This is a repository copy of *Investigating the relationship between social care supply and healthcare utilisation by older people in England*.

Health Economics WILEY

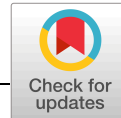# Investigating the relationship between social care supply and healthcare utilization by older people in England

Dan Liu[1,2] | Maria Lucia Pace[3] | Maria Goddard[1] | Rowena Jacobs[1] | Raphael Wittenberg[4] | Anne Mason[1]

[1]Centre for Health Economics, University of York, York, UK

[2]Centre for Health Economics Research and Evaluation (CHERE), University of Technology Sydney, Sydney, New South Wales, Australia

[3]Università Cattolica del Sacro Cuore, Rome, Italy

[4]London School of Economics and Political Science, London, UK

Correspondence
Anne Mason, Centre for Health Economics, University of York, York, UK.
Email: anne.mason@york.ac.uk

Abstract

Since 2010, adult social care spending in England has fallen significantly in real terms whilst demand has risen. Reductions in social care supply may also have impacted demand for NHS services, particularly for those whose care is provided at the interface of the health and care systems. We analyzed a panel dataset of 150 local authorities (councils) to test potential impacts on hospital utilization by people aged 65 and over: emergency admission rates for falls and hip fractures ("front-door" measures); and extended stays of 7 days or longer; and 21 days or longer ("back-door" measures). Changes in social care supply were assessed in two ways: gross current expenditure (per capita 65 and over) adjusted by local labor costs and social care workforce (per capita 18 and over). We ran negative binomial models, controlling for deprivation, ethnicity, age, unpaid care, council class, and year effects. To account for potential endogeneity, we ran instrumental variable regressions and dynamic panel models. Sensitivity analysis explored potential effects of funding for integrated care (the Better Care Fund). There was no consistent evidence that councils with higher per capita spend or higher social care staffing rates had lower hospital admission rates or shorter hospital stays.

KEYWORDS
social care, healthcare, dementia, local government expenditures

JEL CLASSIFICATION
H720, I120, I110

1 | INTRODUCTION

In England, social care is funded from a combination of central government grants, local taxation, transfers from the NHS and user charges. From 2010 to 2015, funding for adult social care in England was cut by £4.6bn which translates into a real terms reduction of 31% (Johnstone, 2015). The cuts to Local Authority (council) budgets coincided with a

period of rising needs for care (Johnstone, 2015), driven in part by an aging population (Amin-Smith, Phillips, & Simpson, 2018).

In 2017, the government announced additional funds for social care and the "social care precept," which gave councils additional taxation powers (Carter, 2017). The aim was to ease pressure on delayed discharges in hospitals (Cabinet Office & Green, 2017). Whilst the measures were broadly welcomed, many considered them insufficient to close the funding "black hole" (Twinch, 2018).

The supply of social care has potential to mitigate demand pressures on the healthcare system (Spiers et al., 2018). If the funding cuts led to higher levels of unmet need for social care, there may have been rises in emergency hospital admissions (Seamer, Brake, Moore, Mohammed, & Wyatt, 2019) and delayed transfers of care (Gaughan, Gravelle, & Siciliani, 2015; Reeves & Baker, 2004). The link between the supply of social care and the demand for healthcare is complex and depends in part on the degree of substitution or complementarity between elements of social care and healthcare (Fernandez, McGuire, & Raikou, 2018; Forder, 2009). Most previous studies have examined the relationship between specific social services—for example, long-term residential care—and healthcare utilization (Fernandez et al., 2018; Fernandez & Forder, 2008; Gaughan, Gravelle, Santos, & Siciliani, 2017a; Gaughan, Gravelle, & Siciliani, 2017b). More recent studies have adopted a broader area-based measure of social care supply, namely per capita expenditure (Crawford, Stoye, & Zaranko, 2018; Seamer et al., 2019).

Our study also uses per capita expenditure to measure social care supply, but we refine this measure so it more accurately reflects purchasing parity across councils. We also test measures of social care staffing on healthcare utilization. Our analyses mainly focus on a group of patients—older people with dementia—whose care pathway involves the provision of both health and social care services and hence, in principle, could be affected by reductions in social care spending.

The paper contributes to a growing economics literature on the interdependencies between social care and healthcare, exploring the degree to which policy changes in one sector impact on the other sector through substitution and spillover effects. We test the impact of two measures of social care supply on four measures of healthcare utilization. Given the risk of endogeneity, we also test instrumental variable (IV) approaches to capture changes in social care supply. We use an IV derived from the social care funding formula and dynamic panel models.

2 | METHODS

2.1 | Data

Details of the datasets used are in Table 1.

2.2 | Outcomes (healthcare utilization)

We analyzed four outcomes to capture different types of healthcare utilization: emergency admissions for falls and for fractured neck of femur; extended stays for 7 or more days, and for 21 or more days.

Emergency admissions due to falls are more common in people with dementia (Tinetti, Speechley, & Ginter, 1988). This is a "front door of the hospital" metric that could plausibly be influenced by the supply of social care. The rate of emergency falls in people 65 and over is a national indicator in the Public Health Outcomes Framework (PHOF). We applied the PHOF indicator definition to Hospital Episode Statistics (HES) data (2009/10 to 2016/17). We restricted the measure to people with dementia, who were identified from a list of ICD10 codes from a previous study (Kasteridis et al., 2015). Rates were expressed per 1000 persons with dementia—a figure derived from GP clinical registers.

People admitted for the treatment of hip fracture (femoral neck fractures [FNF]) are a subset of falls, but there is less ambiguity over the diagnosis and so coding is likely to be more reliable. Like the admissions rate for falls, the rate of hip fractures in older people is a PHOF indicator. PHOF data were available for the period 2010/11 to 2016/17; to derive values for 2009/10, we constructed the indicator from HES data. This indicator was not restricted to individuals with dementia.

We used two measures of extended stay (NHS Improvement, 2017, pp. 1–15), namely 7+ and 21+ days. These measures have been the focus of much policy attention. Patients experiencing these stays have been termed "stranded" and "super stranded" (7 and 21 days respectively) patients and the NHS Long Term Plan set a target to reduce the number of patients experiencing these stays, with support and guidance focused particularly on the latter group (NHS England, 2019). These "back-door" measures are used by policy makers as indicators of poor flow through the care

TABLE 1 Data Sources and derivation of outcomes and explanatory variables

Data set	Reporting level	Period	Variable(s) derived	Variable description	Source
Area cost adjustment	Council[a]	2011/12 – 2013/14	Explanatory variable: Adjuster for adult social care expenditure Instrument for IV analysis	Multiplier used to increase social care budgets in areas where labor input costs are higher. Inverse of multiplier used to make fairer expenditure comparisons across councils	DCLG methodology guides (Department for Communities and Local Government, 2011b, 2013b)
BCF reports	Council	2014/15 (Q4 only) –2016/17	Explanatory variable: Expenditure from pooled funds	Numerator: Total actual BCF expenditure per annum per council Denominator: Mean annual counts of working age council residents claiming DLA or PIP plus council population aged 65+	https://www.england.nhs.uk/ourwork/part-rel/transformation-fund/bcf-plan/
CA	Council	2009/10 – 2017/18	Explanatory variable: Numerator for carer prevalence	Numerator: Mean annual counts of council residents aged 18–64 who were receiving or entitled to CA. Denominator: Council population aged 18–64	https://stat-xplore.dwp.gov.uk
DLA	Council	2009–2016	Explanatory variable: Denominator for BCF spend. From 2013, DLA gradually replaced by PIP	Denominator for per capita spend on the BCF: Mean annual counts of working age council residents claiming DLA or PIP plus council population aged 65+	https://stat-xplore.dwp.gov.uk/webapi/jsf/login.xhtml
HES	Person	2009/10–2016/17	Dependent variable: Extended stays. Dependent variable: Numerator for emergency admissions for falls/FNF	Extended stays: Indicator 1: The proportion of spells in people with dementia with length of stay of seven days or more among all spells. Indicator 2: The proportion of spells in people with dementia with length of stay of 21 days or more among all spells. Emergency admissions: Falls in people with dementia (all years) FNF (2009/10 only)	HES accessed via data sharing Agreement with NHS Digital
CFAS II	Residential setting	2008–2011	Dependent variable: Denominator for emergency admissions for falls	Emergency admissions for falls in people with dementia: Used to derive expected dementia registers	Matthews et al. (2013)

