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Utilisation of personal care services in Scotland: the influence of unpaid carers

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Utilisation of personal care services in Scotland: the influence of unpaid carers

Abstract

Unpaid carers may have an influence on the formal care utilisation of the cared for. Whether this influence is positive or negative will have important implications for the costs of formal care provision. The relationship between unpaid and formal care is of particular importance in Scotland, where personal care is provided for free by Local Authorities, to individuals aged 65+. The existing evidence on the impact of unpaid care on formal care utilisation is extremely mixed, and there is currently no evidence for Scotland. This paper is the first to investigate how the presence of an unpaid carer influences personal care use by those aged 65+ in Scotland, using a unique administrative dataset not previously used in research. Specifically, it uses the Scottish Social Care Survey (SCS) from 2015 and 2016 and compares Ordinary Least Squares (OLS), Generalised Linear Models (GLM), and Two-Part Models (2PM). The results suggest that unpaid care complements personal care services and this finding is robust to a number of sensitivity analyses. This finding may imply that incentivising unpaid care could increase formal care costs, and at the same time it points to the potential for unmet need of those who do not have an unpaid carer. Due to the limitations of the data, future research is necessary.

JEL Classifications: I11, I12, J14.

Keywords: unpaid, care, informal, formal, substitution, complementary, elderly.

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1. INTRODUCTION

Scotland, like much of the developed world, has experienced significant ageing in its population in recent decades, a trend that will continue until at least 2040. This is the result of increased life expectancy and falling fertility rates. A report published by National Records of Scotland (2016b) found that the population aged 65-74 grew by 22% between 2006 and 2016, while those aged 75+ increased by increased by 16%. By 2039, these groups are expected to grow by a further 27% and 85% respectively (National Records of Scotland, 2016b). As the population ages, pressure on health and social care services will increase. This will be further increased if there is an expansion of morbidity, i.e. a larger number of people reaching older ages and developing chronic conditions associated with age. If the ageing population is associated with an expansion of morbidity, as much of the literature suggests (Walter et al., 2016; Campolina et al., 2014; Beltrán-Sánchez et al., 2016), it is likely that population ageing will be associated with an even larger increase in demand for formal care services than that warranted by population ageing alone. Pressure on social care provision is already high in the UK. Age UK (2011) published a report highlighting the issue of under-funding within the UK care system and the knock on effects this has on the quantity and quality of care that is provided. Since funding for social care has not adequately kept up with an increasing number of older people requiring support, a shrinking social care resource is being spread over an increasing number of individuals in need. This inevitably leads to unmet need. In Scotland, spending on social care for older people, i.e. those aged 65+, actually decreased in real terms per capita by 1% between 2003-04 and 2013-14 (Scottish Government, 2015).

Unpaid care might offset pressure on formal care services. Unpaid carers are those who provide care to family members, partners or neighbours because they are frail, ill or have a disability (Carers UK, 2014). They often step in to provide help to older people when they experience difficulties with Activities of Daily Living (ADLs) and Instrumental Activities of Daily Living (IADLs). ADLs are fundamental self-care tasks such as washing, dressing and eating. Care for ADLs is often referred to as personal care. IADLs refer to activities that require more thinking and organisational skills such as shopping, housework, taking medication and paying bills. Help with IADLs is often referred to as home care. The Scottish Government estimates there were 744,000 unpaid carers aged 18+ in Scotland in 2017 (Scottish Government, 2017b). That is around 17% of the adult population (National Records of Scotland, 2016a). In the absence of unpaid care, it seems likely that the demand for state provision would increase. One mechanism to reduce this demand is for policy intervention to incentivise unpaid care. For example, through offering financial support, like the UK Carers Allowance, to unpaid carers DWP (2017). Furthermore, the Scottish Carers Act 2016, to be implemented in April 2018, has been "designed to support carers' health and wellbeing and help caring more sustainable" Scottish Government (2017a). Although the Act is not aimed explicitly at incentivising unpaid care, the benefits set out in the Act could have a motivating effect. However, policies which incentivise unpaid care will only be effective if unpaid care substitutes for formal care, and subsequently reduces overall expenditure on formal care services.

There are currently two competing hypotheses in the literature: the *substitution hypothesis* and the *complementary hypothesis*. The former posits that unpaid care indeed substitutes for formal care. In other words, as unpaid care increases, the utilisation of formal care by the cared for decreases. For example, an unpaid carer might perform tasks such as help with getting dressed, that would otherwise be carried out by a formal carer. The policy implications of this hypothesis might be to encourage unpaid care giving, in an attempt to reduce costs to government. In contrast, the complementary hypothesis suggests that unpaid and formal care are positively related. As unpaid care rises, so does the use of formal care services by the cared for. This might be because unpaid carers demand formal care services on behalf of the cared for. For example, an unpaid carer might provide help with IADLs, but realise that the person they are caring for also needs help with ADLs. They may therefore endeavour to increase the level of support for the cared for by engaging with the formal care sector. At the same time, they might advocate formal care use in order to reduce their own care responsibility (Bass and Noelker, 1987). If correct, this would lead to increased costs to government if it tries to incentivise unpaid care. Conversely, it could increase unmet need if there are disencentives to providing unpaid care, which might ultimately increase public sector costs through more intensive use of health services.

Clearly, the two opposing hypotheses could have significant impacts on the utilisation and consequent costs of formal care services. Thus, in order to design social care policy to respond optimally to the changing structure of the population, it is crucial that the relationship between unpaid and formal care is better understood. This paper aims to facilitate that understanding by investigating how unpaid carers affect older peoples' utilisation of social care services in Scotland.

The existing evidence in the literature is somewhat mixed in terms of which hypothesis holds true for the relationship between unpaid and formal care. Since Greene (1983) published evidence on the substitutability between unpaid and formal care, a significant body of research has supported the substitution hypothesis (Boaz and Muller, 1994; Pezzin et al., 1996; Kehusmaa et al., 2013; Van Houtven and Norton, 2008, 2004; Charles and Sevak, 2005; Lo Sasso and Johnson, 2002; Coughlin et al., 1992). Most recently, Kehusmaa et al. (2013) investigated the effect that unpaid care has on public expenditure for the older in Finland. Their findings showed that elderly people without an unpaid carer had the highest costs of formal care services, whilst those who lived with the person caring for them had the lowest costs. Van Houtven and Norton (2008) and Van Houtven and Norton (2004) both found evidence of substitution when analysing administrative and survey data for older individuals in the US.

On the other hand, there is some evidence in support of the complementary hypothesis Chappell and Blandford (1991); Geerts and Van den Bosch (2012); Litwin and Attias-Donfut

(2009); Bass and Noelker (1987). In particular, Geerts and Van den Bosch (2012) in their analysis of the effect that needs-based entitlements for long-term care has on the dynamics of formal and unpaid care utilisation, found that in all countries studied, formal and unpaid care were more often complements. Furthermore, analysis of European data by Litwin and Attias-Donfut (2009) concluded that unpaid care was often supplemented with formal care.

Some studies have found a mixture of substitution and complementarity effects, depending on the needs of the cared for and the type of formal care service used (Bolin et al., 2008; Bonsang, 2009; Lo Sasso and Johnson, 2002). For example, Bolin et al. (2008) found that whilst unpaid care tended to substitute for formal social care services such as personal and home care, the relationship was in fact complementary for health care services like doctor visits and hospital stays. In addition, Bonsang (2009) finds that the substitution hypothesis holds for services like home care, whilst the complementary hypothesis holds for personal and nursing care. Other authors have suggested that the nature of the relationship between unpaid and formal care depends on the closeness of the unpaid carer and caree relationship. For example, substitution is more likely for spouses and family carers, whilst complementarity is more likely for friends or neighbour carers (Geerlings et al., 2005). Furthermore, some research has found evidence that unpaid care has no effect at all on formal care service utilisation (Weaver and Weaver, 2014; Zhu et al., 2008; Langa et al., 2001).

