[0.010]	[0.031]
	0.813***	0.342***	-0.492***
Age: 70^{+}	[0.033]	[0.011]	[0.039]
	-0.320***	-0.175***	-0.283***
Male	[0.027]	[0.014]	0.130***
	-0.178***	-0.074***	[0.045]
Married	[0.024]	[0.011]	0.156***
	0.016	0.017*	[0.034]
Urban	[0.018]	[0.009]	0.038
	0.028	0.005	[0.029]
Migrant	[0.025]	[0.013]	-0.008
	-0.004	-0.002	[0.041]
Household size	[0.004]	[0.002]	0.006
	0.287***	0.159***	[0.006]
Province of Residence (Ref: South Sulawesi)			
North Sumatra	0.102**	0.071***	-0.089
	[0.051]	[0.024]	[0.071]
West Sumatra	0.222***	0.098***	-0.331***
	[0.060]	[0.025]	[0.073]
South Sumatra	0.02	0.024	0.131
	[0.054]	[0.027]	[0.080]
Lampung	-0.055	-0.018	0.069
	[0.055]	[0.028]	[0.075]
Jakarta	-0.022	-0.011	0.016
	[0.050]	[0.025]	[0.070]
West Java	-0.004	-0.002	0.086
	[0.045]	[0.022]	[0.063]
Central Java	-0.112**	-0.076***	0.188***
	[0.044]	[0.022]	[0.060]
Yogyakarta	-0.262***	-0.150***	0.318***
	[0.046]	[0.024]	[0.066]
East Java	-0.154***	-0.059***	0.579***
	[0.043]	[0.022]	[0.063]
Bali	0.132**	0.094***	0.11
	[0.055]	[0.026]	[0.073]
West Nusa Tenggara	0.133**	0.037	-0.184**
	[0.056]	[0.026]	[0.076]
South Kalimantan	0.019	0.002	-0.01
	[0.059]	[0.029]	[0.083]
Year: (Ref: 1993)			
1997	0.153***	0.142***	-0.210***
	[0.017]	[0.009]	[0.030]
2000	0.102***	0.086***	-0.231***
	[0.017]	[0.010]	[0.031]
Constant	3.589***		
	[0.055]		
Observations	13,395	13,395	13,416
Outcome Mean	3.5	0.27	2.8

Notes: Standard errors are clustered at the household level in brackets. * p<0.10, ** p<0.05, *** p<0.01.

Table 4.A5
Effects of Children's Support on Parental SRH: Instrumental Variable Ordered Probit Estimates

