Sharing the caring? Dynamic interaction between siblings in the provision of care to parents

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Abstract

Adult daughters provide nearly three times as many hours of care to elderly parents as adult sons do. I analyse the role of strategic interaction between siblings in exacerbating this gap in care provision. To do so, I build and estimate a dynamic discrete-choice game in which siblings make location, work and care choices. I find that the opportunity for strategic play increases gender differences in caring responsibilities. Sons in particular strategically shirk providing care as they believe their sibling is relatively likely to provide care in their absence. Counterfactual experiments show that if siblings instead took care, location and work choices independently then the gender care gap would be around 31% smaller. Also, I find that unobserved preference differences between sons and daughters are far more important in driving the gender care gap than observed differences in wages.

JEL classifications: D64, J14, J16

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1 Introduction

Children are a key source of care for their elderly parents: in the US, around 17% of all adult children will provide care to a parent at some point in their lives and conditional on providing positive care hours an adult child will provide on average 77 hours of care per month (Wettstein and Zulkarnain 2017). Studies have shown the adverse effects of caregiving on labour force attachment (Van Houtven, Coe, and Skira 2013) and mental and physical health (Bom et al. 2019), and there is little evidence of caregivers receiving direct contemporaneous cash transfers in exchange for their care (Barczyk and Kredler 2018). It is generally daughters and not sons who select into caregiving (Grigoryeva 2017), with my calculations in this paper showing daughters providing around 3 times the care hours of sons even though all children plausibly benefit from the public good of having their parent cared for. Why do we observe such a gender gap in selecting into this role?

The existing literature has tried to analyse the issue of children providing care to elderly parent(s) either from the perspective of an individual adult child (Ko 2022; Mommaerts 2024; Skira 2015) or with multiple adult children in a static setting (Byrne et al. 2009; Fontaine, Gramain, and Wittwer 2009), imposing different preferences or costs of caring for different types of children to match gaps in care provision. While this literature has yielded many rich insights, it has not accounted for the fact that care provision by children is fundamentally a problem of dynamic interaction. Modelling dynamics is crucial because children's decisions in response to parental health shocks will affect their ability to provide care in the future; modelling interactions is crucial because children make these decisions with the knowledge that their siblings are making similar calculations and because each child's decision affects the optimal behaviour of all their siblings. This creates a space for strategic play over time between siblings to amplify gaps arising from any difference in preferences or costs of caring.

A simple example will illustrate. Suppose Adam and Beth are siblings. Suppose there is something about Beth's preferences or costs for providing care that make her more likely to provide care (she has a lower opportunity cost of providing care, she finds it less burdensome to provide care, their common parent prefers Beth's care, and so on). If Adam and Beth made decisions independently, without regard for what the other was doing, then Beth would on average provide more care because of these differences in preferences and costs. However, if Adam knows Beth is likely to provide care, then other things being equal he will reduce his care effort; Beth, knowing this, will increase her care effort to compensate, meaning Adam could cut his care effort more, and so on. Thus, the possibility for strategic interaction can amplify existing gender care gaps. This amplification could be particularly important in dynamic games where agents' costs and preferences of providing care are not fixed exogenously but are instead endogenously generated by past decisions: Adam will be even less likely to provide care today if he sees today's care decision as locking him in to the caring role in future.

In this paper I explore this type of interaction by situating the decisions of adult children over the care provided to their elderly parents in a rich dynamic model, recognising a) that children may have different preferences over their parent's care arrangements and b) that children can take strategic actions to make it easier for them to provide (or avoid the burden of providing) care in future. In doing so, I make two key contributions to the literature on informal care provision within families. Firstly, I present the first estimates of the importance of strategic interaction in driving the gender care gap: specifically, a baseline estimate that the gender care gap would be 31% smaller for the population studied if there were no strategic interaction between siblings. Secondly, I provide new insight into the drivers of the gender care gap: differences in care provision between sons and daughters are driven much more by differences in preferences than by differences in wages.

To motivate my structural approach, I first use the US Health and Retirement Study to document some stylised facts about the provision of care for elderly parents by their adult children. In keeping with previous results in the literature, I confirm that it is generally daughters who end up providing the care and I exploit variation in gender composition of sibling groups to offer some prima facie evidence that children's caregiving is not independent of the caregiving of their siblings, with care provided by sons being crowded out by care provided by daughters. However, in contrast to previous authors (Barczyk and Kredler 2018; Groneck 2017), I find little evidence of substantive compensation for most caregivers, either in the form of bequests or non-cash inter vivos transfers, which raises the question of what drives these people into the caregiving role.

I then use these stylised facts to motivate a dynamic model of interaction between two adult siblings. Each period, the siblings simultaneously make location, labour and (if their common parent is sick) care decisions. Sons and daughters differ in their preferences for providing care and in their income from working versus not working. Children find it costly to provide care themselves but each child receives a benefit if any child provides care, meaning that the model resembles a public good provision problem. The children split the parent's bequest equally between them when the parent dies but otherwise face no financial incentive to provide care and cannot transfer money between themselves. In keeping with the finding in Hiedemann, Sovinsky, and Stern (2018) about the importance of inertia in caring arrangements, the model incorporates direct or implicit transition costs in changing one's location, labour force participation or caregiving, which in turn imply transition costs associated with changing caring arrangements. In particular, the children suffer a wage penalty if they have been absent from the labour market and they suffer a utility penalty from changing location or starting providing care. These transition costs are the key feature distinguishing this dynamic model from static models of care provision because care, location and work decisions today have a bearing on the optimal decisions in the next period.

I estimate the model by maximising the pseudo log-likelihood of the observed decisions (Aguirregabiria and Mira 2007). In particular, to make the estimation tractable, I use forward simulation to construct agents' value functions using the process set out in Bajari, Benkard, and Levin (2007) and employed in Ko (2022). Key estimated parameters include preference differences for providing care between sons and daughters and parameters capturing the extent to which adult children benefit from their siblings' care provision. I show that the model is able to match key patterns in the data and I carry out statistical tests that reject more parsimonious versions of the model.

I use the estimated model to conduct counterfactual experiments to quantify the drivers of the gender care gap: I examine the relative contributions of wages and preferences to this gap, and I assess the role of strategic interaction in exacerbating this gap. These exercises shed light on what we might expect to happen to the gender care gap in future given broader demographic trends such as a shrinking gender wage gap and rise in one-child families. I find that preferences are far more important than wages in driving the gender care gap, with imposing identical preferences between sons and daughters shrinking the gap by 81%, and I find that if every child assumed that their siblings would never provide care (so that there are no considerations of strategic interaction) then the gap would be 31% smaller.

This paper contributes to the literature on informal care arrangements within families (Byrne et al. 2009; Checkovich and Stern 2002; Fontaine, Gramain, and Wittwer 2009; Hiedemann, Sovinsky, and Stern 2018; Mommaerts 2024; Stern 2023), and in particular to the literature on dynamic strategic interaction over care provision within a family (Barczyk and Kredler 2018; Ko 2022; Sovinsky and Stern 2016). Previous papers on dynamic strategic interaction have focussed on interaction between a parent and child, rather than on strategic interaction between children; instead, to the best of my knowledge this has only been studied in a static setting (e.g. Byrne et al. (2009)), or with strong assumptions about identical preferences between children such that the family can be treated as a unit (e.g. Hiedemann, Sovinsky, and Stern (2018)). By modelling interaction between children in a rich dynamic setting I am able to capture the full importance of strategic play in driving the unequal distribution of the care burden.

Another important methodological contribution of this paper is the modelling of location choice along with caring and labour choices in a dynamic model of care provision. Previous papers have treated child location as fixed (e.g. Ko (2022)) or have modelled the location decision of adult children as a one-shot decision taken early on in life (e.g. Stern (2023)). In practice, adult children can change their location in response to parental health shocks by moving back close to their parents in order to provide care and there is some evidence that they do so (e.g. Hiedemann, Sovinsky, and Stern (2018)). It is important to allow for this channel of behaviour to properly model a child's ability to alter their own cost of providing care and thus their ability to strategically shirk caregiving[1].

This paper is closest in approach to Ko (2022), which models dynamic interaction between a parent and child and uses this to explain low long-term care insurance takeup. I use many of the same modelling assumptions. For instance, I use a similar dynamic framework of non-cooperative interaction over caregiving decisions, combined with a labour participation decision on the part of the child. As suggested above, the key differences are that I model interaction between children, rather than between a parent and a child, in order to work out what drives differences in provision between children, and that I allow children's location to change endogenously. On the other hand, to make the model tractable, I abstract from modelling LTC insurance and in particular the interaction between the LTCI demand and the availability of informal care, a key focus of Ko (2022).

The inclusion of the labour force decision for children, and the emphasis on the costs associated with leaving the labour force to provide care, links this paper to Skira (2015), which presents a dynamic model of women's labour force participation and caregiving for an elderly parent. This paper expands on that paper by modelling the interaction between multiple children and allowing children choice along more dimensions, though this extra complexity comes at the cost of a simpler labour market and wage model than in Skira (2015).

The paper also draws from Hiedemann, Sovinsky, and Stern (2018), which similarly provides dynamic models of care provision within a family and finds important results about the state-dependence of care provision over time. In Hiedemann, Sovinsky, and Stern (2018), because the focus is on a sophisticated treatment of unobserved heterogeneity in a dynamic setting, the authors abstract from within-family strategic interaction. Instead, family members are modelled as having the same preferences over care outcomes, so the family can be treated as a unit. The key contribution of the current paper relative to Hiedemann, Sovinsky, and Stern (2018) is that children in the model are separate decisionmakers with their own preferences and interact non-cooperatively, allowing me to quantify the importance of strategic interaction over time.

Finally, with its emphasis on endogenous location choice and strategic shirking of a

[1]For instance, suppose Adam lives close to his mother but his sister Beth lives far away, and that their mother suddenly falls ill. If Adam and Beth cannot change location, then both Adam and Beth know that the probability of Beth providing care is very low, so Adam is effectively making decisions in isolation over whether to care for his mother. If, on the other hand, Beth is able to move back, or Adam is able to move away, then Adam will see the probability of Beth providing care as higher, so might be more tempted to shirk in the hope that Beth moves back and provides care.

caregiving role the paper builds on work by Konrad et al. (2002), Maruyama and Johar (2017), Rainer and Siedler (2009), and Stern (2023). These papers all examine one-shot location decisions by adult children early in life seeking to avoid the burden of providing care to elderly parents in future[2]. The contribution of this paper relative to these others is that it allows for adult children to change location multiple times over their lives, meaning they can respond to parental health shocks. As outlined above, it is important to model this channel of behaviour in order to better capture the scope for strategic interaction between siblings over caring.

The rest of this paper proceeds as follows. In Section 2 I set out some descriptive evidence about caregiving by adult children of elderly parents. In Section 3 I write down a dynamic model of interaction between siblings in the provision of care. Section 4 discusses data and estimation, providing intuitive arguments for identification and setting out results and model fit. Section 5 shows the results of counterfactual experiments and Section 6 concludes.

2 Descriptive evidence

I use data from the Health and Retirement Study (HRS) between 1998-2018[3]. The HRS asks respondents a battery of questions about their health, financial situation and relationships. In addition, HRS respondents are asked to provide information on any children they have. Notably, the HRS records for each child their income (in brackets), their education, their marital status, whether they live within 10 miles of the parent and how much care they provide to the parent. This allows me to link each parent with their possible child caregivers.

For calculating descriptive statistics and establishing general empirical patterns I use the full sample of respondents to these waves of the HRS who have at least one child record associated with them. This comprises of 35105 unique respondents over the 11 biennial waves, with 200385 respondent-wave observations, meaning that each respondent appears for an average of 5.7 waves. In Appendix A I show some descriptive statistics on the HRS sample.

I now use the HRS sample to present some key facts about the provision of care: namely, that there is a gender gap in the provision of care, the size of this gender gap depends on family composition, and most children do not receive substantial compensation for providing care.

[2]In Konrad et al. (2002), children make a one-shot location decision early in life and then parents can make a decision when they are elderly and need care to live close to a particular child. As discussed in Appendix B, in my data it is children not parents who relocate when the parents need care.

[3]I use the RAND HRS Longitudinal File and the RAND HRS Family Data File and combine these with data from the RAND HRS Fat Files for each of the relevant waves (*HRS* 2024; *RAND* 2024)

2.1 There is a gender gap in the provision of care

Children are an important source of care to parents. In the HRS sample I consider, the average sick[4] parent receives 20 hours of care per month from any daughters they have and 7 hours of care per month from any sons they have, together amounting to around a third of the 77 care hours per month that a sick parent receives from all sources. For sick parents without a spouse, these figures are 32 hours and 12 hours respectively, making up 58% out of a total of 76 hours. In both cases, therefore, daughters provide around 3 times the care hours of sons. Appendix A discusses in more detail the breakdown of care receipt by source.

To identify some predictors of provision of care I use the child records associated with each respondent in the HRS. I run an OLS regression of a dummy for whether a given child provided any care to a sick parent on a set of child and parent demographics[5]. I also regress the log of hours of care provided on the same set of explanatory variables for the subsample of children who provided positive hours of care. These regressions are carried out for the full sample of HRS respondents with children, and are displayed in Table 1 below.

In the Table, Columns 1 and 2 capture the extensive margin of care provision. In each case I regress a dummy for care provision on a set of parent and child characteristics. The difference between Columns 1 and 2 is that in Column 2 I include fixed effects for parent interacted with wave. As such, I consider the role of each child's characteristics relative to his or her siblings in a given wave in determining whether that child provides care to a particular parent[6].

Several important empirical patterns emerge. Note that as I include dummies for the kid being a daughter and the parent being a mother, the omitted category is son-father pairs. The coefficient on "Parent is mother" is essentially 0, suggesting that sons are equally likely to provide care to their fathers as to their mothers. However, the dummy for "Kid is daughter" is positive and significant, so daughters provide slightly more care than sons to fathers, and the interaction between "Kid is daughter" and "Parent is mother" is large and significant, so daughters provide much more care than sons to mothers[7].

[4]For the purposes of this section, I define a parent as being sick if they have any difficulties with any Activities of Daily Living or Instrumental Activities of Daily Living

[5]Note that if two members of a couple respond to the HRS, then any children they have will appear twice in the regressions below, once for each parent. In other words, the observations in this regression are unique parent-child links, rather than unique children

[6]Because the fixed effects capture any variation common to all children of a particular parent in a given wave - e.g. the gender or marital status of the parent - these explanatory variables drop out of Column 2. I also drop "Kid has sister" as a regressor for the fixed effect regression because I am already controlling for whether a given child's gender relative to their siblings through a combination of controlling for the child's gender and the parent $\times$ wave fixed effect.

[7]This interaction between parent and child gender suggests that at least part of the aggregate care

Table 1: Predictors of care provision and the amount of care provided

	Dependent variable:		
	I(Hours help p.m. >0)		log(Hours help p.m)
	(1)	(2)	(3)
Kid is daughter	0.016***	0.020***	0.144*
	(0.003)	(0.003)	(0.056)
Parent is mother	0.000		0.013
	(0.002)		(0.052)
Daughter × Mother	0.051***	0.052***	0.173**
	(0.003)	(0.004)	(0.064)
Kid is eldest	0.001	0.002	0.008
	(0.002)	(0.003)	(0.034)
Kid is youngest	0.009***	0.006*	−0.014
	(0.002)	(0.003)	(0.033)
Kid lives ≤ 10 miles away	0.115***	0.127***	0.517***
	(0.002)	(0.003)	(0.031)
Kid has sister	−0.013***		−0.074*
	(0.002)		(0.034)
Parent in couple	−0.041***		−0.117***
	(0.002)		(0.032)
Kid in couple	−0.024***	−0.022***	−0.469***
	(0.002)	(0.003)	(0.029)
Kid went to college	0.009***	0.013***	−0.222***
	(0.002)	(0.003)	(0.028)
Kid cared in t-1	0.344***	0.367***	0.442***
	(0.003)	(0.009)	(0.029)
Parent × wave FEs	N	Y	N
Observations	109 844	109 863	13 148
Adjusted R^2	0.237	0.414	0.126
Mean dep. var.	0.106	0.106	3.030

Notes: estimation via OLS. Only children of sick parents (ADL or IADL >0) are included. Regression weights are HRS respondent-level weights. In all regressions, other controls are dummies for number of ADL and IADL difficulties, education of parent, number of total kids of the parent, total number of grandkids of the kid, quadratics in age for kid and parent, a dummy for being White Caucasian and log of wealth. For the fixed effects regression, the parent-level controls drop out. Standard errors clustered at the parent × wave level. *p<0.05; **p<0.01; ***p<0.001.

