Formal and Informal Long-Term Care in an Ageing Society

Judith Bom

Colofon
Formal and Informal Long-Term Care in an Ageing Society – Judith Bom

Cover design and layout by Birgit Vredenburg, persoonlijkproefschrift.nl
Printed by Ipskamp Printing | proefschriften.net

Formal and Informal Long-term Care in an Ageing Society

Formele en informele langdurige zorg in een vergrijzende samenleving

Proefschrift

ter verkrijging van de graad van doctor aan de

Erasmus Universiteit Rotterdam

op gezag van de

rector magnificus

Prof.dr. F.A. van der Duijn Schouten

en volgens besluit van het College voor Promoties.

De openbare verdediging zal plaatsvinden op

17 juni 2021

om 10:30 uur

door

Judith Anne Maria Bom

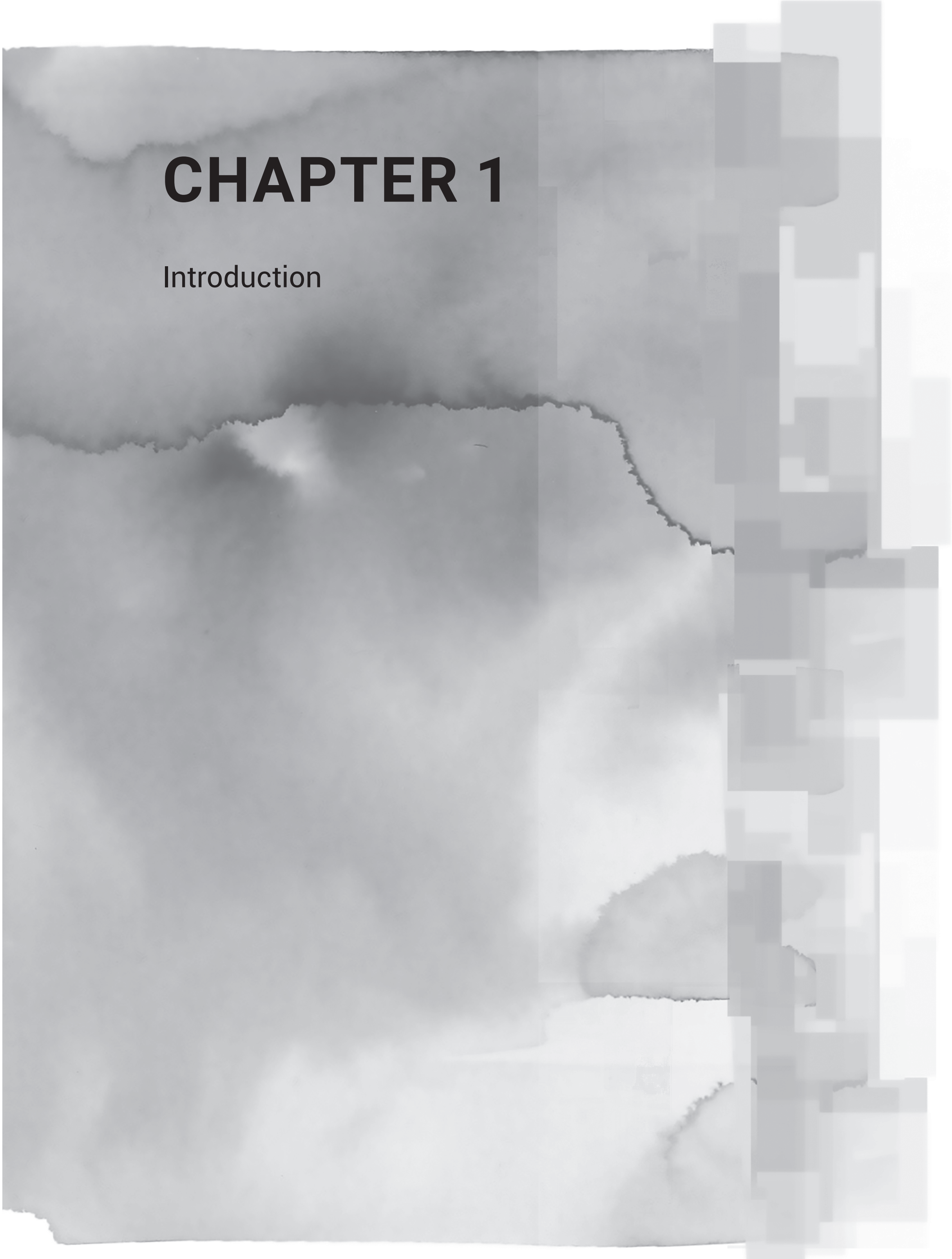
geboren te Wateringen

Erasmus University Rotterdam

Promotiecommissie:

Promotoren:	prof.dr. E.K.A. van Doorslaer prof.dr. F.T. Schut
Overige leden:	dr. M.P. Garcia Gomez prof.dr. N.J.A. Van Exel prof.dr. J. Polder
Copromotor:	dr. P.L.H. Bakx

Table of contents



CHAPTER 1

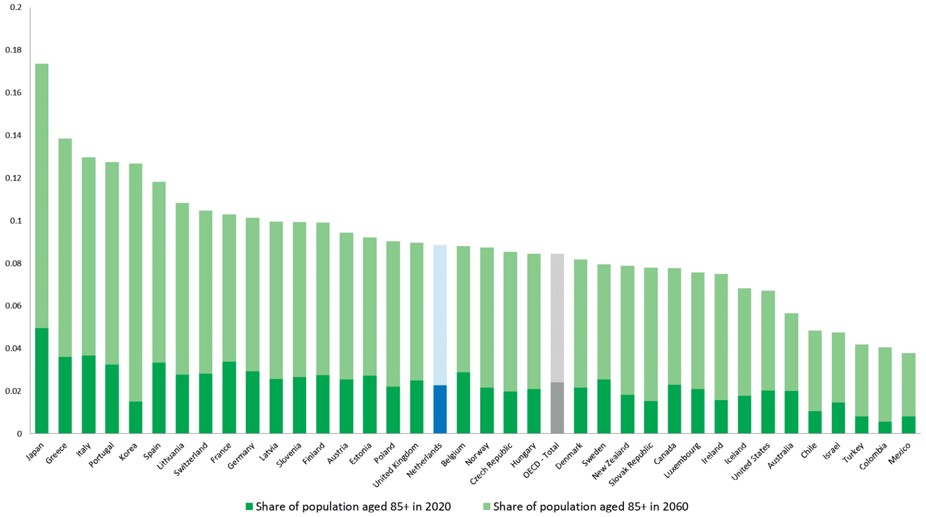
Introduction

1. Introduction

This morning, probably without even noticing, you already performed a variety of tasks. You got up, had some breakfast and got dressed. While these tasks might be common routine for many, they are not for everyone. In old age, carrying out these activities of daily living, might become very difficult to perform and require assistance. The rising demand for such assistance is an important topic in the light of population ageing.

In 2018, almost 20% of the European population was aged 65+, about half of this group reports at least one difficulty with personal care or household activities (Eurostat, 2020a; 2020b). In the next decades this share of elderly is projected to continue to grow in nearly every country around the world (UN, 2019). In addition, the share of the oldest-old, individuals aged 85+, is even expected to double or triple between 2020 and 2060 (Figure 1.1). Despite uncertainty about dependency rates of elderly and medical care advances, this growth in the number of elderly individuals is predicted to lead to a strong increase in the demand for long-term care (LTC) (Colombo et al., 2011; de la Maisonneuve & Martins, 2015; EC, 2018a). LTC here refers to the help or medical support that is provided to elderly who need care for a longer period of time. Textbox 1.1 provides further insight into the different types of care that are defined as LTC.

Figure 1.1: (Predicted) Share of population aged 85+ in 2020 and 2060



Source: OECD statistics (2020a).

This thesis focuses on two types of LTC: informal care and nursing home care. To explain the relevance of focusing on these two types of care, first an overview of country differences in LTC systems and the changing role of informal care and nursing home care within these systems will be given. Subsequently an overview of the specific research questions answered in this thesis will be provided.

Textbox 1.1: Defining long-term care

LTC entails help with personal and household activities and medical support for individuals with a chronic illness or disability (OECD, 2017a). In contrast to curative care, the goal of LTC is not to heal but to relieve or assist. Most of the LTC recipients are not expected to recover from the problems they are facing. Although LTC is not restricted to elderly care users, about two-thirds of LTC is provided to individuals aged 65+ (OECD, 2020b). Throughout this document, when referred to LTC, this can be read as LTC for the elderly.

LTC can entail a wide variety of tasks. It entails medical services such as administering medication or wound dressing, but also help with Activities of Daily living (ADLs)[1] and instrumental Activities of Daily Living (iADLs)[2] like help with getting dressed, or help with household chores (OECD, 2017a). Another common distinction relates to the place of care provision: dependent individuals can receive care in specialized institutions or at home. In most countries the share of individuals receiving formal care at home is much higher than the share of individuals that is institutionalized (OECD, 2020b). Additionally, for many of the dependent elderly, care is provided by friends and family members outside of formal care contracts, which is referred to as informal care.

Country differences in LTC systems

The costs of formal LTC, especially for someone who needs a lot of care, can be substantial. In the Netherlands, one year of nursing home care for example costs between 60.000 and 160.000 Euro (NZa, 2020a). To protect elderly against this financial risk and to ensure access to long-term care, governments often subsidize or organize the provision of formal LTC for at least the individuals with the lowest income and wealth. In most OECD countries the majority of the formal LTC costs is financed from public budgets (OECD, 2020c).

---

[1] ADLs refer to eating, bathing, washing, dressing, getting in and out of bed, getting to and from the toilet and continence management.

[2] iADLs refer to tasks like shopping, doing the laundry, vacuuming, cooking, performing housework, managing finances and using the telephone.

Despite this common feature of financing of LTC from public budgets, LTC systems differ strongly by country. One of the main criteria by which the systems differ is eligibility for publicly funded LTC. Eligibility can either be universal, granted to everyone in need for care, or means-tested, solely available for the least well-off individuals. Next to eligibility, LTC systems also differ in the range of services that is covered and the share of copayments that is required from the users (Colombo et al., 2011).

The differences in LTC systems across countries might derive from different norms and values regarding the division of labour between the family and the state or differences in the size of the country's economy. The characteristics of LTC systems could, in turn, influence the choice between formal and informal care (Bakx et al., 2015a). For example, when copayments for LTC are very high, individuals with a lower income will be more likely to opt for informal care instead of formal care. A less generous formal LTC system hence often means that individuals need to rely more strongly on care from their friends and family. In most countries informal care is even the predominant source of LTC. This importance of informal care within LTC systems, is clearly depicted in Van der Ende et al (2021) where for all countries in the European Union the time values of informal care are estimated. In most countries the estimated values of informal care exceed formal LTC expenditures.

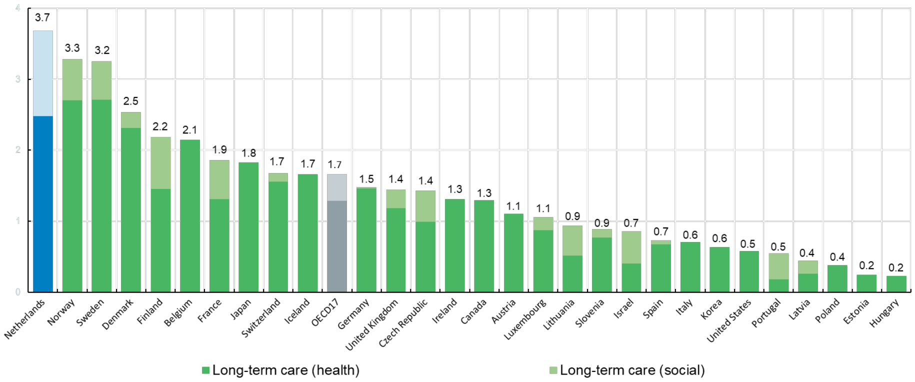
The Netherlands as a specific case

The Netherlands is one of the countries where most of the responsibility for organizing LTC is placed at the state-level. It holds a top position in terms of public LTC expenditures. In 2018, the country ranked 1st among OECD countries, with 3.7% of GDP that was spent on health or social long-term care by government or compulsory insurance schemes (OECD, 2020c) (Figure 1.2). This figure does not include out-of-pocket expenditures made by individuals. In the Netherlands these expenditures are limited: copayments for nursing home care only cover 8 percent of the total expenditures (2020 level – Rijksoverheid 2020), home care copayments are either zero or a monthly rate of at most 17.50 euro (2019 level – Bakx et al., 2020a). These numbers reflect an extensive LTC system where generous and fairly comprehensive support is offered to those in need (Mot, 2010; Colombo et al., 2011).

The Dutch LTC system, like many other systems around the world, is under pressure. While health care expenditures are rising, LTC expenditures have been doing so at an even more rapid pace (OECD, 2020c) and are expected to grow even further in the years to come (De la Maissonneuve & Martins, 2015). These increasing expenditures are not only driven by population ageing, also limited possibilities for increases in labor productivity for care-tasks are identified as a strong driver of the rise in spending (Wouterse et al., 2016). In the Netherlands public expenditures on long-term care are expected to grow by on average 1.6% annually between 2014 and 2030

(Eggink et al., 2017) and are identified as a major threat to the sustainability of public finances (Smid et al., 2014).

Figure 1.2: Public expenditures on formal long-term care expenditures as a % of GDP, 2017



Note: The OECD average only includes 17 countries that report health and social LTC. Source: OECD (2020c)

In part as a response to this growing pressure on its sustainability, the Dutch LTC system was reformed in 2015. The organization and financing of care previously funded via the Exceptional Medical Expenses Act (de Algemene Wet Bijzondere Ziektekosten, AWBZ) was transferred to the LTC Act (Wet langdurige zorg - Wlz), the Social Support Act (Wet maatschappelijke ondersteuning - Wmo) and the Health Insurance Act (Zorgverzekeringswet - Zwv). The newly established LTC Act covers intensive home health care and nursing home care; via the Social Support Act social support is provided and the Health Insurance Act covers home health care and community nursing. The reform aimed to increase both the quality of care and the financial sustainability of the care system by stimulating citizens to seek help in their own social network before turning to government-funded formal care (Ministry of Health Welfare and Sports 2013; WMO 2015). For example, eligibility criteria for institutionalized care became stricter[3] and individuals whose social network is capable of providing sufficient informal care are no longer entitled to formal (social) care provided by municipalities.

The downsides of increased reliance on informal care

With the reform, the Netherlands aimed to shift towards a system in which informal caregivers play a larger role. This trend is not only visible in the Netherlands, but in various countries. In 2010 LTC policymakers from around the world emphasized

---

[3] Already in 2013 nursing home eligiblity became stricter. Individuals with low care needs, defined by the care package (zorgzwaartepakket) they were entitled to, were no longer eligible for nursing home admission. As of 2015 individuals are only entitled to nursing home care in case they need around the clock care or supervision (Zorginstituut, 2019).

that encouraging informal caregiving was one of their top priorities (Colombo et al., 2011). However, while informal care provision may help relieve public expenditures on LTC - a key priority in the light of the growing financial pressure on LTC systems - informal care is not for free.

There are concerns regarding the negative impact of informal care on the labour market and health outcomes of caregivers. Individuals who increase their informal care provision might, for example, reduce their working hours to be able to care for a dependent family member and experience stress, fatigue or physical strain as a result of the care tasks.

Reforms further decrease use of nursing home care
Next to the ambition to increase reliance on informal care, also nursing home care plays an important role in LTC reforms. Various LTC policies specifically steer towards ageing-in-place: In nearly all OECD countries ageing-in-place policies have been implemented (Colombo et al., 2011). These policies aim to stimulate individuals to use home care to remain at home longer instead of making use of nursing home care. Recent Dutch policy changes for example were geared towards this goal by making eligibility rules for nursing home care more stringent and by increasing out-of-pocket costs for institutional care relative to home care.

The justification for ageing-in-place policies is twofold. First, ageing-in-place-policies align with the preference of most elderly to stay at home as long as possible. Very few elderly perceive nursing home care as the preferred type of LTC (Eurobarometer, 2007) and most of them prefer to remain living independently at old age (Costa-Font, 2017). An additional justification for the focus on ageing-in-place from the governmental perspective relies on the idea that home care is perceived as a cheaper alternative to nursing home care. This latter assumption has however been challenged in recent research indicating that while the costs of nursing home care are higher than the costs of home care, nursing home residents have lower medical care expenditures than people with similar care needs staying at home (Bakx et al., 2020b).

The focus on ageing-in-place aligns with longer-term trends. Over time the use of permanent institutional care has already become much less frequent: between 1980 and 2010, the share of the Dutch 80+ population living in institutions has dropped from 63% to 24% (Ministry of Health Welfare and Sports, 2013). This decline in nursing home use is only to a small extent driven by changes in health status of elderly, especially changes in policy, technological advances, like telehealth or home automation, and changes in social norms seem made elderly stay home longer (Alders et al., 2017).

Outline of the thesis

Part 1 – The health effects of providing informal care

The first part of this dissertation focuses on one specific downside of informal care, namely the health effects of care provision. These effects are potentially large and long-lasting as many candidate caregivers are fairly old and vulnerable themselves. Chapter 2 of this thesis provides an overview of the current literature base regarding the causal impact of informal care on the health of the care provider. Does informal care provision indeed lead to worse health and if so, what kind of health effects can be expected?

Chapter 3 and 4 provide insight into how these health effects differ among caregivers, and for example differ between providing care to parents and spouses. Are these health effects mostly borne by a small part of the caregiving population, for example the most vulnerable or heavily burdened group, or are they uniformly distributed among all care givers? And is care provision more straining when done for certain care recipients? Or when done intensively or for long care episodes?

Additionally, it is verified whether the observed health effects can indeed be attributed to the provision of informal care instead of the impact of worrying about an ill family member. The latter is referred to as the family effect (Bobinac et al., 2010). It is important to make a distinction between the family and the caregiving effect as the two effects require different policy responses. Respite care could for example help when someone is overburdened from care tasks, but will not relieve the worries experienced as a result of having an ill family member.

While the focus mainly lies on studying individual differences in chapter 3 and 4, also system and country characteristics may matter. Differences in norms, values and LTC systems may (indirectly) affect informal care provision and may thus make these tasks more or less straining. In chapter 5, the difference in caregiving effects between the Netherlands and the United Kingdom will be analyzed. The United Kingdom makes for an interesting comparator to the Netherlands as it offers a considerably less generous, means-tested LTC system and has strong social norms regarding informal care provision.

Understanding to what extent country-context or individual-characteristics shape the impact of providing informal care is important when further developing LTC policy. The findings help to understand the costs of stimulating informal care provision and may guide policymakers on how to distribute these costs over the population. Additionally, identifying those individuals who are most strongly affected by informal care tasks allows for tailoring of support.

Part 2 – The determinants and impact of a nursing home admission

The second part of the dissertation focuses on nursing home care. Despite a common focus on ageing-in-place, countries differ widely in their institutionalization rates. For example, in the Netherlands about 13% of the 80+ population was institutionalized in 2017, compared to 6% in the United States (OECD, 2020b). These differences can be driven by two elements: population characteristics, like how old, fragile or wealthy the population is, and system and cultural characteristics like access and availability of nursing homes and home health care. Chapter 6 explores the drivers of the differences in nursing home admission rates between the United States, Denmark and the Netherlands. Interestingly, whereas there are more permanent nursing home stays in the Netherlands and Denmark compared to the United States, short-term nursing home stays are much more prevalent in the US. Is the US population solely older or unhealthier, leading to more short-term nursing home admissions, or do the countries differ in the generosity of their systems? Knowing what elements drive differences in nursing home admissions helps in defining LTC policy that suits the needs and preferences of the population.

After focusing on cross-country differences on the determinants of nursing home admissions, the last chapter (chapter 7) of this thesis studies whether elderly are actually better or worse off in terms of well-being once admitted to a nursing home. Elderly often prefer to stay living at home, the general perception of nursing homes is negative, and individuals often fear the move to a nursing home. Actual insight into the well-being of individuals living in nursing homes, and the difference in their well-being compared to individuals who are still living at home, is rather scarce. Are individuals indeed happier at home or do they simply fear the idea of going to a nursing home? Perhaps a move to a nursing home might even be beneficial to highly dependent elderly as it would limit loneliness or increase safety. Insights from this study can help to better understand how the well-being of elderly changes after moving to a nursing home and provide a more nuanced view on the impact of a nursing home admission.

CHAPTER 2

Informal caregiving, a healthy decision? Determinants and health-related consequences of providing informal care

With Pieter Bakx, Erik Schut and Eddy van Doorslaer

An abridged version of this chapter is published as: Bom, J., Bakx, P., Schut, F., & van Doorslaer, E. (2019). The impact of informal caregiving for older adults on the health of various types of caregivers: A systematic review. The Gerontologist, 59(5), e629-e642.

Abstract

The demand for long-term care (LTC) is growing in most OECD countries. LTC can be provided by formal and informal caregivers, and striking the right balance between both types of care is a challenge. We first analyze from an economic perspective the trade-offs involved in this balancing act, by a review of the relevant economic literature. Next, we focus on one particular aspect of this trade-off: the negative health effects of providing informal care by means of a systematic literature review regarding the causal effect of informal caregiving on the health of various subgroups of caregivers.

The review of the economic literature suggests that the individual decision to provide informal care is likely to depend on personal characteristics and the institutional context. Informal caregiving is likely to be concentrated among individuals with lower opportunity costs, or with fewer other activities competing for their time, such as people without a paid job. This implies that the burden of informal caregiving and the associated negative health effects are likely to be unequally distributed across the population.

The systematic literature shows that there is evidence of a negative impact of caregiving on the mental and physical health of the informal caregiver. The presence and intensity of these health effects strongly differ per subgroup of caregivers. Especially female, and married caregivers, and those providing intensive care appear to incur negative health effects from caregiving.

The findings emphasize the need for targeted interventions aimed at reducing the negative impact of caregiving among different subgroups. As the strength and presence of the caregiving effect differ between subgroups of caregivers, policymakers should specifically target those caregivers that experience the largest health effect of informal caregiving.

2.1 Introduction

Many individuals face the decision whether to provide care for a spouse, family member, friend, or neighbor who needs help with running the household or personal care on a regular basis for a longer period. This help is defined as informal care and is typically unpaid. Alternatively, a formal, i.e. professional caregiver, may provide this long-term care (LTC). In all developed countries, governments subsidize or organize some level of formal care. Aside from formal care, also informal care is often promoted by policy. Dutch policy, for example, stimulates citizens to seek help in their own social network before turning to government-funded formal care (WMO, 2015; CIZ, 2017). When informal care and formal care operate as substitutes (see e.g. Bolin et al., 2008; Bonsang, 2009), governments need to balance the costs and benefits of both alternatives to achieve the appropriate mix of the two.

This paper aims to shed light on this LTC puzzle in two ways. First, we analyze the trade-offs that governments face when subsidizing or organizing formal care. We do this by providing an overview of the economic literature regarding these decisions and focusing on what these models mean for the role of government in LTC.

Second, we zoom in on one specific downside of informal care: the individual health effects of providing informal care. We focus on these effects because they are potentially major and irreversible – most caregivers are older and vulnerable themselves – and more difficult to compensate financially than, say, foregone labor market opportunities. In several countries the health effects of informal caregiving have been investigated empirically. However, a systematic overview of the results of these studies is lacking. To fill this gap, we provide a systematic review of the empirical literature aimed at estimating the causal effects of informal care on health. We conclude this paper by summarizing the insights from both theoretical and empirical literature. Based on these insights, we formulate policy recommendations for the Dutch situation.

Textbox 2.1: Financing of long-term care in the Netherlands

The Netherlands has a comprehensive public LTC financing system. This has a legal basis in the Long-Term Care Act (*Wet langdurige zorg* – Wlz), the Social Support Act (Wet *maatschappelijke ondersteuning* – Wmo) and the Healthcare Insurance Act (*Zorgverzekeringswet* – Zvw). The types of LTC covered under these separate acts are respectively (1) institutional care and home health care; (2) social support, assistance, and housekeeping services; and (3) nursing and personal care (Non et al., 2015).

Costs are kept in check through rationing measures that target both the supply and demand side (Bakx et al., 2015b). On the supply side, the provision of LTC is rationed by imposing budgets, i.e. regional provider budgets (and regulated maximum prices) for LTC benefits covered by the Long-Term Care Act and block grants to municipalities for providing Social Support Act services. On the demand side, co-payments are required for care provided through these two Acts. Furthermore, access to care provided under the Long-Term Care Act can only be obtained via the independent care assessment agency (*Centrum Indicatiestelling Zorg*, CIZ). This agency assesses whether someone is eligible for formal care based on centrally set eligibility criteria (CIZ, 2017). Local authorities assess eligibility for care via the Social Support Act. In this eligibility assessment, the social context is taken into account. Hence, individuals are encouraged to rely on their social network before making use of formal care.

Textbox 2.2: Informal care in the Netherlands and Europe

The share of caregivers has risen over the years. In some cases, informal caregivers may be paid from LTC insurance (through cash benefits). Informal care thus does not necessarily refer to unpaid caregivers but to caregivers outside formal employment contracts. According to data from the Dutch Health Monitors of 2012 and 2016 (N > 350,000 in both surveys), weighted to represent the Dutch population, the share of informal caregivers has grown from 19.3% to 23.1% of the adult population. This represents an increase of almost 20% in four years in the total number of informal caregivers. Based on these numbers, we estimate that in 2016 more than 3 million individuals provided some form of informal care. Currently, more females than males provide informal care, although male participation is growing. In 2012, about 30% of the caregivers were male; by 2016, male participation had risen to 35%.

Both male and female caregivers provide around 9.5 hours of care a week on average. This average is higher for older caregivers (aged ≥65) as these provide about 14.5 hours of care a week. A similar trend is present when comparing the caregiving intensity between low-income and high-income quintiles. Individuals in the lowest income quintile provide twice as many hours of informal care compared to individuals in the highest quintile (12 hours compared to 6 hours of care per week). A majority of Dutch caregivers have a paid job, and caregiving is furthermore concentrated among the older inhabitants. Most caregivers are aged 45-60, since of this group over 30% provided informal care in 2016. As to occupation, we note that homemakers, pensioners, and part-time employees more often provide informal care compared to full-time working employees (see table 2.1).

The share of the Dutch population that provides informal care is similar to that in neighboring countries. The Netherlands, and other Northern and Central European countries strongly differ, however, from the countries in Southern and Eastern Europe when it comes to the intensity of care provided. In the Netherlands, about 20% of caregivers provide intensive informal care (20+ hours per week), whereas this share is over 30% in the Czech Republic and about 50% in Spain (Colombo et al., 2011).

Table 2.1: Share of informal caregivers per subgroup

	2012 (% of total)	2016 (% of total)
Full 19+ population	19.3	23.1
By gender		
Men	13.3	16.6
Women	22.6	25.7
By occupation		
Homemaker	24.8	27.8
Part-time employee	23.1	26.4
Full-time employee	15.0	18.7
Pensioner	19.3	24.8
By age		
19-40 years	11.6	13.0
40-65 years	26.0	30.3
65+ years	18.1	22.5
By income		
Lowest income quintile	15.3	16.9
Highest income quintile	21.1	24.1

Note that various confounding variables may underlie these descriptive statistics. Data weighted to represent Dutch population, results based on own calculations using Gezondheidsmonitor 2012 and 2016

Textbox 2.3: The need for government intervention

Expected LTC expenditures over the lifecycle are high – on average about 35,000 euros for men and 91,000 euros for women (Hussem et al., 2016) – and highly uncertain. Therefore, insurance against these costs is welfare-improving. However, private long-term care insurance covers no more than a few percent of all long-term care spending (OECD, 2017b). Reasons for this low uptake include correlated risks, asymmetric information, consumer myopia, and a rational choice of parents who expect that the level of informal care provision will negatively depend on the level of long-term care insurance (see Boyer et al., 2017; Brown & Finkelstein, 2009; and Cremer et al., 2012 for more comprehensive overviews).

This market failure to provide adequate coverage against the financial risks associated with LTC use is one of the reasons for government intervention in LTC financing. An important other reason is solidarity, as irrespective of market failures not everyone has the means to purchase insurance. Public LTC insurance, as opposed to subsidization and regulation, can overcome some of the problems that inhibit adequate private coverage. However, public insurance may be inefficient due to moral hazard, e.g. consumers using more – or more expensive – formal care or because potential informal caregivers underreport their ability to provide care (Barr, 2010; Bakx et al., 2015b).

2.2 The trade-off between formal and informal care: an economic perspective

Not everyone has a potential informal caregiver, and the costs of hiring a formal caregiver can be very high, placing a large financial burden on dependent individuals (Colombo et al., 2011). Furthermore, private LTC insurance that could protect individuals against the high costs of care has limitations, leading to a low uptake (Brown & Finkelstein, 2009). For these reasons, governments often subsidize or even organize the provision of formal long-term care for at least the poorest part of the population. Indeed, in most OECD countries the majority of LTC costs is financed from public budgets (OECD, 2010; European Commission, 2015).

Informal and formal LTC are partly substitutes (e.g. Bolin et al., 2008; Bonsang, 2009), and individuals may decide to use either of the two types of care.[4] Economic literature provides some insight into what determines these decisions. We summarize this literature and discuss potential implications for the role of government in LTC.

2.2.1 The role of labor market productivity

A useful economic model to provide insight into a person's decision to provide informal care is the Roy model about the self-selection of workers into different occupations (Borjas, 1987; Heckman & Honoré, 1990; Heckman & Sedlacek, 1985). Nocera and Zweifel (1996) were the first to apply the Roy model to the decision to provide informal care. In this model, the caregiving decision lies with the caregiver, not with the person in need for care, and the potential caregiver maximizes expected utility. Utility can be derived from consumption, leisure, and potentially from caregiving. In maximizing utility, caregivers face a budget and time constraint.

Because of the trade-off between leisure, paid work, and caregiving, the opportunity costs of caregiving are foregone wages and leisure time. A person's decision to provide care is based on his or her reservation wage for providing care. This is especially dependent on the wage that one could earn in the labor market. Other elements affecting this reservation wage are productivity, real wage, and preferences towards leisure and consumption. Productivity in this model refers to a person's productivity in caregiving and to the productivity in using consumption goods (relative to the price of these goods).

Nocera and Zweifel (1996) conclude that for all individuals the reservation wage for caregiving is positive. The height of this reservation wage, reflecting the willingness

---

[4] Throughout this paper, we make use of economic terminology and refer to the 'decision' to provide informal care instead of 'determinants' of providing informal care, which is more common in e.g. public health.

to provide informal care, could, however, differ. As the reservation wage for care depends on the wage that someone can earn in the labor market, high earners will be less likely to provide informal care, for they would forego more income by providing care. Furthermore, highly productive caregivers, for example because they live closer to the care recipient, would be more inclined to provide care compared to less productive caregivers. Lastly, individuals strongly valuing consumption will be less willing to cut back on working hours and are therefore less likely to provide informal care.

Next to dedicating time to provide care themselves, individuals may help their dependent family member by hiring a formal caregiver. This might especially be the case for individuals who are employed full-time and for relatively high earners. This trade-off is considered explicitly by the Roy model used by De Zwart, Bakx & van Doorslaer (2017), where the decision is framed as a choice between informal caregiving and working but having to pay for formal care. The decision depends on the trade-off between wage and the cost of paying for formal care. This model shows that the individual decision to provide informal care might be driven not only by individual productivity, but also by contextual factors, namely the costs associated with formal care consumption.

This rather simplified model provides two important insights. First, it shows that informal caregiving – and hence the burden of caregiving – is not likely to be equally distributed across the population of potential caregivers: some people are more likely to take on caregiving tasks than others. Second, it shows that in case a government would have perfect information about which people will provide informal care, it may target formal care to people who do not have a potential caregiver in their network.

However, when the government has *imperfect* information, subsidizing formal care may result in moral hazard because people may *pretend* to be unwilling to provide informal care in order to receive governmental aid (Jousten et al., 2005). To reduce moral hazard, a government could take measures to encourage self-selection towards the type of LTC that is optimal from a societal perspective. This will be discussed in the following sections.

2.2.2 The role of intra-family strategic behavior

A second set of economic models focuses on a specific type of potential caregivers and care recipients: adult children who may take care of their parents when these become dependent on help. In these models, caregivers are not viewed as the decision makers but as agents in a principal-agent setting in which they may be convinced to provide care to their principal – their parent – through the prospect of a bequest (Zweifel &

Struwe, 1996; Cremer & Roeder, 2017).[5] These models consider a society consisting of two generations, parents and children, and two periods. Moreover, instead of a distinction between formal and informal LTC, they identify three potential sources of LTC: the family providing informal care, the market providing formal care via private insurance, and the state providing formal care via public insurance. These three options are assumed to be close or perfect substitutes.

In these models, utility-maximizing parents derive utility from wealth. Parents face uncertainty about whether they will become dependent but know under which conditions to expect informal care from their children. Based on the potential help that parents expect from their children in case of illness, the parents decide in the first period whether to spend part of their wealth on private LTC insurance or to save it as a bequest to their children. These expenditures would yield a drop in utility at the cost of the insurance or the bequest. In the second period, parents may become dependent and need LTC, with insurance or informal care protecting them against LTC expenditures. The children decide their level of labor and informal care supply in period two, based on their wage and the expected bequest from their parent.

Cremer and Roeder (2017) show that the outcomes of this strategic game are suboptimal and hence imply that government intervention may be welfare-improving. The authors mention that without government interference, several inefficiencies may arise. First, parents might purchase insufficient insurance when the insurance premium involves significant loading costs or due to limited financial possibilities. Second, the labor supply may be inefficiently low because the level of the bequest depends on the amount of informal care a child is able to supply. Children who work more would have less time to provide informal care. Their parents in turn need to hire formal care, resulting in a lower bequest for the children. A caregiving-dependent bequest hence implies a tax on labor as additional labor earnings are partly 'taxed away' by a drop in the bequest. Third, the supply of informal care might be inefficiently low because children do not account for the possibility that parents value the help of their children more than care provided by a formal caregiver. Parents with limited ability to pay in this model are the ones in highest need of public aid. These parents experience a double burden as they cannot purchase insurance and are unable to induce their children to provide informal care via a bequest.

The authors discuss several interventions to overcome inefficiencies, all differing based on the informational context. A key element in these interventions is the need for subsidization of informal care, as otherwise not enough care is provided. Most importantly, the models show that public aid does not necessarily crowd out informal

---

[5] Knoef and Kooreman (2011) (among others) further extend these models by including siblings' caregiving interactions, but this is beyond the scope of this review.

care when children are non-altruistic. When children solely provide care because their bequest is dependent on doing so, they do not consider publicly provided LTC as an alternative when making their caregiving decision. In case parents do not have the resources to purchase insurance or to transfer part of their wealth to their children, publicly funded care might even enhance informal caregiving. When the state offers some level of public care, parents save money, which they can use as a bequest to induce their children to provide additional informal care.

2.2.3 The role of altruism and social norms

While the previous sets of economic theories assume 'selfish' motives to providing informal care, the third set of theoretic models acknowledges that informal caregiving might be provided as a deed of altruism or due to social norms. Social norms, which make a person feel obliged to provide care, could be culturally determined (e.g. "it is one's duty to care for a sick relative") but can also differ based on caregiver characteristics (e.g. "daughters and daughters-in-law have more caregiving tasks than sons and sons-in-law"). These social norms have been incorporated in some theoretical models. Barigozzi, Cremer and Roeder (2017), for example, assume that daughters feel a stronger obligation to provide care than sons and hence suffer disutility when they provide less informal care than the average child. Social norms may partly explain the observed gender differences in the supply of informal care.

Altruism, on the other hand, refers to the utility that children derive from helping their parents; this concept has thus far received more attention in literature than social norms. Pestieau and Sato (2008) assume that children are altruistic and willing to help their parents if needed.[6] In their model, children derive utility from consumption and providing help. The effect of help on utility depends on the amount of help provided and someone's level of altruism.

The type of help – LTC provision or financial aid – given by children is based on their labor market productivity, as reflected in their labor income. Children with low market productivity lose less when they give up work to provide LTC by dedicating time to their parents. As a result, these children tend to provide a higher level of informal care. The amount of informal care that people are willing to provide drops when their labor productivity increases, down to a certain point where the amount of care provided is minimal. From this point, children earn enough to provide LTC in the form of financial aid. From this point onwards, the level of monetary aid provided increases when productivity increases. If children are altruistic, the model predicts that the total amount of support will be U-shaped.

---

[6] We will focus on the 2008 paper as this one includes the market as a potential source of LTC, whereas the 2006 paper solely accounts for family and state provided care.

The model furthermore assumes that parents know how much help to expect from their children. Based on this knowledge, parents decide to purchase private insurance or to leave part of their wealth to their children. The model demonstrates that differences in the productivity of children may result in inequalities in the care received by their parents. Parents with low- and high-earning children can rely on help from their children. The remaining group has to purchase private insurance or to rely on governmental support. Government support is needed for the parents who do not receive enough help from their children and are unable to purchase private insurance. The state could furthermore improve social welfare by subsidizing informal care when children are not fully altruistic. In such a situation, children do not completely account for the utility gain of their parents and provide less than the optimal value of help.

The authors examine various types of government interventions assuming imperfect information. They show that the optimal type of government intervention is a combination of measures that induce rich parents to purchase private insurance and that guarantee the public provision of care to poor parents. To achieve this, the state should encourage appropriate self-selection by setting the level of subsidy for the uptake of private insurance and the quality level of public nursing homes in such a way that rich parents will value private insurance over public nursing homes.

Cremer, Gahvari and Pestieau (2017) extend this analysis by assuming that different levels of altruism exist. This extension provides insight into the optimal amount and type of LTC insurance that should be supplied considering that the state cannot condition its support on the default of altruism (as this is unobservable and prone to moral hazard). The role of insurance (public and private) is studied assuming two forms of insurance supplied by the public sector: topping up and opting out. Either the state provides a lump-sum subsidy for formal care that persons can top up; or it provides LTC in kind, which elderly people decide to use or to opt out from. Which option leads to the optimal outcome depends on the altruism levels of the children in the population. If most children are highly altruistic, the opting-out scheme is preferable because highly altruistic children will let their parents opt out of this scheme and provide care themselves. After all, these children would provide more help than the state would and hence receive a higher utility from providing care themselves. In this situation, governmental aid is spent solely on those who need it, i.e. parents whose children are not sufficiently altruistic to help. By contrast, a topping-up scheme is optimal when the altruism of most children is very low. As children with low levels of altruism would not provide enough care to be the sole caregivers, a topping-up scheme makes use of their limited supply of informal care instead of letting them opt out from informal care completely. In case children are moderately altruistic, the optimal level and type of public LTC is more difficult to define. Under an opting-out system, the level of public insurance coverage should then be small enough to convince children to provide informal care, leading to a downward distorted supply of publicly provided care.

Both models show that altruistic children, in contrast to selfish children, take governmental interference into account when deciding upon the level of informal care to supply. In such situations, the level of publicly supplied care could crowd out as well as enforce informal care. Although the government is unable to observe altruism directly, it has the possibility to steer informal care decisions, for example via the quality of publicly provided nursing homes, the form of public LTC provision (lump sum or in-kind), and subsidies for the uptake of private LTC insurance.

2.2.4 Societal trade-off between formal and informal care

The above-mentioned models demonstrate (i) how individual characteristics and the institutional context shape a person's caregiving decision and (ii) that government needs to account for the response of caregivers when it intervenes in the financing and provision of LTC. As a variety of elements shape one's decision to provide care, not everyone is equally likely to be a caregiver and therefore not equally likely to experience negative consequences. Combined with the fact that children often cannot fully insure themselves against the negative consequences of caregiving on the market, this provides an efficiency argument for government intervention, either by reducing the need to provide informal care or by compensating caregivers for the negative consequences of caregiving.

However, the government may not be able to achieve the optimal allocation of formal and informal care because of imperfect information about a potential caregiver's ability and willingness to provide informal care, and because of strategic behavior on the part of both caregivers and care recipients. Therefore, governmental policies that reduce the need to provide informal care (e.g. through public provision or private insurance subsidies) should encourage appropriate self-selection to ensure that public money is spent effectively. Potential instruments to achieve this (desirable) self-selection are (i) the quality of publicly provided care, (ii) in-kind provision of care (rather than a lump sum cash benefit), (iii) subsidization of insurance, and (iv) taxation of labor earnings and bequests. However, the three sets of models we have discussed show that the optimal combination of instruments to achieve this self-selection depends on assumptions regarding social norms and the level of altruism of children – two aspects that are notoriously hard to measure.

2.3 Health-related consequences of providing informal care

Our review of the economic literature highlights the complexity of the trade-off between formal and informal care. One important element in this trade-off are the costs of informal caregiving, including the potentially negative health effects on the informal caregiver. We focus on the health effects of informal caregiving for three reasons. First, the effects are potentially major and irreversible, especially considering that most caregivers are older and vulnerable themselves. Second, health effects are a risk for all caregivers whereas labor market effects can only occur for working-age caregivers. Lastly, it is more difficult to financially compensate health effects than other effects such as foregone labor market opportunities.

Several studies have been carried out to assess whether informal care indeed is correlated with the health of the caregiver (e.g. Beach et al., 2000; Schulz et al., 1997), which is confirmed by prior systematic literature reviews and meta-analyses reviewing these studies (e.g. Pinquart & Sörensen, 2003a, 2007; Vitaliano et al., 2003).

However, these reviews did not distinguish between studies that merely study the *correlation* between health and caregiving and those that estimate a *causal* effect. The crucial difference is that the former set of studies conflates differences in health state caused by caregiving tasks with differences caused by other factors. These factors, such as lifestyle and pre-existing health differences are largely unobserved and vary over time, and hence cannot be controlled for in multivariate regressions, even when panel data are available. Hence, these estimates are biased estimates of the true effect that caregiving has on health (Little & Rubin, 2000).

Quasi-experimental methods offer a solution to this problem by carefully modelling the selection into the treatment and control group. Doing so, these methods allow for comparison between caregivers and non-caregivers, and hence make sure that the change in caregiver health is caused by the provision of care and by nothing else (Antonakis et al., 2014). A recent strand of the literature on the relationship between caregiving and health (e.g. Coe & Van Houtven, 2009) makes use of these methods to eliminate bias in the estimates of the caregiving effect caused by unobserved factors and thus allows for causal inference.

To our knowledge, we are the first to review this relatively new strand of literature. To provide an objective, transparent, and replicable overview of the literature, we carry out this review systematically following PRISMA guidelines (Moher et al., 2009). Next to focusing on the causal impact of informal care, we will add to the literature by paying specific attention to subgroups of caregivers. The health impact of care might namely strongly differ by, for example, gender or the type of care provided (Penning & Zu, 2016). We sought to address the following questions: *What causal impact does providing informal care to elderly or older family member have on the health of the caregiver? And how does this caregiving effect differ between subgroups of caregivers?*

2.3.1 Review methodology

Eligibility criteria

We included studies based on the following eligibility criteria:

1. The article focuses on informal caregiving to elderly or older family members.
2. The article estimates the health impact of informal caregiving on the caregiver.
3. The article is aimed at finding a causal relation between informal caregiving and caregiver health using any one of the following methods: propensity score analysis, simultaneous equation models (instrumental variables), regression discontinuity designs, difference-in-difference models or Heckman selection models.
4. The article is written in English.
5. The article is not a conference abstract, letter, note, or editorial.

We defined informal care as providing care to a person in need and limited this definition to care to elderly persons or older family members. This focus excludes looking after (healthy) children or grandchildren, but does not impose any restriction on the age of the caregiver.

To specify our search to studies making causal estimations, we only include articles using quasi-experimental methods that enable causal estimations in nonexperimental settings. We limited our search to five methods for causal inference listed by Antonakis et al. (2010; 2014). Table 2.2 provides a short explanation of these methods. As especially health of individuals could already differ before starting providing care, we exclude studies making use of a matching design that does not match on health of the caregiver.

Table 2.2: Quasi-experimental methods for inferring causality in non-experimental settings

Method	Brief description
Propensity score analysis	Compare individuals who were selected to treatment to statistically similar controls using a matching algorithm
Simultaneous-equation models	Using 'instruments' (exogenous sources of variable that do not correlate with the error term) to purge the endogenous x variable from the bias
Regression discontinuity	Select individuals to treatment using a modeled cutoff
Difference-in-differences models	Compare a group who receive an exogenous treatment to a similar control group over time
Heckman selection models	Predict selection to treatment (where treatment is endogenous) and then control for unmodeled selection to treatment in predicting y.

Note: Taken from Antonakis et al. (2010), for further explanations regarding the summed methods we refer to the original article.

Search strategy and data sources

Our search strategy, which is available as supplementary material, was set up with the help of an information specialist. For all criteria, we defined keywords as well as Medical Subject Headings (MeSH) and Embase Subject Headings (Emtree terms). Databases were searched for combinations of keywords and (if applicable) MeSH or Emtree-terms related to the eligibility criteria: informal caregiving, health impact, and older adults. Additionally, we limited our search to English language studies using one of the quasi-experimental methods to infer causality listed by Antonakis et al. (2010; 2014), and excluded abstracts, letters or editorials.

The following databases covering social sciences as well as bio-medical literature were searched from database inception through April 1, 2018: MEDLINE, Embase, Web of Science, and Scopus. We did not search the CENTRAL database, which covers studies using RCTs, as our research question cannot be answered by studies using this research design. All search results were stored in RefWorks, our main platform for keeping track of the literature review. We did not register a systematic review protocol.

We furthermore used Google Scholar to identify any additional papers. This search engine could help in retrieving papers that (i) have not been published yet, or (ii) missed relevant search terms in their title and abstract. For this manual search, we used a search strategy similar to the search string used for the other databases. We hand-searched the first 150 Google Scholar hits. When articles were deemed eligible for review, they were added to the list of full-text review articles.

Review procedure

Three reviewers screened the titles and abstracts of all articles based on predefined eligibility criteria. Before commencing the review, the criteria were discussed to guarantee shared understanding. The researchers screened the articles (two researchers per article) based on title and abstract. To avoid bias, authors and journal names were not visible during this screening stage. If the article adhered to all inclusion criteria, it was then selected for full-text review. In this second stage, all included articles were reviewed full-text by two researchers based on the inclusion and exclusion restrictions. For both stages, differences in screening results were discussed and resolved by dialogue, and if needed the third researcher would act as judge.

Data abstraction

Data were extracted from the articles included in the review using a predefined extraction table. The following items were recorded from each article: the author(s) and year of publication; country/region of interest; care recipient; definition of informal care; sample characteristics of the caregiver; health outcome measure;

estimation technique; and main findings of the study. As we do not aim to provide a meta-analysis of the results, the main study findings were recorded qualitatively based on presence and direction, not on effect size. The results were synthesized in a narrative review.

Quality assessment

To assess the methodological quality of the studies meeting inclusion criteria, methodological information from the papers was extracted using a predefined extraction form designed to fit the methodologies used in the included articles. This form summarized the most important methodological elements of the papers. We did not calculate quality scores for the studies, but instead explained the methodological differences between the studies in narrative terms.

To assess the quality of studies using propensity score analysis, we follow recent progress in the causal inference literature (Lechner, 2009a) and added a separate check. The quality of matching studies is dependent on the likelihood that the assumptions hold that (i) the propensity score is not affected by whether one is a caregiver (no reverse causality) and (ii) there are no relevant remaining unobserved differences after matching (see Rosenbaum & Rubin (1983) for an overview of all assumptions). The matching approach proposed by Lechner (2009a) makes it credible that these assumptions hold, as it suggests to match individuals on pre-treatment covariates instead of current covariates and to stratify the sample according to care provision in the previous year. The latter suggestion means that individuals who recently started caregiving (and did not do so last year), are only compared to individuals who did not provide care last year either. Doing so, potential influence of the treatment status on the covariates is avoided and pre-treatment differences in health are controlled for. For the studies making use of matching techniques, we evaluated whether this approach is followed.

The quality of the instrumental variables is assessed based on instrument strength. For studies included in this review, it means that the effect of the instrumental variable, for example, a health shock of a parent, has a sufficiently strong effect on informal care provision. This strength of the instrumental variable can be assessed based on the *F*-statistic of excluded instruments. We follow the most commonly used rule of thumb that the *F*-statistic showing the strength of the instrument should be greater than 10 (Staiger & Stock, 1997).

Finally, we assess for all studies whether they accounted for the family effect. This effect refers to the impact of *caring about* an ill family member and is different from the caregiving effect related to the impact of *caring for* someone (Amirkhanyan & Wolf, 2006; Bobinac et al., 2010). Recent literature highlights the importance of considering this effect, as not accounting for it may lead to an overestimation of the caregiving effect (Roth et al., 2015).

2.3.2 Results

Search results

Our searches yielded 1,326 articles in total. After eliminating duplicates, our search findings totaled 661 articles. The hand-search resulted in five additional articles. From these 666 articles, 613 were excluded for a variety of reasons. Often the studies did not focus on informal caregiving but on another type of care. Furthermore, various studies were excluded as they did not estimate the impact of caregiving, but reviewed the efficacy of a specific intervention to improve the health of caregivers. Eventually, 53 articles were selected for full-text review. From these 53 articles, 38 were excluded in the full-text review round. The most prominent reason for exclusion at this stage was that a study did not use any of the defined methods to identify a causal effect. Eventually, 15 articles met all inclusion criteria and were included in this systematic literature review. Figure 2.1 depicts the flowchart of screening phases.

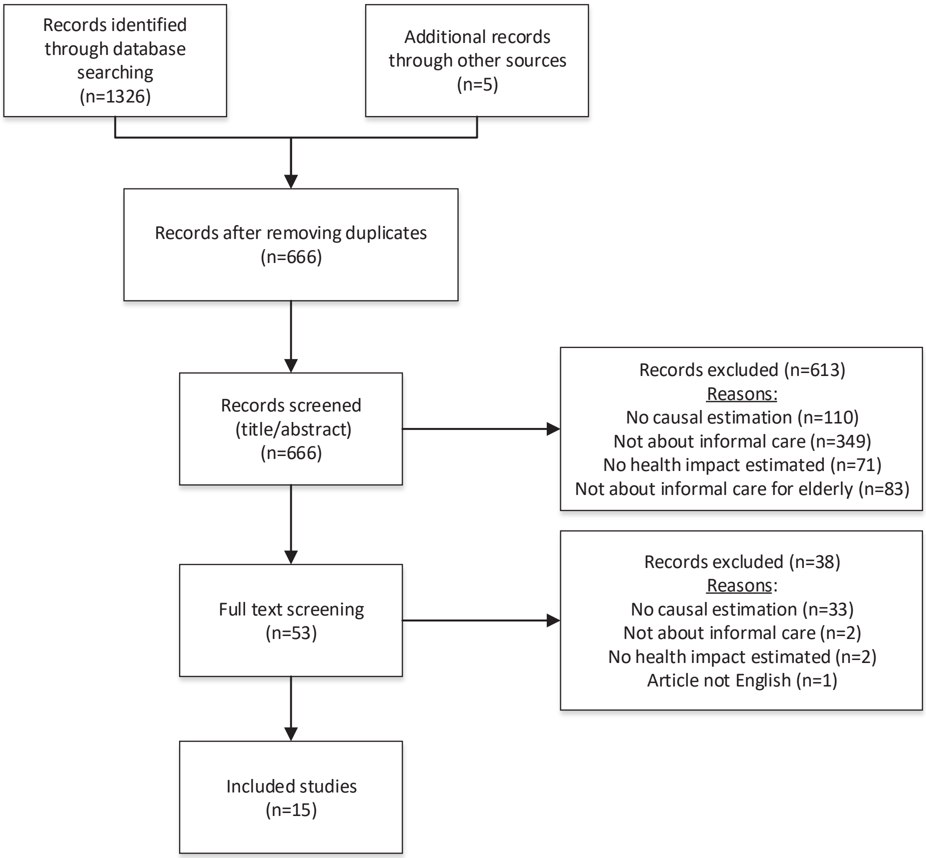
All articles were published recently, the oldest dating from 2009 (Coe & Van Houtven, 2009), the most recent one published in 2017 (De Zwart et al., 2017). The articles were published in a variety of journals, mostly relating to gerontology or health economics. The articles cover various countries of interest, using European data (n=6); Asian data (n=4); US data (n=4), or Australian data (n=1). An extensive overview of all articles is provided in Table 2.3.

Methodological quality of studies included in the review

Table 2.4 presents an extensive overview of the methods per study meeting the inclusion criteria. Three of the 15 studies use simultaneous equation models to estimate the causal impact of providing care. The instrumental variables used in these studies are roughly similar, including indicators of either the health (Do et al., 2015) or the widowhood of the parent (Coe & Van Houtven, 2009; Heger, 2017). The *F*-statistics show that the instrumental variables applied in the main analyses of these studies all have sufficient strength.

Most articles (*n*=12) use a matching design to compare caregivers and noncaregivers. As mentioned in the Method section, we only included studies that matched respondents on the health of the caregiver to avoid omitted variable bias. Six (Brenna & Di Novi, 2016; Di Novi et al., 2015; Kenny et al., 2014; Schmitz & Westphal, 2015; Stroka, 2014; de Zwart et al., 2017) of the 12 matching studies follow the approach of Lechner (2009a) by matching on precaregiving variables and only comparing caregivers with noncaregivers who both did not provide care last year.

Figure 2.1: Flowchart of screening phases



Only two of the studies under review (Do et al. 2015; Heger, 2017) specifically accounted for the family effect. Do and collegues (2015) argued to avoid picking up the family effect by focusing on (i) physical health effects and (ii) females who provide care to their parents-in-law. As the family effect relates to worrying about an ill family member, the authors assumed that these worries do not affect the physical health of the caregiver. They furthermore assumed that this family effect is absent or at least smaller if one's parent-in-law falls ill rather than one's own parent. Heger (2017) aimed to disentangle the family effect from the caregiving effect and estimated the family effect by including a variable representing 'poor health of a parent' and the caregiving effect by including a variable representing 'informal caregiving' in the model. None of the other studies accounted for the family effect, thereby potentially overestimating the effect of caregiving on health.

Table 2.3: Characteristics and results of reviewed studies

Authors	Country /region of interest	Care recipient	Definition of informal care	Sample characteristics of caregivers	Health measure	Methods	Lechner (2009a) matching procedure used	Results (if applicable subgroup for which effect is found)
Brenna and Di Novi (2016)	Europe	Parent	Providing assistance to a parent, step-parent, or parent-in-law at least on a weekly basis *Distinction*: Intensive informal care (excludes caregivers helping with domestic chores)	Women aged 50-75	Depression (Euro-D)	PSM	Yes	↑ Euro-D (Southern Europeans) *larger effect when providing intensive informal care*
Coe and Van Houtven (2009)	US	Parent	Spent at least 100 hours since previous wave/in the last 2 years on helping parents/ mother/father with basic personal activities like dressing, eating, and bathing	Men and women aged 50 - 64, with only a mother alive	Mental health (CES-D 8); physical health (self-assessed health (SAH), diagnosed heart condition and blood pressure).	Simultaneous-equation models (2SLS, Arellano-Bond)	N/A	*Continued caregiving:* ↑ CES-D 8 (married males and females) ↑ Heart condition (single males) ↓ SAH (married females) ↑ SAH (married males) *Effects after 2 years:* ↑ CES-D 8 (married females) ↑ Heart condition (single males) *Initial caregiving:* ↑ CES-D 8 (married females)

Table 2.3: Continued.

