**More long-term care for better health care and vice versa:**

**investigating the mortality effects of interactions between these public sectors**

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**Abstract**

Public health care (HC) and long-term care (LTC) sectors co-exist across several countries in the Organisation for Economic Co-operation and Development. Economic interactions between these two sectors have been found to occur even in the absence of formal integrated care arrangements. We investigate whether and how interactions between the HC and LTC sectors impact mortality. We analyse data on English local authorities in 2014/15 and employ a sequence of cross-sectional econometric specifications based on instrumental variables to identify the effect that LTC expenditure has on mortality through its interactions with HC services, and vice versa. Our findings suggest that any effect of LTC expenditure on mortality is likely to run through the HC sector by allowing the latter to reallocate resources from less to more effective services. An increase in LTC expenditure per user by 10% can indirectly save, on average, about 3 lives per million individuals. In addition, on top of the known HC direct mortality effects, we find that investing an extra £42m in the HC sector – equivalent to a 10% increase in HC expenditure per capita for the average local authority – can decrease the use of LTC services producing around £7.8m of savings. These can generate mortality effects if invested in services having an impact on mortality.

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# Introduction

Public health care (HC) and long-term care (LTC) systems co-exist across several countries within the Organisation for Economic Co-operation and Development (OECD). In these countries, public HC and LTC expenditure (simply HC and LTC expenditure from now on) is substantial (French and Kelly, 2016, Barczyk and Kredler, 2019). With increasing funding constraints and a rapidly aging population, the policy question of whether these systems are financially sustainable is even more crucial (OECD, 2020). Responses to these challenges in the HC sector varied across countries with some countries allowing HC expenditure to increase and others implementing cost containment measures (Reeves et al., 2014). However, the response in the LTC sector of several countries was less varied: to reduce amount of user services and financial remuneration to LTC providers (Joshua, 2017). For example, in the UK between 2010 and 2014, the annual growth of HC expenditure in real terms was still positive and equal to 1.3%, although it decreased compared to a historical annual growth of 4% (NHS England, 2014b). In the same period, however, LTC expenditure decreased in real terms by 1.2% whereas it increased on average every year by 3.2% in the previous decade (Watkins et al., 2017). It is unclear whether and how the greater focus on savings in the LTC sector impacted outcomes relevant to the HC sector because of the interactions between these two sectors. Therefore, evidence on these interactions is of key policy relevance as it contributes to understanding the value of public resources and how they might be best allocated between these sectors.

The importance of interactions between HC and LTC has now been recognised to the point that some countries are moving towards financially and operationally integrated HC and LTC systems (Mason et al., 2015, Baxter et al., 2018). Interactions exist for reasons relating to both the demand for and supply of these services. For example, LTC users who receive support to better cope with their long-term conditions may demand less HC services. Similarly, HC patients receiving interventions which improve their mobility, such as hip replacement, may demand less LTC support (Johri et al., 2003, Wanless et al., 2006). On the supply side, hospitals may be able to discharge patients more quickly if these can be referred to LTC services (Victor et al., 2000, Vetter, 2003).

The economic literature on the interactions between HC and LTC is growing and has focused on the effect of LTC services on hospital outcomes and the substitution between HC and LTC services. Fernandez and Forder (2008) investigate whether LTC services for individuals over 65 in England impact hospital performance measured through discharges, emergency readmissions, average length of stay (LOS) and delayed discharges. They employ a pooled cross-sectional instrumental variable (IV) approach and find consistent evidence that more LTC services improve hospital performance. Other studies examine the effect of care home supply, measured through the number of beds, on hospital delayed discharges in England using panel data methods. Findings from these studies suggest that more care home beds reduce average delayed discharges across local authorities (LAs) (Gaughan et al., 2015, Gaughan et al., 2017b). They also find a reduction in delayed discharge for hip fracture patients but not for stroke patients (Gaughan et al., 2017a).

Some studies explore the substitution between HC and LTC services and show mixed results. Forder (2009) explores whether care homes substitute hospital services for individuals over 65 in England using panel data IV models. The author finds that increasing care home expenditure by £1 reduces hospital expenditure by £0.35, and an effect of identical magnitude exists in the opposite direction. Similarly, Forder et al. (2019) investigate whether the use of home care substitutes general practitioners visits in England using panel data IV models, and they find statistical support for this substitution effect. In addition, Crawford et al. (2021) investigate the impact of cuts to LTC expenditure for people over 65 on emergency care services in England by employing a panel data IV approach. The authors find that reducing LTC expenditure increases visits to accident and emergency departments. Similar findings are suggested by Walsh et al. (2020) who investigate whether home care supply has any effect on emergency inpatient LOS in Ireland by employing panel data models. In contrast, using other variables for emergency care services, Seamer et al. (2019) find no relationship between public LTC expenditure and emergency hospital admissions for elderly people in England using panel data analysis. Liu et al. (2020) also find no relationship between LTC supply, captured by expenditure per capita and staffing levels, and emergency admissions for elderly people in England using panel data IV models.

This literature, however, fails to directly address the question of whether and how these interactions between HC and LTC system impact key health outcomes such as mortality. In addition, the literature investigating the effect of HC and LTC expenditure on mortality in a number of countries has not taken these interactions into account (Bhalotra, 2007, Watkins et al., 2017, Claxton et al., 2018, Vallejo‐Torres et al., 2018, Siverskog and Henriksson, 2019, Martin et al., 2021b). This study attempts to bridge these two strands of literature by investigating whether, how and to what extent interactions between HC and LTC expenditure impact mortality. Although LTC primarily aims to improve wellbeing (Fernandez et al., 2011), we argue that LTC services may have a *direct* mortality effect, i.e. the effect of the LTC services provided regardless of the HC sector (e.g. by preventing fatal falls in the elderly). However, an *indirect* mortality effect may also exist through interactions between the LTC and HC sector. For example, LTC will have a beneficial indirect mortality effect if it allows the HC sector to discharge patients more quickly and to use the resulting freed resources to provide more effective services. Similarly, HC services may impact mortality directly and, in principle, indirectly through interactions with the LTC sector. The investigation of direct and indirect mortality effects in both HC and LTC may have important policy implications. It may inform decision makers about whether and how changes in, for example, the LTC budget may impact the HC system and, through this, health. It may also inform the potential effects of reallocating resources across budgets as well as the potential effect of pooling budgets.

