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Dynamics of later-life caregiving and health. Insights from biomarker data and cognitive tests

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ABSTRACT

As populations age and informal caregiving becomes more widespread, the health consequences of providing care are becoming a key concern for societies. Sociological theories of stress appraisal and role strain posit detrimental consequences to the health and wellbeing of caregivers. Conversely, role enhancement theory holds that caregiving can have positive health consequences. Using data from the English Longitudinal Study of Aging (ELSA) collected among adults aged 50 years or older with a follow-up period of up to 20 years (2002–23, 88,225 observations of 20,217 respondents), we examine associations between transitions into and out of caregiving, and two key health outcomes which have been understudied as consequences of caregiving, namely: allostatic load and cognitive functioning. We estimate asymmetric fixed-effects models which model changes in health outcomes as a function of transitions into and out of caregiving while accounting for unobserved between-person heterogeneity. Our results show that caregiving is associated with better cognitive health for both men and women, but not with improved biomarker-based allostatic load. Results do not differ by caregiving intensity. Our findings provide support for role enhancement theory, suggesting that caregivers benefit in terms of cognitive functioning, even if a biomarker-based approach to measuring stress-related health outcome does not corroborate an overall health benefit. We formulate implications for policy-making and directions for future research.

1. Introduction

Unpaid caregiving, that is, providing support or assistance to others with health-related support needs outside of a formal work contract (also often called informal or family care), is a key linchpin of coping with the rising need for care in aging populations around the world. According to OECD (2021) estimates, around 13% of the European population aged 60 years or older are informal caregivers. According to a report for the British parliament, the estimated number of caregivers in the United Kingdom is 5.2 million, or about 8% of the adult population (Harker et al., 2024). Drawing on a different data source and definition of caregiving, Foster and Foley (2024) estimate the figure to be higher, namely almost 11 million. With population aging, the need for informal care will increase in the foreseeable future, while the ratio of potential caregivers to care recipients will decline (Ribeiro et al., 2021). In recent years, scholars have put more emphasis on the possible consequences of caring, both economically and socially (Broese van Groenou and de Boer, 2016; Hu et al., 2024).

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The health consequences of care are particularly relevant for study, both from a public health and a public policy perspective. If unpaid care is indeed negatively related to health, caregivers may end up needing help themselves, potentially amplifying a worldwide care shortage in a vicious cycle. For more than two decades, most studies agreed on a negative effect of caregiving on mental health and subjective well-being (e.g. Swinkels et al., 2019; Le and Ibuka, 2023; Portier, 2023; Zhang and Bennett, 2024). In terms of physical health, the findings are mixed (Roth et al., 2015; Vlachantoni et al., 2013; Lacey et al., 2024). The general assumption that caregiving is negative for one's health prevails. This is reflected in applied theoretical concepts, such as stress process models or the narrative of 'caregiver burden' (Swinkels et al., 2019). However, studies on mortality (Miyawaki et al., 2019), self-rated health (Vlachantoni et al., 2016), and physical health decline after becoming a caregiver (Georges, 2022) find little evidence for a physical health burden.

Our study takes a fresh look at the consequences of caregiving on later-life health. Based on resource-based and psychological mechanisms, we derive two hypotheses and examine consequences of starting, stopping, intensifying, or reducing care provision to older adults in the second half of life on allostatic load and cognitive functioning—both suited to capture longer-term physical health outcomes. Thus, we answer the following research question: *How are transitions into and out of caregiving in later life associated with changes in allostatic load and cognitive functioning?*

In doing so, we make a number of contributions to the state of knowledge. First, our study responds to calls for a broader understanding of health consequences of care beyond mental health (Roth et al., 2015; Vlachantoni et al., 2013). We focus on two complementary aspects of how health can be gauged: physical health in the form of allostatic load on the one hand, and cognitive functioning on the other. Allostatic load represents the 'wear and tear;' the embodiment of experienced distress throughout one's life at a molecular and cellular level (McLoughlin et al., 2023; Präg and Richards, 2019; Präg et al., 2022). Cognitive functioning is a modifiable resource for living independently and participating in society in later life, while fast cognitive decline poses a major risk factor for dementia (Livingston et al., 2024). Dementia risk is highly modifiable (with estimates ranging up to 40% of dementia cases being avoidable, Livingston et al., 2024). Cognitive functioning is modifiable in the sense that earlier investment into cognitive reserve (via education, labor market participation), lifelong avoidance of risk factors (stress, toxins, cardiovascular disease) and lifelong cognitive stimulation can slow cognitive decline, even after onset of mild cognitive impairments (e.g., Gómez-Soria et al., 2023). Moreover, cognitive health is linked to both allostatic load, as distress has been an explanation for poorer cognitive performance (de Looze et al., 2024) and self-reported memory problems in caregivers (Caswell et al., 2003). Finally, cognitive impairment has emerged as a later-life consequence poor physical (e.g. cardiovascular) and mental health (e.g., depression, Livingston et al., 2024), and unhealthy lifestyles (Jia et al., 2023), and is predicted by allostatic load (D'Amico et al., 2020). Our study thus yields new insights into the *pathways of intersecting health domains* in the context of caregiving.

Second, our study makes a theoretical contribution by integrating several mechanisms that have been proposed in the last decades to understanding health consequences of caregiving. Drawing on resource-based theories and psychological mechanisms, we discuss both potential *positive and negative* effects of caregiving on health. We discuss these mechanisms in the context of the *dynamics* of (starting, intensifying, decreasing, or stopping) caregiving and discuss their interplay for two longer-term measures of health consequences which operate at different levels (Swinkels et al., 2019). From the integration of these mechanisms, we derive and test two hypotheses.

Third, we acknowledge the dynamic nature of informal caregiving, which increasingly takes place in later life (Patterson and Margolis, 2019; Bó, 2022). For many, care provision constitutes a commitment of limited duration, although several caregiving episodes may occur in a lifetime (Verbakel et al., 2024). To capture the two-sided effects of these dynamics—that is: becoming a caregiver and stopping to be a caregiver—we distinguish between *transitions into and out* of caregiving using an asymmetric fixed-effects modeling approach (Allison, 2019). We further extend the approach to distinguishing changes between *intensive and non-intensiv*e caregiving, as this has been shown to be a major factor for the association with health (Lacey et al., 2024). In doing so, our study adds to methodological discussions around endogeneity in the association between care provision and health by acknowledging the dynamics of caregiving in later life (Bom et al., 2019a; Uccheddu et al., 2019).

To test our hypotheses, we analyze the English Longitudinal Study of Aging (ELSA, 2002–19, Steptoe et al., 2013), a biennial household survey representative of the English population aged 50+ living independently. We use the asymmetric fixed effects estimator (Allison, 2019) that allows controlling for all time-constant person-related confounders, irrespective of whether these are observed or unobserved (Coustaury et al., 2023; Wooldridge, 2010). This is important as those with already existing health issues might be more likely to take up caregiving. As most unpaid caregiving happens within the family, some caregivers might have the same predisposition to health issues as the care receivers (Le and Ibuka, 2023). Using both biomarker data from blood samples and nurse interviews (for allostatic load) and results from two memory tests (for cognitive functioning), we use objective measures of health rather than self-assessments. This is important as caregivers might provide subjectively different assessment of their health when confronted with illness on a frequent basis (e.g. McLoughlin et al., 2023).

2. Theoretical considerations

As the literature suggests, the association between caregiving and health may be complex and dynamic. On the one hand, one could assume both positive and negative health consequences of caregiving. On the other hand, transitioning into and out of caregiving may be associated differently with health. To disentangle the ambiguous and dynamic nature of caregiving, we integrate two theoretical perspectives: a psychological approach and a resource-based explanation.

First, a long tradition of psychological approaches have posited *negative effects* of caregiving on wellbeing. The stress process model (Pearlin et al., 1981) has long been applied to caregiving. In this model, caregiving serves as an exogenous shock, affecting wellbeing and mental health, via primary stressors (such as the health issues of a loved one) and secondary stressors (such as adjustment to new or complex tasks of caregiving, Swinkels et al., 2019).

Second, resource-based approaches postulate increased stress arising from caregiving, as caregiving consumes important resources, such as time, or money (Zhang and Bennett, 2024). The time-availability hypothesis suggests that caregiving reduces time for recreation and leisure activities which are both important for health (e.g. Bó, 2022; Urwin et al., 2023). This association should be particularly pronounced if caregiving demands are intensive—that is, when many caregiving hours are needed, or when the care recipient resides within one's household. Furthermore, financial and economic resources are threatened by caregiving in multiple ways. Caregiving may lead to financial disadvantage both directly (e.g. considering the direct costs of caregiving, such as expenses for travel, purchasing medical appliances, and insurances, see Krueger et al., 2023) and indirectly via forgone income when caregivers are less available to the labor market (Weisshaar, 2018), which in the long-term may also affect their pension incomes negatively.