The conflicting evidence in the existing literature highlights the complexity of the relationship between unpaid and formal care. This is further complicated by the ongoing debate of the endogeneity of unpaid care in the analysis. Specifically, there is a concern that there could be a reverse causality occurring between unpaid and formal care. This could be because an unpaid carer could change their care decision to provide unpaid care based on how much formal care is being utilised. Furthermore, there might be other unobserved characteristics, for example health characteristics, which could influence both the demand for formal and unpaid care. Both of these sources of endogeneity would lead to Ordinary Least Squares (OLS) estimates being biased. Some studies have ignored the issue of endogeneity altogether (Kehusmaa et al., 2013; Geerlings et al., 2005; Coughlin et al., 1992). Others have used Instrumental Variables (IV) techniques to try and account for it (Bonsang, 2009; Bolin et al., 2008; Van Houtven and Norton, 2008, 2004; Charles and Sevak, 2005). Overall, there are mixed conclusions on the extent to which endogeneity is an issue. Several authors have found limited evidence of it (Weaver and Weaver, 2014; McMaughan Moudouni et al., 2012; Bolin et al., 2008) and some have found that endogeneity is present and that failing to remedy it alters results considerably (Van Houtven and Norton, 2004, 2008).

In addition to this, some literature has examined how the use of formal care services affects unpaid care (Christianson, 1988; Penning, 2002; Johansson et al., 2003; Shelley and Rose, 2004; Li, 2005; Franca et al., 2008; McNamee, 2006; Arntz and Thomsen, 2011; Pickard, 2012; McMaughan Moudouni et al., 2012). Much of this research has found that there is no relationship between formal care and unpaid care (Penning, 2002; Shelley and Rose, 2004; Li, 2005; McNamee, 2006; McMaughan Moudouni et al., 2012) suggesting that reverse causation might not be an issue.

This paper will provide new evidence on the existence of substitution or complementarity between unpaid and formal care. Specifically, it is the first of its kind to demonstrate how unpaid carers influence personal care use for the over 65s in Scotland. This relationship is of particular interest in Scotland where personal care is provided by Local Authorities (LA) for free to individuals aged 65+. There is currently no evidence on the impact that unpaid carers have on older peoples use of formal care services in Scotland. At the same time there is little evidence for the rest of the UK (Pickard, 2012).

In summary, this paper will use the Scottish Social Care Survey (SCS), a unique administrative dataset which contains information on all social care services delivered to individuals in Scotland, to examine the influence that unpaid carers have on older peoples' use of formal care services in Scotland. In particular, as outlined the focus of this analysis will be on personal care services utilised by Scots aged 65 or over.

The remainder of the paper will be structured as follows: Section 2 describes the data and characteristics of the SCS sample. Section 3 introduces the theoretical framework and discusses the empirical specifications of the models to be estimated. Following this, Section 4 outlines the results and provides a discussion. Finally, Section 5 concludes.

2. DATA

The data used in this paper come from the 2015 and 2016 Scottish Social Care Survey (SCS). This is a comprehensive survey set up by the Scottish Government and administered annually by each of the 32 Local Authorities (LAs) in Scotland. All individuals who receive at least one of seven possible social care services are included in the survey. Those services are: home care, personal care, telecare, meals services, self directed support (SDS), social work and housing support [1]. The SCS contains information on which care packages individuals' are receiving as well as additional information on their basic demographics, needs and unpaid care status.

The focus of this paper is on personal care clients. Personal care in a person's home can be provided directly by the LA or the LA can purchase personal care from the private and voluntary sectors. It is usually intended to help individuals maintain their independence and enable them to continue to live in their own homes. It comprises help with personal hygiene, continence management, food and diet, immobility problems, counselling and support, simple treatments and personal assistance[2]. Personal care at home is free to all individuals aged 65 and over in Scotland, subject to a needs assessment. The SCS collects information on the weekly number of hours of personal care an individual received during the census week.

[1] For a detailed description of the information included in the SCS please see Scottish Government (2016)

[2] The formal definition for personal care can be found in schedule 1 of the Community Care and Health Act 2002.

Sample Selection Criteria

This paper focuses on social care clients' aged 65 and over. As mentioned above, personal care is free to individuals aged 65+ in Scotland and focusing the analysis on this group should limit the potential selection bias that could exist due to differing incomes of clients. In total, in 2015 and 2016, there were 311, 400 social care clients in Scotland aged 65 and over.

Several restrictions are made to this population in order to carry out the analysis for this paper. Firstly, it is restricted to try and include only individuals who receive social care specifically for reasons due to ageing, as opposed to other reasons such as mental health or learning disabilities. To do this, clients who are not assigned 'frail and elderly' or 'dementia' as their primary client group are dropped. Together, these two groups account for around 52% of the sample of clients aged 65+, leaving 150,878 social care clients across the two years. Secondly, only clients who had unpaid carer information available were included. Unfortunately, filling in the information on the unpaid carer status of social care clients is optional for LAs and a large proportion (around 77%) have 'unknown' unpaid care status. Removing these clients results in a final sample of 19,385 individuals in 2015 and 17,510 in 2016, a total of 36,895 [3].

Fig. 1 below shows the proportion of social care clients in each of the 32 LAs aged 65+, then adjusted for the frail, elderly and dementia clients, and lastly adjusted for the unpaid care information. The chart clearly shows how there are most likely substantial recording differences between LAs in terms of the unpaid carer field. For example, despite being the 10th smallest LA in terms of its population aged 65+, East Renfrewshire accounts for the second largest proportion of the final sample of clients. Furthermore, for some LAs, there is no unpaid carer information recorded for any of the social care clients e.g. City of Edinburgh, which is in fact the second largest LA in terms of its population aged 65+. The poor recording of the unpaid care information highlights one of the fundamental difficulties of working with administrative records and raises potential identification concerns for the models estimated in this paper. As such, the model results presented hereafter should be interpreted with these data limitations in mind.

Descriptive Statistics

Table 1 below provides a set of basic descriptive statistics for the whole sample, the personal care clients and the unpaid care clients. Overall, approximately 36% of the whole sample have an unpaid carer, and about 45% receive personal care services. The gender variable is a binary indicator which is equal to 1 if the client is female and 0 if the client is male. The dementia and unpaid carer variables are also binary indicators which are equal to 1 if yes and 0 if no. The age and weekly personal care hours variables are continuous. The number of other services variable

[3] Note that this figure does not reflect the total number of individuals because some clients will appear in the survey in both years. Specifically, 9,146 clients appear in 2015 and 2016, meaning that the total number of individuals in the whole dataset is 27,749

is a count variable from 0 to 5 indicating the number of social care services apart from home care (which includes personal care) a client is receiving. The year indicator variable indicates whether a client received care in 2015 only, 2016 only, or both in 2015 and 2016.

In the various models, which will be outlined in Section 3 below, the estimations are either carried out on the whole sample or on the sample of clients who were receiving personal care services. Thus, as well as displaying descriptive statistics for the whole sample and unpaid care clients, Table 1 also displays descriptives for personal care clients. This will indicate whether or not there are large differences between these groups and the whole sample.

With respect to the whole sample, around 69% are female and the remaining 31% are male. This is similar to the proportions found in the whole population of social care clients aged 65+ in Scotland. These proportions are also very similar for personal care clients and slightly different for unpaid care clients where around 66% are female. The average age of clients is about 84 in all groups.

As mentioned above, one of the client groups assigned to clients is the dementia group. This is not a diagnosed dementia status, it is simply based on care workers assessment of the individual and thus cannot be considered a medical diagnosis. Overall, around 16% of the sample have been assigned to the dementia client group. This is similar for personal care clients. This is slightly lower than the 2017 population estimate of 19.6%, for those aged 65+ (Alzheimer Scotland, 2017; National Records of Scotland, 2016a). In contrast, just over 29% of clients with an unpaid carer have been assigned the dementia client group. This might indicate that individuals with dementia are far more likely to have an unpaid carer looking after them. This finding might also be a consequence of the recording of unpaid care information by Local Authorities.