TABLE 1 (Continued)

4 | WILEY-
Health
Economics

Data set	Reporting level	Period	Variable(s) derived	Variable description	Source
Numbers of nursing home GP patients by practice in england	GP practice	2006/07–2016/17	Dependent variable: Denominator for emergency admissions for falls	Emergency admissions for falls in people with dementia: Used to derive expected dementia registers	2006/07 to 2012/13 data supplied by NHS England NHS Digital archives: 2013/14 data 2015/16–2016/17 data
ONS—census data	Residential setting	2011	Dependent variable: Denominator for emergency admissions for falls	Emergency admissions for falls in people with dementia: Used to derive expected dementia registers.	ONS website
GMS	GP practice	2009/10 – 2016/17	Dependent variable: Denominator for emergency admissions for falls	Emergency admissions for falls in people with dementia: Used to derive expected dementia registers	GMS (2009/10 to 2012/13) were accessed via a data sharing Agreement with NHS Digital. GMS (2013/14–2016/17) is available online
Local authority (council) revenue expenditure and financing england (outturn data—RO3—SOCIAL CARE)	Council	2008/09–2016/17	Explanatory variable: Numerator for per capita gross current expenditure	Numerator (to 2014/15): Social care expenditure for people 65+ including those with mental illness Numerator (from 2014/15): Social care expenditure for people 65+ (sum of five subcategories)	https://www.gov.uk/government/collections/local-authority-revenue-expenditure-and-financing
NMDS-SC	Council	2012/13–2016/17	Explanatory variable: Numerator for staffing measures	Terciles: per capita 18+ WTE direct care staff (excl. professionals) of council social services; Terciles: per capita 18+ WTE direct care staff (incl. professionals) of council social services; Terciles: per capita 18+ WTE direct care staff (excl. professionals) of social services in the independent sector. Terciles: per capita 18+ WTE direct care staff (incl. professionals) of social services in the independent sector.	Accessed via data sharing Agreement with Skills for care
PIP	Council	2013–2016	Explanatory variable: Denominator for BCF spend. From 2013, DLA gradually replaced by PIP.	Denominator for per capita spend on the BCF: Mean annual counts of working age council residents claiming DLA or PIP plus council population aged 65+	https://stat-xplore.dwp.gov.uk/webapi/jsf/login.xhtml

TABLE 1 (Continued)

Data set	Reporting level	Period	Variable(s) derived	Variable description	Source
Population estimates summary for the UK	Council	2010/11–2016/17	Explanatory variable: Denominator for per capita adult social care	Denominator for per capita spend: Total population aged 65+	https://www.ons.gov.uk/peoplepopulationand community/populationandmigration/ populationestimates/datasets/ populationestimatesforukenglandand walesscotlandandnorthernireland
	Council	2010/11–2016/17	Explanatory variable: Denominator for per capita BCF spend	Denominator for per capita spend on the BCF: Working age claimants of DLA/PIP + population 65+	
	Council	2010/11–2016/17	Outcome variable: Denominator for emergency admissions for FNF	Denominator for FNF admissions: Total population aged 65 +	
	Council	2010/11–2016/17	Explanatory variable: Denominator for staffing measures	Denominator for staffing: Total population aged 18+	
	Council	2010/11–2016/17	Explanatory variable: Denominator for carer prevalence	Denominator for carers allowance claimants: Total population aged 18–64	
Public health outcome Framework	Council	2015	Explanatory variable: IMD	IMD: IMD score in 2015	https://fingertips.phe.org.uk/profile/public-health-outcomes-framework
	Council	2011	Explanatory variable: Ethnicity	Ethnicity: The proportion of the population from BME groups	
	Council	2010/11–2016/17	Dependent variable: Emergency hospital admissions due to FNF (2010/11 to 2016/17 only)	Emergency admission rates due to FNF in people aged 65+ per 100,000 population (PHOF methodology used with HES to derive values for 2009/10)	

Notes: BCF: Better Care Fund; BME: black and minority ethnic; CA: Carers Allowance; CCG: Clinical Commissioning Group; CFAS II: Cognitive Function and Aging Study II; DLA, Disability Living Allowance; FNF: Fractured Neck of Femur; GMS: General and Personal Medical Services dataset; HES: Hospital Episode Statistics; IMD: Index of Multiple Deprivation; IV, instrumental variable; NMDS-SC: National Minimum Data Set for Social Care; ONS: Office for National Statistics; PHOF, Public Health Outcomes Framework; PIP: Personal Independence Payment; WTE: whole time equivalent.

[a]The ACA covers "fringe" areas composed of shire districts. See text for how ACA values were converted to values for upper tier councils.

system (NHS Improvement, 2018, pp. 1–49). Although there is often more than one reason for extended stays, the availability of adequate social care support is a major factor, especially for older people (Oliver, 2019).

Both measures of extended stay include emergency and elective admissions for patients aged 65+ who were coded as having a diagnosis of dementia (Kasteridis et al., 2015). In both cases, the denominator was the total number of "spells" (period from admission to discharge) for this patient group, which we constructed from the HES data (2009/10–2016/17). We used all spells from the date when a patient was first diagnosed with dementia, that is, all spells with admission date at or after first recorded diagnosis. The numerator was the total number of spells with a length of stay of at least 7 (or 21) days. Spells beginning before April 1, 2009 and spells starting after March 31, 2016 were excluded. We used 2016/17 data to calculate the length of stay of unfinished spells beginning before March 31, 2016.

2.3 | Measures of social care supply

In England, councils are responsible for adult social care: they assess residents' needs, set eligibility criteria for publicly funded care and commission services. National guidance informs these responsibilities, including national minimum eligibility criteria, a national means test for residential care and guidelines on the means test for community-based care (Department of Health and Social Care, 2018).

Social care is not free at the point of use like the NHS. The means test takes account of both incomes and savings, including, for care home residents, the value of their residential property. People whose savings exceed an upper capital limit (currently £23,250) are not eligible for publicly funded care. Those with savings below this limit are required to contribute from their assessed income above a set threshold.

Most social care services are provided by the independent sector. Councils commission services from these providers, who may also provide services to people purchasing care privately. Those eligible for publicly funded care can choose between a package of care arranged by their council or cash for care (known as a direct payment) that they can use to employ a personal assistant or purchase care.

This social care system is separate from the social security benefits system, which is administered by central rather than local government. Social security disability benefits are not subject to means test but are based on disability levels. Users of social care may receive disability benefits except that publicly funded care home residents lose these benefits four weeks after care home admission. Publicly funded users of community-based care may have their disability benefits taken into account, at least in part, in the means test for their care.

We used two explanatory variables to capture changes in social care supply: expenditure on social care for people aged 65+; and social care staff for people aged 18+. It is important to note that, while the expenditure data relate only to public expenditure and do not include expenditure on privately funded care, the workforce data include staff caring for people receiving privately funded care as well as people receiving publicly funded care. Given the risk of endogeneity associated with these measures, we also tested IVs to capture changes in social care supply.

Our main explanatory variable was per capita council expenditure on social care for older adults (i.e., aged 65 and over). We compiled data on gross current expenditure (GCE) on social care for older people for financial years 2009/10 to 2016/17. GCE is defined as total current expenditure (spending on staff and running expenses) less income from the NHS (or from joint arrangements) but includes income from client contributions (sales, fees, and charges). Whilst there is no "perfect" measure of spend, we chose GCE because it takes account of local capacity to raise funds from clients, which enables councils to cross-subsidize social care provision. It is also the fiscal metric commonly used to denote government spending (NHS Digital, 2016).

In 2014/15, there was a change in the way that social care expenditure on older people was reported. Whereas there was previously only one category, there were five separate categories from 2014/15 onwards. To derive comparable measures, we summed the five categories. We computed per capita values using data on council populations aged 65+.