Authors	Country /region of interest	Care recipient	Definition of informal care	Sample characteristics of caregivers	Health measure	Methods	Lechner (2009a) matching procedure used	Results (if applicable subgroup for which effect is found)
Di Novi, Jacobs and Migheli (2015)	Europe	Parent	Women providing care to elderly parents living in or outside the household in the past twelve months almost weekly or almost daily	Women, aged 50-65 having a parent with bad or very bad health	Self-assessed health; quality of life (CASP-12)	PSM	Yes	↑ SAH (North and Continental European caregivers) ↓ CASP-12 (Continental European caregivers) ↑ self-realized and pleasure in life (caregivers in Continental and Mediterranean Europe) ↓ able to control life and autonomous (caregivers from Continental Europe)
Do, Norton, Stearns and Van Houtven (2015)	South-Korea	Parent (in-law)	Any informal care provided to parents-in-law	Women with living parent (in-law) aged 45+	Pain affecting daily activities; fair or poor self-rated health; any outpatient care use; OOP spending for outpatient care; any prescription drug use; OOP spending prescription drug	Simultaneous-equation models (2SLS, IV-probit)	N/A	↑ Pain affecting daily activities, health self-rated as poor, OOP outpatient care (daughters & daughters-in-law) ↑ Any outpatient care use, any prescription drug use (daughters)

Table 2.3: Continued.

Authors	Country /region of interest	Care recipient	Definition of informal care	Sample characteristics of caregivers	Health measure	Methods	Lechner (2009a) matching procedure used	Results (if applicable subgroup for which effect is found)
Fukahori, Sakai and Sato (2015)	Japan	Family member living in the same household	A family member in the same household who is in need of care	Males and their spouses aged 50-64	Employment rate, working hours, self-reported health, satisfaction with leisure time and life	PSM	No	↓ Likelihood of participating in work No impact on SAH or life satisfaction (results not presented in paper, mentioned in text)
Goren, Montgomery, Kahle-Wrobleski, Nakamura and Ueda (2016)	Japan	Adult relatives with Alzheimer's disease or dementia	Persons currently caring for an adult relative, with Alzheimer's disease or dementia	Men and women aged 18+	Comorbidities; depression (PHQ-9); work productivity (WPAI); SF-36 PCS and MCS; healthcare resource utilization	PSM	No	↑ PHQ-9, MDD ↓ SF-36 PCS, MCS and health utilities ↑ Depression, insomnia, anxiety and pain ↑ Absenteeism, overall work impairment and activity impairment ↑ Emergency room and traditional provider visits in the past six months

Table 2.3: Continued.

Authors	Country /region of interest	Care recipient	Definition of informal care	Sample characteristics of caregivers	Health measure	Methods	Lechner (2009a) matching procedure used	Results (if applicable subgroup for which effect is found)
Heger (2017)	Europe	Parent	Any caregiving activities to parent (help with personal care and practical household help provided outside or inside the household). *Distinction*: daily, weekly and any frequency of caregiving.	Men and women aged 50-70	Depression (EURO-D); indicator whether someone suffers from ≥4 depressive symptoms.	Simultaneous-equation models	N/A	↑ Euro-D, 4+ depressive symptoms (females) *larger effect when more intensive informal care*
Hernandez and Bigatti (2010)	US	Individual with Alzheimer's disease or a physical disability	Caring for an individual with Alzheimer's disease or a physical disability within the past year	Hispanic Americans aged 65+	Depression (CES-D 20)	Direct matching	No	↑ CES-D 20
Hong, Han, Reistetter, and Simpson (2016)	South-Korea	Spouse with dementia	Persons living with a spouse with dementia	Men and women aged 19+	Physician-diagnosed stroke	PSM	No	↑ Odds of stroke

Table 2.3: Continued.

Authors	Country /region of interest	Care recipient	Definition of informal care	Sample characteristics of caregivers	Health measure	Methods	Lechner (2009a) matching procedure used	Results (if applicable subgroup for which effect is found)
Kenny, King and Hall (2014)	Australia	Spouse, adult relative, elderly parent (in law)	Any time spent caring for a disabled spouse, adult relative or elderly parent/parent-in-law in a typical week. *Distinction:* Care burden: Low(less than 5 h/w), moderate (5–19 h/w) and high (20 or more h/w)	16+ males and females	SF-36 PCS and MCS	PSM	Yes	*After 2 years:* ↑ PCS (high care) *Effects for subgroups*: ↓ PCS (high caregiving females with a job) ↓ MCS (high caregiving females with a job) ↑ MCS (high caregiving males without job) *After 4 years:* ↓ PCS (low and moderate care) ↓ MCS (moderate and high care)
Rosso et al. (2015)	US	Family member or friend	Currently helping ≥1 sick, limited, or frail family member, or friend on a regular basis? Distinction Low frequency ≤ 2 times per week; high frequency ≥3 times per week.	Women, 65–80 years old	Walking speed, grip strength, chair stands	PSM	No	*After 6 years:* ↑ grip strength (low-frequency caregivers)

Table 2.3: Continued.

Authors	Country /region of interest	Care recipient	Definition of informal care	Sample characteristics of caregivers	Health measure	Methods	Lechner (2009a) matching procedure used	Results (if applicable subgroup for which effect is found)
Schmitz and Westphal (2015)	Germany	Unknown	Providing ≥2 hours per day on care and support for persons in need of care on a typical weekday	Women aged 18+	SF-12v2 MCS & PCS	PSM	Yes	*Short term:* ↓ MCS *Longer term:* No effects
Stroka (2014)	Germany	Anyone in need	Self-reported informal caregiving to sickness fund to receive allowance *Distinction:* Level of care needed	Males and females aged 35+	Drug intake	PSM + D-in-D	Yes	↑ Intake of antidepressants, tranquilizers, analgesics and gastrointestinal agents *Larger effect when more intensive care*
Trivedi et al. (2014)	US	Family member or friend	Any care provision in the past month to a friend or family member who has a health problem, long-term illness, or disability.	Non-institutionalized U.S. civilian population aged ≥18 years	Self-assessed mental health; general health; perceived social and emotional support; sleep hygiene	PSM	No	↑ Report >15 days of poor mental health & inadequate emotional support; ↓ Report fair or poor health (females) ↑ Report fair or poor health (males) ↓ Receive recommended amount of sleep ↑ Fall asleep unintentionally during the day

Table 2.3: Continued.

Authors	Country /region of interest	Care recipient	Definition of informal care	Sample characteristics of caregivers	Health measure	Methods	Lechner (2009a) matching procedure used	Results (if applicable subgroup for which effect is found)
De Zwart et al. (2017)	Europe	Partner	Daily or almost daily caregiving activities (help with personal care) to partner for ≥3 months in the past 12 months.	Males and females aged 50+	Prescription drugs usage; the number of doctor visits in the past 12 months; EURO-D depression scale; self-perceived health	PSM	Yes	*Short term:* ↑ Euro-D, ↓ self-reported health; ↑ prescription drug use(females), ↑ doctor visits (females) *Longer-term:* No effect

Note: PSM = propensity score matching; 2SLS = two-stage least square; D-in-D = difference-in-difference; IV = instrumental variable; MCS & PCS = Mental Component Scale and Physical Component Scale.

Table 2.4: Methodology of reviewed studies

Authors	Data source	Sample representativeness	Data type	Sample size	Study design	Matching or IV strategy	Methodological quality	Family effect
Brenna and Di Novi (2016)	SHARE, 2004-2007 (2 waves)	Representative for the non-institutionalized population aged 50 and older	Longitudinal	Matched treated/Control 1,138/3,292	PSM	Matched on: demographics; family composition; socio-economic variables; information on parents receiving care; self-reported probability of receiving an inheritance; mental health status and caregiver status at the first wave	Matching quality: matched on caregiver status and mental health in first wave	Not specifically considered
Coe and Van Houtven (2009)	HRS, 1992-2004 (7 waves)	Nationally representative for community based population	Longitudinal	Sample continued caregiving=2,557 Sample initial caregiving=8,007	Simultaneous-equation models (2SLS, Arellano-Bond)	*IV continued caregiving:* Death of mother *IV initial caregiving:* Number of boys/girls in the household	Strength of instrument: F-statistics: 16-837 (continued caregiving) 6-18 (initial caregiving)	Not specifically considered
Di Novi et al. (2015)	SHARE, 2004 & 2006/2007	Representative for the non-institutionalized population aged 50 and older	Longitudinal	Matched treatment/control 535/1,825	PSM	Matched on: socio-economic variables; employment; family composition; occupation and income; previous SAH, CASP and caregiving status	Matching quality: Matched on caregiving status, SAH and CASP in first wave	Not specifically considered

Table 2.4: Continued.

Authors	Data source	Sample representativeness	Data type	Sample size	Study design	Matching or IV strategy	Methodological quality	Family effect
Do et al. (2015)	Korean LSA, 2006-2010 (3 waves)	Nationally representative study of non-institutionalized adults aged 45 years or older	Longitudinal	n = 2,528 (daughters-in-law) n = 4,108 (daughters)	Simultaneous-equation models (2SLS, IV-probit)	IV: ADL limitations of the mother(-in-law) and of the father(-in-law)	Strength of instrument: F-statistics: 86 (daughter-in-law) and 37 (daughter)	Aim to avoid family effect by focusing on physical health and care for parents-in-law
Fukahori et al. (2015)	Japanese panel survey on middle-aged persons, 1997-2005	Randomly selected from the national population	Longitudinal	Matched treated/control 155/155 (males) 188/188 (spouses)	PSM	Matched on: employment, SAH, retirement, age, education and wage	Matching quality: Not matched on pretreatment status.	Not specifically considered
Goren et al. (2016)	Japan National Health and Wellness Surveys 2012-2013	Stratified by sex and age to ensure representativeness of adult population	Cross-sectional	Matched treatment/ control 1297/1297	PSM	Matched on: sex, age, BMI, exercise, alcohol, smoking, marital status, CCI (Charlson comorbidity index), insured status, education, employment, income, and children in household	Matching quality: Not matched on pretreatment status.	Not specifically considered
Heger (2017)	SHARE, 2004-2013 (4 waves)	Representative for the non-institutionalized population aged 50 and older	Longitudinal	n = 3,669 (female) n = 2,752 (male)	Simultaneous-equation models	IV: Indicator of whether one parent is alive	Strength of instrument: F-statistics 18-47	Estimate family effect by adding health of parent as variable to model

Table 2.4: Continued.

Authors	Data source	Sample representativeness	Data type	Sample size	Study design	Matching or IV strategy	Methodological quality	Family effect
Hernandez and Bigatti (2010)	HEPESE, 2000/2001	Representativeness not discussed in article	Longitudinal (one wave used)	Matched treatment/ control 57/57	Direct matching	Matched on: age, gender, socioeconomic status, self-reported health, and level of acculturation	Matching quality: Not matched on pretreatment status.	Not specifically considered
Hong et al., (2016)	Korea Community Health Survey, 2012-2013	Representative of the entire community-dwelling adult population in South-Korea	Cross-sectional	Matched treatment/ control 3,868/3,868	PSM	Matched on: age, sex, education, household income, insurance type, current smoker, current drinker and stress level	Matching quality: Not matched on pretreatment status.	Not specifically considered
Kenny et al. (2014)	HILDA, 2001-2008	Representative sample of private Australian households	Longitudinal	Matched treatment/ control 424 / 424	PSM	Matched on pre-treatment: age, sex, marriage/partner, children, work hours, income, education, country of birth, chronic health condition limiting work, partner with a chronic health condition, another household member with a chronic health condition, having at least one living parent and baseline year	Matching quality: Matched on baseline characteristics (pre-treatment)	Not specifically considered

Table 2.4: Continued.

Authors	Data source	Sample representativeness	Data type	Sample size	Study design	Matching or IV strategy	Methodological quality	Family effect
Rosso et al. (2015)	Woman's Health Initiative Clinical Trial, 1993-1998	Representativeness of sample not mentioned. Participants were recruited at clinical centers across the United States from 1993 to 1998 to participate in clinical trials	Longitudinal	Matched treatment/control 2,138/3,511	PSM	Matched on: socio-demographic variables & health (smoking, chronic illnesses, obesity status)	Matching quality: Matching on baseline characteristics (not pre-treatment)	Not specifically considered
Schmitz and Westphal (2015)	GSOEP, 2002-2010	Representative longitudinal survey of households and persons living in Germany	Longitudinal	Matched treatment/control 1,235/29,942	PSM	Matched on: age of mother/father; mother/father alive; (age) partner; number of sisters; personality traits; socio-economic variables; health status	Matching quality: Matching on health before treatment Sample stratified by care provision at t=-1	Not specifically considered
Stroka (2014)	Techniker Krankenkasser, 2007-2009	Administrative data from largest statutory sickness fund in Germany	Longitudinal	Matched treatment/control 5,696/3,125,140 (males) 7,495/2,085,946 (females)	PSM + D-in-D	Matched on: socio-economic variables; employment; education; work position; health status	Matching quality: Matched pre-treatment, at baseline only non-carers	Not specifically considered

Table 2.4: Continued.

Authors	Data source	Sample representativeness	Data type	Sample size	Study design	Matching or IV strategy	Methodological quality	Family effect
Trivedi et al. (2014)	BRFSS, 2009/2010	Nationally representative survey in the United States	Cross-sectional	Matched treatment/ control 110,514/110,514	PSM	Matched on: socio-economic variables; household situation; employment, income, veteran status, immunizations within the previous year, exercise, tobacco use, self-identified physical disability, obesity status; healthcare access; and survey characteristics	Matching quality: Not matched on pretreatment status.	Not specifically considered
De Zwart et al. (2017)	SHARE, 2004, 2006, 2010, 2013	Representative for the non-institutionalized population aged 50 and older	Longitudinal	Matched treatment/ control 404/10,293	PSM	Matched on: socio-economic variables; household situation; wealth; health status; health and age of spouse	Matching quality: Matched on pretreatment covariates + sample stratified by care provision at $t = -1$	Not specifically considered.

Note: SHARE = Survey of Health, Ageing and Retirement Europe; HRS: Health & Retirement Study; HEPESE = Hispanic Established Populations for the Epidemiologic Study of the Elderly; HILDA = Household, Income & Labour Dynamics in Australia Survey; GSOEP: = German Socio-Economic Panel; BRFSS = Behavioral Risk Factor Surveillance System; PSM = propensity score matching, 2SLS = two-stage least square; D-in-D = difference-in-difference, IV = instrumental variable.

Comparability of studies

The studies that we review use different methods, which complicates comparing effect sizes across studies because, even if estimated on the same study sample, the methods would yield estimates of the effect that are valid for other subgroups of the study samples. With a matching design, caregivers are matched to similar individuals who do not provide care. These studies hence estimated the Average Treatment Effect on Treated (ATT): the health impact of informal care for the current informal caregivers. When using instrumental variables in simultaneous equation models, the Local Average Treatment Effect (LATE) is estimated. This represents the health impact of caregiving for those who started caregiving in response to the instrument, that is, illness or widowhood of a parent.

Hence, there are two potential methodological reasons for any observed differences in effect size between studies included in this review. First, effect sizes could differ as the ATT measures the impact of any form of caregiving while the LATE measures the impact of caregiving in response to severe illness or decease. Second, some studies do not account for the family effect, which leads to different estimates.

The various definitions of informal caregiving and the variety of outcome measures further complicate comparison of the findings of these studies. The definition of informal caregiving differs per study from providing care to a parent ($n = 5$) or spouse ($n = 1$), caring for anyone / a family member or friend ($n = 5$), and informal care for someone with a specific illness (e.g. dementia; $n = 2$). Lastly, two studies (Fukahori et al., 2015; Hong et al., 2016) proxy for informal caregiving by defining caregivers as persons living together with a family member or spouse in need. Although these studies aimed to estimate the impact of informal care, and as such adhere to the inclusion criteria, these rough measures of informal care might lead to underestimations of the caregiving effect because many noncaregivers may be misclassified as caregivers.

In addition, various health measures were used to estimate the impact on health. Studies focus on the mental health impact ($n = 3$), the physical health impact ($n = 4$), or both ($n = 8$). These health states are measured via either validated health measures, drug prescription data, or information on health care usage. The studies also differ in their specification of caregiving, for example, by restricting the sample to respondents who provide more than two hours of informal care per day.

Synthesis of results

The studies included in the review provide a fairly coherent picture. All studies find a short-term negative effect for certain subgroups of caregivers, except for the study by Fukahori and colleagues (2015). An explanation for this latter finding could be the very rough proxy of informal care used in this study: household members were assumed to provide informal care when someone in the household needs care.

While all but one of the studies found a negative effect on the short term, there are interesting differences in the effect sizes between and within the studies. The studies estimating mental health effects all found that caregiving might result in higher prevalence of depressive feelings and lowered mental health scores. Estimates of the physical health impact of informal care were less stable and differed in sign. Many studies found negative physical health effects of caregiving (Coe and Van Houtven, 2009; Do et al., 2015; Goren et al., 2016; Hong et al., 2016; Stroka 2014; Trivedi et al. 2014; De Zwart et al. 2017). These effects relate to a wide variety of physical health outcomes such as increased drug intake (Stroka, 2014; De Zwart et al., 2017) and pain affecting daily activities (Do et al., 2015). In contrast to these negative effects, Di Novi and colleagues (2015), Trivedi and colleagues (2014), and Coe and Van Houtven (2009) found positive effects of informal caregiving on physical health for some specific subgroups. How physical health is measured appears to be crucial: when measured by self-assessed health, the short-run impact of caregiving is positive, whereas negative health effects are found when outcomes are measured by intake of drugs and reported pain. Di Novi and colleagues (2015) claimed that the positive impact of informal care on self-assessed health could be the result of a bias related to reference points. They argued that spending time with a person who is in poor health could lead to an increase in self-assessed health because people may take the poor health of the care recipient as reference point, even though the objective health level of the caregiver could have decreased.

Next to differences with regards to the health outcomes studied, large heterogeneity exists with regard to the subgroup of caregivers for whom the effects are applicable. Many studies only estimated caregiving effects for females as they assumed that mostly women provide or are affected by informal care (Brenna & Di Novi, 2016; Di Novi et al., 2015; Do et al., 2015; Rosso et al., 2015; Schmitz & Westphal, 2015). Studies that did separately estimate health effects for males and females often found that health effects are larger or solely present for females (Heger, 2017; Stroka, 2014; De Zwart et al. 2017). Marital status also seemed to be of effect according to the study of Coe and Van Houtven (2009), which in most cases solely found health effects of informal care for married individuals.

The intensity of provided care appears to be another source of heterogeneity in the health effects of caregiving. Various studies compared average or moderate caregivers with intensive caregivers based on the hours of care provision. These studies (Brenna & Di Novi, 2016; Heger, 2017; Stroka, 2014) found larger health effects when more intensive care is provided.

A clear conclusion regarding the longer-term effects of informal caregiving cannot yet be drawn. As all studies used survey data, many were unable to estimate longer-term caregiving effects. Only five studies estimated effects over a longer period (Coe & Van Houtven, 2009; Kenny et al., 2014; Rosso et al., 2015; Schmitz & Westphal 2015; De Zwart et al., 2017). Both Schmitz and Westphal (2015) and De Zwart et al. (2017) did not find any longer-term effects of informal caregiving on health. Schmitz and Westphal concluded that there might not be large scarring effects of care provision; De Zwart and colleagues mentioned that selective attrition may have biased their results. The other three studies estimating longer-term effects found mixed results, showing both positive and negative effects of informal care. Kenny and colleagues (2014) found negative health effects 2 years after the start of caregiving for working female caregivers and positive effects for non-working caregiving males. Rosso et al. (2015) grouped all persons who provide informal care at baseline and found that after 6 years low-frequency caregivers have greater grip strength (representing physical health) than non-caregivers. The authors, however, control for various health measures but not for baseline grip-strength and mention that the effect might be explained by existing pre-caregiving differences. The study by Coe and Van Houtven (2009) is the only one that compared persons who stopped providing care to persons who continued caregiving for two more years. They found negative mental health effects for females and negative physical health effects for males who continue caregiving.

2.4 Conclusion

Due to population ageing, most OECD countries have to deal with a growing demand for LTC. As often both formal and informal care can meet this demand, the key is to find the right balance between the two types of care. This paper aimed to provide insight into this trade-off by summarizing both theoretical and empirical literature regarding the costs and benefits of formal and informal LTC.

Our review provides two important insights. First, economic theory makes clear that not everyone is equally inclined to provide informal care. Both individual characteristics and the institutional context can shape a person's caregiving decision. Particularly persons with a lower income or who are unemployed are more likely to provide informal care and may thus experience the negative consequences of caregiving.

Second, our systematic literature review shows that there is ample evidence of a negative impact of caregiving on the health of the provider. This caregiving burden can manifest itself both in mental and physical health effects. Interestingly, the presence and intensity of these health effects differ strongly per subgroup of caregivers. Especially female, and married caregivers, and those providing intensive care appear to experience negative health effects of caregiving. These groups might have several other responsibilities on top of caregiving duties, thereby being more strongly affected by the caregiving tasks.

As individuals may not be able to fully insure themselves against the consequences of caregiving, there is a need for government intervention to take away the necessity to provide care or to compensate the caregiver. Public provision of LTC or private insurance subsidies could solve this problem, but they may drive up costs by crowding out too much of the informal care supply. The extent to which crowding out is a problem depends on the strength of the prevailing social norms and altruistic preferences in society.

While this study does not (and did not intend to) offer a conclusive answer regarding the optimal mix of formal and informal care, the paper does highlight the complex trade-off that policymakers face. Formal and informal care each have their own costs and benefits. Subsidizing formal care can be costly but might relieve individuals from the caregiver burden, while stimulating informal care might have the opposite effect. Policies affecting either of the two types of care should therefore always consider their impact on the other form of LTC.

To further improve our understanding of the trade-off between the two types of LTC, we propose the following additional research. First, further research is needed about the different impacts of informal care on various subgroups of caregivers, as current studies do not provide conclusive insight into these differences. Knowing which groups are most strongly affected by informal care and understanding the drivers behind these effects may help policymakers decide how to reduce the negative effects of informal care and to facilitate a better targeting of support for informal caregivers. Second, research is needed into the long-term effects of providing informal care, given that most empirical studies have only measured short-term effects. Third, more research is needed to disentangle the family and the caregiving effect, since the caregiving effect might be overstated in most empirical studies as the family effect was not accounted for. Fourth, it would be worthwhile to gain enhanced insight into the impact of the various types of caregiving and their intensity. Next, given the potentially important role of the institutional context on the caregiving decision, more research on the health effects of informal care in the Dutch LTC system is imperative, since the number of empirical studies of this specific context is very limited.

Finally, this overview of current literature also raises important questions about the trade-off between formal and informal care in a larger context. Societal trends such as increasing female labor force participation and delayed retirement ages could affect the caregiving decision as well. Due to longer and increasing labor force participation, individuals may become less inclined to provide informal care, thus necessitating more formal care. However, when the provision of informal care mainly stems from a feeling of obligation (because of social norms or altruistic preferences), individuals would continue their caregiving duties, thereby facing a double burden of work and informal care. It would be interesting to explore these trends in future research.

Relevance for the Netherlands

Insights from this paper are relevant for the Dutch context. Dutch public long-term care expenditures are among the highest in the OECD and are expected to grow substantially in the coming decades (OECD, 2017b; Eggink et al., 2017). Aside from the increase in long-term care expenditures, we also observe a growing number of Dutch informal caregivers. Between 2012 and 2016 the number of caregivers in the Netherlands grew by 20%, and currently more than 3 million adults are estimated to provide informal care (Gezondheidsmonitor, 2012, 2016). This surge in the supply of informal care could be driven by population ageing but may also be the result of the policy changes related to the Social Support Act, which aim to stimulate reliance on social networks instead of governmental support (WMO, 2015).

An important empirical question is whether the burden of caregiving is equally shared among the Dutch population or whether it is primarily carried by specific subgroups with lower income and labor productivity, as predicted by economic theory. Data from the Health Monitors of 2012 and 2016, weighted to represent the entire Dutch population, show that some groups indeed provide care more often than others (see Table 2.1 in textbox 2.2). In 2016, almost 19% of people with a full-time job (more than 32 working hours a week) provide care compared to just over 26% of employees who work no more than 12 hours a week. Elderly persons also more often provide care than full-time employees, as about one fourth of retirees provide informal care. Although we see an increase in the propensity to provide care among nearly all identified subgroups, especially the participation of elderly rose sharply between 2012 and 2016. In contrast to theory, individuals in higher income groups provide care more often than individuals in lower income quintiles. Various variables may have confounded this result; richer individuals, for example, are often older and hence more likely to care for a spouse or parent. In terms of care intensity, lower income households do provide more hours of informal care.

The differences in the propensity to provide care between the various subgroups highlight the importance of considering the downsides of informal caregiving. After all, policies to stimulate informal care might only reach that part of the population that is already inclined to provide care. As a result, the costs of care affect only a specific part of the population.

In light of the growing number of caregivers, an important question is how to minimize the caregiving burden. Under the Social Support Act (Wet Maatschappelijke Ondersteuning, 2015), Dutch municipalities are obliged to provide support to informal caregivers. Examples of such interventions for caregivers are respite care and support groups. Respite care offers caregivers a short break by temporarily providing formal care to the person in need. Support groups offer advice and enable the sharing of experiences with other caregivers. However, many municipalities find it difficult to target informal caregivers who need this support (VNG, 2016). As shown from our literature review, not all caregivers are similarly affected by their tasks, and hence not all require this type of support. Female and married caregivers, and those providing intensive care turn out to experience larger negative consequences of informal caregiving. Policymakers might therefore especially target interventions to those individuals who need these most.

CHAPTER 3

Health effects of caring for and about parents and spouses

With Pieter Bakx, Frederik Schut & Eddy van Doorslaer

Published in: The Journal of the Economics of Ageing, volume 14, 100-196.

Abstract

Informal caregiving is a potentially attractive alternative to formal care but may entail health costs for the caregiver. We examine the mental and physical health impact of providing informal care and disentangle the caregiving effect – the effect of caring *for* someone in need – from the family effect – the effect of caring *about* someone in need. We account for the main sources of endogeneity in the caregiving decision using Arellano-Bond difference GMM models. We use four waves (2010-2013) of panel data from the Dutch *Study on Transitions in Employment, Ability and Motivation (STREAM)*.

We find that caregiving harms the mental health of caregivers; the effect is more prominent for spousal caregivers. On top of this, a negative health shock of a family member also has a *direct* negative effect on mental health, providing evidence of a family effect. Our findings thus highlight that the total effect of having a sick relative may be underestimated when the family effect is not adequately accounted for. As the caregiving effect differs substantially between various types of caregivers, policies to cushion these effects should specifically target those subgroups of caregivers that carry the largest burden of informal caregiving.

3.1 Introduction

In most Western countries, the demand for long-term care (LTC) is expected to keep rising in the decades to come. For instance, in the Netherlands the demand for LTC is projected to grow at an average annual rate of 1.6% between 2014 and 2030 (Eggink et al., 2017). Part of this growing demand is likely to be met by informal care, i.e. by unpaid care provided by relatives and friends. While the costs of informal caregiving are typically low for the recipient, they may be substantial for the caregiver and society. Various studies found that the stress and physical strain involved in informal caregiving risks hurting the health of caregivers (e.g. Pinquart & Sörensen, 2003). Many of these studies, however, used non-representative samples or focused on the provision of care for a specific disease (Hirst, 2004).

While the recent literature has moved towards estimating the impact of informal caregiving using larger, representative datasets, two main challenges of adequate empirical identification of these effects have emerged. A first challenge relates to the potential endogeneity between the decision to provide informal care and one's own health. Persons with lower health expectations might for example be more inclined to take up the caregiver role for their parents (Schulz, 1990). The other way around, a minimum level of health is required to be able to carry out caregiving tasks, which prevents individuals in very poor health from providing care. In addition, omitted variables may lead to bias when unobserved variables like personality affect both the propensity of providing care and the health of the caregiver.

A second challenge, which has received limited attention thus far, is dealing with the notion that two distinct effects may be present in situations of ill-health of a relative: the family effect and the caregiving effect. The family effect refers to the impact of *caring about* a person and, if living together, the consequences of taking over regular household chores. It is different from the caregiving effect, which is the effect of *caring for* a person in need. Irrespective of care provision, experiencing a health decline of a loved one can have a negative effect on one's own health or well-being (Amirkhanyan & Wolf, 2006; Bobinac et al., 2010).

It is important to make this distinction between the caregiving effect and the family effect, as addressing them adequately would require different government interventions. Respite care, for instance, could alleviate the caregiving effect, but offers no solution to the family effect of worrying about an ill family member. As the caregiving effect and the family effect often occur simultaneously, it is difficult to disentangle them. Yet, not controlling for the family effect might lead to overestimation of the caregiving effect.

This paper aims to improve understanding of the health effects experienced by informal caregivers by separately estimating both effects. In contrast to some earlier studies, we do not apply instrumental variables to estimate the caregiving effect because the validity of the instruments used in previous work can be questioned, and strong and valid instruments are not readily available. Instead, we reduce endogeneity concerns by using Arellano-Bond difference GMM models to control for existing health differences in a first-differences regression.

While most papers focus on either parental or spousal caregiving, we separately estimate the caregiving effect and the family effect for various groups of caregivers. There may be various reasons why the impact of caregiving differs between these care types. As spousal caregivers tend to be older, they often have fewer physical and psychological resources to deal with stress related to caregiving (Pinquart & Sörensen, 2003a). Furthermore, differences in the level of care provision can be large drivers of differences in stress between spousal and parental caregivers (Pinquart & Sorensen, 2011).

3.2 Earlier work on health effects of informal caregiving

A number of studies have attempted to address endogeneity problems when evaluating the health effects of informal caregiving by using instrumental variables (IVs), fixed effects (FE) methods or statistical matching (see Table A3.1 in the Appendix for an overview). The first group of studies used IVs to estimate the impact of informal care provision (Coe & Van Houtven, 2009; Do et al., 2015; Heger, 2017) and found significant negative effects of informal caregiving on the caregiver's health. The IVs employed in these studies all relate to the health of one's parents. The risk of these instruments lies in their potential violation of the exclusion restriction; when a family effect is present, a health shock of a family member is correlated directly to the caregiver's health. Using health of a family member as IV for informal caregiving could therefore overestimate the effect of caregiving on health by attributing the entire difference in health between individuals with and without ill family members to caregiving.

The second group of studies, most closely linked to the set-up of the current paper, aims to estimate a causal impact by controlling for or matching on a large set of covariates. These studies rely on the assumption that they are able to capture all covariates that affect the caregiving decision to make the conditional independence assumption hold. While this is a strong assumption, it might be preferable considering worries related to the validity of IVs. Van den Berg et al. (2014) used FE models on an Australian dataset and found significant negative effects of caregiving on subjective well-being. Using FE models they controlled for time constant heterogeneity, however they did not consider selection into caregiving based on time-variant elements such as previous health. The studies making use of matching (Brenna & Di Novi, 2016; de Zwart et al., 2017; Schmitz & Westphal, 2015), addressed endogeneity of caregiving by statistically matching caregivers and non-caregivers on observable characteristics. By matching on pre-treatment variables, these papers make it credible that treatment is random conditional on controls and hence that an average treatment effect on the treated can be identified. All three papers found negative effects of caregiving on mental health.

Thus far, two studies specifically considered the family effect. Do et al. (2015) aimed to avoid picking up the family effect by only focusing on (i) physical health effects and (ii) females providing care to their parents-in-law. They found negative health effects of providing informal care, but might face difficulties in isolating the family effect from the caregiving effect. For example, as mental and physical health could affect each other, stress related to the family effect may induce physical health problems. Heger (2017) estimated the family effect by including an indicator of poor health of a parent in the model and found a negative effect of poor health of family members on the health of the potential caregiver.

3.3 Methods

To deal with the potential endogeneity between caregiving and own health, we start from the economic intuition behind the caregiving decision as presented by De Zwart et al. (2017). According to their model, a set of elements affect the caregiving decision. The first one relates to personal ability, both reflected in wage and health. Persons with a higher ability might, for example, prefer paid work to providing informal care. Second, availability of other types of informal and formal care might affect the caregiving decision. Household income and size could for example reflect someone's possibilities to purchase formal care or to transfer caregiving duties to family members. Lastly, non-monetary factors such as cultural factors might affect the caregiving decision.

We account for these factors that shape the caregiving decision in three ways. First, we use a first-difference model to control for time-invariant personal characteristics, like personality traits and education.

Second, we deal with differential selection into caregiving by health status by conditioning on the lagged health status. Controlling for lagged health not only deals with reverse causality but also helps to mitigate the issue of unobserved characteristics (cf. Lechner, 2009a). Variations in time-variant factors that are potentially affecting current health status of the respondents occurring in *t–1* and earlier are likely to have also affected lagged health and thus need not to be controlled for anymore. Hence, we assume that no event affected both the propensity to care and one's own health in the past year.

To include a lagged variable while controlling for time-invariant unobservables, we use the Arellano-Bond (1991) (A-B) estimation technique. Including pre-treatment health status in a regular FE or first-difference model is not possible as the lagged dependent variables correlate with the fixed effects in the error term and would give rise to dynamic panel bias. This bias could affect our estimates of the lagged dependent variable, as well as the coefficients of our other independent variables, especially when the dataset contains few waves but many observations (Nickell, 1981). In the A-B first-differences model, the lagged difference in health status H ($\Delta H_{it\text{-}1}$) is instrumented by deeper lags of health (starting with health two waves earlier: $H_{it\text{-}2}$). We can use $H_{it\text{-}2}$ as an instrument for $\Delta H_{it\text{-}1}$ because $H_{it\text{-}2}$ is correlated with $\Delta H_{it\text{-}1}$ but not with $\Delta \varepsilon_{it}$ as long as the error terms are not serially correlated. Following Arellano and Bond (1991), we do not only use the second lag of health, but all available deeper lags of health as instruments. As we have four waves of data, we can include the second and third lag.

Third, we control for remaining observed time-varying factors related to the caregiving decision and own health by including covariates (such as income and marital status) into our models. The main difference between this study and prior studies is that we include measures to capture the family effect in the model. Based on the existing literature, we cannot conceive other important, time-varying factors affecting own health and the caregiving decision.

The resulting dynamic panel data model is estimated using a difference Generalized Method of Moments (GMM) regression.[7] The model is specified as follows:

$$\Delta H_{it\text{-}1} = \beta_1 \Delta H_{i,t\text{-}1} + \beta_2 \Delta IC_{it} + \beta_3 \Delta HF_{it} + \beta_4 \Delta X_{it} + \Delta \varepsilon_{it} \qquad (1)$$

The change in health ΔH_{it} is dependent on the change in one's health status observed one year before, $\Delta H_{i,t\text{-}1}$; on ΔIC_{it}, which indicates the change of the informal care provision status; on ΔHF_{it}, which refers to a change in the health state of the individual's partner or close family member,[8] as well as a vector of changes in individual time-varying characteristics, ΔX_{it}. All time-invariant individual

---

[7] We present robust twostep estimates using the Stata command xtabond2 (Roodman, 2006).

[8] The caregiving effect and the family effect might reinforce each other, for example, when care provision becomes more challenging due to severe illness of the care recipient. Adding an interaction term to the model, we indeed observe a positive interaction between the two effects. We do not include this interaction term in the models presented in this paper, as the approach is highly data demanding.

characteristics are factored out by differencing. Our main parameters of interest are β_2 indicating the caregiving effect, and β_3 indicating the family effect.

3.4 Data

We use the Dutch *Study on Transitions in Employment, Ability and Motivation* (STREAM) panel survey, which includes four annual waves of data ranging from 2010 to 2013. It collects extensive information on determinants of transitions into and out of employment and of work productivity among persons aged 45-64 years. This is also the age group providing most informal care in the Netherlands (Gezondheidsmonitor, 2016). The STREAM sample is stratified at baseline on age and work status and is drawn from an existing internet panel (Ybema et al., 2014). In the first wave, 15,118 persons responded to the survey. In later waves, this original sample was invited to participate again without replacement. Attrition is fairly low: in total almost two-thirds (64%) of the sample responded to all four surveys. The panel data are linked at the individual level to administrative data for all registered inhabitants in the Netherlands obtained via Statistics Netherlands.[9]

Sample

From the 15,118 first wave respondents, we select a subsample of individuals who could potentially provide informal care to their parent or partner. We do so by only including respondents who have a living parent or partner at baseline. As the difference GMM regression requires at least three waves of data, we solely include individuals who responded at least three times to the survey. Table A3.2 in the Appendix provides an overview of the inclusion criteria. Our sample at baseline consists of 4,400 males and 3,528 females; across all waves we have 17,055 male and 13,693 female observations.[10]

Health measurement

The panel data enable us to use four complementary, validated self-reported health outcomes. The first two measures are derived from the SF-12 health survey, which contains questions regarding health during the past four weeks. From this survey, we derive two subscales: the Physical Component Summary Scale (PCS) and the Mental

---

[9] We use non-public microdata which, when adhering to various conditions, can be accessed via a secured remote access connection.

[10] We consider this sample a random subsample, no large discrepancies in observable characteristics between the subsample and total sample were detected.

Component Summary Scale (MCS).[11] Both scales range from 0 to 100, a higher score equals a better health status (Ware et al., 1995).

In addition to these general mental and physical health scores, we use two measures that capture specific aspects of health that are particularly likely to be affected by caregiving; fatigue and depression. Informal caregiving often leads to caregiver fatigue because caregivers may prioritize the patient's needs over their own (Schulz et al., 1990). Additionally, the stress involved in caregiving (Pinquart & Sörensen, 2003a), as well as the stress caused by illness of family members (Amirkhanyan & Wolf, 2006), can lead to an increase in depressive symptoms. Fatigue is measured using the SF-36 vitality subscale (0-100) based on responses to four items[12], where a higher score relates to lower fatigue/higher vitality (Ware et al., 1993).[13] To measure depression, we use the CES-D-10 scale (0-30). A higher score relates to increased presence of depressive symptoms (Andresen, Malmgren, Carter, & Patrick, 1994). Following scoring instructions (Andresen et al., 1994; Ware et al., 1993; Ware et al., 1995), health scores were reported as missing in case the respondent failed to answer any (MCS & PCS), >1 question (CES-D-10) or >2 questions (vitality scale).

Measurement of informal caregiving

The main variable of interest is a binary variable indicating whether someone provided informal care (IC) in the past year. Respondents were asked: 'Did you in the past 12 months spend part of your time on any of the following activities?' When they answer 'Giving informal care' affirmatively, they are considered informal caregivers.[14] In the last two waves of the survey, respondents were also asked to indicate *to whom* they provided care. To analyze differences in the type of care provided, we distinguish between spousal, parental and other types of caregiving in subgroup analyses. Based on the 2012 and 2013 observations, we impute the type of care in the first two waves assuming that the care recipient (parent or spouse) remains the same throughout the years.[15] In Table A3.3 in the Appendix an overview of the number of informal caregivers is given, specified by care recipient. As our sample is limited to respondents aged 45-65 we do not capture the entire caregiving population, especially spousal caregivers tend to be older and hence underrepresented in our data. Our results

---

[11] The scales consists of the following sub-scales: Physical functioning (2 questions), Role-Physical (2 questions), Bodily Pain and General Health, Vitality, Social Functioning, Role-Emotional (2 questions) and Mental Health (2 questions).

[12] The past four weeks: (1) Did you feel full of life? (2) Did you have a lot of energy? (3) Did you feel worn out? (4) Did you feel tired?

[13] Although the vitality subscale was developed as part of a broader health measure, the subscale is used in isolation in various patient populations (e.g. Hewlett et al., 2011).

[14] Informal care (in Dutch: Mantelzorg) refers to providing non-professional care for a person in need in your own close environment, it does not include looking after healthy family members.

[15] This assumption seems credible, between 2012 and 2013 the care recipient changed in only 4% (spouses) and 7% (parents) of the cases.

might therefore underestimate the average health effect for the full population of caregivers, as older caregivers might be more prone to the negative health effects of caregiving (Pinquart & Sörensen, 2003a).

Covariates

As explained in section 3.3, we take first-differences and control for lagged health. We furthermore estimate the family effect by including a variable indicating whether the respondent indicated that a spouse or close family member has become severely ill within the past year. Furthermore, we include the following individual-level covariates: age, age-squared, self-reported financial difficulties[16], percentile group of standardized household income, marital status, having children living at home, employment status[17], and whether or not the father or mother is alive. Finally, we include wave dummies to capture time trends affecting all respondents, including for instance any trends in formal LTC use.[18]

3.5 Results

3.5.1 Descriptive statistics

Table 3.1 presents descriptive statistics for our sample at baseline, stratified by respondent caregiver status. Caregivers are more often females, and have a lower health status at baseline. As expected, informal caregivers more often have ill family members. Table A3.4 in the Appendix presents the descriptive statistics for the sample stratified by gender.

---

[16] This variable equals 1 when the respondent indicated that their household is currently very short or a bit short on money.

[17] Next to health effects, informal care might also affect someone's work situation. Including income and employment as control variables might therefore bias results when these variable act as dependent variables ('bad controls') in the model (Angrist & Pischke, 2008). However, Rellstab et al. (2020) show that, as the Dutch LTC system is generous and comprehensive, there are no direct employment and income effects and hence we include these control variables in the model. When testing this decision empirically, we do not observe large differences in our main estimations dependent on inclusion of these variables.

[18] There are no differences across regions or between households in formal care availability that we need to account for. In general, co-payments are low and income-related and there are virtually no waiting lists for formal care use (Mot, 2010).

Table 3.1: Descriptive statistics of baseline sample

	Never informal caregiver		Ever informal caregiver		
	Mean	**SD**	**Mean**	**SD**	
	1	**2**	**3**	**4**	**3-1**
Health outcomes					
SF-12 physical score	49.27	9.75	48.82	9.98	*
SF-12 mental score	52.64	8.26	51.24	9.46	***
SF-36 vitality scale	66.31	19.11	63.85	19.79	***
CES-D-10 depression index	5.03	4.83	5.70	5.30	***
Health family					
Severe illness of spouse/family member	0.14	0.34	0.27	0.45	***
Severe illness of spouse	0.02	0.15	0.07	0.25	***
Severe illness of close family	0.12	0.32	0.22	0.41	***
Personal characteristics					
Age	53.74	5.52	53.94	5.20	
Age Squared	2,918.66	596.09	2,936.92	562.26	
Gender	0.35	0.48	0.57	0.49	***
Married/registered partnership	0.87	0.34	0.83	0.38	***
Children living at home	0.47	0.50	0.44	0.50	***
Employed	0.89	0.32	0.85	0.35	***
Perc. group household income	68.20	22.71	67.92	23.33	
Financial difficulties	0.19	0.39	0.20	0.40	*
Father alive	0.53	0.50	0.66	0.47	***
Mother alive	0.31	0.46	0.35	0.48	***
Informal caregiving					
Average care duration (# waves)	-	-	2.25	1.25	***
Number of observations in T_1	4,654		3,273		
Total number of observations	17,981		12,758		

Note: SF-12 PCS and MCS and SF-36 Vitality range from 0-100 (lowest - highest level of health). CES-D-10 ranges from 0-30. A score ≥ 10 is considered a sign of depression. *p<0.10, ** p<0.05 *** p<0.01 indicate differences between never and ever informal care sample.

3.5.2 Health effects

The estimation results of the A-B models presented in Table 3.2 suggest that informal caregiving only has a negative effect on mental health as measured by the MCS. The effect is small compared to the mean MCS score (only about 1%). We also observe significant family effects on mental health: a severe illness occurring to a family member leads to a significant decrease in the mental health score of about the same size as the caregiving effect and to a significant increase in depressed feelings.[19] Only changes in a few other covariates (i.e. having financial difficulties, being employed, and mother alive) are associated with health changes.

The family effect is important in itself, but also because omitting it from a regression may lead to an upward bias of the estimate of the caregiving effect. To examine the importance of not considering the family effect on the magnitude of the caregiving effect, we reran our analysis while excluding the family effect. The estimated coefficients of the health effect of informal caregiving in both models are presented in Table 3.3. It shows that ignoring the family effect in these models would, compared to our main model, yield a slightly higher estimate for the caregiving effect for mental health scores, though the difference is not significant. We do not find an effect for the physical health score.

The family effect and the caregiving effect differ by gender (see: Table A3.5 in the Appendix); both the caregiving effect and the family effect only affect the mental health of females.[20] Males, by contrast, experience a physical health decline in response to informal caregiving. This difference does not seem to be driven by hours spent caring, since male and female caregivers in the sample devote roughly the same amount of time to care.

---

[19] In additional regressions we verified whether the family effect differed when including hours of care instead of a dummy for informal care. This turned out not to be the case (results available upon request).

[20] The differences in the caregiving effects by gender are significant for PCS, MCS and CESD at the 0.05, 0.10 and 0.05 level, respectively.

Table 3.2: Arellano-Bond difference GMM regressions

A-B	**Both genders**			
	SF-12 PCS	**SF-12 MCS**	**SF-36 vitality**	**CES-D-10 depression**
Informal care	-0.07 (0.19)	-0.45** (0.22)	-0.49 (0.35)	0.14 (0.10)
Severe illness spouse/family	0.14 (0.15)	-0.43*** (0.17)	-0.29 (0.27)	0.16** (0.08)
Lagged health	0.10*** (0.02)	0.11*** (0.02)	0.09*** (0.02)	0.09** (0.02)
Employed	0.46 (0.29)	-0.23 (0.31)	-1.74*** (0.54)	-0.01 (0.16)
Financial difficulties	-0.22 (0.21)	-0.18 (0.25)	-1.14*** (0.40)	0.32*** (0.12)
Perc. group household inc.	-0.01 (0.01)	0.01* (0.00)	0.01 (0.01)	-0.00 (0.00)
Age	0.43 (0.53)	-0.68 (0.54)	-0.20 (0.97)	0.29 (0.27)
Age Squared/100	-0.47 (0.48)	0.61 (0.48)	0.08 (0.86)	-0.23 (0.24)
Married/Reg. partnership	-0.58 (0.54)	1.18 (0.77)	1.26 (1.11)	-0.65* (0.36)
Children living at home	-0.07 (0.30)	-0.30 (0.33)	-0.48 (0.56)	0.14 (0.16)
Mother Alive	0.10 (0.39)	-0.98** (0.43)	-0.84 (0.70)	0.06 (0.20)
Father Alive	0.54 (0.40)	-0.21 (0.51)	-0.22 (0.74)	0.21 (0.22)
Hansen J-test (p-value)	0.50 (0.78)	0.96 (0.61)	3.2 (0.21)	2.86 (0.24)
Number of instruments	3	3	3	3
N	13,626	13,626	14,824	14,822
Unique individuals	7,430	7,430	7,892	7,893

Note: Robust standard errors are in parentheses. All regressions include wave dummies. *p<0.10, ** p<0.05 *** p<0.01. Depending on the model that is estimated, lagged health refers to the lag of the corresponding dependent variable.

Table 3.3: Coefficients caregiving effect in model with or without family effect

A-B	**Both genders**			
	SF-12 PCS	**SF-12 MCS**	**SF-36 vitality**	**CES-D-10 depression**
Informal care (in model with family effect)	-0.07 (0.19)	-0.45** (0.22)	-0.49 (0.35)	0.13 (0.10)
Informal care (in model without family effect)	-0.05 (0.19)	-0.49** (0.22)	-0.52 (0.34)	0.15 (0.10)

Note: Robust standard errors are in parentheses. Included controls: lagged health, age, age^2, financial difficulties, married, children at home, employed, standardized household income, mother alive, father alive, wave dummies. Regressions include wave dummies. *p<0.10, ** p<0.05 *** p<0.01.

Our A-B models rely on deeper lags of health to instrument the lagged first-difference in health. The first stage results show the relevance of these instruments (Table A3.6): the excluded lagged levels of health are strongly correlated with the lagged difference in health. This is confirmed by the Kleibergen-Paap Wald *rk F*-statistics for the excluded instruments, indicating that the instruments are strong. The Hansen (1982) J-test statistics for overidentifying restrictions provide an indication of the validity of our instruments: for all models, we cannot reject the null-hypothesis that all instruments are valid.[21]

3.5.3 Heterogeneous effects: subsample analyses

In order to assess whether the caregiving effect and the family effect differ for various types of caregiving, we carry out several subsample analyses. These subgroup analyses are of interest in themselves, but also facilitate an easier comparison with prior studies which often focused on subgroups only. First, we analyze whether the provision of more informal care also leads to larger health damage. There indeed appears to be a dose-response relationship: for individuals that start providing at least 8 hours of care per week[22] (31% of the caregivers provide at least this amount of care), the impact of informal care on mental health and vitality is considerably larger than for the group providing less than 8 hours of care per week (Table 3.4).

Table 3.4: A-B estimates for subgroups stratified by caregiving intensity

A-B intensive care	**Both genders**			
	SF-12 PCS	**SF-12 MCS**	**SF-36 vitality**	**CES-D-10 depression**
1-7 hours of informal care	-0.09 (0.20)	-0.32 (0.23)	-0.26 (0.37)	0.13 (0.11)
≥8 hours of informal care	0.01 (0.29)	-0.89*** (0.32)	-1.25** (0.52)	0.17 (0.15)
Illness family member	0.14 (0.15)	-0.42** (0.17)	-0.27 (0.27)	0.16** (0.08)
Hansen J-test	0.5 (0.78)	0.98 (0.61)	3.2 (0.20)	2.85 (0.24)
Number of instruments	3	3	3	3
N	13,626	13,626	14,824	14,822
Unique individuals	7,430	7,430	7,892	7,893

Note: Robust standard errors are in parentheses. Included controls: lagged health, age, age^2, financial difficulties, married, children at home, employed, standardized household income, mother alive, father alive, wave dummies. *p<0.10, ** p<0.05 *** p<0.01.

---

[21] The difference GMM model furthermore relies on the assumption of no serial correlation among the errors, which can be assessed using the test proposed by Arellano and Bond (1991). This test focuses on finding autocorrelation among the differenced error terms. We cannot test for second order autocorrelation, as it requires five waves of data. In the absence of any formal test for this assumption, we rely on Coe and Van Houtven (2009) and Roy and Schurer (2013) who did not find any second order serial correlation of the residuals for mental health in a similar model. We also estimated our model using a deeper lag of health (H_{it-3}) instead of both H_{it-3} and H_{it-2}, which would solve the problem in case any second order correlation was present. Use of this deeper lag of health hardly affected our estimates, supporting the validity of our assumption.

[22] We use the threshold of ≥8 hours following the definition of informal care of Statistics Netherlands (2016).

The caregiving effect is larger when caring for a spouse instead of someone else (Table 3.5). Spousal caregiving especially affects vitality and depression scores. These effects are substantial; caregiving relates to a change of for example more than 10% of the average CES-D-10 score. We also observe a difference in terms of the family effect; a severe illness of a spouse has a negative effect on mental health and vitality scores and increases depression scores, but these effects are absent when a parent or other close family member falls ill.

For all subgroup analyses, the results stratified by gender can be found in the Appendix. Tables A3.7 and A3.8 show that all effects (except for the physical health effect) are larger for females and often significantly different by gender.[23]

Table 3.5: A-B estimates for informal care to various types of care receivers

A-B different caregivers	**Both genders**			
	SF-12 PCS	**SF-12 MCS**	**SF-36 vitality**	**CES-D-10 depression**
Informal care to spouse	-0.82 (0.61)	-1.05 (0.73)	-1.85* (1.04)	0.71** (0.28)
Informal care to parent	0.02 (0.26)	-0.50* (0.30)	-0.09 (0.46)	0.06 (0.15)
Informal care to other person	0.01 (0.28)	-0.29 (0.29)	-0.56 (0.49)	0.08 (0.13)
Spouse severely ill	-0.18 (0.16)	-1.04** (0.43)	-1.51** (0.65)	0.45** (0.19)
Close family member severely ill	0.18 (0.16)	-0.22 (0.18)	0.00 (0.29)	0.10 (0.08)
Hansen J-test	0.53 (0.47)	0.95 (0.33)	3.15 (0.08)	2.85 (0.09)
Number of instruments	3	3	3	3
N	13,626	13,626	14,824	14,822
Unique individuals	7,430	7,430	7,892	7,893

Note: Robust standard errors are in parentheses. Included controls: Lagged health, age, age^2, financial difficulties, married, children at home, employed, financial difficulties, standardized household income, wave dummies. *p<0.10, ** p<0.05 *** p<0.01.

3.5.4 Robustness analyses

Results for several tests of robustness of our model estimates are presented in the Appendix. To test whether the GMM model is able to overcome the dynamic panel bias, we first compare the A-B output with OLS and FE estimation results (Tables A3.9 and A3.10). As OLS (not controlling for individual fixed effects) and FE (suffering

---

[23] The caregiving effect of 1-7 hours of care differs by gender for PCS, MCS and CESD at the 0.05, 0.10 and 0.05 level, for intensive caregiving this difference is present for PCS and vitality at the 0.05 and 0.10 level. The difference in the parental caregiving effect is significantly different by gender for vitality and depression at the 0.01 and 0.10 level. The difference in the spousal caregiving effect by gender is significantly different for PCS, MCS and depression at the 0.05, 0.05 and 0.10 level.

from dynamic panel bias), lead to biases in different directions, the estimates of both models represent upper and lower bounds for our autoregressive coefficient (Bond, 2002). Our A-B estimate of lagged health is indeed bounded by the OLS and FE estimates. The estimated caregiving effect and family effect in both models do not differ substantially from the A-B estimates.

Second, in all our models, we rely on self-reported information regarding health shocks of family members. This variable could be prone to justification bias: caregivers may justify their decision to provide care (and possibly their withdrawal from the labor market) by overstating the need of their family member (Bound, 1991). To rule this out, we rerun all models using a variable indicating the occurrence of a negative health shock of a family member (i.e. parent or spouse) as obtained from administrative data. For this test, we use a variable indicating whether a parent or spouse has become eligible for formal LTC in the current year because this indicates a substantial health decline that causes functional limitations and thus a need for both professional and informal help. The estimated coefficients for the family effect do not differ much between both indicators, except for the coefficient for the MCS which becomes insignificant and positive (Table A3.11). We use severe illness instead of LTC eligibility in the main analyses, as this variable covers a broader set of health problems.

Furthermore, our model might overestimate the caregiving effect when our indicator of the family effect does not capture all family health shocks. To test this, we include a selection of variables regarding the health of spouses and parents from administrative data. These administrative data include annual outpatient prescription drug use at the ATC 3 level, eligibility for publicly funded formal home care and nursing home care, and various types of health insurance spending such as GP care, hospital care and nursing care. As these data contain a very large number of potential indicators that would reduce any omitted variable bias, we use LASSO regression to select the most relevant variables (Belloni et al., 2012). The caregiving effect on mental health persists after adding these additional health variables, which suggests that the effect in the main analysis is robust to more extensive control for the family effect (Table A3.12). As including multiple measures of family health shocks means that the family effect is no longer easy to interpret, we rely on the health shock indicator in our main models.