We explore possible direct and indirect mortality effects by estimating a sequence of econometric specifications using English LA data in 2014/15. Following the literature on the mortality effects (e.g. Claxton et al., 2018, Martin et al., 2021b), we estimate the mortality elasticity of HC and LTC expenditure. These sources of expenditure are likely to be endogenous because they may be correlated with unobserved factors having an impact on mortality, such as unobserved health and care needs. In addition, endogeneity may arise from simultaneity between expenditure and mortality since, for example, higher mortality may determine more investments in HC and LTC (e.g. Aragon et al., 2016). To address endogeneity in HC and LTC expenditure, we follow the approach introduced by Andrews et al. (2017) and Longo et al. (2021), respectively. Both approaches suggest the selection of instruments among variables which determine the level of HC and LTC funding and which can be argued to be exogenous conditional on need and socio-economic variables. This identification strategy estimates a mortality effect that potentially captures both the direct and any indirect mortality effect that may exist. Therefore, we test whether indirect mortality effects exist via an IV regression where mortality is the dependent variable and HC expenditure, LTC expenditure and their interaction are key independent variables. Although this approach can establish the existence of indirect mortality effects, it is unable to disentangle direct and indirect mortality effects. To identify the magnitude of direct and indirect mortality effects, we use a series of IV regressions to explore whether LTC (HC) expenditure impacts level and composition of HC (LTC) expenditure, which are two possible channels for the indirect effect. Changes in the composition are evaluated by analysing the impact of LTC (HC) expenditure on expenditure for HC (LTC) sub-sectors (e.g. elective care for HC, community care for LTC). We then estimate an IV regression which controls for the possible change in the level and composition of expenditure in the other sector. This allows us to identify the indirect mortality effect of each sector that runs through these two possible channels.

This study is structured as follows. The next two Sections summarise the institutional (1.1) and theoretical framework (1.2), defining direct and indirect mortality effects. Section 2 illustrates the methods, Section 3 describes the data and Section 4 provides the results. Finally, Section 5 discusses the results and concludes.

## Institutional framework

The English National Health Service (NHS) provides services which are universal, tax financed, and, mostly, free at the point of delivery. The Department of Health and Social Care (DHSC) assigned an annual fixed budget to each of the 212 health authorities, called clinical commissioning groups (CCGs), and most of this budget was used to purchase pharmaceuticals and secondary HC services from HC providers. Primary HC, commissioning of specialised services and public health were instead managed more centrally. Distribution of funding across CCGs was determined through a funding formula which included a constant amount per capita and some top-ups taking account of local needs. These factors adjusted for age through the age-cost index, needs through a variable capturing past mortality, input prices through the market forces factor (MFF) index, and the distance from target (DFT) index. The DFT index smoothed large and sudden changes to CCG budgets over time when DHSC updated the funding formula to reflect new circumstances of the local populations (NHS England, 2014c). Funding was finally allocated by CCGs across disease areas within their locality.

The English public LTC programme for people older than 18 is called Adult Social Care (ASC). ASC is provided by 152 LAs directly or through external organisations. Unlike NHS services, ASC services are means-tested on the basis of asset and savings and needs, so that individuals with asset and savings greater than £23 thousand are ineligible regardless of their needs. The Care Act 2014 sets out minimum levels of care and the generosity of the eligibility policy beyond these levels has been argued to vary by type of LA because of factors such as innate culture and market conditions (Forder et al., 2014). There are four types of LAs responsible for ASC including unitary, metropolitan and county LAs, and London boroughs (inner and outer). While unitary and metropolitan LAs are responsible for all local services (e.g. education, passenger transport), County LAs and London boroughs share their power with other LAs (e.g. County councils).

LAs fund their services mostly through revenues from council tax on domestic properties and business rates tax on non-domestic properties, and grants from central government (Amin-Smith et al., 2018, Brien, 2018). Local tax revenues and part of the governmental grants are not ring-fenced (Department for Communities and Local Government, 2017). Therefore, the ASC budget is a proportion of the total budget across LAs and this proportion can be flexible to the extent to which LAs are willing to trade off ASC services with other LA services (e.g. children’s and housing services). Governmental grants that are ring-fenced for ASC are distributed across LAs according to the ASC relative needs formula (Department for Communities and Local Government, 2014). This includes a constant amount per capita across LAs and a number of top-ups to account for needs through age, socio-economic deprivation and rurality, and for labour costs through the area cost adjustment (ACA) index.

Integration between the HC and LTC sector in England was introduced with the 1999 Health Act and then re-stated in the NHS Act 2006. These acts allowed both financial and organisational integration: health and local authorities were enabled to pool their budgets, and to mutually delegate functions or provide services jointly. Integration was implemented sparingly and heterogeneously across LAs, and benefits from the new arrangements were unclear (Mason et al., 2015). A mandatory integrated care scheme, called the Better Care Fund (BCF), was announced in 2013 (Department of Health and Social Care, 2013) and fully rolled out in 2015/16. The BCF is a single pooled budget to incentivise CCGs and LAs to work more closely together in their local areas (Bennett and Humphries, 2014). In 2014/15, the financial year of our analysis, a transfer of £1.1bn from the NHS to LAs was arranged in preparation of the BCF scheme. These funds, however, could be spent on any ASC service and did not require CCGs and LAs to pool their budget (NHS England, 2014a).

## Theoretical framework: direct and indirect mortality effects

The level of health across LAs where public HC and LTC are provided can be described as:

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where *healthi* could, for example, be measured by mortality within each LA, *i*, and this is a function *g* of (public) HC and LTC expenditure, *HCi* and *LTCi*, respectively, and *ri*, which captures any other factor impacting health such as need, lifestyle and income of the local populations.

Expenditure in the HC sector is expected to have a direct effect on mortality as one of the key goals of health care services is to improve health. Although the primary aim of LTC expenditure may be to improve user quality of life, LTC services may also have a direct impact on mortality, for example, by preventing fatal falls in elderly people. Therefore, the direct mortality effect can be interpreted as the effectiveness of LTC and HC expenditure in reducing mortality, which we assume to be:

  and .

However, expenditure in one sector may also have an indirect effect on mortality by its impact on the other sector. Suppose we can categorise expenditure for LTC and HC sub-sectors based on their effectiveness (their direct mortality effect). In both sectors, we observe expenditure in a high-effective sub-sector (*LTCihigh* and *HCihigh*) and expenditure in a low-effective sub-sector (*LTCilow* and *HCilow*), such that:

 ,  and ,

 ,  and ,

where θ*i* and φ*i* are the proportion of LTC and HC expenditure, respectively, for the high-effective sub-sector. Therefore:

  and .

The total mortality effect of LTC expenditure can be obtained by total differentiating equation as follows:[[1]](#footnote-2)

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where the first addend is the LTC direct mortality effect, and the second and third addend form the LTC indirect mortality effect via the HC sector. The term *dHCihigh*/*dLTCi* (*dHCilow*/*dLTCi*) in can be re-written as the total derivative of *HCihigh* (*HCilow*) with respect to LTC expenditure as follows:

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where in the presence of a fixed HC budget, like in the UK, *dHCi*/*dLTCi*=0. By replacing and in , and after rearranging, we can write the total mortality effect of LTC expenditure as follows:

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which suggests that the LTC indirect mortality effect (second addend) depends on the ability of the HC sector to reallocate resources from low- to high-effective services, and the difference in effectiveness between these services.