Outcome Variables	(1) **Unhealthy**	(2) **Somewhat Unhealthy**	(3) **Somewhat Healthy**	(4) **Healthy**
Support	-0.007**	-0.067**	0.039***	0.035**
	[0.003]	[0.026]	[0.015]	[0.014]
Age: (Ref: <60)				
Age: 60-69	0.006***	0.069***	-0.039***	-0.037***
	[0.001]	[0.008]	[0.005]	[0.004]
Age: 70^{+}	0.014***	0.128***	-0.087***	-0.056***
	[0.002]	[0.011]	[0.009]	[0.005]
Male	-0.003**	-0.032***	0.019***	0.017***
	[0.001]	[0.011]	[0.006]	[0.006]
Married	-0.004***	-0.040***	0.025***	0.019***
	[0.001]	[0.009]	[0.006]	[0.004]
Urban	-0.001	-0.009	0.005	0.005
	[0.001]	[0.007]	[0.004]	[0.004]
Migrant	0	0.002	-0.001	-0.001
	[0.001]	[0.010]	[0.006]	[0.005]
Household size	0	-0.001	0.001	0.001
	[0.000]	[0.001]	[0.001]	[0.001]
Province of Residence: (Ref: South Sulawesi)				
North Sumatra	0.002	0.022	-0.013	-0.011
	[0.002]	[0.018]	[0.010]	[0.009]
West Sumatra	0.008***	0.082***	-0.048***	-0.042***
	[0.002]	[0.018]	[0.011]	[0.009]
South Sumatra	-0.003	-0.032	0.019	0.017
	[0.002]	[0.020]	[0.012]	[0.010]
Lampung	-0.002	-0.017	0.01	0.009
	[0.002]	[0.018]	[0.011]	[0.010]
Jakarta	0	-0.004	0.002	0.002
	[0.002]	[0.017]	[0.010]	[0.009]
West Java	-0.002	-0.021	0.012	0.011
	[0.002]	[0.016]	[0.009]	[0.008]
Central Java	-0.005***	-0.046***	0.027***	0.024***
	[0.002]	[0.015]	[0.009]	[0.008]
Yogyakarta	-0.008***	-0.079***	0.046***	0.040***
	[0.002]	[0.016]	[0.010]	[0.008]
East Java	-0.014***	-0.143***	0.084***	0.074***
	[0.002]	[0.015]	[0.009]	[0.008]
Bali	-0.003	-0.027	0.016	0.014
	[0.002]	[0.018]	[0.011]	[0.009]
West Nusa Tenggara	0.005**	0.046**	-0.027**	-0.023**
	[0.002]	[0.019]	[0.011]	[0.010]
South Kalimantan	0	0.002	-0.001	-0.001
	[0.002]	[0.020]	[0.012]	[0.010]
Year: (Ref: 1993)				
1997	0.005***	0.050***	-0.026***	-0.029***
	[0.001]	[0.007]	[0.004]	[0.004]
2000	0.005***	0.056***	-0.030***	-0.031***
	[0.001]	[0.007]	[0.004]	[0.004]
Outcome Mean	0.009	0.199	0.721	0.070
Observations	13,416	13,416	13,416	13,416

Notes: Standard errors are clustered at the household level in brackets. * p<0.10, ** p<0.05, *** p<0.01.

Table 4.A6
Robustness Checks: Effects of Children's Support on Parental Health with Extended Controls

Outcome Variables	(1) IV-Probit	(2) 2SLS
	SRH	**ADL score**
Support	0.042*	-0.362***
	[0.032]	[0.133]
Age: (Ref: <60)		
Age: 60-69	-0.048***	0.420***
	[0.010]	[0.038]
Age: 70^{+}	-0.085***	1.269***
	[0.012]	[0.065]
Male	0.01	-0.525***
	[0.015]	[0.056]
Married	0.018*	-0.242***
	[0.011]	[0.050]
Urban	0.013	0.059
	[0.010]	[0.040]
Migrant	0.013	0.053
	[0.013]	[0.051]
Household Size	0.001	-0.016**
	[0.002]	[0.008]
Province of Residence: (Ref: South Sulawesi)		
North Sumatra	-0.066***	0.506***
	[0.022]	[0.097]
West Sumatra	-0.140***	0.586***
	[0.024]	[0.119]
South Sumatra	-0.012	0.223**
	[0.024]	[0.104]
Lampung	0.014	0.067
	[0.025]	[0.104]
Jakarta	-0.032	0.014
	[0.023]	[0.097]
West Java	-0.016	0.043
	[0.020]	[0.085]
Central Java	0.051**	-0.119
	[0.020]	[0.080]
Yogyakarta	0.040*	-0.274***
	[0.023]	[0.090]
East Java	0.104***	-0.281***
	[0.020]	[0.079]
Bali	0.012	0.538***
	[0.024]	[0.105]
West Nusa Tenggara	-0.084***	0.334***
	[0.024]	[0.103]
South Kalimantan	-0.065**	0.183
	[0.026]	[0.116]
Year: (Ref: 1993)		
1997		
	-0.026***	0.506***
2000	[0.010]	[0.035]
Work Status (Ref. Employed		
Job Searching	-0.087*	0.092
	[0.047]	[0.125]
Attending School	-0.338**	0.493
	[0.144]	[0.611]
Housekeeping	-0.068***	0.417***
	[0.011]	[0.045]
Retired	-0.133***	1.252***