Finally, we test the robustness of our results using a different methodology. Instead of the A-B method, we use a bias-correction estimation method to correct for the dynamic panel bias. For this test we make use of the Stata command *xtlsdvc* (Bruno, 2005). The estimated caregiving and family effect closely match our initial results (Table A3.13). We prefer to rely on difference-GMM methods in our main models as it is better suited towards models where the number of observations is large (Bruno, 2005).

3.6 Discussion and conclusion

Illness and frailty may have health consequences for individuals who *care for* and *care about* spouses and parents in bad health, i.e. the caregiving effect and the family effect. Most of the literature to date did not distinguish between these two. Using a Dutch panel survey of respondents aged 45-65, we find evidence for both effects, particularly on mental health. Our estimates of the caregiving effect on mental health are smaller than those of previous studies such as De Zwart et al. (2017) and Schmitz & Westphal (2015). For example Schmitz & Westphal (2015) reported an impact of caregiving on mental health of -2 on the MCS for female caregivers, in contrast to -0.8 in this study.

Our findings contribute to the literature on informal caregiving in a number of ways. First, they highlight the importance of estimating the family effect separately: the onset of an illness of a family member has spillover effects to both caregiving and non-caregiving family members that can add to the burden of providing informal care. Thus, considering the family effect is important, even though in this study controlling for the family effect does not have implications for the estimated caregiving effect itself. Additionally, ignoring the family effect and using health of a family member as an instrument for informal caregiving is problematic because the direct negative effect of the health of a family member on the caregiver's health means that the exclusion restriction of the instrument is likely to be violated.

Second, we conducted interesting subgroup analyses. These indicate that female caregivers experience larger caregiving effects on mental health than male caregivers. Explanations could be that females are more often the primary caregiver and more likely to experience social pressure to become a caregiver (Pinquart & Sörensen, 2003a). The caregiving effect is also especially large for spousal caregivers. This finding may derive from a different intensity of caregiving; descriptive statistics show that spousal caregivers often provide more hours of informal care than other types of caregivers.

The findings of significant negative caregiving effects and family effects on mental health indicate that policymakers who seek to mitigate the negative spillovers from illness of an elderly person should focus on relieving the burden of caregiving activities but should not neglect the other family members. Furthermore, the findings show that the impact of caregiving is not the same for all subgroups of caregivers. Especially female and spousal caregivers experience large negative mental health effects of caregiving. Policymakers could specifically aim to support these groups of caregivers with targeted interventions.

Appendix chapter 3

Table A3.1: Overview of literature regarding health effects of informal caregiving accounting for endogeneity of caregiving.

Authors	Data source	Care recipient	Sample (sample size)	Health measure	Focus on family effect	Estimator	Instrumental variable	Results
Coe and Van Houtven (2009)	HRS, 1992-2004 (7 waves)	Parent	Males and females aged 50 to 64, having only a mother alive (1,467 current caregivers) Distinction married/single	Mental health (CES-D8); Physical health (self-reported health on a 5-point, diagnosed heart condition & blood pressure).	-	IV, Arellano-Bond	(1) Death of a parent (2) Sibling characteristics	(1) Continued caregiving: ↑ CES-D-8 (married males and females) ↑ Heart condition (single males) likelihood of reporting excellent or very good health (↓ married females, ↑ married males) (2) Initial caregiving: ↑ CES-D-8 (married females)
Do et al. (2015)	Korean LSA, 2006-2010 (3 waves)	Parent (in-law)	Women with living parent(in law), aged 45+, (2,528 daughters-in-law & 4,108 daughters)	Pain affecting daily activities; Fair or poor self-rated health; Any outpatient care use; OOP spending for outpatient care; Any prescription drug use; OOP spending prescription drugs.	Claim to avoid family effect by focusing on physical health and care for parents-in-law	IV-2SLS, IV-probit	ADL limitations of the mother(-in-law) and father(-in-law)	↑ Pain affecting daily activities, Health Self-rated as poor, OOP outpatient care (daughters & daughters-in-law) ↑ Any outpatient care use, Any prescription drug use (daughters)

Table A3.1: Continued.

Authors	Data source	Care recipient	Sample (sample size)	Health measure	Focus on family effect	Estimator	Instrumental variable	Results
Heger (2017)	SHARE, 2004-2013 (4 waves)	Parent	Women and men aged 50-70 (3,669 women & 2,752 men)	EURO-D depression scale, indicator whether someone suffers from 4 or more depressive symptoms.	Estimate family effect by adding health of parent as variable to model	IV-FE	Indicator of whether one parent is alive	↑ Euro-D, 4+ depressive symptoms (females) Family effect small
Van den Berg et al. (2014)	HILDA, 2001-2011 (11 waves)	Partner, parent (in-law) or relative	Aged 16+ (23,285 individuals)	Individual subjective well-being	-	FE-ordered logit	NA	↓ Well-being
Schmitz and Westphal (2015)	GSOEP, 2002-2010	Unknown	Women aged 18+, (31,177 person-year observations at t = 0)	SF-12v2 MCS & PCS	-	Matched regression	NA	Short term: ↓ SF-12 Mental Component Summary Scores
Brenna and Di Novi (2016)	SHARE, 2004-2007 (2 waves)	Parent	Women aged 50-75 (N=3,936)	Euro-D depression scale	-	Matched regression	NA	↑ Euro-D (females, Southern European countries)
De Zwart et al. (2017)	SHARE, 2004, 2006, 2010, 2013	Partner	Males and females aged 50+ (N=10,472)	Prescription drugs usage; number of doctor visits in the past 12 months; EURO-D depression scale; self-perceived health.	-	Matched regression	NA	Short term: ↑ Euro-D, ↓ self-reported health; ↑ prescription drug use (females), ↑ doctor visits (females)

Note: For the depression related health scales (CES-D and Euro-D), an increase in the health scale refers to a negative health change (an increase in depressive feelings). For the SF-12 and self-reported health, an increase refers to a positive health change.

Table A3.2: Sample size and sample selection criteria

Inclusion criteria	**Overall sample (% of total)**
Total respondents at T_1 (2010)	15,118
Agreement to be linked to administrative data	13,672 (90.4)
Identified in administrative data	13,398 (88.6)
Did not submit survey twice in same wave	13,218 (87.4)
Having at least one parent alive and/or having a spouse (married or reg. partnership) at T_1	10,855 (71.8)
Fully completed ≥3 surveys	7,928 (52.6)
Total number of respondents included T_1	7,928

Table A3.3: Number of informal caregivers, specified by care recipient

	Males				**Females**			
	2010	**2011**	**2012**	**2013**	**2010**	**2011**	**2012**	**2013**
Total informal caregivers (includes other care recipients)	653	699	697	867	1,156	1,202	1,267	1,168
Started providing informal care		277	320	322		310	337	304
Stopped providing informal care		231	228	168		263	270	253
Average number of hours of informal care per week	8.24	8.19	8.48	8.13	9.01	8.47	8.53	7.97
Providing informal care to close family member (parent)	238[a]	292[a]	394	433	625[a]	686[a]	804	732
Providing informal care to spouse	94[a]	112[a]	140	174	114[a]	128[a]	134	131

a: Imputed based on care recipient in 2012-2013.

Table A3.4: Descriptive statistics of sample at baseline

	Male					Female				
	Never Informal caregiver		Ever Informal caregiver			Never Informal caregiver		Ever Informal caregiver		
	Mean	SD	Mean	SD		Mean	SD	Mean	SD	
Health outcomes										
SF-12 physical score	50.35	8.39	50.35	8.52		47.28	11.59	47.67	10.81	
SF-12 mental score	53.15	7.69	51.72	9.26	***	51.70	9.15	50.88	9.59	**
SF-36 vitality scale	68.24	17.87	66.38	19.58	***	62.79	20.73	61.96	19.74	
CES-D-10 depression scale	4.61	4.49	5.17	5.15	***	5.80	5.31	6.09	5.38	
Health family										
Severe illness spouse/family	0.14	0.34	0.25	0.43	***	0.14	0.35	0.29	0.45	***
Severe illness spouse	0.02	0.15	0.08	0.27	***	0.02	0.15	0.06	0.23	***
Severe illness close family	0.11	0.32	0.18	0.38	***	0,12	0,32	0,25	0,43	***
Personal characteristics										
Age	54.05	5.49	54.54	5.07	***	53.18	5.54	53.50	5.24	
Age Squared	2951.4	594.2	2999.9	551.3	***	2858.9	595.1	2890.2	565.9	
Married/registered partnership	0.89	0.31	0.88	0.33	***	0.82	0.38	0.79	0.41	***
Children living at home	0.49	0.50	0.46	0.50	***	0.44	0.50	0.42	0.49	
Employed	0.93	0.26	0.91	0.29	***	0.81	0.39	0.81	0.39	
Perc. group household income	69.08	21.83	69.16	22.57		66.58	24.14	67.00	23.84	
Financial difficulties	0.17	0.38	0.20	0.40	***	0.22	0.41	0.20	0.40	
Father alive	0.53	0.50	0.62	0.49		0.53	0.50	0.69	0.46	***
Mother alive	0.31	0.46	0.33	0.47	**	0.31	0.46	0.37	0.48	***
Informal caregiving										
Average care duration (# waves)			2.02	1.14	***			2.42	1.22	***
Number of observations in T_1	3,006		1,394			1,648		1,880		

Note: SF-12 PCS and MCS and SF-36 Vitality range from 0-100 (lowest - highest level of health). CES-D-10 ranges from 0-30, a score ≥10 is considered a sign of depression. *p<0.10, ** p<0.05 *** p<0.01 indicate differences between never and ever IC sample.

Table A3.5: A-B estimates for males and females

A-B	Males				Females			
	SF-12 PCS	SF-12 MCS	SF-36 vitality	CES-D-10 depression	SF-12 PCS	SF-12 MCS	SF-36 vitality	CES-D-10 depression
Informal care	-0.56**	-0.06	-0.22	-0.09	0.34	-0.81**	-0.79	0.34**
	(0.27)	(0.29)	(0.48)	(0.14)	(0.27)	(0.32)	(0.49)	(0.14)
Severe illness close family	0.11	-0.37	-0.45	0.15	0.19	-0.51**	-0.14	0.19
	(0.19)	(0.23)	(0.35)	(0.11)	(0.23)	(0.25)	(0.41)	(0.12)
Hansen J-test	0.67	0.18	3.50	0.84	0.18	0.97	0.93	2.71
	(0.71)	(0.91)	(0.18)	(0.66)	(0.91)	(0.62)	(0.63)	(0.26)
Number of instruments	3	3	3	3	3	3	3	3
N	7,588	7,588	8,228	8,222	6,038	6,038	6,596	6,600
Unique indiv.	4,127	4,127	4,377	4,375	3,303	3,303	3,515	3,518

Note: Robust standard errors are in parentheses. Included controls: lagged health, age, age^2, financial difficulties, married, children at home, employed, standardized household income, mother alive, father alive, wave dummies. *p<0.10, ** p<0.05 *** p<0.01.

Table A3.6: First stage statistics of A-B estimations

1st Stage	Both genders			
	1.Lag Δ SF-12 PCS	1.Lag Δ SF-12 MCS	1.Lag Δ SF-36 vitality	1.Lag Δ CES-D-10 depression
2.Lag Health indicator[a]	-0.25*** (0.01)	-0.46*** (0.01)	-0.30*** (0.01)	-0.33*** (0.01)
2.Lag Health indicator	-0.34*** (0.01)	-0.48*** (0.02)	-0.47*** (0.01)	-0.52*** (0.01)
3.Lag Health indicator	0.13*** (0.01)	0.11*** (0.01)	0.31*** (0.01)	0.32*** (0.02)
Kleibergen-Paap Wald *rk* *F*-statistic	446.29	726.89	755.6	624.7
N	13,626	13,626	14,824	14,822

Note: a. As the instrument matrix is not collapsed, we have separate instruments dependent on whether only the 2nd lag, or both the 2nd and 3rd lag of health can be used as instruments. Robust standard errors are in parentheses. These regressions also include: informal care, severe illness of spouse/family member, age, age^2, financial difficulties, children at home, married, employed, financial difficulties, standardized household income, mother alive, father alive, wave dummies. *p<0.10, ** p<0.05 *** p<0.01. Depending on the model that is estimated, lagged health refers to the lag of the corresponding dependent variable.

Table A3.7: A-B estimates for higher intensity informal caregiver

A-B Intensive care	**Males**				**Females**			
	SF-12 PCS	**SF-12 MCS**	**SF-36 vitality**	**CES-D-10 depression**	**SF-12 PCS**	**SF-12 MCS**	**SF-36 vitality**	**CES-D-10 depression**
1-7 hours of informal care	-0.54*	0.10	-0.16	-0.18	0.29	-0.69**	-0.47	0.37**
	(0.30)	(0.32)	(0.53)	(0.16)	(0.28)	(0.33)	(0.52)	(0.15)
≥8 hours of informal care	-0.62	-0.52	-0.39	0.17	0.54	-1.25***	-1.95***	0.25
	(0.38)	(0.45)	(0.71)	(0.23)	(0.42)	(0.45)	(0.74)	(0.20)
Severe illness close family	0.11	-0.36	-0.45	0.14	0.18	-0.50**	-0.12	0.19
	(0.19)	(0.23)	(0.35)	(0.11)	(0.23)	(0.25)	(0.41)	(0.12)
Hansen J-test	0.67	0.18	3.51	0.85	0.18	0.97	0.95	2.73
	(0.72)	(0.91)	(0.17)	(0.65)	(0.92)	(0.62)	(0.62)	(0.26)
Number of instruments	3	3	3	3	3	3	3	3
N	7,588	7,588	8,228	8,222	6,038	6,038	6,596	6,600
Unique indiv.	4,127	4,127	4,377	4,375	3,303	3,303	3,515	3,518

Note: Robust standard errors are in parentheses. Included controls: lagged health, age, age^2, financial difficulties, married, children at home, employed, standardized household income, mother alive, father alive, wave dummies. *p<0.10, ** p<0.05 *** p<0.01.

Table A3.8: A-B estimates informal care to various types of care receivers

A-B	**Males**				**Females**			
	SF-12 PCS	**SF-12 MCS**	**SF-36 vitality**	**CES-D-10 depression**	**SF-12 PCS**	**SF-12 MCS**	**SF-36 vitality**	**CES-D-10 depression**
Informal care to spouse	-1.59**	-0.17	0.92	0.37	0.15	-2.22*	-5.47***	1.20***
	(0.74)	(0.84)	(1.32)	(0.40)	(1.02)	(1.27)	(1.56)	(0.37)
Informal care to parent	-0.66*	0.15	0.17	-0.21	0.55	-0.98**	-0.28	0.28
	(0.34)	(0.39)	(0.62)	(0.20)	(0.36)	(0.43)	(0.66)	(0.20)
Informal care to other person	-0.20	-0.21	-0.78	-0.11	0.16	-0.39	-0.56	0.26
	(0.37)	(0.40)	(0.70)	(0.20)	(0.40)	(0.42)	(0.68)	(0.18)
Severe illness spouse	-0.28	-0.77	-1.20	0.18	-0.03	-1.39**	-1.89*	0.70**
	(0.44)	(0.55)	(0.84)	(0.26)	(0.50)	(0.68)	(0.99)	(0.28)
Severe illness close family	0.15	-0.20	-0.28	0.17	0.21	-0.25	0.26	0.06
	(0.20)	(0.24)	(0.39)	(0.12)	(0.24)	(0.25)	(0.43)	(0.12)
Hansen J-test	0.73	0.16	3.36	0.83	0.17	1.59	1.17	2.74
	(0.39)	(0.69)	(0.07)	(0.36)	(0.68)	(0.21)	(0.28)	(0.10)
Number of instruments	3	3	3	3	3	3	3	3
N	7,588	7,588	8,228	8,222	6,038	6,038	6,596	6,600
Unique indiv.	4,127	4,127	4,377	4,375	3,303	3,303	3,515	3,518

Note: Robust standard errors are in parentheses. Included controls: Lagged health, age, age^2, financial difficulties, married, children at home, employed, financial difficulties, standardized household income, wave dummies. *p<0.10, ** p<0.05 *** p<0.01.

Table A3.9: OLS estimates of main model

OLS	**Both genders**			
	SF-12 PCS	**SF-12 MCS**	**SF-36 vitality**	**CES-D-10 depression**
Informal care	-0.24**	-0.31***	-0.57***	0.18***
	(0.10)	(0.11)	(0.19)	(0.06)
Severe illness spouse/family	-0.22*	-0.80***	-0.90***	0.34***
	(0.12)	(0.13)	(0.22)	(0.07)
Lagged health	0.71***	0.53***	0.69***	0.63***
	(0.01)	(0.01)	(0.01)	(0.01)
Age	-1.38***	-1.01***	-2.55***	0.65***
	(0.16)	(0.18)	(0.32)	(0.10)
Age squared / 100	1.30***	1.01***	2.47***	-0.62***
	(0.15)	(0.16)	(0.28)	(0.09)
Married/Registered partnership	0.13	0.76***	1.21***	-0.47***
	(0.12)	(0.15)	(0.25)	(0.08)
Children living at home	0.42***	0.05	0.50**	-0.08
	(0.09)	(0.11)	(0.19)	(0.06)
Employed	2.63***	1.49***	2.77***	-1.05***
	(0.12)	(0.15)	(0.26)	(0.08)
Financial difficulties	-0.63***	-1.05***	-2.34***	0.77***
	(0.12)	(0.14)	(0.23)	(0.07)
Perc. group household income	0.01***	0.01**	0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Mother Alive	0.17*	0.08	0.24	-0.10*
	(0.09)	(0.10)	(0.17)	(0.05)
Father Alive	0.29*	-0.02	0.19	-0.06
	(0.09)	(0.11)	(0.19)	(0.05)
N	21,539	21,539	22,789	22,787

Note: Robust standard errors are in parentheses. All regressions include wave dummies. *p<0.10, ** p<0.05 *** p<0.01. Depending on the model that is estimated, lagged health refers to the lag of the corresponding dependent variable.

Table A3.10: Fixed effects estimates of main model

Fixed Effects	**Both genders**			
	SF-12 PCS	**SF-12 MCS**	**SF-36 vitality**	**CES-D-10 depression**
Informal care	-0.07	-0.34*	-0.47	0.15*
	(0.17)	(0.18)	(0.30)	(0.08)
Severe illness spouse/family	0.15	-0.35**	-0.23	0.14*
	(0.13)	(0.15)	(0.24)	(0.07)
Lagged health	-0.25***	-0.26***	-0.24***	-0.27***
	(0.01)	(0.01)	(0.01)	(0.01)
Age	0.37	-0.47	-0.45	0.36
	(0.54)	(0.56)	(1.01)	(0.28)
Age squared / 100	-0.43	0.63	0.74	-0.38
	(0.47)	(0.49)	(0.88)	(0.24)
Married/Registered partnership	-0.55	1.73**	1.85**	-1.11***
	(0.50)	(0.60)	(0.93)	(0.31)
Children living at home	0.19	-0.46*	-0.65	0.10
	(0.26)	(0.28)	(0.48)	(0.13)
Employed	0.39	0.22	-1.30***	-0.16
	(0.25)	(0.26)	(0.48)	(0.13)
Financial difficulties	-0.26	-0.42***	-1.46***	0.43***
	(0.18)	(0.21)	(0.35)	(0.10)
Perc. group household income	-0.00*	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.00)
Mother Alive	-0.32	-0.48	-0.49	0.09
	(0.35)	(0.34)	(0.60)	(0.18)
Father Alive	0.60	-0.12	0.32	0.07
	(0.38)	(0.45)	(0.72)	(0.20)
N	21,539	21,539	22,789	22,787
Unique individuals	7,906	7,906	7,957	7,958

Note: Robust standard errors are in parentheses. All regressions include wave dummies. *p<0.10, ** p<0.05 *** p<0.01. Depending on the model that is estimated, lagged health refers to the lag of the corresponding dependent variable.

Table A3.11: Robustness check, using LTC eligibility as health shock

A-B	Both genders			
	SF-12 PCS	SF-12 MCS	SF-36 vitality	CES-D-10 depression
Informal care	-0.01	-0.46**	-0.50	0.12
	(0.19)	(0.22)	(0.35)	(0.10)
LTC-eligibility	-0.34	0.33	0.13	0.26**
	(0.22)	(0.28)	(0.43)	(0.13)
Hansen J-test	0.5	1.09	2.80	3.08
	(0.78)	(0.58)	(0.25)	(0.22)
Number of instruments	3	3	3	3
N	13,485	13,485	14,657	14,656
Unique individuals	7,376	7,376	7,830	7,831

Note: Robust standard errors are in parentheses. Included controls: Lagged health, age, age^2, financial difficulties, married, children at home, employed, financial difficulties, standardized household income and wave dummies. *p<0.10, ** p<0.05 *** p<0.01.

Table A3.12: Robustness check, including additional covariates regarding health of family members

Post-LASSO	Both genders			
	SF-12 PCS	SF-12 MCS	SF-36 vitality	CES-D-10 depression
Informal care	-0.11	-0.39*	-0.45	0.13
	(0.20)	(0.22)	(0.36)	(0.11)
Lagged health	0.09***	0.12***	0.09***	0.09***
	(0.03)	(0.02)	(0.02)	(0.02)
Age squared / 100	-0.04	-0.16*	-0.33**	0.06
	(0.08)	(0.09)	(0.15)	(0.04)
Employed	0.47	-0.29	-1.71***	-0.01
	(0.29)	(0.32)	(0.55)	(0.16)
Poor	-0.28	-0.18	-1.08***	0.30**
	(0.22)	(0.26)	(0.42)	(0.12)
Perc. group household income	-0.01	0.02*	0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.00)
Self-reported illness family	0.10	-0.48***	-0.46*	0.18**
	(0.15)	(0.17)	(0.28)	(0.08)
Children at home	0.03		-0.79	
	(0.31)		(0.58)	
Spouse – prescription for drugs used in diabetes	2.81**			
	(1.20)			
Mother - prescription for drugs for obstructive airway diseases	0.36			
	(0.39)			

Table A3.12: Robustness check, including additional covariates regarding health of family members

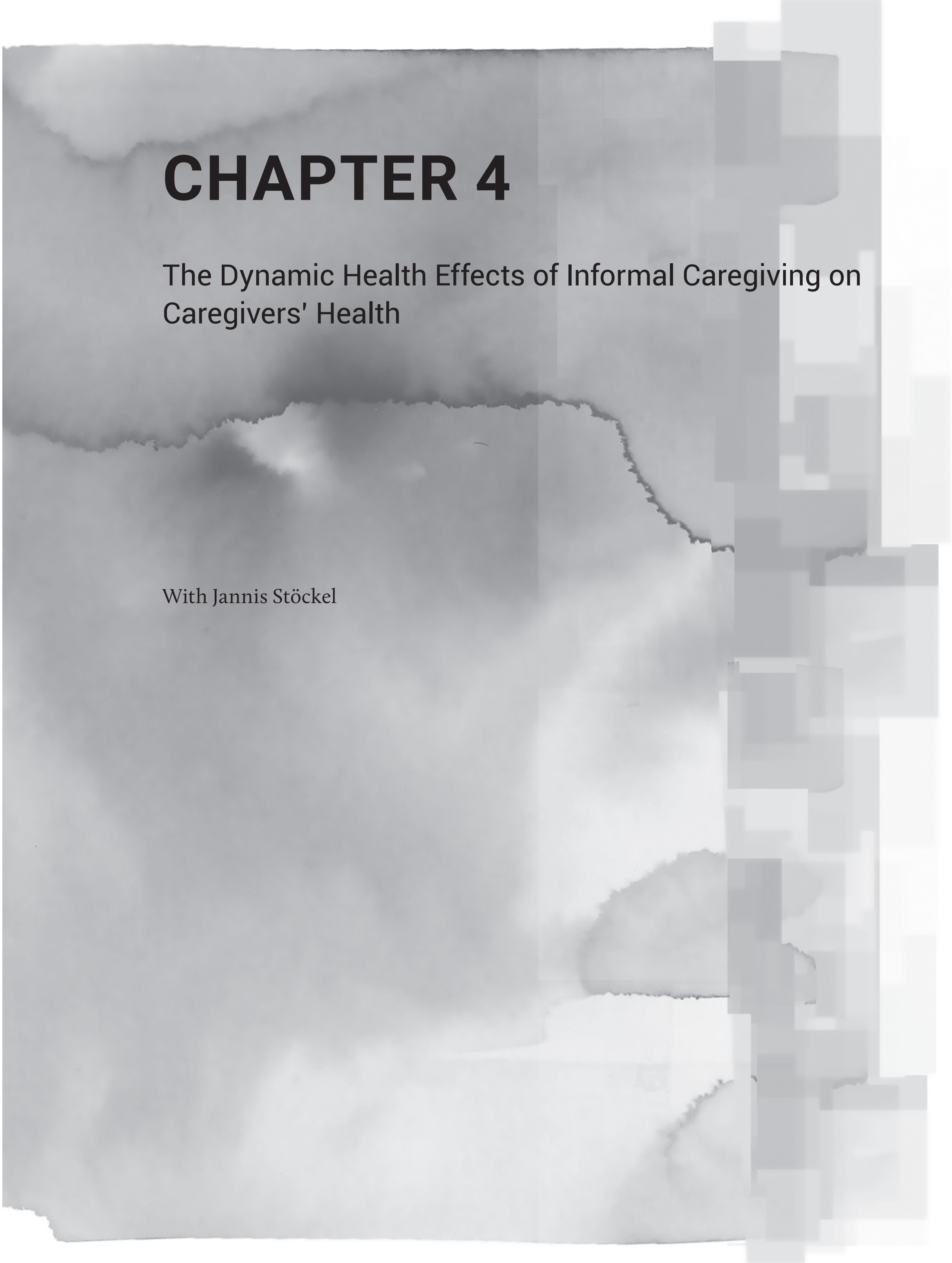
Post-LASSO	**Both genders**			
	SF-12 PCS	**SF-12 MCS**	**SF-36 vitality**	**CES-D-10 depression**
Father - prescription for endocrine therapy	0.06 (0.81)			
Married		0.87 (0.81)	0.78 (1.16)	-0.44 (0.37)
Mother prescription for psycho-analeptics		-0.41 (0.41)	0.07 (0.66)	-0.25 (0.19)
Spouse prescription other products for alimentary tract and metabolism		0.29 (0.83)		
Mother - prescription for digestives. including enzymes		1.03 (1.65)		
Father – health expenses abroad		0.00* (0.00)		
Spouse - prescription for psycho-analeptics			-1.51 (0.94)	
Spouse – Eligible for LTC			-0.88 (1.62)	0.55 (0.51)
Mother - prescription for muscle relaxants				0.37 (0.84)
Father - prescription for antiseptics and disinfectants				-1.86** (0.91)
Hansen J-test	0.23 (0.89)	0.47 (0.79)	2.64 (0.10)	2.71 (0.26)
Number of instruments	3	3	3	3
N	12,791	12,791	13,922	13,919
Unique individuals	6,595	6,595	6,990	6,990

Note: Robust standard errors are in parentheses. All regressions include wave dummies. *p<0.10, ** p<0.05 *** p<0.01. Depending on the model that is estimated, lagged health refers to the lag of the corresponding dependent variable.

Table A3.13: Robustness check, main model using bias correction

Bias correction (99 bootstraps)	**Both genders**			
	SF-12 PCS	**SF-12 MCS**	**SF-36 vitality**	**CES-D-10 depression**
Informal care	-0.14 (0.18)	-0.32* (0.19)	-0.52* (0.30)	0.14* (0.08)
Severe illness spouse/family	0.13 (0.12)	-0.37*** (0.13)	-0.24 (0.22)	0.16** (0.07)
Lagged health	0.09*** (0.01)	0.06*** (0.01)	0.07*** (0.01)	0.06*** (0.01)
Employed	0.39* (0.21)	0.09 (0.23)	-1.54*** (0.44)	-0.09 (0.11)
Financial difficulties	-0.22 (0.20)	-0.34 (0.21)	-1.38*** (0.33)	0.38*** (0.10)
Perc. group household income	-0.01 (0.01)	0.00 (0.01)	0.00 (0.01)	0.00 (0.00)
Age	0.63 (0.49)	-0.97* (0.54)	-0.92 (0.88)	0.45 (0.29)
Age squared / 100	-0.64 (0.45)	0.70 (0.48)	0.35 (0.79)	-0.31 (0.26)
Married/Registered partnership	-0.59 (0.43)	1.51*** (0.46)	1.68** (0.84)	-0.88*** (0.23)
Children living at home	0.14 (0.26)	-0.44 (0.28)	-0.68 (0.51)	0.14 (0.13)
Mother Alive	-0.21 (0.35)	-0.69* (0.38)	-0.67 (0.66)	0.12 (0.19)
Father Alive	0.69** (0.33)	-0.02 (0.36)	0.24 (0.72)	0.01 (0.20)
N	21,539	21,539	22,789	22,787
Unique individuals	7,906	7,906	7,957	7,958

Note: Standard errors are in parentheses. All regressions include wave dummies. *p<0.10, ** p<0.05 *** p<0.01. Depending on the model that is estimated, lagged health refers to the lag of the corresponding dependent variable.



CHAPTER 4

The Dynamic Health Effects of Informal Caregiving on Caregivers' Health

With Jannis Stöckel

Abstract

We estimate the longer-term and dynamic effects of providing informal care on caregivers' health in the United Kingdom. Using propensity score matching to address the endogeneity of informal care provision, we estimate static and sequential matching models exploring health effects at the extensive and intensive margin of informal caregiving and their persistence for up to five years. Further, we account for the family-effect, whether individuals suffer because they care *about* someone, when estimating the caregiving-effect for a subsample of within-household caregivers. Our results suggest substantial negative health effects confined to the mental domain and asymmetrically experienced by caregivers providing more than 20 hours of weekly care. These effects are independent from the family effect. Further, our dynamic sequential matching results indicate that for caregivers providing multiple years of care the negative effects persist.

4.1 Introduction

Ageing populations pose a serious challenge to health care systems in developed economies. The United Kingdom (UK) is an exemplary case, by 2050 more than a quarter of its population is expected to be 65+ and over 10% is predicted to be 80+ (OECD, 2019a), drastically increasing the long-term care (LTC) demand (de la Maisonneuve & Martins, 2015). One solution to meet this demand is to rely on informal care, care provided by friends or relatives. Informal care is often preferred by the care-recipient and is from a governmental perspective a low-cost alternative to formal care. In addition, there is evidence that (partially) substituting formal by (unskilled) informal care does not jeopardize care-recipients' health. Receiving informal care can lower medical expenditures (van Houtven & Norton, 2004, 2008), decrease the likelihood of infections and bedsores (Coe et al., 2019) and improve recipients' mental health (Barnay & Juin, 2016). In the UK, informal care already plays a crucial role in meeting current care demand with more than 18% of the 50+ population providing informal care in contrast to the OECD average of 13.5% (OECD, 2019a).

Despite these benefits there are concerns regarding the impact of informal care on caregivers' labor market and health outcomes. To make informed decisions on adapting current policies to future demands a thorough understanding of such effects is crucial. Previous studies either found no or negative effects of informal care provision on labor market outcomes (see Lilly et al. (2007) and Bauer and Sousa-Poza (2015) for reviews) and considerable health effects for the caregiver due to the mental and physical strain (see Bom et al., 2019a for a review).

Up to now most literature has focused on the immediate impact of care provision, whereas it is also important to understand how these effects develop over time as many caregivers provide several years of care. According to the 2011 UK Census men and women at age 50 can expect to spend 4.9 and 5.9 years of their remaining life providing care (ONS, 2017). It is furthermore important to focus on health outcomes as conflicting hypotheses regarding the impact of duration of caregiving on health exist.[24] There are three opposing hypotheses regarding the association between the duration of informal care provision and the impact of care provision (see for overviews: Townsend et al. 1989, Haley & Pardo, 1989; Pinquart & Sorensen, 2003b).

---

[24] A related literature focuses on the longer-term impact of caregiving on labor market outcomes. Schmitz & Westphal (2017) studied the German context and found informal care provision to have a longer-term impact on labor market outcomes, this effect did not differ dependent on the duration of care provision (e.g. individuals that provided 1 year of care compared to multiple years of care provision). Rellstab et al. (2020) studied the Dutch context and did not find any impact of care provision on labor market outcomes, which they argue might be attributable to the generous formal support system in the Netherlands.

The first hypothesis is called the wear-and-tear hypothesis implying the impact of care provision will worsen over time as coping resources decline and care needs increase. For example, a prolonged exposure to stress arising from care tasks might deplete caregivers' resources to deal with the care strain. The trait hypothesis, on the other hand, suggests that the caregiving burden is constant. Even when health of the care-recipient deteriorates, caregivers maintain a constant level of adaptation. The care providers namely have pre-existing coping skills and resources which remain present during the care task. Lastly, the adaptation hypothesis argues that individuals learn to adapt to the situation. Following this theory, the negative impact of care provision will decline when care tasks are prolonged as caregivers develop new coping strategies or become less affected by the stress involved in their care tasks.

Some studies already investigated how longer-term or high intensity informal caregiving is associated with health. In the UK for example, Hirst (2005), Legg et al. (2013), Vlachantoni et al. (2016) and Lacey et al. (2019) found a correlation between either long-term or high intensity care and negative health outcomes. These studies are, however, unable to make causal claims: is poor health caused by the act of providing informal care or do individuals in poor health more often provide informal care? To study the causal impact of care provision on health one must account for endogeneity concerns resulting from the selection of individuals into informal caregiving. To our knowledge thus far only Schmitz and Westphal (2015) and De Zwart et al. (2017) have studied longer-term health effects of informal caregiving in a causal framework. Using German panel data and focusing on female caregivers, Schmitz and Westphal (2015) find negative mental health effects persisting for up to three years after care provision. De Zwart et al. (2017) used panel data from multiple continental European countries to explore the effect of spousal caretaking among the elderly population. They report negative effects on mental health and increased medical consumption in the first year after care provision. The disappearance of health effects over time could mean that caregiving effects do not last or that individuals find ways to cope with them, however, it might also result from selective attrition as individuals with demanding caregiving tasks are more likely to drop out of the panel.

To better understand the longer-term health effects of care provision we explore the health effects of providing informal care in the UK context using data from the Understanding Society (USoc) longitudinal survey. We estimate both (i) the immediate and longer-term health effects of providing informal care for up to 5 years after the initial caregiving decision and (ii) the effect of providing additional years of care. These effects, and their relation to care intensity and caregiver characteristics, help policymakers to gauge the potential consequences of informal care provision and to identify those subgroups tin largest need of support.

Our study extends the literature on the longer-term health effects of providing informal care for the caregiver in several ways. First, the detailed individual-level information on caregivers and recipients available allows us, unlike most previous studies focusing often on female or spousal caregivers, to explore the heterogeneity of caregiving effects across different groups of caregivers (e.g. by gender, care-recipient and intensity of care). In addition, we can explore whether these caregiving effects are partly explained by the family effect. The family effect refers to the mental strain associated with caring about a close relative in need of care, which is distinct from the caregiving effect that results from providing informal care (Bobinac et al., 2010). Second, we estimate the health effects of multiple years of care provision using a dynamic matching approach (Lechner, 2009b). The added benefit of this approach is that we can investigate the impact of additional years of care provision to determine how health effects evolve with continued caregiving. Lastly, to our knowledge we provide the first causal estimates for caregiving effects for the UK context. While the UK is similar to Germany (studied by Schmitz & Westphal, 2015) with regards to the prominent role of informal caregivers in delivering social care services (Comas-Herrera et al., 2010), the countries differ in their generosity of caregiver allowances and formal care alternatives (Curry et al., 2019). Our results thereby provide new evidence on the existence of caregiving effects and their magnitude from a different institutional context.

We find strong negative effects on mental health that are concentrated among high-intensity caregivers and remain persistent for multiple years. Additionally, our analyses suggest that these effects are not primarily driven by the deteriorating health of a relative or the relationship between caregiver and recipient, and hence are independent from the family effect. Lastly, the estimates from our dynamic matching procedure indicate that the mental health effect of care provision seems to persist over longer care trajectories. Using alternative outcome measures we confirm the consistency of our results and their economic relevance.

4.2 Institutional background

Formal LTC in the UK is organized in a mixed-system combining universal and means-tested benefits. Health services provided by the National Health Service (NHS) are free at the point of delivery and predominantly financed from taxation. The health-related components of LTC, which mostly entail nursing services, are funded via the NHS when granted by the GP (Comas-Herrera et al., 2010). Other types of LTC, such as residential care and help with personal tasks at home, are the responsibility of local authorities (Glendinning, 2013). Access to these services is dependent on locally determined needs-assessments. This care is offered via a safety-net structure requiring individuals to deplete their wealth before becoming eligible for publicly funded care (Colombo et al., 2011).[25] This system ensures that publicly funded LTC services are only provided to those with severe needs and unable to pay themselves (Fernández et al., 2009).[26] In 2015 the UK spent about 1.5% of its GDP on LTC with 23% of these expenditures related to social care (ONS, 2015).

As public LTC services are means-tested, a large part of LTC is provided informally with more than 18% of the UK 50+ population providing care (OECD, 2019a). Additionally, more than a third of all caregivers do so for more than 20 hours per week according to data from the 2011 UK Census (ONS, 2013). In response to this large dependence on informal care, various policies to support informal caregivers (e.g. by providing information or support groups) are in place. The 2014 Care Act gave caregivers the right to receive a needs-assessment and corresponding support services (European Commission, 2018). However, reaching caregivers with the designated support is difficult. Only six percent of caregivers receive any form of local authority support (Yeandle, 2016). Financial support is offered to informal caregivers via a "carer's allowance" (Carers UK, 2016). This allowance, amounting to £66.15 a week (approximately $86) in 2020 (UK Government, 2020) is paid to caregivers who meet restrictive conditions.[27] As the take-up of the allowance and its monetary value is low (Colombo et al., 2011) it is not a potent incentive to take up informal care for the related monetary gain.

4.3 Methods

The decision to provide informal care is not random. Individuals 'select into' informal caregiving, thereby creating endogeneity when studying its impact on health. We aim to overcome this problem by matching individuals on observable characteristics affecting health outcomes and the decision to provide informal care. To do so, we follow the intuition regarding the caregiving decision as proposed by Schmitz and Westphal (2015) who define three areas affecting the transition into informal care. The first are care obligations, as the most important determinant of informal care provision is the presence of a family member in need and the presence of alternative

---

[25] Income and assets (including under certain circumstances housing wealth) are considered. Individuals with assets above GBP 23.250 are ineligible for support. Those with assets between GBP 14.250 - GBP 23.250 (approximately $18.448 - $30.100) are required to contribute to the costs while individuals with assets below GBP 14.250 have their costs completely covered (NHS, 2018a).

[26] In case of self-funding expected costs are about £15/hour (approximately $19) for home care (Age UK, 2019a) and £600 and £800/week (approximately $777 and $1036) for care homes and nursing homes (Age UK, 2019b).

[27] Individuals can receive the carer's allowance when they (i) are aged 16 or over (ii) provide at least 35 hours of care a week; (iii) earn less than £123 per week (approximately $152); (iv) are not full-time students or studying for more than 21 hours a week; (v) normally live in the UK and have been in the UK for at least two of the last three years (UK Government, 2020).

potential caregivers. The second category, willingness to provide care, refers to personality traits and socio-economic characteristics, as these affect individuals' inclination towards providing care. Lastly, the ability to provide care refers to individuals' own health status.

Our empirical strategy builds upon the potential outcomes framework by Rubin (1974) and addresses the endogeneity of providing informal care using regression adjusted propensity score matching (Rubin, 1979). The main assumption underlying propensity score matching is the conditional independence assumption (CIA). The CIA in our context states that after conditioning on a set of observable variables the potential health outcomes for both caregivers and non-caregivers are the same in the absence of informal care provision at all considered time periods. This implies that differences in health outcomes between caregivers and non-caregivers can be attributed to the provision of informal care. Following Lechner (2009), we exploit the panel structure of our data to match individuals upon information from the period directly preceding informal care provision to make this assumption more credible. The advantages of this strategy are that (i) providing care cannot affect the covariates and (ii) the previous caregiving status captures most of the unobserved heterogeneity.

4.3.1 Static matching

Our first aim is to estimate the longer-term impact of becoming an informal caregiver, abstracting from the question of the number of years someone provides care for. This static approach means that we match starting caregivers with non-caregivers and follow these two groups over time. We identify individuals as treated when we observe their transition into caregiving, everyone who does not report any care-episode is included in the control group (untreated).[28]

Propensity scores of providing informal care are estimated using probit models. We estimate the propensity of providing care at t_0 conditional on the variables affecting the transition into care provision at t_{-1}. We use these propensity scores to match treated to untreated individuals. To make use of the large amount of information available in the dataset we use a kernel matching approach that uses weighted

---

[28] Future informal caregivers, although an ideal pool of suitable control group members, are not included in the control group due to the way our data is structured. To maximize the number of observable treated individuals we pool starting caregivers from across waves (more information in the data section). To assess the robustness of this decision we also considered a situation where we only include caregivers in the treatment group if they started to provide care within the first three years of their survey participation. Doing so we include 2,877 individuals in the treatment group and include the remaining future informal caregivers in the control group. The results from this specification show a highly similar pattern to our baseline estimates, although the confidence intervals for the medium and high intensity treatment groups are notably wider (results available upon request).

averaging on the untreated sample to form the counterfactual group.[29] In contrast to alternative matching algorithms, this approach includes nearly all untreated individuals therefore using more information and lowering variance (Caliendo & Kopeining, 2008). This approach is furthermore preferred over for example nearest neighbor matching due to the large number of control variables we match upon and our treated to control ratio. We assess the common support, whether there is sufficient overlap in characteristics between the treated and untreated individuals, as the risk of kernel matching lies in the increased chance of including "bad matches", untreated individuals that are highly dissimilar to the treated group, in the estimation (Caliendo & Kopeining, 2008). Furthermore, as we do not match on actual covariates but on propensity scores, we assess whether balance of covariates is achieved after the matching procedure. We do so by using the standardized bias (Rosenbaum & Rubin, 1985).

Finally, the average treatment effect on the treated (ATT) is estimated by regressing health outcomes on the treatment indicator (providing care) and all control variables used in the propensity score estimation with individuals in the control group weighted by their estimated kernel weights. By regressing on the control variables alongside the treatment indicator we aim to correct for remaining residual differences in the covariate distributions between the treatment and control group (Lechner, 2009b; Rubin 1973). We do not use the covariates from later waves as these might be affected by the treatment. The health impact of providing care is estimated for the immediate time after first reported care provision and up to five years afterwards. Figure 4.1 provides a graphical representation of the static and dynamic matching designs.

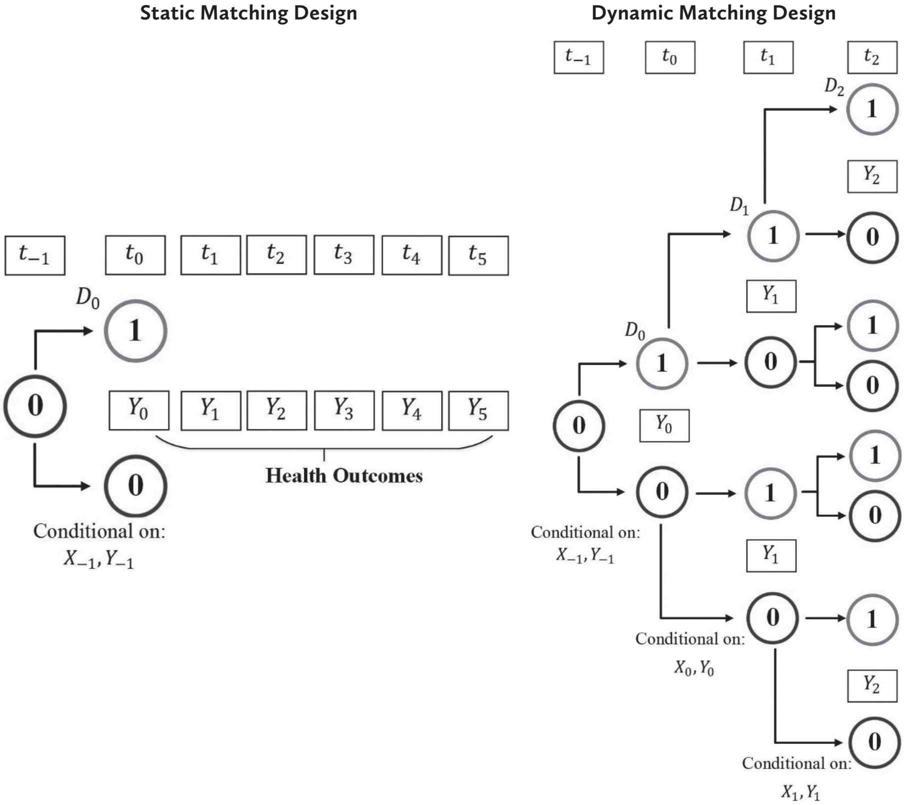
4.3.2 Dynamic sequential matching

The static matching approach aims to answer the question *"If an individual starts to provide informal care in period t_0 (for an undefined time spell) does it change their health outcomes thereafter?"*. The treatment group hence contains individuals who stopped providing care in t_{-1} and those who continued caregiving for various years. This might bias the treatment effect estimates for periods past t_0 as they are partially based on individuals that no longer provide care. To explore to what extent the longer-term treatment effects are driven by multi-period caregivers we use a dynamic matching approach following the work of Lechner & Miquel (2010) and Schmitz & Westphal (2017).

---

[29] We use the Stata command psmatch2 (Leuven & Sianesi, 2003) using an Epanechnikov kernel with a 0.03 bandwidth. The bandwidth choice is a trade-off between a small variance and an unbiased estimate of the true density function (Caliendo & Kopeining, 2008). While not reported in detail we have tested varying bandwidths, e.g. higher and lower bandwidth values of 0.01 and 0.06, with negligible impact on our results.

Figure 4.1: Static and dynamic matching designs. (Own illustrations following Schmitz & Westphal 2017)


Static Matching Design

Dynamic Matching Design

Note: D refers to the decision to either: (1) provide informal care or (0) not to provide informal care at a certain decision node. Y refers to the health outcomes, X refers to the included covariates.

In contrast to the static approach, the dynamic matching explicitly estimates the effect of providing a second (third) year of care while considering a potential effect of caregiving in t_0 (t_1) on health and other endogenous covariates that influence the decision to care provision in subsequent years, such as labour market status. It therefore helps to understand how the health effect of care provision is affected by duration of care and whether the static treatment effects over time are representative for the population of multi-period caregivers. Further it allows us to answer the question whether caregivers adapt to their caregiving responsibilities over time.

The dynamic matching is computationally demanding. It requires the estimation of treatment probabilities at all possible decision nodes, thereby leading to 2^T possible treatment paths where T is the maximum possible treatment duration. Further, it requires the availability of all health outcomes and covariates at the time-period prior to (continued) caregiving as the matching is repeated at all decision nodes. We limit ourselves to the case of $T = 3$ (see Figure 4.1). This is motivated by two considerations. First, for our sample this time-window seems sufficient as the broad majority of caregivers provides a maximum of 3 years of consecutive care.[30] Second, in the dynamic framework time t is not defined relative to the first individual caregiving episode but fixed to allow for all potential treatment pathways to be observed, leading to less observable starting caregivers at t_0.

To illustrate the approach in more detail we provide an example showing the steps undertaken to estimate the marginal effect of providing two years of care instead of one. The treatment group in this example comprises everyone that provided informal care in both waves (t_0 and t_1), whereas the control group consist of everyone that provided care in the first wave (t_0) but not in the second (t_1). In the dynamic matching design in Figure 4.1 this refers to comparing the group that followed the path *0-1-1* with the group following the route *0-1-0*.

Consider a binary indicator D_t encoding care provision in period t. As in the static estimations, we start our analysis by estimating the propensity of providing informal care at the first node ($D_0 = 1$) conditional upon not providing care in the period before, and pre-treatment health outcomes and other covariates using a probit model. The propensity of providing informal care at the first node is: $\Pr(D_0 = 1 \mid X_{-1}, Y_{-1})$. Therefore the resulting estimate is equivalent to the immediate effect (t_0) estimated in the static matching framework.

In extension we also estimate the decision taken at the second node ($D_1 = 1$) where caregivers decide to (dis-)continue caregiving. We estimate the propensity scores of both options conditional upon already being a caregiver and on health and the other observables both at the first and the second node. The propensity of providing informal care at the second node after providing care in the first period is: $\Pr(D_1 = 1 \mid D_1 = 1, X_{-1}, Y_{-1}, X_0, Y_0)$. The propensity of discontinuing care provision is: $\Pr(D_1 = 1 \mid D_0 = 1, X_{-1}, Y_{-1}, X_0, Y_0)$

We use these scores to calculate inverse probability weights (IPW). IPW estimates might be sensitive to very high or low weights from individuals with very high or low propensity scores (Robins et al., 2000). As mentioned by Lechner (2009b) the commonly used solution to this problem is to remove observations with extreme

---

[30] Among the caregivers approximately 46.8% provide one year of care, 20.6% provide two and 13.0% provide three years of care. This leaves 19.6% of the caregivers providing more than three years of consecutive care. These numbers are based on caregivers starting in USoc waves 2-4 allowing all included respondents, in theory, to be able to have a caregiving spell of five or more years. Naturally, caregivers discontinuing their survey participation but continue to provide informal care are not observed.

weights. We do so by dropping all scores for the first decision that are smaller than 5% or larger than 95% of the estimated propensity score distribution.[31] Furthermore, for all scores we condition upon common support: in case no untreated counterparts with a similar propensity score for our treated respondents are present, these treated observations are excluded from the analysis.

Based on the estimated propensity scores we calculate inverse probability weights for both the treatment and the control group. These are defined as follows:

$$\frac{1}{\Pr(D_0 = 1 \mid D_1 = 1, X_{-1}, Y_{-1})) * \Pr(D_1 = 1 \mid D_0 = 1, X_{-1}, Y_{-1}, X_0, Y_0)} \quad \textit{for the treatment group}$$

$$\frac{1}{\Pr(D_0 = 1 \mid D_1 = 1, X_{-1}, Y_{-1})) * \Pr(D_1 = 0 \mid D_0 = 1, X_{-1}, Y_{-1}, X_0, Y_0)} \quad \textit{for the control group}$$

We estimate the dynamic average treatment effect on the treated (those who provide two years of care) by regressing health on the treatment while controlling for remaining differences by adding all covariates from the previous wave and weighting the data using the calculated inverse probability weights. We hence estimate, in this example, the health effects at t_1 of providing care in t_0 and t_1, compared to only providing care at t_0.

This sequential matching strategy was proposed by Lechner (2009b) to estimate treatment effects in settings with dynamic treatment durations. While it follows a similar intuition as the static matching procedure, identification is based on an augmented version of the CIA: the weak dynamic conditional independence assumption. Consider the case above comparing outcomes of two and one years of informal care. The weak conditional independence assumption combines two parts. Firstly, the initial conditional independence assumption stating that potential outcomes in t_0 and t_1 are independent of treatment status in t_0 once we match upon observables at t_{-1}. Secondly, that potential outcomes in t_0 and t_1 are independent of continued treatment in t_1 once we condition on control variables and outcomes at both t_{-1} and t_0 and treatment status at the initial node t_0.

---

[31] To check the robustness of this approach we also estimate our results while (1) dropping scores for the first decision that are smaller than 1% or larger than 99% of the estimated propensity score distribution and (2) dropping scores for all decision nodes that are smaller than 1% or larger than 99% of the estimated propensity score distributions. Qualitatively our results are robust to these different specifications (results available upon request).

4.4 Data

We use data from the Understanding Society (USoc) dataset, also known as the UK Household Longitudinal Study (UKHLS; University of Essex, 2019); an annually conducted representative panel survey of the adult UK population (aged 16+). It started in 2009 with approximately 40,000 respondents across 30,000 households as the successor of the British Household Panel Survey (BHPS), which ended in 2008. In 2010, members of the last BHPS-wave were invited to join the USoc after which an additional 8,000 individuals joined. This paper uses all nine completed waves conducted between 2009 and 2019.[32]

Informal caregivers are identified using the question *"Is there anyone living with you who is sick, disabled or elderly whom you look after or give special help to (for example a sick, disabled or elderly relative/husband/wife/friend etc.)?"*. Individuals providing care outside their own household are identified based on the question *"Do you provide regular service or help for any sick, disabled or elderly person not living with you? [Exclude help provided in course of employment]"*. Apart from being able to identify individuals providing care inside and outside their own household the questionnaire also covers care intensity (hours per week) and the relationship between the caregiver and care-recipient.

We explore differences in the impact of caregiving dependent on the reported hours of care per week. Based on these reported hours of care we split our sample of caregivers in three; low intensity (<10 hours of care per week), medium intensity (between 10 – 20 hours) and high intensity caregivers (more than 20 hours). When evaluating our results, one however must be aware of a potential downward bias in our estimates due to an underrepresentation of caregivers in the upper end of the intensity distribution. The share of high intensity caregivers in our sample (12.8%) is lower compared to the UK Census of 2011 which indicates that nation-wide about 37% of the caregivers provide care for more than 20 hours a week (ONS, 2013) or the 17% reported in the 2014 European Social Survey (ESS, 2014).

4.4.1 Health outcomes

Various studies report the impact of care provision on mental and physical health (e.g. Pinquart & Sörensen, 2003b). To identify potential changes in both health domains we use the SF-12 health questionnaire in which individuals self-report on 12 questions related to various aspects of their own health in the past four weeks. From the survey we derive the physical (PCS) and mental (MCS) component summary

---

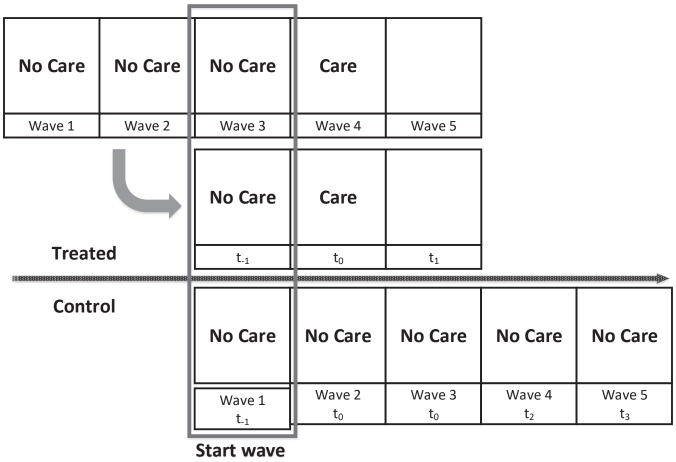
[32] It follows an overlapping panel structure where waves cover two years but overlap for one and individual respondents are surveyed every 12 months. Therefore, nine waves are available for the 10-year time period.

scores which are constructed using different subscales related to physical and mental health.[33] The two health scales are validated for the UK context and range from 0 to 100, where a higher score represents better health. By construction MCS and PCS scores have a mean of 50 and standard deviation of 10 (Ware et al., 1995).

4.4.2 Time structure

For the static matching procedure, we define a relative time variable depending on an individual's first reported care-episode. Figure 4.2 provides a visualization of this time structure. Among caregivers t_{-1} is defined as the period before the first reported caregiving episode. For everyone in the control group t_{-1} is the individual's first appearance as a survey participant in absence of any care episode during their participation. This time structure is chosen to maximize the number of observable treated individuals and is the reason that we are able to study almost 7000 caregivers in our main sample that we can subdivide into different subgroups. However, because of this approach we less precisely identify the estimated treatment effects in the later time points.