Moreover, equation highlights that there are three possible channels that may contribute to an indirect mortality effect. A first channel is *d*φ*i*/*dLTCi* because the indirect mortality effect will increase with the ability of the HC sector to reallocate resources from low- to high-effective services. This is plausible because, for example, LTC users who receive better support to cope with their long-term conditions may request less hospital visits which have little impact on health, such as avoidable emergency care visits. Lower demand for these services releases resources which could be reinvested in more effective HC services, such as elective care. A second channel increasing the indirect mortality effect is *HCi*, if LTC expenditure impacts HC expenditure. As already mentioned, however, this is unlikely to be the case because a fixed HC budget means that no more or less of the whole budget will be spent. Therefore, *HCi* is likely to be a simple constant in the equation, i.e. *dHCi*/*dLTCi*=0. Finally, a third channel is the effectiveness of HC expenditure, *∂g*/*∂HCilow* and *∂g*/*∂HCihigh*, if these vary with LTC expenditure. This is plausible if, for example, greater LTC expenditure frees HC resources to reduce waiting time for elective treatments which, in turn, become more effective. Similarly, if greater LTC expenditure means that doctors in the emergency department can spend more time treating patients with greater health need, emergency services may become more effective. Finally, if greater LTC expenditure improves medication adherence, this may make drugs more effective.

The direct and indirect effect of HC expenditure can be obtained by total differentiating equation as follows:

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where the term *dLTCihigh*/*dHCi* (*dLTCilow*/*dHCi*) can be re-written as the total derivative of *LTCihigh* (*LTCilow*) with respect to HC expenditure as follows:

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Unlike the HC budget, the LTC budget is flexible, such that *dLTCi*/*dHCi* may be non-zero. By substituting and into , and after rearranging, we obtain:

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Equation indicates that the HC indirect mortality effect potentially varies with three channels. A first channel is *d*θ*i*/*dHCi* as this indirect mortality effect will increase with the ability of the LTC sector to reallocate resources from low- to high-effective LTC services. This is plausible because, for example, an increase in HC expenditure may enable patients to live more independently (e.g. due to improved mobility), and this reduces demand for LTC support. Because of this lower demand, the LTC sector may reallocate resources to support other people who could potentially benefit more (e.g. those with unmet needs). A second channel is *LTCi*, which is plausible in the presence of a flexible LTC budget since this implies that LTC expenditure may vary with HC expenditure, i.e. *dLTCi*/*dHCi*≠0 is now possible. Finally, a third channel is the effectiveness of LTC expenditure, *∂g*/*∂LTCilow* and *∂g*/*∂LTCihigh*, which is also a plausible because HC expenditure may in principle impact LTC effectiveness. For example, if LTC users can receive a hip replacement to improve their mobility with a shorter waiting time, then LTC services may be more effective in preventing fatal falls.

In sum, this simple theory model shows that interdependencies between sectors which may impact mortality directly, such as the HC and LTC sector, may generate indirect mortality effects. In the next Section, we illustrate our empirical approach to estimate direct and indirect mortality effects.

# Methods

## Econometric analysis of mortality effects

Our empirical approach aims to estimate mortality effects as one possible measure of marginal productivity. In general, marginal productivity can be defined as the amount of outcome that an individual can obtain for each pound of a certain service received. More precisely, this study focuses on the marginal productivity of HC and LTC expenditure, i.e. the extent to which mortality of a HC patient or LTC user can be reduced by, respectively, each pound of HC or LTC services received. Therefore, in addition to mortality, key variables in our analyses are HC expenditure per capita and LTC expenditure per user.[[2]](#footnote-3) As discussed in Section 1, these are likely to be endogenous because of unobserved confounders and reverse causality. Previous studies address this endogeneity issue using IVs capturing factors which determine the amount of resources to be spent in each sector (Andrews et al., 2017, Claxton et al., 2018, Martin et al., 2021a). These factors are argued to be relevant because they influence spending power, and exogenous conditional on observed confounders measuring need and socio-economic status. In this study, following Andrews et al. (2017) and Martin et al. (2021a), we use three candidate instruments for HC expenditure per capita: DFT index, age-cost index and MFF index. Following Longo et al. (2021), we use the council tax base per user as our primary instrument for LTC expenditure per user.[[3]](#footnote-4) We use these four instruments in all the models presented below, and Section 2.4 includes a full discussion about their validity.

First, we estimate equation to obtain the mortality elasticity of HC expenditure per capita and LTC expenditure per user through the following IV regression:

 

where *mortalityi* is a mortality indicator for LA *i*, *α1* is the intercept, *expenditureiHC* and *expenditureiLTC* are HC expenditure per capita and LTC expenditure per user, respectively, *Xi* is a vector of control variables, and *ε1i* is the error term. We employ an IV approach because the expenditure variables are likely to be endogenous, and estimate by two-stage least square (2SLS) weighting by LA population and estimating robust standard errors.

The key coefficients of interest in are *β1* and *γ1* and they capture the HC and LTC mortality effects, respectively. For example, if *β̂1*>0 (*γ̂1*>0) then a 1% increase in HC (LTC) expenditure per capita (user) increases mortality by a percentage equal to *β̂1* (*γ̂1*).[[4]](#footnote-5) The theory model in Section 1.2 suggests that any sector may generate an indirect mortality effect via another sector, if the latter has a direct mortality effect. In this case, whether *β1* and *γ1* capture either a direct mortality effect, an indirect mortality effect or both depends on whether HC expenditure (per capita) and LTC expenditure (per user) have a direct mortality effect, and whether expenditure in one sector impacts the potential channels generating the indirect mortality effect via the other sectors.

For example, the estimated LTC mortality effect, *γ̂1*, may capture the LTC indirect mortality effect via the HC sector in addition to any direct effect. Insofar as HC has a direct mortality effect, a LTC indirect mortality effect is possible if LTC expenditure impacts the two plausible channels: the composition and effectiveness of HC expenditure. If our regression fails to control for these channels, then *γ̂1* will be unable to disentangle the LTC direct from the indirect mortality effect. The LTC total mortality effect will be:

 

where *γ1direct* and *γ1indirect* capture the LTC direct and indirect mortality effect, respectively, Δ1*γ* is the marginal effect of LTC expenditure on the channels for the LTC indirect mortality effect, and Β1 is the effect of a marginal change in these channels on mortality. Equation suggests that *γ1indirect* takes the form of an omitted variable bias due to the lack of control variables measuring the channels that generate the LTC indirect effect.

Similarly, the estimated HC mortality effect, *β̂1*, may capture the HC indirect mortality effect in addition to any direct effect. This will be the case if HC expenditure impacts the three possible channels generating the indirect effect: level, composition and effectiveness of LTC expenditure. With no controls for these channels, we can expect the HC total mortality effect to be:

 

where *β1direct* and *β1indirect* capture the HC direct and indirect mortality effect, respectively, Δ1*β* is the marginal effect of HC expenditure on the channels for the HC indirect mortality effect, and Γ1 is the effect of a marginal change of these channels on mortality.