Furthermore, a slightly higher proportion of personal care clients have an unpaid carer, 39%

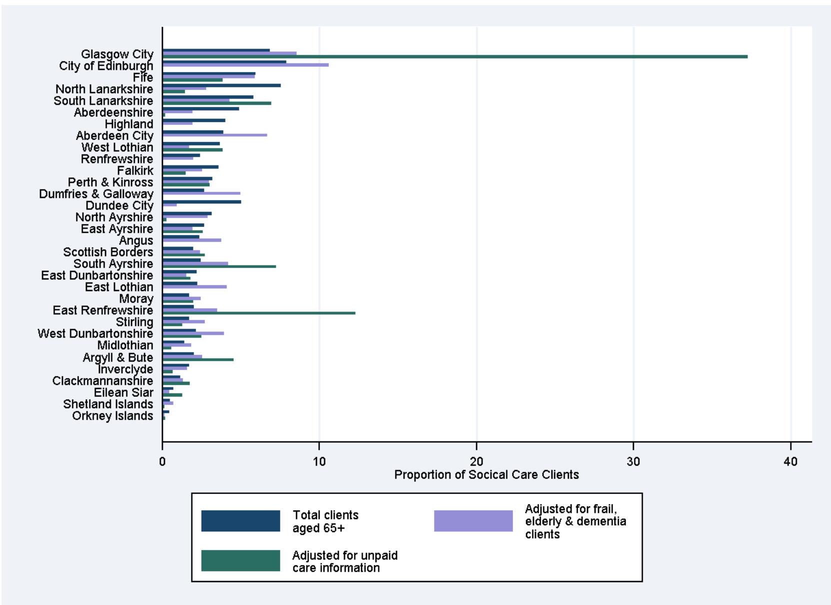

Figure 1: Sample Selection Criteria by Local Authority

Table 1: Descriptive Statistics

	Whole Sample		PC Clients		UC Clients	
	N = 36,895		n = 16,645		n = 13,454	
Variable	No. of Obvs	% of N	No. of Obvs	% of n	No. of Obvs	% of n
Gender						
Female	25,461	69.01	11,693	70.25	8,892	66.09
Male	11,434	30.99	4,952	29.75	4,562	33.91
Age						
Mean	83.77	-	83.76	-	83.94	-
Dementia						
Yes	6,010	16.29	2,432	14.61	3,905	29.02
No	30,885	83.71	14,213	85.39	9,549	70.98
Unpaid Carer						
Yes	13,454	36.47	6,487	38.97	13,454	100
No	23,441	63.53	10,158	61.03	0	0
No. other Services						
Mean	1.48	-	1.43	-	1.83	-
Year Indicator						
2015 only	10,239	36.90	5,414	41.17	4,685	41.82
2016 only	8,364	30.14	4,243	32.26	4,265	38.07
2015 and 2016	9,146	32.96	3,494	26.57	2,252	20.10
Weekly Personal Care Hours						
Min	0	-	0.08	-	0.08	-
Mean	3.09	-	8.38	-	9.03	-
Median	0	-	7	-	7	-
Max	168	-	168	-	168	-

of personal care clients have an unpaid carer, compared to 36% of the whole sample. In terms of the number of other services clients are receiving, there is little difference across the groups. On average, clients receive one service other than home care. Although, clients with an unpaid carer receive two other services on average. This most likely reflects the higher level of need of those individuals.

The year indicator variable splits up the total number of social care clients into one of three groups. Those are, clients who were in 2015 only, 2016 only and those who were in 2015 and 2016 [4]. Of the whole sample, around 37% of clients were 2015 only clients, 30% were 2016 only clients and 33% were receiving some form of care in both years. The fact that their are fewer personal care and unpaid care clients appearing in both years might reflect attrition in the sample as these clients will tend to have higher levels of need.

Lastly, Table 1 also provides information on the distribution of weekly hours of personal care. The mean number of hours of care for the personal care sub-group is around 8 hours per

[4]Note that the sum of clients does not add up to the total as displayed in N unless the group of clients in both years is multiplied by two.

week. For the unpaid care sample this figure is 1 hour higher at 9 hours of personal care per week. However, as is expected, the distribution of hours of personal care is positively skewed and thus the median number of hours of care might provide a more accurate description of the average hours of care. This is 7 hours per week for both the personal care sample and the unpaid care sub-group, descriptively implying that there is no difference in terms of the average hours of care between clients with and without unpaid carers.

The following section will outline the model of interest, explore the difficulties encountered when working with skewed explanatory variables and propose three approaches to estimate the model which account for skewness.

3. METHODOLOGY

The relationship of interest is between the presence of an unpaid carer and an individuals' utilisation of personal care services. Specifically, personal care services PC_i are described as a function of unpaid care UC_i and other observed and unobserved characteristics:

$$PC_i = f(UC_i, X_i, \epsilon_i) \tag{1}$$

Where i indexes individuals for $i = 1...n$, X_i represents other socio demographic and health characteristics of the individual, and ϵ_i is the unobserved error term.

In the empirical estimations of the relationship as described by Eq. 1, the dependent variable is PC_i and is a continuous variable measuring the number of hours of personal care services individual i received during the census week. The explanatory variable of interest, UC_i is a binary indicator which is equal to 1 if the individual was known to have an unpaid carer and 0 if the individual was known not to have an unpaid carer.

As can be seen in the left hand pane of Figure 1, weekly personal care hours are highly positively skewed. In particular, for those who have positive personal care hours, a large proportion of them have very few hours of care and a small proportion have a very large number of hours of care. Specifically, the skewness of the distribution is 3.4. Heavily skewed distributions of health outcomes, such as hours of personal care, is a common problem in the analysis of health care data and especially with expenditure data, which is highly correlated with hours of care. Heavily skewed dependent variables in standard regression models such as Ordinary Least Squares (OLS) can lead non-normal residuals which will yield inconsistent estimates of marginal and treatment effects. Health economists have developed several ways to deal with this problem, three of which are explored in this paper.

The remainder of this section will outline the empirical models to be estimated and the calculations of the incremental effect of the UC variable in each model.

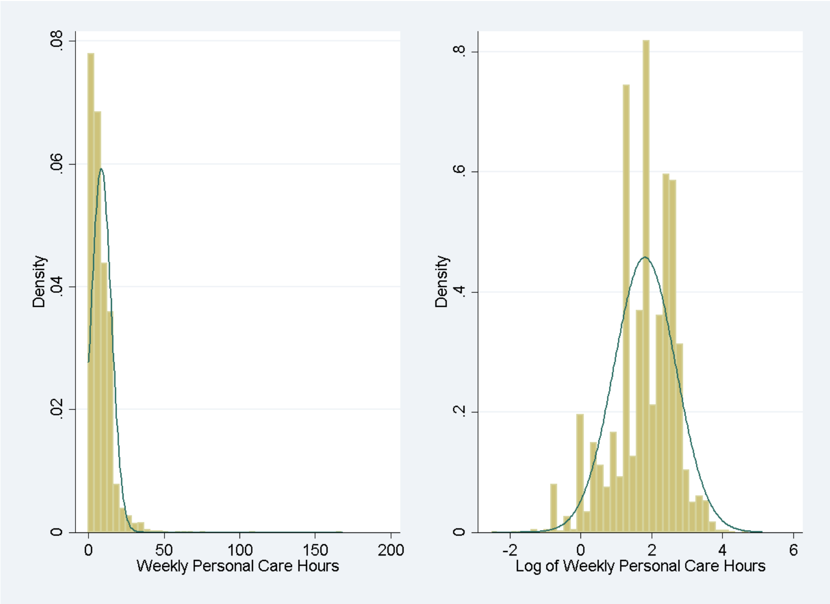

Figure 2: Distribution of Weekly Personal Care Hours

OLS

One approach to dealing with skewed distributions of dependent variables in regression analysis is to transform the dependent variable by taking its natural logarithm to ensure that the disturbance approximates normality. This approach is common in the health economics literature, particularaly in the modelling of utilisation and spending on health resources. (Buntin and Zaslavsky, 2004; Mihaylova et al., 2011). The panel in the right of Fig. 2 shows the distribution of the logged personal care hours for those with non-zero hours of personal care. Clearly, the distribution is more normal for the logged hours of personal care.
The model is estimated via OLS as:

$$E[lnPC_i|UC_i, X_i] = (\beta_{uc}UC_i + \boldsymbol{X_i'\beta} + \epsilon_i) \tag{2}$$

Where $lnPC_i$ is the natural log of positive personal care hours, β_{uc} is the parameter to be estimated on unpaid care (UC_i), $\mathbf{X_i}'$ is the vector of explanatory variables which includes a constant, $\boldsymbol{\beta}$ is the vector of parameters to be estimated, and lastly ϵ_i is the random error term.

Interpreting the marginal effects in log-linear models requires transforming the coefficients such that unit changes in explanatory variables can be interpreted as percent changes in the log of personal care hours. In order to calculate the incremental effect of unpaid care on the raw scale of personal care hours rather than the log of hours, one has to re-transform the dependent variable. This is more complex if the exponentiated error term is not homoskedastic and can lead to inconsistent estimates of the incremental effect (Manning, 1998).