However, both psychological and resource-based models may also argue in favor of a *health-protective effect*. First, role enhancement theory (Mize and Kincaid, 2025; Moen et al., 1992; Rozario et al., 2004) posits that developing a caregiver identity can reduce negative feelings stemming from potentially stressful situations arising in caregiving. From a resource-based perspective, it has been argued that providing care provides opportunities for developing skills and knowledge. Informal caregiving encompasses various roles and tasks (see Brandt et al., 2009), including managerial and communicative aspects. In the context of parenthood, it has been shown that parenting fosters the learning of new skills, thereby promoting cognitive reserve (e.g. Ice et al., 2020), which could similarly apply to other types of unpaid care. Moreover, being a caregiver may stimulate personal growth (e.g. by providing emotional support), and cognitive abilities (e.g. overseeing diagnoses and medication).

A second argument is that providing informal caregiving enlarges individuals' networks (Roth, 2020). Caregiving increases the likelihood of volunteering (Choi et al., 2007), suggesting that caregivers benefit from their involvement, leading to a lower risk of depression and higher levels of caregiver wellbeing (Sibalija et al., 2020). Participation and networks have been documented to promote cognitive functioning (e.g. Litwin and Stoeckel, 2016). Whether these benefits hold for allostatic load or in the context of caregiving, is less well understood and is therefore subject to investigation in this study.

Considering the *dynamics of caregiving,* the positive and negative consequences outlined above may work differently across the transition into and out of caregiving. Stressors and lack of resources may be a *transitory phenomenon* and their impact on health may reverse once the caregiving episode has ended, while skills and networks may be*longer-lasting benefits*. This may lead to the assumption that the transition into caregiving may be negatively associated with health, but the effect should reverse once the caregiving episode ends. However, it is important to recognize that the loss of the caregiver role is often associated with bereavement (Patterson and Margolis, 2019). In particular, widowhood has been associated with increased depression (Luhmann et al., 2012) and lower cognitive functioning. This may reduce the posited longer-lasting benefits.

Taken together, these four mechanisms – stress, loss of resources, gain of skills and networks, and bereavement – suggest a rather negative effect of the changes towards more caregiving on health. Due to the transitory experience of stressors and loss of resources, and the lasting benefits in skills and networks on the one hand, and the shock of bereavement on the other hand, a decrease in health *may rather be temporary*. Yet, given the weight of possible bereaval, we cannot assume a full reversal of the potentially negative effects of caregiving on health after the caregiving episode ends.

Accordingly, we formulate two hypotheses: First, we expect that changes *towards more caregiving* are related to a *decline in health* (Hypothesis H1). Second, we assume that changes *towards less caregiving* are related to*an improvement in health, but with a smaller magnitude* (Hypothesis H2).

Analytically, we test these hypotheses in two ways: In the first step, we conceptualize 'change towards more caregiving' and 'changes towards less caregiving' as the cessation of care, regardless of the intensity of caregiving. In the second step, we provide a more nuanced picture. Focusing on those who transitioned into caregiving, we conceptualize 'changes towards more caregiving' with the transition from non-intensive (less than eight hours per week) to intensive caregiving (more than eight hours per week). 'Changes towards less caregiving' are measured by both stopping care or reducing care from intensive to non-intensive care.

3. Data and methods

3.1. Data: English Longitudinal Study of Aging

We use the English Longitudinal Study of Aging (ELSA, Banks et al., 2024; Steptoe et al., 2013), a nationally representative household survey of men and women living in England aged over 50 years, collecting biennial longitudinal data since 2002, totaling ten waves so far. Data are collected through computer-assisted personal interviews and self-administered questionnaires (for details, see Steptoe et al., 2013). Across the ten waves we analyze, 21,684 participants have taken part in the ELSA data collection, yet the number of participants varies across our analyses, as not every variable was measured in every wave. We explain the sample selection across analyses at the end of this section.

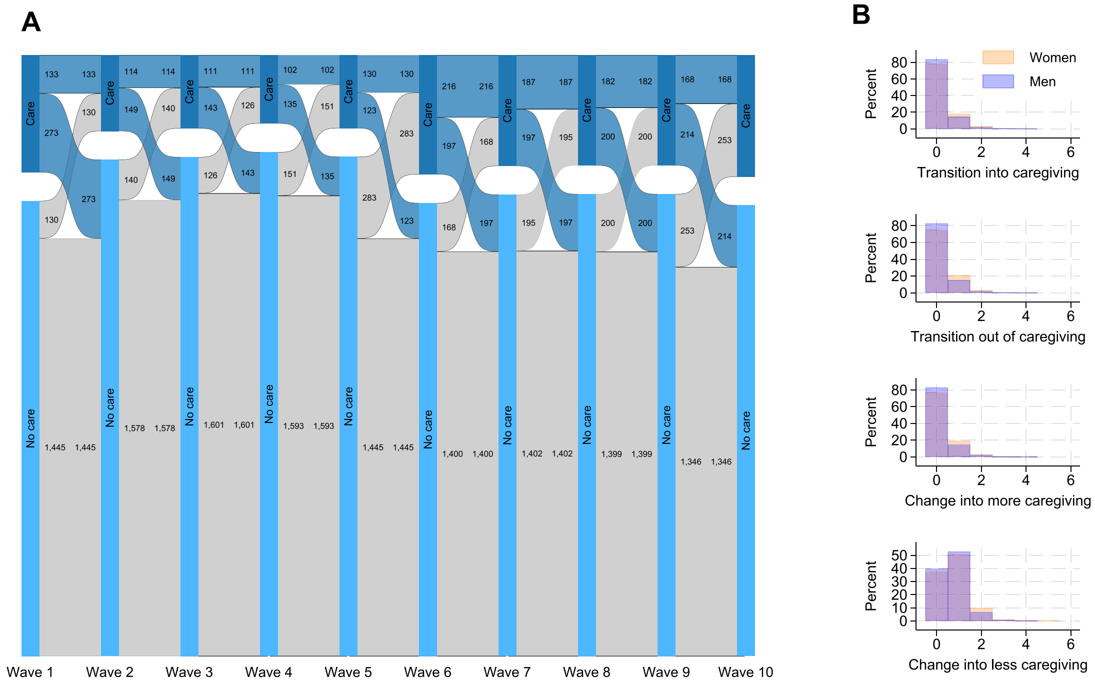

Fig. 1. *Panel A*: Transitions into and out of caregiving. Sankey diagram illustrating the prevalence of transitions into and out of caregiving among $N_{\text{participants}}$ = 1981 who took part in all ten waves. *Panel B*: Number of transitions into and out of caregiving (aggregated at a person-level and averaged across the sample). $N_{\text{observations from men}}$ = 38,709 and $N_{\text{observations from women}}$ = 49,516 and transitions into and out of intense caregiving $N_{\text{observations from men}}$ = 6339 and $N_{\text{observations from women}}$ = 10,732.

3.2. Exposure: Caregiving

We look at two treatment variables. First, we look at transitions into and out of caregiving. Our caregiving variable is based on the Yes/No question 'Did you look after anyone in the past week? This could be your partner or other people in your household or someone in another household?' An interviewer instruction further clarifies 'By "look after" we mean the active provision of care.' If respondents answer with 'Yes,' the follow-up question 'How many hours in the past week did you do this?' is asked.

While the first question does not distinguish between different relationships between caregivers and care recipients (e.g. child care or spousal care) and co-residence with the care recipient, its wording yields a comprehensive assessment of caregiving that is useful for establishing the overall association between caregiving and health outcomes.

The care recipients are relatively diverse. For instance, in wave 1 of data collection, 29% of carers provide care to their spouse or partner, 23% to a parent, 22% to a grandchild, 11% to their child, 10% to a friend or neighbor, 7% to another relative, 6% to a parent-in-law, and 3% to someone else (percentages do not add up to 100 due to multiple responses). Given this diversity, case numbers do not allow to analyze different groups of care recipients.

Second, based on the follow-up question about the number of care hours we distinguish between non-intense and intense caregiving. For our main analysis, we use eight hours as the cut-off for intense caregiving. Even though a cutoff around 8–10 h per week is used in the literature (Boumans and Dorant, 2014; Raiber et al., 2022b), we acknowledge that it is a somewhat arbitrary choice; therefore we investigate other possible cut-offs as a robustness checks.

Panel A of Fig. 1 illustrates the transition into and out of caregiving for the subsample of participants who took part in all ten waves. Caregiving is a highly transitory state: In every wave, the large majority of participants (around 68–81 per cent) did not provide care, and only a smaller share (between 6–14 per cent) started providing care in the following wave. When looking at the participants who do provide care, in every wave it is almost half who stopped providing care in the following wave, whereas between 5 and 10 per cent stayed caregivers between two waves.