## Testing indirect mortality effects

Regression can estimate mortality effects but it is unable to indicate whether an indirect mortality effect via the other sector may exist. To test the existence of such an indirect mortality effect we use the following IV regression:

 

where the only additional term compared to is the interaction between HC expenditure per capita and LTC expenditure per user. We estimate by 2SLS after adding the interaction between the DFT index and the council tax base per user as a fifth instrument. Again, we weight the regression by LA population and estimate robust standard errors.

We use regression to test the statistical significance of *δ̂2*, which indicateswhetherthe mortality elasticity of HC expenditure varies with the level of LTC expenditure and vice versa. If *δ̂2*≠0, then an indirect mortality effect exists in either one or both directions. For example, if *δ̂2*>0 then the mortality elasticity of HC (LTC) expenditure increases with the level of LTC (HC) expenditure. This would indicate that the indirect mortality effect is likely to be detrimental because expenditure in one sector decreases the average effectiveness of expenditure in the other sector.[[5]](#footnote-6)

## Separating out direct and indirect mortality effects

Testing the statistical significance of *δ2* in is unable to identify the magnitude of the direct and any indirect mortality effects which may exist. However, as highlighted in equation (15) and (16), the indirect mortality effect takes a form that is similar to an omitted variable bias. If this is the case, then the direct mortality effect in one sector can be identified by controlling for the channels generating the indirect mortality effect via the other sector. We attempt to control for these channels using what we can observe: changes in the level and composition of expenditure in each sector. Once estimated, the direct mortality effect can be compared with the total mortality effect to obtain the indirect mortality effect. Therefore, we investigate whether expenditure in one sector impacts the level and composition of expenditure in the other sector. We are then able to identify the indirect mortality effect in one sector that runs through changes in the level and composition of expenditure in the other sector by controlling for these channels. If there is no other unobserved factor relating to the possible channels for the indirect mortality effects, then we can also identify the direct mortality effect in each sector.[[6]](#footnote-7)

### Analysis of the impact on level and composition of each type of expenditure

We investigate whether LTC expenditure per user has any impact on the level and composition of HC expenditure per capita through the following 2SLS regression:

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where *expenditureiHCj* is HC expenditure per capita for sub-sector *j*, *πj* is the intercept, *ZiHC* is a vector of instruments for HC expenditure which are used here as control variables, and *τij* is the error term. We estimate with robust standard errors and by weighting for LA population. In the key coefficient of interest is *ωj*, which captures the percentage impact of a 1% increase in LTC expenditure per user on HC expenditure per capita in sub-sector *j*. For example, *ω̂j*>0 then 1% increase in LTC expenditure per user increases HC expenditure per capita in sub-sector *j* by a percentage equal to *ω̂j*.

We set *expenditureiHCj* = *expenditureiHC* in regression to test whether the level of LTC expenditure impacts the level of HC expenditure. We hypothesise no impact given that the HC budget in England is fixed and, therefore, mostly independent from expenditure in the LTC sector. After that, guided by the literature, we explore whether LTC expenditure changes the composition of HC expenditure by focusing on various plausible sub-sectors. We test whether a greater LTC supply reduces expenditure for emergency care (Walsh et al., 2020, Crawford et al., 2021). In addition, we explore whether more resources are invested in non-emergency care activity such as, for example, elective care, outpatient care, and primary care prescribing (more details about non-emergency care services are in Section 3.1). Investments may be focused particularly on those disease areas which already attract most of the HC funding including cancer, circulatory, respiratory and gastro-intestinal disease (Lomas et al., 2019).

We explore whether HC expenditure per capita impacts the level and composition of LTC expenditure per user through the following 2SLS regression:

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where *expenditureiLTCj* isLTC expenditure per user for sub-sector *j*, *μj* is the intercept, *ZiLTC* is avector of instruments for LTC expenditure which are used here as control variables, and *ξij* is the error term. Like in , we estimate with robust standard errors and by weighting for LA population. The key coefficient of interest is *ρj*, and this is interpreted similarly to *ωj*. Using regression , first, we set *expenditureiLTCj* = *expenditureiLTC* and test whether the level of HC expenditure impacts the level of LTC expenditure. In this case, we refrain from making a hypothesis on this impact since the LTC budget can be argued to be flexible and, therefore, the response to changes in HC expenditure may vary across LAs. Then, we test whether a larger HC supply implies lower expenditure on residential and community care (Forder, 2009, Forder et al., 2019). Moreover, more resources may be used on potentially cost-effective LTC services such as short-term reablement and home equipment and adaptations (e.g. Heywood, 2001, Boniface et al., 2013, Lewin et al., 2013). Therefore, we investigate whether HC expenditure impact expenditure on these and other LTC services (more details about LTC services are in Section 3.1).

### Estimating direct and indirect mortality effect

We are able to identify the indirect mortality effect of one sector running through changes in the level and composition in the other sector by controlling for these changes. If there is no other unobserved factor relating to the possible channels for the indirect mortality effects, then we can also identify the direct mortality effect in each sector. A fixed HC budget suggests that any effect of LTC expenditure will be to increase some sub-components of HC expenditure and decrease some others, such that the level of HC expenditure remains constant. In this case, regression would be unable to disentangle LTC direct and indirect mortality effect by controlling only for the level of HC expenditure. Therefore, to estimate the LTC direct mortality effect, we account for changes in the composition of HC expenditure through the following regression:

 

where *expenditureiHCk* is a vector including two variables capturing the sub-components of HC expenditure per capita that decrease and increase, respectively, in response to a change in LTC expenditure per user. We estimate this regression by 2SLS with robust standard errors, weighting for LA population. Once changes in the composition of HC expenditure are accounted for, *γ3* in captures the LTC direct mortality effect if there is no other unobserved factor relating to the channels for the LTC indirect mortality effect. Equation in Section 1.2 indicates that *γ3* captures *∂g*/*∂LTCi* if *d*φ*i*/*dLTCi* can be accounted for and if *∂g*/*∂HCihigh* and *∂g*/*∂HCilow* are not impacted by LTC expenditure, i.e. the effectiveness of sub-components of HC expenditure are unchanged by LTC expenditure. Under these assumptions, by comparing the estimated LTC direct effect, *γ3,* with the LTC total mortality effect, *γ1*, we estimate the LTC indirect mortality effect.