Generalized Linear Model

A second approach to dealing with skewness is to use a Generalized Linear Model (GLM). This approach has increasingly been applied in health economics research (Deb et al., 2017).The GLM framework allows the mean of the dependent variable to be a function of the linear index of covariates and at the same time allows the variance of the dependent variable to be a function of its predicted value through the choice of a suitable distribution family (for general overview see (Deb et al., 2017)).

The model becomes:

$$E[PC_i|UC_i, X_i] = g^{-1}(\beta_{uc}UC_i + \boldsymbol{X_i'\beta} + \epsilon_i) \tag{3}$$

Where g^-1 represents the inverse of the log-link function and the outcome variable is generated by the gamma distribution. The decision to use the log-link function and gamma distribution family is based on Akaike and Bayesian Information Criteria, AIC and BIC respectively, and statistical tests including the Box-Cox and Modified Park tests [5]. The log-link and gamma family is a common choice for GLM models of health care expenditures and costs (Deb et al., 2017, pg.86)

GLM's are especially useful because they model heteroskedasticity directly and they avoid the re-transformation of the outcome variable back to the raw scale as with log-linear models, which means that marginal and incremental effects can more easily be calculated. Specifically in the GLM, the marginal effect of a continuous variable X is:

$$\frac{\partial E[PC_i|UC_i, X_i]}{\partial X} = \beta_x e^{X_i'\beta} \tag{4}$$

Since the unpaid care variable is a binary indicator, the marginal effect is simply the incremental effect on weekly hours of personal care:

$$\frac{\Delta E[PC_i|X_i]}{\Delta UC} = e^{(X_i'\beta|UC=1)} - e^{(X_i'\beta|UC=0)} \tag{5}$$

Of course, the OLS and GLM models are both conditional on an individual having positive personal care hours. This condition results in a loss of information since those clients who do not receive any personal care in the first place are ignored. That is, we know that many clients in fact have zero hours of personal care. The third estimation attempts to account for this.

Two-Part Model

We observe that 55% of the total sample were not receiving personal care and subsequently had zero personal care hours. Using statistical models that ignore this mass at zero might

[5] Please see Appendix A for the output from these tests.

mean that the effects of the explanatory variables on the outcome cannot be generalised to the whole population. Specifically, OLS and GLM only describe the effect at of an unpaid carer on personal care hours for those who receive personal care, however this effect might differ from the effect of an unpaid carer on whether or not a person receives personal care in the first instance. Thus, it is important to explicitly model the mass at zero, and subsequently calculate marginal and incremental effects which account for this.

One model which does this is the two-part model (2PM). It involves firstly estimating the probability of having a non-zero outcome via probit or logit, and subsequently estimating the mean of the outcome, conditional on having a non-zero outcome via OLS or GLM. 2PMs have widely been used and discussed in the health economics literature (Mihaylova et al., 2011; Duan et al., 1984; Mullahy, 1998; Buntin and Zaslavsky, 2004) and have often been shown to outperform other models when a large proportion of zeroes exist in the data (Mihaylova et al., 2011). Moreover, the 2PM is frequently employed within the literature on the relationship between unpaid and formal care(Bonsang, 2009; Charles and Sevak, 2005; Bolin et al., 2008; Van Houtven and Norton, 2004). Unlike selection models such as Heckman's 2-step model, where there are unobserved individuals, we actually observe individuals with zero personal care hours. Intuitively, there are different decisions occurring in the two parts of the 2PM, which implies that covariates may have different effects on the dependent variable each step (Deb and Trivedi, 2002). Firstly an individual decides whether or not to demand any formal care services, and secondly the formal care provider will apply LA guidelines on how much care to supply. The 2PM is therefore appealing in this setting because it takes both decisions into account. Nevertheless, it is worth considering that there are possibly unobserved individuals i.e. those who do not receive social care services at all, and as a result are missing from the dataset. Thus, the 1st Part in the 2PM is estimated for a population who are perhaps already at an increased risk of requiring personal care.

Formally, the 2PM can be written as:

$$Pr[PC_i > 0|UC_i, \boldsymbol{X_i}] = \boldsymbol{\Phi}(\alpha_{uc}UC_i + \boldsymbol{X_i'\alpha} + \xi_i \tag{6}$$

$$E[PC_i|PC_i > 0, UC_i] = g^{-1}(\beta_{uc}UC_i + \boldsymbol{X_i'\beta} + \epsilon_i) \tag{7}$$

The threshold in Eq. 6 is modelled as a binary probit model where Φ represents the cumulative density function of the standard normal distribution. This is known as the 1st part of the 2PM. The dependent variable PC_i and key explanatory variable of interest UC_i are as described above. Here, $\mathbf{X}'$ is a vector of explanatory variables including an intercept. The parameters to be estimated are in the vector $\boldsymbol{\alpha}$ and ξ_i is the error term.

Eq. 7 is a GLM model for individuals with strictly positive hours of personal care and is known as the 2nd part of the 2PM. It is identical to Eq. 3. Once again, g^{-1} is the inverse of the log-link function and the outcome variable, PC_i, is generated by the gamma distribution. The parameters to be estimated are in the vector $\boldsymbol{\beta}$ and ϵ_i is the error term. Estimation of the 2PM is carried out in Stata using the `twopm` command (Belotti, 2015).

Post estimation, the full marginal effects can be calculated:

$$\frac{\partial E[PC_i|UC_i, X_i]}{\partial UC} = e^{X_i'\beta}\phi(\boldsymbol{X}_i'\boldsymbol{\alpha})\alpha_{uc} + \beta_{uc}e^{X_i'\beta}\Phi(\boldsymbol{X}_i'\boldsymbol{\alpha}) \tag{8}$$

Where $\boldsymbol{X}_i'\boldsymbol{\alpha}_i$ are the linear predictions from Eq. 6 and α_{uc} is the estimated parameter on the unpaid care indicator. As before $\boldsymbol{X}_i'\boldsymbol{\beta}_i$ and β_{uc} are the respective predictions from Eq. 7. Finally, ϕ represents the standard normal density function.

Eq. 8 shows the marginal effect for a continuous variable. The incremental effect of the presence of an unpaid carer on personal care hours can be calculated simply as:

$$\frac{\Delta E[PC_i|X_i]}{\Delta UC} = \Phi(\boldsymbol{X}_i'\boldsymbol{\alpha}|UC = 1)e^{(X_i'\beta|UC=1)} - \Phi(\boldsymbol{X}_i'\boldsymbol{\alpha}|UC = 0)e^{(X_i'\beta|UC=0)} \tag{9}$$

Endogeneity

As mentioned in Section 1, there are potential sources of endogeneity that could exist in the model. The first being endogeneity due to omitted variable bias where an omitted variable is correlated with both unpaid care and the dependent variable. This will result in a correlation between unpaid care and the error term, leading to the estimate of the incremental effect of unpaid care being biased. One potential omitted variable is the need of the social care client. The models account for client need via the number of other services variable, and the dementia indicator. If these do not fully reflect client need then the estimate for the parameter on unpaid care could be biased. Furthermore, omitted variable bias might arise from unobserved heterogeneity between clients. A variety of sensitivity analyses, are carried out to check for the extent of endogeneity due to omitted variable bias and these are presented in Appendix A.

In addition to ommitted variable bias, endogeneity might be present due to the potential reverse relationship that could exist between unpaid and formal care services. For example, the number of hours of personal care a person receives might influence the decision of their unpaid carer to provide care. Having said that, it is argued that this is not likely to be the case in Scotland due to the assessment process for personal care. Specifically, following an individuals needs assessment for personal care, the Local Authority must "take account of the views of the individual and their carer, as well as the care the carer is willing and able to provide, before deciding what services to provide to the individual" (Executive, 2003). This would therefore suggest that reverse causality is not likely to be present in the Scottish context. Nevertheless, sensitivity analysis, including an instrumental variables estimation, is carried out to test for the endogeneity of unpaid care. The results are presented in Appendix B.

The next section presents and discusses the model results from the three estimation approaches and sensitivity analyses.

4. RESULTS AND DISCUSSION

Table 2 below displays the model results. The OLS and GLM estimations (this includes part two of the 2PM), are estimated on the sample of individuals who received personal care, whilst part one of the 2PM, as shown in the table, is estimated for the whole sample.