Figure 4.2: Static Dataset – Time structure example (Own visualization)



The analysis sample for the dynamic specification uses an augmented time-structure to allow for the modeling of all decision nodes between t_{-1} and t_0 and the comparison of various care trajectories. The time variable is normalized to t_{-1} being the entry wave of an individual into the panel for those who provide no care at any time-point and caregivers who start providing care within the first four participation waves. To

---

[33] The PCS comprises the subscales: Physical functioning, Role-Physical, Bodily Pain and General Health. The MCS comprises the subscales: Vitality, Social Functioning, Role-Emotional and Mental Health.

increase the number of observable caregivers in the different caregiving trajectories we additionally include individuals whose caregiving trajectory starts after at least four periods of not providing informal care. For these the fifth participation is defined as t_{-1}. We therefore somewhat emulate the time-structuring in the static design by pooling caregivers from different starting waves but allowing these to have caregiving spells of up to three years. The important difference is that not all care-giving trajectories start at t_0 and at all decision nodes the control group contains individuals who will transition into a (multi-period) caregiving spell in future periods.

4.4.3 Sample selection

We construct two distinct datasets to implement the static and dynamic matching procedures. Individuals who identified as caregivers in their first observation period are excluded as transition into caregiving is not observed. For the static estimation we include all individuals that provide information on their health outcomes (t_{-1} and t_0) for at least two time points and provide full information on all covariates used in the propensity score estimation at t_{-1}. Individuals here predominantly drop out of the sample because they are proxy respondents or fail to provide sufficient information on their health outcomes or existing family members.[34] Individuals remain in the sample during the subsequent time points t_1 to $t_5$in case information on the outcome-variables is available. For the dynamic estimation procedure, data requirements are more restrictive as we re-estimate propensity scores at each decision node. For this analysis, only individuals with complete information on all control variables for three waves (t_{-1} to t_1) and full information on outcome variables for four consecutive periods are included in the sample. Table A4.1.1 in the Appendix provides a overview of the exclusion criteria applied to all analysis samples.

4.5 Results

4.5.1 Matching quality

The descriptive statistics for the static matching sample are depicted in Table 4.1. Before the propensity score matching there is strong covariate imbalance between the control and treatment groups. The matching corrects this imbalance.[35] For a detailed overview of the results of the propensity score estimation and the distribution of

---

[34] Co-habiting family members are observed at every wave but family networks outside of respondents' households are only inquired about every second wave.

[35] We calculate the standardized bias for each covariate by taking the difference in means between the treatment and control group and dividing it by the standard deviation of the control group (Rosenbaum & Rubin, 1985). We follow the rule of thumb suggested by Caliendo & Kopeinig (2008) which states that there is sufficient balance when the bias is below 3-5%.

estimated scores please see Appendix A4.3. Four caregivers are identified as off-support and therefore dropped from the analysis.

4.5.2 Static matching results – Treatment effects by care intensity

The results of the static matching procedure will be presented graphically. All underlying estimates are reported in Appendix Tables A4.1.2, A4.1.3 and A4.1.4. While the graphs depict the overall results by caregiving intensity, we will in text also discuss the results by gender. In the baseline analysis we estimate the effect of any informal care provision irrespective of the reported intensity. Figure 4.3 depicts the estimated ATTs on both the (a) mental and (b) physical health scores across time. Throughout the paper, point estimates are depicted by the connected dots while the corresponding confidence interval is indicated by the correspondingly colored lines. In the mental domain we estimate small immediate negative effects of -0.421 ($p<0.01$) at t_0 and -0.624 ($p<0.001$) at t_1 . These effects persist also in latter periods up until t_5 while ranging between -0.383 ($p<0.05$) at t_2 and -0.672 ($p<0.001$) at t_4. In the physical domain baseline estimates indicate a small positive effect of 0.327 ($p<0.001$) at t_0 but no effects thereafter. The separate analyses by gender show that the results are predominantly driven by female caregivers. Female caregivers experience small and persistent negative mental health effects of -0.556 ($p<0.01$) at t_0 to -0.624 ($p<0.05$) at t_5. Male caregivers, do not experience consistent mental or physical health effects except for a negative impact on the MCS of -0.558 ($p<0.05$) at t_2.

Table 4.1: Descriptive Statistics – Treatment and control groups

	Unmatched				Matched Controls		Standardized Bias	
	Treated		Control					
	Mean	SD	Mean	SD	Mean	SD	Unmatched	Matched
Care Obligations								
Mother alive	0.587	0.492	0.697	0.460	0.586	0.492	-23.0	0.1
Age of mother	66.717	9.911	61.140	9.717	66.585	9.627	38.2	0.7
Father alive	0.446	0.497	0.631	0.482	0.441	0.497	-25.5	0.6
Age of father	66.500	8.208	62.529	8.846	66.248	7.569	30.8	1.9
Both parents alive	0.388	0.487	0.596	0.491	0.384	0.486	-28.4	0.5
Living siblings	0.865	0.342	0.885	0.319	0.864	0.343	-4.1	0.2
Living partner	0.703	0.457	0.635	0.481	0.700	0.458	9.6	0.3
Age of partner	51.662	12.387	45.609	11.552	51.517	11.947	34.2	0.6
Willingness to Care								
Age	50.666	16.157	41.288	17.146	50.589	16.296	37.4	0.2
Female	0.592	0.491	0.527	0.499	0.591	0.492	8.8	0.1
Tertiary Education	0.354	0.478	0.386	0.487	0.346	0.476	-4.4	1.0

Table 4.1: Continued.

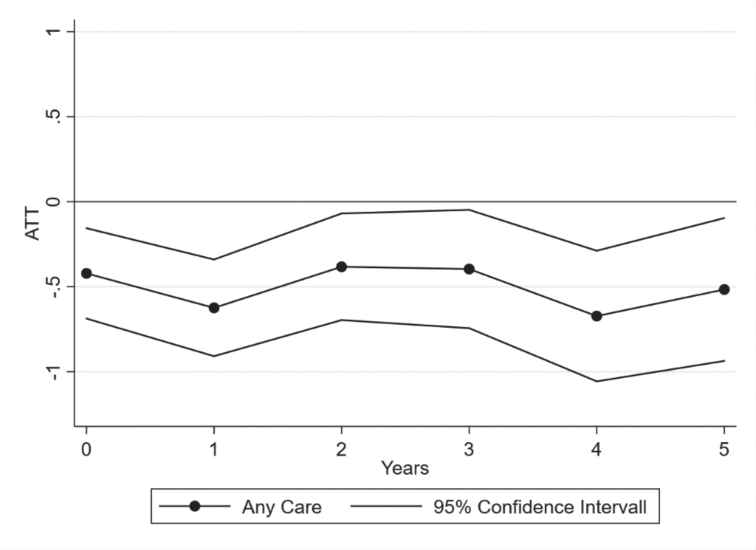
	Unmatched				Matched Controls		Standardized Bias	
	Treated		Control					
	Mean	SD	Mean	SD	Mean	SD	Unmatched	Matched
Secondary Education	0.431	0.495	0.439	0.496	0.433	0.496	-1.0	-0.2
Primary Education	0.215	0.411	0.175	0.380	0.221	0.415	6.7	-0.9
Employed	0.485	0.500	0.567	0.496	0.471	0.499	-11.0	1.7
Self-Employed	0.078	0.268	0.067	0.250	0.077	0.266	2.8	0.2
Working Full-Time	0.397	0.489	0.502	0.500	0.382	0.486	-14.1	1.8
Unemployed	0.045	0.208	0.051	0.219	0.048	0.215	-1.6	-0.9
Retired	0.261	0.439	0.141	0.348	0.264	0.441	21.0	-0.4
Student	0.034	0.181	0.102	0.303	0.034	0.182	-17.2	-0.2
Homecarer	0.060	0.238	0.049	0.216	0.065	0.247	3.3	-1.2
Disabled	0.037	0.189	0.023	0.150	0.040	0.197	5.7	-1.0
Income (logarithmic)	7.258	0.610	7.231	0.624	7.228	0.634	2.9	2.8
HH Income Fraction	0.549	0.313	0.518	0.327	0.550	0.321	6.3	-0.3
Single	0.154	0.361	0.249	0.433	0.153	0.360	-15.5	0.2
Partnership	0.108	0.311	0.160	0.367	0.110	0.313	-10.0	-0.4
Separated/Divorced	0.099	0.298	0.073	0.260	0.101	0.302	6.3	-0.5
Widowed	0.044	0.205	0.043	0.202	0.045	0.208	0.4	-0.4
Married	0.595	0.491	0.475	0.499	0.590	0.492	16.1	0.5
Children in Household	0.310	0.463	0.395	0.489	0.315	0.465	-11.8	-0.6
Children < 14 in Household	0.275	0.447	0.356	0.479	0.278	0.448	-11.6	-0.4
Region: North-East	0.043	0.204	0.037	0.189	0.044	0.206	2,21	-0.2
Region: North-West	0.103	0.304	0.114	0.318	0.102	0.303	-2.4	0.1
Region: Yorkshire	0.069	0.253	0.077	0.267	0.067	0.249	-2.1	0.5
Region: East-Midlands	0.082	0.274	0.077	0.266	0.082	0.274	1.3	0.0
Region: West-Midlands	0.085	0.279	0.074	0.262	0.088	0.283	2.8	-0.6
Region: East England	0.095	0.294	0.092	0.289	0.095	0.293	0.9	0.1
Region: South-East	0.124	0.330	0.136	0.342	0.126	0.332	-2.3	-0.3
Region: South-West	0.100	0.299	0.089	0.284	0.103	0.304	2.5	-0.6
Region: Wales	0.074	0.262	0.067	0.250	0.073	0.260	1.9	0.2
Region: Scotland	0.084	0.278	0.090	0.287	0.082	0.275	-1.5	0.4
Region: Northern Ireland	0.054	0.226	0.046	0.211	0.052	0.222	2.3	0.6
Region: London	0.087	0.281	0.101	0.301	0.087	0.281	-3.3	0.0
Living in Urban Area	0.726	0.446	0.758	0.428	0.728	0.445	-4.9	-0.2
Big-5: Openness	4.577	1.325	4.592	1.272	4.566	1.314	-0.8	0.5
Big 5: Conscientiousness	5.570	1.097	5.444	1.086	5.543	1.110	7.7	1.4

Table 4.1: Continued.

	Unmatched				Matched Controls		Standardized Bias	
	Treated		Control					
	Mean	SD	Mean	SD	Mean	SD	Unmatched	Matched
Big 5: Extroversion	4.618	1.289	4.588	1.299	4.630	1.345	1.6	-0.6
Big 5: Agreeableness	5.691	1.018	5.573	1.027	5.680	1.003	7.7	0.6
Big 5: Neuroticism	3.532	1.447	3.556	1.432	3.526	1.473	-1.2	0.2
Ability to Care								
Self-Assessed Health	2.578	1.054	2.423	1.054	2.607	1.131	9.9	-1.6
SF-12 Mental Score	50.006	9.860	51.109	9.080	49.832	10.436	-7.9	1.0
SF-12 Physical Score	49.435	10.854	51.568	9.970	49.140	11.751	-13.9	1.6
Chronic-Illness/Disability	0.374	0.484	0.287	0.453	0.384	0.486	12.5	-1.2
Functional Limitations	0.552	1.296	0.441	1.221	0.589	1.345	5.9	-1.6
Satisfaction with Health	4.729	1.722	5.091	1.599	4.691	1.764	-14.7	1.3
Satisfaction with Income	4.505	1.689	4.639	1.637	4.455	1.741	-5.5	1.7
Satisfaction with Leisure	4.788	1.676	4.773	1.622	4.779	1.728	0.6	0.3
Satisfaction with Life	5.198	1.472	5.369	1.370	5.165	1.547	-8.1	1.3
GHQ Score	10.250	3.019	10.412	2.729	10.226	2.990	-3.8	0.5
Number of Individuals	6,852		12,970		12,970			

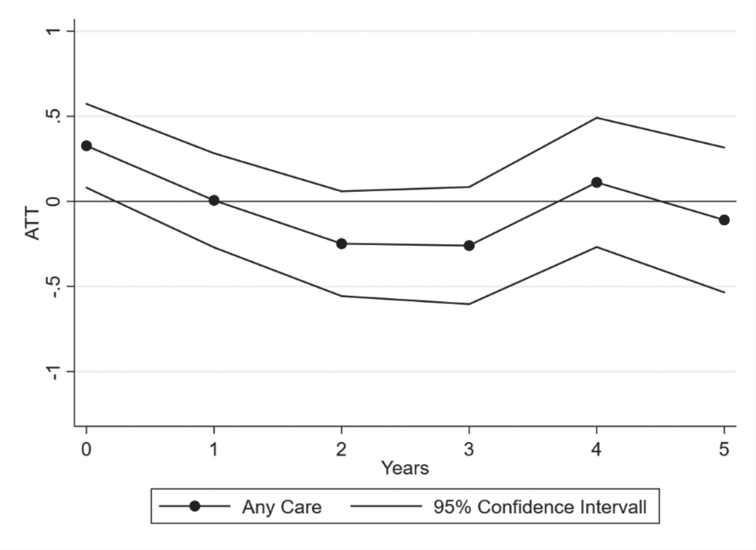
Figure 4.3: Baseline results (any care intensity)

a) Mental Health



Source: USoc Waves 1-9, own calculations. Note: The graph shows the ATT of individuals who start to provide any type of informal care compared to matched non-caregivers from the start of care provision up to 5 years afterwards.

b) Physical Health

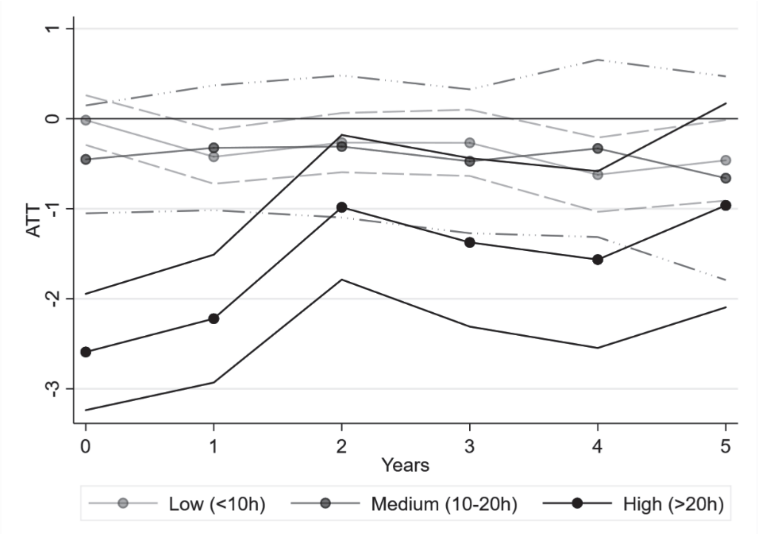


Source: USoc Waves 1-9, own calculations. Note: The graph shows the ATT of individuals who start to provide any type of informal care compared to matched non-caregivers from the start of care provision up to 5 years afterwards.

To explore heterogeneities in the estimated treatment effects we subdivide caregivers into treatment groups according to the reported weekly hours of care. Figure 4.4 plots the results by care intensity for mental (a) and physical health (b). Low intensity caregiving for less than 10 hours per week is depicted in light grey, medium intensity between 10 and 20 hours per week in dark grey, and high intensity caregiving of 20 hours and more in black. Low intensity care is the most commonly observed with 5,069 individuals (74%), followed by 895 high (13%) and 792 (12%) medium intensity caregivers.[36] By construction, effects in latter periods are less precisely estimated as not all caregivers are observed for all years. At t_5 only 1,852 low and 289 medium intensity caregivers (ca. 37%) are observable and only 285 (32%) high-intensity caregivers.

Figure 4.4: Treatment effect by care intensity

a) Mental Health

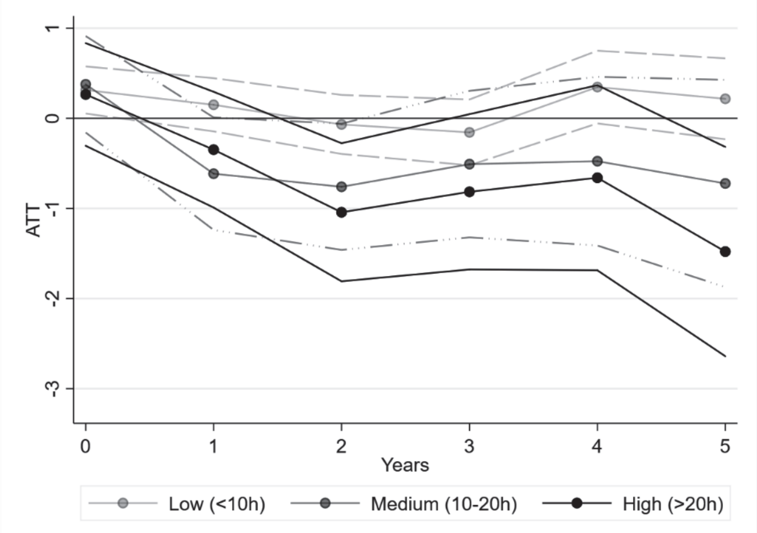


Source: USoc Waves 1-9, own calculations. Note: The graph shows the ATT of individuals who start to provide low, medium or high levels of informal care compared to matched non-caregivers from the start of care provision up to 5 years afterwards.

---

[36] Caregivers providing no intensity information are excluded (92).

b) Physical Health



Source: USoc Waves 1-9, own calculations. Note: The graph shows the ATT of individuals who start to provide low, medium or high levels of informal care compared to matched non-caregivers from the start of care provision up to 5 years afterwards.

The large heterogeneity in the estimated treatment effects underline the importance of care intensity. In the mental domain we find small effects for low intensity caregivers. Although the coefficient is nearly zero and insignificant at t_0 we find a negative effect of -0.423 ($p<0.01$) at t_1 and -0.622 ($p<0.01$) and -0.462 ($p<0.05$) at t_4 and t_5 with coefficients for the intermediate years being of similar size and direction but not significantly different from zero. For medium intensity caregiving the coefficients closely mirror those for low intensity care but are insignificant due to considerably larger standard errors. Among individuals caring for more than 20 hours per week we observe strong initial negative effects of -2.591 ($p<0.001$) at t_0 and -2.221 ($p<0.001$) at t_1. While these effects decrease for subsequent periods, they remain largely persistent with -0.984 ($p<0.05$), -1.374 ($p<0.01$), and -1.565 ($p<0.01$) at t_2 to t_4. The coefficient remains negative at t_5 with -0.964 but is only significant at the 10% level. The previously apparent differences in caregiving effect by gender decrease when stratifying the samples by care-intensity. Both male and female high-intensity caregivers experience negative mental health effects; -2.734 ($p<0.001$) for females and -2.197 ($p<0.001$) for males at t_0.

In the physical domain the pattern across care intensity levels is different. For low intensity caregivers we find a small positive immediate effect of 0.314 ($p<0.05$) at t_0 while for the other intensity groups the coefficient is similar but insignificant. At subsequent periods the estimated effects vary considerably. For low intensity caregivers the estimated coefficients are insignificant while varying around zero. For medium intensity care coefficients are larger and consistently negative, ranging from -0.476 to -0.773, with a significant effect of -0.760 ($p<0.05$) at t_2, while for high intensity caregivers they follow a similar pattern but are larger in size and indicating negative effects of -1.040 ($p<0.05$) and -1.479 ($p<0.05$) at t_2 and t_5. Especially the coefficients for high intensity care seem to follow a downward trend with differences emerging not immediately after care provision started, but in subsequent periods. In the Appendix we provide evidence that this pattern seems driven by age-dependent physical health trends captured inadequately in the matching (see Figures A4.2.1 and A4.2.2).[37] For the remainder of the discussion of our static matching results we will focus on the mental health outcomes. We do so as the observed pattern across specifications indicates that health effects disproportionally occur in the mental health domain. All corresponding results for physical health outcomes are reported in the Appendix. Additionally, in Appendix A4.1 we show that the reported heterogeneous health effects of care provision seem indeed driven by differences in care-intensity not the relationship between the caregiver and care-recipient.

4.5.3 Static matching results – Family effect

Our results indicate strong negative caregiving effects in the mental health domain among high intensity caregivers. However, an alternative explanation could be that these effects are not caused by the act of caregiving itself but rather the health state and/or well-being of the care-recipient. This confounding effect has been identified as the family effect (Bobinac et al., 2010), the impact of individuals caring *about* the care-recipients rather than caring *for* them. From a policy perspective this distinction is highly important as both would require fundamentally different responses from policymakers.

To explore to what extent the estimated effects are driven by the caregiving effect or the family effect, we attempt to account for the family effect when estimating the caregiving effect. To achieve this, we slightly adjust the approach as applied in our main analyses. In this specification we run a model in which we estimate the caregiving effect while considering the family effect. This is achieved by regressing mental health outcomes on the treatment indicator (care provision) and an indicator of the family effect (health shock to a family member) and all control variables used in the propensity score estimation with individuals in the control group weighted by

---

[37] As propensity scores are a summary measure estimated using many covariates, these age-related trends are not guaranteed to be perfectly captured. For example, a younger individual might receive a high propensity score due to his/her physical health being low and/or other strong predictors but would be faced with an entirely different physical health trajectory in the short and medium term compared to an older individual. As illustrated in the Appendix this age-dependent trend is not present for mental health.

their estimated kernel weights. Additionally, we use health information of partners and parents provided at t_{-1} when estimating the propensity scores.[38]

We are only able to run this model for individuals for whom we have information regarding the health status of family members. In USoc this information is solely available for cohabiting family members. We hence restrict our analysis sample to those cohabiting with living parents and/or a partner, with no parents alive outside their household. Among these we only include individuals for which there is health information for living partners and parents available at time points t_{-1} and t_0. Based on the provided information we create a binary variable, representing the family effect, that indicates whether a cohabiting family member experienced a health shock between these two periods. Health shocks are defined as a drop in MCS or PCS of at least 10 points, equivalent to one standard deviation. If family members provide health information at t_{-1} and are not self-reporting in t_0 due to illness or old-age as reported by a proxy respondent this is also considered a health shock.

The outlined approach allows us to account for the family effect to the best of our abilities given the available data. However, this means that we are not estimating both effects separately or quantifying their relative magnitude. Instead, the family effect is decomposed into an unobservable component related to the latent health of family members, captured in the propensity score estimation, and the observable health shock. The analysis sample is reduced considerably as we drop propensity scores below the 5th and above the 95th percentile to ensure covariate balance. This leaves us with 2,878 individuals in the control group and 501 caregivers of which 165 provide high intensity care.

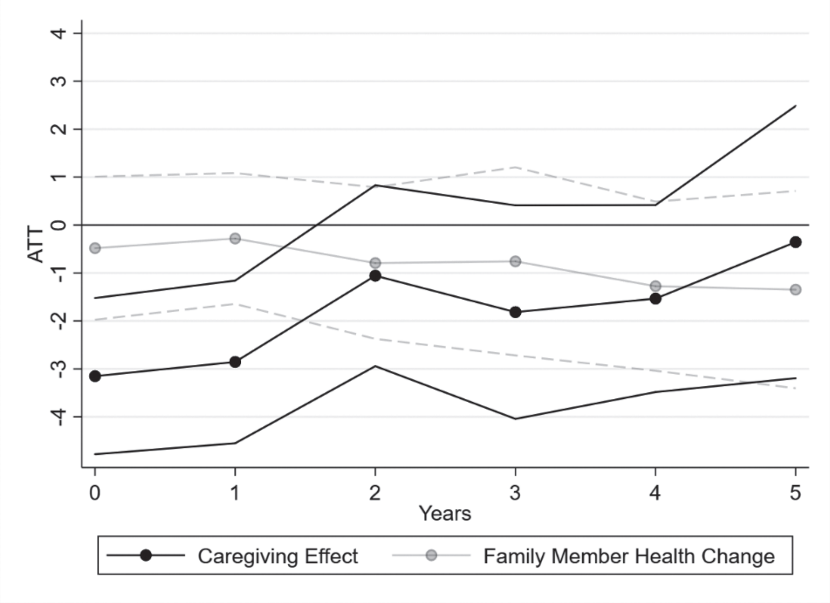
Figure 4.5 depicts the estimated caregiving effects for high-intensity caregivers while accounting for a family member's health shock. The estimated caregiving effects depict a similar pattern as before. The coefficient indicates a strong initial negative effect of -3.151 ($p<0.001$) at t_0 and -2.855 ($p<0.01$) at t_1. The coefficient for the family health shock indicator is consistently negative but remains insignificant throughout all periods.[39] Due to the limited sample size we refrain from estimating the results by gender.

---

[38] The health information used includes MCS, PCS, self-assessed health, number of functional limitations, and the presence of a long-standing illness or disability for cohabiting partners/parents.

[39] Ideally, we would also like to explore whether the caregiving effect is reinforced when caring for someone experiencing a health shock by using an interaction term. However, as correctly identifying the coefficient of the interaction term is highly data demanding it is not feasible given the reduced sample size.

Figure 4.5: Caregiving and family effects (high intensity care)



Source: USoc Waves 1-9, own calculations. Note: For this analysis the sample is restricted to individuals cohabiting with living parents and/or a partner, with no parents alive outside their household. The graph shows the ATT of individuals who start to provide high intensity informal care (≥20 hours a week) to their cohabiting family members compared to matched non-caregivers from the start of care provision up to 5 years afterwards. Additionally, the family effect is measured as a dummy variable indicating whether a cohabiting family member experienced a health shock, a drop in MCS or PCS of at least 10 points, between t_{-1} and t_0. Please note that results are not comparable to the main-model as an augmented sample is used.

4.5.4 Dynamic matching results – Treatment effects by care intensity

Next to estimating the impact of at least one year of care provision, we aim to investigate the impact of providing additional years of informal care. For this dynamic matching approach, we estimate the propensity of (not) providing informal care at every decision node and drop scores in case the observation is off support or out of range. In Appendix A4.4 we report the propensity scores for the different care-trajectories as well as an overview of the excluded individuals. Further, we estimate the treatment effects using the static matching approach for the same sample used in the dynamic matching to provide a comparison between both estimation strategies. For the dynamic matching we merged the groups of medium and high intensity caregivers due to concerns about statistical power. Further we excluded individuals with unstable care trajectories to not wrongfully capture the impact of increasing care intensity among continuing caregivers. The results for both mental and physical health are depicted in Table 4.2.

The first column of Table 4.2 depicts the estimated caregiving effect at t_0 for the first period of informal care. For physical health there are again no negative effects found at this or any other time-point. For mental health both dynamic and static matching indicate a small and insignificant negative coefficient for any care provided of -0.332. When separating the different intensity levels there are no significant differences for low intensity caregivers while for medium or high intensity caregivers the static matching estimates are strongly negative and significant with -1.370 ($p<0.05$).

At t_1 the static matching, which pools both continuing and discontinuing caregivers together, again indicates a continuing negative mental health effect of -1.697 ($p<0.01$). The dynamic matching estimates, which account for the impact of previous-period caregiving on covariates and health outcomes, indicate that the health effects among continuing caregivers are larger. When focusing on the group of continuing caregivers the difference is -1.952 ($p<0.01$) when using the never caregivers as a control group. Explicitly comparing one against two years of medium/high intensity care results in an estimated health impact of the second year of care provision that is again larger at -2.288 ($p<0.05$) although less precisely estimated as this matching is conducted using the small sample of caregivers at t_0. When moving towards a third year of informal care provision the static results at t_2 indicate a negative mental health effect of -1.049 ($p<0.05$). However, when focusing only on the group of continuing caregivers and using the dynamic matching, which considers the health outcomes and covariates at t_1, these significant differences vanish for both the comparison using never caregivers and those who provided two years of care. Please note, however, that here again is conditioned upon health at t_1. This non-negative finding hence does not indicate that the health of individuals providing a 3rd year of care is restored to baseline, but that the 3rd year does not lead to a significant additional negative impact on health conditional on the health effects already experienced in the first two year of care provision.

Table 4.2: Dynamic matching estimates

			Mental Health				
	t=0	**t=1**			**t=2**		
	Static/ Dynamic	**Static**	**Dynamic (2v0)**	**Dynamic (2v1)**	**Static**	**Dynamic (3v0)**	**Dynamic (3v2)**
Any	-0.332	-0.651**	-0.624	-0.252	-0.268	-0.074	-0.145
	(0.208)	(0.222)	(0.365)	(0.461)	(0.221)	(0.393)	(0.651)
Low Intensity	-0.036	-0.366	-0.240	0.123	-0.033	-0.284	0.204
	(0.224)	(0.242)	(0.388)	(0.490)	(0.248)	(0.487)	(0.734)
Medium/High Intensity	-1.370*	-1.697**	-1,952**	-2.288*	-1.049*	0.685	1.717
	(0.482)	(0.500)	(0.713)	(1.025)	(0.473)	(0.610)	(1.694)
			Physical Health				
	t=0	**t=1**			**t=2**		
	Static/ Dynamic	**Static**	**Dynamic (2v0)**	**Dynamic (2v1)**	**Static**	**Dynamic (3v0)**	**Dynamic (3v2)**
Any	0.052	-0.191	-0.133	0.172	0.037	0.118	0.007
	(0.196)	(0.214)	(0.350)	(0.463)	(0.221)	(0.396)	(0.616)
Low Intensity	0.203	-0.118	-0.222	0.106	0.204	0.688	-0.008
	(0.218)	(0.245)	(0.380)	(0.519)	(0.254)	(0.437)	(0.656)
Medium/High Intensity	-0.470	-0.365	0.466	1.000	-0.562	-0.515	-1.224
	(0.434)	(0.424)	(0.430)	(0.923)	(0.439)	(1.725)	(0.738)
Treatment (Control)	1348 (16081)	1348 (16081)	552 (14782)	552 (768)	1348 (16081)	311 (13511)	311 (205)
Low Intensity	1019 (16081)	1019 (16081)	411 (14782)	411 (585)	1019 (16081)	220 (13511)	220 (170)
Medium/High Intensity	312 (16081)	312 (16081)	138 (14782)	138 (168)	312 (16081)	86 (13511)	86 (35)

Note: The static and dynamic results at t=0 slightly differ at the second decimal as either matching or inverse probability weighting is used, the depicted results are the static results. The table provides the dynamic ATT, the additional effect of providing a second/third year of informal care compared to not providing informal care, one year of care only or two years of care. It solely compares the health of treated and matched controls based on the information from the directly preceeding wave. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are in parentheses. Please note that the displayed static results are based on a different sample than the baseline static results as a differnty conditioned sample is used See the Appendix for more details. Source: USoc, own calculations.

4.6 Robustness checks

To assess the sensitivity of our estimates to our empirical specification and violations of the identifying assumptions we performed multiple robustness checks.[40] The observed mental health effects could be explained by an ongoing trend that started before informal care provision as individuals might anticipate future care-obligations based on observed deteriorating health states of family members. For a subset of caregivers, we observe their mental and physical health for multiple periods prior to providing care. Appendix Figure A4.2.1 plots the mean MCS and PCS for all intensity levels for up to four years prior to providing informal care. There is little evidence that the observed results are driven by a distinct negative trend in caregivers' mental health starting before the actual onset of care provision. As explained in Appendix A4.2, for physical health a downward sloping trend seems to be present.

Another concern might be the occurrence of other external shocks, such as a deceased family member, that affects mental health outcomes in the periods after caregiving started. Including information on a deceased family member (mother, father or partner) does not explain the observed effects (see Appendix Table A4.2.1). Additionally, we conducted the simulation-based sensitivity analysis proposed by Ichino et al. (2008) to explore the robustness of our results to a violation of the CIA. The detailed procedure is outlined in the Appendix and Figure A4.2.4 plots our static matching results for mental and physical health effects of high-intensity care provision and their upper- and lower-bound ATT estimates based on the simulations. The results show that even in case of a severe violation of the CIA the initial health effect of intensive informal care provision remains negative and significant.

Further, we explore the existence of a potential downward bias underlying our results due to selective attrition. We follow De Zwart et al. (2017) by splitting our sample into two groups and re-estimating the initial treatment effects. For the first group we observe health states past t_1, while for the second group we can only observe health immediately after providing informal care due to permanent survey attrition. Figure A4.2.5 plots the treatment effects for both groups and indicates that the attrition sample experiences more persistent negative effects directly before discontinuing their participation, but no physical health effects. These results indicate some evidence for a downward bias in our estimated treatment effects for mental health in later periods.

---

[40] Appendix A4.2 additionally contains the results of a re-estimation of the treatment effects when separately matching by intensity of care and dropping the upper/lower 5% of propensity scores to explore the impact of the overall matching quality on our results. The results remain highly similar.

While the SF-12 scores allow us to measure mental and physical health, the interpretation of effect sizes is not straightforward. To do so we use two additional outcome measures. We consider a general subjective well-being measure, life-satisfaction, and a mental health screening questionnaire, the general health questionnaire (GHQ). Appendix Figure A4.2.7 and Table A4.2.5 present the corresponding results. When considering alternative outcome measures our results remain generally the same, indicating an asymmetric effect on subjective well-being and mental health especially among high-intensity caregivers. However, the results for GHQ scores depict a pronounced dose-response relationship, not observed when using MCS as the mental health measure. Further, these results also indicate that the decrease in mental health is economically relevant as the number of individuals with surpassing screening thresholds increases substantially by 4 to 8% depending on the used measure and applied threshold.

A concern for our dynamic matching approach stems from the fact that for the later waves we condition on a large set of covariates as all intermediate covariates at each node are included. To check whether our propensity score estimates are suffering from overfitting we follow Lechner (2008) and condition on a smaller set of covariates capturing the most recent information and limited information (socio-economic status and health outcomes) from the previous decision nodes. The results from this alternative specification which are presented in Table A4.2.6 are similar to our main analysis. Additionally, we check whether our results are sensitive to more stringent regression adjustment by, next to conditioning on the full set of covariates from the previous wave also conditioning on health-related covariates from all preceding waves. This does not substantially alter our estimates (Table A4.2.7).

4.7 Discussion & conclusion

Providing informal care can have negative health effects for informal caregivers. Based on the current literature there is an insufficient understanding of how these effects persist over time, differ by care-intensity and duration, and whether observed mental health effects are attributable to caregiving itself or the family effect. We answer these questions by estimating the long-term and dynamic effects of caregiving on caregivers' health using a UK panel survey.

While early studies on cross-sectional data commonly report caregivers to have low physical health (Carretero et al., 2009), we only find mixed evidence for a causal relationship. Our estimates indicate that informal care leads to a small and short-lived increase in physical health among caregivers providing less than 20 hours of weekly care. A potential alternative explanation for this finding could however be that self-reported physical health is prone to bias as caregivers might change their opinion about their own health by taking the health of the care-recipient as a reference point (Di Novi et al., 2015). For caregivers providing more than 20 hours of care the physical health trajectory is downward sloping in the years after becoming a caregiver. However, we caution against interpreting these results as evidence for a cumulative negative effect of informal care on physical health. As shown in Appendix A4.2 this is partially driven by an age-related trend that is not fully captured by the matching estimator while in addition the dynamic matching results provide no indication that physical health effects increase over time.

For caregivers' mental health outcomes, we find immediate and persisting negative effects of providing care. These effects are heterogeneous and mostly incurred by individuals providing more than 20 hours of care per week. The initial negative effects on mental health slowly decrease in size throughout the years but remain persistent up to four and five years after initial care provision depending on the specification. These effects are, potentially due to limited attrition, more persistent than estimates from previous studies that only found direct effects (De Zwart et al., 2017) or effects up to the first three years of care provision (Schmitz & Westphal, 2015). We however still find evidence for selective attrition among those experiencing the strongest initial health losses, suggesting that we might underestimate health effects in later periods (see Appendix Figure A4.2.5). Additionally, our estimates may be downward biased as high-intensity caregivers are underrepresented in our sample.

For these high intensity caregivers (individuals providing ≥20 hours a week) the estimated negative health effects are similar in magnitude compared to earlier results by Schmitz & Westphal (2015) who focus on individuals providing at least three hours of care on a weekday (≥15 hours). For intensive caregivers the results hence seem robust across different countries with different care systems. For low intensity caregivers this is however not the case: Schmitz & Westphal already find a strong negative effect of -1.9 on the MCS for individuals providing one hour of care per weekday, whereas we do not observe health effects for individuals providing less than 20 hours of care per week in the UK. There might be several explanations for this difference. The intensity levels of care provision are, first, not completely similar and the composition of caregivers within these groups might differ. Second, country differences in the long-term care system and support options might drive changes in the size of the caregiving effect as well as they influence both the selection into care as well as the caregiving experience.

Our results also suggest that it is not the family effect, the impact of caring about someone, but the caregiving effect, the impact of caring for someone, that is driving the observed mental health effects. These results are in line with the findings of Bom et al. (2019b), who used administrative data to identify the family effect among a sample of Dutch caregivers. However, we had to restrict our analysis sample to a small subset of predominantly spousal caregivers to estimate caregiving effects while accounting for family-members' health. This subsample is restricted but still highly insightful as it is especially this subgroup among which we would expect the largest potential for family effects driving the observed mental health differences.

Lastly, our dynamic matching results provide insights into the extent to which the static results, indicating decreasing mental health effects over time, are representative for the population of individuals that provide care for multiple consecutive years. There is evidence that the static results do not sufficiently capture that among individuals who provide care for more than one year the mental health effects do not improve over time. Rather for these multi-year caregivers' mental health remains to be negatively affected. At the same time, we also find no clear evidence that the additional years of care past the second year increase the negative mental health effect if intensity remains stable over time. However, as we excluded individuals whose caregiving spells coincide with increasing (or decreasing) care intensity the results need to be interpreted with this caveat in mind.

Our study also has several limitations. First, one might question the use of self-reported health measures and prefer, in our case unavailable, administrative information like medical claims or admission data. We believe that given the population we are studying, informal caregivers, these self-reported health measurements better capture changes in health than information regarding health care usage. For mental health this is especially the case as often not all individuals suffering from mental health problems receive or seek treatment. Additionally, administrative information can only capture actual consumption but highly burdened caregivers might forego medical care. Foregoing care could be directly caused by the intensity of caregiving as well as the potential stigma associated with seeking help as a caregiver itself. In addition, our results remain unchanged when using alternative outcome measures (see Appendix Figure A4.2.3) and indicate that the reported effects are economically relevant from the individuals' perspective. This leaves us confident that the reported mental health effects are of interest to policymakers wishing to assess the extent of spillover effects arising from the reliance on informal care to meet social care demands.

While our rich dataset allowed us to explore the health effects of informal care provision along multiple dimensions not all desired information is available. The first one refers to our measure of care intensity: self-reported caregiving hours. Increased hours are likely to reflect a larger overall caregiving burden, however, the tasks performed by caregivers are highly disease-specific and play an important role in the experienced caregiving burden (Pearlin et al., 1990). Therefore, reported hours are an incomplete measure inadequately capturing an important source of the mental and physical strain associated with caregiving. A related cause for uncertainty is the absence of information on why informal care was taken up and discontinued, a process that itself could affect especially mental health outcomes. Another concern refers to our focus on informal caregiving irrespective of whether this occurs alongside formal care as the USoc does not capture such services consistently. Therefore, we cannot explore to what extent these services might serve as a complement or substitute to informal care or help to mitigate the negative health effects in the medium and long run.[41] Ideally future research would have insight into the type of caregiving tasks, formal care use and information on reasons for care take up and discontinuation.

Lastly, an important limitation of our study is its reliance on a matching-based identification strategy and the underlying assumptions. While we do test the robustness of our results to violations of the main identifying assumption ideal strategy would rely on exogenous variation in informal caregiving. Earlier studies exploring the short-term health effects of informal caregiving often relied on parental health shocks or the number of siblings as an instrumental variable. However, the exogeneity of parental health shocks is at least questionable (Schmitz & Westphal, 2015) while a general concern is whether the estimated local average treatment effects can be generalized for the entire treatment population (Angrist & Imbens, 1995). Recent studies such as Bakx et al. (2020b) or Fischer & Müller (2020) exploited institutional rules and reforms in countries' LTC-sectors as a source of credible exogenous variation in the uptake of formal and informal care use. In our case, however, such an identification strategy was not feasible.

To conclude, our results confirm previous studies reporting negative mental health effects of informal care provision and show that the effects persist up to four or five years after initial care provision. Our estimates suggest that most UK caregivers do not experience adverse health outcomes after providing informal care. However, especially high-intensity and persisting caregivers show to be most strongly affected by informal caregiving. In addition, we document evidence that these effects are driven by the uptake of informal care and unlikely to be explained by the direct effect of family members' poor health or experienced health shocks to the care-recipient. Given the increasing reliance on informal care, these results provide useful insights for policymakers facing difficult trade-offs regarding the allocation of limited resources to support caregivers. Our results indicate that especially high-intensity and long-term caregivers should be targeted to offset the substantial negative health effects. While informal care provides undisputable benefits to public health care

---

[41] USoc wave 7 did include a detailed survey module on informal and formal care sources for recipients; 47% report informal care as the only source of care with 44% reporting a mix of formal and informal care and 8% formal care only. Hours of informal care received are highly similar irrespective of whether it is provided alongside formal care or not. Detailed results are available upon request.

systems and care-recipients the consequences for those providing the care need to be accounted for.

Appendix chapter 4

A4.1 – Dataset conditioning and detailed results

Table A4.1.1: Dataset conditioning

Description	Observations (Individuals)
Merged USoc waves 1-9 (2009-2019)	407,722 (85,908)
Panel A: Static Matching Data Conditioning	
Excluding individuals not providing caregiving information	374,903 (79,377)
Excluding respondents with single or non-consecutive initial first two observations.	314,124 (57,619)
Conditioning on non proxy respondents and full set of control variables at t=-1 and health outcomes in t>=0 at t=-1 and t=0	259,675 (54,796)
Excluding individuals starting as caregivers in their first wave.	228,478 (50,293)
Conditioning on non proxy respondents and full set of control variables at t=-1 and health outcomes in t>=0 for all time points (hence excluding observations in all time points in case of missing information at t=-1 or t=0).	137,313 (22,286)
Excluding individuals without consecutive observations at t=-1 and t=0	123,739 (19,822)
Analysis Dataset:	123,739 (19,822)
Panel B: Static Matching Family Effect Subsample	
Static matching analysis sample - baseline specification	19,822
Reduce sample to individuals cohabiting with partner and/or parents.	7,554
Remove individuals without living parents and without partner.	5,626
Remove caregivers providing care outside their own household.	4,321
Remove individuals for which cohabitees health is not observed in t=-1 and t=0	3,766
Analysis Dataset:	23,672 (3,766)
Panel C: Dynamic Matching Data Conditioning	
Excluding individuals not providing caregiving information proxy respondents, and individuals without information on health outcomes	303,434 (73,052)
Excluding individuals not participating for at least four consecutive waves.	205,418 (33,000)
Excluding individuals without complete information on control variables.	106,004 (19,762)
Excluding individuals unstable care trajectories	99,540 (19,365)
Excluding individuals to ensure that individuals are not included twice (as individuals starting care provision are pooled forward)	77,460 (19,365)
Analysis Dataset:	77,460 (19,365)

Table A4.1.2: Static estimation results stratified by gender and care intensity

	Full Sample											
	t=0		t=1		t=2		t=3		t=4		t=5	
	MCS	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**
Any Care	-0.421**	0.327**	-0.624***	0.006	-0.383*	-0.248	-0.396*	-0.260	-0.672***	0.111	-0.52*	-0.109
	(0.135)	(0.126)	(0.145)	(0.141)	(0.156)	(0.157)	(0.177)	(0.175)	(0.196)	(0.193)	(0.214)	(0.217)
Low Intensity	-0.016	0.314*	-0.423**	0.149	-0.266	-0.068	-0.268	-0.156	-0.622**	0.346	-0.46*	0.216
<10h weekly care	(0.141)	(0.133)	(0.153)	(0.151)	(0.168)	(0.167)	(0.188)	(0.186)	(0.210)	(0.206)	(0.228)	(0.228)
Medium Intensity	-0.452	0.377	-0.324	-0.615	-0.309	-0.760*	-0.473	-0.508	-0.331	-0.476	-0.661	-0.773
10-20h weekly care	(0.306)	(0.273)	(0.353)	(0.318)	(0.402)	(0.357)	(0.408)	(0.415)	(0.502)	(0.477)	(0.577)	(0.587)
High Intensity	-2.591***	0.264	-2.221***	-0.348	-0.984*	-1.040*	-1.374**	-0.816	-1.565**	-0.660	-0.963	-1.479*
>20h weekly care	(0.329)	(0.290)	(0.362)	(0.328)	(0.410)	(0.391)	(0.477)	(0.439)	(0.501)	(0.524)	(0.578)	(0.592)
Control		12,970		12,290		10,409		9,590		8,545		8,050
Treatment		6,848		5,723		4,802		4,134		3,193		2,461
Low		5,069		4,264		3,600		3,121		2,402		1,852
Medium		792		684		556		485		373		289
High		895		699		588		473		377		285
	Females Only											
	t=0		t=1		t=2		t=3		t=4		t=5	
	MCS	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**
Any Care	-0.556**	0.432*	-0.792***	-0.034	-0.206	-0.419*	-0.469*	-0.702**	-0.775**	-0.124	-0.62*	-0.375
	(0.187)	(0.169)	(0.200)	(0.190)	(0.221)	(0.213)	(0.247)	(0.235)	(0.268)	(0.259)	(0.294)	(0.286)
Low Intensity	-0.106	0.446*	-0.527*	0.155	-0.115	-0.257	-0.341	-0.508*	-0.725*	0.130	-0.442	0.056
<10h weekly care	(0.196)	(0.179)	(0.212)	(0.204)	(0.233)	(0.227)	(0.262)	(0.249)	(0.287)	(0.278)	(0.311)	(0.303)
Medium Intensity	-0.611	0.314	-0.374	-0.93*	-0.549	-0.353	-0.288	-1.105*	-1.097	-0.430	-1.55*	-1.018
10-20h weekly care	(0.421)	(0.374)	(0.466)	(0.423)	(0.514)	(0.473)	(0.545)	(0.541)	(0.676)	(0.620)	(0.763)	(0.750)

Table A4.1.2: Continued.

High Intensity	-2.734***	0.349	-2.741***	-0.396	-0.394	-1.494**	-1.583*	-1.602**	-1.245	-1.126	-1.321	-2.264**
>20h weekly care	(0.433)	(0.375)	(0.470)	(0.426)	(0.522)	(0.505)	(0.629)	(0.574)	(0.641)	(0.636)	(0.778)	(0.778)
Control		6,839		6,514		5,540		5,118		4,540		4,292
Treatment		4,054		3,408		2,854		2,464		1,925		1,487
Low		2,954		2,499		2,098		1,827		1,416		1100
Medium		472		415		335		293		232		176
High		576		451		385		308		252		189
Males Only												
	t=0		**t=1**		**t=2**		**t=3**		**t=4**		**t=5**	
	MCS	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**
Any Care	-0.164	0.248	-0.301	0.076	-0.558*	0.058	-0.137	0.420	-0.489	0.542	-0.295	0.326
	(0.189)	(0.184)	(0.202)	(0.207)	(0.224)	(0.226)	(0.247)	(0.258)	(0.279)	(0.288)	(0.307)	(0.328)
Low Intensity	0.149	0.213	-0.206	0.157	-0.445	0.267	-0.048	0.387	-0.507	0.714*	-0.468	0.446
<10h weekly care	(0.196)	(0.196)	(0.213)	(0.221)	(0.235)	(0.240)	(0.259)	(0.274)	(0.300)	(0.300)	(0.335)	(0.345)
Medium Intensity	-0.112	0.514	-0.185	-0.165	0.324	-1.498**	-0.396	0.262	1.062	-0.459	0.888	-0.210
10-20h weekly care	(0.431)	(0.398)	(0.541)	(0.479)	(0.589)	(0.532)	(0.617)	(0.653)	(0.710)	(0.753)	(0.841)	(0.923)
High Intensity	-2.197***	0.135	-1.263*	-0.309	-1.881**	-0.241	-0.774	0.468	-2.223**	0.334	-0.196	-0.095
>20h weekly care	(0.499)	(0.463)	(0.551)	(0.500)	(0.652)	(0.609)	(0.716)	(0.644)	(0.810)	(0.912)	(0.803)	(0.974)
Control		6,131		5,776		4,869		4,472		4,005		3,758
Treatment		2,794		2,315		1,948		1,670		1,268		974
Low		2,117		1,765		1,502		1,294		986		752
Medium		320		269		221		192		141		113
High		319		248		203		165		125		96

*p<0.05, ** p<0.01, ***p<0.001, standard errors in parentheses.

Table A4.1.3: Treatment effects including care-relationship interaction terms

	Any Care											
	t=0		**t=1**		**t=2**		**t=3**		**t=4**		**t=5**	
	MCS	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**
Any Care	-0.093	0.124	-0.044	-0.049	0.006	-0.237	0.001	-0.523	-0.684*	0.028	-0.161	0.026
	(0.202)	(0.195)	(0.225)	(0.229)	(0.249)	(0.244)	(0.272)	(0.283)	(0.304)	(0.315)	(0.345)	(0.350)
Spousal Care	-1.805***	-0.523	-1.615***	-0.657	-1.388***	-0.467	-1.486**	-0.422	-1.442**	-0.290	-1.557*	-0.552
	(0.318)	(0.309)	(0.359)	(0.343)	(0.397)	(0.408)	(0.476)	(0.473)	(0.524)	(0.545)	(0.638)	(0.607)
Parental Care	-0.008	0.073	-0.350	0.190	-0.132	0.023	-0.403	0.680*	0.214	0.097	0.236	0.007
	(0.253)	(0.233)	(0.278)	(0.275)	(0.309)	(0.299)	(0.348)	(0.339)	(0.387)	(0.382)	(0.428)	(0.429)
Control		12,970		12,290		10,409		9,590		8,545		8,050
Treatment		6,848		5,723		4,802		4,134		3,193		2,461
Spousal Care		1,002		813		663		536		422		316
Parental Care		2,826		2,406		2,040		1,776		1,389		1,094
	High Intensity Care											
	t=0		**t=1**		**t=2**		**t=3**		**t=4**		**t=5**	
	MCS	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**
Any Care	-3.020***	-0.241	-1.972**	-0.240	-0.194	-1.500*	-1.860*	-1.460	-1.880	-0.296	-0.748	-1.100
	(0.606)	(0.533)	(0.732)	(0.652)	-(1.628)	(0.722)	(0.889)	(0.773)	(1.095)	(0.984)	(1.031)	(1.011)
Spousal Care	-0.009	0.566	-0.590	-0.006	-1.628	0.241	-0.423	1.086	-0.381	0.227	-1.381	0.768
	(0.759)	(0.697)	(0.874)	(0.803)	(0.949)	(0.941)	(1.154)	(1.016)	(1.319)	(1.302)	(1.464)	(1.364)
Parental Care	-0.062	0.344	0.604	-0.403	-0.369	2.043	2.830*	0.629	2.151	0.058	2.550	1.680
	(1.063)	(0.838)	(1.130)	(0.994)	(1.207)	(1.114)	(1.274)	(1.164)	(1.661)	(1.509)	(1.953)	(1.475)
Control		12,970		12,290		10,409		9,590		8,545		8,050

Table A4.1.3: Continued.

Treatment	895	699	588	473	377	285
Spousal Care	361	279	232	179	147	107
Parental Care	199	161	141	110	91	65

*p<0.05, ** p<0.01, ***p<0.001, standard errors in parentheses.

Table A4.1.4: Family and caregiving effect after PSM re-estimation

	t=0		**t=1**		**t=2**		**t=3**		**t=4**		**t=5**	
	MCS	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**
High Intensity	**-3.151*****	0.469	**-2.855****	-0.148	-1.057	-1.200	-1.816	-0.398	-1.533	1.868	-0.355	0.578
>20h weekly care	(0.831)	(0.799)	(0.865)	(0.872)	(0.962)	(1.200)	(1.136)	(1.180)	(0.994)	(1.264)	(1.448)	(1.566)
Family Health Shock	-0.482	0.701	-0.281	0.723	-0.793	0.787	-0.757	-0.119	-1.275	0.428	-1.347	1.631
	(0.761)	(0.705)	(0.696)	(0.756)	(0.806)	(0.918)	(1.000)	(1.008)	(0.899)	(1.003)	(1.049)	(1.084)
Control		**2,878**		**2,708**		**2,264**		**2,058**		**1,879**		**1,726**
Treatment		165		134		110		83		73		46
Family Health Shock		683		626		518		442		417		374

*p<0.05, ** p<0.01, ***p<0.001, standard errors in parentheses.

A4.2 – Additional analyses and robustness checks

Physical Health Effects and by Age-related Trends

Figure A4.2.1: Age distribution by caregiving status & health trends

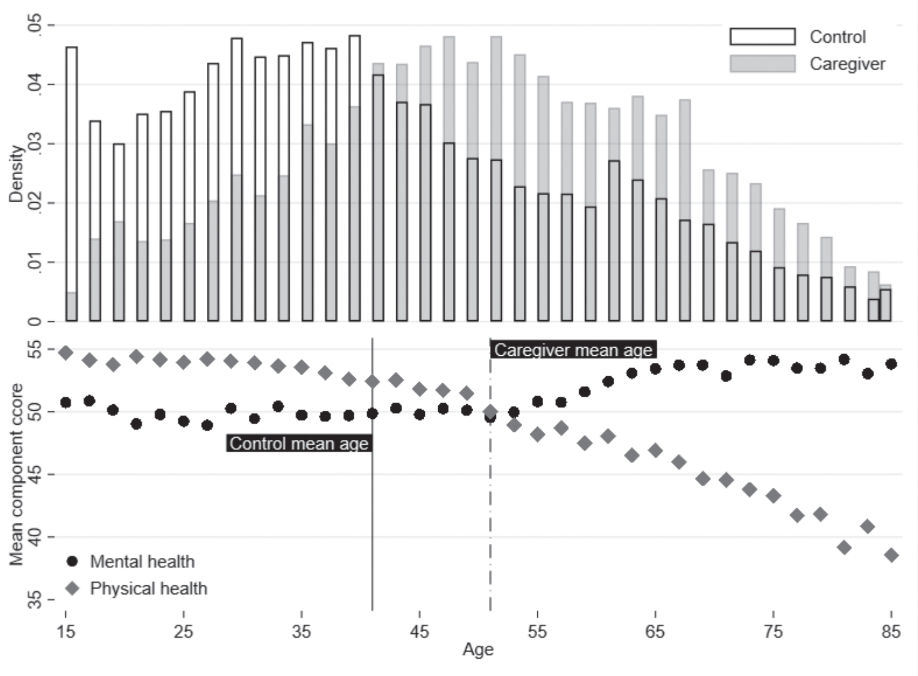


Figure A4.2.3 plots the age-distribution of caregivers and non-caregivers as well as the mean mental and physical component scores by age in two-year groups and using information of all individuals before any caregiving occurs and for the unmatched sample. The figure illustrates why we suspect that the physical health effects documented among (high-intensity) caregivers are partially driven by the fact that our matching approach inadequately captures ageing-related physical health trends across the lifecycle.