Council budgets are adjusted using the Area Cost Adjustment (ACA) to reflect the higher cost of inputs in London and certain parts of the South-East compared with the rest of England (Darton et al., 2010). The ACA reflects differences in labor costs (LCA) and business rates, but only the LCA element is used to adjust allocations for adult social care (Department for Communities and Local Government, 2013b). We used the LCA to deflate per capita expenditure back to pre-adjusted values so that coefficients on the expenditure variable would be interpreted consistently.

The ACA takes a value of 1 for "average" areas and a value above 1 for higher cost areas. We converted these to LCAs based on the approach in the ACA methodology guides (Department for Communities and Local Government,

2011b; Department for Communities and Local Government, 2013b). For councils without a 1:1 mapping to ACA area, we calculated a weighted average LCA value using population size as the weights (Department for Communities and Local Government, 2011a).

Workforce data were sourced from the National Minimum Dataset for Social Care (NMDS-SC) and were available for the period 2012/13 to 2016/17 (Table 1). We used four whole time equivalent measures of adult social care staff, all of whom provide front-line (direct) care to clients. We differentiated them by employer (councils or the independent sector) and by whether or not they were classed as professionals. The great majority of publicly funded as well as privately funded social services for older people are provided by the independent sector. The "non-professional" group includes care workers, community support workers and personal assistants. The "professional" group includes allied health professionals, registered nurses, occupational therapists and social workers. Therefore, there were two staff variables for each employer type: one with non-professionals only (i.e., excluding professionals), and one including both non-professionals and professionals.

We derived per capita values using the council population aged 18 and over.[1] To test for non-linearity, we derived terciles, that is, low (reference), medium and high levels.

2.4 | Control variables

To control for confounding factors, our models also included a measure of deprivation (the 2015 Index of Multiple Deprivation score), and the percentage of the council population who were of Black and Minority ethnicity. These two control variables were reported in the PHOF. We also controlled for the age structure of the council population (percentages aged 65–74, 75–84, and 85+), and included council class[2] and year effects.

We controlled for the supply of unpaid care using benefits data from the Department for Work and Pensions. Carer's Allowance (CA) is a non-contributory benefit for people who care for a severely disabled person for at least 35 h a week. Some claimants are entitled to CA, but do not receive it because they receive another benefit or State Pension. We constructed an indicator to capture the prevalence of "full-time" unpaid carers of working age. The numerator was the mean annual values of all entitled cases aged 18 to 64 in each council, and the denominator was the council population aged 18 to 64. The measure can therefore be viewed as the "tip of the iceberg" of unpaid care and has risen substantially over time (Figure 1).

2.5 | Modeling and analysis

2.5.1 | Negative binomial model

The unit of analysis was the council. For the count outcome variables, we used random effects negative binomial models (RENB) to deal with overdispersion (Greene, 2007). The RENB model (Hausman, Hall, & Griliches, 1984; Greene, 2007) assumes that the count of the outcome (e.g., number of hospital stays of 7 days or longer) in council i and year t follows a Poisson distribution with parameter $\tilde{\lambda}_{it}$ which in turn follows a gamma distribution $gamma(\lambda_{it}, \delta_i)$ where λ_{it} is specified as in Equation (1).

$$\lambda_{it} = exp(\beta_1 m_{it} + \beta_2 x_{it} + \beta_3 T_t + log(W_{it})) \tag{1}$$

In the above, m_{it} is the main explanatory variable (expenditure or staffing); x_{it} includes council level covariates; T_t is a set of dummy variables for year effects; and W_{it} is an exposure term. The RENB model introduces randomness both across councils and across years. For a given council even if the observed covariates do not change over time, the counts are drawn from Poisson distributions with different parameters $\tilde{\lambda}_{1t}, ..., \tilde{\lambda}_{it}$.

The parameter δ_i is included as a random effect that varies randomly across councils to capture unobserved and time invariant features of councils. To integrate the parameter δ_i out of the marginal probability, Hausman et al. (1984) used a beta distribution with parameters a and b for the ratio $\delta_i/(1 + \delta_i)$.

We ran separate RENB models to test the effects of council expenditure and social care staffing levels on our four outcomes.

2.5.2 | IV model

The levels of council expenditure and staffing for adult social care partly reflect the level of need for health and care in the local area. For example, an area with persistently high levels of extended stays may put more resources into adult social care to tackle the problem. This means there is a potential endogeneity issue: higher spend may be associated with worse outcomes not because more money causes poorer performance but because historically poorer performance has called for higher levels of spend. A potential solution to endogeneity is the use of IVs. However, identifying suitable instruments can be challenging.

Previous studies have identified different instruments for social care supply. Forder (2009) used two needs factors (income and use of informal care) and three supply factor (prevailing house prices, lagged use of communal establishments and population density) as instruments for care home utilization. However, these factors may be less suitable for capturing social care supply more generally, as this covers home-based as well as institutional care. Crawford et al. (2018) used a Bartik or shift-share approach, instrumenting current spend by its historical distribution in 2000. This is unsatisfactory for our purposes, since it ignores temporal changes in the relative distribution of funds allocated to councils, which could then affect their per capita spend. Claxton, Lomas, and Martin (2018) used elements of the funding formula as an instrument for examining the impact of NHS expenditure on outcomes (Claxton et al., 2018). As this explicitly recognizes changes in financial allocations, we applied the funding formula approach to derive an instrument for social care supply.

Social care funding is allocated to councils using a formula to account for local differences in capacity to provide services where differences are due to exogenous factors (Forder & Vadean, 2018, pp. 1–54). The current version is the relative needs formula (Darton et al., 2010) and is derived by quantifying the relationship between spend and outcomes using data at the small area level. For older people's adult social care, the formula includes a basic amount per client, plus top-ups for age, deprivation, low income and sparsity. Finally, the total is adjusted by the LCA to account for differences in labor costs (Department for Communities and Local Government, 2013a).

We considered the elements of the funding formula as potential instruments, but age, deprivation, low income and sparsity are all clearly related to our outcomes (i.e., measures of healthcare utilization). However, LCA appears suitable as a potential instrument in linear models. A council whose LCA is above 1 has higher input costs than a council with an LCA of 1. All other things being equal, the council with higher input costs can provide fewer services and/or treat fewer clients. In this scenario, the LCA would be positively correlated with unadjusted per capita spend on social care.

However, if the LCA perfectly adjusted for differences in input cost then the LCA should not be correlated with adjusted per capita spend. A priori, it seems unlikely that the adjustment would be perfect. First, values may be out-of-date, as they are based on historical survey data on the wages of private sector staff (Department for Communities and Local Government, 2013b). Second, the distribution of and variation in social care sector wages may differ from those of the private sector. Third, the assumed proportion of labor costs in total costs may be too low, especially in high cost areas.

In our data, the correlation between adjusted spend and the LCA is positive (0.3634) and statistically significant at the 5% level. This suggests the LCA adjustment is imperfect but is therefore suitable as a potential instrument. The instrument also needs to be uncorrelated with the error term, and to mitigate this risk we include an array of control variables to account for confounders such as deprivation.