Table 4.A6
Robustness Checks: Effects of Children's Support on Parental Health with Extended Controls

Outcome Variables	(1) IV-Probit **SRH**	(2) 2SLS **ADL score**
	[0.012]	[0.068]
Other	-0.197***	1.415***
	[0.020]	[0.124]
Education (Ref. Unschooled)	0.001	-0.138***
Grade School	[0.010]	[0.040]
	0.035**	-0.329***
Junior High school	[0.018]	[0.062]
	0.042**	-0.301***
Senior High school	[0.021]	[0.076]
	0.053	-0.443**
College	[0.062]	[0.184]
	0.066*	-0.307***
University	[0.035]	[0.100]
	0.155	0.512
Other	[0.119]	[0.691]
	0.011**	-0.051***
Total Expenditure	[0.004]	[0.018]
		1.428***
Constant		[0.200]
		0.092
Observations	12,970	12,949
Outcome Mean	0.80	1.07
First Stage Diagnostics		
Instrument (No. of male children)	0.081***	
	[0.003]	
Kleibergen–Paap F-stat	683	
Partial R-squared	0.092	

Notes: Standard errors are clustered at the household level in brackets. * p<0.10, ** p<0.05, *** p<0.01.

Table 4.A7.1
The Effect of Children's Support on Total and Heal Expenditure: Baseline and 2SLS Estimates

Outcome Variables	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
	Total Expenditure	**Total Expenditure**	**Health Expenditure**	**Health Expenditure**
Support	1.012***	-0.027	-0.097**	0.374**
	[0.094]	[0.025]	[0.050]	[0.151]
Age: (Ref: <60)	-0.322***	-0.192***	0.023	-0.032
Age: 60-69	[0.028]	[0.024]	[0.049]	[0.051]
	-0.485***	-0.347***	0.110*	0.044
Age: 70^{+}	[0.041]	[0.036]	[0.064]	[0.067]
	0.488***	0.089***	-0.032	0.151**
Male	[0.048]	[0.028]	[0.053]	[0.077]
	0.339***	0.239***	0.271***	0.316***
Married	[0.037]	[0.032]	[0.057]	[0.059]
	0.799***	0.751***	0.623***	0.649***
Urban	[0.030]	[0.027]	[0.050]	[0.051]
	-0.322***	-0.192***	0.023	-0.032
Province of Residence: (Ref: South Sulawesi)				
North Sumatra	0.243***	0.169**	0.792***	0.812***
	[0.077]	[0.073]	[0.147]	[0.147]
West Sumatra	0.501***	0.567***	1.006***	0.961***
	[0.078]	[0.072]	[0.155]	[0.156]
South Sumatra	0.099	0.14	0.579***	0.540***
	[0.090]	[0.085]	[0.152]	[0.152]
Lampung	-0.053	0.004	0.274*	0.237
	[0.079]	[0.074]	[0.147]	[0.146]
Jakarta	0.899***	0.940***	1.198***	1.172***
	[0.078]	[0.071]	[0.148]	[0.148]
West Java	0.236***	0.375***	0.742***	0.664***
	[0.071]	[0.064]	[0.133]	[0.135]
Central Java	0.007	0.084	0.296**	0.249*
	[0.071]	[0.065]	[0.137]	[0.138]
Yogyakarta	-0.157**	-0.041	0.032	-0.034
	[0.077]	[0.070]	[0.145]	[0.146]
East Java	-0.059	-0.026	0.091	0.06
	[0.068]	[0.063]	[0.134]	[0.134]
Bali	0.341***	0.299***	0.484***	0.493***
	[0.081]	[0.076]	[0.156]	[0.157]
West Nusa Tenggara	-0.056	0.125*	-0.141	-0.237
	[0.079]	[0.070]	[0.144]	[0.147]
South Kalimantan	0.195**	0.301***	0.310**	0.253*
	[0.088]	[0.081]	[0.151]	[0.153]
Year: (Ref: 1993)				
1997	0.591***	0.632***	0.516***	0.499***
	[0.023]	[0.021]	[0.053]	[0.053]
2000	1.389***	1.426***	1.164***	1.150***
	[0.023]	[0.021]	[0.049]	[0.049]
Constant	9.407***	9.905***	9.069***	8.849***
	[0.084]	[0.067]	[0.141]	[0.154]
Observations	13,325	13,325	10,102	10,102

Notes: Standard errors are clustered at the household level in brackets. * p<0.10, ** p<0.05, *** p<0.01.