We explore this explanation by separately re-estimating our main results by age group, splitting the sample into those aged 50+ and those below 50.[42] The results indicate no physical health effects among older individuals while among younger individuals the results pattern persists.

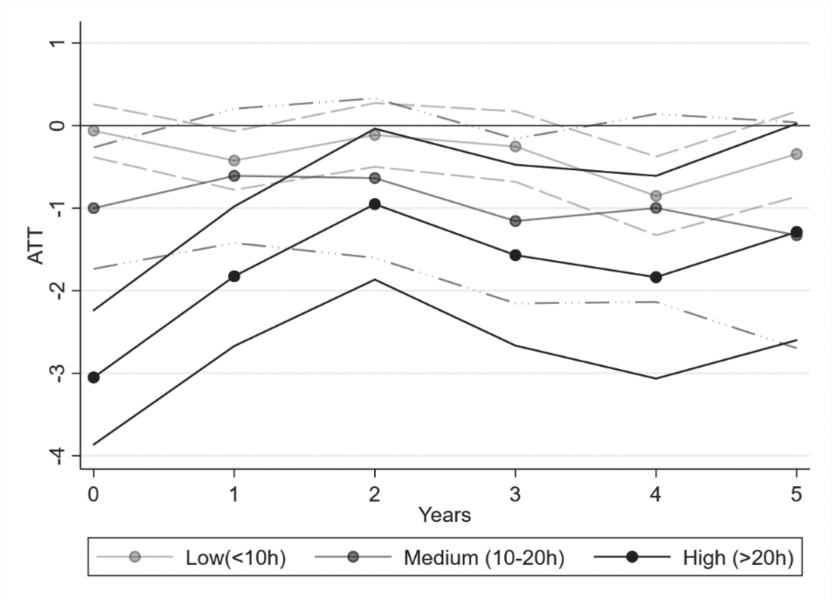
---

[42] We have also tried other splitting points (40, 45, 55, 60) with all results supporting the described relationship.

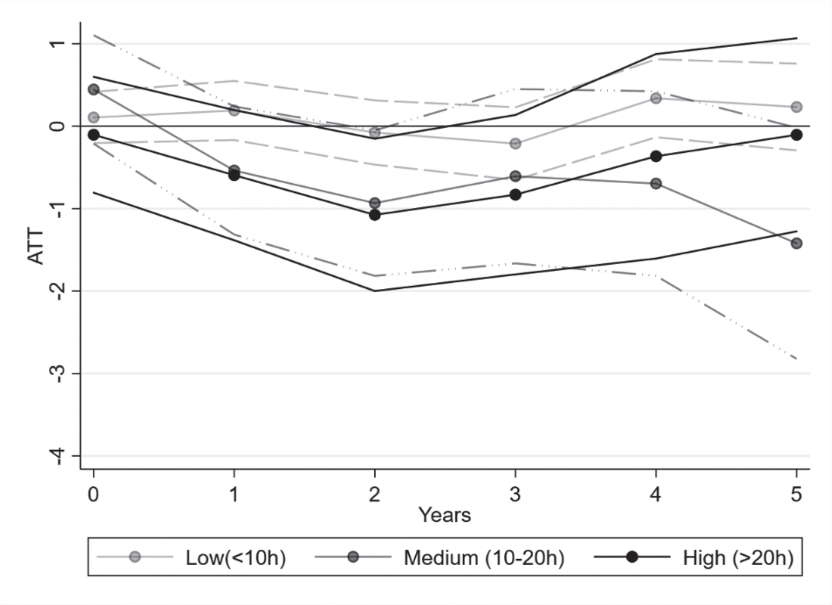
Propensity score matching by intensity and selective propensity score inclusion

Figure A4.2.1: Static results by intensity and selective propensity score inclusion

a) Mental Health



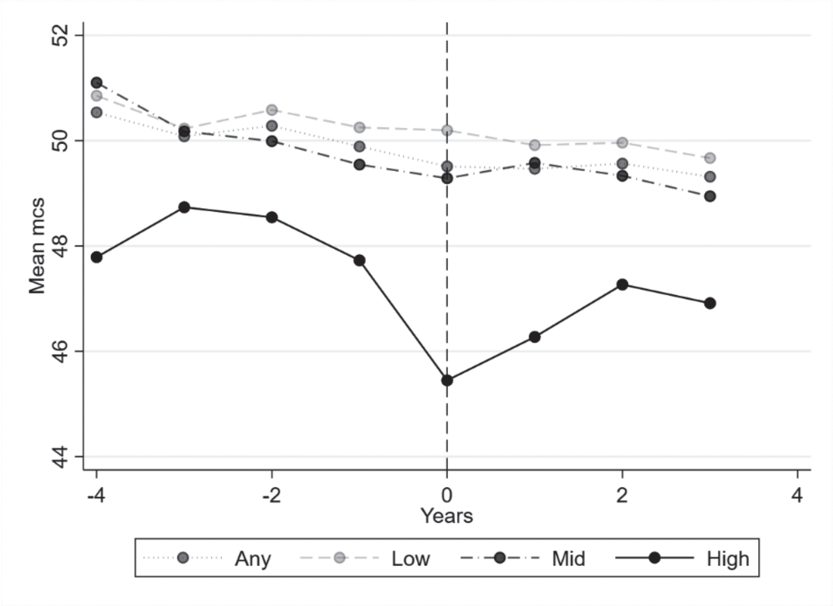
b) Physical Health



Pre-treatment trends

Figure A4.2.3: Mean MCS/PCS before informal care onset by intensity

a) Mental Health



b) Physical Health

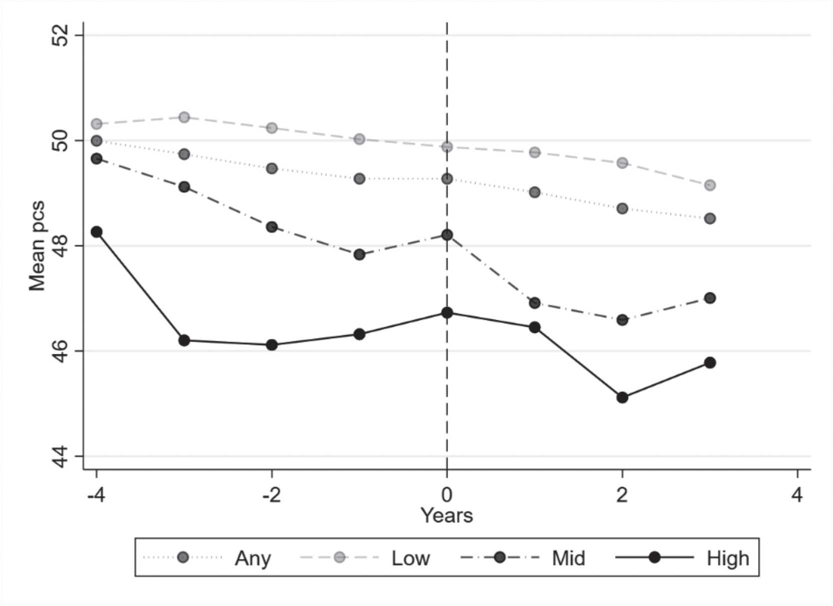


Table A4.2.1: Bereavement effects

	t=0		t=1		t=2		t=3		t=4		t=5	
High Intensity	-3.043***	0.123	-2.001***	-0.406	-1.036*	-0.995	-1.449**	-0.845	-1.520**	0.171	-0.852	-0.472
>20h weekly care	(0.382)	(0.342)	(0.413)	(0.383)	(0.452)	(0.458)	(0.539)	(0.492)	(0.580)	(0.610)	(0.651)	(0.656)
Death in the Family	-4.474***	1.068	-3.110**	1.755*	-6.150***	2.151	-6.598***	4.174***	-5.043***	0.104	-5.920***	3.532*
	(1.231)	(0.755)	(1.094)	(0.847)	(1.644)	(1.230)	(1.430)	(0.985)	(1.400)	(1.123)	(1.287)	(1.404)
Control		12,970		12,290		10,409		9,590		8,545		8,050
Treatment		895		699		588		473		377		285
Death in the Family		163		185		177		170		159		153

*p<0.05, **p<0.01, ***p<0.001, standard errors in parentheses.

Bereavement effects

We use the available information on the living status of close family members (parents or partner) to explore whether the observed treatment effects are explained by the death of a family member. As the group of informal caregivers is older than the overall sample and more likely to have family members in poor health they are also more likely to experience a death in the family during the observation period. As in our main specification we do not account for such shocks this could lead to a wrongful attribution of the differences in (mental) health outcomes between treatment and control groups due to providing informal care and not the experienced loss of a family member. Indeed, high-intensity informal caregivers are more likely to experience the death of a close family member. While within the control group around 6.93% of all individuals experience the death of a close family member between t_0 and t_5. This rate is 11.15% among high-intensity caregivers. Table A4.2.1 reports the static matching results when including a binary indicator for a given family member being reported deceased at a given *t*. In line with expectations such an event has no effect on physical health but strong negative effects on mental health. However, given that the estimated treatment effects remain largely unaffected the difference in health outcomes between caregivers and control group are not explained by such time-varying shocks.

Simulated violation of the conditional independence assumption

In this sensitivity analysis we focus on high-intensity caregivers and mental health outcomes to test the robustness of our main result. Our estimation strategy relies on the conditional independence assumption (CIA) stating that selection into treatment is driven only by observable variables. We use a rich set of covariates covering multiple dimensions relevant to the selection into informal caregiving and mental health in the propensity score estimation, hence we argue that the CIA is likely to hold. However, the CIA is untestable and unobserved variables might be influencing the selection into informal caregiving and mental health outcomes, thereby biasing our estimates. To assess the robustness of our estimates to such a violation we follow Ichino et al. (2008) who propose a simulation-based sensitivity analysis for matching estimators. We only roughly sketch the underlying procedure and intuition behind the procedure. A more elaborate discussion can be found in Ichino et al. (2008).

Consider the conditional independence assumption in our context:

$$Y_t^0 \perp\!\!\!\perp T \mid X_{-1}, Y_{-1} \; \forall \, t$$

After conditioning on a set of pre-treatment control (X_{-1}) and outcome variables (Y_{-1}) the potential outcomes in a given period *t* in absence of informal care provision (Y_t^0) across treatment and control groups are the same. Now consider that this assumption is violated due to a confounder U. If we additionally condition on this confounder the CIA would be satisfied:

$$Y_t^0 \perp\!\!\!\perp T \mid X_{-1}, Y_{-1}, U \; \forall \, t$$

Ichino et al. (2008) outline a sensitivity analysis that simulates a binary U in the context of a binary outcome variable. A binary U is attractive as its distribution can be expressed by four parameters p_{ij} where i indicates the treatment status (0,1) and j indicates the outcome status (0,1). For continuous outcomes they propose a transformation of the continuous outcome:

$$\hat{Y} = \begin{cases} 1, & Y > \bar{Y} \\ 0, & else \end{cases}$$

In our case we set $\bar{Y}$ equal to the sample mean of MCS across high-intensity caregivers and the overall control group. The four p_{ij} that determine the distribution of U are defined as:

$$\begin{aligned} p_{01} &= \Pr(U = 1 \mid T = 0, \hat{Y} = 1) \\ p_{00} &= \Pr(U = 1 \mid T = 0, \hat{Y} = 0) \\ p_{11} &= \Pr(U = 1 \mid T = 1, \hat{Y} = 1) \\ p_{10} &= \Pr(U = 1 \mid T = 1, \hat{Y} = 0) \end{aligned}$$

These p_{ij} describe the distribution of U:

$$\begin{aligned} Pr(U = 1) = p_{11} \Pr\big(\hat{Y} = 1 \big| T = 1\big) \Pr(T = 1) + p_{10} \Pr\big(\hat{Y} = 0 \big| T = 1\big) \Pr(T = 1) \\ + p_{01} \Pr\big(\hat{Y} = 1 \big| T = 0\big) \Pr(T = 0) + p_{00} \Pr\big(\hat{Y} = 0 \big| T = 0\big) \Pr(T = 0) \end{aligned}$$

Ichino et al. (2008) propose to choose the values of p_{ij} in such a way to deliberately control for the selection effect s of U on treatment uptake and the outcome effect d of U on the probability to observe $\hat{Y} = 1$. These effects are defined as:

$$s = p_{1\cdot} - p_{0\cdot}$$

where

$$p_{i\cdot} = \Pr(U = 1 \mid T = i) = p_{i0} * \Pr\big(\hat{Y} = 1 \big| T = i\big) + p_{i1} * \Pr\big(\hat{Y} = 1 \big| T = i\big) \; with \; i \in \{0{,}1\}$$

The outcome effect is defined as

$$d = p_{01} - p_{00}$$

The sensitivity analysis is then conducted by choosing a set of p_{ij} that model a confounder with specific selection and outcome effects. Given these values for s and d one has to assume a value for $\Pr(U = 1)$ and the relationship between p_{11} and p_{01} in order to be able to solve the equations for $\Pr(U)$, d, and s for all p_{ij}. We follow the example given by Ichino et al. (2008) by assuming $\Pr(U = 1) = 0.5$ and $p_{11} - p_{01} = 0$ to solve for all of p_{ij} given the empirically observed $\Pr(\bar{Y} = i \,|T = i)$ and $\Pr(T = i)$.

As an example consider an unobserved confounder with negative selection ($s < 0$) and positive outcome effect ($d < 0$). This might be the unobserved availability of resources to purchase formal care services by the recipient itself. As informal care is largely done by family-members the availability of resources is likely to decrease the likelihood of (high-intensity) informal care provision while increasing mental health in the absence of treatment. By not accounting for such a confounder our estimation would therefore underestimate the effect of informal care on mental health. By selecting the magnitude and direction of selection and outcome effects and the corresponding p_{ij} the effect of U is simulated by drawing repeatedly from a Bernoulli distribution with the desired distributional properties. Robust estimates of both the ATT and the corresponding standard errors are then given by their averages across these simulations.

To calibrate the sensitivity analysis, we need a starting point of selection and outcome effects to obtain the parameters p_{ij} for the distribution of a realistic confounder. Ichino et al. (2008) recommend inspecting the selection and outcome effects of important covariates in the propensity score estimation in order to find reasonable values for the simulation. Table A4.2.2 depicts the estimated effects (d and s) and the parameters (p_{ij}) for all covariates used in the estimation of propensity scores and using the mental component scores as the outcome of interest. These are obtained by using a customized version of the user-written command for Stata by Nannicini (2007) implementing the sensitivity analysis proposed by Ichino et al. (2008). Please note that continuous variables were adapted to comply with the binary nature of U by transforming them into categorical variables.

Table A4.2.2: Estimated selection and outcome effects

Variable	p11	p10	p01	p00	p1.	p0.	s	d
Care Obligations								
Mother alive	0.48	0.56	0.66	0.75	0.53	0.70	-0.17	-0.09
Mother aged <49	0.06	0.06	0.12	0.15	0.06	0.13	-0.07	-0.03
Mother aged 50-59	0.13	0.15	0.21	0.24	0.14	0.22	-0.08	-0.03
Mother aged 60-69	0.12	0.17	0.20	0.22	0.15	0.21	-0.06	-0.02
Mother aged 70-79	0.08	0.12	0.10	0.10	0.11	0.10	0.01	0.00
Mother aged 80-89	0.08	0.05	0.03	0.03	0.06	0.03	0.03	0.00
Mother aged >90	0.91	0.94	0.87	0.84	0.93	0.86	0.07	0.03
Father alive	0.36	0.48	0.60	0.68	0.43	0.63	-0.20	-0.08
Father aged <49	0.03	0.03	0.08	0.10	0.03	0.09	-0.06	-0.02
Father aged 50-59	0.10	0.13	0.17	0.21	0.12	0.19	-0.07	-0.04
Father aged 60-69	0.11	0.14	0.20	0.22	0.13	0.21	-0.08	-0.02
Father aged 70-79	0.05	0.12	0.11	0.11	0.09	0.11	-0.02	0.00
Father aged 80-89	0.05	0.06	0.03	0.02	0.05	0.03	0.02	0.01
Father aged >90	0.95	0.96	0.90	0.89	0.96	0.90	0.06	0.01
Both parents alive	0.32	0.41	0.56	0.64	0.38	0.60	-0.22	-0.08
Living siblings	0.84	0.86	0.87	0.90	0.85	0.88	-0.03	-0.03
Living partner	0.73	0.75	0.67	0.59	0.74	0.64	0.10	0.08
Partner aged <29	0.04	0.05	0.10	0.11	0.05	0.10	-0.05	-0.01
Partner aged 30-39	0.11	0.15	0.18	0.19	0.13	0.19	-0.06	-0.01
Partner aged 40-49	0.10	0.16	0.15	0.15	0.14	0.15	-0.01	0.00
Partner aged 50-59	0.13	0.11	0.09	0.07	0.12	0.08	0.04	0.02
Partner aged 60-69	0.13	0.11	0.10	0.05	0.12	0.08	0.04	0.05
Partner aged 70-79	0.15	0.12	0.04	0.02	0.13	0.03	0.10	0.02
Partner aged 80-89	0.08	0.05	0.00	0.00	0.06	0.00	0.06	0.00
Partner aged >90	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Willingness to Care								
Own age <29	0.12	0.12	0.26	0.33	0.12	0.29	-0.17	-0.07
Own age 30-39	0.15	0.23	0.23	0.24	0.19	0.23	-0.04	-0.01
Own age 40-49	0.14	0.18	0.18	0.20	0.16	0.18	-0.02	-0.02
Own age 50-59	0.16	0.16	0.12	0.11	0.16	0.12	0.04	0.01
Own age 60-69	0.18	0.15	0.13	0.07	0.16	0.11	0.05	0.06
Own age 70-79	0.19	0.11	0.07	0.04	0.15	0.06	0.09	0.03
Own age 80-89	0.06	0.04	0.02	0.01	0.05	0.02	0.03	0.01
Own age >90	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Female	0.59	0.68	0.50	0.58	0.64	0.53	0.11	-0.08

Table A4.2.2: Continued.

Variable	p11	p10	p01	p00	p1.	p0.	s	d
Education: Primary/Other lower	0.32	0.33	0.18	0.17	0.33	0.18	0.15	0.01
Education: Secondary	0.41	0.40	0.43	0.45	0.41	0.45	-0.04	-0.02
Educaiton: Tertiary	0.27	0.26	0.39	0.38	0.27	0.39	-0.12	0.01
Self employed	0.06	0.04	0.07	0.06	0.05	0.07	-0.02	0.01
Unemployed	0.07	0.07	0.04	0.06	0.07	0.05	0.02	-0.02
Employed	0.35	0.35	0.58	0.55	0.35	0.57	-0.22	0.03
Working full-time	0.28	0.24	0.51	0.49	0.25	0.50	-0.25	0.02
Retired	0.36	0.27	0.17	0.10	0.31	0.14	0.17	0.07
In education/other	0.04	0.02	0.09	0.12	0.03	0.10	-0.07	-0.03
Homecarer	0.09	0.15	0.04	0.06	0.13	0.05	0.08	-0.02
Disabled	0.03	0.10	0.01	0.05	0.07	0.02	0.05	-0.04
Income Quintile 1 (Lowest)	0.24	0.27	0.18	0.23	0.25	0.20	0.05	-0.05
Income Quintile 2	0.26	0.25	0.19	0.20	0.25	0.20	0.05	-0.01
Income Quintile 3	0.21	0.23	0.21	0.19	0.22	0.20	0.02	0.02
Income Quintile 4	0.16	0.16	0.21	0.20	0.16	0.20	-0.04	0.01
Income Quintile 5 (Highest)	0.14	0.10	0.22	0.19	0.12	0.21	-0.09	0.03
HH Income Fraciton > 0.5	0.51	0.50	0.50	0.48	0.50	0.49	0.01	0.02
Married	0.62	0.62	0.51	0.42	0.62	0.48	0.14	0.09
Single	0.14	0.12	0.22	0.29	0.13	0.25	-0.12	-0.07
Separated/Divorced	0.09	0.10	0.07	0.08	0.10	0.07	0.03	-0.01
Widowed	0.04	0.03	0.04	0.04	0.03	0.04	-0.01	0.00
Partnership	0.11	0.13	0.16	0.17	0.12	0.16	-0.04	-0.01
Children in HH	0.30	0.40	0.38	0.42	0.36	0.39	-0.03	-0.04
Young children in HH	0.28	0.38	0.34	0.38	0.33	0.36	-0.03	-0.04
Region: North-East	0.04	0.05	0.04	0.04	0.05	0.04	0.01	0.00
Region: North-West	0.12	0.13	0.11	0.12	0.12	0.11	0.01	-0.01
Region: Yorkshire	0.06	0.08	0.08	0.08	0.08	0.08	0.00	0.00
Region: East Midlands	0.08	0.09	0.07	0.08	0.08	0.08	0.00	-0.01
Region: West Midlands	0.05	0.09	0.07	0.08	0.07	0.07	0.00	-0.01
Region: East England	0.11	0.07	0.10	0.09	0.08	0.09	-0.01	0.01
Region: London	0.08	0.08	0.09	0.11	0.08	0.10	-0.02	-0.02
Region: South East	0.09	0.10	0.14	0.13	0.10	0.14	-0.04	0.01
Region: South West	0.09	0.07	0.09	0.08	0.08	0.09	-0.01	0.01
Region: Wales	0.11	0.10	0.06	0.07	0.11	0.07	0.04	-0.01
Region: Scotland	0.10	0.07	0.10	0.08	0.08	0.09	-0.01	0.02
Region: Northern Ireland	0.06	0.07	0.05	0.05	0.07	0.05	0.02	0.00

Table A4.2.2: Continued.

Variable	p11	p10	p01	p00	p1.	p0.	s	d
Living in urban area	0.72	0.78	0.74	0.78	0.75	0.76	-0.01	-0.04
Big 5: Openness	0.55	0.48	0.55	0.53	0.51	0.55	-0.04	0.02
Big 5: Conscientiousness	0.62	0.49	0.57	0.45	0.55	0.52	0.03	0.12
Big 5: Extraversion	0.56	0.48	0.56	0.49	0.52	0.54	-0.02	0.07
Big 5: Agreeableness	0.67	0.62	0.60	0.55	0.64	0.58	0.06	0.05
Big 5: Neuroticism	0.36	0.64	0.38	0.68	0.52	0.50	0.02	-0.30
Ability to Care								
Self-Assessed Health	0.46	0.67	0.37	0.52	0.59	0.43	0.16	-0.15
MCS	0.72	0.33	0.78	0.41	0.49	0.63	-0.14	0.37
PCS	0.52	0.43	0.72	0.66	0.46	0.69	-0.23	0.06
LSI	0.35	0.48	0.25	0.34	0.43	0.29	0.14	-0.09
Number of Functional Limitations	0.23	0.36	0.14	0.23	0.30	0.18	0.12	-0.09
Satisfaction with Health	0.52	0.30	0.65	0.44	0.39	0.57	-0.18	0.21
Satisfaction with Income	0.59	0.38	0.67	0.49	0.47	0.60	-0.13	0.18
Satisfaction with Leisure	0.70	0.49	0.69	0.50	0.58	0.62	-0.04	0.19
Life Satisfaction	0.69	0.38	0.73	0.46	0.51	0.63	-0.12	0.27
GHQ Score	0.80	0.50	0.83	0.52	0.62	0.72	-0.10	0.31

The largest outcome and selection effects in absolute terms are estimated for the set of pre-treatment health and well-being outcomes which is also precisely why we condition on pre-treatment outcomes. The second largest absolute selection and outcome effects are estimated for working full-time ($s = -0.25$) and scoring above four on the neuroticism seven-point scale ($d = -0.30$). For the sensitivity analysis we select two pairs of and to obtain upper and lower bounds for our ATT estimates. These are $s \in \{-0.25, 0.25\}$ and $d = 0.30$.[43]

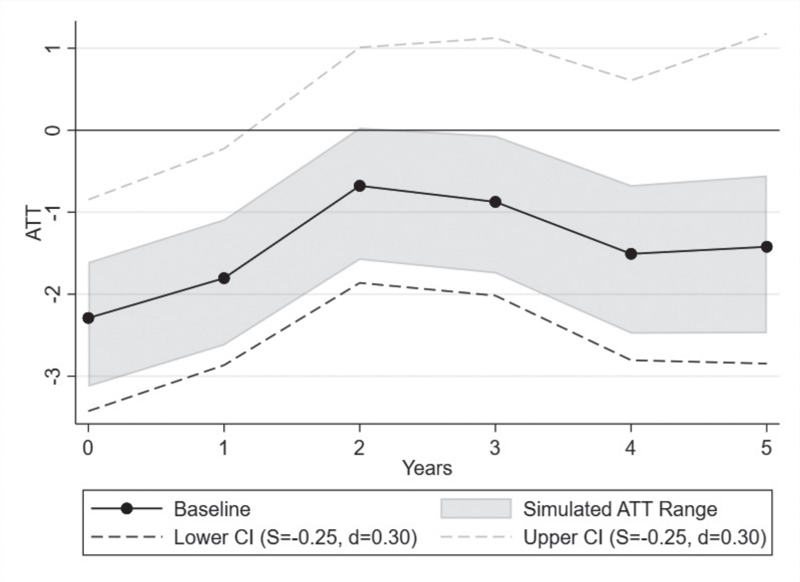
Figure A4.2.4 plots our static matching results for mental health effects of high-intensity care provision and their upper- and lower-bound ATT estimates based on the simulations.

---

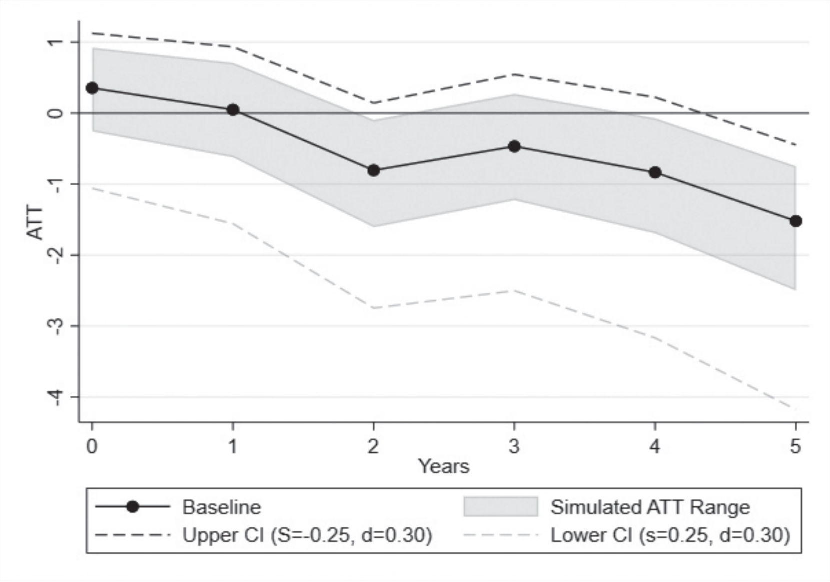
[43] The selection effects for physical health are analogous. The outcome effects differ in an expected manner with the largest effects occurring among own health outcomes and age-related covariates, representing the fact that physical health is more age-dependent than mental health. For both the maximum outcome and selection effects depict a similar range, hence we use the same simulated effects for both outcomes.

Figure A4.2.4: Simulated violation of the CIA

a) Mental Health



b) Physical Health

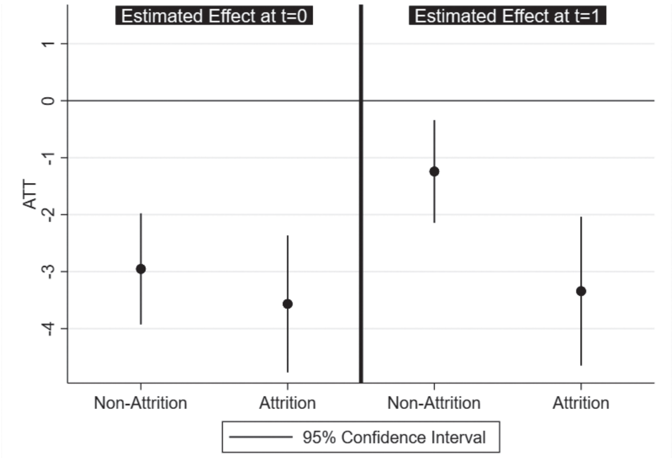


The results show that even when simulating a hypothetical confounder that combines the largest selection and outcome effects observed among the rich pool of observed variables already used in our matching procedure the immediate treatment effects would not vanish completely. These results provide additional confidence that the estimated negative mental health effects are not simply a chance finding or attributable to a conceivable violation of the CIA. It is crucial to note that this sensitivity analysis has an important drawback as it does operate under the assumption that the modelled effects are time-invariant. However, given that there are other concerns about the treatment effects in the longer-term, such as selective attrition driven by caregiving burden, we argue that to test our main finding this simulation is still insightful.

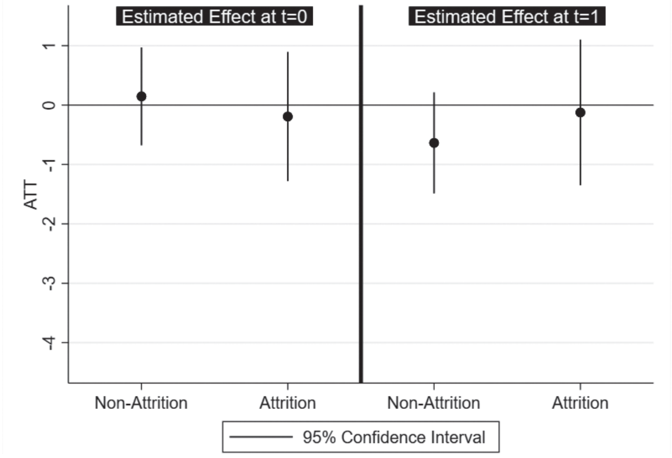
Selective attrition

Figure A4.2.5: Initial treatment effect (high intensity) by attrition

a) Mental Health



b) Physical Health



Robustness checks dynamic sample

Table A4.2.3 – Robustness check: Regression adjustment at all nodes

	Mental Health						
	t=0	**t=1**			**t=2**		
	Static/ Dynamic	**Static**	**Dynamic (2v0)**	**Dynamic (2v1)**	**Static**	**Dynamic (3v0)**	**Dynamic (3v2)**
Any	-0.332	-0.651**	-0.627	-0.212	-0.268	-0.125	-0.590
	(0.208)	(0.222)	(0.353)	(0.449)	(0.221)	(0.373)	(0.593)
Low Intensity	-0.036	-0.366	-0.261	0.160	-0.033	-0.303	0.263
	(0.224)	(0.242)	(0.372)	(0.487)	(0.248)	(0.460)	(0.686)
Medium/High Intensity	-1.370*	-1.697**	-1.893**	-2,533*	-1.049*	0.530	3.267
	(0.482)	(0.500)	(0.706)	(1.028)	(0.473)	(0.586)	(2.382)
	Physical Health						
	t=0	**t=1**			**t=2**		
	Static/ Dynamic	**Static**	**Dynamic (2v0)**	**Dynamic (2v1)**	**Static**	**Dynamic (3v0)**	**Dynamic (3v2)**
Any	0.052	-0.191	-0.146	0.159	0.037	-0.059	-0.055
	(0.196)	(0.214)	(0.332)	(0.437)	(0.221)	(0.368)	(0.579)
Low Intensity	0.203	-0.118	-0.259	0.037	0.204	0.243	-0.179
	(0.218)	(0.245)	(0.369)	(0.497)	(0.254)	(0.424)	(0.671)
Medium/High Intensity	-0.470	-0.365	0.642	1.672	-0.562	-0.588	-0.269
	(0.434)	(0.424)	(0.529)	(0.878)	(0.439)	(0.621)	(1.962)
Treatment	1,348	1,348	552	552	1,348	311	311
(Control)	(16,081)	(16,081)	(14,782)	(768)	(16,081)	(13,511)	(205)
Low Intensity	1,019	1,019	411	411	1,019	220	220
	(16,081)	(16,081)	(14,782)	(585)	(16,081)	(13,511)	(170)
Medium/High	312	312	138	138	312	86	86
Intensity	(16,081)	(16,081)	(14,782)	(168)	(16,081)	(13,511)	(35)

Source: USoc, own calculations. *p<0.05, ** p<0.01, ***p<0.001, standard errors in parentheses.

Table A4.2.4 - Robustness check: Limiting covariates in propensity score estimations

	Mental Health						
	t=0	**t=1**			**t=2**		
	Static/ Dynamic	**Static**	**Dynamic (2v0)**	**Dynamic (2v1)**	**Static**	**Dynamic (3v0)**	**Dynamic (3v2)**
Any	-0.332	-0.651**	-0.624	-0.184	-0.268	0.040	-0.387
	(0.208)	(0.222)	(0.367)	(0.466)	(0.221)	(0.410)	(0.684)
Low Intensity	-0.036	-0.366	-0.270	0.146	-0.033	-0.169	-0.196
	(0.224)	(0.242)	(0.394)	(0.501)	(0.248)	(0.496)	(0.741)
Medium/High Intensity	-1.370*	-1.697**	-1.902**	-1.879	-1.049*	0.766	1.227
	(0.482)	(0.500)	(0.706)	(1.012)	(0.473)	(0.670)	(1.882)
	Physical Health						
	t=0	**t=1**			**t=2**		
	Static/ Dynamic	**Static**	**Dynamic (2v0)**	**Dynamic (2v1)**	**Static**	**Dynamic (3v0)**	**Dynamic (3v2)**
Any	0.052	-0.191	-0.111	0.262	0.037	0.131	-0.018
	(0.196)	(0.214)	(0.350)	(0.461)	(0.221)	(0.391)	(0.628)
Low Intensity	0.203	-0.118	-0.163	0.200	0.204	0.526	-0.274
	(0.218)	(0.245)	(0.380)	(0.519)	(0.254)	(0.439)	(0.673)
Medium/High Intensity	-0.470	-0.365	0.400	0.930	-0.562	-0.795	0.011
	(0.434)	(0.424)	(0.576)	(0.905)	(0.439)	(0.751)	(1.626)
Treatment (Control)	1,348 (16,081)	1,348 (16,081)	553 (14,800)	553 (773)	1,348 (16,081)	314 (13,712)	314 (218)
Low Intensity	1,019 (16,081)	1,019 (16,081)	412 (14,800)	412 (588)	1,019 (16,081)	219 (13,712)	219 (182)
Medium/High Intensity	312 (16,081)	312 (16,081)	138 (14,800)	138 (170)	312 (16,081)	90 (13,712)	90 (36)

Source: USoc, own calculations. *p<0.05, ** p<0.01, ***p<0.001, standard errors in parentheses.

Alternative outcomes measures

We explore the existence and magnitude of treatment effects on mental health using two alternatives but closely related outcome measures to assess the robustness of our results and their economic relevance. Firstly, we explore the effect of providing informal care on individual's life satisfaction. Life satisfaction is measured in the UKHLS by asking individuals about their overall level of satisfaction with their life in general and offering a discrete seven-point scale ranging from *"completely dissatisfied"* (1) to *"completely satisfied"* (7).[44] The second alternative outcome measure

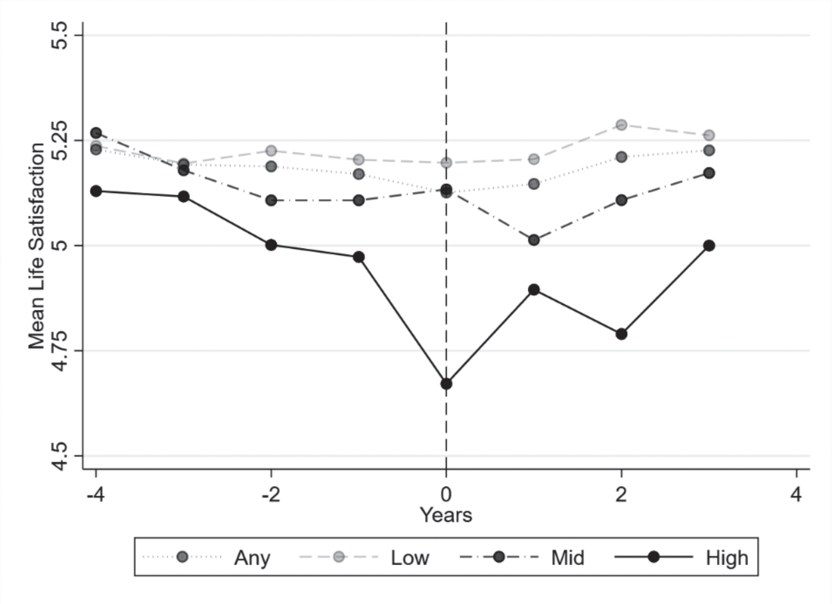
---

[44] For simplicity, we treat life satisfaction as a continuous variable in order to be able to conduct the analysis without having to switch from our regular matching adjusted regression framework to an ordered response model.

is the General Health Questionnaire (GHQ). The GHQ is a screening device to identify individuals at high risk of developing a non-psychotic minor psychiatric disorder such as anxiety or depression in general population surveys or outside of clinical environments (Goldberg et al., 1997). Respondents' answers to the 12 items are transformed to a single score on a 0 (best) to 12 (worst) scale. To ease the visual interpretation of results in line with the other outcomes measures we have inverted the scale to range from 12 (best) to 0 (worst) so that negative coefficients indicate negative mental health effects. Figure A4.2.6 plots mean life satisfaction and inversed GHQ scores prior and after informal care onset. Importantly, the mental health focused GHQ scores do not depict strong negative trends prior to informal care provision for high-intensity caregivers, however with the start of caregiving scores among this group fall drastically.

Figure A4.2.6: Mean life satisfaction and inversed GHQ scores

a) Life Satisfaction



b) Inversed GHQ Scores

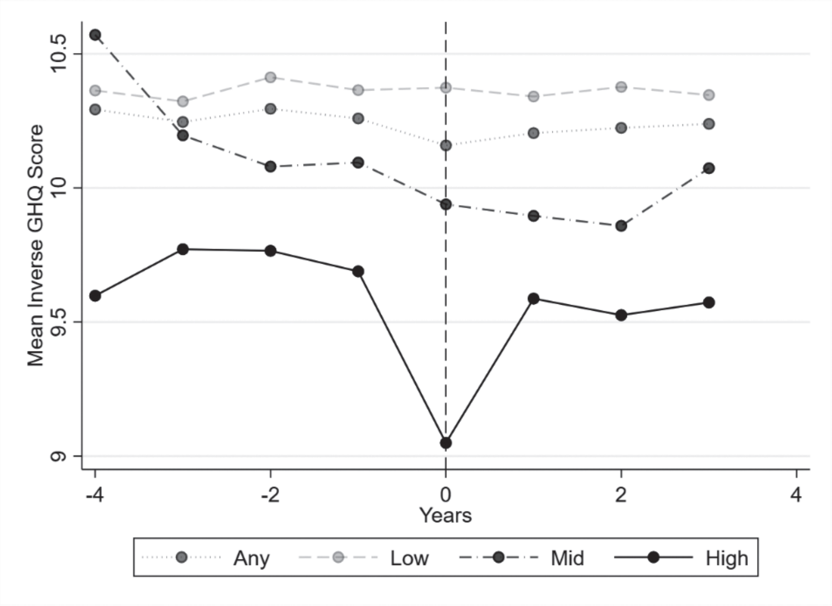
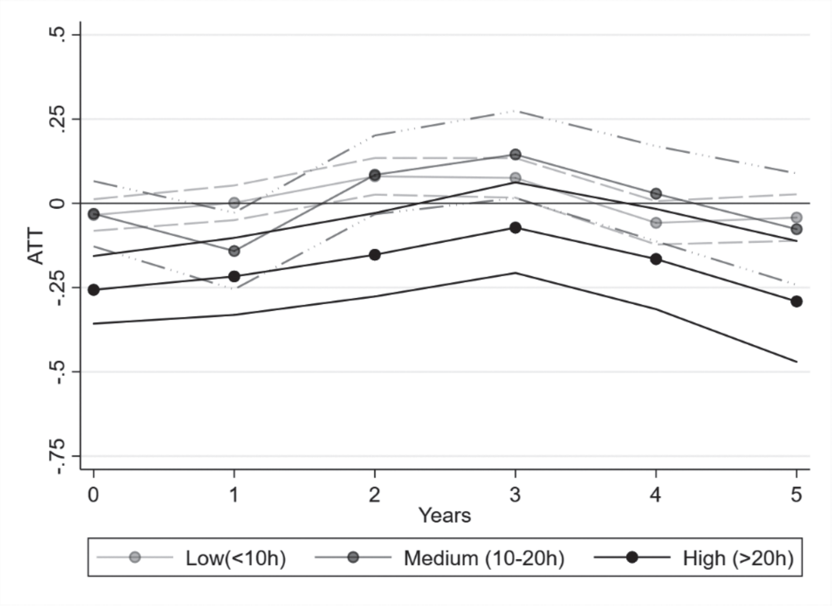


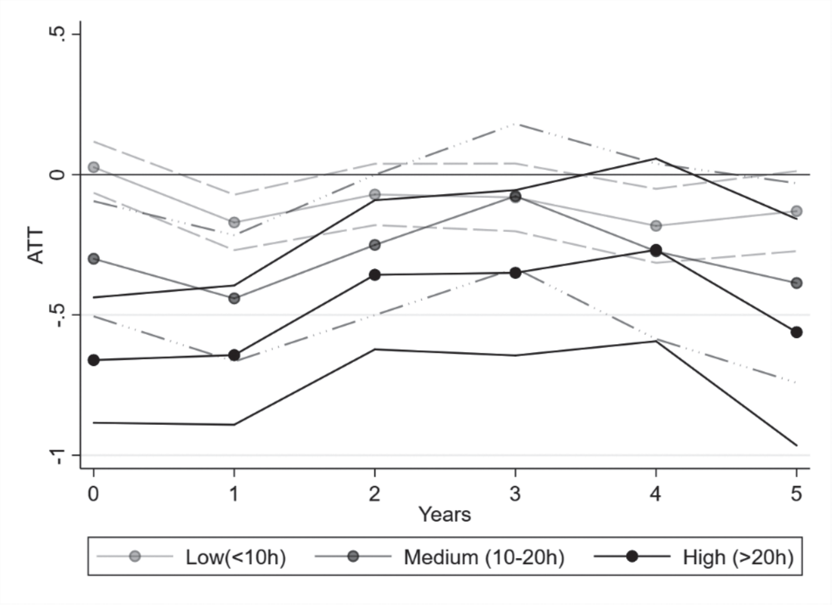
Figure A4.2.7 panel a) depicts the estimated treatment effects across the care-intensity levels. The overall structure of results across time and care intensity is generally in line with the overall results based on the SF-12 MCS. Figure A4.2.7 panel b) depicts the caregiving effects across intensity levels on reported GHQ scores. Interestingly our results using the GHQ as an outcome measure indicate a clearer dose-response relationship between informal care intensity in hours per week and mental health effects than our results using the MCS to measure mental health. For low intensity caregiving the coefficient for t_0 is zero but all subsequent coefficients are negative with those for t_2 and t_4 being significant with -0.170 ($p<0.001$) and -0.184 ($p<0.01$). The mental health effects increase with higher intensity. Among medium intensity caregivers the estimated initial effects are -0.301 ($p<0.01$) and -0.441 ($p<0.001$) at t_0 and t_1 while remaining similar in size and negative for later periods. The strongest and most persistent effects are found for high intensity caregivers with strong initial negative health effects of -0.663 ($p<0.001$) and -0.643 ($p<0.001$) at t_0 and t_1 that decrease to -0.355 ($p<0.01$) by t_2 but remain negative and persistent. This previously non-existent dose-response relationship might be explained by the fact that the GHQ is a more precise mental health measure as its 12 questions are solely focused on the mental and not he physical domain.

Figure A4.2.7: Treatment effects by intensity – Life satisfaction and GHQ

a) Life Satisfaction



b) Inversed GHQ Score



To assess the practical implications of these results we convert the GHQ scores into a ‘caseness’ dummy. Following this definition, individuals scoring a 4 and above are identified as being a “case”, meaning that these individuals experience high mental strain and are at risk of developing a mental disease. This definition does not indicate the definitive presence of a minor psychiatric disease, however, individuals scoring a 4 and above on the GHQ survey in a primary care environment should be referred to a mental health specialist for further investigation due to concern for their long-term mental health (Jackson, 2007).

Across non-caregivers 16.31% of individuals cross this threshold at the pre-treatment period while the share is identical among low-intensity caregivers. Among medium-intensity caregivers the share is already considerably higher before care-provision (21.97%) and even more so for the high-intensity group (26.15%). In the period of first informal care provision these shares increase with caregiving intensity; for low intensity caregivers to 17.10%, for medium intensity to 23.99% and to 30.50% for high intensity caregivers. Table A4.2.5 depicts the dynamic results for the alternative outcome measures.

Table A4.2.5. Estimated effects of care trajectories using alternative mental health outcomes

	LS						
	t=0	**t=1**			**t=2**		
	Static/ Dynamic	**Static**	**Dynamic (2v0)**	**Dynamic (2v1)**	**Static**	**Dynamic (3v0)**	**Dynamic (3v2)**
Any	-0.016	-0.037	-0.04	0.01	0.015	-0.05	-0.10
	(0.037)	(0.037)	(0.06)	(0.08)	(0.037)	(0.07)	(0.12)
Low Intensity	0.012	0.037	0.107	0.136	0.033	-0.033	-0.130
	(0.041)	(0.040)	(0.056)	(0.080)	(0.042)	(0.073)	(0.123)
Medium/High Intensity	-0.127	-0.275***	-0.411**	-0.377*	-0.037	-0.044	-0.242
	(0.078)	(0.083)	(0.125)	(0.183)	(0.037)	(1.135)	(0.350)
	GHQ						
	t=0	**t=1**			**t=2**		
	Static/ Dynamic	**Static**	**Dynamic (2v0)**	**Dynamic (2v1)**	**Static**	**Dynamic (3v0)**	**Dynamic (3v2)**
Any	-0.091	-0.167*	-0.12	-0.00	-0.118	-0.11	-0.17
	(0.069)	(0.069)	(0.12)	(0.15)	(0.076)	(0.12)	(0.24)
Low Intensity	0.031	-0.061	-0.064	0.016	-0.053	-0.124	0.180
	(0.073)	(0.075)	(0.128)	(0.163)	(0.084)	(0.149)	(0.253)
Medium/High Intensity	-0.487**	-0.557***	-0.421*	-0.369	-0.293	-0.058	-0.860

Table A4.2.5. Continued.

	GHQ						
	t=0	t=1			t=2		
	Static/ Dynamic	Static	Dynamic (2v0)	Dynamic (2v1)	Static	Dynamic (3v0)	Dynamic (3v2)
	(0.161)	(0.160)	(0.214)	(0.308)	(0.169)	(0.212)	(0.630)
Treatment (Control)	1,348 (16,081)	1,348 (16,081)	552 (14,782)	552 (768)	1,348 (16,081)	311 (13,511)	311 (205)
Low Intensity	1,019 (16,081)	1,019 (16,081)	411 (14,782)	411 (585)	1,019 (16,081)	220 (13,511)	220 (170)
Medium/High Intensity	312 (16,081)	312 (16,081)	138 (14,782)	138 (168)	312 (16,081)	86 (13,511)	86 (35)

Source: USoc, own calculations. *p<0.05, ** p<0.01, ***p<0.001, standard errors in parentheses.

A4.3 – Static matching

Table A4.3.1: Propensity score estimation results

	Coefficient	Standard Error
Care Obligations		
Mother alive	0.551***	(0.047)
Age of mother	0.010***	(0.002)
Father alive	0.450***	(0.058)
Age of father	0.010***	(0.002)
Both parents alive	-0.734***	(0.062)
Living siblings	-0.110***	(0.031)
Living partner	0.297***	(0.059)
Age of partner	0.016***	(0.001)
Willingness to Care		
Age	0.013***	(0.002)
Female	0.121***	(0.023)
Education: Tertiary (*Ref: Secondary*)	-0.160***	(0.023)
Education: Primary/Other lower	-0.192***	(0.029)
Job Status: Self-Employed (*Ref: Employed*)	0.086*	(0.038)
Job Status: Unemployed	0.069	(0.054)
Job Status: Retired	0.077	(0.045)
Job Status: Homecarer	0.168**	(0.050)
Job Status: Disabled	0.131	(0.073)
Job Status: Student/Other	-0.174**	(0.058)

Table A4.3.1: Continued

	Coefficient	**Standard Error**
Working Full-Time	-0.183***	(0.031)
Income (logarithmic)	0.111***	(0.020)
HH Income Fraction	0.071	(0.042)
Marital Status: Partnership (*Ref: Married/Widowed*)	0.028	(0.033)
Marital Status: Single	0.321***	(0.069)
Marital Status: Sperated/Divorced	0.234***	(0.062)
Children in Household	-0.015	(0.054)
Children < 14 in Household	0.042	(0.055)
Region: North-East (*Ref: London*)	0.181**	(0.059)
Region: North-West	0.014	(0.044)
Region: Yorkshire	0.027	(0.049)
Region: East-Midlands	0.145**	(0.048)
Region: West-Midlands	0.153**	(0.047)
Region: East England	0.061	(0.046)
Region: South-East	-0.010	(0.042)
Region: South-West	0.112*	(0.046)
Region: Wales	0.164**	(0.048)
Region: Scotland	0.046	(0.047)
Region: Northern Ireland	0.279***	(0.055)
Living in Urban Area	0.037	(0.023)
Big-5: Openness	0.011	(0.008)
Big 5: Conscientiousness	0.026**	(0.010)
Big 5: Extroversion	0.026**	(0.008)
Big 5: Agreeableness	0.029**	(0.010)
Big 5: Neuroticism	-0.004	(0.008)
Ability to Care		
Self-Assessed Health	-0.083***	(0.014)
SF-12 Mental Score	-0.019***	(0.002)
SF-12 Physical Score	-0.013***	(0.002)
Chronic-Illness/Disability	0.057*	(0.026)
Number of Functional Limitations	-0.128***	(0.012)
Satisfaction with Health	-0.063***	(0.008)
Satisfaction with Income	-0.024**	(0.008)
Satisfaction with Leisure Time	-0.005	(0.008)
Satisfaction with Life	0.003	(0.010)
GHQ Score	0.023***	(0.005)

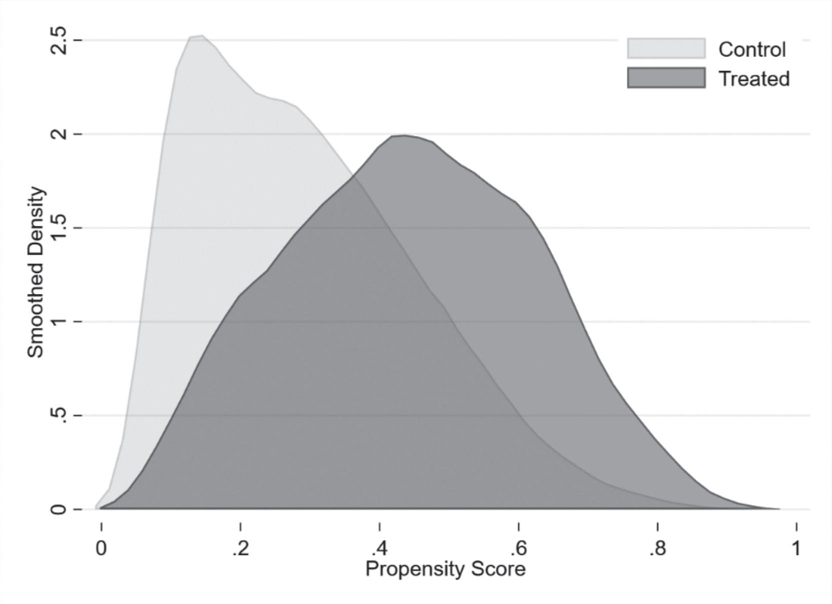
Table A4.3.1: Continued

	Coefficient	Standard Error
Observations		19,822
Log-Likelihood		-11,240.66
Chi^2		2,676.72
Prob > Chi^2		0.000
Pseudo R^2		0.1204

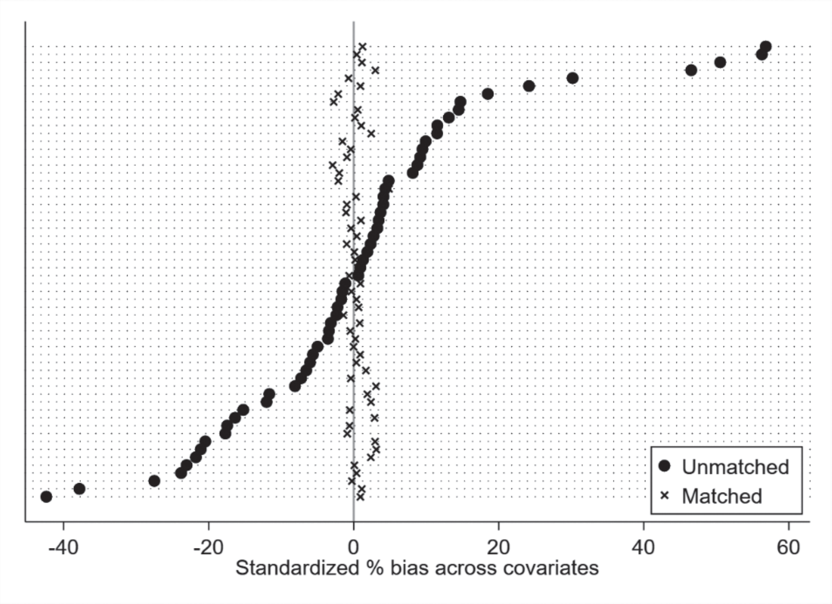
*p<0.05, **p<0.01, ***p<0.001, standard errors in parentheses. Source: USoc, own calculations.