3.3. Outcomes

Lasting consequences of caregiving should be particularly well detectable in allostatic load and cognitive functioning as they that represent longer-term and irreversible consequences of exposure to stress (McEwen and Stellar, 1993; Marin et al., 2011).

Allostatic load. Allostatic load was measured using the method established by Richards et al. (2023). We use nine biomarkers from four organ systems: cardiovascular (systolic and diastolic blood pressure), inflammation (C-reactive protein and fibrinogen), metabolic (glycosylated hemoglobin, high-density lipoprotein to total cholesterol ratio, triglycerides, and fasting blood glucose), and body fat deposition (body mass index). Each biomarker was dichotomized, taking a value of 1 if it exceeded a clinical threshold—either based on literature-defined cut-off points or falling into the high-risk quartile (see Table A.1). We derive a score for each of the four organ systems in which each indicator is given equal weight. We further consider diagnoses and medication use. The scale was normalized to have a mean of 0 and a standard deviation of 1. Higher allostatic load indicates a *worse* health status, representing higher multi-system physiological dysregulation. Further details about the allostatic load construction can be found in the Appendix. Biomarkers for allostatic load were only collected in waves 2, 4, 6, 8, and 9. Our analyses will thus be based on different samples and sample sizes depending on the outcome variable used.

Cognitive function. *Working memory* is a key domain of cognitive functioning and has been assessed as early as in the 1980s as a part of standardized instruments to detect dementia (Morris et al., 1988). Memory is typically measured with participants' immediate and delayed recall capacity of an auditive word-learning list. Often used is a ten-word learning list, which has been shown to be a good predictor for mild cognitive impairment and later trajectories of cognitive health (Jia et al., 2023), and works in a language and culture-insensitive way as well as across different age groups (Ren et al., 2024). Specifically, participants were read a list of ten words and were asked to recall as many words as possible from the list, first immediately and then after a standardized delay during which the participants answered other survey questions. In line with standard practice (Batty et al., 2016), we use the average of the immediate and delayed results (Pearson correlation $r = .74$) as a measure of memory. The scale was normalized to have a mean of 0 and a standard deviation of 1.

Both outcome variables are only weakly correlated at $r = -.17$, as illustrated in Fig. A.4. The direction of the correlation indicates that participants with lower allostatic load have higher memory functioning, thus strengthening the association between lower stress and better cognitive skills.

3.4. Covariates

We take into account a number of time-varying covariates that might confound the association between caregiving and health, while all time-constant confounders are already accounted for by the fixed-effects estimator. Time-varying covariates include *age*, *marital status* (four categories), the number of young (0–13 y.) and older (14–18 y.) *children in the household*, the number of *grandchildren* (irrespective of living inside or outside the household), the number of living *siblings*, whether the participants' *father* and *mother* are still alive, as well as *income* (logged) and *wealth* (IHS transformed). We further control for survey waves using indicator variables.

3.5. Statistical analyses

We use an asymmetric fixed-effects approach (Allison, 2019) to test our hypotheses regarding the consequences of transitions into and out of (intensive) caregiving. This approach has two advantages. Firstly, fixed-effects estimators allow us to account for factors that confound the relationship between care and health, and not just factors that have been observed, but also unobserved factors, as long as the latter are constant over time. This means that our models adjust for any time-constant factors, such as personality traits or genetic dispositions, that might drive both caregiving and health outcomes without the need to explicitly include them in our models.

Secondly, the asymmetric fixed-effects estimator allows us to distinguish between transitions into and out of caring and to allow their magnitude to be distinct (hence, asymmetric). This goes beyond the standard fixed-effects approach which constrains the magnitude of the association to be equally strong both for transitions into and out of the treatment to be the same. This assumption is likely not tenable when it comes to transitions into and out of caring, as our theoretical mechanisms and a recent empirical study suggest (Uccheddu et al., 2019).

In order to estimate asymmetric fixed-effects models, we first identify the 'positive' and the 'negative' components of change, that is, transitions into and out of, respectively, caregiving. This is computed based on the binary exposure variables measuring caregiving (and intense caregiving) x_{it}:

$$x_{it}^{+} = x_{it} - x_{it-1} \text{ if } x_{it} - x_{it-1} > 0, \text{ otherwise } 0$$

$$x_{it}^{-} = -(x_{it} - x_{it-1}) \text{ if } x_{it} - x_{it-1} < 0, \text{ otherwise } 0$$

We then calculate the sum of each of the two components of caregiving:

$$z_{it}^{+} = \sum_{s=1}^{t} x_{is}^{+}$$

$$z_{it}^{-} = \sum_{s=1}^{t} x_{is}^{-}$$

z_{it}^{+} then indicates the accumulated transitions into (intensive) caregiving and z_{it}^{-} the accumulated transitions out of (intensive) caregiving. Histograms of these variables are shown in Panel B of Fig. 1.

In the final model, the two measures of accumulated transitions (into with z_{it}^{+}, out of with z_{it}^{-}) are added as follows:

$$Y_{it} = \alpha_t + \beta^{+} z_{it}^{+} + \beta^{-} z_{it}^{-} + \gamma_i + \epsilon_{it}$$

with α_t as the intercept which is allowed to vary at each wave, β^{+} and β^{-} are the effects of transitions into and out of (intense) care, respectively, γ_i are unobserved time-constant factors and ϵ_{it} is an error term.

Since the transition into caregiving, the likelihood of taking up time-intensive caregiving, and their consequences are gendered, we estimate separate models for men and women.

We did not introduce time lags for our exposure variables because there is a natural time order in the survey items, with caregiving and health both measured contemporaneously, but caregiving likely not having started on the day of measurement and is already ongoing, while health refers to the day of measurement.

To test our hypotheses, we use two ways of measuring caregiving added in separate models, which is the exposure variable. First, we measure care as a dichotomous variable in all waves indicating whether a person has provided support with personal care to someone inside or outside their household in the last week (no/yes). Here z_{it}^{+} indicates the accumulated transitions into (starting) caregiving and z_{it}^{-} the accumulated transitions out of the caregiving status. As an example, a person that first starts to care, stops, and then starts again would have two transitions towards care ($z_{it}^{+} = 2$) and one away ($z_{it}^{-} = 1$). Second, to test whether our hypotheses also hold with regard to changes in caregiving intensity which is defined as providing at least eight hours of care weekly. For those analyses, we remove observations that are never observed as being a caregiver, and investigate changes into intensive caregiving and out of intensive caregiving, meaning towards stopping care and low intensity. Thus, in those models z_{it}^{+} indicates the accumulated transitions into intensive caregiving and z_{it}^{-} the accumulated transitions out of intensive caregiving.

Robustness checks. We conduct a range of robustness checks to assess the sensitivity of our findings to some assumptions. First, we use an alternative measure of cognitive function, executive function based on an animal-naming test. Second, as there is no consensus in the literature about where intense caregiving starts, we consider all possible cut-offs, starting from eight hours per week up to forty hours per week.

3.6. Selection of cases

The number of participants and observations varies across the different models and analytical states we present. The main reasons for this variation are the availability of measures across panel waves and the requirements of the various types of analyses. While cognitive function was included in all ten waves, allostatic load is only available in waves 2, 4, 6, 8, and 9. Hence, the number of participants and observations is lower for analyses with the allostatic load outcome. (Our secondary cognitive function outcome used for robustness checks, executive function, was included in all survey waves but not in wave 6, leading to a somewhat smaller sample.)

In terms of requirements of analyses, our descriptive analyses show the prevalence of caregiving transitions (into, and out of) and the stability in caregiving or non-caregiving. Panel A of Fig. 1 shows a Sankey diagram for only the 1,981 participants who took part in all ten waves of ELSA data collection, also known as a balanced panel. While this is arguably a small and likely select subsample of ELSA, it helps to illustrate variation in our exposure variable. Multivariate fixed effects estimators generally can handle unbalanced panel data. The asymmetric fixed effects estimator (Allison, 2019) used in our main analyses presented in Fig. 3 does require that there are no gaps in observations. For the multivariate analyses, a fully balanced panel is not needed, but respondents' individual observations will only be considered if they stem from subsequent panel waves.

4. Results

4.1. Descriptive findings

Panel B of Fig. 1 shows the cumulative exposure to caregiving, stratified by sex. The top panel shows that women contribute more exposure to caregiving than men, both in terms of transitions into caregiving as well as out of caregiving. For transitions into intense, 8+ hour caregiving, we see the same pattern.