Using continuous outcome variables, we employed linear random effects models (xtivreg in Stata). We jointly estimated the following IV system of two equations:

$$y_{it} = \beta_0 + \beta_1 \tilde{m}_{it} + \beta_2 x_{it} + \beta_3 T_t + u_i + v_{it} \quad i = 1, ..., N; \ t = 1, ...T \tag{2}$$

$$\tilde{m}_{it} = \beta_0 + \beta_1 z_{it} + \beta_2 x_{it} + \beta_3 T_t + g_i + e_{it} \quad i = 1, ..., N; \ t = 1, ...T \tag{3}$$

where z_{it} is the instrument that influences per capita GCE ($\tilde{m}_{it}$) but is uncorrelated with error terms ($u_i + v_{it}$); y_{it} is the outcome variable; β_0 is a constant. To account for within-council serial correlation, we clustered standard errors at the same level as the random effect (i.e., at the council level) (Cameron & Miller, 2015; Moulton, 1990). All analyses were undertaken in Stata 14.2 (StataCorp LP).
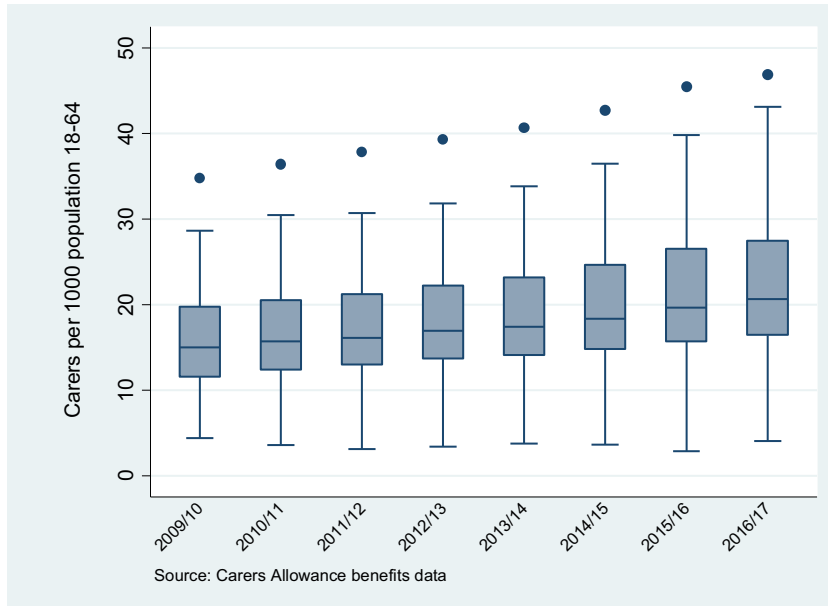
2.5.3 | Dynamic panel model

The dynamic Panel model is a good alternative way to deal with the endogeneity issue in a panel model when good instruments are not available. Furthermore, they are better at characterizing the economic relationship involving a dynamic adjustment process by including the lags of the dependent variable. Dynamic panel models are designed for situations where there is autocorrelation within the units (serial correlation) but not across them (cross sectional dependence) (Roodman, 2009). We confirmed the validity of these assumptions using relevant tests (xtqptest, xtcdf).

Given the presence of the autoregressive parameter, this model is estimated using the Generalized Method of Moments (GMM), which produces consistent parameter estimates for a dynamic panel with small T and large N (Arellano & Bond, 1991; Blundell & Bond, 1998). For the continuous outcome variables (rates), we estimated the following form:

$$y_{it} = \beta_0 + \beta_1 y_{i,t-1} + \beta_2 m_{it} + \beta_3\, m_{i,t-1} + \beta_4 x_{it} + \beta_5 T_t + \alpha_i + v_{it}\; i = 1, ..., N;\; t = 1, ... T \qquad (4)$$

where y_{it} is the dependent variable and $y_{i,t-1}$ is its first lag; β_0 is a constant; $m_{i,t}$ is the main explanatory variable and $m_{i,t-1}$ is its first lag, α_i is the council-specific fixed effects (FE)[3], and v_{it} is the idiosyncratic time-varying error. These two components together constitute the composite error term.

In our analysis, this model has been estimated using the system GMM method, because it leads to the result with the lowest bias. Blundell and Bond (1998) stated that first difference GMM often reports large finite sample bias and poor precision in simulation estimation. We used two-step GMM which is more efficient than one-step GMM (Roodman, 2009). The system GMM method considers a system of equations formed by the equation in first-differences and the equation in levels. Variables in levels are instrumented with suitable lags of their own first differences. This approach has to satisfy the assumption that these differences are uncorrelated with the regression residuals. The Hansen J test, which is reported in this paper, is the test of overidentifying restrictions and is used to verify that the instruments are exogenous as a group. The validity of the internal instruments lagged for two or more periods requires the absence of autocorrelation in the time-varying error term v_{it}. The Arellano-Bond (1991) test, AR (2), tested for autocorrelation in the second-differenced errors.

2.6 | Sensitivity analysis

Introduced in 2015/16, the Better Care Fund (BCF) is the only mandatory policy to support integration (Department of Health and Department for Communities and Local Government, 2017). Health and social care funds are pooled into

local budgets so that healthcare commissioners and councils can jointly agree how to spend the funds (£5.3bn in 2015/16, £5.8bn in 2016/17). The NHS must contribute a minimum level of funds to adult social care and many areas choose to pool more than required.

The BCF is not part of councils' financial allocations, but provides additional funds for adult social care. As only two years of BCF data were available (Table 1), its effect was tested in a sensitivity analysis and using RENB models.

For the numerator, we used actual (reported) expenditure by councils, rather than planned expenditure. As the BCF is targeted at both older people and at working-age people with disabilities (HM Treasury, 2013, pp. 1–68), the denominator accounted for both groups. We derived per capita values based on the sum of the council population over 65 and the number of working age people entitled to either disability living allowance or to personal independence payments.

We conducted two additional sensitivity analyses (see Appendix S1). We tested two alternative measures of falls; and tested the robustness of our findings for the count data models using fixed effects Poisson models instead of random effects negative binomial models (RENB).

3 | RESULTS

3.1 | Descriptive analysis

Table 2 reports descriptive statistics.

The rate of FNF per 100,000 population fell over the study period due to rises in the population of older people rather than because of a decline in the number of cases (Figure 2). Nonetheless, the overall decline in the rates of both falls and FNF are unexpected and the reasons are unclear: whereas changes in coding practice could theoretically explain changes in the rate for falls, this is unlikely to be the case for changes in the rate of FNF.

Of hospital admissions for people with dementia, 39% lasted 7 days or longer and 15% lasted at least 21 days. The rates rose over time in both outcome measures (Figure 2).

Over the period 2009/10 to 2016/17, the adjusted GCE on social care per person aged 65+ averaged approximately £950. Spend per head fluctuated over the study period, falling from £1253 in 2009/10 to £825 in 2016/17, a reduction of 34% over 7 years (Figure 3).

3.2 | Regression results

Social care expenditure was unrelated to any of the four healthcare utilization outcomes (Tables 3–6). Social care staffing was negatively associated with extended stays only when models also accounted for independent sector staff; otherwise, the relationship between staffing and the four outcomes was statistically insignificant (Table 4).

There was a small positive association between expenditure, measured using GCE per head (adjusted by the LCA), and extended stays of 7+ days, but spend was not associated with stays in excess of 3 weeks (Table 3)

We used LCA as an IV for GCE, which can be considered to be a strong instrument as the F statistic value was around 10 or higher in the first-stage estimation (Claxton et al., 2018). Expenditure was unrelated to any of the four outcomes (Table 5).

The dynamic panel model (Table 6) found no significant association between expenditure and any of the four outcomes. The conservative threshold of the Hansen J test's p-value is in the interval 0.1–0.25 (Roodman, 2009). The Hansen J test is always within this interval, except in the models for FNF.[4] None of the models reports serial correlation between the errors higher than the expected first-order serial correlation. All the models passed the AR (2) tests as indicated by the insignificant p-values, demonstrating that there is no autocorrelation in the second-differenced errors. This indicates that all the lags used are good instruments for the system of equations.

The relationship between unpaid care and outcomes is shown in Tables 3, 5 and 6. Councils with higher prevalence of unpaid care had higher admissions rates for FNF (Table 5) but lower admission rates for falls and a lower proportion of hospitalized patients with extended stays of 21+ days (Table 3, Panels A and B; Table 6).