The effect of HC expenditure may also be to increase some sub-components of LTC expenditure and decrease others. It is possible that the decrease in some sub-components of LTC expenditure may offset the increase in other sub-components leaving the level of LTC expenditure unchanged. However, in the context of a flexible LTC budget this is not necessarily that case and HC expenditure may cause a change in both the level as well as composition of LTC expenditure. Therefore, by controlling only for the level of LTC expenditure, would be unable to disentangle HC direct and indirect mortality effect unless HC expenditure increases or decreases expenditure for all LTC sub-components in the same way (changing the level of LTC expenditure without changing its composition) or if the effect of HC on both level and composition is strongly correlated; for example, if expenditure in some or all LTC subsectors changes in the same direction as total expenditure.[[7]](#footnote-8) Otherwise, the HC direct mortality effect can be estimated using the following regression which is similar to :

 

where *expenditureiLTCk* is a vector including two variables capturing the sub-components of LTC expenditure per user that decrease and increase, respectively, in response to a change in HC expenditure per capita. Also is estimated by 2SLS with robust standard errors, weighting for LA population. After accounting for changes in the level and composition of LTC expenditure, *β4* in captures the HC direct mortality effect if there are no other unobserved factors relating to the channels for the HC indirect mortality effect. Looking at , this means that *β4* captures *∂g*/*∂HCi* if *dLTCi*/*dHCi* and *d*θ*i*/*dHCi* can be accounted for and if *∂g*/*∂LTCilow* and *∂g*/*∂LTCihigh* are not impacted by HC expenditure. Under these assumptions, this can then be compared with the HC total mortality effect, *β1*, to estimate the HC indirect mortality effect.

## IV approach

We use the DFT index, the age-cost index, and the MFF index as instruments for HC expenditure and council tax base per user as the primary instrument for LTC expenditure. Martin et al. (2021a) discuss the validity of the three instruments for HC expenditure in the context of a regression where the dependent variable is age-standardised mortality like in this study. In sum, these instruments are argued to be relevant (i.e. correlated with HC expenditure) because they determine the amount of HC funding available to CCGs. The DFT index reflects various policy choices which can be argued to be independent from age-standardised mortality or other health outcomes (Carr-Hill et al., 1997).[[8]](#footnote-9) In addition, conditional on our controls for health needs, the DFT index is unlikely to be correlated with unobserved determinants of age-standardised mortality. The age-cost index captures the impact of the age and gender profile of the local population on the HC costs. Importantly, as our mortality indicator is age-standardised, any correlation between this and the age-cost index cannot occur via age. On the other hand, the MFF index reflects HC labour and capital prices in each locality. Both age-cost and MFF index may capture differences in costs across LAs only imperfectly. We have no reason to believe that errors in these adjustments will have a direct effect on age-standardised mortality. Moreover, conditional on health needs, these errors are unlikely to be correlated with unobserved factors impacting age-standardised mortality (Propper and Van Reenen, 2010). Therefore, the only plausible pattern for these adjustment errors to impact mortality is via HC expenditure.

Similarly, we argue that these instruments for HC expenditure per capita are equally valid when used in regression , where the dependent variable is LTC expenditure per user or one of its sub-categories. This is because English LAs in 2014/15 experienced low integration between HC and LTC funding systems and, therefore, expenditure in these two sectors were driven by mostly independent decision-making processes. Therefore, conditional on observed needs, elements of the funding rules in one sector are unlikely to have a direct impact on expenditure in the other sector. This implies that instruments for HC expenditure are likely to be conditionally exogenous in regression and likely to impact LTC expenditures only via HC expenditure.

The council tax base per user is measured as the standardised number of domestic properties per user.[[9]](#footnote-10) This is argued to be correlated with LTC expenditure per user because it is a key determinant of the funding available to LAs for the provision of local services including LTC. In addition, it is likely to be exogenous conditional on socio-economic factors. This is because it reflects the historical urban development across LAs (e.g. tangible cultural heritage) which is unlikely to be correlated with LTC outcomes and needs. Therefore, conditionally on our controls, the council tax base per user is argued to impact our dependent variables only via LTC expenditure per user. However, unlike Longo et al. (2021), for whom the dependent variable is a LTC-specific measure of user quality of life (Netten et al., 2012), our dependent variables are age-standardised mortality, in regression , , and , and HC expenditure per capita variables, in regression . This implies that the council tax base per user can potentially determine the spending level of LA non-LTC services which might impact mortality and HC expenditure. The Local Government Association (2017) suggests that council tax revenues mostly fund LTC services and, to a lesser extent, education, transport, housing, cultural, environmental and planning services on top of police and fire rescue services. Therefore, we test the robustness of our results to controlling for these LA expenditures. We test also instruments’ relevance using the common rule of thumb of a first-stage F-statistic greater than 10 (Staiger and Stock, 1994). Thanks to the availability of multiple instruments, we test also whether these are likely to be exogenous using an over-identification test (Sargan, 1958, Sargan, 1988). Finally, under the potential outcome model framework (Rubin, 1974, Rubin, 1978), our estimates of the mortality effects have a local average treatment effect (LATE) interpretation. This is discussed, together with the required assumption of monotonicity, in Section A2 of the Appendix.

# Data

We collect and construct LA data for the financial year 2014/15, unless indicated otherwise, using multiple sources as detailed in Table A1.

## Mortality and expenditure

Our key dependent variable is the 2015 age-standardised mortality rate for all causes including deaths at all ages. Other key variables are HC and LTC expenditure variables. The HC expenditure variables (relate to the financial year 2014/15 and) are extracted from NHS England’s programme budgeting dataset and are mapped from CCGs to LAs.[[10]](#footnote-11) They include total HC expenditure, expenditure for emergency care, and for other forms of care. In turn, emergency care expenditure includes expenditure for non-elective admissions, accident and emergency services, emergency transport and other emergency services (e.g. triage based in accident and emergency departments, walk-in-centres). Non-emergency care expenditure includes expenditure for day case and elective care, outpatient care, unbundled and high cost care (including diagnostic imaging, critical care and drugs and devices), and other secondary care services (e.g. planned procedures not carried out, outpatient visits not attended). Non-emergency care expenditure includes also primary care prescribing, direct access to diagnostic imaging for suspected cancer patients, community and integrated care, and end-of-life care. Finally, it includes expenditure for running the HC service.

The LTC expenditure variables capture total LTC expenditure and expenditure for all sub-sectors including residential, nursing care and community care, social support, short-term care (e.g. vision rehabilitation, other reablement services to improve independence), equipment and adaptations, and universal information and early support services. We analyse also expenditure for social care activities (e.g. frontline assessment of new users, review of existing users) and for commissioning and service delivery (e.g. strategic business direction, business planning). All LTC expenditure variables are defined as gross expenditure minus capital charges. Gross expenditure includes user contributions but it excludes income from the NHS to avoid double counting with HC expenditure.[[11]](#footnote-12) HC expenditure per capita and LTC expenditure per user variables are obtained by dividing the expenditure variables by, respectively, population and number of LTC users across LAs. Table 1 includes descriptive statistics for these expenditure variables.

## Controls and instruments

As our instruments are valid conditionally on observed HC and LTC needs and socio-economic status as discussed in Section 2.4, we control for several covariates capturing these factors. We capture disability levels using the proportion of people who are blind or partially sighted and deaf or hard of hearing, and the 2015 index of disability deprivation. We control for socio-economic factors using population density, the 2010 index of multiple deprivation, the 2015 index of education and income deprivation, and the gross disposable household income per capita (averaged between 2014 and 2015). As Longo et al. (2021) suggests, LTC expenditure per user is likely to capture both treatment intensity and eligibility effects, but this generates a downward bias on the overall effect. Therefore, we control for eligibility levels through the type of LA (see Section 1.1) to identify the treatment intensity effect on mortality. Other controls capture some LTC users’ characteristics and these are the proportion of female users and users aged 65 or older, their cognitive status, measured as the proportion of those receiving an easy-read version of the Adult Social Care Survey questionnaire or some form of help to complete the questionnaire. We account also for informal unpaid carers’ characteristics as captured by the proportion of female carers, carers aged 65 or older, and carers whose care recipient is aged 65 or older. In addition, we control for the proportion of carers who are retired, those experiencing a clash between work and the caring role, and carers receiving help to complete their Survey of Adult Carers questionnaire. Finally, we control for carer experience as measured by the overall time spent in the caring role.