Table 4.A7.2
The Effect of Children's Support on Food and Recreation Expenditure: Baseline and 2SLS Estimates

Outcome Variables	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
	Food Expenditure	**Food Expenditure**	**Recreation Expenditure**	**Recreation Expenditure**
Support	-0.019	1.037***	-0.220**	0.14
	[0.023]	[0.087]	[0.093]	[0.250]
Age: (Ref: <60)				
Age: 60-69	-0.180***	-0.310***	-0.074	-0.141
	[0.022]	[0.027]	[0.089]	[0.104]
Age: 70^{+}	-0.275***	-0.415***	-0.055	-0.134
	[0.032]	[0.037]	[0.125]	[0.137]
Male	0.068***	0.473***	0.128	0.251**
	[0.025]	[0.044]	[0.091]	[0.123]
Married	0.247***	0.349***	0.018	0.052
	[0.029]	[0.035]	[0.107]	[0.108]
Urban	0.475***	0.525***	0.529***	0.540***
	[0.023]	[0.026]	[0.090]	[0.090]
Province of Residence: (Ref: South Sulawesi)				
North Sumatra	0.234***	0.309***	-0.011	-0.004
	[0.065]	[0.070]	[0.498]	[0.490]
West Sumatra	0.488***	0.422***	0.186	0.14
	[0.065]	[0.071]	[0.493]	[0.487]
South Sumatra	0.210***	0.165**	-0.034	-0.049
	[0.076]	[0.082]	[0.496]	[0.490]
Lampung	0.025	-0.033	-0.512	-0.604
	[0.068]	[0.074]	[0.511]	[0.513]
Jakarta	0.686***	0.642***	0.369	0.365
	[0.061]	[0.068]	[0.479]	[0.472]
West Java	0.327***	0.185***	0.221	0.183
	[0.056]	[0.064]	[0.483]	[0.477]
Central Java	0.06	-0.018	-0.155	-0.173
	[0.059]	[0.065]	[0.485]	[0.478]
Yogyakarta	-0.106*	-0.224***	-0.255	-0.275
	[0.061]	[0.069]	[0.482]	[0.475]
East Java	0.03	-0.005	-0.326	-0.348
	[0.055]	[0.061]	[0.484]	[0.478]
Bali	0.363***	0.405***	-0.269	-0.246
	[0.063]	[0.069]	[0.492]	[0.483]
West Nusa Tenggara	0.230***	0.046	-0.697	-0.764
	[0.062]	[0.071]	[0.493]	[0.490]
South Kalimantan	0.295***	0.185**	-0.407	-0.446
	[0.070]	[0.078]	[0.505]	[0.499]
Year: (Ref: 1993)				
1997	0.629***	0.588***	0.437***	0.430***
	[0.020]	[0.022]	[0.100]	[0.099]
2000	1.383***	1.346***	1.131***	1.135***
	[0.021]	[0.023]	[0.094]	[0.094]
Constant	9.276***	8.770***	8.654***	8.498***
	[0.060]	[0.075]	[0.509]	[0.503]
Observations	13,286	13,286	1,868	1,868

Notes: Standard errors are clustered at the household level in brackets. * p<0.10, ** p<0.05, *** p<0.01.