Overall, the signs of coefficients in the OLS and GLM estimations are in line with a priori expectations. In particular, age is shown to have a positive relationship with weekly hours of personal care. Hours increase with age and become significant among the oldest age groups. This is consistent with the idea that ageing is associated with increased frailty and likelihood of dementia. In addition to age, clients who have been assigned the 'dementia' client group have higher weekly personal care hours on average, reflecting the higher level of need of dementia clients. However, this effect is small and only significant at the 10% level in the OLS estimation. Moreover, the greater the number of other services a client is receiving, i.e. over and above home care, the higher are their weekly personal care hours. This effect is significant at the 1% significance level in both models. The number of other services variable will act as a proxy for level of need and thus the positive relationship is what one would expect. As for the unpaid carer variable, the coefficients are positive and highly significant in both estimations, suggesting that weekly personal care hours are higher on average for clients with an unpaid carer compared to those without, other things being equal. This finding provides support for the complementary hypothesis.

With respect to gender, there are no significant differences in weekly hours of personal care between men and women. Furthermore, OLS finds that there is no difference in weekly personal care hours between years, whilst GLM predicts that weekly personal care hours are higher on average in 2016 compared to 2015.

The third column in Table 2 shows the results from the 1st part of the 2PM. Thus, the dependent variable is the probability of receiving personal care, or in other words, the probability of having positive weekly personal care hours. As with the OLS and GLM estimations, age has a positive impact on the probability of receiving personal care. However, this effect seems to decrease as age increases and becomes insignificant into the oldest age groups. Furthermore, the 2PM predicts that females are significantly more likely to receive personal care than males and clients are more likely to receive personal care in 2016 compared to 2015. Interestingly, the probit model predicts that clients with dementia are significantly less likely to receive personal care compared to non-dementia clients. Furthermore, the model shows that the higher the number of other services a client receives, the less likely they are to receive personal care. This reflects the fact that the other services are possibly preventing older people from requiring personal care. For example, meals and telecare services. Lastly, the model predicts that clients with an unpaid carer are significantly more likely to receive personal care services. This is in accordance once again with the complementary hypothesis.

In terms of the incremental effect of an unpaid carer on weekly hours of personal care, the

Table 2: Model Results

Variable	OLS	GLM	2PM (P1)
Aged 70-79	0.0118	-0.0334	0.185***
	(0.0423)	(0.0435)	(0.0374)
Aged 80-89	0.0624	0.00234	0.129***
	(0.0409)	(0.0424)	(0.0361)
Aged 90-99	0.113***	0.0476	0.0543
	(0.0429)	(0.0436)	(0.0379)
Aged 100-109	0.237***	0.144*	0.0383
	(0.0907)	(0.0783)	(0.084)
Female	0.00281	-0.00349	0.0491***
	(0.0161)	(0.0148)	(0.0149)
Has Unpaid Carer	0.145***	0.139***	0.230***
	(0.0195)	(0.0185)	(0.0198)
No. Other Services	0.123***	0.0927***	-0.181***
	(0.0108)	(0.00987)	(0.0106)
Dementia	0.0421*	0.0252	-0.141***
	(0.0234)	(0.0224)	(0.0218)
2016	0.0278	0.0416***	0.279***
	(0.0172)	(0.0155)	(0.0155)
Constant	1.528***	2.017***	-0.133
	(0.164)	(0.162)	(0.162)
AIC	34362.5	84814.5	131272.2
BIC	34610.6	85062.7	131834.2
Observations	13,616	13,616	36,891
ME	1.015***	1.178***	1.163***

*t statistics in parentheses; * p <0.10, ** p <0.05, *** p <0.01*

results are consistent across the three models. With OLS, the coefficient on the carer dummy indicates that those with an unpaid carer have higher weekly personal care hours by about 14.5%. As discussed in Section 3, calculating marginal and incremental effects in models with a log-transformed dependent variable requires re-transformation back to the raw scale. This re-transformation depends on the estimated errors from the model which can be incorrect if these errors are heteroskedastic. A Breusch-Pagan test for constant variance of the residuals in the OLS estimation finds that heteroskedasticity is present in the model. As a result, calculating the incremental effect of unpaid care is not appropriate. Instead, we can use the coefficient of 0.145 and apply it to the median personal care hours to get an estimate of the effect in terms of the average number of hours of weekly personal care. This gives a figure of about 1 hour per week. That is, those with an unpaid carer receive about 1 hour more per week of personal care.

With GLM, the incremental effect of an unpaid carer can be calculated using Eq. 5. This results in a positive incremental effect of 1.18 hours per week. This result is significant at the 1% significance level. In other words, those with an unpaid carer receive, on average, about 1 hour and 11 minutes more personal care per week, all other things being equal.

Moreover, the incremental effect of unpaid care in the 2PM, calculated using Eq. 9, which takes into account the probability of receiving personal care, is 1.16 hours per week. That is, personal care clients with an unpaid carer receive around 1 hour and 10 minutes more per week compared to personal care clients without an unpaid carer, ceteris paribus. Once again, this result is statistically significant at the 1% level.

The small difference in the predicted incremental effect of unpaid care on hours of weekly personal care between the three estimations is promising, showing that the findings are robust across different methods of estimation. This has been shown to be the case in previous research which compares methods for modelling skewed health care data (Buntin and Zaslavsky, 2004). In terms of deciding which estimation is the most appropriate, specification tests, including Pregibon's link and Ramsey's RESET tests, find that the model as estimated with OLS is possibly misspecified, whilst GLM is correctly specified. As outlined in Section 3, the 2PM is generally preferred in this setting because it takes into account the full incremental effect of unpaid care, incorporating the two parts of the decision process in determining personal care utilisation. This is also the approach taken by the vast majority of the literature (Bonsang, 2009; Van Houtven and Norton, 2004, 2008; Weaver and Weaver, 2014).

On the whole, the results outlined in this section show that, unpaid care tends to complement personal care services. That is, in general, the presence of an unpaid carer is associated with an increase in the number of weekly personal care hours. This finding supports the complementary hypothesis and might suggest that unpaid carers are demanding formal care services on behalf of the person they are caring for. These results are also in line with some of the existing literature which finds that a complementary relationship exists between unpaid and formal care (Geerts and Van den Bosch, 2012; Litwin and Attias-Donfut, 2009). Furthermore, this result might not be surprising given the sample of individuals analysed in this paper are likely to be of a higher dependency level. Specifically, the sample are aged 65+ and requiring personal care as oppose to help with non-personal care tasks. Intuitively, a complementary relationship might be expected for those with a higher level of dependency since it might be that unpaid carers, who are most likely to be partners or children, are less able to help with personal care tasks such as bathing and toileting. Moreover, for parents who are getting care from their children, they might be less willing to let their child help them with such tasks. This finding is consistent with Bonsang (2009) who finds evidence of complementarity for nursing care.

However, the findings are in contrast to much of the existing literature which finds evidence of a negative relationship between unpaid care and formal care Van Houtven and Norton (2004, 2008); Charles and Sevak (2005); Bolin et al. (2008); Lo Sasso and Johnson (2002). This might also be explained by the fact that due to personal care services being free for the over 65s in Scotland, unpaid carers might not be making the same financial calculations as would be the case in jurisdictions where personal care bears a financial cost. That is, if the cost of personal care were to fall on the unpaid carer, there is more likely to be a substitution.

Sensitivity Analysis

As mentioned in Section 3, a variety of sensitivity analysis are carried out to check for the extent of endogeneity. One source of endogeneity is ommitted variable bias from not accounting fully for individual need. In order to remedy this, the model is adapted by including an indicator, 'Multi Staff', to more fully account for the level of need of the individual. The Multi Staff variable indicates whether or not the person required two members of personal care staff. This will capture the level of need of the client in the sense that it is likely those who have substantial mobility problems who require two or more staff to help them with personal care tasks. Those clients are therefore likely to be receiving more care per week. The Multi Staff information is available only for 2016 clients, which is approximately 52% of personal care clients. Thus, estimations which include this indicator are carried out only on the 2016 sample. The results are shown in Table A1.

Overall, the results are similar to the model results shown in Table 2 and they consistently show that unpaid carers have a positive influence on weekly hours of personal care. Moreover, the marginal effect of an unpaid carer as estimated by the 2PM also suggests that an unpaid carer increases personal care hours by about 1 hour and 10 minutes per week.