Fig. 2 shows the association between caregiving on the one hand and allostatic load and cognitive functioning on the other in a cross-sectional perspective. Panel A shows that allostatic load for men is similar irrespective of whether they provide care or not; for women however, allostatic load is lower among those who provided care in the last week. The difference is almost .10 standard deviations, a small effect. The allostatic load of caregiving women is also lower than the allostatic load of men. Panel B shows that men who provided care in the last week have better memory than men who did not provide care, the difference being .07 standard deviations. The same pattern is found for women but even more pronounced: on average, caregiving women have .20 standard deviations better memory than non-caregiving women. Further, men have generally worse memory than women.

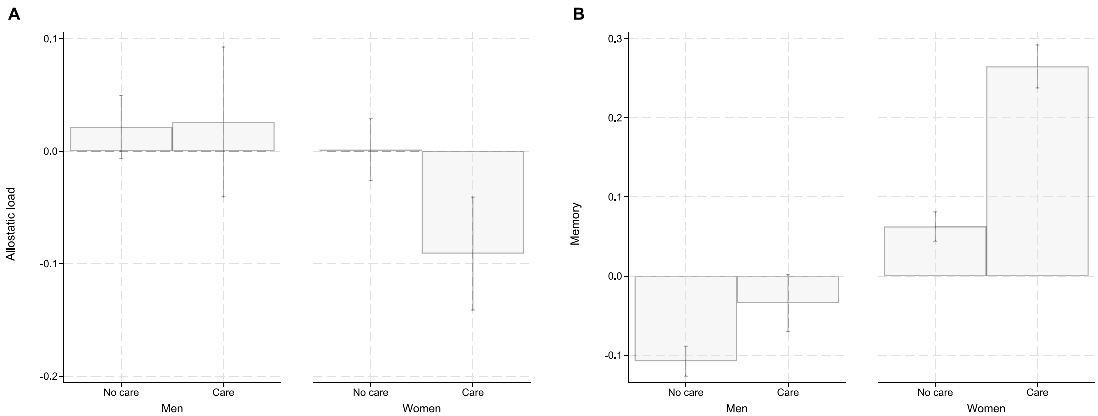

Fig. 2. *Panel A*: Women who have provided care in the week prior to the interview have lower allostatic load than women who did not give care, as well as men (regardless of whether they were caregivers or not). Means (95% confidence intervals based on cluster-robust standard errors) of allostatic load by sex and caregiving for pooled dataset, $N_{\text{observations}} = 20{,}607$. *Panel B*: Women who have provided care in the last week have better memory than women who did not give care and than men. Men who have not provided care in the last week have worse memory than men who provided care and than women. Means (95 % confidence intervals based on cluster-robust standard errors) of memory by sex and caregiving for pooled dataset, $N_{\text{observations}} = 88{,}225$.

4.2. Asymmetric fixed effects analysis

Fig. 3 depicts the coefficients from the asymmetric fixed effects models. The upper Panel A of Fig. 3 shows the associations between transitioning into and respectively out of caregiving for the two measures of health for all respondents. The lower Panel B shows the associations between increasing and respectively lowering caregiving intensity (using a threshold of eight weekly hours spent caregiving) and our two health measures. All estimates are presented separately for women (the hollow circles) and men (the filled circles).

Regarding transitions between becoming a caregiver, we find that the transition into caregiving was associated with better health for men. For them, we find a negative association with allostatic load, indicating better physical health, and a positive association with memory, indicating better cognitive health. Those associations are different from 0 at conventional levels of statistical precision, yet the effect sizes, .08 standard deviations for allostatic load and .05 standard deviations for memory, are small. For women, we also see a small improvement of memory function upon caregiving initiation (.09 standard deviations); however, there is no statistically significant association with allostatic load. Those results give no support to Hypothesis H1, which had stipulated that changes towards more caregiving are related to a decline in health. The transition out of caregiving, however, is not associated with changes in health neither for any gender nor any of our two outcome variables, lending no support to Hypothesis H2, which had posited that changes towards less caregiving were related to health improvement.

When turning to changes in the intensity of caregiving (using a sample of caregivers only) in Panel B of Fig. 3, the picture changes. Women's memory functioning increases (.07 standard deviations) when they intensify their caregiving engagement, but men's does not. Neither does allostatic load change, and decreasing caregiving in terms of weekly hours is also not associated with either indicator of health. We thus conclude that it is rather caregiving itself and not its intensity that promotes men's health. For women, we find a consistent pattern for both caregiver status and intensity transitions.

4.3. Robustness checks

As an alternative to memory functioning, we considered one salient dimension of executive function (semantic verbal fluency, see Gonzalez-Burgos et al., 2019; Maseda et al., 2014), which was measured using a word-finding task with good psychometric properties (Ardila et al., 2006). Using verbal fluency as an alternative outcome, the results are very similar to the results for memory functioning for both men and women.

Alternative cutoff points for intense care were selected at all possible values between eight weekly hours and 40 weekly hours. Fig. B.7 in the Appendix presents the results of the 33 separate regression models, indicating the coefficient resulting from each individual cutoff. These results confirm the findings from Fig. 3. Regardless of the cut-off chosen, men's transition into more intense care is not associated with changes in health, whereas for women, an increase in caregiving is associated with better memory functioning.

5. Discussion

Our study was motivated by the mixed evidence on the linkage between caregiving and health, and the complex and overlapping nature of different psychological, economic, social and personal consequences of caregiving. The literature overview suggests that the association between caregiving and health might be positive or negative—depending on the type and intensity of caregiving, and

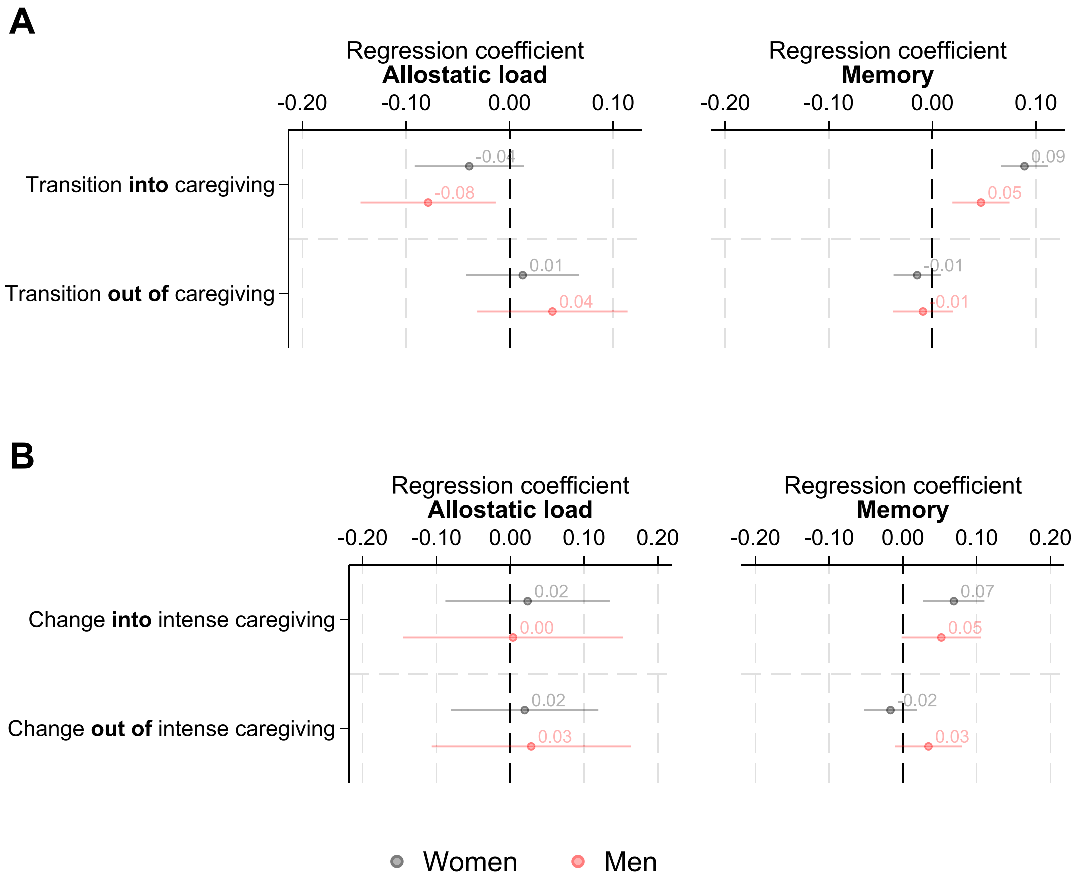

Fig. 3. *Panel A*: Transitioning into caregiving is associated with lower allostatic load for men. Transitioning into caregiving is associated with better memory, and this association is stronger for women than for men. *Panel B*: Women's memory functioning improves when they intensify their caregiving engagement. Coefficients from asymmetric fixed effects models controlling for age, marital status, children, grandchildren, siblings, parents, income, and wealth. Spikes denote 95% confidence intervals. Full models reported in the Appendix, Tables A.3 and A.4.

the health outcome considered. Despite the availability of high-quality longitudinal data in many Western countries, the direction of this association remains unclear. Our study aimed to take a fresh look at the problem by studying the transitions into and out of caregiving separately, thus acknowledging the dynamics of caregiving. Moreover, we focus on two carefully selected outcome variables, which provide a complementary picture of the different mechanisms that we identified from the theoretical literature.