Youngest children are slightly more likely to provide care than either eldest children or children who are neither youngest nor eldest, though this is much less of a predictor of care provision than the child being a daughter.

Kids are unsuprisingly much more likely to provide care if they live close to their parent. However, it is unclear whether these are children who were living within 10 miles of their parent before the health shock occurred (e.g. they never left the local area) or whether these are children who move back to provide care[8]. If the latter, then this suggests the welfare costs of providing care are greater, because they involve the cost in time and money of relocating, possibly changing jobs, and so on. Also, children moving back to provide care would point to a greater role for strategic interaction because children have more control over whether they are in a position to provide care. I examine this question in Appendix B, considering kids' location choices around their parent falling sick, exploiting the panel nature of the data to conduct an event study. The results offer some evidence that daughters in particular do move closer to parents following a parental health shock.

Kids are less likely to provide care if they have at least one sister[9], a phenomenon to my knowledge first noted by Grigoryeva (2017). The fact that children provide less care if they have a sister hints at the role of strategic interaction between siblings, discussed in more detail in the next section.

Both the parent having a spouse and the kid having a spouse are negatively associated with the probability of the kid providing care. The former is presumably due in part to there being a better "outside option" of care receipt for parents who have spouses; the latter may be because partnered kids have more demands on their time, or have a different set of parents-in-law that they need to spend time with, and so on.

More educated kids are more likely to provide care. Interestingly, this result holds even in Column 2, i.e. even controlling for unobserved heterogeneity at the parent-wave level through a fixed effect. In other words, kids who are more educated than their siblings are more likely to provide care than their siblings. This is striking because this provides some prima facie evidence against the hypothesis that children with a lower opportunity cost of providing care in terms of foregone wages will provide more care. Instead, it

gap is driven by the fact that women are overrepresented among the elderly needing care because fathers tend to die younger than mothers. Indeed, in the estimation sample for Table 1, 61% of parents are mothers. As a rough calculation, the results in Table 1 suggest that if instead there was a 50:50 split of mothers and fathers in the sample then other things being equal daughters would be 4.2pp more likely to provide care in the aggregate rather than 4.7pp, after controlling for all other regressors. This is because $0.61\times(0.051+0.016-0)+0.39\times(0.016-0) = 0.047$ but $0.5\times(0.051+0.016-0)+0.5\times(0.016-0) = 0.042$.

[8]Hiedemann, Sovinsky, and Stern (2018) consider the potential endogeneity of location, finding some evidence that location is endogenous, although the authors argue that any ensuing bias will be small in magnitude.

[9]Note that one of the controls in this regression, as set out in the note beneath Table 1, is the number of children, so this dummy does not just capture the effect of the kid in question having at least one sibling.

seems that within a particular family it is the more educated, and thus likely the higher earning, child who ends up providing more care. This point will be revisited when discussing the results of the estimation of the structural model.

Finally, the coefficient on the dummy for care in the previous period is very large and significant, being more than three times the mean of the dependent variable. This points at the existence of inertia in care arrangements, as discussed in Hiedemann, Sovinsky, and Stern (2018): not only do most sick elderly people have a single primary caregiver, but also care arrangements do not tend to change over time.

Column 3 captures the intensive margin: for those providing positive hours of care, I regress the log of hours of help provided per month on the same explanatory variables as the first column. I do not include FEs here because many parents have only one child providing positive care hours to them in a given wave.

Similar patterns emerge. Daughters provide more care, even conditional on provision of care. This is particularly true when considering care given to mothers. Kids provide much more care if they live close, and slightly less care if they have a sister. It is interesting that conditional on providing care, having a spouse means a kid provides much less care, approximately half of what they would provide if they were single. This negative association is much stronger than the negative association between the parent having a spouse and hours of care provided by the kid. Also, although more educated kids are more likely to provide positive hours of care, they provide less care conditional on positive provision than less educated kids. Finally, if a kid provided care in the previous period then they provide significantly more care in the current period.

2.2 The gender care gap depends on family composition

The fact that kids provide less care when they have at least one sister hints that they might reduce their care effort if they know a sister will "step up" in their absence. Here I consider this point in more detail.

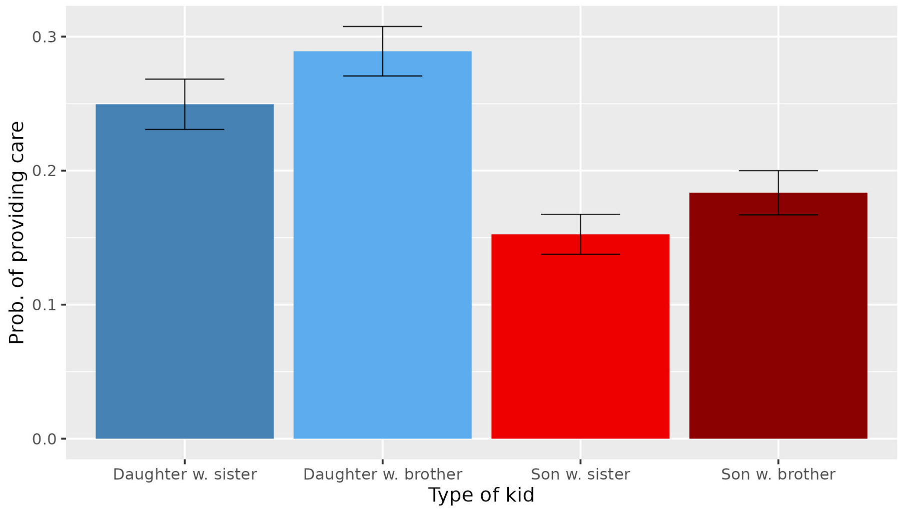
In principle one could examine the role of strategic interaction between children by making use of data on only children in the data, i.e. children without brothers or sisters. If the ratio of care hours by only daughters to only sons is less than the ratio of care hours of daughters to sons within multiple child families, then this suggests that agents change their behaviour depending on the presence of siblings. Table 7 in Appendix A makes this comparison and finds that there is indeed a substantial difference.

The problem with using this approach to identify the role of strategic interaction in driving the gender care gap is that the number of children that a family has is likely endogenous. Parents have a significant degree of control over how many children they have, and thus the number of children they have will likely be correlated with observed and unobserved heterogeneity at the level of the parent.

Instead, I exploit variation in the gender composition of children, holding fixed the total number of children. In particular, I consider care provision by sons and daughters in two-child families. While gender composition could itself be endogenous[10] this is plausibly much less of a concern than for the number of children.

Figure 1 shows the probability of providing any care to a sick single[11] parent for different children in two-child families. The first bar is the probability of providing care by a daughter who has a sister, the second bar is probability of providing care by a daughter with a brother, and so on.

Figure 1: Probability of providing care by type of kid



Notes: probabilities of providing care to a sick single parent for daughters whose only sibling is a sister, daughters whose only sibling is a brother, sons whose only sibling is a sister and sons whose only sibling is a brother.

Figure 1 suggests that daughters provide more care when their other sibling is a brother than when their other sibling is a sister; similarly, sons provide more care when their other sibling is a brother than when their other sibling is a sister. In other words, the graph suggests that relative to the case when their sibling is of the same gender as them, daughters increase their care and sons decrease their care when the sibling is of the opposite gender. An interpretation of this would be that sons shirk caregiving when they know their sisters will "step up" to fill the breach; conversely, daughters put in more effort to compensate for their brothers' shirking.

In Appendix A, Figure 7, I present further information on the implications of this for

[10] For instance, if parents decide to keep having children until they have a daughter, then they are in some sense choosing the final gender composition of their children. Angrist and Evans (1998) use the sex mix of the first two children to predict whether a woman will have a third child, exploiting parents' preferences in general for having children of both sexes. Preferences for having children of both sexes - or alternatively preferences for having at least one daughter - might be plausibly correlated with e.g. expected care need in old age.

[11] I focus here on single parents because in married couples the partner tends to be the primary caregiver and because children of single parents will be the focus of my model.

total child-provided care hours received by the parent. I also discuss the issue of the influence of family composition of a person's family-in-law on their caring decisions, and argue that it is not of first-order importance to consider interaction between nuclear families as well as within nuclear families when it comes to the provision of care[12].

2.3 Most child caregivers do not receive substantial compensation

There is little prima facie evidence of child caregivers in the US receiving contemporaneous cash compensation from their parents (Barczyk and Kredler 2018; Groneck 2017). It is possible, however, that children are compensated by their parents in other ways. I consider here whether caregiving children receive higher bequests. In Appendix C, I discuss two other candidate mechanisms of compensation, namely that children are compensated through the provision of rent-free accommodation and through the provision of childcare.

2.3.1 Compensation through bequests

Groneck (2017) uses 2002-2012 HRS Exit data on the bequests of single parents to argue that children who provide care receive more bequests than their non-caring siblings. He finds that, using family fixed effects to control for heterogeneity at the level of the family, a child who provides care is 5.4pp more likely to receive a bequest and, considering only children of parents with a positive estate to bequeath, children who provide care receive on average \$19.6k more than their siblings who do not provide care[13].

To assess this mechanism, I carry out a set of fixed effects regressions of measures of bequests on child characteristics, using 2002-2018 HRS Exit data, i.e. using three more waves of HRS Exit data[14]. In each case, the regression takes the form:

$$Y_i = \alpha_f + X_i\beta + \gamma CARE_i + \epsilon_i \tag{1}$$

where Y_i is the outcome variable[15], α_f is a fixed effect for family f, X_i is a vector of

[12] More broadly, parents who only have sons see a drop off in the total hours of care they receive from their family, so daughters-in-law are clearly not generally stepping in and compensating for their husbands lack of care. For sick single parents with two children, those with two sons receive 39 hours of care from all family sources per month on average, compared to 54 hours for parents with one son, one daughter and 58 hours for parents with two daughters.

[13] As well as the family fixed effects model, Groneck (2017) also presents results from a 2SRI model and a Tobit model.

[14] As far as possible I use the same methods of sample selection and of construction of measures of bequests as in Groneck (2017). I would like to thank Max Groneck for sharing his replication code.

[15] This is either a dummy for receiving any bequest or the size of the bequest that child i receives in

controls (see notes of Table 2), and $CARE_i$ is a dummy for whether child i provided care with (I)ADLs before the parent's death.

The main results of these regressions confirm the findings of Groneck (2017): using the longer HRS 2002-2018 exit sample, I find that a child who provides care is 4.9pp more likely to receive a bequest and considering only children of parents with a positive estate to bequeath, children who provide care receive on average $14.3k more than their siblings who do not provide care.

However, as pointed out in Groneck (2017), many parents do not have an estate to bequeath in the first place: in my 2002-18 HRS Exit sample, only 54% of children have parents who die with a positive estate to bequeath. As such, it is difficult to infer from these headline results how much extra the *typical* child would expect to receive relative to their siblings if they provide care[16]. To assess this, I carry out a series of further regressions of the size of a bequest that a child receives on the same RHS variables but in each case changing the subsample of observations used.

Table 2: Bequest received by care provided

	Dependent variable:				
	Bequest received ($1000 in USD2012)				
	(1)	(2)	(3)	(4)	(5)
$CARE_i$	14.283***	8.318***	6.731***	4.082***	3.118***
	(3.052)	(1.777)	(1.438)	(0.744)	(0.526)
Parent FEs	Y	Y	Y	Y	Y
Observations	6681	12 428	12 303	11 805	11 185
Adjusted R^2	0.828	0.838	0.851	0.802	0.730
Mean Dep. Var	64.094	34.456	25.693	13.801	8.288

Notes: estimation via OLS. Column 1 considers only those children of parents with a positive estate at death. Column 2 considers all children. Column 3 drops children of parents with estates above the 99th percentile. Column 4 drops children of parents with estates above the 95th percentile. Column 5 drops children of parents above the 90th percentile. Controls are age of child, child education, child income, whether the child owns a home, whether the child lives within 10 miles of the parent, whether the child is co-resident with the parent and frequency of contact with the parent. *p<0.05; **p<0.01; ***p<0.001.

Column 1 shows the baseline result, using only the children of parents with a positive estate to bequeath. In Column 2, I run the regression for all children, including the 46%

2012 dollars

[16]Groneck (2017) does examine how bequests change along the wealth distribution by carrying out the regression in Equation 1 individually for each quintile of total family bequests, finding that in each case caregiving children receive higher bequests than their non-caregiving siblings. However, the regressions still condition on the parent having a positive amount to bequeath.

of children whose parents die without a positive estate to bequeath. As such, rather than only capturing the intensive margin of bequest receipt, I capture the intensive and extensive margins together. The coefficient on $CARE_i$ is cut almost in half as a result of expanding the sample.

The baseline result is also significantly driven by extreme results towards the top of the distribution of wealth. In Columns 3, 4 and 5, I restrict the sample of Column 2. In Column 3, I drop children of parents with estates above the 99th percentile in size; in Column 4, I drop children of parents above the 95th percentile; and in Column 5, I drop children of parents with estates above the 90th percentile.

As more and more of the children of richer parents are dropped, the coefficient on $CARE_i$ unsurprisingly gets smaller. What is notable, however, is that even considering the bottom 90% of children in terms of parental wealth (i.e. looking at Column 5), the coefficient is much smaller (around $5\times$) than the headline result[17].

As such, it is interesting and important that on average, the mean caregiving child receives a significantly larger bequest than the mean non-caregiving child within a particular family. However, the results above suggest that the typical e.g. median caregiving child can expect much less in the way of compensation for providing care.

In Appendix C I discuss two other mechanisms by which children might be compensated for providing care: through rent-free accommodation and through childcare. In neither case do I find convincing evidence that caregiving children receive substantial compensation through these channels. As such, overall, the evidence of this section suggests that although some child caregivers to parents may receive compensation for doing so, whether in the form of increased bequests, rent-free accommodation or childcare, this is not the case for most child caregivers. This is important because it implies the gender care gap is a welfare-relevant gap: it is not that daughters are more likely to provide care yet receive compensation for doing so, rather they provide largely uncompensated care.

The results above suggest that many elderly people rely on their children to provide care, yet there is unequal sharing of the caring responsibility among the children. In particular, daughters are more likely to provide care. Sons who have a sister act strategically by reducing their care effort knowing their sisters will "step up" in their absence; conversely, daughters with brothers put in more effort to compensate for the fact that their brothers are less likely to provide care.

[17] According to Genworth (2024), formal care in the form of a full-time homemaker health aide costs \$4760 per month in 2012 USD, suggesting that if we interpret the extra bequest for caregiving children as payment for their lifetime labour then these children are being paid a very small fraction of the market rate for care work, given that children often provide care for months or years at a time.

3 Model

3.1 Model overview

The model consists of a repeated game between two agents: Child A (elder) and Child B (younger). The two agents have a common single elderly parent. The parent is entirely passive in the sense that their decisions are entirely determined by state variables and their children's decisions.

At the start of each period, the parent experiences health and wealth shocks. After these shocks are realised, if the parent is still alive, the two agents simultaneously make (discrete) location, labour and care provision decisions and flow payoffs are realised. If the parent is sick and child i provides care but child j does not then both children derive a benefit from care being provided but only child i bears the cost of the provision of care. In this sense, the game resembles a public good provision problem: it is costly to provide the public good (informal care to a parent), yet both children derive a benefit if this good is provided. If neither child provides care then the parent pays for formal care out of pocket, decreasing the potential bequest that the children receive. When the parent dies, then their remaining wealth is split equally between the children as a bequest.