TABLE 2 Descriptive Statistics (annual values)

Variable	Years		Mean	Standard deviation	Minimum	Maximum	N
Outcomes							
FNF admissions (all), rate per 100,000 65+[a]	2009/10–2016/17	FNF adm rate	607.4	74.7	287.5	1063.8	1204
		FNF, count	372.4	333.5	<6	1882	1204
		Pop 65+	60786.9	54098.3	470	305,924	1204
Falls admissions rate per 1000 patients with dementia[b]	2009/10–2016/17	Falls adm rate	120.0	35.1	31.6	256.8	1216
		Falls, count	459.6	395.7	<6	2415	1216
		Pop w dementia	4066	3696	26	19,478	1216
% Extended stays in patients with dementia, rate (of all stays)	2009/10–2015/16	7+ days	38.9	5.8	21.0	57.6	1064
		21+ days	15.3	3.2	5.5	27.6	1064
Social care supply							
GCE per 65+ (£)	2009/10–2016/17	GCE pp	948.2	302.3	5.9	2497.4	1214
BCF spend per 1000 (18–64 with disability; or 65+) (£)	2015/16–2016/17	BCF spend per 1000	539.9	539.1	195.2	4941.9	300
Council WTE staff per 1000 pop 18+[c]	2012/13–2016/17	Direct care excl. professionals	1.2	0.7	0	4.9	753
		Direct care incl. professionals	1.7	0.8	0	5.7	753
Independent sector WTE staff per 1000 pop 18+		Direct care excl. professionals	14.0	4	6.6	78.9	755
		Direct care incl. professionals	14.9	4.8	6.8	80.4	755
Controls							
Deprivation[d]	2015	IMD 2015	23.0	8.1	5.7	42.0	1216
Ethnicity	2011	% BME	16.4	16.2	1.2	71.0	1216
Age groups	2009/10–2016/17	% 65 to 74	8.8	2.3	3.2	15.1	1216
		% 75 to 84	5.4	1.3	2.0	9.0	1216
		% 85+	2.2	0.6	0.7	4.2	1216
Unpaid care prevalence	2009/10–2016/17	"Full-time" carers per 1000 pop 18-64	18.8	7.1	2.9	46.9	1216

Note: Values are for the whole dataset, not for estimation samples (which vary across models). Small numbers suppressed to protect against disclosure.

Abbreviations: BCF, Better Care Fund; BME: black and minority ethnic; FNF: fractured neck of femur; GCE, gross current expenditure; IMD: Index of Multiple Deprivation; PHOF, Public Health Outcomes Framework; WTE: whole time equivalent.

[a]In all years, PHOF values are missing for City of London and Isles of Scilly. In 2016 there are also missing values for Nottingham and Nottinghamshire.

[b]Counts are from GP registers.

[c]In 2013 and 2014, values for Norfolk are missing. The Isles of Scilly has been included with Cornwall for all years of WTE staff data. In 2012–2015, councils in Torbay and NE Lincolnshire employed no social care staff.

[d]Deprivation scores range from 0–100, with higher scores indicating higher levels of deprivation.

3.3 | Sensitivity analysis

Adjusting for the impact of the BCF had no effect on these results, except that the positive association between spend and extended stays (7+) was no longer statistically significant (Table 3, Panel C). This apparent discrepancy may be due to the smaller number of observations available for analysis (only 2 years of BCF data were available).
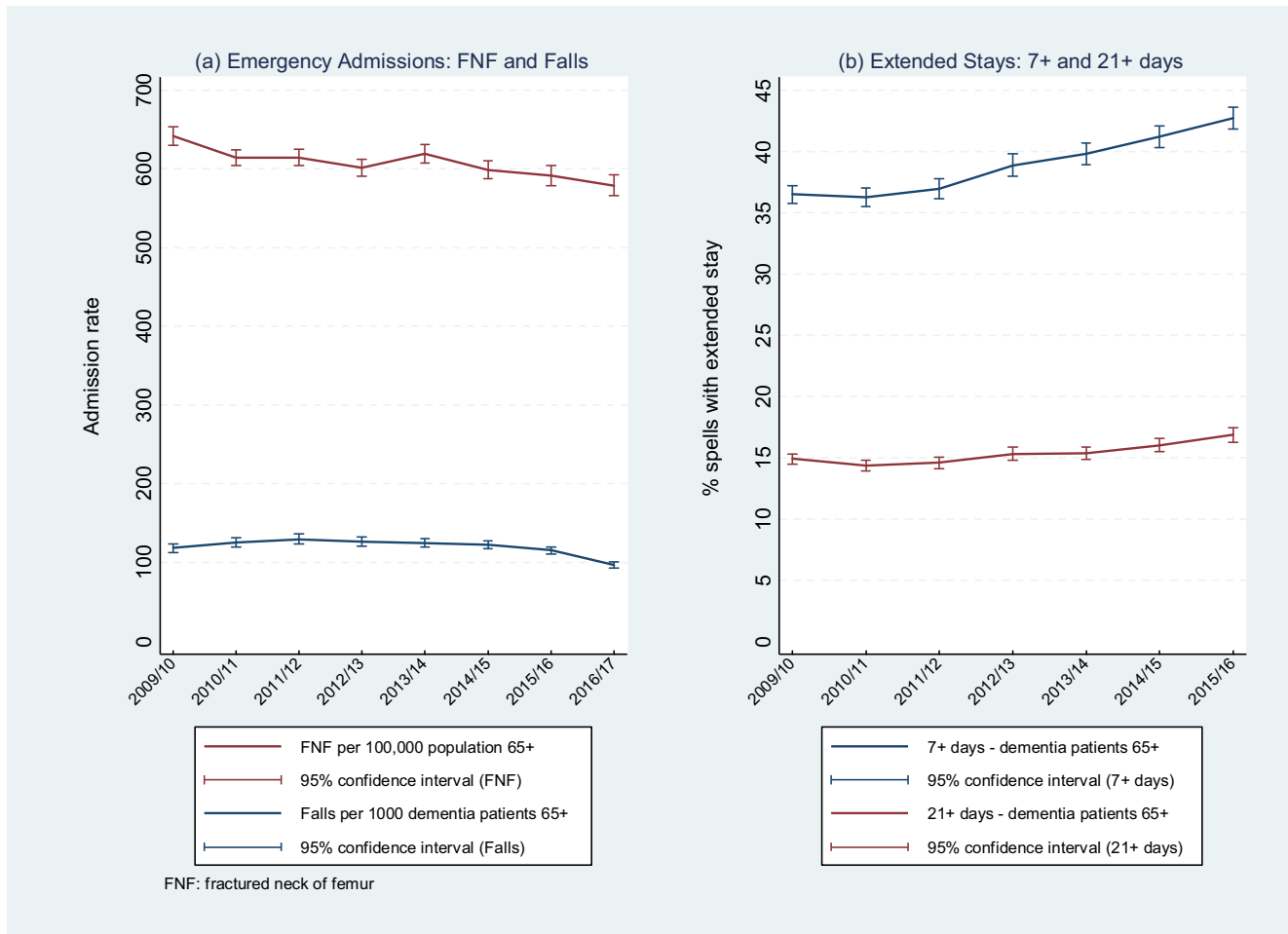
FIGURE 2 Outcomes: (a) Trends in emergency admissions for fractured neck of femur (FNF) and Falls; (b) Trends in extended stays of 7+ and 21+ days

The Appendix S1 provides results from the remaining sensitivity checks. Findings were robust. The relationship between falls and social care variables (spend and staffing) was not statistically significant, regardless of how falls were measured. Findings from the fixed effects Poisson regressions were generally consistent in sign and statistical significance.

4 | DISCUSSION

The aim of this study was to test whether recent changes in the supply of social care in England have had spillover effects on the use of healthcare. We linked multiple national datasets to analyze the effects of changes in social care expenditure and staffing on a range of healthcare utilization outcomes.

There was no conclusive evidence that councils with higher per capita spend on social care for older people had lower emergency admission rates or shorter hospital stays. The use of IVs supported these findings.

As an alternative to spend, we used social care workforce measures to capture changes in social care supply. The only statistically significant finding was that councils with higher rates of independent social care staffing had lower rates of extended stays.

The effect of "full-time" unpaid care on outcomes was mixed. There was tentative evidence of a protective effect on admissions for falls and on extended stays of 21+ days, but higher levels of unpaid care were also associated with higher rates of FNF.