In addition to not fully accounting for need in the model, other unobserved heterogeneity might also bias the estimates presented above. Since the SCS is a longitudinal survey, with clients being observed over time, a fixed effects estimation will control for these unobserved differences between individuals, which could be biasing the estimates in the pooled models. Therefore, as a sensitivity check, a fixed effects estimation is carried out for those clients who were present in the dataset in 2015 and 2016, and receiving personal care in both years. As presented in Table 1 there were 3,494 clients who received personal care in both 2015 and 2016, that is about 27% of personal care clients. This model is estimated for those clients who switched from not having an unpaid carer to having one, to isolate the effect of unpaid care [6].

Table A2 shows the results from the fixed effects estimation. The carer dummy in this model shows the incremental effect of unpaid care for those individuals who did not have a carer in 2015 but subsequently had one in 2016. The coefficient on the unpaid care dummy indicates that the presence of an unpaid carer is associated with an increase in hours of personal care by 0.87 hours per week, or 52 minutes. This result is significant at the 10% level and reconfirms the results found in previous models that unpaid carers have a positive influence on the number of hours of personal care received by the person they are caring for.

Furthermore, as outlined in Section 1 there is an ongoing discussion in the literature surrounding the existence of a reverse relationship between unpaid care and formal care. Specifically, the number of hours of personal care a person receives might influence the decision of

[6] Those who switched from having an unpaid carer in 2015 to not having one in 2016, are removed from the estimation. This is the case for less than 1% of the total sample who were present in both years

the unpaid carer to provide care to that person. Although, as discussed in Section 3, this is not likely to be true in Scotland given the process for receipt of free personal care. Nonetheless, several additional analyses are carried out to check for the extent of endogeneity of unpaid care.

Firstly, the model is re-estimated for those clients who appeared in 2016 only. Estimating the models for individuals only present in 2016 acts as a check against reverse causality, assuming that those who were not present in 2015, were receiving social care for the first time in 2016 and as a result the decision of their unpaid carer to provide care is less likely to be influenced by the number of hours of care the client is receiving. The results are shown for the basic models as well as for the extended model where Multi-Staff is included in Table B1. Overall, the results are consistent with the previous findings.

Secondly, a first difference model for those clients who received personal care in both 2015 and 2016, and who did not change unpaid care status between the years is estimated. In this way, reverse causality cannot occur because unpaid care status remains unchanged between the two years and thus isn't influenced by the change in personal care hours. This approach will offer some insight into the extent to which there exists a reverse causality between personal care hours and unpaid care status. The model is estimated via basic OLS. Similarly to running the models for individual years, this approach serves merely as a sensitivity check to see if the incremental effect of unpaid care changes. In total, 9,146 clients received some form of social care in both years, that is 33% of the total number of individuals in the sample. Of those, only 3% changed unpaid care status over time. Thus, few observations are lost. The results are shown in Table B2. Once again, the results re-confirm the complementary hypothesis.

Lastly, an instrumental variables (IV) analsyis is carried out. IV involves sourcing exogenous variation in the unpaid care variable UC, which does not directly influence the dependent variable PC. Such exogenous variation takes the form of an instrument. Of the literature which implements IV techniques, the most commonly used instruments are varying characteristics of the care givers. Much of the literature focusses explicitly on children caring for parents, hence among the most frequently used instruments are proportion of daughters, distance to nearest child and age of eldest child (Bonsang, 2009; Bolin et al., 2008; Van Houtven and Norton, 2008, 2004; Charles and Sevak, 2005). Unfortunately, since the SCS data are collected for administrative purposes, there is limited opportunity for finding suitable instruments. However, some publically available datazone[7] level information from the 2011 Census is used to constuct an instrument. The IV used is the proportion of single person households in the datazone in which an individual resides. Living in an area in which there are a high proportion of single person households is likely to be negatively correlated with an individuals unpaid care status since an older persons unpaid carer is often living with them. Thus, receipt of unpaid care is less likely in an area with a high proportion of single person households.

[7] A datazone is a small-area statistical geography in Scotland containing populations of between 500 and 1,000 residents.

The model is estimated via Two-Stage Least Squares. The results from the second stage IV are shown in Table B3. The Cragg-Donald Wald F-statistic from the first stage regression is greater than 10, indicating that the instrument is strongly correlated with the suspect endogenous regressor. Moreover, the large p-value on the endogeneity test of the unpaid carer variable concludes that it can in fact be treated as exogenous. This is consistent with the argument that unpaid care is less likely to be endogenous in Scotland due to the fact that the availibility and willingness of an unpaid carer to provide care is explicitly taken into account before allocating personal care resources to the individual.

On the whole, the results from all sensitivity analysis consistently point to a positive relationship between unpaid care and personal care use for the over 65s in Scotland.

5. CONCLUSION

The ageing shift occurring in populations across the developed world has the potential to increase pressures on long term care provision. In Scotland, the proportion of the population aged 65-74 is projected to increase by 27% by 2039, whilst the population aged 75+ is expected to grow by a staggering 85% (National Records of Scotland, 2016b).

As individuals continue to live into older ages they are more likely to require care for frailty and chronic conditions, especially if ageing is associated with an expansion of morbidity (Walter et al., 2016; Campolina et al., 2014; Beltrán-Sánchez et al., 2016). This care can be provided through paid care, also known as formal care, or by unpaid carers. In Scotland, formal care services are organised and often provided by Local Authorities (LAs) within the Scottish Government. Thus, any increased pressure on those services inevitably raises concerns regarding the costs of care provision. If unpaid care substitutes for formal care, governments might consider policies which incentivise unpaid care, in order to reduce costs by reducing the demand for formal care services. In fact, the UK government offers an incentive to unpaid carers in the form of the weekly Carers Allowance (DWP, 2017).

However, evidence in the existing literature is extremely mixed. Some pieces of research have found evidence suggesting unpaid care substitutes for formal care, whilst others has found that it in fact complements formal care. The influence that unpaid care has on formal care services will undoubtedly have considerable implications on the utilisation and subsequent costs of those services. It is therefore vital that the relationship between the two is fully investigated, so that long term care policy can be developed to appropriately respond to an ageing population. This issue is particularly important in Scotland, where personal care services are free to those aged 65+ and there is currently no evidence on how unpaid care and formal care services interact for this group.

This paper is the first to utilise a unique administrative dataset in Scotland to investigate the influence that unpaid carers have on personal care utilisation by the 65+. Specifically, it uses data from the Scottish Social Care Survey (SCS), from 2015 and 2016, and looks at how the presence of an unpaid carer influences the number of hours of personal care the cared for receives in a week. One of the issues in modelling hours of care is that the distribution is heavily skewed. Thus, three basic estimation approaches are taken which deal with the skewness in different ways. Firstly, an Ordinary Least Squares (OLS) model of the log of personal care hours. Secondly, a Generalized Linear Model (GLM) to allow for the correct calculation of marginal effects, which cannot be achieved if the errors are heteroskedastic in the OLS model. Lastly, a Two-Part Model (2PM)- the most common estimation procedure in the literature on paid and unpaid care - which accounts for the full marginal effect, given that there are a large proportion of individuals with zero hours of personal care. The 2PM is presented as the most appealing estimation approach in this setting.

The model results from the three approaches to estimation consistently find that unpaid care tends to complement personal care services. In particular the incremental effect of an unpaid carer is 1 hour 10 minutes per week in the 2PM. These findings are consistent with the literature which supports the complementary hypothesis (Geerts and Van den Bosch, 2012; Litwin and Attias-Donfut, 2009), as well as with those which find complementarity is more likely to exist for those with high levels of need Bonsang (2009), which it is argued the sample of individuals analysed here has.

The complementarity result is robust to adding in an additional control for client need and to accounting for unobserved heterogeneity. Moreover, sensitivity analysis which looks into the potential endogeneity of unpaid care suggests that reverse causality is not an issue in the Scottish context.

The finding of complementarity in Scotland for those aged 65+ might also be unsurprising given that personal care is free for those individuals. To expand, unpaid care is generally provided by a spouse or an older child. In jurisdictions where personal care bears a financial cost, it might fall on the unpaid carer to finance this. To do this they might choose to supply more hours in the labour market and therefore devote less time to providing unpaid care. In Scotland, where there is no cost attached to personal care, unpaid carers are more likely to advocate on behalf of the cared for to ensure they get the care they require, compared to jurisdictions where there is a cost associated with formal care.