3.2 Environment

Time is discrete, with each period lasting 2 years, matching the gap between HRS interview waves. The parent's health in period t is given by $h_t \in \{0, 1, 2, 3\}$, where $h_t = 0$ denotes that the parent is healthy, $h_t = 1$ denotes that the parent has moderate care needs, $h_t = 2$ denotes that the parent has severe care needs and $h_t = 3$ denotes that the parent is dead. At the start of the game, the parent is healthy, has age age_0 (with a maximum age of 100), and the game ends when the parent dies. The parent's health follows a first-order Markov process, with transition probabilities varying by current health, age and permanent income. I assume health transitions are exogenous and do not depend on informal care receipt, following the findings of Byrne et al. (2009) that care receipt does not substantively change health.

3.2.1 Choices

Each period the two children simultaneously make location, labour market and care decisions. Each child i can choose *Near* or *Far* as their location, where *Near* means the child lives within 10 miles of the parent and *Far* means the child lives further than 10 miles away[18], and each child can choose *No work* or *Work* as their labour market

[18] I assume all moving is done by children, and parental location is held fixed. As set out in Appendix B, in my HRS descriptives sample approximately four times out of five when a child lives far in one wave

choice. If their parent is healthy ($h_t = 0$), children choose *No care provision* by default; if their parent is sick ($h_t = 1$ or $h_t = 2$) children choose either *Care provision* or *No care provision.* Thus in general in each period t each child i makes a single discrete choice d_t^i out of the feasible set of choices F_t, where F_t has $2 \times 2 \times 1 = 4$ elements if the parent is healthy and $2 \times 2 \times 2 = 8$ elements if the parent is sick.

3.2.2 Preferences

Child i's per period flow utility when the parent is alive is:

$$u_i(d_t^i, d_t^j, s_t, \epsilon_t^i) = g(c_t^i, l_t^i) + \omega(d_t^i, d_t^j, s_t) + \phi(d_t^i, s_t) + \epsilon_t^i(d_t^i) \tag{2}$$

The first component of utility is $g(\cdot)$, which captures utility from consumption c_t^i and leisure l_t^i. The other components of utility are $\omega(\cdot)$, which captures the (dis-)utility associated with the provision and receipt of care, $\phi(\cdot)$ which captures the (dis-)utility associated with the child's location choice, and a Type 1 Extreme Value preference shock ϵ_t^i associated with child i's discrete choice d_t^i. The (dis-)utility associated with the provision and receipt of care and with the location choice depends on the set of common states s_t as well as both children's care decisions. The preference shock ϵ_t^i is *iid* across choices, children and time and has scale one.

The $\omega(\cdot)$ function takes the form:

$$\omega(d_t^i, d_t^j, s_t) = \omega_{pg}(d_t^i, d_t^j, s_t) + \omega_{warm}(d_t^i, s_t) \tag{3}$$

Here, $\omega_{pg}(\cdot)$ ("public good") captures the benefit to child i of their parent receiving informal care when sick, regardless of who provides the care. In other words, this is the benefit the child derives from the public good of having a cared-for parent[19], which is why it depends on child j's care choice as well as child i's.

The other term in the equation for $\omega(\cdot)$, namely $\omega_{warm}(\cdot)$, captures the "net warm glow" to child i of they themselves being the child who provides care - in other words, the net utility benefit associated with the act of providing care. This is part of utility does not depend on the other child's care choice. Note that it is plausible that the "net warm glow" of caring for a parent is negative, once the mental and physical burden of providing the care is taken into account. I defer the exact parameterization of $\omega_{pg}(\cdot)$, $\omega_{warm}(\cdot)$ and $\phi(\cdot)$ to Section 3.4.

and near in the next it is because the child has moved rather than the parent moving.

[19] In particular a parent who receives care from a family member, rather than from a formal source.

3.2.3 Resources

As in Ko (2022), children divide their time between work, care time and leisure, and do not save any of their income. As such, they face two budget constraints, one for consumption and one for leisure:

$$c_t^i = w(d_t^i, s_t) \tag{4}$$

$$l_t^i = \bar{H} - H_{kt}^i - H_{wt}^i \tag{5}$$

In the first constraint, $w(\cdot)$ is the equivalised income function, determining child i's equivalised income (and hence consumption) as a function of their discrete choice d_t^i and the set of common states s_t (which will include elements like demographics). In the second constraint, $\bar{H}$ is the total amount of hours available per period, H_{kt}^i is hours spent caring and H_{wt}^i is hours spent working.

3.2.4 Parental wealth and bequests

As set out above, the parent's decisions in the model are entirely determined by state variables and their children's choices.

The parent starts the model with assets a_0. Their budget constraint takes the form:

$$a_{t+1} = a_t - (c_t^P - y^P) - ltc_t + b_t + \xi_{t+1} \tag{6}$$

Thus, assets tomorrow are equal to assets today minus consumption net of permanent income $(c_t^P - y^P)$, minus out-of-pocket long-term care costs ltc_t, plus government benefits (including Medicaid) b_t and an *iid* wealth shock ξ_{t+1}, with distribution $N(\mu_\xi, \sigma_\xi^2)$.

I assume the parent always consumes their permanent income, so $c_t^P - y^P = 0$.

Long-term care costs are 0 when the parent is healthy. I assume that government benefits are such as to guarantee each parent their permanent income in consumption[20], i.e.

[20] This is not a substantive assumption: the decisionmakers in the model, i.e. the children, only care about whether their parent receives care and how much wealth they would receive as a bequest. Thus, having a Medicaid consumption floor and having parents consume at this lower level when they have no assets would produce the same behaviour in children, because parents' wealth would be the same.

$$b_t = max(0, ltc_t - a_t - \xi_{t+1}) \tag{7}$$

Thus, when the parent is healthy in period t, we will have that

$$a_{t+1} = max(0, a_t + \xi_{t+1}) \tag{8}$$

i.e. assets will follow a random walk (with drift, if $\mu_\xi \neq 0$), subject to the constraint that they are positive. Similarly, if the parent is sick ($h_t > 0$) but receives care from at least one child, then they have no need to pay for formal care, so $ltc_t - b_t = 0$ still and the process for wealth is the same.

If, instead, the parent is sick and receives no care from a child, then they face positive long-term care costs. The amount of out-of-pocket cost that a parent faces will depend on the severity of their condition. The process for wealth in this case will be:

$$a_{t+1} = max(0, a_t - ltc_t + \xi_{t+1}) \tag{9}$$

When the parent dies, their assets are split equally among their two children (regardless of who if anyone provided more care). Following Ko (2022), I assume that the children's terminal value is then the utility they would get from working full-time for the next T_{beq} periods, optimally splitting the consumption of the bequest over those periods, which provides a terminal payoff for the children to close the model[21].

In summary, apart from the direct utility benefit and cost to them of doing so, children are incentivised to provide informal care when their parent is sick to stop their potential bequest being run down. This matches the mechanism in other papers like Ko (2022) and Barczyk and Kredler (2018).

3.3 Equilibrium

Let $\sigma^i(s_t, \epsilon_t^i)$ be child i's strategy, i.e. a mapping from the set of common states at t, denoted by s_t, and the vector of preference shocks, to the child's set of feasible actions

[21]It may seem contradictory to include a bequest channel in the model when in Section 2 I argued that most children do not receive substantive compensation for their care in the form of bequests. However, the difference is that in Section 2 I was arguing that caregiving children do not tend to receive substantively more than their non-caregiving siblings. This is consistent with children still being motivated to provide care to prevent the overall level of the bequest - and hence their (equal) share of the bequest - from decreasing in size.

in t, denoted by F_t, which will depend on the health of the parent[22]. Then, let $\sigma = \{\sigma^i, \sigma^j\}$ be the strategy profile across the children.

The child i's value function is

$$V^i(s_t, \epsilon_t^i, \sigma) = \max_{d_t^i \in F_t} \left\{ E[u^i(d_t^i, d_t^j, s_t, \epsilon_t^i) + \beta V^i(s_{t+1}, \epsilon_{t+1}^i, \sigma) | s_t, d_t^i, \sigma] \right\} \tag{10}$$

Let the child i's choice-specific value function for d_t^i be their expected flow payoff from choosing d_t^i, less the value of the preference shock associated with d_t^i, plus the expectation of their discounted future value function:

$$v^i(d_t^i, s_t, \sigma) = E[\pi(d_t^i, d_t^j, s_t) + \beta V^i(s_{t+1}, \epsilon_{t+1}^i, \sigma) | s_t, d_t^i, \sigma] \tag{11}$$

where $\pi(d_t^i, d_t^j, s_t) = u(d_t^i, d_t^j, s_t, \epsilon_t^i) - \epsilon_t^i(d_t^i)$.

Then, the strategy profile σ^* is a Markov Perfect Equilibrium iff:

$$\sigma^{*i}(s_t, \epsilon_t^i) = \text{argmax}_{d_t^i \in F_t} \left\{ v^i(d_t^i, s_t, \sigma) + \epsilon_t^i(d_t^i) \right\} \tag{12}$$

for all t, for all s_t, for all ϵ_t^i and for all $i \in \{A, B\}$. This equilibrium condition captures the idea that in an equilibrium, each player's strategy is a best response to all other players' strategies.

The model will not in general have a unique equilibrium, because players move simultaneously when making decisions. I will assume that in each family in the data the same unique equilibrium is being played. This is a strong assumption but it is difficult to allow for multiple equilibria in estimation given the relatively small number of periods when I observe each family[23]. Alternatively, I could change the model to ensure there is a unique equilibrium by specifying that players move sequentially in each period, with knowledge of the previous player's move, but it is not clear on what basis to select the first-mover in each case, and the model would be assuming significant differences between the first- and second-moving child that plausibly do not exist in reality. Moreover, the estimation results in Section 4 indicate that children's care decisions are not strongly correlated conditional on unobservables suggesting that there is not a significant problem of multiple equilibria or other unobserved heterogeneity at

[22] For instance, when the parent is sick, F_t will equal {(0, 0, 0), (0, 0, 1), (0, 1, 0), (0, 1, 1), (1, 0, 0), (1, 0, 1), (1, 1, 0), (1, 1, 1)}, where the first element in each triple is the care choice, the second element is the location choice and the third element is the labour market choice; when the parent is healthy, F_t will consist only of the first four of these eight triples.

[23] This stands in contrast to examples from the industrial organisation literature, where long panels for each market mean that an econometrician could allow for each market to have its own equilibrium, see e.g. Aguirregabiria, Collard-Wexler, and Ryan (2021)

the family level in the data. I do however account for the possibility of multiple equilibria when conducting counterfactual exercises in Section 5.

3.4 Functional forms and parameterisation

In this subsection I discuss the exact functional forms I choose to provide structure to the model.

3.4.1 Utility over consumption and leisure - $g(\cdot)$

I assume that agents have Cobb-Douglas preferences over consumption and leisure:

$$g(c_t^i, l_t^i) = \theta_c \log(c_t^i) + \theta_l \log(l_t^i) \tag{13}$$

.

The scale of the parameters is normalised by the variance of the *iid* Type 1 Extreme Value preference shock in Equation 2, which I set equal to 1.

3.4.2 "Public good" component of care utility - $\omega_{pg}(\cdot)$

As set out above, $\omega_{pg}(\cdot)$ captures the benefit to a child of their parent receiving some form of informal care, regardless of which child provides it. Letting k_t^i be a dummy for whether child i provides care at t, I write it as:

$$\omega_{pg}(\cdot) = \begin{cases} \alpha_{h1}, & \text{if } h_t = 1 \ \& \ k_t^i + k_t^j > 0. \\ \alpha_{h2}, & \text{if } h_t = 2 \ \& \ k_t^i + k_t^j > 0. \\ 0, & \text{otherwise.} \end{cases} \tag{14}$$

Thus, for instance, if the parent has health $h_t = 1$ and at least one child provides care ($k_t^i + k_t^j > 0$) then both children receive benefit α_{h1}, regardless of who actually provided the care. The benefit they derive potentially varies with the severity of the health condition of the parent.

3.4.3 "Net warm glow" component of care utility - $\omega_{warm}(\cdot)$

The function ω_{warm} captures the utility net benefit to child i of they themselves providing care (i.e. regardless of what their sibling does):

$$\omega_{warm}(\cdot) = \begin{cases} X_t^i \gamma & \text{if } h_t > 0 \ \& \ k_t^i > 0. \\ \\ 0, & \text{otherwise.} \end{cases} \tag{15}$$

where X_t^i is a set of characteristics of the child and parent. In particular, X_t^i contains controls for:

- The severity of parental health problems ($h_t = 1$ or $h_t = 2$). It is plausible both that the cost of providing care, and the "warm glow" from doing so (or guilt from not doing so) will vary with the severity of the parent's health problems;
- Whether the child lives further than 10 miles from the parent at the time of providing care. This is to capture the extra time and money spent in travelling to provide care;
- Whether the child lived further than 10 miles from the parent at the start of the game. Briefly, this is because it is possible that children who live far from their parents at the start of the game are systematically different from those who live near in terms of unobserved attitude or affection towards a parent. This issue is discussed in more detail in Appendix D;
- Whether the child is a son. Allowing the net benefit of providing care to depend on child i's gender means that the model allows for there to be unobserved preference differences between men and women when it comes to the provision of care to their parents. In principle, this simple preference difference could capture lots of different types of differences in the situations of sons and daughters. For instance, if the coefficient on son^i is negative, this could capture the fact that daughters genuinely derive more enjoyment from providing care than sons; or that daughters are "better" are providing care than sons in the sense that for a given unit of costly effort daughters will provide more effective care than sons; or that parents prefer receiving care from daughters rather than sons, and it is costly to go against parents' wishes; or that it is costly to go against some norm in society regarding daughters' role as primary caregiver; or some combination of these explanations. For instance, Byrne et al. (2009) argue both that daughters are better at providing care than sons and experience less burden from doing so. For the sake of tractability of the model I do not distinguish between these separate drivers of preference difference between sons and daughters.
- Whether the parent is a father, and an interaction between parent and child gender. This is to allow for the stylised fact from Section 2 that mothers receive more care

overall and that daughters seem to provide relatively more care to mothers while sons provide relatively more care to fathers

- Whether the child is switching from non-provision to care provision this period. This is to capture an important dynamic aspect of care provision, namely the inertia of care provision arrangements: families tend to have a primary caregiver which does not change over time (Hiedemann, Sovinsky, and Stern (2018). It is important to include this term for the sake of capturing the nature of strategic interaction between children. If providing care in one period causes a child to be "locked in" to the caregiving role, in the sense that the cost of them providing care in subsequent periods will be much lower than that of their siblings, then this makes the initial strategic interaction between the children at the point of a parent falling sick more significant in explaining the distribution of care roles into the future;
- Whether the child is the younger of the two children ("seniority"), and an interaction between seniority and child gender, to capture any social norms or preference differences connected with being the eldest/youngest child, and in particular with being an eldest/youngest daughter.

I write Equation 15 out in full in Appendix D, where I also discuss the issue of unobserved heterogeneity in preferences for providing care.

3.4.4 Location choice utility - $\phi(\cdot)$

The flow utility from location choice is comparatively simple:

$$\phi(\cdot) = \phi_{far} far_t^i + \phi_{move} I(far_t^i \neq far_{t-1}^i) \tag{16}$$

Thus, children derive (dis-)utility from living far from their parents, and also derive (dis-)utility from changing their location. These parameters thus capture whether overall it is more attractive to live far from one's parents for whatever reason, and how costly it is to move.

4 Estimation

4.1 Estimation sample

For the estimation sample I use data from HRS Waves 4 to 14 (1998-2018). I select those families with one surviving parent and exactly two child records in a given year, where the parent is aged between 55 and 85 in the first observation in the data[24].

[24] If the family is observed at parent ages before 55, I drop all observations until the parent is 55.

I drop any parents who hold long-term care insurance[25]. I drop any cases where in the first period where the family is observed the parent is sick and either child provided care in the previous period. I do this so at the start of the sample I avoid an "initial conditions" problem of children already having selected into caregiving, as discussed in Appendix D. Finally, in cases where data on care, work, location, education or marital status of child, or health of the parent, are missing for a single wave I impute this from the child's data in the previous period but if the data missing for more than one consecutive wave I drop the family from the first wave with missing data.