Previous studies have also focused on older people, but findings are mixed. Forder (2009) identified cost substitution effects between residential long-term care and hospitals and vice versa. Seamer et al. (2019) analyzed a 10-year
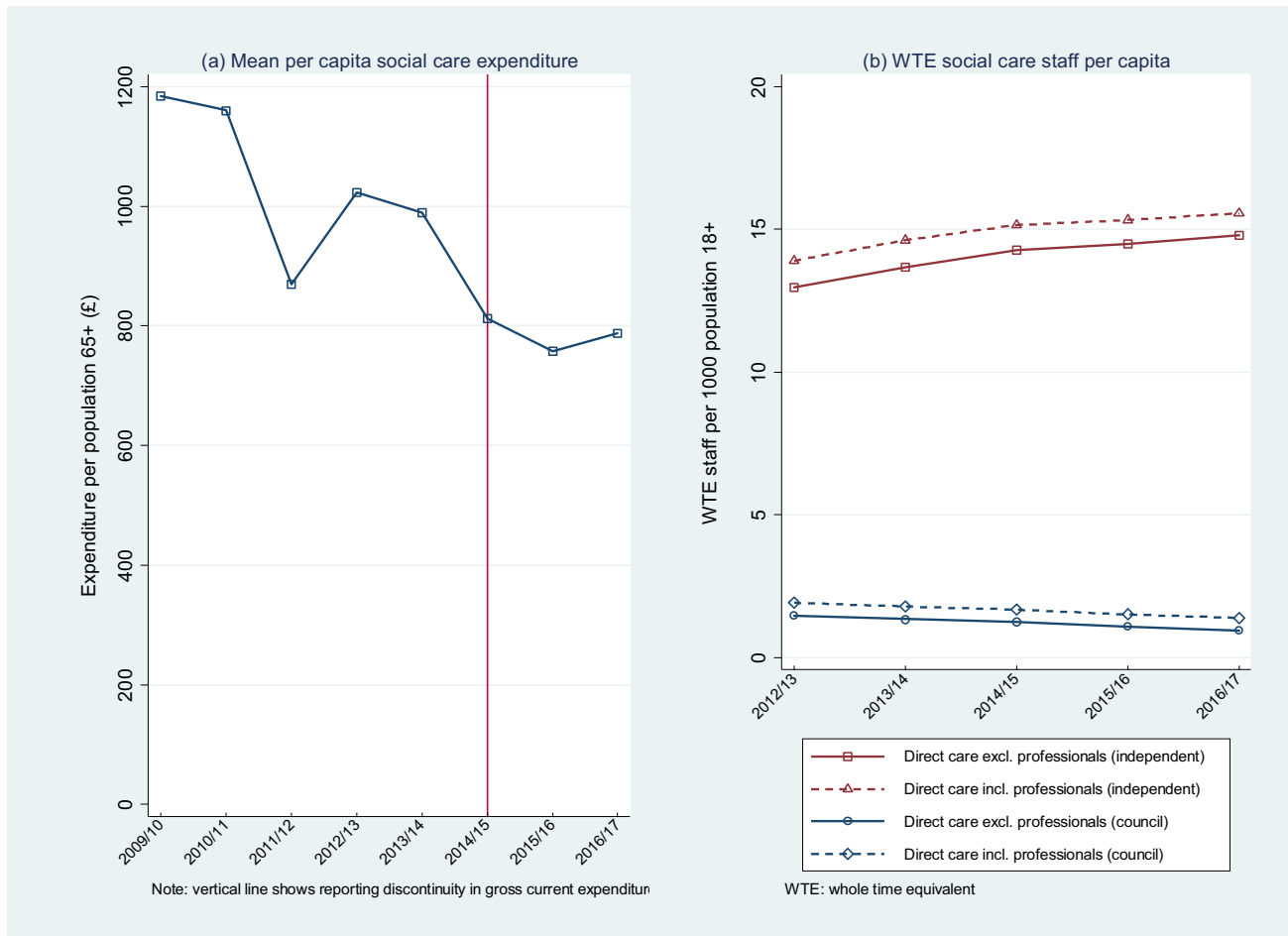
FIGURE 3 Measures of social care supply: (a) Mean per capita expenditure per population 65+ (b) Mean whole time equivalent (WTE) social care staff per 1000 population 18+

panel of data covering 132 councils. They found no relationship between social care spend and emergency admissions (all cause) or admissions for ambulatory care sensitive conditions. Their findings were robust to different model specifications (Seamer et al., 2019). Crawford et al. (2018) used a 6-year panel of data from 143 councils to test for an impact on Accident and Emergency (A&E) utilization. Lower social care spend—which was instrumented using a Bartik approach—was associated with significantly higher A&E utilization, particularly in people aged 85 and over (Crawford et al., 2018).

Our study offers several methodological advances to the evidence base. First, we tested a wider range of measures than previous studies, including both "front-door" hospital measures (admissions for falls and for FNF) and "back-door" measures (extended length of stay).

Second, unlike previous studies that have focused exclusively on changes in social care expenditure (Crawford et al., 2018; Seamer et al., 2019), we used two approaches to measuring social care supply: GCE on older adults, and workforce measures for both council employees and the independent sector. We used gross (rather than net) current expenditure, because this takes account of local capacity to raise funds from clients, enabling councils to cross-subsidize care for the most vulnerable clients. We adjusted spend to account for variations in local purchasing power. Further, we conducted sensitivity analysis to test the added impact of the BCF, money that is not captured within councils' annual financial returns.

Third, we used two IV approaches to manage the potential problem of endogeneity—this may arise if local decisions on social care spending are informed by the supply and quality of local NHS services. We used the LCA as an instrument, which performed well, and a dynamic panel model, which incorporated lags of outcome measures and lags of spend. Crawford et al. (2018) compared standard regression (OLS), an FE model, and IV method (a Bartik approach).

	(1)	(2)	(3)	(4)
	FNF	**Falls**	**7+**	**21+**
Panel A: Gross expenditure pp (adjusted), age 65+				
Expenditure pp	1.000	1.000	1.000***	1.000
	[1.000, 1.000]	[1.000, 1.000]	[1.000, 1.000]	[1.000, 1.000]
Unpaid care	1.003	0.988***	1.001	0.990**
	[1.000, 1.006]	[0.982, 0.994]	[0.997, 1.005]	[0.984, 0.996]
N	1203	1214	1063	1063
Panel B: Gross expenditure pp (adjusted), age 65–74; 75–84; 85+				
Expenditure pp	1.000	1.000	1.000***	1.000
	[1.000, 1.000]	[1.000, 1.000]	[1.000, 1.000]	[1.000, 1.000]
Unpaid care	1.005***	0.987***	1.000	0.988***
	[1.002, 1.008]	[0.981, 0.994]	[0.997, 1.004]	[0.982, 0.995]
N	1203	1214	1063	1063
Panel C: Gross expenditure pp (adjusted), BCF spend pp, age 65–74; 75–84; 85+				
Expenditure pp	1.000	1.000	1.000	1.000
	[1.000, 1.000]	[1.000, 1.000]	[1.000, 1.000]	[1.000, 1.000]
BCF	1.000	1.000	1.000	1.000
	[1.000, 1.000]	[1.000, 1.000]	[1.000, 1.000]	[1.000, 1.000]
Unpaid care	1.006*	0.996	1.003	0.994
	[1.001, 1.011]	[0.985, 1.006]	[0.995, 1.010]	[0.981, 1.007]
N	299	300	150	150

TABLE 3 Regression results: effects of social care expenditure

Note: Exponentiated coefficients; 95% confidence intervals in brackets. Stata model: xtnbreg. FNF fractured neck of femur; 7+ [21+]: extended stay of 7 [21] days or longer.

Abbreviations: BCF, Better Care Fund; FNF, fractured neck of femur; pp, per person.

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Unlike our study in which findings were robust to alternative specifications, Crawford et al. (2018) found results were sensitive to choice of model, with results from the OLS and FE inconsistent with those from the IV model.

Fourth, the analyses controlled for the local prevalence of "intensive" informal care, which is an important confounding factor when attempting to isolate the effect of formal social care on healthcare use. Crawford and colleagues also used the CA data to generate a measure of informal care (Crawford et al., 2018). We refined this measure, restricting it to working age adults: many older full time carers do not apply for the benefit as their state pension makes them ineligible, so they are not counted in the CA data. To obtain a more complete picture of the prevalence of informal care, we combined data on recipients with those who were eligible for, but did not actually receive, CA.