Our instruments for HC expenditure variables are the DFT index, the age-cost index and the MFF index. To instrument LTC expenditure variables we use the council tax base per user which is calculated as the standardised number of domestic properties per user. We use also the business rates tax base per user, calculated as the number of non-domestic properties per user adjusted by the proportion of business rates tax revenues retained locally. Finally, another instrument is the 2013/14 ACA index (Longo et al., 2021). All the variables described here are summarised in Table 2, and a short description of these variables is in Section A3 of the Appendix.

# Results

Table 3 reports HC and LTC mortality effects estimated by regression in column 1. We find that a 1% increase in HC expenditure per capita and LTC expenditure per user reduces mortality, on average, by 0.26% and 0.03%, respectively. These results are statistically significant at the 1% level. These results are in line with the expectation that both HC and LTC expenditure may reduce mortality, but they do not provide any hint about the existence of indirect mortality effects. For this reason, Table 3 reports, in column 2, the results from regression which tests whether indirect mortality effects may exist. We find that the interaction between HC expenditure and LTC expenditure is negative (‑0.304) and statistically significant at the 5% level. This suggests that indirect mortality effects in either both or one direction are likely to exist.

In regression we use all three candidate instruments for HC expenditure as well as council tax base per user. In regression , we add a fifth instrument obtained by multiplying the DFT index by the council tax per user.[[12]](#footnote-13) Table 3 reports the first-stage Kleibergen-Paap F-statistic and the result of the over-identification test. In addition, key first-stage results of all regressions are reported in Table A2 of the Appendix. As a preliminary indication of weak instruments, we consider the rule of thumb of an F-statistic lower than 10. On this basis, the F-statistic suggests that instruments are unlikely to be weak in regression but might be weak in regression (column 2). Therefore, following Andrews (2018), we run a two-step procedure on regression . This procedure offers a formal way to, first, test instrument strength and, after that, estimates weak-instrument-robust confidence intervals if instruments are tested to be weak. It suggests that our instruments in regression are unlikely to be weak (see Section A4 of the Appendix for more details). Moreover, to address potential concerns on the validity of the council tax base per user in regression , as discussed in Section 2.4, we estimate with additional controls capturing expenditure per capita for other services (e.g. education, police). We find that our results are robust as showed in Table A3 of the Appendix. Finally, the over-identification test for both regression and , suggests that the instruments are likely to be exogenous.

The left panel of Table 4 includes the results about the impact of LTC expenditure on level and composition of HC expenditure (see regression in Section 2.3.1). We find no effect of LTC expenditure on the level of HC expenditure. This result is in line with our expectations related to the existence of a fixed HC budget. We then investigate whether and how the composition of HC expenditure changes in response to LTC expenditure by focusing on multiple HC sub-sectors. We find that a 1% increase in LTC expenditure reduces expenditure for non-elective admissions, accident and emergency services, unbundled critical care, and direct access diagnostic imaging by 0.09% (statistically significant at 1% level), 0.09% (at 10% level), 0.19% (at 1% level) and 0.31% (at 1% level), respectively. We find also that a 1% increase in LTC expenditure increases expenditure for running the HC system and end of life care by 0.11% (statistically significant at 1% level) and 0.32% (at 5% level), respectively. In addition, for the HC sub-sectors not showing any statistical responsiveness (even weak at the 10% level) to LTC expenditure, we explore whether any response can be estimated when focusing on the four disease areas attracting most HC funding. We argue that, within each of these sub-sectors, only some disease areas can be responsive and this can be difficult to detect when focusing on all diseases. Therefore, for each of these sub-sectors, we focus on the largest two disease areas, which include cancer and circulatory diseases, and the largest four disease areas, which include also respiratory and gastro-intestinal diseases. We find that a 1% increase in LTC expenditure increases expenditure for outpatient care in the largest two and four disease areas by 0.16% (statistically significant at 5% level) and 0.09% (at 10% level), respectively, and it reduces unbundled diagnostic imaging in the largest four disease areas by 0.76% (at the 5% level). These results suggest that the composition of HC expenditure changes while its level remains constant in response to LTC expenditure. Therefore, the LTC mortality effect estimated through regression (‑0.032), is likely to capture both LTC direct and indirect mortality effects.

The right panel of Table 4 includes the results about the effect of HC expenditure on level and composition of LTC expenditure (see regression in Section 2.3.1). In this case, we find that a 1% increase in HC expenditure per capita reduces LTC expenditure per user by 0.61%. This effect is driven by reductions in expenditure for nursing care, community care, social support, and equipment and adaptations by 1.20% (statistically significant at 10% level), 1.10% (at 1% level), 4.51% (at 5% level) and 3.46% (at 10% level), respectively. This finding suggests that the effect of HC on the composition of LTC expenditure is likely to be strongly correlated with the effect of HC on the level of LTC expenditure because the effect of HC on expenditure for sub-sectors is in the same direction as total LTC expenditure. Therefore, the HC mortality effect estimated through regression and shown in Table 3 (‑0.257), is likely to only capture the HC direct mortality effect. Table A4 and Table A5 of the Appendix show that instruments are, overall, likely to be relevant and exogenous.

In sum, from regression , while the estimated HC mortality effect is likely to capture only the HC direct mortality effect, the estimated LTC mortality effect is likely to capture both LTC direct and indirect mortality effects. To disentangle LTC direct and indirect mortality effect we use regression which controls for the change in the composition of HC expenditure by including the portion of HC expenditure that decreases and increases, respectively, in response to a marginal change in LTC expenditure per user (see Section 2.3.2). We construct these two variables based on our results from regression presented above. The portion of HC expenditure that decreases as a result of the effect of LTC expenditure (simply, decreasing portion of HC expenditure) is on average £254 amounting to 20.2% of HC expenditure per capita. This portion includes expenditure for non-elective admissions (£186 on average), accident and emergency services (£33), unbundled diagnostic imaging for the largest four disease areas (£4), unbundled critical care (£21), and direct access diagnostic imaging (£9). The portion of HC expenditure that increases as a result of the effect of LTC expenditure (simply, the growing portion of health care expenditure) is on average £61 equal to 4.8% of HC expenditure per capita. This includes expenditure for outpatient activity in the largest four disease areas (£26 on average), end of life care (£10), and running the HC service (£25). Finally, the portion of HC expenditure which is not impacted by LTC expenditure is on average £942, i.e. 74.9% of HC expenditure per capita. Once constructed, the decreasing and growing portion of HC expenditure are used in regression to control for the change in the composition of HC expenditure. This model has three endogenous variables (decreasing and increasing portion of HC expenditure per capita and LTC expenditure per user) and the four usual instruments. Table 5 shows the results. We find that once we account for the change in the composition of HC expenditure, the LTC mortality effect is no longer statistically significant. This suggests that the whole LTC mortality effect estimated through is likely to be indirect. In addition, we find that a 1% increase in the growing portion of HC expenditure has a statistically significant (at 5%) mortality effect (0.16% reduction), while there is no statistical effect of the decreasing portion of HC expenditure. The first-stage F-statistic is below 10 also in this case, but the formal test suggested by Andrews (2018) indicates that our instruments are unlikely to be weak (see Section A4 of the Appendix for more details).