Figure A4.3.1: Propensity score distribution and bias reduction – Static matching

a) Propensity Score Distribution



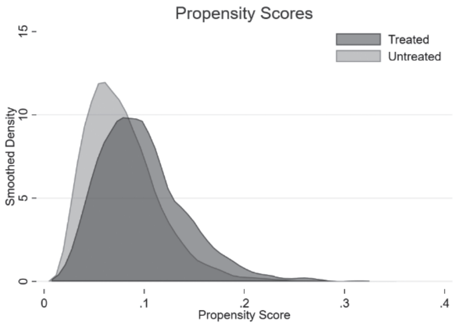
b) Standardized Bias Reduction after Matching



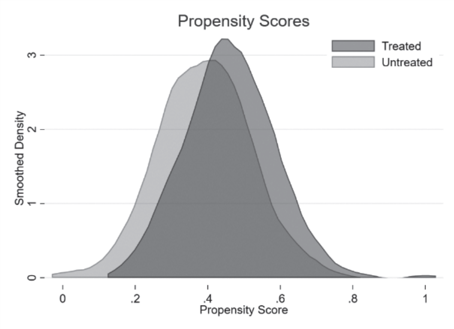
A4.4 – Dynamic sequential matching

Figure A4.4.1: Estimated propensity scores

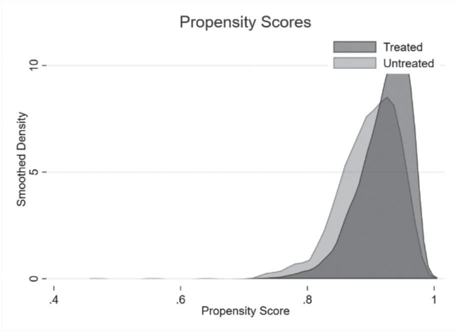
a) Propensity to start IC (Pr (D_0=1|X_{-1}, Y_{-1}))



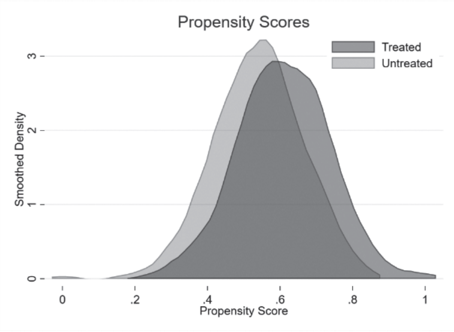
b) Propensity of IC after IC in year 1 (Pr(D_1=1 | D_0=1, X_{-1}, Y_{-1}, X_0, Y_0)



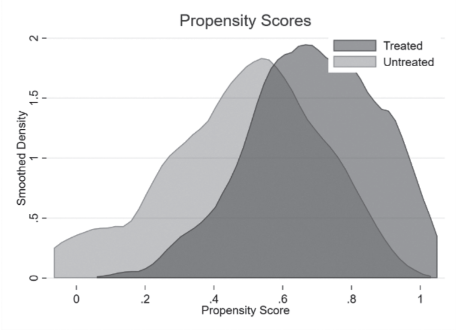
c) Propensity of no IC after no IC in year 1 (Pr(D_1=0 | D_0=0, X_{-1}, Y_{-1}, X_0, Y_0)



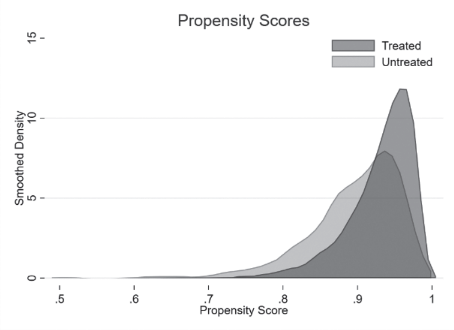
d) Propensity of no IC after IC in year 1 (Pr(D_1=0 | D_0=1, X_{-1}, Y_{-1}, X_0, Y_0)



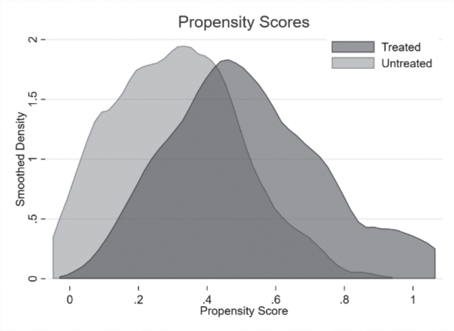
e) Propensity of IC after 2 years of IC (Pr(D_2=1 | D_1=1, D_0=1, X_{-1}, Y_{-1}, X_0, Y_0, X_1, Y_1)



f) Propensity of no IC after 2 years of no IC (Pr(D_2=0 | D_1=0, D_0=0, X_{-1}, Y_{-1}, X_0, Y_0, X_1, Y_1)



g) Propensity of no IC after 2 years of IC (Pr(D_2=0 | D_1=1, D_0=1, X_{-1}, Y_{-1}, X_0, Y_0, X_1, Y_1)



h) Propensity of no IC after IC in t=0 and no IC in t=1 (Pr(D_2=0 | D_1=0, D_0=1, X_{-1}, Y_{-1}, X_0, Y_0, X_1, Y_1)

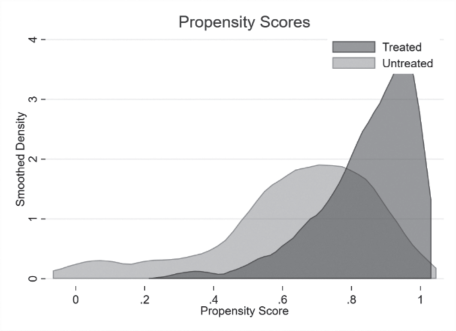


Table A4.4.1: Overview excluded propensity scores

Informal Care Trajectory	**Off support**
Initial informal care (Pr (D_0=1|X_{-1}, Y_{-1}))	0
2nd year of care provision (Pr(D_1=1 | D_0=1, X_{-1}, Y_{-1}, X_0, Y_0)	5
2nd years of no care provision (Pr(D_1=0 | D_0=0, X_{-1}, Y_{-1}, X_0, Y_0)	27
Informal care at t_0 but not t_1 (Pr(D_1=0 | D_0=1, X_{-1}, Y_{-1}, X_0, Y_0)	27
3rd year of care provision (Pr(D_2=1 | D_1=1, D_0=1, X_{-1}, Y_{-1}, X_0, Y_0, X_1, Y_1)	25
3rd year of no care provision (Pr(D_2=0 | D_1=0, D_0=0, X_{-1}, Y_{-1}, X_0, Y_0, X_1, Y_1)	310
Informal care at t_0 and t_1 but not t_2 (Pr(D_2=0 | D_1=1, D_0=1, X_{-1}, Y_{-1}, X_0, Y_0, X_1, Y_1)	107
Informal care at t_0 but not t_1 and t_2 (Pr(D_2=0 | D_1=0, D_0=1, X_{-1}, Y_{-1}, X_0, Y_0, X_1, Y_1)	18

Note: Additionally, 1774 propensity scores at the first node are excluded as a results of being out of range (<5% or >95%).

CHAPTER 5

Is the grass greener on the other side? The health impact of providing informal care in the UK and the Netherlands

With Jannis Stöckel

Published in: Bom, J., & Stöckel, J. (2021). Is the grass greener on the other side? The health impact of providing informal care in the UK and the Netherlands. Social Science & Medicine, 269, 113562.

Abstract

Facing rapidly ageing populations, many Western countries aim to stimulate informal care provision as a way to meet the growing long-term care (LTC) demand. While various studies report the impact of providing informal care on the health of caregivers, it is less clear whether and to what extent this impact differs across countries. Using propensity score matching we match caregivers to similar non-caregiving individuals using four waves of the Dutch Study on Transitions in Employment, Ability and Motivation and the UK Household Longitudinal Study. The samples consist of 8,129 Dutch and 7,186 UK respondents, among which respectively 1,711 and 1,713 individuals are identified as caregivers.

We explore whether the health impact of providing informal care differs by country once similar caregivers, in terms of the intensity of provided care, are compared. In both countries we find negative mental health effects of providing informal care. While these effects slightly differ by country, the main differences arise between subgroups of caregivers. Individuals that provide more than 20 hours of informal care per week, and those who face a double burden of care and full-time employment experience the most severe negative mental health effects. These results indicate that health effects of providing informal care are mediated by the specific caregiving context, allowing policymakers to use information on this context to provide targeted aid. In addition, it suggests that previously reported differences of caregiving effects across countries could be driven by differences in the population of informal caregivers which are shaped by countries' LTC policies.

5.1 Introduction

Facing rapidly ageing populations, many Western countries search for ways to meet the growing long-term care (LTC) demand. Informal care, care provided by friends and family members, is one of the ways in which this demand can be (partially) met while limiting direct monetary costs. Reliance on informal care, however, is not without disadvantages. Next to its potential impact on caregivers' labor market participation, various studies indicate that the provision of informal care negatively affects informal caregivers' health (see Bom et al., 2019a for a review). These health effects are not the same for all caregivers. Individual and contextual elements like age, the intensity of care provided and other responsibilities like formal employment may affect the care burden (e.g. Pearlin et al. 1990, Pinquart & Sorensen, 2011). At the same time, country-level factors like welfare state generosity and cultural norms might also influence the impact of caregiving as they shape the societal environment in which informal care is provided (Brandt, 2013).

The country specific context can affect the health impact of providing informal care in various ways. First, country specific elements could influence the type and intensity of provided care (Brandt, 2013). The *specialization theory* hypothesizes that in countries with a generous welfare state, division of labor between formal and informal caregivers is higher (Motel-Klingebiel et al., 2005; Igel et al., 2009). While formal LTC professionals provide intensive, highly skilled care services, informal caregivers can dedicate themselves to lower intensity care activities. In less generous welfare states, on the contrary, family members are required to provide highly intensive care themselves. Accordingly, this implies that the generosity of LTC schemes directly shapes the population of informal caregivers, both regarding the care intensity as well as who provides care in the light of other obligations, such as childcare or paid work. There is evidence for the LTC system generosity directly influencing the population characteristics of informal caregivers (Bakx et al., 2015a). Differences in the composition of the caregiver population could lead to differences in the average and aggregate health impact of relying on informal caregivers as highly intensive and specialized care tasks are often more stressful for caregivers (Pearlin et al., 1990).

A second way in which the country context might affect the relationship between informal care and caregivers' health points towards social norms and expectations about the family's role in meeting care demand. In countries where caregiving is considered a duty of family-members, informal caregivers might feel more pressured to provide care (Verbakel, 2014). This role-captivity, the feeling of being obliged to provide care, might influence the impact of care tasks on well-being (Pearlin et al., 1990). Additionally, the availability of formal care could influence one's experience of informal care. Knowing that formal care would be available if needed might affect the perceived control and hence the ability to deal with the situation (Wagner & Brandt, 2018). Furthermore, countries could differ in the depth and efforts to identify and help caregivers in need of support, which might affect the experience of care provision as well (Kaschowitz & Brandt, 2017).

Some studies investigated the relation between informal caregiving and health from a cross-country perspective using cross-sectional data. Dujardin et al. (2011) for example compared the health differences between informal caregivers and non-caregivers in the UK and Belgium using census data and found that high intensity British caregivers have better health than their Belgian counterparts.

More recently, various studies used the European SHARE panel dataset to estimate the cross-country health effect of informal caregiving with differing conclusions. Brenna & Di Novi (2016) estimated the effect of informal care to mothers on caregiving daughters' health using propensity score matching methods to address endogeneity concerns. Their results indicate a North-South-gradient in the mental health effects of caregiving with negative effects only occurring within the context of Southern-European countries where LTC schemes provide little public support. Uccheddu et al. (2019) studied transitions into and out of spousal caregiving in Europe using fixed-effects models and again found that health effects are strongest in Southern and Eastern European countries. Kaschowitz & Brandt (2017) use the same dataset in combination with comparable panel data from the UK to estimate a set of fixed-effects models. Contrary to the results mentioned above, they find that caregiving negatively affects mental health across most European countries, irrespective of the specific policy context. Instead, the caregiving context, whether care is provided inside or outside the household, and the likely associated differences in care intensity seem to be the main determinant of the size of the observed differences. However, as informal care intensity is not captured in the SHARE data Kaschowitz & Brandt (2017) cannot test this hypothesis. Lastly, Van den Broek & Grundy (2018) studied the difference between caregiving effects in Sweden and Denmark by using a difference-in-differences approach to explore the impact reduced formal LTC availability in Denmark. Using the respective SHARE country samples, their results indicate that the reduced LTC availability led to lower quality of life among Danish caregivers. Hence, they conclude that LTC coverage directly shapes the impact of caregiving on caregivers' mental health, however again unavailable information on care intensity obstructs a more in-depth analysis that would allow policymakers to identify those groups of caregivers most vulnerable to insufficient LTC coverage.

A limitation of the current studies is hence that they incorporate little information on the caregiving intensity. As a result, they cannot determine whether the observed average differences in health effects are driven by differences in the caregiving population (e.g. a higher share of high-intensity caregivers) or whether other country differences (like support options and social norms) play a role as well. The current study combines two independent panel datasets from the Netherlands and the UK which contain detailed information on the caregiving context. This allows us to explore whether caregiving effects differ by country once compared at similar intensity levels. Additionally, similarity and size of both datasets facilitates a two-country comparison, instead of grouping several countries with different long-term care systems together. Lastly, we focus on starting informal caregivers. This allows us to measure the causal impact of becoming an informal caregiver on individuals' health without the potential bias that results from jointly analyzing longer-term and starting caregivers. We therefore contribute to the ongoing debate on the cross-country differences in caregiving effects by disentangling these effects at the intensive and extensive margin, an important distinction for LTC policymakers.

5.2 Background

To study the difference in caregiving effects between the Netherlands and the UK it is important to understand the differences in their LTC systems. Table 5.1 provides an overview of their LTC systems. Both countries are relatively similar in terms of the share of (dependent) elderly within the population, with slightly more elderly in the Netherlands. However, they differ strongly in terms of LTC expenditures.

5.2.1 Generosity of LTC systems

The difference in public LTC-spending reflects the generosity of their LTC systems. The Netherlands has a universal and comprehensive LTC system, irrespective of age or income, everyone requiring care is entitled to the benefits of this scheme (Mot, 2010). The system is largely publicly funded, copayments contribute only a small fraction (Maarse & Jeurissen, 2016). These copayments depend on type and duration of care, age, household composition, income, and (as of 2013) wealth. The payments are capped and cannot exceed the household income (Bakx et al., 2020a).

In the UK LTC is organized in a mixed-system combining universal and means-tested benefits. Health services and health related LTC components, such as nursing care, are provided for free by the National Health Service (NHS) (Colombo et al., 2011). Home care, day care and nursing home care are the responsibility of local authorities (Glendinning, 2013). This care is offered via a safety-net structure requiring users to deplete their wealth before obtaining publicly funded care (Colombo et al., 2011). Individual income and assets determine whether a service is (partly) covered (NHS, 2018b). Currently only individuals with assets below GBP 14,250 (approximately €16,886) will receive full-coverage (NHS, 2018a).

5.2.2 Role of informal carers in the system and available support

In both countries informal care is common: about 17-18% of the 50+ population identified him/herself as an informal caregiver (OECD, 2019a). However, the average time spent caring strongly differs. According to the European Social Survey of 2014, 17% of the UK caregivers provides more than 20 hours of care per week compared to 8% in the Netherlands. This higher number of intensive informal caregivers in the UK seems to reflect the country's strong reliance on informal caregivers, which can be a result of only publicly funding non-health related formal LTC in case of low income/wealth and primarily directing formal care at people who do not receive informal care (Comas-Herrera et al., 2010). Both countries offer a wide range of support to informal caregivers and are among the few countries that have a national policy that targets this group. Furthermore, both countries offer (under different regulations) financial support, respite care, training and counseling for caregivers (Courtin et al., 2014).

5.2.3 Hypotheses concerning the impact of informal care

Facing a different context, we formulate the following hypotheses regarding the differences in caregiving effects between the Netherlands and the UK: (i) As it offers more generous formal LTC compared to the UK, we expect caregivers in the Netherlands to 'specialize' and provide more low intensity care which might have a lower impact on their health. (ii) Additionally, norms and caregiving support might affect the relation between informal care provision and health, irrespective of the type of care that is provided. Whereas both countries offer a relatively comparable level of support for caregivers, norms potentially differ. Responses to the Eurobarometer (2007) for example indicate that UK citizens more often consider elderly care the responsibility of the family. More recent studies, although not using identical questions, also indicate different norms between the UK and the Netherlands. In 2016, 9% of the UK population stated that care to older individuals should be primarily provided by family and friends (British Social Attitudes Survey, 2016), while only 4% of Dutch respondents indicated that care for a dependent parent was predominantly a task for the family (De Klerk et al., 2017). These different attitudes might make caregivers in the UK feel more pressured towards providing care. Therefore, we expect a larger caregiving burden among UK caregivers compared to similar Dutch caregivers.

5.3 Methods

It is not possible to study the impact of informal care provision on health by comparing the health of caregivers and non-caregivers as certain individuals, for example those with lower health, might be more likely to provide informal care. To account for these selection effects, we use propensity score matching.

Table 5.1: Key figures regarding the LTC systems in the Netherlands and the UK

	Netherlands	**United Kingdom**
Share of population aged 65+[1]	18.7%	18.1%
Share of 65+ reporting some/ severe limitations in daily activities[2]	47.9%	44.9%
LTC expenditures (health and social components) governmental and compulsory schemes (% GDP)[3]	3.7%	1.4%
Beds in LTC facilities per 1000 65+ inhabitants[4]	74.8	45.6
% informal caregivers among 50+ population[5]	16.8%	18.2%
% of caregivers providing at least 20 hours of care per week[6]	8%	17%
Care services available to informal caregivers[7]	Carers and care receivers allowance, additional benefits, paid leave, unpaid leave, flexible work arrangements, training/ education, respite care, counseling	Carers and care receivers allowance, additional benefits, unpaid leave (for couple days under emergency situations), flexible work arrangements, training/education, respite care, counseling

Note: Data concerning 2017 from 1. OECD (2020d); 2. OECD (2019a); 3. OECD (2020c) and 4. OECD (2020b). 5. Data for 2017 from SHARE/ELSA from OECD (2019a), UK in this case refers to England. 6. European Social Survey (2014). 7.Data from Colombo et al. (2011) for 2010.

Following Schmitz & Westphal (2015) we construct a score of someone's propensity of providing informal care. This propensity score of informal caregiving is based on various elements that might affect the caregiving decision. The variables included can be grouped into three categories. The first, care obligations, covers information on parents and spouses to capture the presence of individuals in potential need of care. We further include whether both parents are alive and whether siblings are present to capture alternative informal care sources. The second category contains information on respondents themselves such as personal characteristics (age, sex), socio-economic status (marital and employment status, household income) and household structure. The third category contains information on individuals' health status and the self-reported presence of long-standing illnesses/disability. The complete list of variables used can be found in Table 5.2 as well as Appendix Table A5.1 and A5.2.

By matching caregivers and non-caregivers based on their propensity of providing informal care we assume that the remaining difference in health is due to caregiving.

Or phrased differently, in absence of informal care provision the health of caregivers and matched non-caregivers would be similar and differences are causally attributable to informal caregiving. This assumption of conditional independence is the main assumption underlying our estimation strategy. To make it more credible, we follow Lechner (2009b) and match upon control variables reported in the year before caregiving starts as the previous caregiving status captures most unobserved heterogeneity and to ensure that informal caregiving cannot affect the covariates.

The propensity scores are calculated using probit models that estimate the propensity of starting informal care provision conditional upon all variables potentially affecting the care decision in the preceding wave. We separately estimate these propensity scores for the Dutch and UK sample using the same approach and covariates.

After estimating the propensity scores, we match starting caregivers to non-caregivers using a kernel matching approach. We make use of the Stata command psmatch2 (Leuven & Sianesi, 2003) using an Epanechnikov kernel with a bandwidth of 0.03. Using alternative specifications with higher and lower bandwidth values (0.01 and 0.06) led to highly similar results (results available upon request). We regress informal care provision on health while adding all covariates from the pre-treatment wave. Adding the covariates to the regression next to matching based on the same covariates is referred to as double-robust. This corrects for remaining differences in covariates distributions between the two groups (Lechner, 2009b; Rubin, 1979). With this analysis we estimate the average treatment effect on the treated (ATT). The ATT represents the mean difference in health between the group of informal caregivers (the treated) and the matched non-caregiving individuals.

We assess whether our matching strategy achieved its goal of balancing covariates using the standardized bias (Rosenbaum & Rubin, 1985). The standardized bias can be calculated for each covariate in the model by taking the difference in means between the treatment and control group and dividing it by the standard deviation of the control group.

5.4 Data

We use two similar datasets providing representative samples of the Dutch and UK population. The Study on Transitions in Employment, Ability and Motivation (STREAM) panel survey was carried out in the Netherlands. We include the first four waves of data annually collected via self-completion online surveys from 2010 to 2013 among the Dutch population aged 45-64 years. This sample is drawn from an existing internet panel (Ybema et al., 2014). For the UK we use the first four waves of the United Kingdom Household Longitudinal Survey, commonly known as Understanding Society (USoc; University of Essex, 2019). Data from the USoc is collected online or via face-to-face interviews among the 16+ population, data collection is annually and started 2009. Ethics approval has been obtained by the USoc and STREAM researchers and therefore no further ethical approval was required.

5.4.1 Informal care definition

We construct a binary variable indicating whether an individual provides informal care. In the Dutch survey informal caregivers are identified in case they positively answered to the following question and answer option: *'Did you in the past 12 months spend part of your time on any of the following activities?'* answer option: *'Giving Informal Care'.* In the UK sample individuals are identified as caregivers in case they affirmatively answered to at least one of the following two questions: '*Is there anyone living with you who is sick, disabled or elderly whom you look after or give special help to (for example a sick, disabled or elderly relative/husband/wife/friend etc.)?'* or *'Do you provide regular service or help for any sick, disabled or elderly person not living with you? [Exclude help provided in course of employment]'*. Both studies furthermore ask for care intensity, the average number of hours someone provides informal care per week. For both we construct dummy variables indicating low intensity (less than 10 hours of care per week), medium intensity (between 10 – 20 hours of care per week) and high intensity caregivers (more than 20 hours of care per week).

5.4.2 Health outcomes

To capture the health effect of informal caregiving we use the 12-item Short Form Health Surveys (SF-12). This health survey consists of 12 self-reported questions related to health in the past four weeks. Based on these questions the Physical Component Summary (PCS) and the Mental Component Summary (MCS) can be derived, relating to physical and mental health. Both scales are validated and range from 0 (lowest health) to 100 (optimal health) and transformed to have a mean of 50 and a standard deviation of 10 (Ware et al., 1995).

5.4.3 Other covariates

We estimate the individual's propensity of providing informal care based on a broad set of variables that might affect someone's caregiving decision and health status. Variables related to the health and demographics of the respondent are present in both datasets and in most cases easily comparable as (a) they use the same instruments (e.g. the MCS and PCS) or (b) because the questions are straightforward and highly similar in both countries (e.g. age or employment status of respondent). We however want to match on a broad set of variables that also contains information about the income and family structure of the respondent. This information is available in the USoc but not in STREAM. We therefore enrich the Dutch survey dataset with information from administrative sources covering information on: personal and household income from the tax authority and information about the family structure from the municipal register.

For the variables related to family structure we argue that the differences between the self-reported versus administrative data are minimal. Comparing self-reported and tax-registered income we however must be careful as self-reported income might suffer from reporting bias. However, we use the variables to predict informal care provision separately for both countries, hence no direct comparison between both values is needed. For our analysis we assume that any reporting bias in the income variable is stable throughout the income distribution of the respective country sample. An overview of the definition and source of all used variables is available in the Supplementary material.

5.4.4 Sample selection

In order to make both datasets comparable we restrict the samples as follows: (i) We include respondents aged 45-65 in the first wave; (ii) we use information from the first four waves of the surveys ranging from 2009/2010 – 2013/2014. These selection criteria are motivated by the fact that the Dutch dataset only covers individuals aged 45-65 and we have access to its first four waves spanning 2010 to 2013, hence we use a similar subset of the USoc data. Further, (iii) we condition the datasets on availability of all control variables in the first wave and all needed outcome variables in the first and second wave; (iv) we exclude all individuals that already provided informal care in the first wave as we only look at starting caregivers. Eventually the samples consist of 8,141 Dutch and 7,187 UK respondents.

5.4.5 Time structure

For both datasets we define a relative time variable (*t*) whose value depends on an individual's first reported care-episode (see figure 5.1 for a graphical representation). Within the control group t_{-1} is normalized to the individuals first appearance in the survey as these respondents do not report any care episode during their participation. Among caregivers t_{-1} is defined as the period before the first reported caregiving episode. For example, an individual entering the panel in 2010 and responding to the survey for four consecutive waves but only starting to provide informal care in wave 4 is included for two periods, t_{-1} (wave 3) to t_0 (wave 4). This time structure is chosen to maximize the number of informal caregivers that we can observe.

5.5 Results

5.5.1 Descriptives & matching results

Table 5.2 provides an overview of the composition of caregivers in both datasets. These samples are constructed to maximize the number of starting caregivers and hence contain all individuals who started care provision in 2011-2013. There are slightly more starting caregivers in the UK where about 24% of the sample starts care provision compared to 21% of the Dutch sample. The share of female and parental caregivers is higher in the UK than in the Netherlands and a larger share of the caregivers in the UK provides medium or high intensity care compared to the Dutch sample. About half of the caregivers in both countries have a full-time job next to their caregiving duties.

Figure 5.1: Visualization of the constructed time structure of the sample (Own visualization)

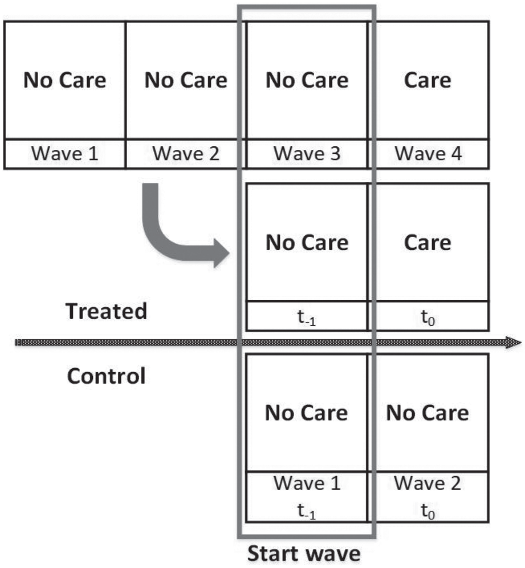


Table 5.2: Descriptive statistics of both samples

	Dutch Sample		UK Sample	
Starting caregiver (% of sample)	1,711	(21.1%)	1,713	(23.8%)
Female caregivers (% of caregivers)	865	(50.6%)	1,019	(58.5%)
Low Intensity caregivers	1,378	(80.5%)	1,302	(76.0%)
Medium Intensity caregivers	181	(10.6%)	205	(12.0%)
High Intensity caregivers	135	(7.9%)	177	(10.3%)
Spousal caregivers[1]	203	(12.0%)	214	(12.0%)
Parental caregivers[1]	688	(40.0%)	954	(56.0%)
Full-time employed (% of sample)	4,634	(57.0%)	3,863	(53.8%)
Full-time employed & caregiver (% of caregivers)	856	(50.0%)	844	(49.3%)
Number of Individuals	8,129		7,186	

Note: 1. Dutch values are imputed as information on care recipient for the Dutch data is only available in 2012-2013. Sources: STREAM Wave 1-4 & USoc Wave 1-4.

To match caregivers and non-caregivers we estimate propensity scores of providing informal care. Table 5.3 provides an overview of the propensity score estimations. In both samples especially the variables related to care obligations are strongly correlated to someone's propensity of providing informal care. As parents tend to provide care to each other, the presence of both parents is negatively associated with informal care. The age of these parents, which acts as a crude proxy for the rate of dependency of the individual, increases the informal care propensity. Furthermore, females and more highly educated individuals are more likely to provide care whereas the presence of young children is negatively related to informal care provision. For an overview of the distribution of the propensity scores, please see Figure A5.1.

In both countries informal caregivers differ from non-caregivers. As can be seen in Appendix Tables A5.1 and A5.2 there is a strong imbalance between the individuals that started to provide care and those who did not do so. This imbalance is depicted in Figure 5.2 by plotting the pre-matching (black) and post-matching (grey) standardized bias values for each control included. Before the matching there is considerable imbalance between the non-caregiver and caregiver samples with many variables exceeding the 3-5% standardized bias threshold (grey bar). The matching succeeds in correcting this imbalance with the standardized bias between the matched control group and the treatment group falling below the thresholds for all considered variables. For all analyses we exclude respondents that were identified as off support, this equals to 1 in the UK and 12 in the Dutch sample.

Table 5.3: Propensity score estimates

	Dutch sample		UK sample	
	Coefficient	Standard Error	Coefficient	Standard Error
Care Obligations				
Mother alive	0.425***	(0.044)	0.451***	(0.047)
Father alive	0.429***	(0.069)	0.428***	(0.071)
Both parents alive	-0.259**	(0.084)	-0.459***	(0.085)
Living partner	0.103*	(0.042)	0.063	(0.043)
Living siblings	-0.003	(0.051)	-0.061	(0.056)
Age of mother	0.023***	(0.005)	0.026***	(0.005)
Age of father	0.022***	(0.006)	0.023***	(0.006)
Age of partner	-0.000	(0.004)	0.008*	(0.003)
Personal Characteristics and Socio-Economic Status				
Age	0.014**	(0.005)	-0.003	(0.005)
Female	0.309***	(0.043)	0.113**	(0.039)

Table 5.3: Continued.

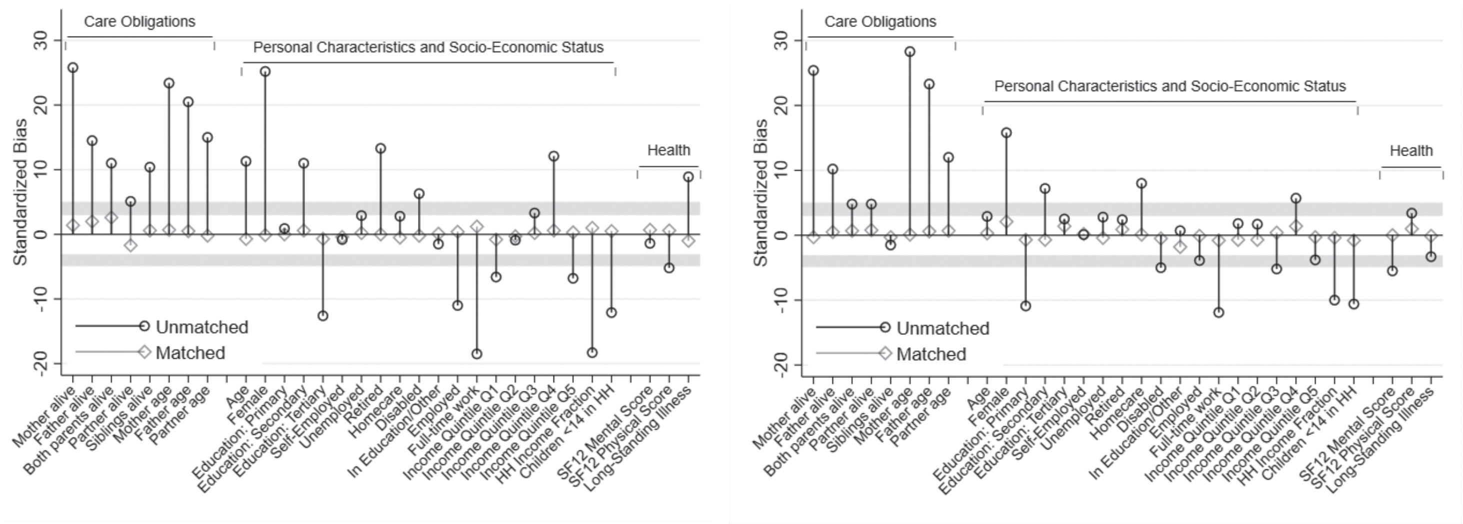
	Dutch sample		UK sample	
	Coefficient	Standard Error	Coefficient	Standard Error
Secondary Education (*Ref. Primary education*)	0.154***	(0.041)	0.156***	(0.044)
Tertiary Education	0.232***	(0.045)	0.098*	(0.048)
Self-employed (*Ref. Employed*)	-0.138	(0.064)	0.036	(0.057)
Unemployed	0.118	(0.104)	0.064	(0.087)
Retired	0.396***	(0.094)	-0.016	(0.065)
Homecarer	0.109	(0.153)	0.124	(0.093)
Disabled	0.121	(0.084)	-0.167	(0.093)
Studying or other activities	-0.273	(0.437)	0.003	(0.260)
Working Full-Time	-0.071	(0.047)	-0.167**	(0.049)
Income quintile 2 (Ref. Income quintile 1)	-0.007	(0.050)	0.066	(0.053)
Income quintile 3	-0.038	(0.052)	0.066	(0.055)
Income quintile 4	0.054	(0.054)	-0.051	(0.059)
Income quintile 5	0.158**	(0.057)	0.072	(0.060)
HH Income Fraction	-0.066	(0.084)	-0.034	(0.070)
Children<14 in household	-0.097	(0.057)	-0.146**	(0.052)
Health				
SF-12 Mental Score	-0.001	(0.002)	-0.006**	(0.002)
SF-12 Physical Score	0.001	0.002	0.000	(0.002)
Longstanding illness	0.107**	(0.038)	-0.033	(0.040)
Observations		8141		7187
Pseudo R^2		0.06		0.05

*p<0.05, **p<0.01, *** p<0.001, standard errors in parentheses. Sources: STREAM Wave 1-4 & USoc Wave 1-4.

5.5.2 Main results

Our baseline analysis estimates the impact of any informal care provision on health. Throughout the main text we present our results graphically, results tables can be found in Appendix A5.3 to A5.5. Figure 5.3 presents the impact of any care provision on (a) mental and (b) physical health. The bar presents the ATT, the confidence intervals are depicted at 95%. Dutch caregivers experience a direct negative mental health effect of -0.70 (p<0.001), whereas the negative impact of care provision in the UK is considerably smaller and insignificant. For physical health, on the contrary, informal care provision has a positive effect of 0.69 (p<0.01) in the UK whereas no significant impact is present among the Dutch caregivers.

Figure 5.2: Standardized bias before and after matching

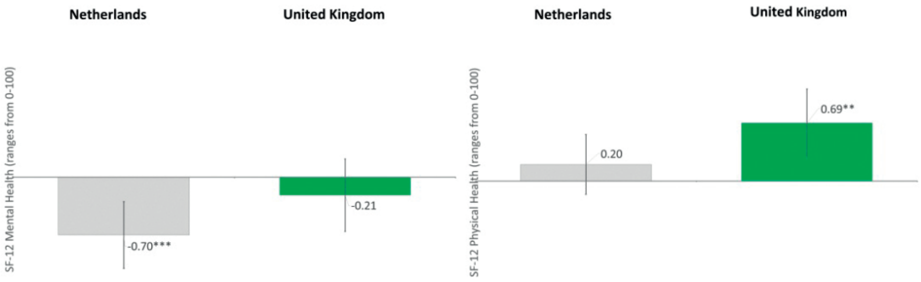


(a) Dutch sample

(b) UK sample

Note: The grey lines mark the standardized bias range of 3-5%, following the rule of thumb suggested by Caliendo & Kopeinig (2008) we consider balance to be sufficient when the bias is below 3-5%. Sources: STREAM Wave 1-4 & USoc Wave 1-4.

Figure 5.3: Impact of any informal caregiving on mental/physical health



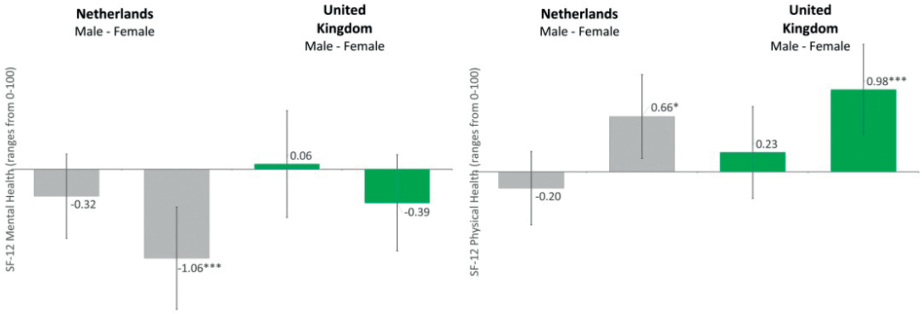
(a) Mental health

(b) Physical health

Confidence intervals at 95%, *p<0.05, **p<0.01, *** p<0.001. Sources: STREAM Wave 1-4 & USoc Wave 1-4.

As some studies indicate potential differences in the caregiving effect between males and females, we separately estimate the caregiving effect for both genders. When stratifying Dutch caregivers by gender we find a negative mental health effect of -1.06 ($p<0.001$) for females and no significant impact on males. In the UK, the mental health impact of care provision is larger for females than for males although both estimates are insignificant at a 95% level. Turning to physical health, we observe a different pattern. In both countries any informal care provision has a positive effect on the physical health of female caregivers. For male caregivers no effects are found in the physical health domain in either of the two countries.

Figure 5.4: Impact of any informal care on mental/physical health by gender



(a) Mental health

(b) Physical health

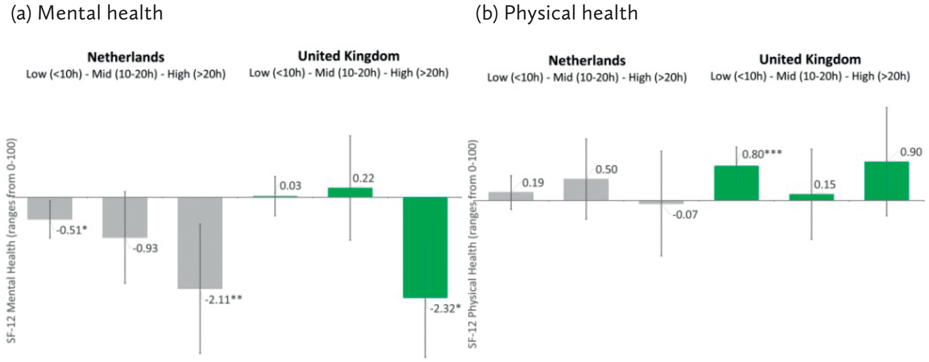
Confidence intervals at 95%, *p<0.05, **p<0.01, *** p<0.001. Sources: STREAM Wave 1-4 & USoc Wave 1-4.

By comparing the health impact of any care provision between both countries we ignore underlying differences in the composition of the caregiver population. This composition might however differ per country, for example as a result of differences in the LTC system. As presented in Table 5.2, there are for example slightly more medium and high intensity caregivers in the UK. To compare similar caregivers, we construct three groups based on the hours of care provided.

Figure 5.5 presents the treatment effects when separately estimated for low, medium and high intensity caregivers. The figure clearly depicts that the impact of care provision strongly differs by the amount of care provided. In both countries, high intensity caregivers experience the largest mental health effects. This health impact of providing more than 20 hours of informal care per week is similar in both countries with an impact of -2.11 (p<0.01) on the MCS in the Netherlands compared to -2.32 (p<0.01) in the UK. The pattern of the impact of informal care provision by care intensity however slightly differs between the two countries. In the Netherlands, a clear dose-response relationship is visible; all caregivers experience negative mental health effects that grow in response to care intensity. In the UK, low and medium intensity care providers are not affected, only high intensity caregivers experience a strong decline in their mental health.

The intensity-patterns also differ when focusing on physical health. In the Netherlands, no health effects are present when separating the sample by care intensity. In the UK, an initial positive physical health effect is present for low intensity caregivers and absent for medium intensity caregivers. For individuals providing more than 20 hours of care per week the estimates seem to point again to a positive effect although the results are insignificant.

Figure 5.5: Impact of informal caregiving on mental/physical health by care intensity



(a) Mental health

(b) Physical health

Confidence intervals at 95%, *p<0.05, **p<0.01, *** p<0.001. Sources: STREAM Wave 1-4 & USoc Wave 1-4.

Next to the intensity of care provided, other contextual elements could influence the care burden. Individuals might for example experience increased caregiving strain when providing informal care in combination to full-time employment.

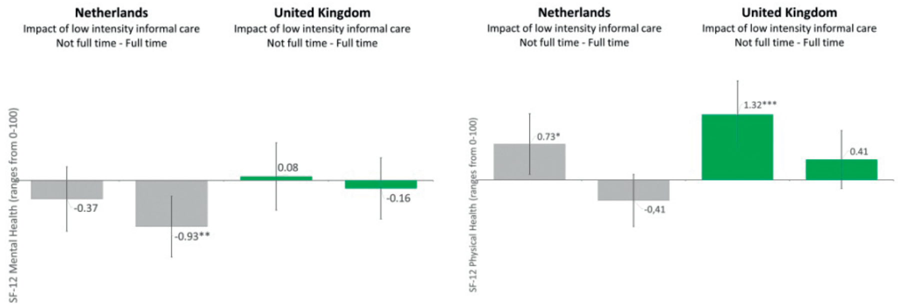
Facing multiple responsibilities might namely lead to cross-pressures, like fatigue or dissatisfaction about decreased productivity at work due to caregiving tasks (Pearlin et al., 1990). Using German data, Schmitz & Stroka (2013) found that individuals experiencing a double burden of care and work were more likely to use antidepressant drugs and tranquillizers. Again, country differences in terms of available alternatives and norms and support could make this situation more prevalent or straining.

To estimate the impact of care provision for individuals experiencing a double burden we compare the health impact of care provision between individuals in full-time employment to those not working full-time. We solely focus on individuals with stable workforce participation to exclude individuals that overcome the double burden of care and work by cutting down on working hours. In our samples this relates to excluding 7% (Netherlands) to 10% (UK) of our sample as these individuals experience changes in their work participation (from full-time to no work/part-time and vice versa). Starting informal caregivers seem slightly more likely to adjust their work participation than the control group of non-caregivers. In the UK, 10.7% of the starting caregivers change work participation compared to 9.6% in the control group. In the Netherlands these numbers equal 7.6% and 6.8%. Additionally, due to sample size limitations we solely compare employment status by individuals providing either low or medium to high intensity care provision (>10 h of care per week).

Figure 5.6 shows that the experienced mental health effect of providing low intensity informal care slightly differs by employment status. In the Netherlands, the estimates of the caregiving effect point in the negative direction for all low intensity caregivers. The impact is however larger and significant (-0.93, $p<0.01$) among full-time workers. In the UK no mental health effects are present for either of the two groups. With regards to physical health effects we observe larger differences between full-time working individuals and those who work less hours or not at all. In both countries, the latter group experiences a positive physical health effect of caregiving of respectively 0.73 ($p<0.05$) and 1.32 ($p<0.001$). This effect on physical health is absent or even negative among full-time working individuals.

A double burden might especially be present for individuals who next to a full-time job provide many hours of informal care. Figure 5.7 shows that in both countries indeed the mental health effect of providing more than 10 hours of informal care per week is larger for individuals working full-time. Interestingly the mental health effect of medium or high-intensity care even becomes insignificant among individuals who do not work full-time. For physical health, the initial positive effects disappear when focusing on intensive informal care.

Figure 5.6: Impact of low informal caregiving on mental/physical health by employment

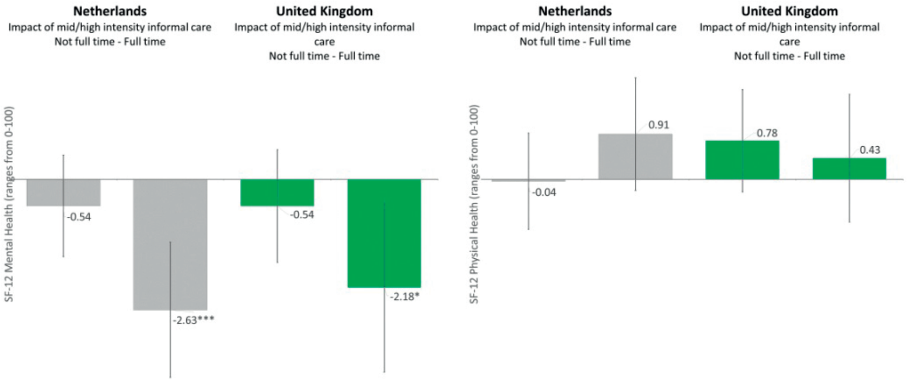


(a) Mental health

(b) Physical health

Confidence intervals at 95%, *p<0.05, **p<0.01, *** p<0.001. Sources: STREAM Wave 1-4 & USoc Wave 1-4.

Figure 5.7: Impact of mid/high intensity informal caregiving on mental/physical health by employment



(a) Mental health

(b) Physical health

Confidence intervals at 95%, *p<0.05, **p<0.01, *** p<0.001. Sources: STREAM Wave 1-4 & USoc Wave 1-4.

5.6 Robustness checks

To assess the robustness of our results we perform various robustness checks First, we assess whether our results are robust to our choices in the matching strategy. We check whether our results are driven by extreme propensity scores by excluding the highest/lowest 5%. Additionally, we check whether our results differ when re-estimating the propensity scores for the intensity groups separately. The results are highly comparable to those presented in the main specification (detailed results are available upon request).

Second, we test how sensitive our results are with regards to a violation of the main identifying assumption of conditional-independence. We follow Ichino et al. (2008) who propose a simulation-based sensitivity analysis for propensity-score based treatment effects to unobserved variables that should have been included in the propensity score estimation. In the given context such an unobserved variable might be personality characteristics or norm perceptions that would influence an individual's likelihood to provide care (selection effect *s*) and their mental health in absence of providing care (outcome effect *d*). Another motivation for such a sensitivity analysis is the fact that we only observe caregivers before care provision (t_{-1}) and when they report to have started caregiving (t_{-0}). We therefore cannot observe the actual moment of caregiving onset while additionally the actual cause for caregiving onset might have a direct effect (e.g. a health shock to a family member).

The method simulates a confounder with specific values for *s* and *d* in order to assess the sensitivity of estimated treatment effects to the inclusion of such unobserved confounders. Table 5.4 depicts our estimated treatment effects when simulating a confounder that combines the strongest observed selection and outcome effects. As the estimated values illustrate, our results are robust to such a simulated confounder. Table S5.2 in the Supplementary Material depicts the estimated selection and outcome effects for all our covariates.

Table 5.4: Mental Health Effects of High Intensity Caregiving - Sensitivity Analysis

	Dutch Sample		**UK Sample**	
	MCS	**PCS**	**MCS**	**PCS**
Confounder with properties: s=-0.2 d=0.15	-2.716***	-1.109	-2.478***	0.408
	(0.849)	(0.743)	(0.789)	(0.779)
Confounder with properties: s=0.2 d=0.15	-2.875***	-1.103	-2.910***	0.073
	(0.843)	(0.728)	(0.784)	(0.757)
Confounder with properties: s=-0.2 d=0.45	-2.548***	-1.143	-2.149***	0.646
	(0.863)	(0.766)	(0.824)	(0.814)
Confounder with properties: s=0.2 d=0.45	-3.131***	-1.124	-3.519***	-0.418
	(0.868)	(0.739)	(0.789)	(0.761)
Control	6418		5473	
Treatment	135		177	

*p<0.05, **p<0.01, *** p<0.001, standard errors in parentheses. Sources: STREAM Wave 1-4 & USoc Wave 1-4.

5.7 Discussion & conclusion

While several studies have reported negative health effects of informal care provision on the caregivers' health, there remains uncertainty with regards to their causal nature and the differences of these effects across countries and caregiver subgroups. Using a propensity score matching approach and two comparable panel-data sets, we estimated the health impact of providing care in the UK and the Netherlands. Doing so, we investigated whether observed average health differences between informal caregivers and non-caregivers within and across countries are attributable to the composition of the caregiver populations in each country.

First, our results highlight the link between the generosity of LTC systems and the hours of informal care provision. We hypothesized that the share of high intensity caregivers would be higher in the UK than in the Netherlands as the LTC system is less generous. In our samples this is indeed the case with slightly more caregivers providing more than 10 hours of weekly care in the UK compared to the Netherlands. However, it is noteworthy that our samples seem to understate the true differences that become apparent when looking at population wide estimates (ONS, 2013; de Klerk et al., 2017) or results from the ESS (2014) which indicate that the share of intensive caregivers is much higher in the UK.

Second, we show the importance of considering care-intensity when comparing average caregiving effects across countries. In both countries especially individuals providing more than 20 hours of weekly care experience large negative mental health effects. Individuals providing less intensive care do not experience any mental health effect (United Kingdom) or a similar negative but considerably smaller one (Netherlands). These findings are consistent with the findings of Kaschowitz & Brandt (2017) who hypothesized that differences between groups of caregivers (like care intensity) determine the average impact of caregiving.

Third, our results uncover interesting patterns regarding the physical health effects of caregiving. We observe small positive physical health effects among caregivers who provide less than 10 hours of care per week and (for the Dutch sample) do not work full-time. While these small positive effects disappear with increasing care intensity, they indicate that low intensity caregiving might lead to small increases in physical health, possibly due to increased physical activity. However, these results should be taken with a pinch of salt. Di Novi et al. (2015) point out that self-reported health measures are prone to bias as individuals might change their judgement by taking the care-recipients health as a reference point. Although our use of a multi-item physical health measure that emphasizes the ability to perform certain tasks should mitigate this concern, it cannot be ruled out.

Lastly, our analyses indicate that especially caregivers who combine caregiving with full-time employment experience large negative mental health effects. These results are estimated only on those individuals who are in stable full-time employment and hence exclude individuals who, potentially as a result of their caregiving tasks, changed their employment status. This could for example be the case when someone reduced working hours due to caregiving-related health issues. While this might introduce a downward bias and raise concerns about the external validity of our results, recent evidence suggests that there is no effect of informal caregiving on labour force participation in both countries (Heitmüller, 2007; Rellstab et al., 2020). In the UK, intensive caregiving might however affect the number of hours worked (Heitmüller & Inglis, 2007). As across countries the relationship between informal care and labour market outcomes is diverse (for a review see Bauer & Sousa-Poza, 2015), there is nonetheless a need for further research into the complex relationship between health, labour market outcomes and the long-term care system.

The bulk of our results suggests that once the focus is narrowed to specific subgroups of caregivers the effects of informal caregiving are similar despite large differences across country's LTC systems. However, some differences between both countries still emerge. Dutch low-intensity caregivers experience small negative mental health effects whereas this is not the case in the UK. In turn, only UK caregivers experience small positive health effects among low-intensity caregivers while in the Netherlands this only occurs among unemployed or part-time working individuals. Lastly, there is some suggestive evidence that women in the Netherlands experience a larger mental health burden. These differences can be driven by variation in support options or attitudes towards care provision, but also by differences in the type of care provided (e.g. personal care, household help) or the associated social norms. The country-specific differences in effect size are however considerably smaller compared to differences between subgroups of caregivers.

While our study provides important insights, there are several limitations that need to be taken into account when interpreting our results. First, we rely on a matching based empirical strategy aimed at estimating the causal effect of informal care on health. Matching estimators require the conditional independence assumption to hold and while we attempt to explore the impact of a potential violation of this assumption, an ideal empirical strategy would rely on plausible exogenous variation in informal caregiving status. As pointed out by Schmitz & Westphal (2015) many of the commonly applied instrumental variables in this literature, such as the presence of siblings or health shocks, are not without their own drawbacks. A more credible source of variation could be obtained from policy variation as recently done by Bakx et al. (2020b). However, given our cross-country perspective such an empirical strategy is not feasible.

A second limitation is that we cannot disentangle the caregiving effect, the impact of caring for someone, from the family effect, the impact of caring about someone (Bobinac et al., 2010). Possibly the observed mental health effects are driven by severe illness of a family member instead of the act of caring itself. Previous studies investigating the caregiving and family effect in the Netherlands (Bom et al., 2019b) and the UK (Stöckel & Bom, 2020) however found that inclusion of an indicator of the family effect does not affect the estimates of the caregiving effect. In addition, the absence of strong negative health effects among high-intensity caregivers who are not in full-time work seems to contradict that the effects we find are driven by the family effect. Importantly though this does not mean that there is no direct mental health effect associated with concerns regarding family members' health. Rather it seems likely that such an effect is already captured when conditioning on the mental health outcomes in the year prior to providing informal care.

Lastly, while the used datasets allow for similar matching, we still lack some important information that ideally should be considered. We rely on self-reported hours as our measure of care intensity. While this measure seems sufficient to capture the general differences between intensity levels it would be ideal to not only observe hours but also the specific tasks that were conducted as they are highly disease-specific and differ with regards to their perceived burden (Pearlin, 1990). In addition, we cannot observe the consumption of formal care.

Concluding, our results provide insights for both researchers and policymakers. First, they indicate that especially differences in caregiver characteristics drive the differences in observed health effects of care provision across countries. These insights can be used to specifically target support to those caregivers who experience the largest burden: those who provide most hours or care and those experiencing a double burden of care and full-time employment. Second, while we do not find large differences in health effects between both countries when comparing similar caregivers, this does not mean that country characteristics do not play a role. In countries with more generous LTC systems, and hence more formal care alternatives to informal care, less individuals seem to provide highly intensive care. As a result, less individuals experience severe health effects of care provision. It is important for policymakers to be aware of this relation between the coverage of LTC systems and the composition (and hence experienced health effects) of caregivers in order to make deliberate trade-offs between the aggregate costs of formal care versus the implications of informal care.

Appendix chapter 5

Table A5.1: UK Sample Descriptive Statistics – Treatment and Control Groups

UK	**Treated**		**Control**		**Matched Controls**		**Standardized Bias**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Un matched**	**Matched**
Care Obligations								
Mother alive	0.56	0.50	0.44	0.50	0.56	0.50	25.40	-0.30
Father alive	0.34	0.47	0.29	0.46	0.34	0.47	10.20	0.50
Both parents alive	0.26	0.44	0.24	0.42	0.25	0.43	4.80	0.70
Living partner	0.67	0.47	0.65	0.48	0.67	0.47	4.80	0.80
Living siblings	0.90	0.31	0.90	0.30	0.90	0.30	-1.50	-0.30
Age of mother	78.32	4.85	77.01	4.37	78.30	4.96	28.30	0.10
Age of father	78.76	3.52	77.97	3.25	78.72	3.50	23.30	0.60
Age of partner	54.4	6.87	53.55	7.22	40.71	24.11	12.00	0.70
Willingness to Care								
Age	53.99	5.76	53.82	5.99	53.97	5.77	2.90	0.30
Female	0.60	0.49	0.52	0.50	0.58	0.49	15.80	2.10
Secondary Education	0.40	0.49	0.36	0.48	0.40	0.49	7.20	-0.70
Tertiary Education	0.38	0.48	0.36	0.48	0.37	0.48	2.50	1.40
Primary Education	0.23	0.42	0.28	0.45	0.23	0.42	-10.90	-0.70
Self-Employed	0.10	0.30	0.10	0.30	0.10	0.30	0.10	0.20
Unemployed	0.06	0.23	0.05	0.22	0.06	0.23	2.80	-0.40
Retired	0.14	0.35	0.14	0.34	0.14	0.35	2.40	0.90
Homecarer	0.05	0.22	0.03	0.18	0.05	0.21	8.00	0.10
Disabled	0.06	0.23	0.07	0.25	0.06	0.23	-5.00	-0.50
Education_other	0.00	0.06	0.00	0.06	0.00	0.07	0.70	-1.80
Employed	0.59	0.49	0.61	0.49	0.59	0.49	-3.90	-0.10
Full-time employee	0.49	0.50	0.55	0.50	0.50	0.50	-11.90	-0.80
Income quintile 1	0.23	0.42	0.25	0.43	0.21	0.41	1.80	-0.70
Income quintile 2	0.21	0.41	0.20	0.4	0.20	0.40	1.70	-0.70
Income quintile 3	0.20	0.4	0.19	0.39	0.17	0.37	-5.20	0.40
Income quintile 4	0.17	0.38	0.19	0.39	0.19	0.39	5.70	1.40
Income quintile 5	0.19	0.40	0.17	0.38	0.23	0.42	-3.80	-0.30
HH Income Fraction	0.54	0.31	0.57	0.31	0.54	0.31	-10.00	-0.40
Children < 14 in Household	0.14	0.35	0.18	0.38	0.14	0.35	-10.60	-0.80

Table A5.1: UK Sample Descriptive Statistics – Treatment and Control Groups

UK	Treated		Control		Matched Controls		Standardized Bias	
	Mean	SD	Mean	SD	Mean	SD	Unmatched	Matched
Ability to Care								
SF-12 Mental Score	50.60	9.61	51.13	9.59	50.58	9.87	-5.50	0.00
SF-12 Physical Score	49.48	11.1	49.09	11.57	49.33	11.44	3.40	1.00
Longstanding illness	0.40	0.49	0.42	0.49	0.41	0.49	-3.30	-0.10
Number of Individuals	1,714		5,473		5,473			

Source: USoc Wave 1-4.