I am left with an estimation sample of 8444 family-wave observations, consisting of 2459 families who are in the sample for an average of 3.4 waves each. I split the estimation sample into two groups: those where the parent is aged 55-69 in the first observation ("younger"), and those where the parent is aged 70-85 in the first observation ("older"). I assume that all those in the younger group are aged 63 in the first period and all those in the older group are aged 78 in the first period. I also split the estimation sample into those who are above and below median parental permanent income[26].

4.2 Parameters from outside the model

Many of the parameters of the model I set using values from the literature or directly from the data. The choices are summarised in Table 3 below.

In Appendix E, I discuss in more detail how I arrive at these external parameters.

4.3 Parameters estimated inside the model

I estimate the rest of the model by maximising the pseudo likelihood of agents' choices (Aguirregabiria and Mira 2007). There are 16 parameters to be estimated, summarised in Table 4 below.

I follow Ko (2022) in using the insight of Bajari, Benkard, and Levin (2007) regarding exploiting the linearity of the flow payoff function, thus the value function, to speed up estimation.

My approach is as follows. I start by estimating agents' conditional choice probabilities (CCPs) in each state using a logit regression of observed choices in the data on state variables[27]. I then use these CCPs to construct the value functions via simulation.

Specifically, let the true probability of child i choosing discrete choice d_t given state variables s_t and strategy profile σ be:

[25] I drop these parents because I do not model LTCI choice or coverage. Only 10% of the full HRS sample has LTCI.

[26] I calculate each parent's PI as the mean of their income for each period that they are observed in the data.

[27] The state variables in the model are the gender, starting location, education, marital status, previous location, previous caring and previous labour force decision of each child; the gender, health, wealth, permanent income group, starting age (older/younger) and age difference from starting age of the parent

Table 3: External parameters

Parameter	Value	Source
Health transition probabilities	-	HRS
Formal care cost p.a., $h_t = 1$	\$15.0k	Genworth (2024)
Formal care cost p.a., $h_t = 2$	\$74.6k	Genworth (2024)
Informal care hours p.w., $h_t = 1$	13	HRS
Informal care hours p.w., $h_t = 2$	25	HRS
Full-time work hours p.w	35	Author's choice
μ_ξ	-\$2.0k	HRS
σ_ξ	\$115.3k	HRS
Income process	-	PSID
Initial age	{63, 78}	HRS
Terminal age	100	Author's choice
T_{beq}	5	Author's choice
Age gap to elder child	24	HRS
Age gap to younger child	29	HRS
β	0.93	Author's choice

Notes: see Appendix E for detail on how these values are chosen or estimated.

$$P^i(d_t|s_t,\sigma) = \int I(\sigma^i = d_t|\epsilon_t^i) f(\epsilon_t^i) d\epsilon_t^i \tag{17}$$

i.e. the probability that d_t is the option "chosen" by i's strategy given the preference shocks.

I estimate the sample analogue of Equation 17 from the data using a logit regression, regressing observed choices on the set of observed common states in the data s_t. This produces estimates of the form $\hat{P}^i(d_t|s_t)$[28].

Using the fact that preference shocks are *iid* Type 1 Extreme Value, the choice-specific value function for choice d_t, relative to some reference choice d_t^0, will be:

$$v^i(s_t, d_t, \sigma) - v^i(s_t, d_t^0, \sigma) = \ln P^i(d_t|s_t,\sigma) - \ln P^i(d_t^0|s_t,\sigma) \tag{18}$$

and thus I can recover an estimate of the strategy of child i using:

[28]There is no equivalent of σ in this expression because strategies are not directly observed. Recall that I assume that there is only one equilibrium being played in the data, thus all children must be using the same strategy conditional on whether they are the older or younger child

Table 4: Parameters estimated inside the model

Parameter	Description
Consumption and leisure	
θ_c	Weight on consumption
θ_l	Weight on leisure
Child's "public good" utility of providing care given that...	
α_{h1}	Parent is in moderate bad health
α_{h2}	Parent is in severe bad health
Child's "net warm glow" utility of providing care given that...	
γ_{h1}	Parent is in moderate bad health
γ_{h2}	Parent is in severe bad health
γ_{son}	Child is a son
γ_{dad}	Parent is a father
γ_{start}	Child starts providing care this period
$\gamma_{origfar}$	Child originally lived far from parent
γ_{far}	Child currently lives far from parent
$\gamma_{youngest}$	Child is youngest sibling
$\gamma_{youngest \times son}$	Child is youngest sibling and is a son
$\gamma_{dad \times son}$	Parent is a father and child is a son
Child's utility from location choice given that...	
ϕ_{far}	Child lives far from parent
ϕ_{move}	Location choice utility, child moved this period

Notes: see Section 3 and Appendix D for discussion of how these parameters enter into a child's utility function.

$$\hat{\sigma}^i(s_t, \epsilon_t^i) = \text{argmax}_{d_t^i \in F_t} \left\{ \ln \hat{P}^i(d_t^i | s_t) - \ln \hat{P}^i(d_t^{i0} | s_t) + \epsilon_t^i(d_t^i) \right\} \tag{19}$$

which is derived by substituting the sample analogue of Equation 18 into the definition of equilibrium in Equation 12 [29].

Given the policy function estimates $\hat{\sigma}$, I estimate the value functions by using $\hat{\sigma}$ to simulate forward and summing up flow payoff in each period. I do this for S simulation draws and then take the mean of each simulated value function as my estimate. As in Ko (2022), because the flow payoff functions, hence the value functions, are linear in parameters, this simulation procedure has only to be done once. This is because the value function $V(s_t, d_t, \sigma)$ can be written as $W(s_t, d_t, \sigma)\theta$, where θ is the vector of parameters to be estimated and where $W(s_t, d_t, \sigma)$ does not depend on unknown parameters, so I only need to estimate $W(s_t, d_t.\sigma)$ once and then scale by the candidate parameter value θ. I then choose the θ to maximise the pseudo likelihood of the observed choices, as in Aguirregabiria and Mira (2007). This process is discussed in more detail in Appendix F.

4.4 Identification

I here provide some informal arguments for how the parameters of the model can be identified by variation in the data.

The relative size of the consumption and leisure preference parameters is pinned down by agents' work and care choices. First, the more that people in general choose full-time work rather than no work, the more important is consumption relative to leisure for them. Also, working hours are the same regardless of demographics but certain demographics (e.g. being a man) are associated with a bigger income, hence consumption, when working relative to not working. This provides extra variation in the incentive to work rather than to take leisure which will provide better identification of the relative sizes of the consumption and leisure parameters.

The preference for living far from one's parent is pinned down by the proportion of children who live far from their parent, and the transition cost of changing location is pinned down by the rate of transition between the two location statuses.

The overall motivation to provide care – i.e. the sum of the "public good" and "net warm glow" parameters – is pinned down by different rates of providing care according to different demographics in the data.

Finally, the relative sizes of the "public good" and "net warm glow" parameters is pinned down by variation in the probability of each child's sibling providing care.

[29] To do this one must recognise that $\text{argmax}_{d_t^i \in F_t} \left\{ v^i(d_t^i, s_t, \sigma) + \epsilon_t^i(d_t^i) \right\} = \text{argmax}_{d_t^i \in F_t} \left\{ v^i(d_t^i, s_t, \sigma) - v^i(d_t^{i0}, s_t, \sigma) + \epsilon_t^i(d_t^i) \right\}$ for reference choice d_t^{i0}

Consider two children, Arnold and Bob, who belong to two different families. Arnold and Bob are identical apart from the fact that Arnold's sibling has demographics associated with providing a lot of care (e.g. Arnold has a sister) but Bob's sibling has demographics associated with not providing much care (e.g. Bob has a brother). If Bob is just as likely to provide care as Arnold, this suggests that the "public good" motivation to provide care is much less than the "net warm glow" motivation, because Bob's lower probability of having a sibling "step up" to cover Bob's failure to provide care does not change how likely he is to provide care. However, if Bob is more likely to provide care than Arnold, this suggests that the "public good" motivation is important. In other words, Bob is more motivated to provide care because he knows it is unlikely his sibling will provide the public good if he does not, whereas Arnold is comfortable shirking and letting his sister provide care. Thus, the extent to people like Bob provide more care than people like Arnold pins down the relative roles of "public good" motivations and "net warm glow" motivations.

4.5 Results

The results of the estimation are given in Table 5 below. I estimate standard errors using 20 bootstrap replications.

For the Baseline model (Column 1), the key results are as follows. Children in the model are estimated to have low preference for leisure relative to consumption[30]: the estimates imply that on average agents would be willing to give up 16% of their leisure time for around a 10% increase in their equivalised consumption.

As for the "public good" care choice parameters, having a parent with either moderate or severe care needs receive informal care from their children is a public good for those children: both children derive a notable positive benefit regardless of who provides the care, though the coefficient for severe health problems is not significant at the 5% level (though it is significant at the 10% level). Interestingly, the public good benefit seems to be larger when the parent's health problems are moderate rather than severe, though the difference is not statistically significant.

As for the "net warm glow" care choice parameters, it is important to recognise that the reference category of child in the estimation is a daughter who lives close to their parent (both now and at the start of the game), who provided care the previous period, who is the elder of the two children and whose parent is a mother[31]. Thus, γ_{h1} and γ_{h2} reflect the net warm glow to this type of child from providing care when the parent has

[30] The scale of all coefficients is determined by the variance of the Type 1 Extreme Value preference shock, which I have normalised to 1.

[31] This is because I estimate coefficients on dummies for being a son, for living far from the parents in the current period and at the start of the game, for starting providing care this period, for being the younger of the two children and for the gender of the parent, thus the omitted category is as described

Table 5: Estimation results

	(1) Baseline	(2) No PG utility	(3) No gender diff.	(4) No health diff.
Consumption and leisure params				
θ_l - weight on leisure for K	0.948***	0.950***	0.952***	0.939***
	(0.058)	(0.059)	(0.062)	(0.059)
θ_c - weight on consumption for K	1.478***	1.478***	1.479***	1.473***
	(0.034)	(0.035)	(0.034)	(0.033)
Public good care params				
α_{h1} - P in moderate bad health	1.539**	-	1.750***	1.115*
	(0.539)	-	(0.527)	(0.459)
α_{h2} - P in severe bad health	1.104	-	1.223*	-
	(0.580)	-	(0.557)	-
Net warm glow care params				
γ_{h1} - P in moderate bad health	-0.682	0.602***	-1.037*	-0.146
	(0.505)	(0.159)	(0.490)	(0.438)
γ_{h2} - P in severe bad health	0.011	0.884***	-0.261	-
	(0.524)	(0.158)	(0.491)	-
γ_{son} - K is a son	-0.455*	-0.508*	-	-0.461*
	(0.217)	(0.215)	-	(0.216)
γ_{start} - K just starting caring	-1.201***	-1.327***	-1.232***	-1.260***
	(0.141)	(0.122)	(0.139)	(0.139)
$\gamma_{origfar}$ - K originally lived far	0.037	0.011	0.053	0.055
	(0.128)	(0.126)	(0.125)	(0.124)
γ_{far} - K currently lives far	-0.919***	-0.954***	-0.917***	-0.927***
	(0.170)	(0.170)	(0.171)	(0.167)
$\gamma_{younger}$ - K younger of two siblings	0.107	0.124	0.130	0.112
	(0.139)	(0.131)	(0.118)	(0.135)
$\gamma_{younger \times son}$ - K younger & K son	0.045	0.031	-	0.033
	(0.295)	(0.289)	-	(0.292)
γ_{dad} - P is father	-0.434*	-0.343*	-0.278	-0.436*
	(0.182)	(0.163)	(0.159)	(0.174)
$\gamma_{dad \times son}$ - P father & K is son	0.372	0.387	-	0.419
	(0.276)	(0.270)	-	(0.270)
Location choice params				
ϕ_{far} - K currently lives far	0.041**	0.045**	0.040*	0.041**
	(0.016)	(0.016)	(0.016)	(0.016)
ϕ_{move} - K moved location	-1.494***	-1.495***	-1.494***	-1.494***
	(0.012)	(0.012)	(0.012)	(0.012)
LR test statistic	-	16.211	13.718	9.046
p-value	-	<0.001***	0.001**	0.011*

Notes: "P" refers to the parent and "K" refers to the kid. Estimation via PML maximization. Standard errors calculated using 20 bootstrap replications.*p<0.05; **p<0.01; ***p<0.001.

moderate and severe care needs respectively. The other γ parameters modify this net warm glow for other types of child.

Sons have a bigger utility cost of providing care than daughters: γ_{son} is negative and significant[32]. To provide a sense of the economic significance of the estimated parameter, the estimates imply that if a daughter with certain demographics was indifferent between providing care or not, an agent who was identical apart from the fact that he was a son instead would have to receive a 31% increase[33] in equivalised consumption as compensation for providing care to be indifferent between providing care and not.

Unsurprisingly there are major start-up costs associated with providing care: γ_{start} is negative and significant. This lines up with the results in Ko (2022) and Skira (2015).

Whether a child lived far from the parent at the start of the game does not have a significant impact on their net benefit of providing care, as $\gamma_{origfar}$ is estimated as a noisy zero. In other words, these children do not seem to be systematically different (above and beyond their original location choice) from other children who near to the parent at the start of the game. However, whether or not a child lives near the parent at the point of providing care is very important to their net benefit of providing care: the coefficient γ_{far} is negative and significant.

Younger children do not seem to be systematically different to older children when it comes to the provision of care as neither $\gamma_{younger}$ nor $\gamma_{younger \times son}$ is significant.

The results for the gender of the parent match up with the stylised empirical facts. Fathers are less likely to receive care than mothers ($\gamma_{dad} < 0$), but the gender gap in care for fathers in less than the gender gap in care for mothers ($\gamma_{dad \times son} > 0$), though this latter coefficient is not statistically significant.

Finally, as for the location choice parameters, children have a slight preference for living far from their parent. Moreover, switching from living far to living near or vice versa incurs a major utility cost for the child as ϕ_{move} is negative and significant. This allows the model to match inertia in location choice over time.

4.5.1 Alternative specifications

Columns 2 to 4 of Table 5 present some alternative specifications of the model. In Column 2, the "public good" motive to provide care is set to 0 (i.e. $\alpha_{h1} = \alpha_{h2} = 0$), so agents derive utility from their parent receiving care only if they are the ones providing it. In Column 3, sons and daughters have the same preferences over providing care to

[32]This shows that for sons who are the eldest child of a mother vs. daughters who are the eldest child of a mother, the sons suffer a bigger cost. The coefficient $\gamma_{younger \times son}$ is slightly positive, suggesting that this gap is slightly smaller when considering sons who are the youngest child vs. daughters who are the youngest child, and the coefficient on $dad \times son$ is positive, suggesting that the gap is smaller when considering sons of fathers vs. daughters of fathers

[33]This comes from $0.455/\ 1.478 \approx 0.31$, where 1.478 is the coefficient on the log of equivalised consumption.

parents (i.e. $\gamma_{son} = \gamma_{younger \times son} = \gamma_{dad \times son} = 0$). In Column 4, children's caregiving preferences are the same regardless of whether the parent is in moderate bad health or severe bad health (i.e. $\alpha_{h1} = \alpha_{h2}$ and $\gamma_{h1} = \gamma_{h2}$).

For Column 2, the one notable change to the estimated coefficients is that γ_{h1} and γ_{h2} are now positive and significant because children need an "extra" motivation to provide care given the "public good" motivation is no longer operative. The model fit is worse: in the final rows of the table, I report the result of a Likelihood Ratio test relative to the baseline model, where it can be seen that the test statistic is significant at the 0.1% level[34].

For Column 3, it is notable that the "public good" parameters are bigger and the "net warm glow" parameters are smaller (more negative). Intuitively, this is because when there are no preference differences between sons and daughters, there is less strategic shirking in the model, because there are fewer cases where one child thinks that their sibling is in a much better position than they are to provide care. Thus, to match the amount of strategic shirking in the data, more weight is given to the "public good" motivation to provide care as this increases strategic shirking. The model fit is much worse: the LR ratio test statistic is highly significant.