Applying asymmetric fixed effects models on longitudinal ELSA data, our findings show support for role enhancement and cognitive benefits arising from caregiving rather than caregiving being a stressor that threatens resources. Starting to provide health-related care can improve cognitive functioning. This finding aligns with research on social and emotional benefits of caregiving, and cognitive benefits from childrearing (Ice et al., 2020). Not finding a significant change in health for transitions out of caregiving highlights the ambiguous nature of this experience. As we suspected, stressors, and the stimulating effects of caregiving fall away, but often, the transition out of caregiving goes along with the death of a loved one.

5.1. Limitations

Despite the notable contributions that our study makes, there are a number of limitations we would like to discuss. First, our study focused on the intensity of caregiving, measured with weekly care hours provided. Caregiving is a complex and multidimensional activity, which varies in other characteristics, such as the relationship between caregiver and care-receiver, co-residence with care-receiver, and the number and type of caregiving tasks. Caregiving intensity, measured with caregiving hours, overlaps with these other distinctive features of caregiving (Broese van Groenou et al., 2013). Thus, our study is not able to cover all potential (complex) mechanisms driving health outcomes.

Second, allostatic load measures were only collected every second wave, as they are expensive and time-consuming to collect and require further processing using various algorithms (see McLoughlin et al., 2020). With a gap of multiple years between the measures, we might not be able to track short-term effects of caregiving dynamics. It is not surprising that our results are somewhat less robust and magnitudes are smaller. Compared to other longitudinal and population-based studies on aging (e.g. SHARE, TILDA), however, having such high-quality measures every other wave is an improvement over earlier studies.

Third, the fixed-effects estimator has, as mentioned before, many desirable properties: It is particularly effective at controlling for time-invariant confounders – both observed and unobserved – by leveraging within-participant variation over time (Wooldridge, 2010). This makes it a powerful tool for disentangling the impact of caregiving on health from stable characteristics such as genetic predisposition, personality traits, childhood circumstances, or baseline health that might otherwise bias the results. However, the method cannot, in itself, establish causality. While our models account for important time varying confounders such as family status and wealth, we cannot account for unobserved time-varying confounders or dynamic relationships such as reverse causation, where changes in health might also influence caregiving. Without additional, strong assumptions about the temporal structure of events (e.g. Leszczensky and Wolbring, 2022) or bringing in exogenous variation from randomization or natural experiments, fixed-effects estimates remain vulnerable to these forms of endogeneity, limiting their capacity for straightforward causal interpretation. Given the practical difficulties of identifying the correct temporal spacing and order of the caregiving–health relationship, of randomizing care provision, and of finding natural experiments that have external validity, we maintain that our results based on objective measures of later-life health, which draw on within-variation, and disentangle transitions into and out of caregiving are rigorous and will move the field forward.

5.2. Research implications

Our findings and the limitations suggest avenues for future research. First, more detailed research, including causes of stopping to care (e.g. death of care recipient versus recovery), could help shed more light on this complex transition. Building on the positive relationship with health that we find here, the exact health-enhancing mechanisms need to be isolated, and measured. Such insights provide the foundation for fostering positive consequences of caregiving via policy implications or support programs.

Another avenue would be to look at the specific caregiving activities they perform (e.g. physical care, social support, practical help, and emotional support, respectively, the mix of these different forms of support, see e.g. Brandt et al., 2009), or to take a nuanced perspective on different subgroups of caregivers, e.g. partners or spouses, adult children, other relatives, or non-relatives (Bom et al., 2019b; Grigoryeva, 2017). For the labor market consequences of care, Moussa's (2019) review of the evidence reveals important differences between the groups. Notably, the distinction has been less studied when it comes to physical or cognitive health consequences (see the overview by Bom et al., 2019b, where most evidence pertains either to mental health or well-being, or does not distinguish between caregivers to parents, spouses and other relatives, or non-kin). A theoretical discussion and nuanced empirical investigation into the heterogeneity of caregiving, including relationship with recipient, or caregiving location (Kaschowitz and Brandt, 2017) would be desirable to better identify the most vulnerable groups of caregivers. Our study's focus on care intensity empirically connects to the caregiving relationship and the location of caregiving, as both are related to caregiving intensity (e.g. spousal care often occurs in the household and mostly has a higher intensity, Broese van Groenou et al., 2013) and are, thus, partly but not fully covered in our study.

Moreover, one reason why we do find fewer (statistically significant) effects on allostatic load could be due to limited frequency these biomarkes were collected. Ideally more frequent biomarker measures would be needed to better understand the consequences of caregiving on allostatic load, which represents an important dimension of 'wear and tear' on caregivers' physical conditions.

Finally, to ensure the generalizability of our results to other contexts, a replication using other data sets, preferably from different institutional or cultural country contexts, is needed. Our findings align with existing literature, indicating that the health consequences of caregiving – whether negative or positive – are influenced by the specific health dimensions being studied (Longobardo et al., 2023). Yet, in contrast to other studies focusing on mental health (Bom et al., 2019b), we find slightly protective effects, which may speak for a hypothesis of skill building and cognitive benefits of unpaid family care for women (Ice et al., 2020) as well as the protective benefits of social networks (e.g. Litwin and Stoeckel, 2016; Sibalija et al., 2020), which are enhanced due to caregiving (Choi et al., 2007; Roth, 2020). Building on our insights, future studies could for instance take an outcome-wide approach to identify the different domains and measures of health which are sensitive to caregiving. This may support developing interventions targeted at caregivers to protect health domains which are vulnerable to caregiving distress and enhance those which yield a benefit from caregiving.

6. Conclusion

Despite these limitations, the results of this study are informative for future research. They take the call for asymmetric fixed-effects panel models (Allison, 2019) seriously and expand on previous studies focusing on transitions into and out of spousal caregiving (Uccheddu et al., 2019). Those models automatically account for unobserved heterogeneity due to time-stable factors confounding the relationship between caregiving and health. Yet, we remain cautious in interpreting our results in a causal fashion due to potential unobserved heterogeneity in time-varying factors we might have missed. Our results confirm that caregiving dynamics are associated asymmetrically with health. However, since the literature on caregiving effects on health is mixed, we suggest moving beyond stressors and resources, and complementing the picture with psychological mechanisms, asking the old question of which social comparisons are related to health and wellbeing and how they work.

The COVID-19 pandemic has insistently illustrated that the value of care – be it formal, service-based, or informal, provided by family members, friends, and neighbors – in aging societies needs to be strengthened (Budnick et al., 2021; Calarco, 2024). Although this is not a new call, the persistent shortage of skilled labor and many accounts of overburdened caregivers during the COVID-19 pandemic urge us to address this issue with greater urgency. Not least, heat waves, occurring more frequently due to climate change, have been shown to increase the risk of stroke among older populations (Ebi et al., 2021), increasing the need for informal care.

Taken together, our insights are informative for future crises that threaten population health and may be followed by stay-at-home orders (Raiber et al., 2022a). In the future, ad-hoc family-based care may occur more unprecedentedly and more frequently.

Our findings are furthermore also relevant for policy-making and the organization of care. While it is a promising finding that caregiving can also be associated with better health even with time-constant unobserved heterogeneity adjusted for, it remains to be emphasized that caregiving has other, long-term, costs, particularly for labor market participation and financial wellbeing (Bertogg and Settels, 2025; Raiber et al., 2022b). Therefore, our findings do not negate the fact that providing informal care remains a significant risk factor for social exclusion.

CRediT authorship contribution statement

Ariane Bertogg: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Patrick Präg:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Klara Raiber:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

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Appendix A. Additional information

A.1. Allostatic load details

Allostatic load was measured according to the procedure established by Richards et al. (2023). It draws on nine biomarkers, collected in Waves 2, 4, 6, 8, and 9. Four biomarkers – systolic blood pressure (SBP), diastolic blood pressure (DBP), weight, and height – were obtained through physical measurements. SBP and DBP (in millimeters of mercury) were measured three times, and the mean of valid readings was used. We used weight and height measurements, collected in kilograms and meters, respectively. Body mass index (BMI) was calculated as weight divided by the square of height. The remaining biomarkers—high-density lipoprotein and total cholesterol (in mg/dl); triglycerides (in mg/dl); fasting blood glucose (FBG, in mmol/l); glycosylated hemoglobin (HbA1c, in %); fibrinogen (in mg/dl); and C-reactive protein (CRP, mg/dl)—were derived from blood samples.