Table 4.A8.1
Causal Mediation Analysis: The Effect of Children's Support on Parental ADL Through Expenditure Mechanisms

	(1)	(2)	(3)	(4)
Mediators	**Total Expenditure**	**Medical Expenditure**	**Food Expenditure**	**Recreation Expenditure**
Support	0.014	-0.083	0.016	-0.12
	[0.042]	[0.083]	[0.042]	[0.219]
Total Expenditure	-0.452***			
	[0.112]			
Medical Expenditure		-0.972**		
		[0.421]		
Food Expenditure			-0.456***	
			[0.109]	
Recreation Expenditure				-0.205
				[0.772]
Age: (Ref: <60)				
Age: 60-69	0.515***	0.632***	0.518***	0.693***
	[0.042]	[0.067]	[0.040]	[0.115]
Age: 70^{+}	1.595***	1.820***	1.621***	1.742***
	[0.078]	[0.118]	[0.074]	[0.207]
Male	-0.510***	-0.569***	-0.519***	-0.671***
	[0.042]	[0.072]	[0.041]	[0.144]
Married	-0.234***	-0.085	-0.232***	-0.246*
	[0.058]	[0.143]	[0.059]	[0.138]
Urban	0.408***	0.693***	0.288***	0.087
	[0.091]	[0.268]	[0.064]	[0.410]
Province of Residence: (Ref: South Sulawesi)				
North Sumatra	0.432***	1.064***	0.451***	0.246
	[0.117]	[0.391]	[0.116]	[0.273]
West Sumatra	0.754***	1.487***	0.717***	0.347
	[0.149]	[0.476]	[0.144]	[0.314]
South Sumatra	0.091	0.531	0.123	0.294
	[0.124]	[0.324]	[0.124]	[0.313]
Lampung	-0.034	0.196	-0.026	0.329
	[0.124]	[0.241]	[0.124]	[0.601]
Jakarta	0.326**	1.018*	0.211	0.074
	[0.154]	[0.541]	[0.134]	[0.369]
West Java	0.096	0.640*	0.08	0.076
	[0.109]	[0.364]	[0.105]	[0.286]
Central Java	-0.237**	0.005	-0.258***	0.024
	[0.100]	[0.225]	[0.098]	[0.274]
Yogyakarta	-0.610***	-0.618***	-0.637***	-0.33
	[0.107]	[0.197]	[0.105]	[0.322]
East Java	-0.387***	-0.312*	-0.362***	-0.036
	[0.098]	[0.189]	[0.096]	[0.367]
Bali	0.601***	0.935***	0.629***	0.864*
	[0.131]	[0.299]	[0.130]	[0.458]
West Nusa Tenggara	0.218*	-0.011	0.266**	-0.134
	[0.120]	[0.212]	[0.120]	[0.606]
South Kalimantan	0.072	0.162	0.07	0.076
	[0.135]	[0.259]	[0.133]	[0.410]
Year: (Ref: 1993)				
1997	0.773***	1.021***	0.770***	0.409
	[0.080]	[0.230]	[0.078]	[0.384]
2000	0.966***	1.444***	0.950***	0.392
	[0.163]	[0.495]	[0.154]	[0.899]
Constant	5.509***	9.887***	5.275***	2.806
	[1.112]	[3.822]	[1.013]	[6.698]
Observations	13,304	10,085	13,265	1866

Notes: Standard errors are clustered at the household level in brackets. * p<0.10, ** p<0.05, *** p<0.01.

Table 4.A8.2
Causal Mediation Analysis: The Effect of Children's Support on Parental SRH Through Expenditure Mechanisms