Finally, for Column 4, the only coefficients that change notably are α_{h1} and γ_{h1}, with both shifting towards 0. Again, the model fit is significantly worse.

4.6 Model fit

To assess model fit I generate simulated data on care, work and location choices for 10000 families using the model.

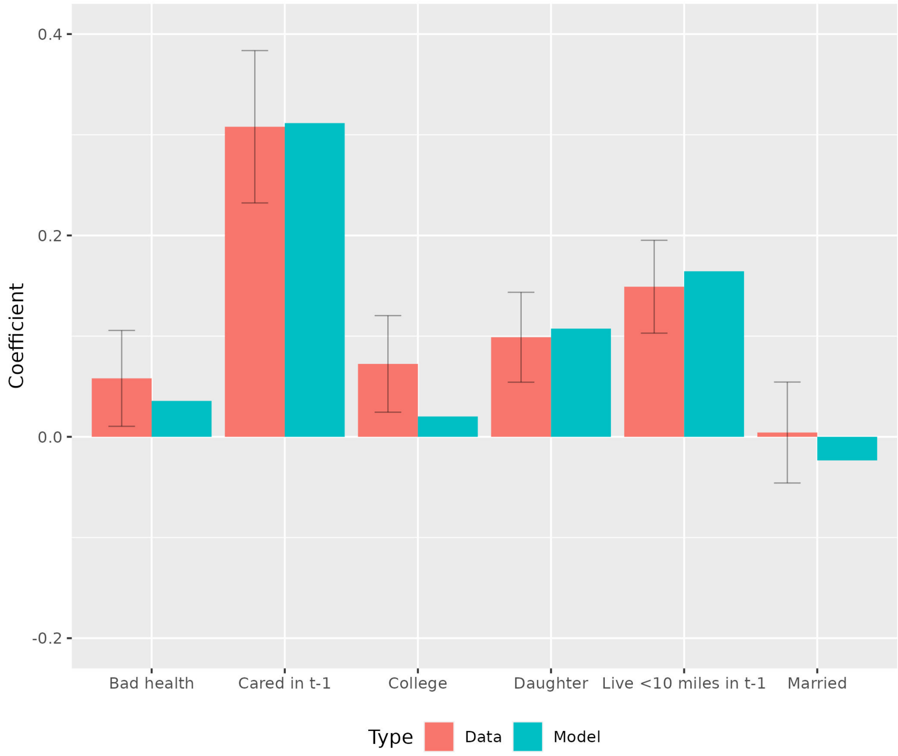
For each simulation, I draw a family's initial observation from the data, assign that family the health states of the parent observed in every period in the data, and simulate the choices they would make according to the estimated model. The family drops out of the simulation in the same period they drop out of the data.

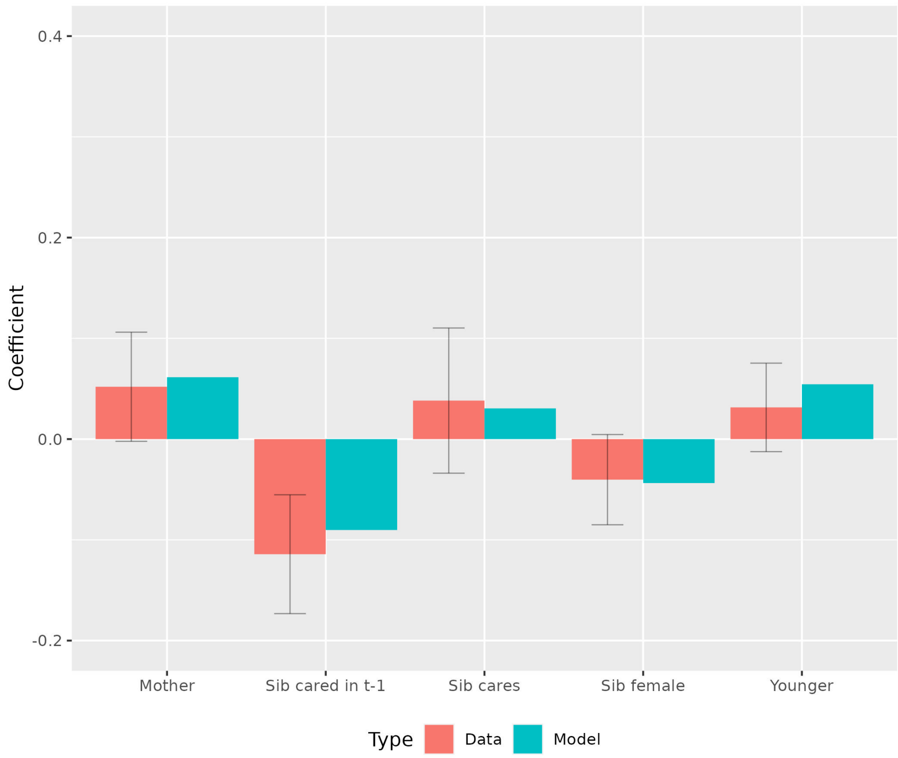
Figure 2 shows the results of an OLS regression of a dummy for a child providing any care, conditional on their parent having health problems, on a set of observables, for both the real data and the model simulated data.

The fit is broadly good. In particular, the coefficients on the dummy for whether the child provided care the previous period, the dummy for the child being a daughter and the dummy for whether the child lived within 10 miles in the previous period match well across the real data and the simulated data. It is notable that the coefficient on "Sib cares", i.e. a dummy for whether the child's sibling provides care in the current period, is not statistically significant. If it were statistically significant that would

[34]For the purposes of carrying out the test I treat the pseudo-likelihood as if it were a likelihood, so I am only approximating the true LR test.

Figure 2: Results from regression of care dummy on observables - data versus model





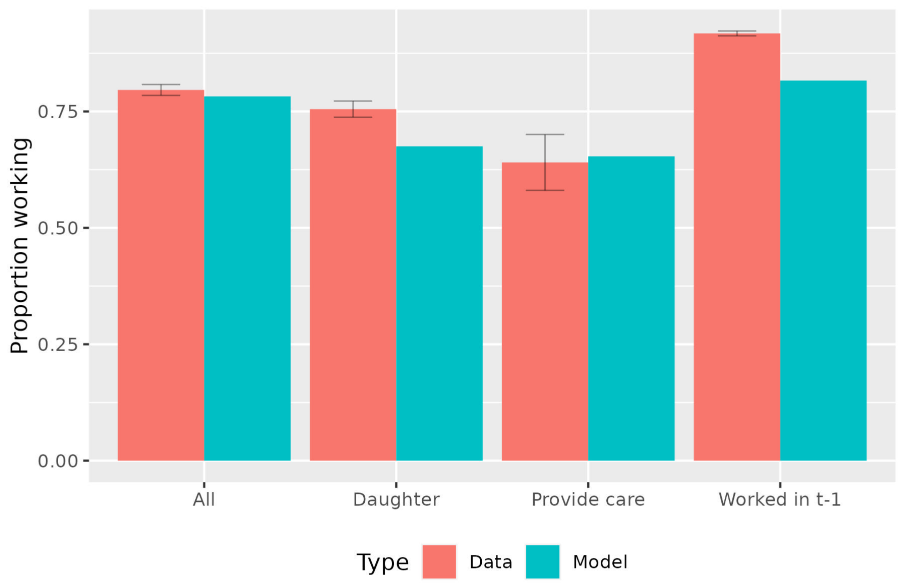
Notes: estimation via OLS. Standard errors clustered at household level. Error bars represent 95% confidence intervals. For the real data, N=1474. “Bad health” is a dummy for whether the parent is in the most severe health category. “Sib” refers to the child’s sibling, so e.g. “Sib cares” is a dummy for whether the child’s sibling provided care in the current period. Other regressors (not shown) are the education, marital status, location and care provided last period of the sibling, as well as the inverse hyperbolic sine of wealth and a polynomial in age; in no case were these extra omitted coefficients significantly different from their simulated counterparts at the 5% level.

suggest that the model had been mis-specified, because if preference shocks are iid over time and across players then conditional on observables agents' decisions should be independent (Aguirregabiria and Mira 2019).

There is one notable failure of model fit however: the coefficient on the dummy for whether the child went to college. This is positive and significant in the data but close to 0 in the model, so the model does not replicate the empirical pattern that more educated children are more likely to provide more care. The mechanical reason for this is that the only role of education in the model is in the income equation. As shown in Appendix E, the coefficient on College $\times$ Works is actually slightly negative, suggesting that the gap between log income of college and non-college educated children is smaller when both children are working than when they are not working, or that in other words college educated children have a lower opportunity cost of working, but this differential is not big enough to drive more educated children to provide more care than less educated children. Thus assuming no preference difference for more educated children implies that the model will be unable to match the fact that more educated children provide more care. Why exactly education has a positive impact on care provision is an important and interesting question but is beyond the scope of this paper.

I also assess the model's fit when it comes to the work decision. To do this, I use the simulated data to calculate the proportion of people working in every period and compare these rates to those from the real data. The results are shown in Figure 3.

Figure 3: Proportion of children working - data versus model



Notes: standard errors clustered at household level. For the four cases, N in the real data is 16888, 8593, 434 and 13642 respectively.

Again, the fit is reasonably good. The model matches the proportion of people working in the real data well, and also matches the proportion of people working while also providing care, and thus seems to capture the trade-off between working more and providing care to one's parent. However, the model understates the proportion of daughters who work (and correspondingly overstates the proportion of sons who work). Also, the model understates the persistence of working arrangements: in the data, conditional on working in $t-1$, the probability of working in t is 92%, whereas in the model it is only 82%. One explanation for this is that the only source of persistence in working arrangements in the model is that there is a wage penalty for not having worked the previous period, incentivising agents to not take breaks from working for a period. A more sophisticated model of labour market choices would allow for different preferences for work in the population so that those who are less work-averse select into working, adding a different form of persistence into the labour market choice. In Appendix H, I present further figures showing that the model is also able to broadly match levels of children living near parents by gender and parental health status.

5 Counterfactuals

In this section I use the estimated model to evaluate some counterfactuals of interest. I focus on two cases: analysing the relative contributions of wages and preferences to the gender care gap, and quantifying the importance of strategic interaction in exacerbating the gender care gap. The first of these exercises gives insight into how much of a narrowing of the gender care gap we can expect from a narrowing of the gender wage gap. The second of these exercises is useful because of what it can tell us about the likely consequences of increasing numbers of one-child families - for whom strategic interaction between children is irrelevant - on the gender care gap.

5.1 Wages vs. preferences in the gender care gap

In the estimated model, daughters differ from sons in two fundamental ways. First, daughters are less averse to providing care[35], and daughters face lower opportunity costs of providing care as their wages are lower. Both of these drive daughters to provide more care than sons in the model, as in the data. It is interesting to consider which of these is the stronger driver of the gender care gap.

To do this, I consider sons' and daughters' care rates in the counterfactual case where there are no preference differences between sons and daughters. In particular, I set sons preferences for providing care so that they are the same as daughters' preferences in the original model.[36].

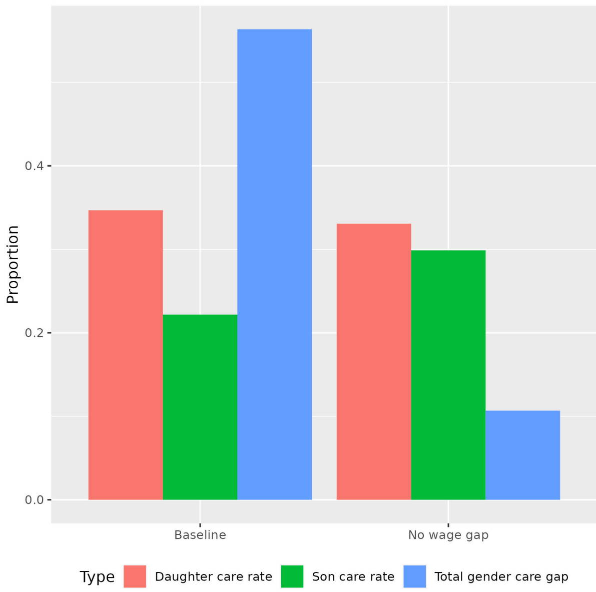
[35]Though, as discussed in Section 3 above, the parameter on daughter's utility net benefit of providing care captures not only the daughter's attitude to the provision of care but also factors like social norms, so daughters might be just as averse as sons to providing care, but face greater social pressure to do so.

[36]Specifically, I set $\gamma_{son} = \gamma_{son \times younger} = \gamma_{dad \times son} = 0$.

Evaluating counterfactuals of this nature is difficult in a model with multiple equilibria. To make any progress, I must make some assumptions about the counterfactual equilibrium that is selected when parameters change. I adapt the approach of Aguirregabiria and Ho (2012) in imposing smoothness assumptions on the equilibrium selection mechanism and using a Taylor approximation around the original estimated equilibrium to approximate the new counterfactual equilibrium when policies change. More detail on these steps is given in Appendix G.

The results of the counterfactual analysis are shown in Figure 4. The figure shows the care rates of sons and daughters, as well as the percentage gender care gap[37], both in the baseline model (left-hand set of bars) and the counterfactual of interest (right-hand set of bars).

Figure 4: Gender care gap - no preference difference between sons and daughters



Notes: "care rate" is the probability of providing care conditional on having a sick parent. "Total gender care gap" how much larger, in percentage terms, daughters' care rate is relative to sons' care rate.

Figure 4 shows that if sons had the same preferences over care as daughters, then their care rate would rise significantly, and daughters' care rate would drop slightly[38]. The net effect of this is that parents receive more care from their children - as sons are less averse to providing care - and the gender care gap shrinks from 56% (i.e. daughters are 56% more likely to provide care than sons, conditional on having a sick parent) to 11%, a decrease of 45 percentage points, or 81% of the original gender care gap. In other words, around four-fifths of the gender care gap is explained by unobserved preference

[37] Namely, how much more likely daughters are to provide care relative to sons, expressed in percentage terms.

[38] The daughters' care rate drops because, if they have brothers, they respond strategically to their brothers providing more care by providing less care themselves.

differences. In Appendix H I back up this finding by considering an alternative case where preferences are fixed but the gender wage gap is equalised. In that case, the change in the gender care gap is negligible[39].

This is a striking and somewhat surprising result. Mechanically, it is driven by the low preference for leisure estimated in the model. The wage gap is relevant to the care decision only to the extent that work choices and care choices correlate with each other: if work and care choices were made entirely independently of one another, the wage would have no impact on a child's incentive to provide care. Moreover, work choices and care choices correlate with each other only to the extent that a child values leisure, and both working and providing care eat into their leisure time. If there were no time cost associated with providing care, or more broadly if the child suffered no loss of leisure utility from working and caring at the same time, then the care decision would be independent of the work decision. Thus, the fact that the estimate for preference for leisure is low dampens the importance of the gender wage gap in driving the gender care gap.

This being said, there is some prima facie evidence in the data to suggest that opportunity cost differentials between children in the same family do not drive differences in care provision. The fixed-effects regressions in Table 1 in Section 2 showed that using parent-wave fixed effects, a child with more education - hence, one might assume, a higher opportunity cost of providing care in terms of foregone wages - relative to their siblings is in fact more likely to provide care. In this light, the fact that gender wage gaps explain so little of the gender care gap is less surprising[40].

Two remarks are in order on this counterfactual. First, the fact that so much of the gender care gap is driven by unobservable preference differences is in one sense discouraging because we have little insight into the nature and causes of this preference difference. However, in a different sense it is important and interesting that so little of the gender care gap is driven by differences in opportunity costs as this suggests that even if the gender wage gap shrinks, there will not necessarily be a significant reduction in the gender care gap, as the causes of the gender care gap are more deep-rooted. Second, just because the gender care gap is largely driven by differences in preferences for providing care does not mean it is necessarily benign, in the sense that plausibly it is benign for people who have a taste for doing a task to self-select into performing that task. The preference differences here capture not only daughters' enjoyment, or lack of burden, of providing care, but also the extent to which daughters might suffer from

[39]Note that even if there were no preference differences and no wage differences between sons and daughters in the model there would likely still be some gender care gap because of other covariates which correlate both with gender and with the probability of providing care, such as living close to one's parents, or not having worked in the previous period at the start of the model.