We calculated allostatic load in two steps (Gruenewald et al., 2012; Read and Grundy, 2014). In the first step, we recoded each biomarker based on its cut-off point (Table A.1). For the high-density lipoprotein/total cholesterol ratio, triglycerides, HbA1c, fibrinogen, and CRP, the cut-off point was defined as the top quartile. For other measures, we used established clinical cut-off values. Biomarkers were categorized as 1 if they exceeded the cut-off values and 0 if they were below.

Doctor diagnoses and medication use were also considered in constructing the allostatic load. SBP and DBP were coded as 1 if respondents had been diagnosed with cardiovascular diseases or were on medication for hypertension. FBG was coded as 1 if respondents had been diagnosed with diabetes mellitus, and HbA1c was coded as 1 if respondents were on blood glucose-lowering medication or insulin. Following prior research indicating that cholesterol, blood glucose, and blood pressure-lowering medications reduce CRP values by 25–30 per cent, we coded CRP as 1 if participants used these medications (Prasad, 2006).

In the second step, we calculated scores for each organ system. The nine biomarkers represented four organ systems: cardiovascular (SBP and DBP), inflammation (CRP and fibrinogen), metabolic (HbA1c, high-density lipoprotein/total cholesterol ratio, triglycerides, and FBG), and body fat (BMI). Each indicator within an organ system was given equal weight–for example, the cardiovascular system had two biomarkers, each contributing half a point. We then summed the scores for these four organ systems, with scores ranging from 0 to 4. Higher allostatic load scores indicated greater multi-system physiological dysregulation.

A.2. Association between the two main outcomes

The two outcome variables allostatic load and cognitive functioning are only weakly correlated at $r = -.17$, as can be seen in Fig. A.4. The direction of the correlation indicates that participants with lower allostatic load have higher memory functioning, thus strengthening the association between functioning lower stress and better cognitive functioning.

A.3. Descriptive statistics

Table A.2 shows descriptive statistics for the data used in the analyses.

Table A.1
Biomarkers used for allostatic load and cut-off values (following Richards et al., 2023).

Biomarker	Cut-off value
Cardiovascular	
Systolic blood pressure	≥ 140 mmHg
Diastolic blood pressure	≥ 90 mmHg
Inflammation	
C-reactive protein	Top quartile
Fibrinogen	Top quartile
Metabolic	
Glycosylated haemoglobin	Top quartile
High-density lipoprotein/total cholesterol ratio	Top quartile
Triglycerides	Top quartile
Fasting blood glucose	≥ 7 mmol/l
Body fat	
BMI	≥ 30 kg/m^2

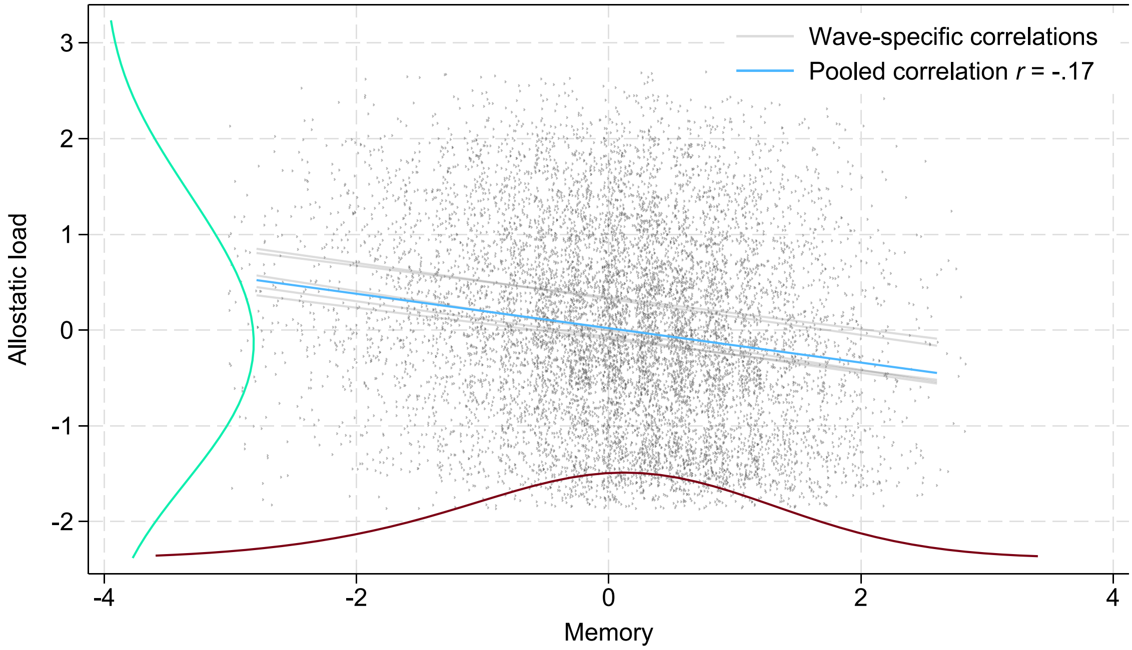

Fig. A.4. Correlation of memory and allostatic load. Scatterplot (data points jittered), densities, and linear fit, it of the two outcome variables allostatic load and memory, $N_{\text{observations}} = 20{,}599$.

A.4. Tables underlying Fig. 3

See Tables A.3 and A.4.

Appendix B. Robustness checks

B.1. Using an alternative measure of cognitive functioning

Executive function (semantic verbal fluency) was measured using a word-finding task: Participants had to name as many animals as possible within one minute (range: 0–67). The scale was normalized to have a mean of 0 and a standard deviation of 1. The question was not asked in Wave 6 of ELSA.

Table A.2
Descriptive statistics for men and women. Proportions unless otherwise stated.

	Men		Women	
Allostatic load (mean *(SD)*)	0.022	(0.977)	−0.015	(1.018)
Memory (mean *(SD)*)	−0.098	(0.957)	0.099	(1.007)
Transition into caregiving:				
0	0.836		0.783	
1	0.143		0.181	
2	0.019		0.033	
3	0.002		0.003	
4	0.000		0.000	
Transition out of caregiving:				
0	0.827		0.753	
1	0.152		0.210	
2	0.019		0.034	
3	0.002		0.003	
4	0.000		0.000	
Change into more intense caregiving:				
0	0.829		0.774	
1	0.146		0.193	
2	0.022		0.029	
3	0.003		0.003	
4	0.000		0.000	
Change out of more intense caregiving:				
0	0.398		0.380	
1	0.529		0.508	
2	0.067		0.100	
3	0.006		0.012	
4	0.000		0.001	
5	0.000		0.000	
Young children (0–13 y.):				
0 children	0.968		0.969	
1 child	0.022		0.022	
2 children	0.008		0.007	
3+ children	0.002		0.002	
Older children (14–18 y.):				
0 children	0.959		0.961	
1 child	0.035		0.034	
2 children	0.006		0.005	
3+ children	0.000		0.000	
Marital status:				
Married/cohabiting	0.792		0.650	
Divorced/separated	0.080		0.124	
Widowed	0.070		0.182	
Single, never married	0.058		0.044	
Number of living siblings:				
None	0.210		0.198	
1	0.317		0.322	
2	0.217		0.213	
3	0.120		0.121	
4+	0.136		0.146	
Number of grandchildren:				
None	0.378		0.339	
1	0.094		0.088	
2	0.126		0.128	
3	0.092		0.093	
4+	0.310		0.352	
Father still alive	0.087		0.105	
Mother still alive	0.192		0.216	
Age (mean *(SD)*)	66.388	(9.584)	65.767	(10.452)
Income (logged, mean *(SD)*)	5.727	(0.691)	5.630	(0.695)
Wealth (IHS, mean *(SD)*)	9.489	(5.858)	9.067	(5.939)
N person–year observations	38,709		49,516	

Table A.3
Allostatic load and memory regressed on caregiving transitions, asymmetric fixed-effects regression.