## Direct and indirect effects on mortality

The results discussed above are summarised in Table 6. They suggest that LTC expenditure is likely to have an indirect mortality effect only, whereas HC expenditure may have both direct and indirect mortality effects. This Section provides some back-of-the-envelope calculations to quantify these potential effects. Our findings suggest that an increase in LTC expenditure by 10%, i.e. by £863 (= £8,633 x 10%), can *indirectly* save more than 3 lives per million individuals (= 1,010 deaths per million individuals x -0.032% x 10) in the average LA.

In the HC sector, our estimate of the direct mortality effect suggests that by increasing HC expenditure by 10%, i.e. by £126 (= £1,257 x 10%), 26 lives per million (= 1,010 deaths per million x -0.257% x 10) can be saved in the average LA. Moreover, our results suggest that an HC indirect mortality effect is unlikely to exist because, as LTC has no direct effect on mortality, the sub-categories of LTC expenditure are also unlikely to have a direct mortality effect. However, we find that an increase in HC expenditure leads to lower LTC expenditure: for every additional £126 per capita (=£1,257 x 10%) spent in HC services, the average LA can save £524 per user (=£8,633 x -0.607% x 10). In other words, investing an extra £42m (=£126 per capita x 333,083 people) generates savings for about £7.8m (=£524 per user x 14,885 users). These savings may translate in further mortality effects depending on LAs’ future spending decisions. If spent on LTC services, savings may favour the HC sector via the LTC indirect mortality effect. On the other hand, it is unclear whether investing savings on other LA services (e.g. children services, housing services) may yield further mortality effects: mortality effects of these other LA services are unexplored.

# Discussion and conclusions

This paper investigates whether interactions between the HC and LTC sector in England impact mortality. Interactions between these two sectors imply that expenditure decisions in one sector may have consequences on services in the other sector and, through the latter, on mortality. Our findings indicate that any LTC mortality effect may run through the HC sector. This is because the LTC sector may prevent the use of emergency services and which potentially have little or no effect on mortality enabling the HC sector to shift resources towards more effective services (e.g. outpatient activity). Through this mechanism, the average LA can indirectly save on average more than 3 lives per million individuals by increasing LTC expenditure per user by £863. The absence of a LTC direct mortality effect may not be surprising since the primary goal of LTC is to improve quality rather than length of life (Fernandez et al., 2011). The estimated LTC mortality effect is likely to be net of the mortality effects of privately funded LTC and informal care as these are likely to have a substitution relationship with publicly funded LTC. In addition, our results suggest that only a HC direct mortality effect is likely to exist. However, an additional £42m spent in HC services is estimated to produce £7.8m of savings in the LTC sector. These savings are likely to reflect a reduction in demand for LTC services: by meeting health needs, the additional HC services also address or prevent care needs. Therefore, in this case, savings are likely to come with no health loss due to the LTC indirect mortality effect. A health loss via the indirect effect would exist only if the additional HC services were, at least in part, funded by displacing LTC services. This is because, for example, displacing LTC services might increase demand in emergency departments leading hospitals to reallocate resources from (more effective) elective to (less effective) emergency services. This is, however, unlikely as the HC and LTC sectors in England, at the time of analysis, were mostly independent. Therefore, further mortality effects may exist depending on how LAs decide to spend these savings.

A limitation of this study is that there might be other unobserved factors relating to the channels for the indirect mortality effects, which we are unable to control for. For example, changes in the composition within the observed sub-components of HC expenditure may impact the effectiveness of HC expenditure, one possible channel for the LTC indirect mortality effect. Suppose greater LTC expenditure means that some elective patients can be discharged more quickly, as some studies suggest (e.g. Gaughan et al., 2017a). Then, other elective patients will wait less and may benefit more from treatment. As we do not observe expenditure for monitoring and treating elective patients, we are unable to control for this potential channel. In addition, other factors such as medication adherence may impact the effectiveness of HC expenditure. For example, if greater LTC expenditure improves medication adherence, this may impact the effectiveness of drugs. As discussed in Section 2.1, no controls for the possible channels generating the LTC indirect mortality effect implies that our estimated LTC direct mortality effect will be biased upwards: it will capture the direct effect as well as the portion of indirect effect which is not accounted for. Hence, the estimated LTC indirect mortality effect will be biased downwards as part of the indirect effect will be captured by the (upwardly biased) direct effect. But since these biases will have the same size (and opposite sign), the LTC total mortality effect remains unbiased. Moreover, this study suggests that the LTC indirect mortality effect is as large as the LTC total mortality effect. Therefore, controlling for the changes in the observable composition of HC expenditure is likely to account for most of the channels generating the LTC indirect mortality effect. One further limitation of this study is that, by analysing the effects of LTC expenditure for *all* users, our estimates are unable to capture the potential heterogeneity of these effects driven by factors such as age or health condition. Finally, our cross-sectional analysis uses a sample of 146 LAs which covers 96% of the population (146 out of 152 LAs). To reduce endogeneity concerns, it includes several covariates (more than 30) but this also reduces degrees of freedom and statistical power. Moreover, despite the high number of covariates, our cross-sectional analysis may still bear some risks of endogeneity bias due to potential unobservable confounders. Future research could explore the implementation of panel data methods to test the sensitivity of the current results. These methods will provide greater statistical power through a larger number of observations and a way to control for time-invariant unobserved heterogeneity.

Overall, our findings may have relevant implications for HC and LTC decision makers. They suggest that budget decisions in the LTC sector may impact mortality through their effects on the HC sector. On the other hand, budget decisions in the HC sector may generate savings in the LTC sector which may be used to improve other outcomes relevant to LAs (e.g. quality of life). Alternatively, with a pooled HC and LTC budget the benefits of these savings could be shared between the sectors allowing investment in HC services to improve health. Therefore, moving towards an operationally and financially integrated care system which enhances and coordinates more formally interactions between the HC and LTC sector appears to have the potential to improve the marginal productivity of both sectors.