However, our study also has limitations. One important drawback is that social care data were available only at council level. The absence of routine individual-level data on formal and informal social care receipt meant it was not possible to test whether individuals who received social care were at lower risk of hospitalization or extended stay. Therefore, it is important to stress that our findings do not imply that changes in an *individual's* social care receipt have no impact on their healthcare utilization or on their health or wellbeing.

A second limitation is that significant unexplained variability in hospital utilization measures remained after adjusting for a range of confounding factors. This probably reflects differences in patient case mix—such as multi-morbidity—that are not captured by area level measures.

Third, our study could not identify *how* councils spent their budgets, that is, variations in the types and levels of services delivered. Two councils with same per capita spend may provide very different services, and target different subgroups of client. These differences are likely to influence healthcare utilization.

TABLE 4 Regression results: effects of social care staffing rates

	(1) FNF	(2) Falls	(3) 7+	(4) 21+
Panel A: Direct care staff excl. professionals (council), age 65–74; 75–84; 85+				
Medium (council)	0.996	0.988	0.994	1.004
	[0.980, 1.012]	[0.961, 1.015]	[0.979, 1.009]	[0.979, 1.029]
High (council)	0.986	0.999	0.996	1.021
	[0.966, 1.006]	[0.964, 1.036]	[0.976, 1.016]	[0.987, 1.056]
N	751	755	604	604
Panel B: Direct care staff incl. professionals (council), age 65–74; 75–84; 85+				
Medium (council)	0.995	0.986	0.996	1.002
	[0.979, 1.010]	[0.961, 1.012]	[0.981, 1.010]	[0.978, 1.027]
High (council)	0.992	0.999	0.988	1.016
	[0.972, 1.012]	[0.965, 1.035]	[0.969, 1.008]	[0.982, 1.050]
N	751	755	604	604
Panel C: Direct care staff excl. professionals (council and independent), age 65–74; 75–84; 85+				
Medium (council)	0.997	0.989	0.992	0.999
	[0.981, 1.013]	[0.963, 1.017]	[0.977, 1.007]	[0.975, 1.024]
High (council)	0.986	1.001	0.993	1.017
	[0.966, 1.007]	[0.966, 1.038]	[0.973, 1.013]	[0.983, 1.052]
Medium (independent)	0.996	1.008	0.981*	0.985
	[0.977, 1.015]	[0.975, 1.041]	[0.963, 0.999]	[0.956, 1.015]
High (independent)	1.006	1.021	0.967**	0.939**
	[0.982, 1.030]	[0.979, 1.066]	[0.944, 0.990]	[0.903, 0.976]
N	751	755	604	604
Panel D: Direct care staff incl. professionals (council and independent), age 65–74; 75–84; 85+				
Medium (council)	0.996	0.987	0.994	0.999
	[0.980, 1.012]	[0.962, 1.013]	[0.980, 1.008]	[0.975, 1.023]
High (council)	0.992	1.000	0.987	1.013
	[0.972, 1.013]	[0.965, 1.035]	[0.967, 1.006]	[0.980, 1.047]
Medium (independent)	0.993	0.998	0.986	0.979
	[0.974, 1.012]	[0.966, 1.032]	[0.968, 1.003]	[0.951, 1.008]
High (independent)	1.013	1.028	0.973*	0.935***
	[0.990, 1.038]	[0.986, 1.073]	[0.950, 0.995]	[0.900, 0.971]
N	751	755	604	604

Note: Exponentiated coefficients; 95% confidence intervals in brackets. The low tercile of staffing is the reference category. In Panels A and B, models included only staff employed by councils. In Panels C and D, models included staff employed by both councils and the independent sector. Stata model: xtnbreg.

Abbreviation: FNF, fractured neck of femur.

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

	(1) FNF	(2) Falls	(3) 7 +	(4) 21 +
Expenditure pp	−0.035	0.019	0.000	0.001
	[−0.130, 0.061]	[−0.018, 0.055]	[−0.009,0.008]	[−0.002, 0.005]
Unpaid care	1.841	−1.133*	0.060	0.127
	[−1.319, 5.002]	[−2.226, −0.041]	[−0.309, 0.190]	[−0.290, 0.036]
N	1203	1214	1063	1063

TABLE 5 Regression results—Instrumental variable method using LCA

Note: 95% confidence intervals in brackets. Stata model: ivreg.

Abbreviation: FNF, fractured neck of femur; LCA, labor cost adjustment; pp, per person.

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

TABLE 6 Regression results—Dynamic model

	(1) FNF	(2) Falls	(3) 7+	(4) 21+
Expenditure pp	0.174	0.017	−0.005	−0.003
	[−0.137, 0.485]	[−0.057, 0.091]	[−0.014, 0.003]	[−0.009, 0.003]
L.expenditure pp	−0.017	0.011	0.003	0.001
	[−0.148, 0.115]	[−0.032, 0.053]	[−0.002, 0.008]	[−0.002, 0.005]
L.FNF	0.139*			
	[0.005, 0.274]			
L.Falls		1.031***		
		[0.700, 1.361]		
L.7 days+			0.705***	
			[0.534, 0.877]	
L.21 Days+				0.857***
				[0.725,0.988]
Unpaid care	1.521	−0.398*	0.027	0.001
	[−1.468, 4.510]	[−0.769, −0.026]	[−0.034, 0.088]	[−0.046, 0.048]
Hansen *J* test	3.781	2.416	1.597	7.122
Hansen *J* test: *p* value	0.286	0.12	0.206	0.212
AR (1) test	−5.121	−3.275	−7.151	−6.343
AR (1) test *p*-value	0	0.001	0	0
AR (2) test	−0.477	0.945	0.092	−0.685
AR (2) test *p*-value	0.633	0.345	0.927	0.494
N	1050	1062	911	911
No. instruments	20	15	19	16

Note: 95% confidence intervals in brackets. Stata model: xtabond2 L.variable indicates a 1 year lag of the variable. Hansen test—see text for interpretation.

Abbreviations: FNF, fractured neck offemur; pp, per person.

*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

A simplistic conclusion would be that reductions in social care spending have had little impact on the NHS. However, there are at least two reasons why policy makers should not be complacent.

First, due to data availability, our study assessed potential impacts up to March 2017. Until this time, councils may have had sufficient reserves, or been able to make cuts elsewhere in their budgets, in order to protect spending on adult care social services for older people. However, budget reductions subsequently became more acute and councils may no longer be able to protect spending for vulnerable older adults.

Second, we found tentative evidence that higher levels of care provided by unpaid carers may have had protective effects on older people in terms of reducing the rates of extended stays in hospital. If unpaid care were substituting for cuts to council provision, this begs the question about sustainability. Therefore, extending these analyses to cover subsequent years could demonstrate whether any effects were sustained or not.

Future research should be based on comprehensive and better quality data, ideally at the level of the individual. The priority would be to establish a collection of routine data on individuals' use of health and social care—including use of unpaid care. Not only would this support a robust analysis of the relationship between social care supply and healthcare utilization, it could also support the delivery of personalized, integrated care. Ideally, these datasets would also collect information on health and wellbeing, enabling a robust assessment of the benefits and unintended effects of policies.

CONFLICT OF INTEREST
The authors have no conflicts of interest to declare.

ETHICAL APPROVAL
As this study uses existing datasets, there was no requirement for ethical review.

ORCID
Dan Liu https://orcid.org/0000-0002-1891-9352
Maria Lucia Pace https://orcid.org/0000-0002-9657-3756
Maria Goddard https://orcid.org/0000-0002-1517-7461
Rowena Jacobs https://orcid.org/0000-0001-5225-6321
Raphael Wittenberg https://orcid.org/0000-0003-3096-2721
Anne Mason https://orcid.org/0000-0002-5823-3064

ENDNOTES
[1] The NMDS-SC does not report separately numbers of staff working with older people.
[2] There are four classes of councils with responsibility for social care: London boroughs, unitary authorities, shire counties and metropolitan boroughs. We used unitary authorities as the reference category.
[3] Given the presence of fixed effects, these models do not include the deprivation index and the percentage of black and minority ethnicity.
[4] However, in these two models it was the best combination of instruments for the two equations. Basically, we instrumented the first difference equation with y_{it-2} and y_{it-3} and the equation in level with all the available first differences for the dependent variable and the main endogenous variable (expenditure).