	Allostatic Load		Memory	
	Women	Men	Women	Men
Transition into caregiving	−0.04	−0.08*	0.09***	0.05***
	(0.03)	(0.03)	(0.01)	(0.01)
Transition out of caregiving	0.01	0.04	−0.01	−0.01
	(0.03)	(0.04)	(0.01)	(0.01)
Age	0.06*	0.05*	−0.02*	−0.02
	(0.02)	(0.02)	(0.01)	(0.01)
Marital status (*Ref.* married/cohabiting)				
Divorced/separated	0.02	0.15	−0.06*	0.02
	(0.07)	(0.09)	(0.02)	(0.03)
Widowed	0.12**	0.12	−0.06**	0.01
	(0.05)	(0.07)	(0.02)	(0.03)
Single, never married	0.45*	0.04	−0.07	0.03
	(0.21)	(0.15)	(0.07)	(0.07)
Young children in household (*Ref.* none)				
1 child	0.03	0.01	−0.10***	−0.07*
	(0.08)	(0.08)	(0.03)	(0.03)
2 children	0.07	−0.22	−0.19***	−0.14**
	(0.18)	(0.13)	(0.05)	(0.05)
3+ children	0.12	−0.38	−0.22*	−0.01
	(0.53)	(0.25)	(0.11)	(0.10)
Older children in household (*Ref.* none)				
1 child	0.03	−0.06	−0.08***	−0.07**
	(0.06)	(0.06)	(0.02)	(0.02)
2 children	0.00	−0.06	−0.18***	−0.02
	(0.17)	(0.13)	(0.05)	(0.05)
3+ children	0.00		−0.05	−0.13
	(.)		(0.20)	(0.20)
No. of grandchildren (*Ref.* none)				
1	−0.04	−0.06	0.04*	0.08***
	(0.04)	(0.04)	(0.02)	(0.02)
2	−0.04	0.05	0.13***	0.10***
	(0.05)	(0.05)	(0.02)	(0.02)
3	−0.09	0.02	0.13***	0.11***
	(0.05)	(0.05)	(0.02)	(0.02)
4+	−0.10	0.02	0.17***	0.13***
	(0.05)	(0.06)	(0.02)	(0.02)
No. of living siblings (*Ref.* none)				
1	−0.06	−0.04	0.11***	0.05
	(0.06)	(0.06)	(0.02)	(0.03)
2	−0.03	−0.14	0.18***	0.06
	(0.07)	(0.08)	(0.03)	(0.03)
3	−0.06	−0.14	0.23***	0.14***
	(0.09)	(0.10)	(0.04)	(0.04)
4+	0.01	−0.14	0.27***	0.10*
	(0.11)	(0.12)	(0.04)	(0.05)
Father still alive (*Ref.* not alive)	0.02	0.12*	−0.12***	−0.09***
	(0.05)	(0.06)	(0.02)	(0.02)
Mother still alive (*Ref.* not alive)	0.07	−0.01	−0.10***	−0.10***
	(0.04)	(0.04)	(0.02)	(0.02)
Household income (ln)	−0.01	0.00	0.00	−0.01
	(0.02)	(0.02)	(0.01)	(0.01)
Household wealth (IHS)	−0.00*	0.01**	−0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	−3.54*	−3.20*	1.24*	1.03
	(1.52)	(1.47)	(0.56)	(0.62)
Wave dummies	Yes	Yes	Yes	Yes

(*continued on next page*)

Table A.3 (*continued*).

	Allostatic Load		Memory	
	Women	Men	Women	Men
p-value	0.341	0.272	0.000	0.008
N observations	11,312	9,295	49,516	38,709
N participants	5,508	4,630	11,143	9,074

Notes: Standard errors in parentheses. p-value at bottom result of F-test of difference between positive and negative transition coefficients.* $p < 0.05$,** $p < 0.01$,*** $p < 0.001$.

Table A.4
Allostatic load and memory regressed on changes into and out of intense caregiving, asymmetric fixed-effects regression.

	Allostatic Load		Memory	
	Women	Men	Women	Men
Change into more caregiving	0.02	0.00	0.07**	0.05
	(0.06)	(0.08)	(0.02)	(0.03)
Change into less caregiving	0.02	0.03	−0.02	0.03
	(0.05)	(0.07)	(0.02)	(0.02)
Age	−0.07	−0.06	−0.04	−0.04
	(0.07)	(0.09)	(0.02)	(0.03)
Marital status (*Ref.* married/cohabiting)				
Divorced/separated	0.13	0.34	−0.02	−0.01
	(0.22)	(0.29)	(0.05)	(0.07)
Widowed	0.18	0.20	−0.06	0.03
	(0.10)	(0.19)	(0.04)	(0.06)
Single, never married	1.67*	0.14	−0.06	−0.04
	(0.67)	(0.47)	(0.17)	(0.16)
Young children in household (*Ref.* none)				
1 child	−0.15	0.35	0.04	−0.09
	(0.21)	(0.34)	(0.07)	(0.10)
2 children	0.16	0.79	−0.03	−0.23
	(0.44)	(0.97)	(0.13)	(0.16)
3+ children	0.00	−0.42	−0.44	0.55
	(.)	(0.58)	(0.37)	(0.47)
Older children in household (*Ref.* none)				
1 child	0.41	0.27	−0.02	−0.11
	(0.23)	(0.24)	(0.07)	(0.08)
2 children	0.00	0.35	−0.10	0.04
	(.)	(0.39)	(0.17)	(0.19)
3+ children			−0.11	0.02
			(0.78)	(0.41)
No. of grandchildren (*Ref.* none)				
1	0.04	−0.13	−0.00	0.17**
	(0.12)	(0.15)	(0.05)	(0.06)
2	−0.06	0.12	0.09	0.13*
	(0.13)	(0.17)	(0.05)	(0.06)
3	−0.18	−0.07	0.15**	0.13
	(0.14)	(0.20)	(0.06)	(0.07)
4+	−0.03	0.05	0.19**	0.16*
	(0.15)	(0.21)	(0.06)	(0.07)
No. of living siblings (*Ref.* none)				
1	0.02	0.14	0.12*	0.06
	(0.14)	(0.20)	(0.05)	(0.07)
2	0.01	0.21	0.19**	−0.08
	(0.18)	(0.25)	(0.07)	(0.09)
3	0.08	0.04	0.14	0.01
	(0.21)	(0.32)	(0.09)	(0.11)
4+	0.49	−0.14	0.15	−0.01
	(0.26)	(0.39)	(0.10)	(0.13)

(*continued on next page*)

Table A.4 (*continued*).

	Allostatic Load		Memory	
	Women	Men	Women	Men
Father still alive (*Ref.* not alive)	0.21	0.42*	−0.08	−0.02
	(0.11)	(0.17)	(0.04)	(0.06)
Mother still alive (*Ref.* not alive)	−0.06	−0.04	−0.08*	−0.08
	(0.08)	(0.12)	(0.03)	(0.04)
Household income (ln)	−0.06	−0.03	−0.00	−0.00
	(0.05)	(0.07)	(0.02)	(0.02)
Household wealth (IHS)	−0.01	0.03**	−0.00	0.01**
	(0.01)	(0.01)	(0.00)	(0.00)
Constant	4.27	2.57	2.40	2.64
	(4.03)	(5.50)	(1.32)	(1.68)
Wave dummies	Yes	Yes	Yes	Yes
p-value	0.516	0.709	0.041	0.009
N observations	2,583	1,515	10,732	6,339
N participants	1,559	987	2,906	1,877

Notes: Standard errors in parentheses. *p*-value at bottom result of *F*-test of difference between positive and negative transition coefficients.* $p < 0.05$,** $p < 0.01$,*** $p < 0.001$.

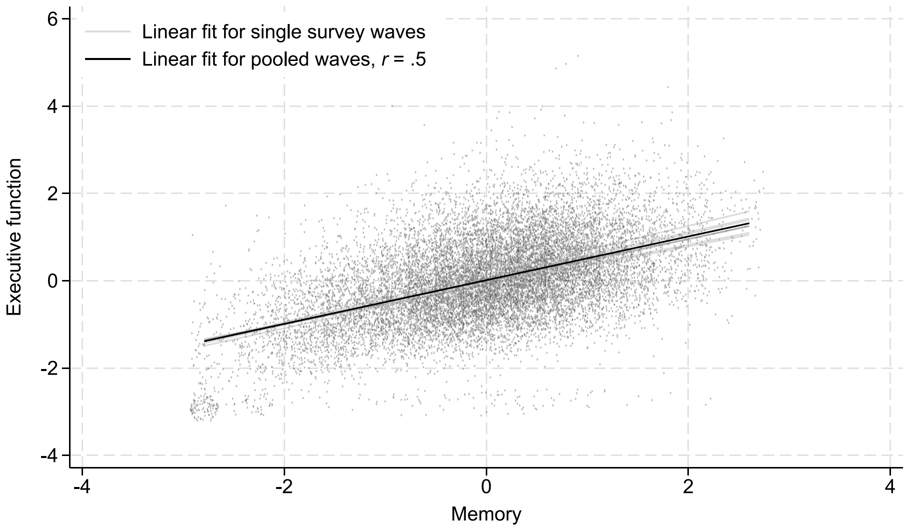

Fig. B.5. Memory and fluency are correlated. Scatterplot (data points jittered) of memory and fluency pooled across waves, linear fit for single waves and for all waves pooled. $N_{\text{observations}} = 72{,}145$.