The existence of a complementary relationship between unpaid and formal care are concerning in two dimensions. Firstly, it might mean that as the Scottish population ages and family members take on the role of unpaid carers, the costs to LAs of providing care to older individuals will increase as unpaid carers demand services on behalf of the cared for. If this is the case, planning for future social care spending will have to take this into account. Secondly, there is a concern that there could be unmet need for those individuals who do not have an unpaid carer. This is especially highlighted in the 1st part of the 2PM, in which it is predicted that those with unpaid carers are significantly more likely to receive personal care services in the first place.

There are however, several caveats in this paper which warrant comment. Firstly, it is highly debated within the literature whether or not there is a reverse causality between formal and unpaid care, which would result in the unpaid care variable being endogenous and parameter estimates biased. Although an IV regression has been carried out it was not possible to conduct an overidentification test to check if the instrument is valid i.e. uncorrelated with the error term. Thus, the results presented should be interpreted with some caution. Secondly, the analysis is somewhat constrained by the sample selection criteria, which in the case of the unpaid care information, is poorly recorded by LAs. Specifically, there are considerable differences in the proportions of LAs who are recording the unpaid care information, which could introduce sample selection bias into the models. Thirdly, the variables which attempt to control for the need/health status of care clients are only proxies and might not fully capture the care needs of individuals. The SCS does collect more detailed need information by means of an Indicator of Relative Need (IoRN) score, but as with the unpaid need variable, this is optional information and is only available for a very small proportion of social care clients. Lastly, the analysis is limited in that it cannot distinguish between different types of unpaid carers. For example, it is unknown if the carer is a child caring for a parent outside the household, or a partner caring for their other half in their own home. This information would be useful to check if the results would differ depending on the relationship between caree and carer, which some evidence suggests is the case (Geerlings et al., 2005).

The limitations outlined have highlighted some of the drawbacks associated with using administrative records for research. Although in theory these records capture population level data, they are frequently fraught with missing information, differences in recording procedures, and often lack suitable variables for identification purposes. At the same time, administrative records allow researchers to access a wealth of information that simply cannot be collected in surveys for data protection reasons. With this in mind, future research would benefit hugely from using both administrative and survey data, ideally linked together. This would grant a comparison of results across data types, in addition to improved models for identification, to check whether or not the complementary relationship between unpaid and formal care as suggested by the analysis here still holds.

Notwithstanding these limitations, this paper has used Scotland's unique Social Care Census (SCS) to estimate the effect that unpaid carers have on older people's use of personal care services. The results consistently suggest that there is a complementary relationship between unpaid care and personal care services in Scotland and these results are robust to a variety of sensitivity checks.

Appendix A

Table A1: Extended Model Results

Variable	OLS	GLM	2PM (P1)
Aged 70-79	0.0322	-0.0289	0.250***
	(0.0575)	(0.0583)	(0.0537)
Aged 80-89	0.0679	0.0103	0.227***
	(0.0556)	(0.0571)	(0.0517)
Aged 90-99	0.147**	0.0886	0.155***
	(0.0582)	(0.0587)	(0.0542)
Aged 100-109	0.221*	0.129	0.0984
	(0.123)	(0.0916)	(0.118)
Female	0.0322	0.0405**	0.0922***
	(0.0216)	(0.0182)	(0.0214)
Has Unpaid Carer	0.117***	0.102***	0.241***
	(0.0269)	(0.0226)	(0.0284)
No. Other Services	0.129***	0.0950***	-0.141***
	(0.0146)	(0.0123)	(0.0154)
Dementia	0.0697**	0.0543*	-0.0171
	(0.0322)	(0.0291)	(0.031)
Two or More Staff	1.010***	0.917***	-
	(0.0405)	(0.0293)	-
Constant	1.365***	1.721***	0.0568
	(0.0772)	(0.0722)	(0.0789)
AIC	17105.2	43723.5	90659
BIC	17283.4	43901.8	91016.7
Observations	7,019	7,019	36,891
ME	0.819***	0.889***	1.19***

*t statistics in parentheses; * p <0.10, ** p <0.05, *** p <0.01*

Table A2: Fixed Effects

Variable	Fixed Effects
Has Unpaid Carer	0.866*
	(0.464)
No. Other Services	0.699***
	(0.152)
Dementia	2.749***
	(0.923)
Constant	6.915***
	(0.257)
AIC	27803.2
BIC	27830.4
Observations	6,636

*t statistics in parentheses; * p <0.10, ** p <0.05, *** p <0.01*

Appendix B

Table B1: 2016 Only Clients

Variable	OLS	OLS	GLM	GLM	2PM (P1)	2PM (P1)
Aged 70-79	0.0405	0.0356	0.0168	0.0152	0.340***	0.340***
	(0.0794)	(0.0761)	(0.0799)	(0.0687)	(0.0736)	(0.0736)
Aged 80-89	0.04	0.0539	0.0166	0.0486	0.313***	0.313***
	(0.0769)	(0.0738)	(0.0774)	(0.0669)	(0.0711)	(0.0711)
Aged 90-99	0.119	0.125	0.0999	0.123*	0.282***	0.282***
	(0.0822)	(0.0788)	(0.0808)	(0.0706)	(0.0761)	(0.0761)
Aged 100-109	0.232	0.173	0.154	0.123	0.0312	0.0312
	(0.255)	(0.244)	(0.156)	(0.144)	(0.211)	(0.211)
Female	-0.012	0.00138	-0.0112	0.0066	0.102***	0.102***
	(0.0327)	(0.0313)	(0.0289)	(0.0266)	(0.0308)	(0.0308)
Has Unpaid Carer	0.116***	0.0715*	0.131***	0.0716*	0.234***	0.234***
	(0.042)	(0.0403)	(0.0396)	(0.0368)	(0.0409)	(0.0409)
No. Other Services	0.126***	0.124***	0.0923***	0.0945***	0.0126	0.0126
	(0.0223)	(0.0214)	(0.0196)	(0.0176)	(0.0206)	(0.0206)
Dementia	0.0756*	0.0613	0.0429	0.0213	0.00267	0.00267
	(0.0437)	(0.0419)	(0.042)	(0.0358)	(0.0372)	(0.0372)
Two or More Staff	-	1.039***	-	0.952***	-	-
	-	(0.0603)	-	(0.0424)	-	-
Constant	1.485***	1.389***	1.781***	1.670***	-0.503***	-0.503***
	(0.113)	(0.109)	(0.107)	(0.0935)	(0.109)	(0.109)
AIC	8674.2	8389.8	20955	20740.2	31436.9	31222
BIC	8827.3	8548.9	21108.1	20899.3	31788.4	31580.6
Observations	3,369	3,369	3,369	3,369	8,352	8,352
ME	0.812***	0.5005***	1.081***	0.592*	1.118***	0.9844***

*t statistics in parentheses; * p <0.10, ** p <0.05, *** p <0.01*

Table B2: First Differences: 2015 and 2016 Clients

Variable	First Differences
Has Unpaid Carer	1.203***
	(0.17)
No. Other Services	0.374***
	(0.135)
Dementia	1.274
	(0.971)
Constant	-1.244***
	(0.0593)
AIC	55675.3
BIC	55703.7
Observations	8,829
ME	1.203***

*t statistics in parentheses; * p <0.10, ** p <0.05, *** p <0.01*

Table B3: Instrumental Variables: 2016 clients[8]

Variable	IV
Has Unpaid Carer	1.144
	(0.713)
Aged 70-79	0.0732
	(0.0801)
Aged 80-89	0.0951
	(0.0780)
Aged 90-99	0.173**
	(0.0869)
Aged 100-109	0.193
	(0.140)
Female	0.0557
	(0.0352)
No. Other Services	0.108***
	(0.0241)
Dementia	-0.0347
	(0.0904)
Constant	0.832
	(0.519)
Observations	6,991
Cragg-Donald Wald F statistic	12.8
Endogeneity test p-value	0.1334
*t statistics in parentheses; * p <0.10, ** p <0.05, *** p <0.01*	

[8] Only 2016 data is used because it has 2011 datazones recorded which are compatible with the datazone level IV.

REFERENCES

Age UK, 2011. Care in crisis: causes and solutions. Written by Andrew Harrop, Director of Policy and Puclic Affairs, Public Policy Department, Age UK.

Alzheimer Scotland, 2017. Statistics: Estimated number of people with dementia in scotland 2017.
URL https://www.alzscot.org/assets/0002/5517/2017_Webpage_-_Update_Headline.pdf

Arntz, M., Thomsen, S. L., 2011. Crowding out informal care? evidence from a field experiment in germany. Oxford Bulletin of Economics and Statistics 73 (3), 398–427.