REFERENCES
Amin-Smith, N., Phillips, D., & Simpson, P. (2018). *Adult social care funding: A local or national responsibility?* (IFS Briefing Note No. BN227). London: Institute for Fiscal Studies.
Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies, 58*, 277–297.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87, 115–143.

Cabinet Office, & Green, D. (2017, November 16). *Government to set out proposals to reform care and support.* Press Release. London, UK: Cabinet Office. Retrieved from https://www.gov.uk/government/news/government-to-set-out-proposals-to-reform-care-and-support

Cameron, A. C., & Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources*, 50, 317–372.

Carter, R. (2017, March 8). *Budget 2017: Social care gets £2bn funding boost.* London, UK: CommunityCare. Retrieved from https://www.communitycare.co.uk/2017/03/08/budget-2017-social-care-gets-2bn-funding-boost/

Claxton, K., Lomas, J., & Martin, S. (2018). The impact of NHS expenditure on health outcomes in England. *Health Economics*, 27, 1017–1023. https://doi.org/10.1002/hec.3650

Crawford, R., Stoye, G., & Zaranko, B. (2018). The *impact of cuts to social care spending on the use of accident and emergency departments in England* (IFS Working Paper W18/15). London: Institute for Fiscal Studies, 29. https://doi.org/10.1920/wp.ifs.2018.W1815

Darton, R., Forder, J., Netten, A., Bebbington, A., Holder, J., & Towers, A.-M. (2010). Slicing up the pie: Allocation of central government funding of care of older people. *Social Policy & Administration*, 44, 529–553.

Department for Communities and Local Government. (2011a). *The local government finance report (England) 2011/2012. Annex H: Area cost adjustment factors*, (pp. 1–164). London, UK: The Stationery Office. https://webarchive.nationalarchives.gov.uk/20140505130053/, http://www.local.communities.gov.uk/finance/1112/lgfr1112s/index.htm

Department for Communities and Local Government. (2011b). Methodology Guide for the Area Cost Adjustment 2011/12 and 2012/13. 17.

Department for Communities and Local Government. (2013a). Methodology Guide for Adults' Personal Social Services Relative Needs Formulae 2013/14. 11.

Department for Communities and Local Government. (2013b). Methodology Guide for the Area Cost Adjustment 2013/14. 17.

Department of Health and Department for Communities and Local Government. (2017). *Integration and Better Care Fund policy framework 2017-19*, (pp. 1–34). London, UK: Integration, Local Devolution and Policy Improvement Unit. https://www.gov.uk/government/publications/integration-and-better-care-fund-policy-framework-2017-to-2019

Department of Health and Social Care. (2018). Care and support statutory guidance: using the Care Act guidance. Vol. 2020.

Fernandez, J.-L., & Forder, J. (2008). Consequences of local variations in social care on the performance of the acute health care sector. *Applied Economics*, 40, 1503–1518.

Fernandez, J.-L., McGuire, A., & Raikou, M. (2018). Hospital coordination and integration with social care in England: The effect on post-operative length of stay. *Journal of Health Economics*, 61, 233–243.

Forder, J. (2009). Long-term care and hospital utilisation by older people: An analysis of substitution rates. *Health Economics*, 18, 1322–1338.

Forder, J., & Vadean, F. (2018). *Estimating relative needs formulae for new forms of social care support* (PSSRU Discussion paper No. 2877/2). Canterbury, UK: Personal Social Services Research Unit, University of Kent. Retrieved from https://www.pssru.ac.uk/pub/DP2877_2.pdf

Gaughan, J., Gravelle, H., Santos, R., & Siciliani, L. (2017a). Long-term care provision, hospital bed blocking, and discharge destination for hip fracture and stroke patients. *International Journal of Health Economics and Management*, 17, 311–331.

Gaughan, J., Gravelle, H., & Siciliani, L. (2015). Testing the bed-blocking hypothesis: Does nursing and care home supply reduce delayed hospital discharges? *Health Economics*, 24(Suppl. 1), 32–44.

Gaughan, J., Gravelle, H., & Siciliani, L. (2017b). Delayed discharges and hospital type: Evidence from the English NHS. *Fiscal Studies*, 38, 495–519.

Greene W. H. (2007). *Fixed and random effects models for count data*. (Leonard N. Stern School of Business Paper No. ISSN 1547-3651). Retrieved from SSRN: https://ssrn.com/abstract=990012 or http://dx.doi.org/10.2139/ssrn.990012.

Hausman, J., Hall, B. H., & Griliches, Z. (1984). Econometric models for count Data with an application to the patents-R & D relationship. *Econometrica*, 52, 909–938.

HM Treasury. (2013). *Spending round 2013. Cm 8639*, (–). London, UK: The Stationery Office Limited. Retrieved from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/209036/spending-round-2013-complete.pdf

Johnstone, R. (2015). Social care funding cut by a third since 2010, ADASS survey finds. Public Finance 4 June. Retrieved from https://www.publicfinance.co.uk/news/2015/06/social-care-funding-cut-third-2010-adass-survey-finds

Kasteridis, P., Mason, A., Goddard, M., Jacobs, R., Santos, R., & McGonigal, G. (2015). The influence of primary care quality on hospital admissions for people with dementia in England: A regression analysis. *PloS One*, 10, e0121506.

Matthews, F. E., Arthur, A., Barnes, L. E., Bond, J., Jagger, C., Robinson, L., ... Ageing, C. (2013). A two-decade comparison of prevalence of dementia in individuals aged 65 years and older from three geographical areas of England: Results of the cognitive function and ageing study I and II. *Lancet*, 382, 1405–1412.

Moulton, B. R. (1990). An illustration of a pitfall in estimating the effects of aggregate variables on micro units. *Review of Economics and Statistics*, 72, 334–338.

NHS Digital. (2016). *Personal social services: Expenditure and unit costs: England 2015-16*, Leeds, UK: Health and Social Care Information Centre. https://files.digital.nhs.uk/publicationimport/pub22xxx/pub22240/pss-exp-eng-15-16-fin-rep.pdf

NHS England. (2019). New NHS plan to help patients avoid long hospital stays. *NHSE News* 19 August.

NHS Improvement. (2017). Process and definitions for the daily situation report web form. Daily Situation Report Guidance. London, UK: NHS Improvement.

—WILEY—

NHS Improvement. (2018). *Guide to reducing long hospital stays*. London, UK: NHS Improvement. Retrieved from https://improvement.nhs.uk/documents/2898/Guide_to_reducing_long_hospital_stays_FINAL_v2.pdf

Oliver, D. (2019). David Oliver: Guidance tools won't solve long hospital stays. *BMJ*, *367*, l5870.

Reeves, D., & Baker, D. (2004). Investigating relationships between health need, primary care and social care using routine statistics. *Health & Place*, *10*, 129–140.

Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. *Stata Journal*, *9*, 86–136.

Seamer, P., Brake, S., Moore, P., Mohammed, M. A., & Wyatt, S. (2019). Did government spending cuts to social care for older people lead to an increase in emergency hospital admissions? An ecological study, England 2005-2016. *BMJ Open*, *9*, e024577.

Spiers, G., Matthews, F. E., Moffatt, S., Barker, R. O., Jarvis, H., Stow, D., ... Hanratty, B. (2018). Impact of social care supply on healthcare utilisation by older adults: A systematic review and meta-analysis. *Age and Ageing*, *48*, 57–66.

Tinetti, M. E., Speechley, M., & Ginter, S. F. (1988). Risk factors for falls among elderly persons living in the community. *New England Journal of Medicine*, *319*, 1701–1707.

Twinch, E. (2018). Councils face 'almost impossible struggle' to fund social care. Public Finance March 22. Retrieved from https://www.publicfinance.co.uk/news/2018/03/councils-face-almost-impossible-struggle-fund-social-care

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.