Table A5.2: Dutch sample Descriptive Statistics – Treatment and Control Groups

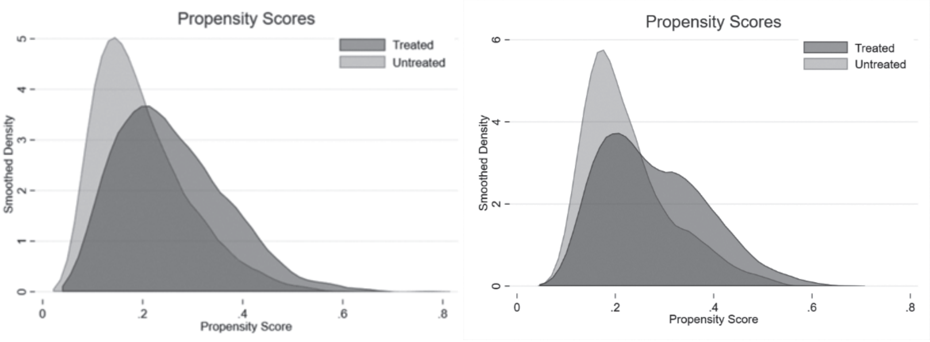
	Treated		Control		Matched Controls		Standardized Bias	
	Mean	SD	Mean	SD	Mean	SD	Unmatched	Matched
Care Obligations								
Mother alive	0.56	0.50	0.44	0.50	0.56	0.50	25.80	1.40
Father alive	0.32	0.47	0.25	0.43	0.30	0.46	14.50	2.00
Both parents alive	0.24	0.42	0.19	0.39	0.22	0.42	11.00	2.60
Living partner	0.72	0.45	0.70	0.46	0.73	0.44	5.10	-1.70
Living siblings	0.88	0.33	0.84	0.37	0.88	0.33	10.40	0.60
Age of mother	80.52	4.71	79.44	4.57	44.96	4.83	23.40	0.70
Age of father	80.39	37.64	79.74	3.10	24.94	3.12	20.50	0.50
Age of partner	54.47	5.63	54.60	5.56	39.73	5.66	15.00	-0.20
Willingness to Care								
Age	54.83	5.31	54.22	5.56	54.83	5.38	11.30	-0.70
Female	0.51	0.50	0.38	0.49	0.51	0.49	25.20	-0.10
Secondary Education	0.38	0.49	0.38	0.48	0.38	0.48	0.90	0.00
Tertiary Education	0.37	0.48	0.32	0.47	0.37	0.44	11.00	0.60
Primary Education	0.25	0.43	0.31	0.46	0.25	0.27	-12.60	-0.70
Self-Employed	0.08	0.27	0.08	0.28	0.08	0.17	-0.80	-0.40
Unemployed	0.03	0.17	0.02	0.16	0.03	0.21	2.90	0.20
Retired	0.05	0.22	0.02	0.16	0.04	0.12	13.30	0.00
Homecarer	0.01	0.11	0.01	0.10	0.01	0.27	2.80	-0.50
Disabled	0.08	0.27	0.06	0.24	0.08	0.03	6.3	-0.20
Education_other	0.00	0.03	0.00	0.04	0.00	0.43	-1.50	0.10
Employed	0.75	0.43	0.79	0.41	0.75	0.50	-11.00	0.40

Table A5.2: Dutch sample Descriptive Statistics – Treatment and Control Groups

	Treated		**Control**		**Matched Controls**		**Standardized Bias**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Un matched**	**Matched**
Full-time employee	0.50	0.50	0.59	0.49	0.49	0.40	-18.50	1.20
Income quintile 1	0.21	0.41	0.24	0.43	0.19	0.40	-6.60	-0.80
Income quintile 2	0.19	0.39	0.22	0.41	0.19	0.40	-0.90	-0.30
Income quintile 3	0.20	0.40	0.20	0.41	0.20	0.40	3.30	0.20
Income quintile 4	0.20	0.40	0.18	0.39	0.20	0.40	12.10	0.60
Income quintile 5	0.20	0.40	0.15	0.36	0.21	0.41	-6.80	0.30
HH Income Fraction	0.76	0.30	0.81	0.27	0.76	0.30	-18.30	1.00
Children < 14 in Household	0.10	0.31	0.14	0.35	0.10	0.30	-12.10	0.50
Ability to Care								
SF-12 Mental Score	52.19	8.70	52.31	8.56	52.11	8.79	-1.40	0.70
SF-12 Physical Score	48.43	9.99	48.95	9.87	48.36	10.40	-5.20	0.60
Longstanding illness	0.65	0.48	0.60	0.49	0.65	0.48	8.90	-1.00
Number of Individuals	1,723		6,418		6,418			

Source: STREAM Wave 1-4

Figure A5.1: Propensity score distributions



(a) The Netherlands

(b) United Kingdom

Sources: STREAM Wave 1-4 & USoc Wave 1-4.

Table A5.3: Estimation results by care intensity

	Dutch Sample		UK Sample	
	MCS	**PCS**	**MCS**	**PCS**
Any care	-0.698***	0.197	-0.211	0.687**
	(0.204)	(0.183)	(0.219)	(0.207)
Low intensity	-0.510*	0.186	0.025	0.802***
<10h weekly care	(0.222)	(0.200)	(0.231)	(0.224)
Medium intensity	-0.930	0.495	0.215	0.147
10-20h weekly care	(0.530)	(0.475)	(0.601)	(0.533)
High intensity	-2.106**	-0.068	-2.322**	0.898
>20h weekly care	(0.775)	(0.620)	(0.739)	(0.641)
Control		6,418		5,473
Treatment		1,711		1,713
Low		1,378		1,302
Medium		181		205
High		135		177

*p<0.05, **p<0.01, *** p<0.001, standard errors in parentheses. Sources: STREAM Wave 1-4 & USoc Wave 1-4.

Table A5.4: Estimation results by gender

	Dutch Sample				UK Sample			
	Males		**Females**		**Males**		**Females**	
	MCS	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**	**MCS**	**PCS**
Any care	-0.321	-0.196	-1.059***	0.658	0.063	0.231	-0.390	0.977***
	(0.258)	(0.245)	(0.312)	(0.268)	(0.326)	(0.307)	(0.293)	(0.280)
Control		3,953		2,465		2,644		2,829
Treatment		846		865		694		1,019

*p<0.05, **p<0.01, *** p<0.001, standard errors in parentheses. Sources: STREAM Wave 1-4 & USoc Wave 1-4.

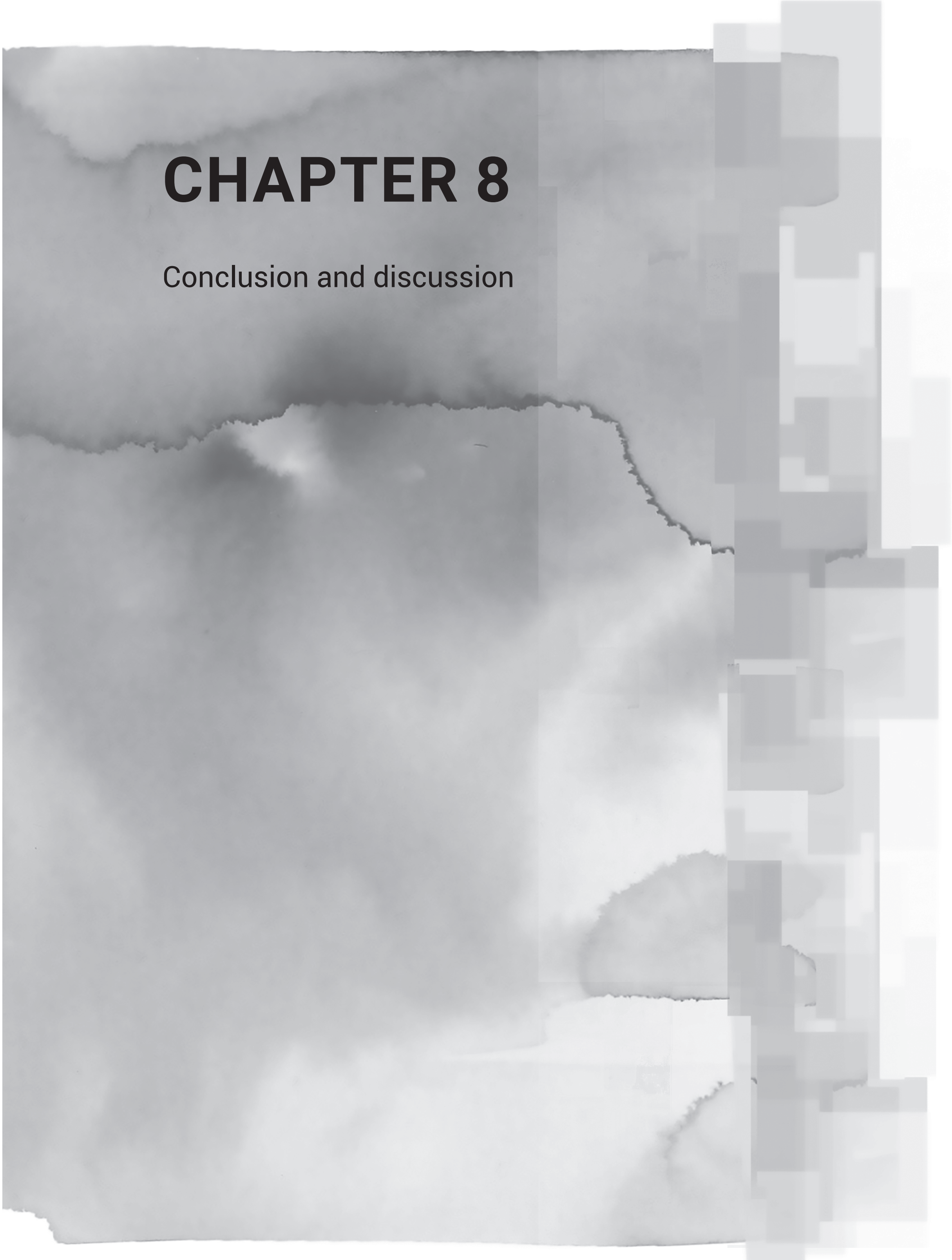
Table A5.5: Estimation results by care intensity and employment-status

	Dutch Sample		UK Sample	
	MCS	**PCS**	**MCS**	**PCS**
Not full-time work & <10h	-0.374	0.725*	0.082	1.317***
	(0.336)	(0.305)	(0.360)	(0.360)
Full-time work & <10h	-0.932**	-0.412	-0.156	0.412
	(0.312)	(0.276)	(0.316)	(0.299)
Not full-time & >=10h	-0.535	-0.040	-0.542	0.778
	(0.620)	(0.522)	(0.604)	(0.543)
Full-time & >=10h	-2.633***	0.911	-2.179*	0.426
	(0.674)	(0.565)	(0.882)	(0.668)
Control				
Not full-time		2,520		2,276
Full-time		3,459		2,670
Treatment				
Not full-time & Low IC		638		566
Full-time & Low IC		639		598
Not full-time & High IC		184		240
Full-time & High IC		120		125

*p<0.05, **p<0.01, *** p<0.001, standard errors in parentheses. Sources: STREAM Wave 1-4 & USoc Wave 1-4.

CHAPTER 8

Conclusion and discussion



8. Conclusion

Faced with an ageing population and rising health care costs, LTC systems are under pressure in many countries. To safeguard the fiscal and financial stability of these LTC systems, policymakers are considering a variety of options to reduce public LTC expenditures. Two potential solutions are often identified in this regard: stimulating informal care provision and ageing-in-place. This thesis focuses on two questions related to these presumed solutions by studying the health impact of providing informal care and the determinants and impact of a nursing home admission.

8.1 Research findings

Informal care has a negative impact on the health of informal caregivers

A large part of the demand for LTC is met by informal caregivers. This type of care is often preferred by both the dependent elderly as well as the informal care providers themselves. Additionally, increased reliance on informal caregivers could potentially substitute for collectively funded care. While informal caregivers provide care against no or low direct payments, this does not mean that informal caregiving does not have any costs. Individuals give up some of their time to provide care, which might come at the cost of labor force participation. Additionally, the act of providing care can be highly burdensome for the caregiver. The provision of informal care could lead to both physical health effects, like back aches or fatigue, as well as stress leading to mental health problems.

In the first part of this thesis the potential health effects of providing informal care are studied. The systematic literature review in chapter 2 indicates that there is a substantial body of literature that finds negative health effects of informal care provision. These studies show that informal care provision can have an impact on both the physical and mental health of care providers, and that these effects differ between subgroups of caregivers.

Many of the studies included in the review, however, did not make any attempt to disentangle the health impact of caring for someone from the health impact of worrying about an ill family member. Being aware of this distinction is important, as the prevention of these different causes of negative health effects may require different interventions. Chapter 3 and 4 explicitly take the so called family effect of worrying about an ill family member into account. In both a Dutch and UK sample, we find that controlling for the family effect does not affect the estimated health effects of care provision. The act of providing informal care directly affects someone's health.

The health effects of informal care provision are not the same for everyone. Individual and contextual characteristics, like the type of care provided or the circumstances under which this care is provided, can lead to a differential impact of informal care. A more thorough understanding of these differences can help to shape more adequate informal care support. Chapters 3, 4 and 5 all demonstrate that the intensity of the informal care provision is critical: the more care that is provided, the larger the experienced health effects. In the Netherlands any level of care provision negatively impacts health, while particularly large negative health effects are found among those individuals providing more than 20 hours of care a week. In the UK, predominantly individuals providing more than 20 hours of care a week face large mental health effects of care provision. Chapter 4 shows that the larger impact of informal care among spousal caregivers, compared to for example individuals providing care to their parents, is mainly explained by higher care intensity: spousal caregivers tend to provide more hours of care compared to other informal care providers. This higher care intensity, not the relationship with the care recipient, explains the larger health effects among this group of caregivers. In addition, mental health issues related to care provision are more prevalent when there are other responsibilities that compete for time. Especially individuals who provide many hours of informal care next to full-time employment are heavily affected by their care tasks (chapter 5).

Next to the immediate negative health effects of providing informal care, care provision can have longer-term effects. By following individuals after the start of care provision this thesis shows that the initial negative effects on mental health slowly decrease in size throughout the years, but remain persistent up to four or five years (chapter 4).

In contrast to individual differences, country differences that are for example related to the LTC system or social norms, do not seem to lead to large differences in health effects when similar caregivers are compared. Chapter 5 shows that very comparable health effects of care provision are observed for high intensity caregivers in the Netherlands and the United Kingdom. Even in a generous LTC system like the Netherlands, individuals can experience negative health effects of intensive care provision. However, this does not imply that differences in generosity of the LTC system are irrelevant. Country characteristics can drive the demand for (highly intensive) informal care. A generous LTC system may limit the number of individuals who provide many hours of informal care, thereby limiting the number of caregivers who suffer from the health consequences of doing so.

The move to a nursing home is not dictated by disability only

Next to incentivizing informal care, there is the widespread ambition to delay nursing home admissions and/or to stimulate substitution of nursing home care with home care. Despite this universal trend of stimulating ageing-in-place, nursing home care use still widely differs across countries. To some extent, these differences can be explained by country-specific population characteristics. For example, a higher share of dependent elderly within a population may lead to higher LTC use. Additionally, system and cultural differences like accessibility of LTC and preferences towards informal care play a role in determining nursing home use. A better understanding of the sources of these differences in LTC use is critical in shaping policies that promote an appropriate care mix for dependent elderly.

Chapter 6 investigates what may explain the very different patterns of nursing home admissions in the Netherlands, Denmark and the US. In the US, the probability of a nursing home admission in the next two years among the 65+ community residing population is 6.6%, which is much higher than in the Netherlands (4.2%). In part, this can be explained by country-specific population characteristics. There are, for example, more dependent elderly among the community dwelling population in the US than in the Netherlands. Next to population characteristics, system differences, such as the generosity and organization of the system, play a role as well. In the US, elderly more often make use of short-term (often post-acute) nursing home care, potentially because of limited home care use options and high hospitalization rates among elderly. In contrast, long-term nursing home admissions are far more prevalent in the Netherlands and Denmark: for dependent elderly or elderly aged 85+, the probability of a nursing home admission of more than 100 days is much higher in the two European countries.

These findings highlight the importance of distinguishing different types of nursing home care: the ‘average’ nursing home admission may be very different across countries. Specifically, the separation of short (often post-acute) and longer-term nursing home admissions turned out to be critical for understanding the differences between US and European nursing home admissions. Furthermore, the findings indicate that nursing home admissions are not solely determined by the health or disability of elderly. System-related and culture-related country differences in nursing home care are equally important.

An important argument for the current ageing-in-place policies hinges on the assumption that individuals often fear the ‘last move’ to a nursing home and that this means that they are indeed better off at home. Chapter 7 compares the well-being of different groups of nursing home entrants in the months before and after moving to a nursing home. We do not find any association between nursing home admissions and self-reported well-being scores. Moving to a nursing home hence does not seem as detrimental to someone’s well-being as is often conjectured, at least for the majority of the population that ends up moving to a nursing home at some point in their life. In contrast to commonly heard stories, in our sample health and well-being issues are nearly equally prevalent shortly before and after moving to a nursing home. This seems to suggest that not nursing home admissions themselves are associated with lower perceived well-being, but rather that nursing homes admissions cater for individuals who already face falling levels of well-being.

8.2 Implications for policy

LTC policy decisions should better take into account the implications for informal care provision

The findings from this thesis provide some important lessons for policy. First of all, it is important to understand that long-term care entails much more than only formal care that is provided by professionals. A large part of the care for elderly is provided outside of formal care contracts, by friends and family members of the individual in need of help. In most EU-countries the estimated costs of informal care even exceed the expenditures on formal LTC (Van der Ende et al., 2020).

When (re)designing LTC policies, informal care providers should always be considered an important target group. Changes in the system will not only affect the elderly and formal care providers but also friends and family members who may consider to provide informal care. For example, increasing copayments for formal care can raise the demand for informal care and may therefore lead to the provision of more (intensive) informal care. This also implies that countries considering an expansion of publicly financed LTC coverage should realize that its benefits reach beyond the dependent elderly. Also the large group of potential informal care providers can benefit from an extended LTC coverage, as it may reduce the demand for informal care.

Formal and informal LTC are two interconnected care types which should be considered together. The recent covid-19 pandemic highlighted the importance of being aware of the crucial role informal caregivers play within LTC systems. In the midst of the pandemic, visit regulations for Dutch nursing homes were tightened and the availability of home care was limited. These policy changes had large implications for informal caregivers who were required to provide much more informal care or could not continue their caregiving tasks. However, there was little acknowledgement of the impact of these decisions on informal caregivers and their ability to provide care (SCP, 2020).

Support to informal caregivers should be targeted towards those in highest need

While the increased reliance on informal care could lessen public LTC expenditures, it simultaneously entails negative health consequences for those who take up caregiving tasks. This transition from formal to informal care affects the distribution of the care burden in society. While formal LTC is predominantly funded via collectively paid premiums and taxes, the burden of informal care falls on a fairly small group. Additionally, not everyone is equally inclined to provide informal care, and in the Netherlands it is often the able elderly who provide informal care. The negative health effects of care provision are therefore often borne by individuals who are already vulnerable or at risk of needing care themselves.

These elements highlight the need to alleviate the care burden, which can be done via several routes. One of the solutions is aiming to distribute the burden more equally. The majority of Dutch informal caregivers indicates to enjoy providing care tasks for their family members (Plaisier et al., 2015), and many individuals state that they would be willing to provide informal care (De Klerk et al., 2017). Preferably, less vulnerable informal care providers should be attracted to limit the need for high-intensity care providers, for example by considering potential additional informal caregivers in someone's social environment during screenings for formal care (Kooiker et al., 2019).

Next to, where possible, aiming to attract more care providers, current caregivers can be assisted with targeted support. In general two types of caregiver support can be identified. Caregivers can be supported by reducing the amount of required informal care for example by offering respite care, other formal care or assistive technology. Additionally, support options could be aimed at improving coping skills for example via support groups. Evidence points towards the effectiveness of various forms of both types of informal care support (with strongest evidence for replacement care, flexible working conditions, therapy, training and support groups) and indicates that often a combination of the two may be optimal (Brimblecombe et al., 2018).

Currently, many European countries offer some support to informal caregivers, most often in the form of financial support, respite care or training. The scale and scope of these services thus far is however limited and few countries aim to systematically identify caregivers and assess their needs (Mosca et al., 2017; Courtin et al., 2014). While in the Netherlands municipalities are obliged to provide support to informal caregivers, many often fail to help those who need support (VNG, 2016; Feijten et al., 2017).

To enhance the take up of support services it is important to understand the reasons for the low uptake. In the Netherlands limited supply of information and the (perceived) difficulty of getting access to support options seem to be the most prominent reasons for not using support options (Feijten et al. 2017). Improving efforts to inform informal caregivers about the available support options at the municipal level could increase uptake. Additionally, knowing who is (more strongly) affected by the provision of informal care can aid in targeting support and helps in deciding how to spend scarce resources. The findings in this thesis indicate that especially female, high-intensity and double burdened caregivers are the ones who experience the largest mental health effects and therefore are in the highest need for support.

Three options to deal with the rising demand for LTC

So how should be dealt with the increasing demand for LTC that is expected in the coming decades? To preserve the current standard of care, there are three options to deal with the rising demand for LTC: (1) increase reliance on informal care, (2) higher individual copayments for formal care or (3) more public funding of formal care.

The first option of increasing reliance on informal care means that the costs of the increasing demand for LTC will be borne by a small group with a limited ability to carry these (e.g. older caregivers). As discussed above, this could lead to an unequal distribution of the care burden. Additionally, attracting sufficient informal care providers to meet demand may become difficult as the number of potential caregivers is expected to decrease in the coming decades. This is the result of various societal and demographic changes like an increasing female labour participation, increasing retirement age and divorce rates and decreasing family size and cohabitation with close family members (Colombo et al., 2011). Research predicts that in the Netherlands, the number of available informal caregivers around every care recipient will decline from 5 in 2018 to 3 in 2040 (Kooiker et al., 2019).

The second option, increasing individual copayments, obliges individuals to pay a larger share of their LTC expenditures themselves, thereby limiting the growth of public LTC expenditure and potentially limiting unnecessary care use. This approach might, however, induce inequality as well. Some of the costs that would otherwise have been funded by the society as a whole are now borne by those in need for care. This group is often the group with the lowest financial means (Bakx et al., 2020a). When increasing copayments, one should protect this group, for example with additional subsidies or income dependent copayments.

The third option is increasing public expenditures on LTC. This option entails that the increasing need for LTC care would – at least partially – be met with formal care, paid from public means. The resulting increase of public LTC expenditures might crowd out other public expenditures (CPB, 2019), induce overconsumption of LTC (Non, 2017) and lead to potentially unwanted redistribution of costs between the generations, meaning that more costs will be borne by the younger generations (Wouterse & Smid, 2017). Proposals to increase copayments or informal care supply are hence no perfect solutions, but not acting on the foreseen increase in demand for LTC, is not a perfect alternative either. As all options entail pros and cons, a combination of the options seems to be the most straightforward possibility. The optimal division will differ per country and, among other things, depend on the value the public attaches to equal division of costs and equal access to LTC.

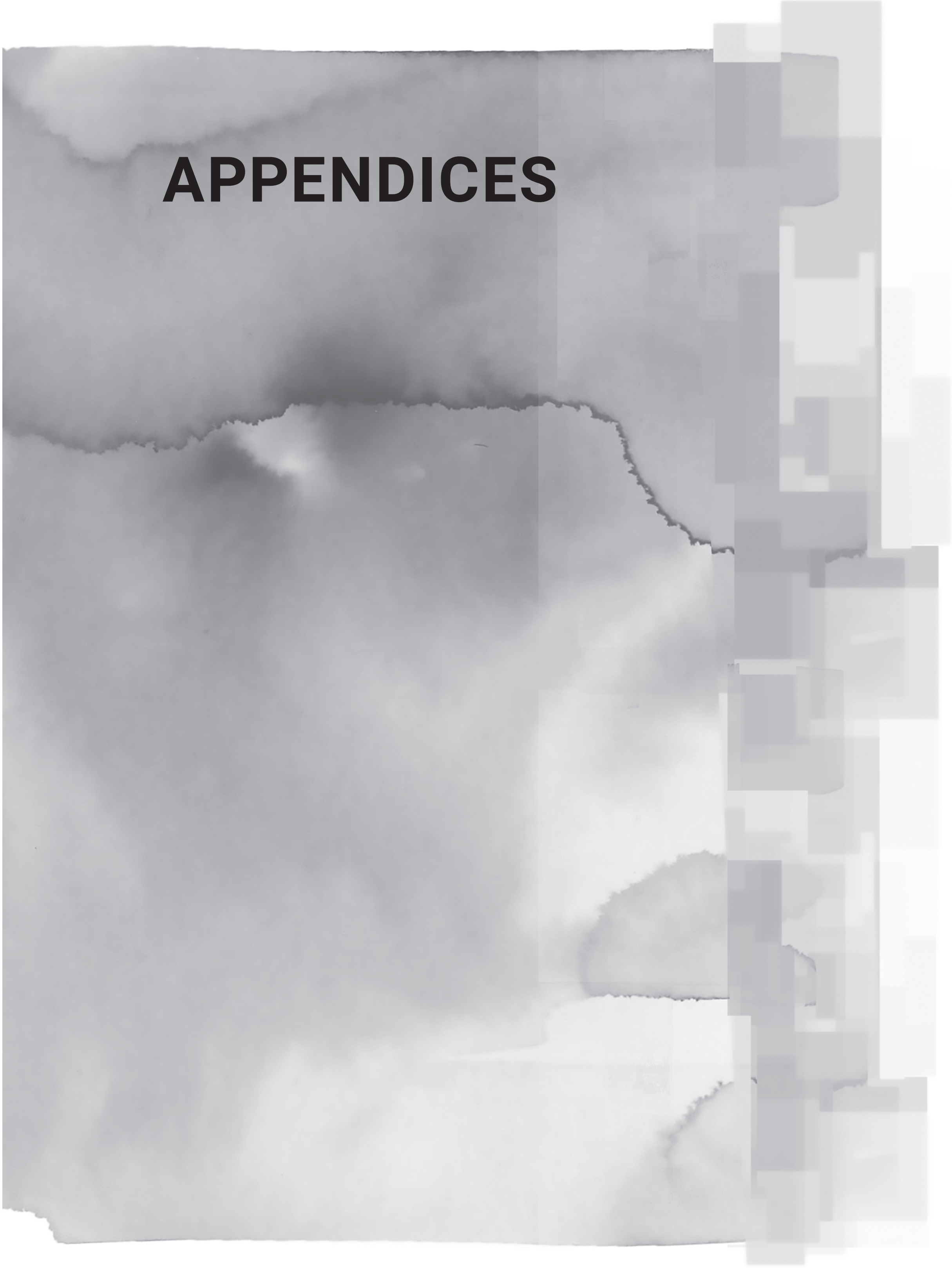
The most appropriate balance between nursing home care and ageing-in-place differs per country

Nursing home admissions are not only driven by individual health but also by many other factors, like the generosity of the system and the prevailing social norms. As a result, the degree towards which individuals are stimulated to age-in-place is likely to differ across the globe based on cultural and system differences: there is no uniform optimal balance between staying at home (supported by either home care or informal care) and moving to a nursing home.

To develop LTC policies that fit country characteristics, and to aid individuals in decision making regarding where to live in the last years of life, policymakers first of all need to know more about life in a nursing home. One option to gain more insight would be to encourage large panel-data surveys to continue interviewing respondents after a nursing home admission. Currently few surveys manage to follow individuals into their nursing homes.

Additional information can aid further development of LTC policies and can help in careful assessment of the available care options in the last years of life. While ageing-in-place may be the preferred option for many, it may not be an option for all (Commissie Toekomst zorg thuiswonende ouderen, 2020). For some individuals, it may become too unsafe to continue living at home given the intensity of home healthcare they need. Moreover, for those individuals staying at home is not cheaper (considering formal care expenditures) than transitioning to a nursing home (Bakx et al,. 2020b). When also considering the informal care demand, it might even be more prominent that for some individuals the costs of staying home can become very high.

APPENDICES



Acknowledgements by chapter

Chapter 2

The authors thank Sara Rellstab for her contributions to the review process and Wichor Bramer for his help with drafting the search query. Additionally we thank the Community Health Services, Statistics Netherlands & National Institute for Public Health and the Environment for access to survey data. This study has been carried out with financial support from the Network for Studies on Pensions, Aging and Retirement. Grant name: Optimal saving and insurance for old age: The role of public long term care insurance.

Chapter 3

The authors gratefully acknowledge comments on earlier versions of this article by Johan Bonekamp, Rudy Douven, Agnès Gramain, Sara Rellstab and Marianne Tenand. We also thank participants of various seminars and conferences for useful comments and discussion, and TNO and Statistics Netherlands for providing access to survey and administrative data. This study received financial support from the Network for Studies on Pensions, Aging and Retirement. Grant: Optimal saving and insurance for old age: The role of public-long term care insurance.

Chapter 4

We gratefully acknowledge comments provided by Cameron Birchall, Joaquim Vidiella-Martin, Sara Rellstab, Pieter Bakx, Eddy van Doorslaer, Erik Schut, Job van Exel, and Werner Brouwer, participants at the LSE Care Policy Evaluation Centre seminar, the KU Leuven Public Economics seminar, the 2019 lowlands Health Economic Study Group, the 2019 UK Health Economists' Study Group summer meeting, the 2019 International Health Economics Congress and the ESE/ESHPM PhD Research Symposium. This study received financial support from the Network for Studies on Pensions, Ageing and Retirement Grant *optimal saving and insurance for old age: The role of public-long term care insurance* (Bom) and the Erasmus Initiative *Smarter Choices for Better Health* at Erasmus University Rotterdam (Stöckel). All remaining errors are our own.

Chapter 5

We gratefully acknowledge comments provided by Pieter Bakx, Erik Schut, and Eddy van Doorslaer, participants at the LSE Care Policy Evaluation Centre seminar, the 2019 International Health Economics Congress and the ESE/ESHPM PhD Research Symposium. We thank TNO, Statistic Netherlands and the Institute for Social and Economic Research for providing access to survey and administrative data. The used non-public microdata from Statistics Netherlands is available for scientific research under certain conditions and a confidentiality agreement. For further information: microdata@cbs.nl. This study received financial support from the Network for

Studies on Pensions, Ageing and Retirement Grant *optimal saving and insurance for old age: The role of public-long term care insurance* (Bom) and the *Smarter Choices for Better Health Initiative* financed by the Erasmus University Rotterdam (Stöckel). All remaining errors are our own.

Chapter 6

Acknowledgements

We gratefully acknowledge valuable contributions to this study from Julie Uldum Lyhr. Additionally, we acknowledge comments to earlier versions of this paper provided by Marianne Tenand and the ESHPM LTC focus group. This study received financial support from the Network for Studies on Pensions, Ageing and Retirement Grant *optimal saving and insurance for old age: The role of public-long term care insurance.*

Data acknowledgements

This paper uses data from several sources. For the US data, data from wave 11 and 12 of the Health and Retirement Study is used. This dataset is produced and distributed by the University of Michigan with funding from the National Institute on Aging (grant number NIA U01AG009740). Ann Arbor, MI. It uses data from RAND HRS Longitudinal File 2014 V3 (2019) and RAND HRS Tax Calculations 2014 V2 (2018) produced by the RAND Center for the Study of Aging, with funding from the National Institute on Aging and the Social Security Administration. Santa Monica, CA.

For the European data the paper uses data from SHARE Wave 5 (DOI: 10.6103/SHARE.w5.700), see Börsch-Supan et al. (2013) for methodological details. *The SHARE data collection has been funded by the European Commission through FP5 (QLK6-CT-2001-00360), FP6 (SHARE-I3: RII-CT-2006-062193, COMPARE: CIT5-CT-2005-028857, SHARELIFE: CIT4-CT-2006-028812), FP7 (SHARE-PREP: GA N°211909, SHARE-LEAP: GA N°227822, SHARE M4: GA N°261982) and Horizon 2020 (SHARE-DEV3: GA N°676536, SERISS: GA N°654221) and by DG Employment, Social Affairs & Inclusion. Additional funding from the German Ministry of Education and Research, the Max Planck Society for the Advancement of Science, the US National Institute on Aging (U01_AG09740-13S2, P01_AG005842, P01_AG08291, P30_AG12815, R21_AG025169, Y1-AG-4553-01, IAG_BSR06-11, OGHA_04-064, HHSN271201300071C) and from various national funding sources is gratefully acknowledged (see www.share-project.org).*

The Dutch SHARE results are linked to Dutch administrative data using non-public microdata from Statistics Netherlands (CBS). Under certain conditions and a confidentiality agreement, these microdata are accessible for statistical and scientific research. For further information: microdata@cbs.nl. Exploitation of the data and publication of the results are made in compliance with the European privacy legislation (GDPR, May 25th 2018).

The Danish SHARE results has been linked to several Danish administrative registers through social security numbers. Physically these administrative micro data are located on specific computers at Statistics Denmark and may not be transferred to computers outside Statistics Denmark due to data security considerations. Researchers and their research assistants are allowed to use these data under certain conditions and a confidentiality agreement, if their research project is approved by Statistics Denmark, and if they are affiliated with a research institution accepted by Statistics Denmark. For further information: https://www.dst.dk/en/TilSalg/Forskningsservice.

Chapter 7

We gratefully acknowledge comments provided by Pearl Dykstra, Leonie Sundmacher, Erik Schut, Eddy van Doorslaer and participants at the 2019 Netspar Pension Workshop and the 2020 EuHEA student-supervisor online conference. Additionally we thank the Community Health Services, Statistics Netherlands & National Institute for Public Health and the Environment for access to survey data. This study received financial support from the Network for Studies on Pensions, Ageing and Retirement Grant *optimal saving and insurance for old age: The role of public-long term care insurance.*

Summary

Populations are ageing rapidly in many countries, leading to an increasing demand for long-term care (LTC). This care refers to help or medical support that is provided to elderly who are in need for care for a longer period of time. LTC can be provided at home or in institutions and consists of informal care, care provided by friends and family members, and formal care, care provided by professionals. The increasing care demand pressures LTC systems in many countries. To safeguard stability of these systems, various options to reduce LTC expenditures are currently considered. Stimulating informal care provision and ageing-in-place are often identified as two potential solutions in this regard. This thesis focuses on two questions related to these presumed solutions by studying the differential health impact of providing informal care and the determinants and impact of a nursing home admission.

Part 1 - The health effects of providing informal care

Informal care could potentially substitute collectively funded formal LTC, thereby limiting formal care expenditures. While informal caregivers provide care against no or low direct payments, this does not imply that informal caregiving does not cost anything. Informal care provision is time consuming which might hinder labor force participation. Moreover, providing care can be demanding leading to mental or physical health effects for the care provider him or herself.

This thesis (chapter 2) provides an overview of the current literature on the health effects of providing informal care. The systematic literature review shows that a large base of literature points towards negative health effects of informal care provision. Most of these studies however do not separate the impact of caring for a family member from the impact of caring about a family member, the so-called family effect. It is however important to make a distinction between these two elements as both require different interventions and not accounting for the family effect might lead to an overestimation of the impact of providing informal care. Additionally, insights into the impact of informal care were thus far mostly limited to the United States or several European countries pooled together.

Chapter 3 adds to the literature by studying the health impact of care provision in the Netherlands. This is an interesting focus area as the Netherlands is a specific case: It has a comprehensive LTC system and is one of the countries with the highest public LTC expenditures. In this chapter both mental and physical health effects of providing informal care are estimated for a sample of 45-65 year old individuals while aiming to account for the family effect. Results indicate that, irrespective of the presence of a family effect, providing informal care can have significant negative impact on one’s mental health. The effects are larger for female and spousal caregivers, which might be driven by the intensity of care provided by these groups.

Chapter 4 has a similar set-up, but studies the health effects of informal care provision in the United Kingdom (UK). In contrast to the Netherlands, the UK LTC system is less comprehensive and mainly targeted at those with the lowest means. In the UK, informal care provision also leads to mental health problems, however solely among individuals who provide at least 20 hours of care a week. Subgroup analyses show that the large health effects among spousal caregivers are indeed driven by hours of care provision, not the relationship with the care recipient. Next to studying the direct health effects of care provision, longer-term health effects are studied. The initially experienced mental health issues diminish, but persist for 4 to 5 years, indicating that individuals might only adapt to or recover from intensive caregiving tasks slowly.

Insights from both Dutch and UK data are combined in chapter 5. In this chapter the health effects of informal care provision in both countries are compared to each other. As differences in norms, values and LTC systems might (indirectly) affect informal care provision it is interesting to understand how this leads to differences in experienced health effects of informal care provision. Is it easier to provide informal care in one of the two countries, for example because of a more generous LTC system or differences in norms and values?

This chapter shows that in both countries the intensity of the provided care is a large driver of the experienced health effects: Individuals who provide more than 20 hours of informal care per week experience the largest negative mental health effects. The more care someone provides, the more straining the situation becomes. However, while no large differences in health effects between both countries are found when comparing similar caregivers, this does not mean that country characteristics do not play a role. In the UK, where the LTC system is less generous, the share of caregivers providing highly intensive informal care is larger.

Part 2 – The determinants and impact of a nursing home admission

In the second part of the thesis the focus shifts from informal care to formal care. Next to incentivizing informal care, there is the widespread ambition to delay nursing home admissions and/or to stimulate substitution of nursing home care with home care. Despite this universal trend of stimulating ageing-in-place, nursing home care use widely differs across countries. A better understanding of the sources of these differences in LTC use is critical in shaping policies that promote an appropriate care mix for dependent elderly.

Chapter 6 explores this latter topic by investigating differences in nursing home admission rates between the United States, Denmark and the Netherlands. In the US, the probability of a nursing home admission in the next two years among the 65+ community residing population is much higher than in the Netherlands. In part, this can be explained by country-specific population characteristics. There are, for example, more dependent elderly among the community dwelling population in the US than in the Netherlands. Next to population characteristics, system differences, such as the generosity and organization of the system, play a role as well. In the US, elderly more often make use of short-term (often post-acute) nursing home care, potentially because of limited home care options and high hospitalization rates among elderly. In contrast, long-term nursing home admissions are far more prevalent in the Netherlands and Denmark. These findings highlight the importance of distinguishing different types of nursing home care: the 'average' nursing home admission may be very different across countries. Furthermore, the findings indicate that nursing home admissions are not solely determined by the health or disability of elderly. System-related and culture-related country differences in nursing home care play an important role as well.

Lastly, chapter 7 explores the levels of wellbeing of Dutch elderly in the period just before and after nursing home admission. Ageing-in-place policies often hinge on the assumption that elderly fear the last move and are better off at home. This chapter investigates the well-being of elderly just before and after a nursing home admission. Doing so, we explore whether nursing home residents are better or worse off than the not-yet-admitted. We do not find any association between nursing home admissions and self-reported well-being scores. Health and well-being issues show to be nearly equally prevalent right before and after a nursing home admission. We hence do not find evidence for the commonly held belief that nursing homes have a large negative effect on one's well-being. The findings seem to suggest that not nursing home admissions themselves are associated with lower perceived well-being, but rather that nursing homes admissions cater for individuals who already face falling levels of well-being.

Samenvatting

In veel landen is de bevolking sterk aan het vergrijzen, wat leidt tot een toenemende vraag naar langdurige zorg. Deze zorg heeft betrekking tot hulp of medische ondersteuning die wordt geboden aan ouderen die voor langere tijd een zorgbehoefte hebben. Deze zorg kan zowel thuis als in verpleeghuizen worden geboden en bestaat uit informele zorg, zorg verleend door familie of vrienden, en formele zorg, verleend door professionals. De toenemende vraag naar langdurige zorg zorgt ervoor dat in veel landen langdurige zorgsystemen onder druk komen te staan. Om de stabiliteit van deze systemen te waarborgen, worden momenteel verschillende opties overwogen om de uitgaven aan langdurige zorg te verminderen. Het stimuleren van informele zorgverlening en langer thuis wonen van ouderen worden in dit verband vaak gezien als twee mogelijke oplossingen. Dit proefschrift richt zich op twee vragen met betrekking tot deze veronderstelde oplossingen door het bestuderen van de gezondheidseffecten van het verlenen van informele zorg en de determinanten en impact van een verpleeghuisopname.

Deel 1 - De gezondheidseffecten van mantelzorg

Informele zorg of mantelzorg kan mogelijk collectief gefinancierde formele langdurige zorg vervangen en zo de zorguitgaven beperken. Hoewel mantelzorgers zorg verlenen tegen geen of lage directe betalingen, betekent dit niet dat het verlenen van mantelzorg geen kosten met zich meebrengt. Informele zorgverlening is tijdrovend, wat de arbeidsparticipatie kan belemmeren. Bovendien kan het verlenen van zorg veeleisend zijn, wat kan leiden tot mentale of fysieke gezondheidseffecten voor de zorgverlener zelf.

Dit proefschrift (hoofdstuk 2) geeft een overzicht van de huidige literatuur over de gezondheidseffecten van het verlenen van mantelzorg. Uit een systematisch literatuuronderzoek blijkt dat een groot deel van de literatuur wijst op negatieve gezondheidseffecten voor de mantelzorger zelf. De meeste van deze studies maken echter geen onderscheid tussen het effect van het zorgen voor een familielid en het effect van het zorgen maken over een familielid, het zogenaamde *family effect*. Het is echter belangrijk om een onderscheid te maken tussen deze twee elementen, aangezien beide effecten verschillende interventies vereisen en het niet meenemen van het *family effect* zou kunnen leiden tot een overschatting van het effect van het verlenen van mantelzorg. Daarnaast zijn inzichten in het effect van informele zorg tot nu toe meestal beperkt gebleven tot de Verenigde Staten of een aantal Europese landen samen.

Hoofdstuk 3 vult de literatuur aan door van de gezondheidseffecten van het verlenen van mantelzorg in Nederland het bestuderen. Nederlands is hierin een interessant aandachtsgebied: Het heeft een zeer uitgebreid langdurige zorgsysteem en is een van de landen met de hoogste overheidsuitgaven aan langdurige zorg. In dit hoofdstuk worden zowel de mentale als fysieke gezondheidseffecten van het verlenen van informele zorg geschat voor een steekproef van 45-65 jarigen, waarbij er wordt getracht het *family effect* los te koppelen van het effect van het verlenen van mantelzorg. De resultaten tonen dat, ongeacht de aanwezigheid van een *family effect*, het verlenen van mantelzorg een significante invloed kan hebben op de mentale gezondheid. De effecten zijn groter voor vrouwen en partners die zorg verlenen, wat kan worden veroorzaakt door de intensiteit van de zorg die door deze groepen wordt verleend.

Hoofdstuk 4 heeft een vergelijkbare opzet, maar bestudeert de gezondheidseffecten van informele zorgverlening in het Verenigd Koninkrijk (VK). In tegenstelling tot Nederland is hier het langdurige zorgsysteem minder uitgebreid en vooral gericht op personen met de minste financiële mogelijkheden. Ook in het VK blijkt dat informele zorgverlening leidt tot mentale gezondheidsproblemen, echter alleen bij personen die ten minste 20 uur per week zorg verlenen. Uit subgroep analyses blijkt dat het grotere gezondheidseffect onder personen die mantelzorg verlenen aan hun partner inderdaad wordt veroorzaakt door het aantal uren zorg en niet de relatie met de zorgontvanger. Naast het bestuderen van de directe gezondheidseffecten van de zorgverlening worden nu ook gezondheidseffecten op langere termijn bestudeerd. De aanvankelijk ervaren mentale gezondheidsproblemen nemen af in grootte, maar houden 4 tot 5 jaar aan, wat aangeeft dat mensen zich mogelijk alleen langzaam aanpassen aan of herstellen van intensieve zorgtaken.

Inzichten uit zowel Nederlandse als Britse data worden gecombineerd in hoofdstuk 5. In dit hoofdstuk worden de gezondheidseffecten van de mantelzorg in beide landen met elkaar vergeleken. Aangezien de verschillen in normen, waarden en langdurige zorgsystemen van landen (indirect) van invloed kunnen zijn op mantelzorg, is het interessant om te begrijpen hoe dit leidt tot verschillen in ervaren gezondheidseffecten van de mantelzorg. Is het gemakkelijker om informele zorg te verlenen in een van de twee landen, bijvoorbeeld vanwege een genereuzer zorgsysteem of verschillen in normen en waarden?

In beide landen is de intensiteit van de geleverde zorg een grote drijvende kracht voor de ervaren gezondheidseffecten: Personen die meer dan 20 uur per week informele zorg verlenen, ondervinden grote negatieve gevolgen voor de mentale gezondheid. Hoe meer zorg iemand verleent, hoe meer belastend de situatie wordt. Hoewel er geen grote verschillen in gezondheidseffecten tussen beide landen worden gevonden bij het vergelijken van gelijksoortige zorgverleners, betekent dit niet dat landkenmerken geen rol spelen. In het Verenigd Koninkrijk, waar het langdurige zorgsysteem minder genereus is, biedt een groter deel van de informele zorgverleners zeer intensieve informele zorg.

Deel 2 - De determinanten en gevolgen van een verpleeghuisopname

In het tweede deel van het proefschrift verschuift de focus van informele zorg naar formele zorg. Naast het stimuleren van informele zorg is er de wijdverbreide ambitie om verpleeghuisopnames uit te stellen en/of substitutie van verpleeghuiszorg door thuiszorg te stimuleren. Ondanks deze universele trend om langer thuis wonen te bevorderen bestaan er grote verschillen in verpleeghuiszorg gebruik tussen landen. Een beter begrip van de oorzaken van de verschillen in het gebruik van langdurige zorg is van cruciaal belang bij het uitstippelen van beleid dat een passende zorgmix voor afhankelijke ouderen bevordert.

Hoofdstuk 6 verkent dit laatste onderwerp door de verschillen in verpleeghuisopname tussen de Verenigde Staten (VS), Denemarken en Nederland te onderzoeken. In de VS is de kans op een verpleeghuisopname in de komende twee jaar onder 65-plussers veel groter dan in Nederland. Voor een deel kan dit worden verklaard door verschillen in bevolkingskenmerken. Zo kampen ouderen in de VS vaker met beperkingen dan in Nederland. Naast bevolkingskenmerken spelen ook systeemverschillen, zoals de generositeit en organisatie van het systeem, een rol. In de VS maken ouderen vaker gebruik van kortdurende (vaak post-acute) verpleeghuiszorg, mogelijk vanwege beperkte mogelijkheden voor thuiszorggebruik en hoge ziekenhuisopnamecijfers onder ouderen. Langdurige verpleeghuisopnamen komen daarentegen vaker voor in Nederland en Denemarken.

Uit deze bevindingen blijkt hoe belangrijk het is onderscheid te maken tussen de verschillende soorten verpleeghuiszorg: de “gemiddelde” verpleeghuisopname kan van land tot land sterk verschillen. Bovendien wijzen de bevindingen erop dat verpleeghuisopnamen niet uitsluitend worden bepaald door de gezondheid of de beperkingen van ouderen. Systeem- en cultuurgebonden verschillen tussen landen in de verpleeghuiszorg spelen hierin ook een belangrijke rol.

Tot slot gaat hoofdstuk 7 in op het welbevinden van Nederlandse ouderen in de periode vlak voor en na een verpleeghuisopname. *Ageing-in-place* beleid is vaak gebaseerd op de aanname dat ouderen bang zijn voor de laatste verhuizing en beter af zijn thuis. Dit hoofdstuk onderzoekt het welzijn van ouderen vlak voor en na een verpleeghuisopname. Daarbij gaan we na of verpleeghuisbewoners beter of slechter af zijn dan personen die nog niet zijn opgenomen. We vinden geen verband tussen verpleeghuisopname en zelf gerapporteerde welzijnsscores. Gezondheids- en welzijnsproblemen blijken vrijwel even vaak voor te komen vlak voor als na een verpleeghuisopname. We vinden dus geen bewijs voor de overtuiging dat verpleeghuizen een groot negatief effect hebben op iemands welzijn. De bevindingen lijken er eerder op te wijzen dat niet de verpleeghuisopname zelf geassocieerd is met een lager ervaren welzijn, maar dat verpleeghuisopnames zorg leveren aan personen die al kampen met een dalend welzijnsniveau.

List of publications

In this thesis

Bom, J., Bakx, P., Schut, F., & van Doorslaer, E. (2019). The impact of informal caregiving for older adults on the health of various types of caregivers: A systematic review. *The Gerontologist*, *59*(5), e629-e642.

Bom, J.A.M., Bakx, P.L.H. Schut, F.T. & van Doorslaer, E.K.A. (2018). *Informal caregiving, a healthy decision? Determinants and health-related consequences of providing informal care.* Netspar Survey Paper, no 52. Tilburg: Netspar

Bom, J., Bakx, P., Schut, F., & Van Doorslaer, E. (2019). Health effects of caring for and about parents and spouses. *The Journal of the Economics of Ageing*, *14*, 100196.

Stöckel, J. & Bom, J. (2020) *The Dynamic Effects of Informal Caregiving on the Caregivers' Health.* Netspar Discussion Paper 02/2020-011. Tilburg: Netspar

Bom, J., & Stöckel, J. (2021). Is the grass greener on the other side? The health impact of providing informal care in the UK and the Netherlands. *Social Science & Medicine*, 269, 113562.

Other academic and professional publications

Bakx, P.L.H., Bom, J.A.M., van Doorslaer, E.K.A., Hussem, A., Schut F.T. & Wouterse B. (2018). *Wie zorgt en betaalt voor de ouderen van morgen?* Netspar Brief, no 14. Tilburg: Netspar

Bakx, P.L.H. Bom, J.A.M. Tenand M. & Wouterse B. (2020). *Eigen bijdrage aan ouderenzorg.* Netspar Design Paper, no 139. Tilburg: Netspar

Bom, J., Wouterse, B., Bakx, P. & Tenand, M. (2020). Grote verschillen in eigen bijdrage aan ouderenzorg. *Geron*, *22*(4). https://gerontijdschrift.nl/artikelen/grote-verschillen-in-eigen-bijdrage-aan-ouderenzorg/

Van der Ende, M., van Seben, R., van Exel, J. Bom, J, Sapulete, S., and Geijsen, T. (2021). *Study on exploring the incidence and costs of informal long-term care in the EU.* ECORYS and Erasmus University Rotterdam (forthcoming).

Lenzen, S., Bakx, P., Bom, J. & van Doorslaer, E. (2021). Health care use and out-of-pocket spending by persons with dementia differ between Europe and the US. *Medical Care* (forthcoming).

About the author

Judith Bom (1991) attended the Erasmus University Rotterdam, where she completed a BSc in International Business Administration and a MSc in Management of Innovation in 2013. Subsequently, she completed a MSc in Health Economics, Policy and Law at the same university in 2014. Following her master graduation she worked for governmental organizations in strategy and finance. In 2016 she returned to the Erasmus University to pursue a PhD in Health Economics at the Erasmus School of Health Policy and Management.

At the Erasmus School of Health Policy and Management, Judith studies and teaches about long-term care. Her research focuses on long-term care in the Netherlands and abroad and resulted in this thesis. The work was part of the Netspar project Optimal Insurance in Old Age. Next to work on her thesis Judith participated in a project for the European Commission on informal long-term care. Additionally, she obtained her University Teaching Qualification and was involved in coordinating and teaching in several courses at the faculty. After her graduation, Judith remains affiliated to the Erasmus University Rotterdam.

References

Actiz (2012). De verpleeg- en verzorgingshuiszorg en thuiszorg in kaart. https://www.actiz.nl/stream/c-kaartenboek-zorg

Actiz (2017). Geriatrische revalidatiezorg. https://www.actiz.nl/thema/zorg/geriatrische-revalidatiezorg

Aeldresagen (2020). Nursing homes. https://www.aeldresagen.dk/viden-og-raadgivning/hjaelp-og-stoette/plejebolig-og-plejehjem

Age UK (2019a). Paying for homecare. https://www.ageuk.org.uk/information-advice/care/paying-for-care/paying-for-homecare/

Age UK (2019b). Paying for a care home. https://www.ageuk.org.uk/information-advice/care/paying-for-care/paying-for-a-care-home/

Alders, P., Costa-Font, J., de Klerk, M., & Frank, R. (2015). What is the impact of policy differences on nursing home utilization? The cases of Germany and the Netherlands*. Health Policy*, *119*(6), 814-820. doi: 10.1016/j.healthpol.2015.02.006.

Alders, P., Comijs, H. C., & Deeg, D. J. (2017). Changes in admission to long-term care institutions in the Netherlands: comparing two cohorts over the period 1996–1999 and 2006–2009. *European Journal of Ageing*, *14*(2), 123-131.

Amirkhanyan, A. A. & Wolf, D. A. (2006). Parent care and the stress process: Findings from panel data. *Journal of Gerontology: series B*, *61*(5), 248-255. doi: 10.1093/geronb/61.5.S248.

Andresen, E. M., Malmgren, J. A., Carter, W. B., & Patrick, D. L. (1994). Screening for Depression in Well Older Adults: Evaluation of a Short Form of the CES-D. *American Journal of Preventive Medicine*, *10*(2), 77–84. https://doi.org/10.1016/s0749-3797(18)30622-6

Angrist, J. D., & Imbens, G. W. (1995). Two-stage least squares estimation of average causal effects in models with variable treatment intensity. *Journal of the American statistical Association*, *90*(430), 431-442.

Angrist, J. D., & Pischke, J. S. (2008). *Mostly Harmless Econometrics: An Empiricist's Companion.* Princeton, NJ: Princeton University Press.

Antonakis, J., Bendahan, S., Jacquart, P., & Lalive, R. (2010). On making causal claims: A review and recommendations. *The Leadership Quarterly*, *21*(6), 1086-1120. doi.org/10.1016/j.leaqua.2010.10.010

Antonakis, J., Bendahan, S., Jacquart, P., & Lalive R. (2014). *Causality and endogeneity: Problems and solutions*. In D.V. Day (Ed.), The Oxford Handbook of Leadership and Organizations (pp. 93-117). Oxford: Oxford University Press. doi:10.1017/CBO9781107415324.004.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, *58*(2), 277–297. https://doi.org/10.2307/2297968.

Avendano, M., Glymour, M., Banks, J., &. Mackenbach, J. (2009). Health Disadvantage in US Adults Aged 50 to 74 Years: A Comparison of the Health of Rich and Poor Americans With That of Europeans *American Journal of Public Health*, *99*(3). 10.2105/AJPH.2008.139469.

Bakx, P., De Meijer, C., Schut, F. & Van Doorslaer, E. (2015a). Going formal or informal, who cares? The influence of public long-term care insurance. *Health Economics*, *24,* 631-643. DOI:10.1002/hec.3050.

Bakx, P., Chernichovsky, D., Paolucci, F., Schokkaert, E., Trottmann, M., Wasem, J., & Schut F. (2015b). Demand-side strategies to deal with moral hazard in public insurance for long-term care. *Journal of Health Services Research & Policy*, 20(3), 170-176. https://doi.org/10.1177/1355819615575080.