[40]Groneck (2017) similarly notes that there is little evidence that children with higher opportunity costs are less likely to provide care.

going against parental preferences or societal gender norms. These latter two forms of preference difference are plausibly less benign. Thus, just because the gender care gap is largely driven by preference differences does not mean that it is not a matter of policy interest.

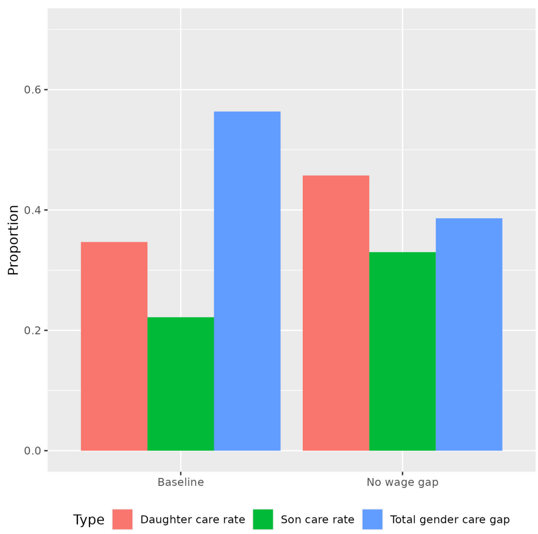
5.2 The role of strategic interaction

I also examine how big a role strategic interaction plays in the gender care gap. If sons' care is crowded out by their sisters' care, it is interesting to consider how much smaller the gender care gap would be - i.e. how much more care sons would provide, relative to daughters - if the sons had no sisters to rely on to "step up" and provide the care.

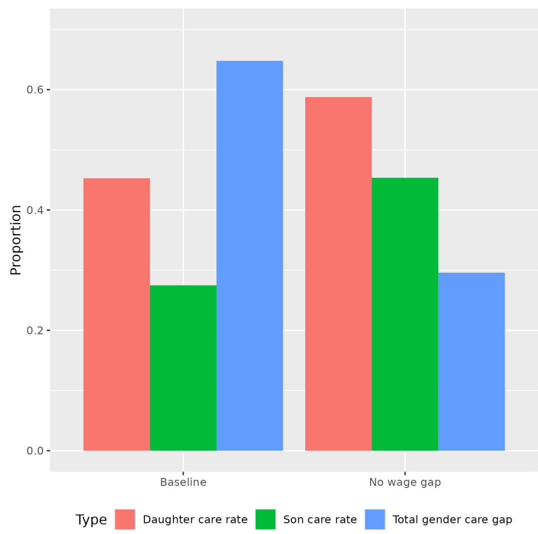
To do this, I use the model to generate simulated choices while imposing that child i's sibling never provides any care, and that child i knows this to be the case. This counterfactual captures what might happen to child i's caring behaviour if child i's sibling made a binding commitment to provide no care, or if they moved away to the other side of the world, or if they died. In other words, each child in this case is acting as if they are an only child at every point that they make a decision, as they ignore the possibility that their sibling could provide any care.

The results are presented in Figure 5 below. The left-hand panel assesses the change in the gender care gap for the whole population. The right-hand panel assesses the change in the gender care gap only for those families where in the original data both children start the model living close to their parents.

Figure 5: Gender care gap with no interaction



(a) All families



(b) Families where both children start close

Notes: "care rate" is the probability of providing care conditional on having a sick parent. "Total gender care gap" how much larger, in percentage terms, daughters' care rate is relative to sons' care rate.

For the whole population, both female and male care rates (i.e. the probability of providing care given one's parent is sick) increase relative to baseline: all children provide more care because they no longer have a sibling to "step up" and provide care if they shirk, with the result that parents receive more care from their children. The proportional increase is greater for men than for women, so the gender care gap shrinks by around 18 percentage points, or 31%.

For the population of families where both children live near their parent at the start of the model, the effect is stronger: the gender care gap shrinks by 35 percentage points, or around 54%. The effect of strategic interaction is stronger in these cases because the existence of a sibling is more relevant to child i's decisionmaking. If both child i and child i's sibling live close to a parent, then it is more likely that child i's sibling would provide care if child i shirks. Hence, the sudden absence of child i's sibling in the counterfactual makes a bigger difference to child i's decisionmaking than if child i's sibling lived far away.

Note that the effect of different preferences by gender on the gender care gap overlaps with the effect of strategic interaction on the gender care gap. This is because in the no-different-preferences counterfactual, I take account of agents' strategic responses to the change in parameters, which will amplify the initial effect of the change in parameters[41].

6 Conclusion

In this paper I presented a dynamic discrete-choice model of strategic interaction between siblings in providing care to a common elderly parent. The model allowed for endogenous location and work status by letting each child make care, work and location choices every period, and the model isolated the role of interdependence of children's care decisions by separately estimating the utility each child receives from providing care themselves and the utility they receive from having their parent cared for by anyone. By considering non-cooperative interaction between sets of siblings over time, and allowing multiple dimensions of choice for each child in each period, the model goes beyond existing models in the literature and allows a detailed examination of what drives differences in care provision within families, particularly by gender of the child.

The results of the estimation suggest that having a parent receive care is a public good for all children yet it is costly for each child to provide care. Hence, children strategically shirk and underprovide care relative to how much they would provide if they did not have a sibling. Sons shirk relatively more than daughters and strategic

[41]Note, for example, that in Figure 4 the female care rate decreases slightly. This is because daughters respond to sons raising their care effort by cutting their own care effort, which would not be the case if I were ignoring strategic interaction

interaction of this nature explains around 31% of the total gender care gap.

Also, the results of the estimation show that it is unobserved preference differences for providing care between sons and daughters, rather than differences in opportunity costs through the gender wage gap, that are the chief driver of differences in care rates between sons and daughters. Thus, even if the gender wage gap were to close this would not substantially change the division of caring responsibilities between sons and daughters.

For reasons of tractability I have significantly simplified the decision set of children in the model (e.g. they do not save, and only have binary location, work and care choices), and have omitted the parent as a player altogether. Future work might consider including the parent - or, ideally, the parent and their spouse, if any - and allowing all players a richer choice set, to see if the conclusions of the more restricted model presented here still hold.

Moreover, this paper leaves unresolved the exact drivers of preference differences between sons and daughters when it comes to the provision of care. Future work could decompose this preference difference, into (for instance) the enjoyment, or lack of burden, daughters derive from providing care versus the burden daughters' experience from going against parental preferences or social norms, while maintaining the setting of dynamic interaction. This would allow a more sophisticated treatment of what policy approaches, if any, are to be used to reduce the gender care gap.

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Appendices

A Supplementary descriptive figures and tables

A.1 HRS sample descriptive statistics

Table 6 presents some key descriptive statistics on the full sample of HRS respondents for Waves 4 to 14. This is the sample used to establish the stylised facts in Section 2. I also include statistics for the subsample of single respondents and the subsample of single respondents with exactly two children because the estimation will focus on these groups.

Table 6: Descriptive statistics

	All	Single respondents	Single respondents, 2 kids
Female	0.59	0.76	0.75
Age	67.08	71.27	70.77
Couple	0.67	0.00	0.00
Kids	3.38	3.18	2.00
- of which live within 10 miles	0.97	1.00	0.65
White Caucasian	0.76	0.69	0.74
Homeowner	0.76	0.57	0.61
Some college	0.43	0.36	0.42
Wealth ($1000s)	117	73	107
Observations	200 385	67 123	17 812

Notes: all statistics are weighted means using HRS respondent-level weights, apart from wealth, which is a weighted median to reduce the impact of outliers. As wealth is measured at the household rather than individual level, I allocate half of each couple household's wealth to each member of the couple. Dollar values here and throughout are expressed in 2010 dollars using the CPI.

The overall HRS sample skews female, given lower life expectancy for men. About two-thirds of respondents are in a couple, about three-quarters are homeowners and about one-half had at least some college education.

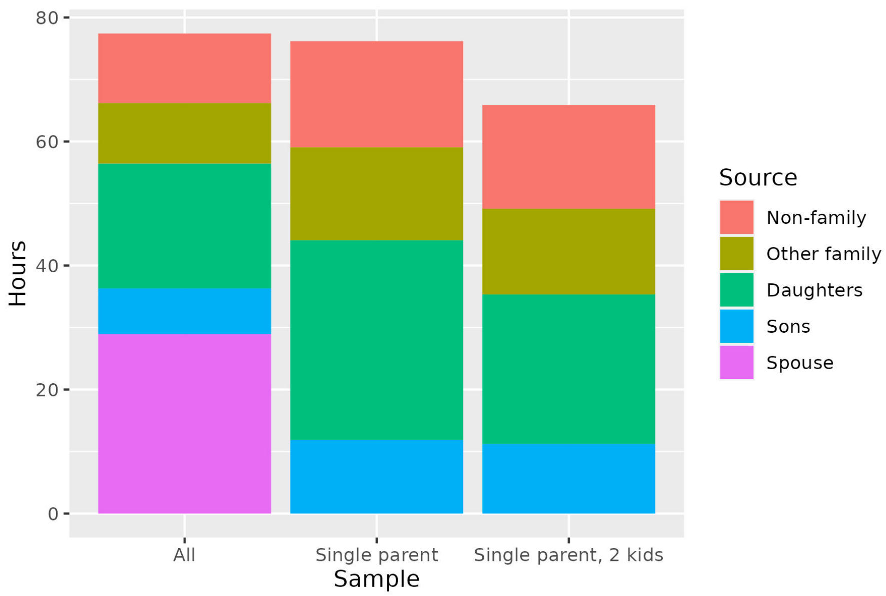
The subsample of singles is notably more female, slightly older, and less likely to own a home or to have gone to college. Median wealth is considerably less than in the full sample. Single respondents are also slightly less likely to be white. It is notable that the average number of kids is lower for single respondents, yet the average number of kids living within 10 miles is higher, suggesting that a higher proportion of the children of single parents live near their parent.

Finally, the subsample of single respondents with exactly two kids is slightly richer and more educated than the subsample of all single respondents. Indeed, along the wealth, education and race dimensions this subsample more closely resembles the full HRS sample than it does the subsample of singles.

A.2 Hours of care received by care source

Figure 6 presents information on the sources of care to elderly people. Each bar shows mean hours of care received by given sick elderly person[42] by each of five possible sources: spouses, sons, daughters, other family members and non-family sources. I calculate this separately for the whole sample, the subsample of single respondents and the subsample of single respondents with only two children. Note that I do not condition on positive care provision here so the graph captures both the intensive and extensive margins of care provision. Also, employees of institutions are excluded from calculations of total care receipt in the HRS, so the "Non-family" care does not include e.g. care provided by workers in a nursing home.

Figure 6: Hours of care per month by care source



Notes: sick parents (ADLs or IADLs >0) only. "Non-family" care excludes care from employees of institutions.

For the sample as a whole, spouses provided the biggest share of care. A given sick elderly person will receive around 29 hours of care per month from a spouse, compared to 7 hours from any sons they have, 20 hours from any daughters they have, 10 hours from other family members and 11 hours from non-family sources, adding up to a total of around 77 hours of care.

For the sample of single respondents only, it is notable that the average amount of care hours received stays approximately the same. In other words, all of the other sources of

[42] For the purpose of this section, "sick" people are those who have difficulty with at least one Activity of Daily Living (ADL) or at least one Instrumental Activity of Daily Living (IADL).

care increase their output to compensate for the lost care from the spouse. In particular, daughters are the biggest single source of care, and provide much more care than sons.

Comparing this to the sample of single respondents with two kids, the sum of care hours from children decreases somewhat, leading to a decrease in the total amount of care received, simply because there are fewer candidate children to provide the care. It is notable that the difference between daughters' care hours and sons' care hours is less pronounced when there are only two children. This is because in many two-child families there are no daughters, hence sons cannot leave it to their sisters to provide the care so must "step up" themselves.

Note that despite the appearance of the graph, the typical sick elderly individual does not receive care from many sources in roughly equal amounts. Instead, most elderly people will have at most one primary caregiver. In the full sample, 75% of people receiving help with IADLs, ADLs or finances from at least one person receive help from exactly one person.

A.3 Gender care gaps across family type

The Table below presents measures of care provision by sons and daughters in families of different types.

Table 7: Ratios of sons' care to daughters' care by family type

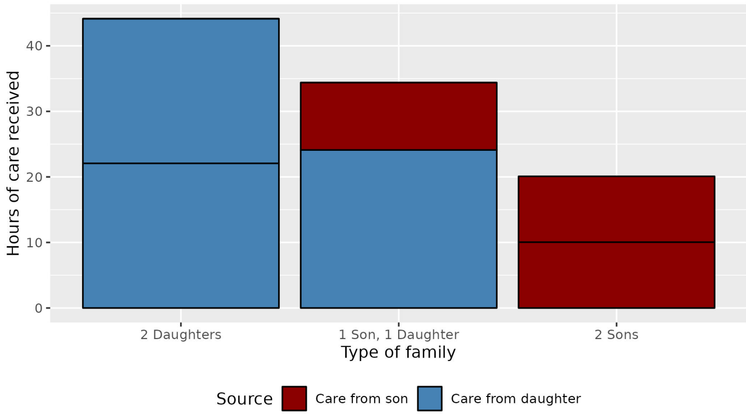
	I(Provides care)			Care hours		
	Son	Daughter	Ratio	Son	Daughter	Ratio
One-child family	0.17	0.27	1.57	12.85	26.88	2.09
Two-child daughter+son family	0.10	0.19	1.91	5.90	15.24	2.58
Two-child D+D family	-	0.17	-	-	13.26	-
Two-child S+S family	0.12	-	-	6.20	-	-

Notes: only sick parents (difficulties with at least one ADL or IADL) included. "I(Provides care)" is a dummy for whether the child provides any care, "Care hours" is a measure of care hours per month. "Ratio" is daughters' mean outcome variable divided by sons' mean outcome variable - i.e. a measure of how much more care daughters provide than sons.

A.4 Care received by family composition

Figure 7 shows the mean child-provided care hours received by sick single parents of two children depending on the gender composition of their children. Parents with more daughters clearly receive higher overall child-provided care hours than parents with fewer daughters.

Figure 7: Mean care hours received by composition of kids



Notes: sick parents (ADLs or IADLs >0) only.

A.5 Caring and in-laws

So far I have been ignoring the fact that a married couple has in general two sets of parents that they could care for: in heterosexual couples, the husband's parents and the wife's parents. Moreover, if those two sets of parents live far from each other, each married couple can choose only one to care for. How exactly a married couple addresses this problem has significant welfare implications. For instance, it could be that a married couple decides which set of parents to care for depending on the probability of each set of parents receiving care from other sources, in which case there is some redistribution of care effort to those who need it most. A full examination of this complicated issue is beyond the scope of this paper and in any case would require more in-depth data than the HRS provides on siblings-in-law and parents-in-law. However, some preliminary steps can be taken in this direction.

It has already been established above that a given child X is more likely to provide care to their parent if they have no sisters to "step up" in their absence. However, to examine how married couples make decisions of who to care for, we need to consider whether child X is less likely to provide care to their parent if their spouse Y does not have any sisters. If this were the case, it would suggest that X and Y are deciding which set of parents to care for depending on how likely they are to receive care from other sources. Table 8 below assesses the importance of this channel. It reports results of a linear probability model with the LHS variable being a dummy for whether an HRS respondent[43] ("R") lives within 10 miles of their mother, and the key RHS variables being dummies for whether R and their spouse respectively have any sisters and the

[43]Note that this regression uses data on HRS respondents' location relative to their parents, rather than the location of the children of HRS respondents relative to HRS respondents themselves, as is the setting for the rest of the paper. This is because there is no information in the survey on the families of the spouses of the children of HRS respondents.

total number of siblings that R and their spouse have[44]. I restrict the sample to only those married HRS respondents with living mothers and whose spouses have at least one parent alive. Column 1 shows results for the whole sample and Column 2 limits the regression to only male HRS respondents.