	(1)	(2)	(3)	(4)
Mediators	**Total Expenditure**	**Health Expenditure**	**Recreation Expenditure**	**Food Expenditure**
Support	-0.012	0.002	0.143	-0.012
	[0.010]	[0.016]	[0.113]	[0.010]
Total Expenditure	0.080***			
	[0.026]			
Health Expenditure		0.144*		
		[0.082]		
Recreation Expenditure			0.646	
			[0.433]	
Food Expenditure				0.079***
				[0.026]
Age: (Ref: <60)				
Age: 60-69	-0.053***	-0.071***	-0.035	-0.054***
	[0.010]	[0.013]	[0.066]	[0.010]
Age: 70^{+}	-0.117***	-0.145***	-0.144	-0.124***
	[0.016]	[0.020]	[0.092]	[0.015]
Male	-0.002	0.006	-0.006	0
	[0.010]	[0.014]	[0.083]	[0.010]
Married	0.01	-0.003	-0.004	0.01
	[0.013]	[0.027]	[0.080]	[0.013]
Urban	-0.044**	-0.072	-0.313	-0.022
	[0.022]	[0.052]	[0.236]	[0.015]
Province of Residence: (Ref: South Sulawesi)				
North Sumatra	-0.073***	-0.175**	-0.047	-0.077***
	[0.028]	[0.076]	[0.326]	[0.028]
West Sumatra	-0.207***	-0.297***	-0.256	-0.202***
	[0.034]	[0.093]	[0.337]	[0.033]
South Sumatra	-0.002	-0.065	-0.068	-0.01
	[0.029]	[0.063]	[0.326]	[0.029]
Lampung	0.03	-0.006	0.288	0.027
	[0.029]	[0.045]	[0.401]	[0.029]
Jakarta	-0.090**	-0.17	-0.272	-0.070**
	[0.036]	[0.105]	[0.358]	[0.032]
West Java	-0.038	-0.108	-0.184	-0.035
	[0.026]	[0.069]	[0.333]	[0.025]
Central Java	0.064***	0.044	0.081	0.065***
	[0.023]	[0.041]	[0.321]	[0.023]
Yogyakarta	0.089***	0.101***	0.193	0.094***
	[0.025]	[0.035]	[0.330]	[0.025]
East Java	0.108***	0.104***	0.207	0.102***
	[0.022]	[0.033]	[0.341]	[0.022]
Bali	-0.001	-0.035	0.094	-0.007
	[0.029]	[0.056]	[0.342]	[0.030]
West Nusa Tenggara	-0.089***	-0.054	0.401	-0.099***
	[0.029]	[0.040]	[0.435]	[0.030]
South Kalimantan	-0.064*	-0.057	0.125	-0.065**
	[0.033]	[0.049]	[0.369]	[0.033]
Year: (Ref: 1993)				
1997	-0.064***	-0.089**	-0.317	-0.063***
	[0.019]	[0.044]	[0.200]	[0.019]
2000	-0.131***	-0.178*	-0.771	-0.125***
	[0.038]	[0.096]	[0.494]	[0.037]
Constant	-0.007	-0.548	-4.755	0.056
	[0.262]	[0.740]	[3.746]	[0.242]
Observations	13,325	10,102	1,868	13,286

Notes: Standard errors are clustered at the household level in brackets. * p<0.10, ** p<0.05, *** p<0.01

Appendix 4.B

Appendix 4.B presents supplementary descriptive statistics and diagnostic analyses supporting the empirical results discussed in Chapter 4. It includes the pairwise correlations among key variables and summary statistics of the mechanism variables used in the causal mediation analysis. As well an overview of mediation analysis framework used in Section 4.5.4. These materials provide additional context for the main findings in this study.

Table 4.B1
Pairwise Correlations

	ADL score	SRH	Support	Age	Sex	Married	Urban	Migrant	Household size	Province	No. Male Children
ADL score	1.000										
SRH	-0.406*	1.000									
Support	0.131*	-0.048*	1.000								
Age	0.348*	-0.140*	0.138*	1.000							
Sex	-0.178*	0.025*	-0.425*	0.039*	1.000						
Married	-0.233*	0.075*	-0.273*	-0.236*	0.407*	1.000					
Urban	0.007	0.021*	-0.050*	-0.029*	-0.008	-0.042*	1.000				
Migrant	0.049*	0.018*	0.353*	0.041*	-0.242*	-0.127*	0.012	1.000			
Household size	-0.066*	0.023*	-0.117*	-0.148*	0.087*	0.151*	0.137*	-0.056*	1.000		
Province	-0.027*	0.019*	0.016	-0.022*	0.010	0.006	-0.033*	-0.069*	0.004	1.000	
No. Male Children	0.019	0.008	0.374*	-0.035*	-0.221*	-0.084*	0.044*	0.355*	0.323*	-0.036*	1.000