Bakx, P., Bom, J., Tenand, M., & Wouterse, B. (2020a). Eigen bijdrage aan ouderenzorg. Netspar Design Paper 13. https://www.netspar.nl/publicatie/eigen-bijdrage-aan-ouderenzorg/

Bakx, P., Wouterse, B., van Doorslaer, E., & Wong, A. (2020b). Better off at home? Effects of nursing home eligibility on costs, hospitalizations and survival. *Journal of Health Economics*, *73*, 102354.

Barczyk, D. & Kredler, M. (2019). Long-Term Care Across Europe and the United States: The Role of Informal and Formal Care. *Fiscal studies*, *40*(3), 329-373. 10.1111/1475-5890.12200.

Barigozzi, F., Cremer H., & Roeder K. (2017). Caregivers in the Family: Daughters, Sons and Social Norms. IZA Discussion Paper No. 10862. http://ftp.iza.org/dp10862.pdf

Barnay, T., & Juin, S. (2016). Does home care for dependent elderly people improve their mental health? *Journal of Health Economics*, *45*, 149-160. https://doi.org/10.1016/j.jhealeco.2015.10.008.

Barr N. (2010). Long-term care: a suitable case for social insurance. *Social Policy & Administration*, *44*(4): 359-374. doi:10.1111/j.1467-9515.2010.00718.x.

Bauer, J. M., & Sousa-Poza, A. (2015). Impacts of informal caregiving on caregiver employment, health, and family. *Journal of Population Ageing*, 8(3), 113-145.

Beach, S. R., Schulz, R., Yee, J. L., & Jackson, S. (2000). Negative and positive health effects of caring for a disabled spouse: Longitudinal findings from the Caregiver Health Effects Study. *Psychology and Aging*, *15*(2), 259–342. doi.org/10.1037//0882-7974.15.2.259.

Beaumaster, S., Chien, S., Crosswell, A., Lin, A., Phillips, D., Valev, M., … Lee J. (2018). Harmonized HRS Documentation. Version B 2018. USC Dornsife, Centre for Economic and Social Research, Program on Aging, Health, and Policy.

Beaumaster, S., Chien, S., Lau, S., Lin, A., Meijer, E., Phillips, D., … Lee J. (2017). Harmonized SHARE Documentation. Version D2 2017. USC Dornsife, Centre for Economic and Social Research, Program on Aging, Health, and Policy.

Belloni, A., Chen, D., Chernozhukov, V., & Hansen, C. (2012). Sparse Models and Methods for Optimal Instruments with an Application to Eminent Domain. *Econometrica*, *80*(6), 2369–2429. https://doi.org/10.3982/ECTA9626.

Bobinac, A., Van Exel, N. J. A., Rutten, F. F. H., & Brouwer, W. B. F. (2010). Caring for and caring about : Disentangling the caregiver effect and the family effect. *Journal of Health Economics*, 29(4), 549–556. https://doi.org/10.1016/j.jhealeco.2010.05.003.

Böckerman, P., Johansson, E., & Saarni, S. I. (2012). Institutionalisation and subjective wellbeing for old-age individuals: is life really miserable in care homes?. *Ageing and Society*, *32*(7), 1176.

Bolin, K., Lindgren, B., & Lundborg, P. (2008). Informal and formal care among single-living elderly in Europe. *Health Economics*, 17, 393–409. doi: 10.1002/hec.1275.

Bom, J., Bakx, P., Schut, F., & van Doorslaer, E. (2019a). The Impact of Informal Caregiving for Older Adults on the Health of Various Types of Caregivers. *The Gerontologist*, *59*(5), e629-e642. https://doi.org/10.1093/geront/gny137.

Bom, J., Bakx, P., Schut, F., & van Doorslaer, E. (2019b). Health effects of caring for and about parents and spouses. *The Journal of the Economics of Ageing*, 14. https://doi.org/10.1016/j.jeoa.2019.100196.

Bond, S. R. (2002). Dynamic panel data models: a guide to micro data methods and practice. *Portuguese economic journal*, *1*(2), 141-162.

Bonsang, E. (2009). Does informal care from children to their elderly parents substitute for formal care in Europe? *Journal of Health Economics*, *28*, 143–154.

Borjas, G. J. (1987). Self-selection and the earnings of immigrants. *The American Economic Review*, *77*(4), 531-553.

Börsch-Supan, A. (2019). Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 5. Release version: 7.0.0. SHARE-ERIC. Data set. DOI: 10.6103/SHARE.w5.700.

Börsch-Supan, A., & Jürges, H. (2005). The Survey of Health, Aging, and Retirement in Europe – Methodology. http://www.share-project.org/fileadmin/pdf_documentation/ Methodology/Methodology_2005.pdf

Börsch-Supan, A., M. Brandt, C. Hunkler, T. Kneip, J. Korbmacher, F. Malter, B. Schaan, S. Stuck, S. Zuber (2013). Data Resource Profile: The Survey of Health, Ageing and Retirement in Europe (SHARE). *International Journal of Epidemiology*. DOI: 10.1093/ije/dyt088.

Bound, J. (1991). Self-Reported Versus Objective Measures of Health in Retirement Models. The *Journal of Human Resources*, *26*(1), 106–138. https://doi.org/10.2307/145718.

Boyer, M., De Donder, P., Fluet, C., Leroux, M., & Michaud P. (2017). Long-term care insurance: Knowledge barriers, risk perception and adverse selection. NBER Working paper, http://www.nber.org/papers/w23918.pdf

Brandt, M. (2013). Intergenerational Help And Public Assistance In Europe: A Case Of Specialization? *European Societies*, *15*(1), 26-56. https://doi.org/10.1080/14616696.2012.726733.

Brenna, E. & Di Novi C. (2016). Is caring for older parents detrimental to women's mental health? The role of the European North-South gradient. *Review of Economics of the Household*, 14(4), 745-778. doi:10.1007/s11150-015-9296-7.

Brimblecombe, N., Fernandez, J. L., Knapp, M., Rehill, A., & Wittenberg, R. (2018). Review of the international evidence on support for unpaid carers. *Journal of Long-Term Care*, (September), 25-40.

Brown, J. R. & Finkelstein, A. (2009). The private market for long-term care insurance in the United States: A review of the evidence. *Journal of Risk and Insurance*, *76*(1), 5-29. doi:10.1111/j.1539-6975.2009.01286.x.

Bruno, G. S. F. (2005). Approximating the bias of the LSDV estimator for dynamic unbalanced panel data models. *Economics Letters*, *87*(3), 361–366. https://doi.org/10.1016/j.econlet.2005.01.005.

Buurman-van Es, B. (2020). Kortdurende zorg bij ouderen als antwoord op spoedzorg. *Huisarts en Wetenschap, 63*(1), 37-40. Doi:10/10.1007/s12445-019-0362-x.

Caliendo, M., & Kopeinig, S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, *22*(1), 31-72. https://doi.org/10.1111/j.1467-6419.2007.00527.x

Carers UK (2016). State of Caring 2016. https://www.carersuk.org/for-professionals/policy/policy-library/state-of-caring-2016

Carretero, S., Garcés, J., Ródenas, F., & Sanjosé, V. (2009). The informal caregiver's burden of dependent people: Theory and empirical review. *Archives of gerontology and geriatrics*, *49*(1), 74-79. https://doi.org/10.1016/j.archger.2008.05.004.

Chan, K.S., Kasper, J.D., Brandt, J., & Pezzin, L.E. (2012). Measurement Equivalence in ADL and IADL Difficulty Across International Surveys of Aging: Findings From the HRS, SHARE, and ELSA. *The Journals of Gerontology, Series B: Psychological Sciences and Social Sciences*, *67*(1), 121–132. doi:10.1093/geronb/gbr133.

Christensen, B.J., Gørtz, M. & Kallestrup-Lamb, M. (2016). Medical Spending in Denmark. *Fiscal studies*, 37(3–4), 461–497. https://doi.org/10.1111/j.1475-5890.2016.12119.

CIZ (2013). Begeleiding in beeld: Feiten en cijfers over cliënten met een indicatie van het CIZ.

CIZ (2015). Eerstelijnsverblijf. Gebruik subsidieregeling 2015.

CIZ (2017). Beleidsregels indicatiestelling WLZ 2017. https://www.zorgwijzer.nl/wp-content/uploads/CIZ-Beleidsregels_2017.pdf

CIZ (2018). Beleidsregels indicatiestelling Wlz 2018. https://www.ciz.nl/images/pdf/beleidsregels/Beleidsregels_indicatiestelling_Wlz_2018.pdf

Coe, N. B. & Van Houtven C. H. (2009). Caring for mom and neglecting yourself? The health effects of caring for an elderly parent. *Health Economics*, 18(9), 991-1010. doi: 10.1002/hec.1512.

Coe, N. B., Guo, J., Konetzka, R. T., & Van Houtven, C. H. (2019). What is the marginal benefit of payment-induced family care? Impact on Medicaid spending and health of care recipients. *Health Economics*, *28*(5), 678-692. https://doi.org/10.1002/hec.3873.

Colombo, F., Llena-Nozal, A., Mercier, J., & Tjadens, F. (2011). *Help Wanted? Providing and paying for long-term care*. OECD Health Policy Studies, OECD Publishing. http://dx.doi.org/10.1787/9789264097759-en.

Comas-Herrera, C., Pickard, L., Wittenberg, R., Malley, J., & King, D. (2010). The long-term care system for the elderly in England. European Network of Economic Policy Research Institutes. ENEPRI RESEARCH REPORT NO. 74 CONTRIBUTION TO WP1 OF THE ANCIEN PROJECT.

Commissie Toekomst zorg thuiswonende ouderen (2020). Oud en zelfstandig in 2030: Een reisadvies. Den Haag: Ministerie van Volksgezondheid, Welzijn en Sport.

Costa-Font, J. (2017). “Institutionalization aversion” and the willingness to pay for home health care. *Journal of Housing Economics*, *38*, 62-69.

Courtin, E. Jemiai, N. & Mossialos, E. (2014). Mapping support policies for informal carers across the European Union*, Health Policy*, *118*(1): 84-94, https://doi.org/10.1016/j.healthpol.2014.07.013.

CPB (2019). Verkenning Middellangetermijn 2022-2025. https://www.cpb.nl/middellangetermijnverkenning-2022-2025

Cremer, H., Gahvari, F., & Pestieau, P. (2017). Uncertain altruism and the provision of long term care. *Journal of Public Economics*, *151*, 12-24. doi:10.1016/j.jpubeco.2017.05.001.

Cremer, H., Pestieau, P., & Ponthiere, G. (2012). The economics of long-term care: a survey. *Nordic Economic Policy Review*, *2*. 107-148.

Cremer, H. & Roeder, K. (2017). Long-term care policy with lazy rotten kids. *Journal of Public Economic Theory*, *19*, 583-602.

Curry, N., Schlepper, L. & Hemmings, N. (2019). What can England learn from the long-term care system in Germany? Research report, Nuffield Trust.

De Boer, Alice en Mirjam de Klerk (2015). Mantelzorgers: wie helpt wie, waarmee en hoe. In: Mirjam de Klerk, Alice de Boer, Inger Plaisier, Peggy Schyns en Sjoerd Kooiker (red.), Informele hulp: wie doet er wat? Omvang, aard en kenmerken van mantelzorg en vrijwilligerswerk in de zorg en ondersteuning in 2014 (p. 65-88). Den Haag: Sociaal en Cultureel Planbureau.

De Groot, A.J. & Vreeburg, E.M. (2019). Geriatrische revalidatiezorg: samen werken aan herstel! *Bijblijven: tijdschrift praktische huisartsengeneeskunde*, *35*(2), 8-14. https://doi.org/10.1007/s12414-019-0016-8.

De Hond, A. Bakx, P. & Versteegh, M. (2019). Can time heal all wounds? An empirical assessment of adaptation to functional limitations in an older population. *Social Science & Medicine*, 222: 180-187. https://doi.org/10.1016/j.socscimed.2018.12.028.

De Jong Gierveld, J. & van Tilburg, T.G. (1999). *Manual of the Loneliness Scale*. VU University Amsterdam, Department of Social Research Methodology (ISBN 90-9012523-X).

De Jong, A. & Kooiker, S. (2018). Regionale ontwikkelingen in het aantal potentiële helpers van oudere ouderen, 1975-2040, Den Haag: PBL.

De Klerk, M., de Boer, A., Plaisier, I. & Schyns, P. (2017). Voor elkaar? Stand van de informele hulp in 2016. Sociaal en Cultureel Planbureau.

De la Maisonneuve, C., & Martins, J. O. (2015). *The future of health and long-term care spending.* OECD Journal: Economic Studies, 2014/1, 61-96. https://doi.org/10.1787/19952856.

De Luca, G., Rossetto, C., & Malter, F. (2015). "Sample design and weighting strategies in SHARE Wave 5". In: SHARE Wave 5: Innovations & Methodology. Munich: MEA, Max Planck Institute for Social Law and Social Policy: 75–84.

De Meijer, C., Bakx, P., Koopmanschap, M. & van Doorslaer E. (2015). Explaining declining rates of institutional LTC use in The Netherlands: a decomposition approach. *Health Economics*, *24*: S18-S31.

De Meijer, C.A.M., Koopmanschap, M.A., Koolman, X.H.E., van Doorslaer, E.K.A. (2009). The Role of Disability in Explaining Long-Term Care Utilization*, Medical Care, 47*(11):1156-63. doi: 10.1097/MLR.0b013e3181b69fa8.

De Zwart, P. L., Bakx, P., & van Doorslaer, E. K. A. (2017). Will you still need me, will you still feed me when I'm 64? The health impact of caregiving to one's spouse. *Health Economics*, *26*, 127-138. https://doi.org/10.1002/hec.3542.

Di Novi C., Jacobs, R., & Migheli, M. (2015). The quality of life of female informal caregivers: From Scandinavia to the Mediterranean Sea. *European Journal of Population*, *31*(3), 309-333. doi:10.1007/s10680-014-9336-7.

Diepstraten, M., Douven, R., & Wouterse, B. (2020). Can your house keep you out of a nursing home?. *Health Economics*, *29*(5), 540-553.

Do, Y. K., Norton, E. C., Stearns, S. C., & Van Houtven, C. H. (2015). Informal Care and Caregiver's Health. *Health Economics*, *24*(11): 224-237. Doi:10.1002/hec.3012.

Dujardin, C., Farfan-Portet, M. I., Mitchell, R., Popham, F., Thomas, I., & Lorant, V. (2011). Does country influence the health burden of informal care? an international comparison between Belgium and Great Britain. *Social Science and Medicine*, *73*(8), 1123-1132.

Dykstra, P. A., van Tilburg, T. G., & de Jong Gierveld, J. (2005). Changes in Older Adult Loneliness. *Research on Aging*, *27*(6), 725-747. doi:10.1177/0164027505279712.

Eggink, E., Ras, M., & Woittiez, I. (2017). Dutch long-term care use in an ageing population. The *Journal of the Economics of Ageing*, *9*, 63-70. doi:10.1016/j.jeoa.2016.08.00.

ESS Round 7: European Social Survey Round 7 Data (2014). Data file edition 2.2. NSD - Norwegian Centre for Research Data, Norway – Data Archive and distributor of ESS data for ESS ERIC. doi:10.21338/NSD-ESS7-2014.

Eurobarometer (2007). Special Eurobarometer 283: Health and Long-Term Care in the European Union European Union portal, Brussels. https://ec.europa.eu/commfrontoffice/publicopinion/archives/ebs/ebs_283_en.pdf

European Commission (2015). The 2015 Ageing Report Economic and budgetary projections for the 28 EU Member States (2013–2060). EUROPEAN ECONOMY 3|2015.Brussels: European Commission. doi:10.2765/877631.

European Commission (2018a). The 2018 Ageing Report Economic and Budgetary Projections for the EU Member States (2016-2070), EUROPEAN ECONOMY Institutional Paper 079.

European Commission (2018). Informal care in Europe: Exploring Formalisation, Availability and Quality. https://ec.europa.eu/social/main.jsp?catId=738&langId=en&pubId=8106&type=2&furtherPubs=no

Eurostat (2017). Final report of the expert group on quality of life indicators. Via. https://ec.europa.eu/eurostat/documents/7870049/7960327/KS-FT-17-004-EN-N.pdf/f29171db-e1a9-4af6-9e96-730e7e11e02f

Eurostat (2020a). Population structure and ageing. Accessed on 18 August 2020. https://ec.europa.eu/eurostat/statistics-explained/index.php/Population_structure_and_ageing

Eurostat (2020b). Disability statistics. Accessed on 18 August 2020. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Disability_statistics_-_elderly_needs_for_help_or_assistance

Feijten, P., Schellingerhout, R., de Klerk, M., Steenbekkers, A., Schyns, P., Vonk, F., Marangos, A.M., de Boer, A. & Heering, L. (2017). *Zicht op de Wmo 2015. Ervaringen van melders, mantelzorgers en gespreksvoerders*. Den Haag: Sociaal en Cultureel Planbureau.

Fernández, J.-L., Forder, J., Truckeschitz, B., Rokosova, M., & McDaid, D. (2009). *How can European states design efficient, equitable and sustainable funding systems for long-term care for older people?,* Policy Brief No. 11, World Health Organisation Europe, Copenhagen.

Fischer, B., & Müller, K. U. (2020). Time to care? The effects of retirement on informal care provision. *Journal of Health Economics*, *73*, 102350.

French, E. B., McCauley, J., Aragon, M., Bakx, P., Chalkley, M., Chen, S. H., ... & Fan, E. (2017). End-of-life medical spending in last twelve months of life is lower than previously reported. *Health Affairs*, *36*(7), 1211-1217.

Fukahori, R., Sakai, T., & Sato, K. (2015). The effects of incidence of care needs in households on employment, subjective health, and life satisfaction among middle-aged family members. *Scottish Journal of Political Economy*, 62(5), 518-545. doi:10.1111/sjpe.12085.

Gaugler, J. E., Suval, S., Anderson, K. A., & Kane, R. L. (2007). Predicting nursing home admission in the U.S: a meta-analysis. *BMC Geriatrics*, *7*(13). https://doi.org/10.1186/1471-2318-7-13.

Gezondheidsmonitor (2012). Own calculations using: Public Health Monitor 2012 of the Community Health Services, Statistics Netherlands and the National Institute for Public Health and the Environment.

Gezondheidsmonitor (2016). Own calculations using: Public Health Monitor 2016 of the Community Health Services, Statistics Netherlands and the National Institute for Public Health and the Environment.

GGD (2012). Factsheet gezondheidsmonitor. https://vng.nl/files/vng/vng/Documenten/actueel/beleidsvelden/openbare_gezondheid/2012/20120709_GGD_factsheetgezondheidsmonitor.pdf

GGD-GHOR (2016). Achtergrondinformatie gezondheidsmonitor Volwassen en Ouderen 2016. https://www.ggdghor.nl/media/filebank/cfed9c936eb444f683a7e451fc669899/gezondheidsmonitor-volwassen-en-ouderen-2016.pdf

Glendinning, C. (2013). *Long Term Care Reform in England: A Long and Unfinished Story in Reforms*. In Ranci, C. & Pavolini, E. (Ed.) Long-Term Care Policies in Europe. New York: Springer.

Goffman, E. (2009). Asylums. *Essays on the social situation of mental patients and other inmates.* Garden City: Anchor Books.

Goldberg, D. P., Gater, R., Sartorius, N., Ustun, T. B., Piccinelli, M., Gureje, O., & Rutter, C. (1997). The validity of two versions of the GHQ in the WHO study of mental illness in general health care. *Psychological medicine*, *27*(1), 191-197.

Goren, A., Montgomery, W., Kahle-Wrobleski, K., Nakamura, T., & Ueda, K. (2016). Impact of caring for persons with Alzheimer's disease or dementia on caregivers' health outcomes: Findings from a community based survey in Japan. *BMC Geriatrics*, *16*(1), 122. doi:10.1186/s12877-016-0298-y.

Grabowski, D. C. (2007). Medicare and medicaid: conflicting incentives for long-term care. The *Milbank Quarterly*, *85*(4), 579-610.

Grenade, L., & Boldy, D. (2008). Social isolation and loneliness among older people: issues and future challenges in community and residential settings. *Australian Health Review*, *32*(3) 468 - 478. https://doi.org/10.1071/AH080468.

Groot, W. (2000). Adaptation and scale of reference bias in self-assessments of quality of life. *Journal of Health Economics*, *19*(3), 403–420. https://doi.org/10.1016/S0167-6296(99)00037-5.

Hackert, M.Q.N, Brouwer, W.B.F, Hoefman, R.J, & van Exel, N.J.A. (2019). Views of older people in the Netherlands on wellbeing: A Q-methodology study. *Social Science & Medicine*, *240*, 112535.

Haley, W. E., & Pardo, K. M. (1989). Relationship of severity of dementia to caregiving stressors. *Psychology and Aging*, *4*, 389-392. https://doi.org/10.1037/0882-7974.4.4.389.

Hansen, L. (1982). Large Sample Properties of Generalized Method of Moments Estimators. *Econometrica*, *50*(4), 1029–1054. https://doi.org/10.2307/1912775.

Heckman, J. J. & Honoré, B. E. (1990). The empirical content of the Roy model. *Econometrica*, *58*(5), 1121-1149. doi:10.2307/2938303.

Heckman, J. J. & Sedlacek, G. (1985). Heterogeneity, aggregation, and market wage functions: An empirical model of self-selection in the labor market. *Journal of Political Economy*, *93*(6), 1077-1125. doi:10.1086/261352.

Heger, D. (2017). The Mental Health of Children Providing Care to their Elderly Parent. *Health Economics*, *26*(12), 1617–1629. https://doi.org/10.1002/hec.3457.

Heger, D. and Korfhage, T. (2018). Care choices in Europe: To Each According to His or Her Needs? *INQUIRY: The Journal of Health Care Organization, Provision and Financing*, *55*, 1-16.

Heitmueller, A. (2007). The chicken or the egg?: Endogeneity in labour market participation of informal carers in England. *Journal of Health Economics*, *26*(3), 536-559. https://doi.org/10.1016/j.jhealeco.2006.10.005.

Heitmueller, A., & Inglis, K. (2007). The earnings of informal carers: Wage differentials and opportunity costs. *Journal of Health Economics*, *26*(4), 821-841. 10.1016/j.jhealeco.2006.12.009.

Henchoz, K., Cavalli, S. & Girardin, M. (2008). Health perception and health status in advanced old age: A paradox of association. *Journal of Aging Studies, 22*(3), 282-290. https://doi.org/10.1016/j.jaging.2007.03.002.

Hernandez, A. M. & Bigatti, S. M. (2010). Depression among older Mexican American caregivers. *Cultural Diversity & Ethnic Minority Psychology*, *16*(1), 50-58. doi:10.1037/a0015867.

Hewlett, S., Dures, E., & Almeida, C. (2011). Measures of fatigue. *Arthritis Care and Research*, 63(S11), S263-S286. https://doi.org/10.1002/acr.20579.

Hirst, M. (2004). Health Inequalities and Informal Care: End of Project Report. Social Policy Research Unit, retrieved from: https://www.york.ac.uk/inst/spru/pubs/pdf/healthinequalities.pdf

Hirst, M. (2005). Carer distress: a prospective, population-based study. *Social Science & Medicine*, *61*(3), 697-708.

Hong, I., Han, A., Reistetter, T. A., & Simpson, A. N. (2016). The risk of stroke in spouses of people living with dementia in Korea. *International Journal of Stroke: Official Journal of the International Stroke Society*, *12*(8), 851-857. doi:10.1177/1747493016677987.

Hurd, M. Michaud, P. & Rohwedder, S. (2017). Distribution of lifetime nursing home use and of out-of-pocket spending. *PNAS,* 12, 114 (37) 9838-9842. https://doi.org/10.1073/pnas.1700618114.

Hussem, A., van Ewijk, C., ter Rele, H. & Wong, A. (2016). The Ability to Pay for Long-Term Care in the Netherlands: A Life-cycle Perspective. *De Economist*, *164*(2), 209-234. https://doi.org/10.1007/s10645-016-9270-7.

Ichino, A., Mealli, F., & Nannicini, T. (2008). From temporary help jobs to permanent employment: what can we learn from matching estimators and their sensitivity?. *Journal of Applied Econometrics,* 23(3), 305-327. https://doi.org/10.1002/jae.998.

Igel, C., Brandt, M., Haberkern, K. and Szydlik, M. (2009). Specialization between family and state. Intergenerational time transfers in western Europe, *Journal of Comparative Family Studies*, *40*(2): 203-226. https://doi.org/10.3138/jcfs.40.2.203.

Jackson, C. (2007). The general health questionnaire. *Occupational medicine*, *57*(1), 79-79.

Jousten, A., Lipszyc, B., Marchand, M., & Pestieau, P. (2005). Long term care insurance and optimal taxation for altruistic children. *FinanzArchiv*, *61*, 1–18.

Juster, F.T., & Suzman, R. (1995). An overview of the Health and Retirement Study. *Journal of Human Resources, 30*(suppl):S7-S56. doi: 10.2307/146277.

Kaschowitz, J., & Brandt, M. (2017). Health effects of informal caregiving across Europe: A longitudinal approach. *Social Science & Medicine*, *173*, 72-80. https://doi.org/10.1016/j.socscimed.2016.11.036.

Kenny, P., King, M. T., & Hall, J. (2014). The physical functioning and mental health of informal carers: Evidence of care-giving impacts from an Australian population-based cohort. *Health and Social Care in the Community*, *22*(6), 646-659. doi:10.1111/hsc.12136.

Kessler, R. C., Andrews, G., Colpe, L. J., Hiripi, E., Mroczek, D. K., Normand, S. L., ... & Zaslavsky, A. M. (2002). Short screening scales to monitor population prevalences and trends in non-specific psychological distress. *Psychological medicine*, *32*(6), 959-976.

Kim, H.B. & Lim, W. (2015). Long-term care insurance, informal care, and medical expenditures. *Journal of Public Economics*, *125*, 128-142. https://doi.org/10.1016/j.jpubeco.2014.12.004.

Knoef, M. & Kooreman, P. (2011). The Effects of Cooperation: A Structural Model of Siblings' Caregiving Interactions. IZA Discussion Paper No. 5733. https://ssrn.com/abstract=1855185

Kok, L., Berden, C., & Sadiraj, K. (2015). Costs and benefits of home care for the elderly versus residential care: a comparison using propensity scores. *The European Journal of Health Economics*, *16*(2), 119-131. doi: 10.1007/s10198-013-0557-1.

Kolenikov, S., & Angeles, G. (2004). The use of discrete data in PCA: theory, simulations and applications to socioeconomic indices. Working Paper (University of North Carolina, Chapel Hill). Retrieved from http://www.cpc.unc.edu/measure/publications/wp-04-85

Kooiker, S., de Jong, A., Verbeek-Oudijk, D. & de Boer, A. (2019). Toekomstverkenning mantelzorg aan ouderen in 2040. Sociaal & Cultureel Planbureau. https://www.scp.nl/publicaties/publicaties/2019/11/08/toekomstverkenning-mantelzorg-aan-ouderen-in-2040

Lacey R.E., McMunn A., & Webb, E. (2019). Informal caregiving patterns and trajectories of psychological distress in the UK Household Longitudinal Study. *Psychological Medicine*, *49*, 1652–1660. https://doi.org/10.1017/S0033291718002222.

Lechner, M. (2009a). Long-run labour market and health effects of individual sports activities. *Journal of Health Economics*, *28*(4), 839-854. doi:https://doi.org/10.1016/j.jhealeco.2009.05.003.

Lechner, M. (2009b). Sequential causal models for the evaluation of labor market programs*. Journal of Business & Economic Statistics*, *27*(1), 71-83. https://doi.org/10.1198/jbes.2009.0006.

Lechner, M. & Miquel, M. (2010). Identification of the Effects of Dynamic Treatments by Sequential Conditional Independence Assumptions. *Empirical Economics*, *39*(1), 111-137. https://doi.org/10.1007/s00181-009-0297-3.

Legg. L., Weir, C.J., Langhorne, P., Smith, L.N., Stott, D.J. (2013). Is informal caregiving independently associated with poor health? A population-based study. *J Epidemiol Community Health*, *67*, 95–97.

Leuven, E., & Sianesi, B. (2003). PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing. Boston College Department of Economics, Statistical Software Components. Downloadable from http://ideas.repec.org/c/boc/bocode/s432001.html.

Lilly, M.B., Laporte, A. & Coyte, P.C. (2007). Labor market work and home care's unpaid caregivers: A systematic review of labor force participation rates, predictors of labor market withdrawal, and hours of work. *Milbank Quarterly*, *85*, 641-690. https://doi.org/10.1111/j.1468-0009.2007.00504.x.

Little, R. J. & Rubin, D. B. (2000). Causal Effects in Clinical and Epidemiological Studies Via Potential Outcomes: Concepts and Analytical Approaches. *Annual Review of Public Health*, *21*, 121-145. doi.org/10.1146/annurev.publhealth.21.1.121.

Lo Sasso, A., Armstrong, D., Forte, G. & Gerber, S. (2020). Differences in starting pay for male and female physicians persist; explanations for the gender gap remain elusive. *Health Affairs*, 39, 256-263.

Luppa M., Luck T., Weyerer S., König H.-H., Brähler, E. & Riedel-Heller, S. G. (2010). Prediction of institutionalization in the elderly. A systematic review. *Age and Ageing, 39*(1), 31–38. https://doi.org/10.1093/ageing/afp202.

Maarse, J. A. M. H., & Jeurissen, P. P. P. (2016). The policy and politics of the 2015 long-term care reform in the Netherlands. *Health Policy*, *120*(3), 241-245. 10.1016/j.healthpol.2016.01.014.

Ministry of Health Welfare and Sports (2013). Hervorming langdurige zorg naar een waardevolle toekomst. Letter to the Parliament, April 25 2013, Den Haag.

Moher, D., Liberati, A., Tetzlaff, J., Altman, D.G., Altman D., Antes G., Atkins D., (...), Tugwell, P. (2009). Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement. *PLoS Medicin*e. *6*(7). https://doi.org/10.1371/journal.pmed.1000097.

Mosca, I., Van Der Wees, P. J., Mot, E. S., Wammes, J. J., & Jeurissen, P. P. (2017). Sustainability of long-term care: puzzling tasks ahead for policy-makers. *International Journal of Health Policy and Management*, *6*(4), 195-205.

Mot, E. (2010). The Dutch System of Long-Term Care, CPB Document, No. 204. Netherlands Bureau for Economic Policy Analysis, The Hague. Retrieved from: https://www.cpb.nl/sites/default/files/publicaties/download/dutch-system-long-term-care.pdf

Motel-Klingebiel, A., Tesch-Römer, C. and von Kondratowitz, H.-J. (2005). Welfare states do not crowd out the family : evidence for mixed responsibility from comparative analyses. *Ageing & Society*, *25*, 6, 863–882. https://doi.org/10.1017/S0144686X05003971.

Musumeci, M., Chidambaram, P. & O'Malley Watts, M. (2019). Key Questions About Medicaid Home and Community-Based Services Waiver Waiting Lists. Kaiser Family Foundation. https://www.kff.org/medicaid/issue-brief/key-questions-about-medicaid-home-and-community-based-services-waiver-waiting-lists/

Nannicini, T. (2007). Simulation-based sensitivity analysis for matching estimators. *The Stata Journal*, *7*(3), 334-350.

NatCen Social Research (2017). British Social Attitudes Survey, 2016. [data collection]. UK Data Service. SN: 8252, http://doi.org/10.5255/UKDA-SN-8252-1.

NHS (2018a).When the council might pay for your care. https://www.nhs.uk/conditions/social-care-and-support-guide/money-work-and-benefits/when-the-council-might-pay-for-your-care/

NHS (2018b). Financial assessment. https://www.nhs.uk/conditions/social-care-and-support-guide/help-from-social-services-and-charities/financial-assessment-means-test/

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica: Journal of the econometric society*, 1417-1426.

Nocera, S. & Zweifel, P. (1996). Women's role in the provision of long-term care, financial incentives, and the future financing of long-term care. *Developments in Health Economics and Public Policy*, 5, 798-102.

Non, M. (2017). Co-payments in long-term home care: do they affect the use of care? CPB Discussion Paper 363.

Non, M., Torre, A., van der Mot, E., Eggink, E., Bakx, P., & Douven, R. (2015). Keuzeruimte in de langdurige zorg. CPB & SCP. https://www.cpb.nl/sites/default/files/publicaties/download/cpb-scp-boek-18-keuzeruimte-de-langdurige-zorg.pdf

NZa (2018). Marktscan acute zorg 2017. https://puc.overheid.nl/nza/doc/PUC_3650_22/

NZa (2019). Prestatiebeschrijvingen en tarieven zorgzwaartepakketten. Separate documents for tariffs 2011/2017. https://puc.overheid.nl/nza/doc/PUC_21612_22/

NZa (2020a). Beleidsregel prestatiebeschrijvingen en tarieven zorgzwaartepakketten en volledig pakket thuis 2020 - BR/REG-20124a. https://puc.overheid.nl/nza/doc/PUC_277076_22/2/

NZa (2020). Open Dis Data. DBC Zorgproducten per jaar. https://www.opendisdata.nl/downloads

OECD (2005). Long-term care for older people. OECD Publishing, Paris. http://dx.doi.org/10.1787/9789264015852-en.

OECD (2010). Health systems accounts database, via Colombo, F., Llena-Nozal, A., Mercier, J., & Tjadens, F. (2011). Help Wanted? Providing and paying for long-term care. OECD Publishing, Paris. doi: http://dx.doi.org/10.1787/9789264097759-en.

OECD (2017a). A System of Health Accounts 2011: Revised edition, OECD Publishing, Paris, https://doi.org/10.1787/9789264270985-en.

OECD (2017b). Health Statistics. Retrieved from https://stats.oecd.org

OECD (2019a). Health at a Glance 2019: OECD Indicators, OECD Publishing, Paris, https://doi.org/10.1787/4dd50c09-en.

OECD (2019b). Focus on Out-of-Pocket Spending: Access to care and Financial protection. https://stats.oecd.org/health/health-systems

OECD. (2019c). Health statistics: Long-Term Care Resources and Utilisation & Health expenditures and financing. https://stats.oecd.org/Index.aspx?DataSetCode=SHA#

OECD (2020a). Population predictions. https://stats.oecd.org/Index.aspx?DataSetCode=POPPROJ#

OECD (2020b). Long-term care resources and utilization. https://stats.oecd.org/index.aspx?DataSetCode=HEALTH_STAT#

OECD (2020c). Health expenditure and financing. https://stats.oecd.org/Index.aspx?DataSetCode=SHA

OECD (2020d). Long term care. https://www.oecd.org/els/health-systems/long-term-care.htm

Olsen, C., Pedersen, I., Bergland, A., Enders-Slegers, M. J., Joranson, N., Calogiuri, G., & Ihlebaek, C. (2016). Differences in quality of life in home-dwelling persons and nursing home residents with dementia - a cross-sectional study. *BMC Geriatrics*, *16*, 137. doi: 10.1186/s12877-016-0312-4.

ONS (2013). 2011 Census Analysis: Unpaid care in England and Wales, 2011 and comparison with 2001. https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/healthcaresystem/articles/2011censusanalysisunpaidcareinenglandandwales2011andcomparisonwith2001/2013-02-15

ONS (2015). UK Health Accounts reference tables. - Long-term care expenditure by function and financing scheme in 2015. https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/healthcaresystem/bulletins/ukhealthaccounts/2015

Osterman, P. (2017). *Who will care for Us? Long-term care and the long-term workforce*. New York: Russell Sage Foundation.

Pearlin, L. I., Mullan, J. T., Semple, S. J., & Skaff, M. M. (1990). Caregiving and the stress process: An overview of concepts and their measures. *The Gerontologist*, *30*(5), 583-594. https://doi.org/10.1093/geront/30.5.583.

Penning, M. J. & Wu, Z. (2016). Caregiver Stress and Mental Health: Impact of Caregiving Relationship and Gender. *The Gerontologist*, *56*(6), 1102–1113. doi.org/10.1093/geront/gnv038.

Pestieau, P. & Sato, M. (2006). Long term care: The state and the family. *Annales d' Économie et de Statistique*, *83/84*, 151-166.

Pestieau, P. & Sato, M. (2008). Long term care: The state, the market and the family. *Economica*, *75*, 435–454. doi:10.1111/j.1468-0335.2007.00615.x.

Pinquart, M., & Sörensen, S. (2001). Loneliness in older adults: A Meta-Analysis. *Basic and applied social psychology*, *23*(4), 245–266.

Pinquart, M., & Sörensen, S. (2003a). Differences between caregivers and noncaregivers in psychological health and physical health: a meta-analysis. *Psychology and aging*, *18*(2), 250-267. https://doi.org/10.1037/0882-7974.18.2.250.

Pinquart, M., & Sörensen, S. (2003b). Associations of Stressors and Uplifts of Caregiving With Caregiver Burden and Depressive Mood: A Meta-Analysis, *The Journals of Gerontology: Series B*, *58*(2), 112–128. https://doi.org/10.1093/geronb/58.2.P112.

Pinquart, M. & Sörensen, S. (2007). Correlates of physical health of informal caregivers: a meta-analysis. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences, 62*(2), 126–137.

Pinquart, M., Sorensen, S. (2011). Spouses, Adult Children, and Children-in-Law as Caregivers of Older Adults: A Meta-Analytic Comparison. *Phychology and aging*, *26*, 1–14. https://doi.org/doi:10.1037/a0021863.

Plaisier, I., de Boer, A. de & de Klerk, M. (2015). Gevolgen van mantelzorgen. In: Mirjam de Klerk, Alice de Boer, Inger Plaisier, Peggy Schyns en Sjoerd Kooiker (red.), Informele hulp: wie doet er wat? Omvang, aard en kenmerken van mantelzorg en vrijwilligerswerk in de zorg en ondersteuning in 2014 (p. 65-88). Den Haag: Sociaal en Cultureel Planbureau.

Port, C. L., Gruber-Baldini, A. L., Burton, L., Baumgarten, M., Hebel, J. R., Zimmerman, S. I., & Magaziner, J. (2001). Resident Contact With Family and Friends Following Nursing Home Admission. *The Gerontologist*, *41*(5), 589–596.

Prieto-Flores, M. E., Forjaz, M. J., Fernandez-Mayoralas, G., Rojo-Perez, F., & Martinez-Martin, P. (2011). Factors associated with loneliness of noninstitutionalized and institutionalized older adults. *Journal of Aging and Health*, *23*(1), 177-194. doi: 10.1177/0898264310382658.

Purser, J.L. Fillenbaum, G.G. Pieper, C.F., & Wallace, R.B. (2005). Mild cognitive impairment and 10-year trajectories of disability in the Iowa established populations for epidemiologic studies of the elderly cohort. *Journal of the American Geriatrics Society*, *53*(11), 1966–1972.

Rapp, T., Apouey, B.H., & Senik, C. (2018) The impact of institution use on the wellbeing of Alzheimer's disease patients and their caregivers. *Social Sciences & Medicine*, *207*, 1-10. doi: 10.1016/j.socscimed.2018.04.014.

Rellstab, S., Bakx, P., García-Gómez, P., & van Doorslaer, E. (2020). The kids are alright - labour market effects of unexpected parental hospitalisations in the Netherlands. *Journal of Health Economics*, *69*. https://doi.org/10.1016/j.jhealeco.2019.102275.

Rijksoverheid (2020). Zorguitgaven en -ontvangsten Wlz. https://www.staatvenz.nl/content/zorguitgaven-en-ontvangsten-wlz

Robins, J. M., Hernan, M. A., & Brumback, B. (2000). Marginal Structural Models and Causal Inference in Epidemiology. *Epidemiology*, *11*, 550–560. https://doi.org/10.1097/00001648-200009000-00011.

Roodman, D. (2006). How to Do xtabond2: An Introduction to "Difference" and "System" GMM in Stata. *The Stata Journal, 9*, 86–136. https://www.stata-journal.com/article.html?article=st0159

Rosenbaum, P., & Rubin, D. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*, 41–55. doi:10.2307/2335942.

Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician*, *39*(1), 33-38. https://doi.org/10.2307/2683903.

Rosso, A. L., Lee, B. K., Stefanick, M. L., Kroenke, C. H., Coker, L. H., Woods, N. F., & Michael, Y. L. (2015). Caregiving frequency and physical function: The women's health initiative. *The Journals of Gerontology - Series A: Biological Sciences and Medical Sciences, 70*(2), 210-215. doi:10.1093/gerona/glu104.

Roth, D.L., Fredman, L. & Haley, W.E. (2015). Informal Caregiving and Its Impact on Health: A Reappraisal From Population-Based Studies. *The Gerontologist*, *55*(2), 309–319. doi.org/10.1093/geront/gnu177.

Roy, J., & Schurer, S. (2013). Getting stuck in the blues: Persistence of mental health problems in Australia. *Health Economics, 22*(9), 1139–1157. https://doi.org/10.1002/hec.2967.

Rubin, D. B. (1973). The use of matched sampling and regression adjustment to remove bias in observational studies. *Biometrics, 29*, 185-203. https://doi.org/10.2307/2529685.

Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of educational Psychology*, *66*(5), 688-701. https://doi.org/10.1037/h0037350.

Rubin, D. B. (1979). Using multivariate matched sampling and regression adjustment to control bias in observational studies. *Journal of the American Statistical Association*, *74*(366a), 318-328. 10.2307/2286330.

Schmitz, H., & Stroka, M. A. (2013). Health and the double burden of full-time work and informal care provision—Evidence from administrative data. *Labour Economics*, 24, 305-322. https://doi.org/10.1016/j.labeco.2013.09.006.

Schmitz, H. & Westphal, M. (2015). Short- and medium-term effects of informal care provision on female caregivers' health. *Journal of Health Economics*, *42*, 174-185. doi:10.1016/j.jhealeco.2015.03.002.

Schmitz, H., & Westphal, M. (2017). Informal care and long-term labor market outcomes. *Journal of Health Economics*, *56*, 1-18. https://doi.org/10.1016/j.jhealeco.2017.09.002.

Schulz, R. (1990). *Theoretical perspectives on caregiving: concepts, variables, and methods*. In B. A. Biegel DE (Ed.), Aging and Caregiving: Theory, Research and Policy (pp. 27–52). Sage Publications, New York.

Schulz, R., Newsom, J., Mittelmark, M., Burton, L., Hirsch, C., & Jackson, S. (1997). Health effects of caregiving: The caregiver health effects study: An ancillary study of the Cardiovascular Health Study. *Annals of Behavioral Medicine, 19*, 110–116. doi:10.1007/BF02883327.

Schulz, R., Visintainer, P., & Williamson, G. M. (1990). Psychiatric and Physical Morbidity Effects of Caregiving. *Journal of Gerontology*, *45*(5), 181-191.

SCP (2020). Positie mantelzorgers verdient meer aandacht bij mogelijke tweede coronagolf. https://www.scp.nl/actueel/nieuws/2020/07/13/positie-mantelzorgers-verdient-meer-aandacht-bij-mogelijke-tweede-coronagolf

Smid, B., ter Rele, H., Boeters, S., Draper, N., Nibbelink, A. & Wouterse, B. (2014). *Minder zorg om vergrijzing*. CPB Boek 12. CPB: The Hague.

Staiger, D. & Stock, J.H. (1997). Instrumental variables regression with weak instruments. *Econometrica*, *65*(3), 557-586. doi:10.2307/2171753.

Statistics Netherlands (2015). Gezondheidsmonitor 2012, Opbouw en instructie totaalbestand. https://www.cbs.nl/nl-nl/onze-diensten/maatwerk-en-microdata/microdata-zelf-onderzoek-doen/microdatabestanden/gezondheidsmonitor-2012-opbouw-en-instructie-totaalbestand

Statistics Netherlands (2016). Mantelzorg. Retrieved from: https://www.cbs.nl/nl-nl/artikelen/nieuws/2016/45/een-op-zeven-mantelzorgers-vindt-zichzelf-zwaarbelast/mantelzorg

Statistics Netherlands (2017). Documentatie Gezondheidsmonitor Volwassen en Ouderen 2016. https://www.volksgezondheidenzorg.info/sites/default/files/gemon.pdf

Statistics Netherlands (2019a). Onderzoeksbeschrijving Gezondheidsmonitor. https://www.cbs.nl/nl-nl/onze-diensten/methoden/onderzoeksomschrijvingen/aanvullende%20onderzoeksbeschrijvingen/gezondheidsmonitor-onderzoek-naar-de-gezondheid-en-de-gezondheidsbeleving-van-burgers-op-landelijk-en-lokaal-niveau

Statistics Netherlands (2019b). AWBZ/Wlz-zorg in natura; productie (uitgaven en volume). https://statline.cbs.nl/StatWeb/publication/?DM=SLNL&PA=82789ned

Stöckel, J. & Bom, J. (2020) The Dynamic Effects of Informal Caregiving on the Caregivers' Health. Netspar Discussion Paper 02/2020-011. https://www.netspar.nl/publicatie/the-dynamic-effects-of-informal-caregiving-on-caregivers-health/

Stroka, M. A. (2014). The Mental and Physical Burden of Caregiving Evidence from Administrative Data. Ruhr Economic Papers. Retrieved from https://www.econstor.eu/bitstream/10419/93178/1/780314565.pdf

Tenand, M., Bakx, P., & van Doorslaer, E. (2020). Eligibility or use? Disentangling the sources of horizontal inequity in home care receipt in the Netherlands. *Health economics*, *29*(10), 1161-1179.

Thuis in het Verpleeghuis (2020). Dagbesteding in het verpleeghuis: 10 voorbeelden van georganiseerde activiteiten. https://www.waardigheidentrots.nl/praktijk/dagbesteding-in-verpleeghuis-georganiseerde-activiteiten/

Townsend, A., Noelker, L., Deimling, G., & Bass, D. (1989). Longitudinal impact of interhouse caregiving on adult children's mental health. *Psychology and Aging*, *4*, 393-401. https://doi.org/10.1037/0882-7974.4.4.393.

Trivedi, R., Kristine B., Bouldin, E. D., Eugenio, E., Zeliadt, S. B., Nelson, K., Rosland, A., Szarka, J. G., & Piette, J. D. (2014). Characteristics and well-being of informal caregivers: Results from a nationally representative US survey. *Chronic Illness*, *10*(3), 167-179. doi:10.1177/1742395313506947.

Uccheddu, D., Gauthier, A. H., Steverink, N., & Emery, T. (2019). The pains and reliefs of the transitions into and out of spousal caregiving. A cross-national comparison of the health consequences of caregiving by gender. *Social Science & Medicine*, *240*, 112517.

UK Government (2020). Carer's allowance. https://www.gov.uk/carers-allowance

United Nations (2019). World population prospects. https://population.un.org/wpp/DataQuery/

University of Essex. Institute for Social and Economic Research (2019). Understanding Society: Waves 1-9, 2009-2018 and Harmonised BHPS: Waves 1-18, 1991-2009. [data collection]. 12th Edition. UK Data Service. SN: 6614, http://doi.org/10.5255/UKDA-SN-6614-13.

US Department for Health and Human Services (2020a). Medicare. Retrieved 23-03-2020 from https://longtermcare.acl.gov/medicare-medicaid-more/medicare.html

US Department for Health and Human Services (2020b). State Medicaid programs. Retrieved 23-03-2020 from https://longtermcare.acl.gov/medicare-medicaid-more/medicaid/medicaid-long-term-care-services.html

Van Campen, C., Vonk, F., & van Tilburg, T. (2018). Kwetsbaar en eenzaam? Risico's en bescherming in de ouder wordende bevolking. Sociaal & Cultureel Planbureau. https://www.scp.nl/Publicaties/Alle_publicaties/Publicaties_2018/Kwetsbaar_en_eenzaam

Van den Berg, B., Fiebig, D. G., & Hall, J. (2014). Well-being losses due to care-giving. *Journal of Health Economics*, *35*(1), 123–131. https://doi.org/10.1016/j.jhealeco.2014.01.008.

Van den Broek, T., & Grundy, E. (2018). Does long-term care coverage shape the impact of informal care-giving on quality of life? A difference-in-difference approach. *Ageing and Society*, *40*(6), 1291-1308. 10.1017/S0144686X18001708.

Van der Ende, M., van Seben, R., van Exel, J. Bom, J, Sapulete, S., and Geijsen, T. (2020), Prevalence and cost of informal care. ECORYS and Erasmus University Rotterdam (forthcoming).

Van Ginneken E. & Kroneman M. (2015). Long-term care reform in the Netherlands: too large to handle?. *Eurohealth system and policies*, *21*(3), 47–50. dx.doi.org/10.1016/j.healthpol.2016.01.014.

Van Houtven, C. H., & Norton, E. C. (2004). Informal care and health care use of older adults. *Journal of Health Economics*, *23*(6), 1159-1180. https://doi.org/10.1016/j.jhealeco.2004.04.008.

Van Houtven, C. H., & Norton, E. C. (2008). Informal care and Medicare expenditures: testing for heterogeneous treatment effects. *Journal of Health Economics*, *27*(1), 134-156. https://doi.org/10.1016/j.jhealeco.2007.03.002.

Van Tilburg, T.G., & De Jong Gierveld, J. (1999). Cesuurbepaling van de eenzaamheidsschaal. *Tijdschrift voor Gerontologie en Geriatrie*, *30*, 158- 163. http://hdl.handle.net/1871/39713.

Verbakel, E. (2014). Informal caregiving and well-being in Europe: What can ease the negative consequences for caregivers? *Journal of European Social Policy*, *24*(5), 424-441. https://doi.org/10.1177/0958928714543902.

Verbeek-Oudijk, D., & van Campen, C. (2017). Ouderen in verpleeg- en verzorgingshuizen. Sociaal & Cultureel Planbureau. www.scp.nl/Publicaties/Alle_publicaties/Publicaties_2017/Ouderen_in_verpleeghuizen_en_verzorgingshuizen

Vermeulen, W. (2015). Decentralization of social policy in the Netherlands. CPB Background Document. https://www.cpb.nl/sites/default/files/publicaties/download/cpb-background-document-decentralization-social-policy-netherlands.pdf

Vitaliano, P. P., Scanlan, J. M., & Zhang, J. (2003). Is caregiving hazardous to one's physical health? A meta-analysis. *Psychological Bulletin*, *129*(6), 946-972. doi:10.1037/0033-2909.129.6.946.

Vlachantoni, A., Robards, J., Falkingham, J., Evandrou, M. (2016). Trajectories of informal care and health. *SSM—Population Health*, *2*, 495–501.

VNG (Association of Netherlands Municipalities) (2016). Uitkomsten inventarisatie mantelzorgbeleid gemeenten. https://vng.nl/files/vng/pagina_attachments/2016/uitkomsten_inventarisatie_mantelzorgbeleid_gemeenten_-_maart_2016.pdf

Vyas, S. & Kumaranayake, L. (2006). Constructing socio-economic status indices: how to use principal components analysis. *Health Policy and Planning*, *21*(6), 459-68. 10.1093/heapol/czl029.

Wagner, M., & Brandt, M. (2018). Long-term care provision and the well-being of spousal caregivers: An analysis of 138 european regions. *Journals of Gerontology - Series B Psychological Sciences and Social Sciences*, *73*(4), e24-e34.

Ware, J. E., Kosinski, M., & Keller, S. D. (1995). SF-12: How to score the SF-12 physical and mental health summary scales (2nd. ed). Boston, Massachusetts, The Health Institute, New England Medical Center.

Ware, J. E., Snow, K. K., Kosinski, M. A., & Gandek, B. (1993). SF-36 Health Survey Manual and Interpretation Guide. Boston, Massachusetts, The Health Institute, New England Medical Center.

Werner, R. M., Coe, N. B., Qi, M., & Konetzka, R. T. (2019). Patient outcomes after hospital discharge to home with home health care vs to a skilled nursing facility. *JAMA internal medicine*, *179*(5), 617-623.

Wet Maatschappelijke Ondersteuning 2015 (Social Support Act) (2015). https://wetten.overheid.nl/BWBR0035362/2020-07-01

Who cares? The pandemic shows the urgency of reforming care for the elderly. (2020, July 25). The Economist,. https://www.economist.com/international/2020/07/25/the-pandemic-shows-the-urgency-of-reforming-care-for-the-elderly

World Bank (2019). Education statistics. https://datacatalog.worldbank.org/dataset/education-statistics

Wouterse, B., H. ter Rele & van Vuuren, D. (2016). Financiering van de zorg op lange termijn, CPB Policy Brief 2016/10.

Wouterse, B & Smid, B. (2017). How to finance rising costs of Long Term Care? Four alternatives for the Netherlands. *Fiscal Studies,* 38(3): 369-391.

Wouterse, B., Hussem, A., Wong, A. (2019). The welfare effects of copayments in long-term care. CPB discussion paper. https://www.cpb.nl/sites/default/files/omnidownload/cpb-discussion-paper-394-The-welfare-effects-of-co-payments-in-long-term-care_0.pdf

Ybema, J. F., Geuskens, G. A., Van Den Heuvel S. G., De Wind A., Leijten, F. R. M., Joling, C., et al. (2014). Study on transitions in employment, ability and motivation (STREAM): The design of a four-year longitudinal cohort study among 15,118 persons aged 45 to 64 years. *British Journal of Medicine & Medical Research, 4*(46), 1383-1399.

Yeandle, S. (2016). Caring for our carers: An international perspective on policy developments in the UK. *Juncture*, *23*(1), 57-62. https://doi.org/10.1111/j.2050-5876.2016.00896.x

Young, C., Hall, A.M., Gonçalves-Bradley, D.C., Quinn, T.J., Hooft, L., van Munster, B.C., Stott, D.J. (2017). Home or foster home care versus institutional long-term care for functionally dependent older people. *Cochrane Database of Systematic Reviews*, 4 (CD009844). doi: 10.1002/14651858.CD009844.pub2.

Yun, M.S. (2004). Decomposing differences in the first moment. *Economics Letters*, *82*, 275–280. https://doi.org/10.1016/j.econlet.2003.09.008.

Yun, M.S. (2008). Identification problem and detailed Oaxaca decomposition: a general solution and inference. *Journal of Economic and Social Measurement*, *33*, 27–38. 10.3233/JEM-2008-0296.

Zorginstituut (2019). ZorgCijfers Monitor. Op de drempel van het verpleeghuis. https://www.zorginstituutnederland.nl/publicaties/rapport/2018/12/21/gebruik-en-kosten-van-ouderenzorg-2013-–-2016

Zorginstituut Nederland (2020). Begeleiding (Wlz). https://www.zorginstituutnederland.nl/Verzekerde+zorg/persoonlijke-verzorging-begeleiding-en-verpleging-wlz/begeleiding-wlz

Zuvekas, S.H. & Taliaferro, G.S. (2003). Pathways to access: Health insurance, the health care delivery system and racial/ethnic disparities 1996-1999. *Health Affairs*, *22*, 139-153.

Zvw (Health Insurance Act) (2013). 2.5c https://wetten.overheid.nl/BWBR0018492/2016-01-01#Hoofdstuk2_1_Artikel25c

Zweifel, P. & Strüwe, W. (1996). Long-term care insurance and bequests as instruments for shaping intergenerational relationships. *Journal of Risk and Uncertainty*, *12*(1), 65–76.