Executive function measures a dimension of cognitive function that is distinct from memory, as indicated by their high, yet far from perfect correlation of .51 (Fig. B.5). Using verbal fluency as an alternative outcome, the results are very similar to the results for memory functioning for both men and women (see Fig. B.6).

B.2. Alternative cutoffs for intense caregiving

Fig. B.7 shows the association to more and less intense caregiving on the one hand and allostatic load and memory on the other, stratified by all cutoffs between eight and 40 h per week. There is no association between caregiving transitions and allostatic load for men and women, irrespective of where we set the cutoff for intense caregiving. When looking at memory, transitioning into more intense caregiving goes along with a better memory for women, and again, this is irrespective of where the cutoff for intense caregiving is set.

Data availability

Data (Banks et al., 2024) as well as programming code for data preparation and analysis are publicly available: https://dx.doi.org/10.17605/OSF.IO/H9SVA.

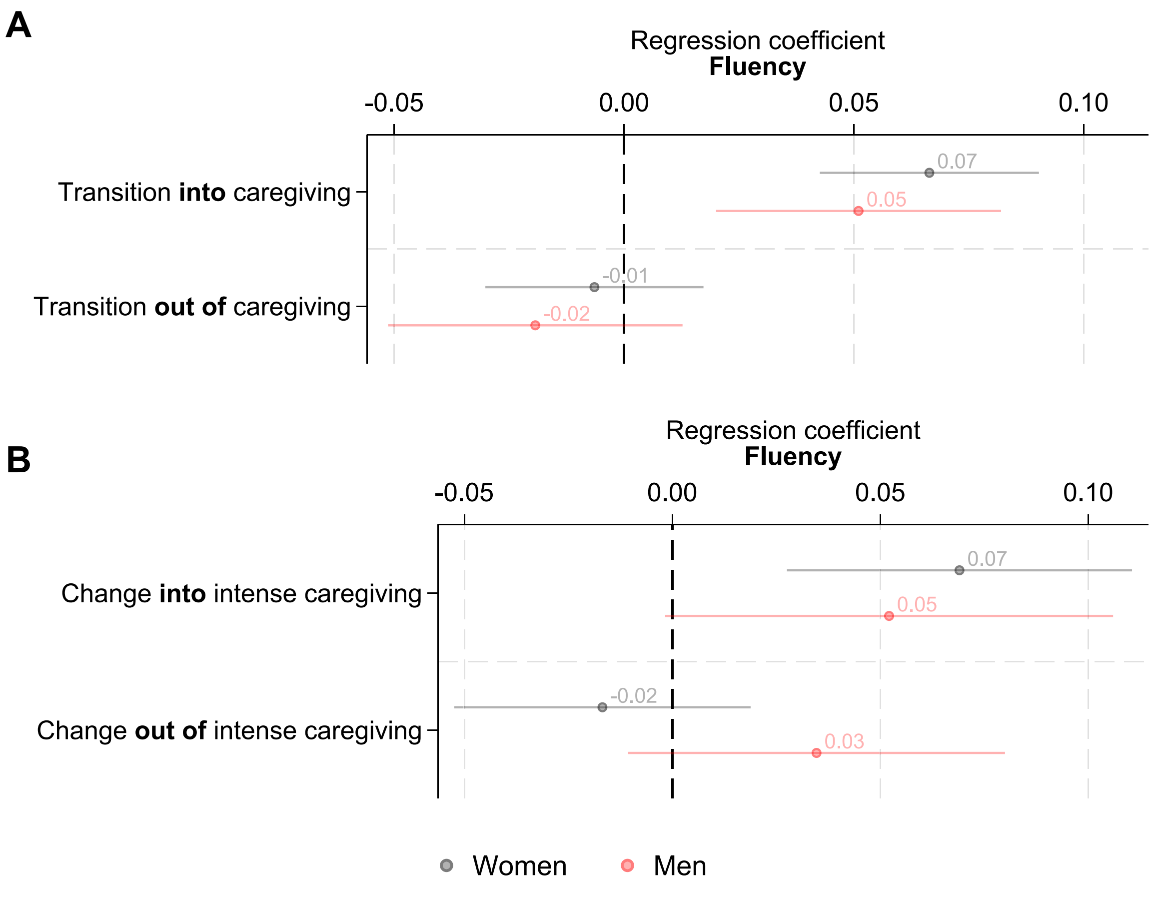

Fig. B.6. Transitioning into caregiving is associated with better fluency for women and men. Changing into more intense caregiving is associated with better fluency for women. Coefficients from asymmetric fixed effects models controlling for age, marital status, children, grandchildren, siblings, parents, income, and wealth.

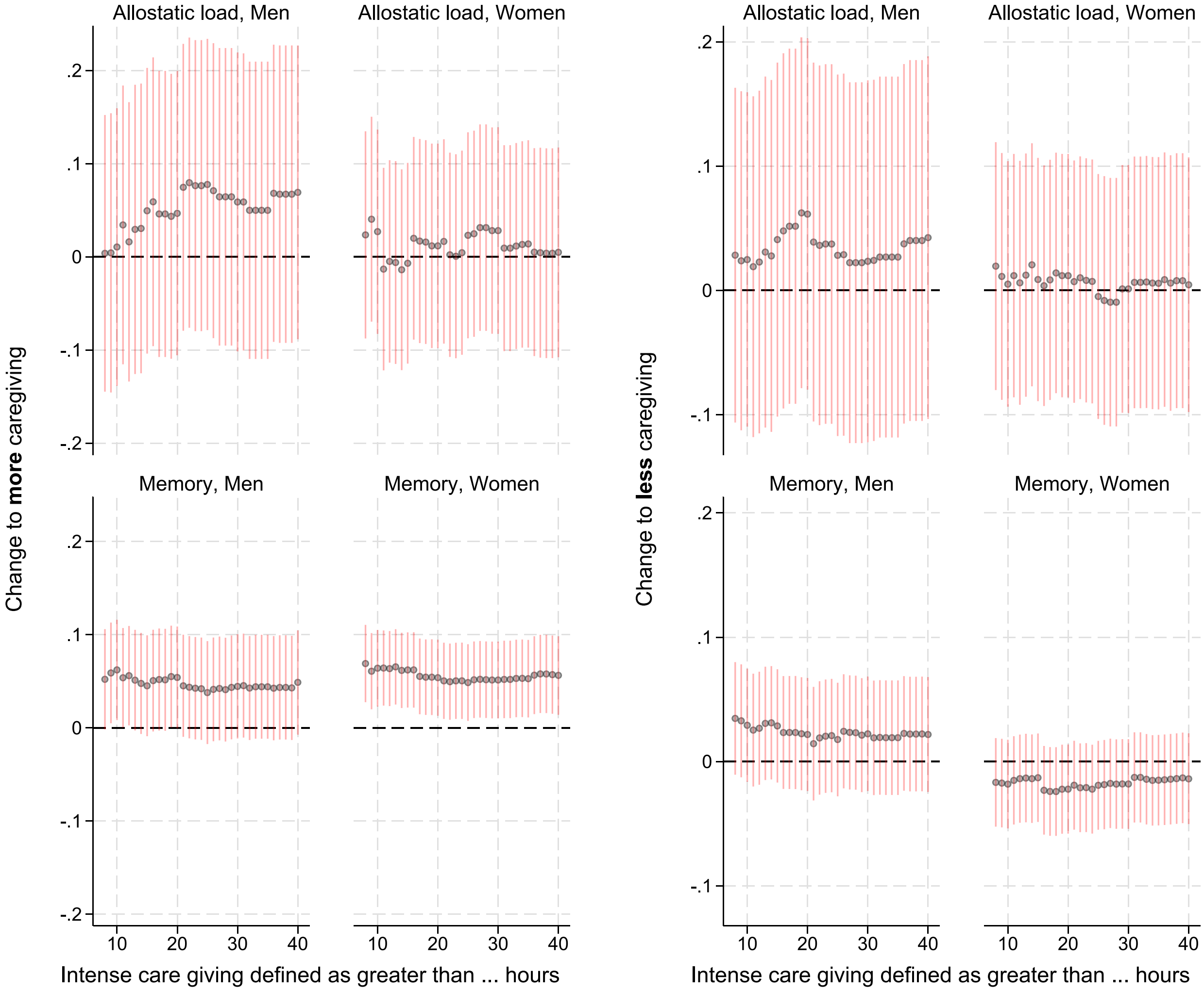

Fig. B.7. Transitioning into more intense caregiving goes along with a better memory for women, independent of the cutoff value for intense caregiving. Coefficients from asymmetric fixed effects models controlling for age, marital status, children, grandchildren, siblings, parents, income, and wealth.

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