* Shows significance at the 0.05 level

Table 4.B2 Summary Statistics of Mechanisms Variables

	Mean	Std. Dev.	N
Total Expenditure	11.21	1.26	13,304
Medical Expenditure	10.51	1.92	10,085
Food Expenditure	10.47	1.13	13,265
Recreation Expenditure	9.59	1.56	1,866

Notes: Sample weights are used.

4.B2 Causal Mediation analysis

Causal mediation analysis purpose is to separate the total treatment effect (TE) into the indirect effect (IE) caused by the mediating variables (M), known as the mediators, and the direct effect (DE) of the treatment on the outcome of interest. Dipple et al. (2020) proposed the following three step procedures.

First, estimate the TE of the treatment on the outcome, instrumented by the variable Z, represented by β_1 in Eq. (4.3).

Second, estimate the effect of the treatment on the mediating variable, instrumented by the variable Z, represented by β_1 in Eq. (4.4).

Third, estimate the DE of the treatment on the outcome by means of estimating the mediating variable on the outcome variable, instrumented by the variable Z and conditioning on the treatment, represented by DE_1 in Eq. (4.5).

To calculate the IE, simply take the difference between the TE and DE (*IE* = *TE* – *DE*) or alternatively by multiplying the coefficients of M_1 and ${B_1}^{y_m}$ (β_1 in Eq. (4.3).

$$y = \beta_0 + \beta_1 treatment + \ \beta_2 X + u_1 \tag{4.3}$$

$$y_m = \beta_0 + \beta_1 treatment + \ \beta_2 X + u_2 \tag{4.4}$$

$$y = \beta_0 + M_1 mediator + \ \beta_1 X + DE_1 treatment + \ u_3 \tag{4.5}$$

Where (in this context) y denotes the two different health outcomes (SRH and ADL score); y_m is the different mediating outcomes; $mediator$ is the mediating variables tested; $treatment$ is a binary indicator of whether parents receive support from their children; X is a vector of control variables capturing household and individual characteristics; and u is an error term.

CHAPTER 5

Conclusion

The economic implications of the ageing population phenomenon pose significant challenges to governments globally, demanding innovative and specific measures to sustain the wellbeing of those individuals most vulnerable. In light of this, this thesis investigated how intergenerational support through care, financial, and knowledge (educational spillovers), affects the wellbeing of the older generation and how workplace policies enhance the provision of support for working-age adults. Depending on the institutional and cultural context each chapter focused on a specific form of upward support from children to parents across three distinct national contexts: Indonesia, UK, and US.

Beyond the specific contributions of each chapter to the existing literature, the thesis makes methodological innovations to draw robust causal inferences by addressing endogeneity concerns through utilising various estimation methods such as FE-2SLS, 2SLS and nonparametric analysis. The three chapters collectively contribute to the existing literature related to intergenerational support by examining various aspects of support in three separate countries. The chapters show that the type, purpose and effectiveness of the support provided are influenced by distinctive policies, cultural norms, economic conditions, and institutional arrangements. For instance, in a high-income nation like the UK, which is highly dependent on the informal care sector and is consistently developing flexible labour regulations, this research provides new evidence on how institutional policies can either promote or hinder informal caregiving. The US offers a unique context for evaluating the educational spillovers characterised by its familial value of achievement and significant dependence on family educational investment and how it influences health and healthcare decision-making. In a low and middle-income setting like Indonesia, both financial and instrumental support are culturally driven and essential elements of the welfare of the elderly population. These unique contexts demonstrate how intergenerational support remains a crucial element of family networks across cultures and highlights how different societies support the ageing population.