Bass, D. M., Noelker, L. S., 1987. The influence of family caregivers on elder's use of in-home services: An expanded conceptual framework. Journal of Health and Social Behavior, 184–196.

Belotti, F., 2015. twopm: Two-part models. Stata Journal 15 (1), 3–20(18).
URL http://www.stata-journal.com/article.html?article=st0368

Beltrán-Sánchez, H., Jiménez, M. P., Subramanian, S., 2016. Assessing morbidity compression in two cohorts from the health and retirement study. Journal of epidemiology and community health 70 (10), 1011–1016.

Boaz, R. F., Muller, C. F., 1994. Predicting the risk of "permanent" nursing home residence: the role of community help as indicated by family helpers and prior living arrangements. Health services research 29 (4), 391.

Bolin, K., Lindgren, B., Lundborg, P., 2008. Informal and formal care among single-living elderly in europe. Health economics 17 (3), 393–409.

Bonsang, E., 2009. Does informal care from children to their elderly parents substitute for formal care in europe? Journal of health economics 28 (1), 143–154.

Buntin, M. B., Zaslavsky, A. M., 2004. Too much ado about two-part models and transformation?: Comparing methods of modeling medicare expenditures. Journal of Health Economics 23 (3), 525 – 542.
URL http://www.sciencedirect.com/science/article/pii/S0167629604000220

Campolina, A. G., Adami, F., Santos, J. L. F., Lebrão, M. L., 2014. Expansion of morbidity: trends in healthy life expectancy of the elderly population. Revista da Associação Médica Brasileira 60 (5), 434–441.

Carers UK, 2014. Facts about carers. Tech. rep., Carers UK.

Chappell, N., Blandford, A., 1991. Informal and formal care: exploring the complementarity. Ageing and society 11 (03), 299–317.

Charles, K. K., Sevak, P., 2005. Can family caregiving substitute for nursing home care? Journal of health economics 24 (6), 1174–1190.

Christianson, J. B., 1988. The evaluation of the national long term care demonstration. 6. the effect of channeling on informal caregiving. Health services research 23 (1), 99.

Coughlin, T. A., McBride, T. D., Perozek, M., Liu, K., 1992. Home care for the disabled elderly: predictors and expected costs. Health Services Research 27 (4), 453.

Deb, P., E.C., N., W.G., M., 2017. Health Econometrics Using Stata. Stata Press.

Deb, P., Trivedi, P. K., 2002. The structure of demand for health care: latent class versus two-part models. Journal of health economics 21 (4), 601–625.

Duan, N., Manning, W. G., Morris, C. N., Newhouse, J. P., 1984. Choosing between the sample-selection model and the multi-part model. Journal of Business & Economic Statistics 2 (3), 283–289.

DWP, 2017. Carer's allowance. Department for Work and Pensions.
URL https://www.gov.uk/carers-allowance

Executive, S., 2003. Free personal and nursing care-consolidated guidance.

Franca, A., Guilley, E., et al., 2008. The interface between formal and informal support in advanced old age: a ten-year study. International Journal of Ageing and Later Life 3 (1), 5–19.

Geerlings, S. W., Pot, A. M., Twisk, J. W., Deeg, D. J., 2005. Predicting transitions in the use of informal and professional care by older adults. Ageing and Society 25 (01), 111–130.

Geerts, J., Van den Bosch, K., 2012. Transitions in formal and informal care utilisation amongst older europeans: the impact of national contexts. European Journal of Ageing 9 (1), 27–37.

Greene, V. L., 1983. Substitution between formally and informally provided care for the impaired elderly in the community. Medical care, 609–619.

Johansson, L., Sundström, G., Hassing, L. B., 2003. State provision down, offspring's up: the reverse substitution of old-age care in sweden. Ageing and Society 23 (03), 269–280.

Kehusmaa, S., Autti-Rämö, I., Helenius, H., Rissanen, P., 2013. Does informal care reduce public care expenditure on elderly care? estimates based on finland's age study. BMC health services research 13 (1), 317.

Langa, K. M., Chernew, M. E., Kabeto, M. U., Katz, S. J., 2001. The explosion in paid home health care in the 1990s: who received the additional services? Medical care 39 (2), 147–157.

Li, L. W., 2005. Longitudinal changes in the amount of informal care among publicly paid home care recipients. The Gerontologist 45 (4), 465–473.

Litwin, H., Attias-Donfut, C., 2009. The inter-relationship between formal and informal care: a study in france and israel. Ageing and Society 29 (01), 71–91.

Lo Sasso, A. T., Johnson, R. W., 2002. Does informal care from adult children reduce nursing home admissions for the elderly? INQUIRY: The Journal of Health Care Organization, Provision, and Financing 39 (3), 279–297.

Manning, W. G., 1998. The logged dependent variable, heteroscedasticity, and the retransformation problem. Journal of health economics 17 (3), 283–295.

McMaughan Moudouni, D. K., Ohsfeldt, R. L., Miller, T. R., Phillips, C. D., 2012. The relationship between formal and informal care among adult medicaid personal care services recipients. Health services research 47 (4), 1642–1659.

McNamee, P., 2006. Effects of free personal care policy in scotland. examination of trends in the use of informal and formal care at home and in residential care. Securing Good Care for Older People: Taking a Long-term View. Kings Fund, London, Appendix.

Mihaylova, B., Briggs, A., O'hagan, A., Thompson, S. G., 2011. Review of statistical methods for analysing healthcare resources and costs. Health economics 20 (8), 897–916.

Mullahy, J., 1998. Much ado about two: reconsidering retransformation and the two-part model in health econometrics. Journal of health economics 17 (3), 247–281.

National Records of Scotland, 2016a. Mid 2016 Population Estimates Scotland.

National Records of Scotland, 2016b. Scotland's population: The registrar general's annual review of demographic trends. Annual Report of the Registrar General of Births, Deaths and Marriages for Scotland 2016, 162nd Edition.

Penning, M. J., 2002. Hydra revisited substituting formal for self-and informal in-home care among older adults with disabilities. The Gerontologist 42 (1), 4–16.

Pezzin, L. E., Kemper, P., Reschovsky, J., 1996. Does publicly provided home care substitute for family care? experimental evidence with endogenous living arrangements. Journal of Human Resources, 650–676.

Pickard, L., 2012. Substitution between formal and informal care: a 'natural experiment'in social policy in britain between 1985 and 2000. Ageing and Society 32 (07), 1147–1175.

Scottish Government, 2015. Expenditure on adult social care services, scotland, 2003-04 to 2013-14.

Scottish Government, 2016. Social care survey data specification 2016.
URL http://www.gov.scot/Topics/Statistics/Browse/Health/SocialCareSurvey/SC16

Scottish Government, 2017a. Carers (scotland) act 2016.
URL http://www.gov.scot/Topics/Health/Support-Social-Care/Unpaid-Carers/Implementation/Carers-scotland-act-2016

Scottish Government, 2017b. Unpaid carers.
URL http://www.gov.scot/Topics/Health/Support-Social-Care/Unpaid-Carers

Shelley, W.-M. I., Rose, R. M., 2004. Trade-offs between formal home health care and informal caregiving. Journal of Family and Economic Issues 25 (3).

Van Houtven, C. H., Norton, E. C., 2004. Informal care and health care use of older adults. Journal of health economics 23 (6), 1159–1180.

Van Houtven, C. H., Norton, E. C., 2008. Informal care and medicare expenditures: testing for heterogeneous treatment effects. Journal of health economics 27 (1), 134–156.

Walter, S., Beltrán-Sánchez, H., Regidor, E., Gomez-Martin, C., Del-Barrio, J. L., Gil-de Miguel, A., Subramanian, S., Gil-Prieto, R., 2016. No evidence of morbidity compression in spain: a time series study based on national hospitalization records. International journal of public health 61 (7), 729–738.

Weaver, F. M., Weaver, B. A., 2014. Does availability of informal care within the household impact hospitalisation? Health Economics, Policy and Law 9 (1), 71.

Zhu, C. W., Torgan, R., Scarmeas, N., Albert, M., Brandt, J., Blacker, D., Sano, M., Stern, Y., 2008. Home health and informal care utilization and costs over time in alzheimer's disease. Home health care services quarterly 27 (1), 1–20.

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