Table 8: Caring and in-laws

	Dependent variable:	
	R lives within 10 miles of R's mother	
	(1)	(2)
R has sister	−0.034**	−0.057***
	(0.011)	(0.016)
R's total siblings	−0.006**	−0.003
	(0.002)	(0.003)
R's spouse has sister	−0.002	0.001
	(0.011)	(0.015)
R's spouse total siblings	0.004*	0.006*
	(0.002)	(0.003)
Observations	12 791	6464
Adjusted R^2	0.013	0.013
Mean dep. var.	0.347	0.352

Notes: estimation via OLS. "R" stands for HRS Respondent. Column 1 is for all Respondents, Column 2 is for men only. Other controls are R's gender (Column 1 only), homeownership status, whether white Caucasian, education and a polynomial in age. *p<0.05; **p<0.01; ***p<0.001.

People are less likely to live within 10 miles of their mother (and thus be in a position to provide care) if they have a sister, and if they have many siblings. However, the association between R's location decision and the family structure of R's spouse is less clear cut. It seems that R is more likely to live near their mother if R's spouse has many siblings - which is consistent with R and R's spouse deciding to live near R's mother rather than the spouse's parent if they believe the spouse's parent will be well cared for anyway - but the association is weak.

As such, while the issue of links between the provision of care in different nuclear families through in-law relationships is important and deserving of further attention, it does not appear to be a first-order issue for the purposes of this paper, so I will largely leave it aside.

[44]Other RHS regressors are R's gender (in the regression with both male and female respondents), homeownership status, whether white Caucasian, education and a polynomial in age.

B Children's location and parental health

To examine the effect of health shocks to parents on kids' location decisions I carry out an event study using the respondent-kid data in the HRS. I use as my sample all the children of a parent who is observed falling sick in the data. I run the following regression:

$$Y_{ijt} = \alpha_{ij} + \kappa_t + \sum_{k \in -3,-2,0,1,2} \beta_k I(Period_{jt} = k) + X_{ijt}\gamma + \epsilon_{ijt} \tag{20}$$

In this regression, Y_{ijt} is a dummy for whether child i lives within 10 miles of a parent j and $Period_{jt}$ captures the period relative to the period where the parent j falls sick for the first time (i.e. in that period, $Period_{jt} = 0$). X_{it} is a set of time-varying controls[45]. I include child $\times$ parent fixed effects α_{ij} and wave fixed effects κ_t.

Figure 8 plots the results of this estimation. I estimate Equation 20 separately for sons and daughters. The height of each line at period k is the value of β_k estimated from the regressions.

In the left-hand panel I include all children. In the right-hand panel, to avoid concerns about it being parents who choose which child to move close to, I drop any parents who are observed moving house in the sample. This is not a very substantive restriction because in my estimation sample in only 21% of cases where a parent lives more than 10 miles from a given child in $t-1$ and lives within 10 miles in t, it is the parent who has moved, not the child. In other words, in roughly four fifths of cases it is the children who move close to the parent rather than the other way round[46].

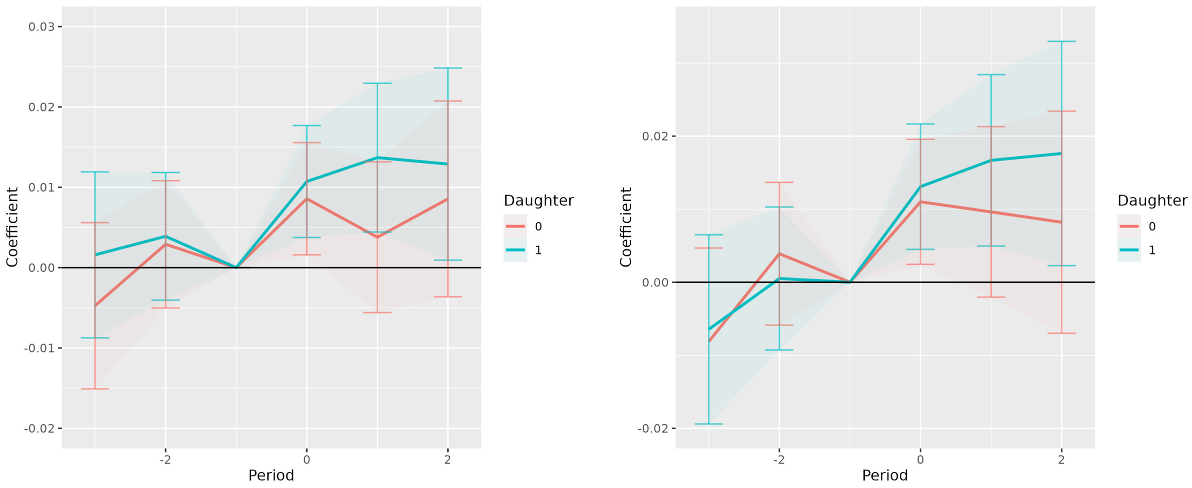
The figures suggest that children are more likely to live closer to their parent after a parent falls ill, with this estimated association being larger for daughters. To put the magnitudes of the coefficients into context, in the estimation sample for panel a) the proportion of kids who live within 10 miles of the relevant parent was 37.0% for sons and 38.7% for daughters.

Thus, there is some evidence to suggest that children do move back to live near their parents when their parents fall sick. This is particularly true of daughters.

[45] In this case, I control for polynomials in age of parent and child, couple status of parent and child and dummies for HRS waves.

[46] If we consider only cases where the parent and child live withing 10 miles of each other in t and not $t-1$, *and* parent has fallen sick for the first time in the data in t, then in 24% of these cases it is the parent who moves.

Figure 8: Children's location before and after health shocks



(a) All children (b) Children of parents who do not move

Notes: estimation via OLS. Standard errors clustered at child × parent level. Confidence bands show 95% confidence intervals.

C Other possible mechanisms of compensation

C.1 Compensation through rent-free accommodation

Some authors (e.g. Barczyk and Kredler (2018)) have argued that in addition to bequests children are compensated through rent-free accommodation when they are providing care to their parents.

HRS respondents are not directly asked whether their co-resident children pay any rent, but can gain more insight by looking a generation upwards: while there are no data in the HRS on whether the children of survey respondents pay rent to the respondents when they live with the respondents, there is information on whether survey respondents themselves pay any rent when they live with their parents.

Table 9 presents these results. Column 1 shows proportions of tenure type for all respondents in the sample, where each observation is a respondent-wave combination. Column 2 shows tenure types for the subsample of respondents who provide more than 40 hours of care per month (following Barczyk and Kredler (2018)) I call these "heavy helpers"[47]). Column 3 restricts this further to those heavy-helping respondents who co-reside with one of their parents.

The results in Column 2 suggest that only 5% of those providing over 40 hours of care per month to a parent live rent-free. It is important to note that the HRS sample will not be fully representative of the sample of all carers - for instance, the HRS starts

[47]HRS respondents are asked how many hours of personal care they provided to their parents since the last interview. I take this figure and divide it by 24 to arrive at the amount per month, given interviews are biennial.

Table 9: Tenure type by amount of care

	All respondents	"Heavy helpers"	HH+co-reside with parent
Own	0.79	0.81	0.69
Rent	0.17	0.13	0.15
Live rent-free	0.03	0.05	0.14
Other	0.01	0.01	0.02
Observations	172 145	1802	468

Notes: data from HRS Waves 5 to 14 (2000-18). All statistics are weighted means using HRS respondent-level weights.

interviewing respondents at age 50 whereas the median age of a heavy helper in Barczyk and Kredler (2018) is 48 - so the average HRS respondent will be older, thus likely richer and less in need of rent-free accommodation, than the average carer. However, even with these caveats, the evidence on children receiving rent-free accommodation as compensation for care provision seems mixed.

This is important because if children do not receive rent-free accommodation in exchange for providing care, and do not receive substantively more by way of bequests, then this casts doubt on the suggestion that care hours are provided in exchange for a financial transfer of some kind.

C.2 Compensation through childcare

Finally, it might be argued that children provide care to their parents in exchange for childcare (i.e. care of the grandchildren) received from their parents. In other words, there is a dynamic contract between children and parents: in some period, the parent cares for their grandchildren, and in another period, the children provides care to the parent.

To investigate whether this channel of exchange exists I regress a dummy for whether a kid provides care to a parent, conditional on that parent being sick, on a set of explanatory variables, notably including a dummy for whether that kid is ever observed receiving childcare from that parent[48].

Table 10 reports the results. In Column 1, I regress the care dummy on the base set of explanatory variables. In Column 2, I add an interaction between the dummy for whether the kid is ever observed receiving childcare from the parent and the dummy for whether the kid lives within 10 miles of the parent. Columns 3 and 4 are the same as Columns 1 and 2 except parent-level fixed effects are used.

The results in Columns 1 and 3 suggest a substantive association between whether a kid ever received help with childcare from a parent and whether the kid provides care to the

[48] In particular, this dummy variable is equal to one for a given wave if the parent says that they or their spouse spent more than 100 hours caring for their (great-)grandchildren via that child

Table 10: Childcare and caring for parents

	Dependent variable:			
	Kid provides care			
	(1)	(2)	(3)	(4)
Kid ever recd childcare	0.022***	0.039***	0.021***	0.036***
	(0.002)	(0.003)	(0.004)	(0.004)
Kid lives $\leq$ 10 miles away	0.153***	0.164***	0.157***	0.166***
	(0.002)	(0.002)	(0.003)	(0.004)
Kid ever recd childcare $\times$ Kid lives $\leq$ 10 miles away		-0.036***		-0.033***
		(0.004)		(0.007)
Parent FEs	N	N	Y	Y
Observations	101 208	101 208	101 208	101 208
Adjusted R^2	0.174	0.175	0.282	0.289
Mean dep. var.	0.112	0.112	0.112	0.112

Notes: estimation via OLS. In all regressions, other controls are dummies for number of ADL and IADL difficulties, education of kid and parent, number of total kids of the parent, quadratics in age for kid and parent, a dummy for being White Caucasian, log of wealth and a dummy for being eldest/youngest child. For the fixed effects regression, the parent-level controls drop out. Standard errors clustered at the parent level. *p<0.05; **p<0.01; ***p<0.001.

parent: kids who received childcare are (using the results from Column 3) 2.1pp more likely to provide care, relative to a mean probability of providing care of 11.2%. However, the inclusion of the interaction term in Columns 2 and 4 shows that this association is largely driven by kids who live further than 10 miles from their parent in the current period. For those kids who live further than 10 miles, those who received childcare in the past are (using the results from Column 4) 3.6pp more likely to provide care than those who did not receive childcare. However, for those kids who live within 10 miles of their parents, the difference in probabilities is only $3.6 - 3.3 = 0.3$pp. One explanation for this is that within the group of kids who live more than 10 miles from parents, those who received childcare from parents are more likely to live closer (e.g. 20 miles away) than those who did not. As such, while this basic analysis clearly does not rule out a childcare-eldercare exchange channel, there seems to be little indication that kids provide care to parents in exchange for parents providing childcare for the kids.

D Model discussion

D.1 $\omega_{warm}(\cdot)$ in full

In full, Equation 15 takes the form:

$$\omega_{warm}(\cdot) = \begin{cases} \gamma_{h1} + \gamma_{far} far_t^i + \gamma_{origfar} far_0^i + \gamma_{son} son^i & \text{if } h_t = 2 \ \& \ k_t^i > 0. \\ +\gamma_{dad} dad + \gamma_{start} start_t^i + \gamma_{younger} I(i = B) & \\ +\gamma_{younger \times son} I(i = B) \times son^i & \\ +\gamma_{dad \times son} dad \times son^i, & \\ & \\ \gamma_{h2} + \gamma_{far} far_t^i + \gamma_{origfar} far_0^i + \gamma_{son} son^i & \text{if } h_t = 2 \ \& \ k_t^i > 0. \\ +\gamma_{dad} dad + \gamma_{start} start_t^i + \gamma_{younger} I(i = B) & \\ +\gamma_{younger \times son} I(i = B) \times son^i & \\ +\gamma_{dad \times son} dad \times son^i, & \\ & \\ 0, & \text{otherwise.} \end{cases} \tag{21}$$

Here, far_t^i is a dummy for whether child i lives far (i.e. more than 10 miles) from their parent at time t, son^i is a dummy for whether child i is a son, dad is a dummy for whether the parent is a father, $start_t^i$ is a dummy for whether child i is starting providing care this period, and $I(i = B)$ is a dummy for whether child i is the younger of the two siblings.

D.2 Unobserved heterogeneity

Any dynamic model of this kind faces an important problem of unobserved heterogeneity (Aguirregabiria, Collard-Wexler, and Ryan 2021). The model imposes that the only form of unobserved heterogeneity takes the form of *iid* preference shocks independent across agents and across time. In particular, the model does not allow for permanent unobserved heterogeneity, in the form of – for instance – different unobserved levels of affection in the relationship between a particular child and a particular parent. This could create problems because each child's initial conditions – for instance, their starting location, work and care choice – could be correlated both with this unobserved heterogeneity and with the child's endogenous state variables at the time of making location, work and care choices in period t. For instance, children who feel more affection for their parents may a) be more likely to live near their parent at the start of the game and b) be more likely to provide care when their parent falls sick in period t. Due to inertia in location choice, a child who starts the model living near their parent is likely to be living near their parent in period t. However, this would lead to the model overestimating the importance of current location in determining the cost of providing care, because the children who currently live near their parents are a selected sample who are more likely to have unobservable characteristics causing them to have a higher preference for providing care.

I address this problem by allowing children to have different "net warm glow" utility from providing care depending on whether they live far from their parent at the start of period 1, i.e. at the very start of the game. This is the role of the $\gamma_{origfar}$ parameter. This is meant to capture the fact that children living near their parent at the start of the game may be systematically different in terms of their relationship with their parent and their preference for providing care to children who live far from their parent. In effect, I am using the child's initial location choice as a proxy for their unobserved type, and I am allowing types to differ in how much "net warm glow" they derive from providing care.

I take a different approach when it comes to previous caring status – in the estimation sample selection, described in more detail in Section 4, I drop any observations where the parent is sick in their first period in the data and where any child provided care in the previous period. It is important to drop these cases because these are families where a child has already selected into caregiving. Using the same example as above, there will be a correlation between unobserved "affection" between parent and child and initial caregiving status, and between initial caregiving status and caregiving at time t. By imposing that every child has the same initial conditions in terms of previous caregiving I am able to model any selection into caregiving as endogenous within the model.

I do not take extra steps to control for agents' starting labour force status both to keep the model tractable through avoiding extra state variables and because it is less clear how initial work status would correlate with preference for providing care.

E Parameters calculated outside the model

E.1 Care choices, costs and hours

I define child i as providing care in a given period if their parent reports receiving 8 or more hours a month, or 2 hours a week, in help from child i. The reason for setting a non-zero cutoff in care hours to qualify as providing care is that there is significant variation in the number of hours that children are reported as providing, conditional on providing positive hours. As such, to focus on cases where care effort is roughly comparable across children, I count as providing care only those who provide a substantial amount of care, which I set as being 8 or more hours per month[49].

I assume that children who are the only provider of informal care to their parent provide 13 hours per week when their parent has $h_t = 1$ and 25 hours per week when

[49] 29% of children in the estimation sample with positive care hours reported providing less than 8 hours per month, but these children provided only 1.4% of the aggregate care hours.

their parent has $h_t = 2$, matching mean hours of care provided by such children in my model estimation sample[50]. I also assume that when two children provide care at the same time, they each provide half of these totals.

The formal care cost values come from Genworth (2024). I assume those parents who have $h_t = 1$ and receive no informal care are forced to pay for a home health aide, either out of pocket or through Medicaid if eligible, who works the same hours over the two years (1268) that a child would provide in informal care, at a cost of \$15.0k per year in 2010 dollars. I assume that parents who have $h_t = 2$ and receive no informal care live in a semi-private room in a nursing home, at a cost of \$76.6k per year.

E.2 Health and health transition probabilities

To estimate health transition probabilities I first must decide what conditions in the data match with belonging to the various health states in the model. I estimate care need in the data by a multi-step process:

1 - Using the estimation sample, I regress the probability of a parent receiving *any* type of care - be it formal or informal, from any source - on a set of objective health measures in the HRS[51]. Although care receipt is endogenous, the existence of means-tested formal care through Medicaid suggests that care receipt from any source will be a reasonable indicator of actual care need.