Across these three contexts, the empirical analysis reveals consistent positive effects of intergenerational support. In chapter two, in the UK, FWAs exert a significant positive causal effect on children providing informal care for their parents. In chapter three, in the

US, children's educational attainments has a causal positive effect on parental mental health. In chapter four, in Indonesia, receiving intergenerational support from children improves parental wellbeing. The findings collectively highlight the critical role of intergenerational support in addressing the challenges associated with demographic aging, particularly since formal welfare systems in several countries are either structurally ill-equipped, underfunded, or inadequately developed to meet the growing demand for care.

Although the chapters examined various types of intergenerational support for example, caregiving in the UK, knowledge-based in the US and both financial and instrumental assistance in Indonesia, they share common mechanisms. The effect of support in its various forms and institutional and cultural settings is mostly mediated through time freedom, financial relief and the exchange of knowledge and emotional support. In chapter two, FWAs in the UK are entirely mediated by increased time freedom. The fundamental idea is that individuals using FWAs can control their own time and schedule, thereby having more time availability to perform any non-work-related activities, such as caring. In chapter three, parental mental health improvements in the US are consistent with mechanisms operating through financial relief (such as financial transfers) and increased contact or communication (through preventive care measures and frequency of contacts). In chapter four, the improvement of the elderly wellbeing in Indonesia is mediated generally by financial relief measures such as increased total and medical expenditure levels.

Table 5.1
Summary of Chapters

	Chapter Two: UK	Chapter Three: US	Chapter Four: Indonesia
Research Focus	Effect of FWAs on informal care provision	Effect of children's college attainment on parental mental health	Effect of financial and instrumental support on parental health outcomes
Identification Strategy	IV Strategy & Fixed Effects Models	Nonparametric Partial Identification	IV Strategy
Primary Outcomes	Informal Care Provision	Parental Mental Health (CES-D)	ADL SRH
Main Results	FWAs increase the probability of providing care	College graduate children improves mental health	Support reduces ADL and improves SRH
Mechanisms	Time Availability & Freedom	Financial Relief Knowledge & Emotional Support	Financial Relief

As summarised in Table 5.1, the findings from the three chapters offer several implications for ageing and family policy specific to each cultural and institutional setting. They offer strong arguments for enhancing both public and private support networks for the benefit of the wellbeing and welfare of parents and working adults. For the UK, workplace policies should reduce barriers and further strengthen the rights of FWAs, particularly for high intensity carers. Government may provide incentives to companies for adopting friendly caregivers' environments. These policies could be generalised to other developed nations with similar labour market and care responsibilities. For the US, the benefits of children's college attainment on parental mental health highlight that educational investments can be promoted as an indirect public health strategy targeted at improving parental wellbeing and reducing the prevalence of mental disorders. Policies should expand accessibility and improve college education affordability through grants, as such policies not only yield benefits for individual human capital but also have positive externalities that extend beyond individual gains. The education spillover effects may apply to other contexts where educational achievement is highly valued culturally and where families make significant sacrifices to invest in children's education. This is particularly relevant in societies with high medical and educational costs. For Indonesia, policies should encourage and promote familial responsibilities in providing support to parents. However, formal support schemes and subsidies should be developed to complement family-based support, particularly for those aged over 70 and living in rural areas. These policies can be generalised to other countries with similar family support systems and limited state-sponsored support systems.

Further research should explore a thorough analysis of gender dynamics of intergenerational support, particularly in the sense that support is highly gendered depending on the form and context. Further studies should incorporate parental expectations, more specifically gendered expectations and how they shape intergenerational support exchanges. Future investigations are warranted to build on the causal inferences drawn from this thesis. These studies could utilise different quasi-experimental designs to establish causality, such as difference in difference. Such approaches would complement and strengthen the current findings. Future research could utilise a harmonised dataset across various countries to provide a comprehensive understanding of how institutional contexts affect intergenerational support. Lastly, further research may investigate how formal governmental support and benefits programs and intergenerational support work together to enhance the wellbeing and welfare of the ageing population. Additionally, studies could examine whether such informal support from children potentially crowds out the effect of formal support systems.

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