2 - I use the regression to assign predicted care need to for each parent in each wave, i.e. the probability of receiving any type of care that their objective health measures imply, according to the regression.

3 - I class as having moderate care needs ($h_t^i = 1$) all those between the 90th and 95th percentile of predicted care need and I class as having severe care needs ($h_t^i = 2$) all those who above the 95th percentile

Table 11 below presents statistics on objective health measures by assigned h_t^i. As expected, ADL difficulties, IADL difficulties and memory disease are very low for those with $h_t = 0$ and increase with h_t.

Then, for the health transition probabilities themselves I estimate a probit model for period t health state as a function of $t-1$ health state as well as age, age squared and permanent income, using the model estimation sample.

[50]To calculate these means, I winsorize care hours at the 10th and 90th percentile to reduce the influence of outliers.

[51]In particular, the explanatory variables are a dummy for 0 ADL difficulties, a dummy for 0 IADL difficulties, quadratics in ADL difficulties and IADL difficulties, all interacted with a dummy for whether the parent suffers from a memory disease and interacted with a quadratic in age.

Table 11: Objective health statistics by model health state

	$h_t = 0$	$h_t = 1$	$h_t = 2$
# ADL difficulties	0.22	2.16	2.98
# IADL difficulties	0.12	2.46	3.81
Memory disease	0.01	0.11	0.39

Notes: h_t=0, 1, 2 refer to no care needs, moderate care needs and severe care needs respectively. Each value in the table is the mean of the left hand variable for people in the relevant health state in the model estimation sample.

E.3 Work hours and income process

I assume that if a child is working (a state which captures both full- and part-time work) then they work 35 hours per week.

As for the income process, I assume the log of equivalised income is linear in parameters. In particular, $\log(w)$ is a function of age, age squared, gender, couple status, education, work choice in the previous period and work choice in the current period. The reason why income in t might depend on work choice in $t-1$, even conditional on work choice in t, is that leaving the labour market to provide care will impose a penalty on future wages through, for instance, loss of human capital. This is a mechanism examined by Skira (2015) in assessing the cost of care provision by in terms of foregone current and future wages.

The HRS reports child income only in broad brackets so is not very useful for getting at measures of e.g. the gender wage gap. Instead, I use data from the PSID Family File (*PSID* 2024) from 1999 to 2019. I select an estimation sample of individuals with one sibling who are aged between 21 and 60. For this estimation sample, I regress log equivalised income on explanatory variables including demographics and labour market choice. Table 12 presents the results of this estimation.

E.4 Other parameters

To estimate the mean and variance of the wealth shock I consider wealth changes in my estimation sample of HRS data for people who are healthy in both waves, hence who do not face any impact of long-term care costs on their wealth. I winsorize the wealth changes at the 10th and 90th percentiles to reduce the impact of measurement error. The mean and standard deviation of the wealth changes are -$2.0k and $115.3k respectively.

A parent's maximum age is assumed to be 100. When parents die their bequest is split equally between their children. As in Ko (2022), the children then consume the bequest over the next T_{beq} periods while working full-time – this provides a terminal payoff for the children to close the model. I assume $T_{beq} = 5$ so children spread their bequest consumption over the following 10 years.

Table 12: Estimated income process

	Dependent variable:
	Log of biennial equivalised income
Constant	7.775***
	(0.203)
Age	0.082***
	(0.010)
Age sq.	−0.001***
	(0.0001)
Female	0.107**
	(0.037)
College	0.547***
	(0.029)
Couple	0.372***
	(0.018)
Couple × Female	0.363***
	(0.024)
Worked in t	1.384***
	(0.223)
Age × Worked in t	−0.035***
	(0.010)
Age sq. × Worked in t	0.0003*
	(0.0001)
Worked in $t-1$ × Worked in t	0.518***
	(0.051)
College × Worked in t	−0.049
	(0.032)
Female × Worked in t	−0.234***
	(0.068)
Female × Worked in $t-1$ × Worked in t	−0.182**
	(0.061)
Observations	19,544
Adjusted R^2	0.315

Notes: estimation via OLS. Data from the PSID Family File 1999-2019. Individuals considered to be Working if they work more than 100 hours per year. Household income is equivalised by dividing by the square root of the number of household members, counting children as half a household member. *p<0.05; **p<0.01; ***p<0.001.

I assume parents in the “older” group (70-85 years old in their first observation in the data) start the model aged 78 and parents in the “younger” group (55-69) start the model aged 63. I assume that the elder child is 24 years younger than the parent, and the younger child is 29 years younger than the parent, matching mean age gaps in the HRS data.

Finally, I assume the discount factor β is equal to 0.93. Note that each period lasts 2 years so this corresponds to an annual discount factor of $\sqrt{0.93} = 0.964$.

F Pseudo maximum likelihood estimation

The likelihood function for the observed choices is given by:

$$L^*(\theta) = \prod_{n=1}^{N} \prod_{\tau=1}^{T_n} P^A_{\sigma^*}(d^A_{n\tau}|s_{n\tau}, \theta) P^B_{\sigma^*}(d^B_{n\tau}|s_{n\tau}, \theta) \tag{22}$$

where T_n is the total number of periods for which family n with children A and B is observed in the data and $P_{\sigma^*} = \{P^A_{\sigma^*}, P^B_{\sigma^*}\}$ is the set of optimal decision rules for the two children, obtainable through solving the model fully.

To avoid the significant computational cost of solving the model fully, I instead maximise the pseudo likelihood function (Aguirregabiria and Mira 2007). This uses an approximation of P_{σ^*} using the first-stage estimates of the value functions of the two agents. In particular, given a set of first-stage policy function estimates $\hat{\sigma} = \{\hat{\sigma}^A, \hat{\sigma}^B\}$, the pseudo likelihood function will be:

$$L(\theta, \hat{\sigma}) = \prod_{n=1}^{N} \prod_{\tau=1}^{T_n} \Lambda^A_{\sigma^*}(d^A_{n\tau}|s_{n\tau}, \hat{\sigma}, \theta) \Lambda^B_{\sigma^*}(d^B_{n\tau}|s_{n\tau}, \hat{\sigma}, \theta) \tag{23}$$

where $\Lambda^i_{\sigma^*}(d^i_{n\tau}|s_{n\tau}, \hat{\sigma}, \theta)$ is the policy iteration operator for child i, given by:

$$\Lambda^i_{\sigma^*}(d^i_{n\tau}|s_{n\tau}, \hat{\sigma}, \theta) = \frac{\exp(\hat{v}^i(s_{n\tau}, d^i_{n\tau}, \hat{\sigma}, \theta)}{\sum_{d^{i'}_{n\tau} \in F^i_{n\tau}} \exp(\hat{v}^{i'}(s_{n\tau}, d^{i'}_{n\tau}, \hat{\sigma}, \theta)} \tag{24}$$

In other words, the policy iteration operator is an approximation of the true optimal decision rules which updates the first-stage policy function estimates $\hat{\sigma}$ by using these first stage policy function estimates to generate implied choice specific value functions $\hat{v}(\cdot)$ and then using these choice-specific value functions to recover approximate optimal decision rules in each state. The $\hat{v}(\cdot)$ terms are recovered by the simulation procedure described in the main text.

I then maximise the pseudo likelihood to recover the two-step CCP estimator $\hat{\theta}$:

$$\hat{\theta} = \arg\max L(\theta, \hat{\sigma}). \tag{25}$$

G Evaluating counterfactuals

In this appendix I outline the approach for evaluating counterfactuals in models with multiple equilibria, set out in Aguirregabiria and Ho (2012).

A (Markov Perfect) equilibrium of the game can be written as a fixed point:

$$\mathbf{P} = \Psi(\theta, \mathbf{P}) \tag{26}$$

where $\mathbf{P}$ is the vector of choice probabilities for each player in each state, $\Psi(\cdot)$ is a vector-valued best response function for each player and state and θ is the vector of parameters. In other words, in equilibrium, choice probabilities must be best responses to everyone's choice probabilities, given the parameters.

A complication in this model is that there are multiple equilibria: there are multiple solutions to Equation 26. The model is thus completed by an equilibrium selection mechanism $\pi(\theta)$, which selects a set of equilibrium choice probabilities from all the possible sets of equilibrium choice probabilities associated with θ.

Let $\mathbf{P_0}$ be the true population choice probabilities and let θ_0 be the true parameter vector governing these choices. It must be the case that $\mathbf{P_0} = \Psi(\theta_0, \mathbf{P_0})$. Even though the exact form of $\pi(\theta)$ is not known, it is known that $\pi(\theta_0) = \mathbf{P_0}$.

Let $\hat{\theta}$ and $\hat{\mathbf{P}}$ be consistent estimates of θ_0 and $\mathbf{P_0}$. Suppose a researcher is interested in what the counterfactual equilibrium is at θ^*, i.e. the researcher wants to evaluate $\pi(\theta^*)$. Then, assuming that $\pi(\cdot)$ is continuously differentiable around $\hat{\theta}$, the researcher can use the following Taylor approximation to approximate $\pi(\theta^*)$ around $\hat{\theta}$:

$$\pi(\theta^*) \approx \pi(\hat{\theta}) + \frac{d\pi(\hat{\theta})}{d\theta'}(\theta^* - \hat{\theta}) \tag{27}$$

Using the fact that $\pi(\hat{\theta})$ is equal to $\hat{\mathbf{P}}$ and to $\Psi(\hat{\theta}, \hat{\mathbf{P}})$, one can differentiate $\pi(\hat{\theta})$ with respect to θ and solve for $\frac{d\pi(\hat{\theta})}{d\theta'}$, substituting into Equation 27 to arrive at:

$$\pi(\theta^*) \approx \hat{\mathbf{P}} + \left(I - \frac{d\Psi(\hat{\theta}, \hat{\mathbf{P}})}{d\mathbf{P}'}\right)^{-1} \frac{d\Psi(\hat{\theta}, \hat{\mathbf{P}})}{d\theta'}(\theta^* - \hat{\theta}) \tag{28}$$

All objects in Equation 28 are known to the researcher or in principle calculable from what is known to the researcher. The expression in Equation 28 also captures the fact that the counterfactual equilibrium probabilities will depend both on the direct effect of the parameters on the probabilities, captured by $\frac{d\Psi(\hat{\theta},\hat{\mathbf{P}})}{d\theta'}$, and the indirect strategic effect through the change in other players' equilibrium choices, captured by $\left(I - \frac{d\Psi(\hat{\theta},\hat{\mathbf{P}})}{d\mathbf{P}'}\right)^{-1}$.

A complication of this approach is that the matrix $\left(I - \frac{d\Psi(\hat{\theta},\hat{\mathbf{P}})}{d\mathbf{P}'}\right)$ is very large with dimension equal to the number of states multiplied by the number of players multiplied by the number of choices (less 1). In my case calculating and inverting such a matrix would be very costly.

Instead, I calculate a restricted version of the above equation. In a departure from Aguirregabiria and Ho (2012), I impose that the derivative of best responses in state x to the other player's play in state y is non-zero only when $x = y$. This amounts to assuming that in the new equilibrium child i adjusts their strategy taking account of any change in strategy by child j for the current period but is myopic about any changes to j's (or i's) strategy in future periods. I then calculate Equation 28 separately for each state. This means that the dimension of the matrix to be inverted in each equation is now only equal to the number of players times the number of choices (less 1), making the problem tractable. From these restricted versions of Equation 28 for each state I recover the counterfactual conditional choice probabilities in each state, and thus carry out counterfactual analysis.

H Model fit and counterfactuals

H.1 Model fit - location

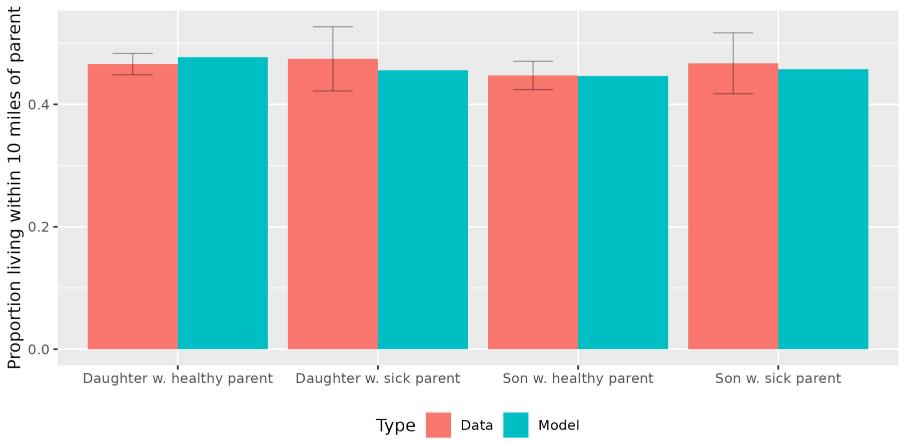
The main text discusses the model's ability to match the change in child location by gender when a parent becomes sick. Figure 9 shows proportions of children living within 10 miles of their parent, by child gender and parental health status.

The fit is good, though there is not a large amount of variation to match in the real data.

H.2 Counterfactual - no gender wage gap

In the main text I consider a counterfactual where I set preference differences between men and women to 0. I argue that the fact that doing so reduces the gender care gap by around four-fifths shows that the gender *wage* gap is not a significant driver of the gender care gap. It is not differences in observed opportunity costs between men and

Figure 9: Proportion of children living near parents - data versus model



Notes: standard errors clustered at household level. For the four cases, N in the real data is 7832, 761, 7582 and 713 respectively.

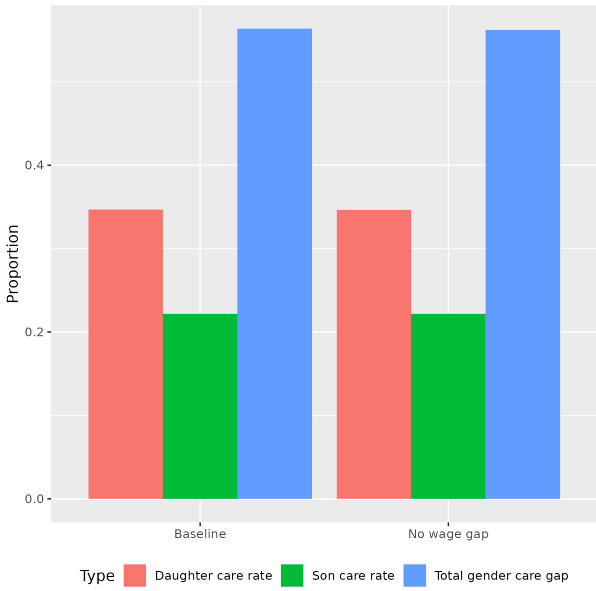
women, but rather their differences in preferences[52] that creates the gap in care provision. To illustrate this point further, I conduct an extra counterfactual experiment: I set eliminate the gender wage gap, so that women's equivalised income function is exactly the same as men's in the original model[53].

Figure 10 below shows the result of this counterfactual exercise. There is negligble change in the caregiving behaviour of women and men: the gender care gap shrinks by 0.3%. Thus, this backs up the finding in the main text that it is overwhelmingly preference differences which drive the gender care gap.

[52]As discussed above, "preferences" here includes the effects of e.g. social norms placed on women as care providers.

[53]Each child's value function is non-linear in the wage, so it is more difficult to evaluate counterfactuals by taking the derivatives of the probabilities of providing care with respect to the wage parameters and using these as part of the Taylor approximation approach set out in Appendix G. For this reason I do not use the full method as set out in Appendix G for this counterfactual. Instead, I simply alter the wage gap parameters, holding all other parameters constant, and recalculate agents' value functions and resulting behaviour, ignoring any complications around multiple equilibria. For this reason, the counterfactual results presented here are less reliable than those in the main text (though they are broadly consistent with those in the main text).

Figure 10: Counterfactual - no gender wage gap



Notes: "care rate" is the probability of providing care conditional on having a sick parent. "Total gender care gap" how much larger, in percentage terms, daughters' care rate is relative to sons' care rate.