However, integrating sectors of such a high complexity can be a demanding task for any country requiring substantial resources and time. Moreover, learnings from current studies on integrated care models suggest that, although pooling budgets may facilitate integration (Stokes et al., 2019), the effects of these models (e.g. the effect of reducing emergency care activity) are likely to be yielded in the longer-term (Morciano et al., 2020) rather than in the short-run (Stokes et al., 2020). Building on this evidence, our findings suggest that the implementation of an integrated care system has the potential to be financially sustainable and welfare-enhancing by reducing costs and improving outcomes. These implications may hold true also for countries with little integrated care arrangements since interactions between HC and LTC sector are likely to exist regardless of such arrangements. As discussed in Section 1.1, our analysis covers the financial year 2014/15 when no or little integrated care arrangements were in place across English LAs.

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**Tables and figures**

Table 1 – Descriptive statistics on HC and LTC expenditure variables.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Variable |   | Total |   | Largest two disease areas |   | Largest four disease areas |
|   | Mean | Std dev | Prop |   | Mean | Std dev |   | Mean | Std dev |
| Health care expenditure per capita |   | 1,257 | 145 | 100.0% |   |   |   |   |   |   |
| Health care expenditure per capita for emergency care |   | 276 | 36 | 22.0% |   | 40 | 7 |   | 106 | 16 |
| Health care expenditure per capita for non-elective admissions |   | 186 | 30 | 14.8% |   | 32 | 7 |   | 90 | 16 |
| Health care expenditure per capita for accident and emergency |   | 33 | 8 | 2.6% |   | 2 | 0 |   | 5 | 1 |
| Health care expenditure per capita for emergency transport |   | 33 | 5 | 2.6% |   | 6 | 1 |   | 11 | 2 |
| Health care expenditure per capita for other emergency care expenditure |   | 24 | 9 | 1.9% |   | 0 | 1 |   | 1 | 2 |
| Health care expenditure per capita for non-emergency care |   | 981 | 125 | 78.0% |   | 85 | 16 |   | 178 | 30 |
| Health care expenditure per capita for day case and elective care |   | 141 | 24 | 11.2% |   | 31 | 6 |   | 55 | 9 |
| Health care expenditure per capita for outpatient care |   | 105 | 17 | 8.3% |   | 13 | 3 |   | 26 | 6 |
| Health care expenditure per capita for unbundled diagnostic imaging |   | 12 | 5 | 0.9% |   | 1 | 2 |   | 4 | 4 |
| Health care expenditure per capita for unbundled critical care |   | 21 | 6 | 1.7% |   | 5 | 2 |   | 13 | 4 |
| Health care expenditure per capita for unbundled drugs and devices |   | 25 | 8 | 2.0% |   | 1 | 1 |   | 4 | 2 |
| Health care expenditure per capita for other secondary care |   | 40 | 29 | 3.2% |   | 3 | 3 |   | 6 | 5 |
| Health care expenditure per capita for primary care prescribing |   | 151 | 28 | 12.0% |   | 23 | 6 |   | 57 | 15 |
| Health care expenditure per capita for direct access diagnostic imaging |   | 9 | 6 | 0.7% |   | 0 | 1 |   | 1 | 1 |
| Health care expenditure per capita for community and integrated care |   | 442 | 84 | 35.2% |   | 7 | 7 |   | 11 | 8 |
| Health care expenditure per capita for end of life care |   | 10 | 6 | 0.8% |   | 1 | 2 |   | 1 | 2 |
| Health care expenditure per capita for running costs |   | 25 | 6 | 2.0% |   | 0 | 0 |   | 0 | 0 |
| Long-term care expenditure per user |   | 8,633 | 3,709 | 91.2% |   |   |   |   |   |   |
| Long-term care expenditure per user for nursing care |   | 763 | 442 | 8.8% |   |   |   |   |   |   |
| Long-term care expenditure per user for residential care |   | 2,488 | 1,112 | 28.8% |   |   |   |   |   |   |
| Long-term care expenditure per user for community care |   | 3,144 | 1,426 | 36.4% |   |   |   |   |   |   |
| Long-term care expenditure per user for social support |   | 181 | 175 | 2.1% |   |   |   |   |   |   |
| Long-term care expenditure per user for short term care |   | 295 | 238 | 3.4% |   |   |   |   |   |   |
| Long-term care expenditure per user for equipment and adaptations |   | 140 | 130 | 1.6% |   |   |   |   |   |   |
| Long-term care expenditure per user for information and early support |   | 130 | 120 | 1.5% |   |   |   |   |   |   |
| Long-term care expenditure per user for social care activities |   | 889 | 719 | 10.3% |   |   |   |   |   |   |
| Long-term care expenditure per user for commissioning and service delivery |   | 608 | 701 | 7.0% |   |   |   |   |   |   |
| Observations |   | 146 |   | 146 |   | 146 |
| Std dev=standard deviation; Prop=proportion of total expenditure |

Table 2 – Descriptive statistics.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable | Mean | Std dev | Min | Max |
| Mortality rate | 1,010 | 129 | 542 | 1,381 |
| Public expenditure and activity |   |   |   |   |
| Health care expenditure (£000s) | 412,417 | 275,171 | 10,709 | 1,758,229 |
| Population | 333,083 | 229,434 | 6,139 | 1,509,301 |
| Health care expenditure per capita | 1,257 | 145 | 979 | 1,744 |
| Long-term care expenditure (£000s) | 107,488 | 72,326 | 6,502 | 437,516 |
| Number of long-term care users | 14,885 | 12,316 | 270 | 65,770 |
| Long-term care expenditure per user | 8,633 | 3,709 | 1,776 | 28,451 |
| Covariates on local authority population |   |   |   |   |
| Disability |   |   |   |   |
| Prop people who are blind or partially sighted | 0.5% | 0.1% | 0.1% | 1.3% |
| Prop people who are deaf or hard of hearing 2010 | 0.4% | 0.3% | 0.0% | 1.6% |
| Index of disability deprivation | 0.097 | 0.631 | -1.801 | 1.509 |
| Socio-economic status |   |   |   |   |
| Population density | 0.269 | 0.314 | 0.006 | 1.490 |
| Index of multiple deprivation 2010 | 23.421 | 8.575 | 5.447 | 43.447 |
| Index of education deprivation | 21.900 | 8.518 | 3.928 | 44.199 |
| Prop of people who are income deprived | 15.7% | 5.0% | 5.2% | 28.0% |
| Gross disposable household income per capita | 19,569 | 7,562 | 12,157 | 61,798 |
| Covariates on long-term care users and carers |   |   |   |   |
| Long-term care eligibility policy |   |   |   |   |
| London borough local authority (ref) | 22.6% |   | 0 | 1 |
| County local authority | 15.1% |   | 0 | 1 |
| Metropolitan local authority | 24.7% |   | 0 | 1 |
| Unitary local authority | 37.7% |   | 0 | 1 |
| User characteristics |   |   |   |   |
| Prop female users | 60.0% | 5.0% | 36.9% | 72.9% |
| Prop users aged 65 or older | 60.9% | 7.3% | 40.9% | 81.7% |
| Prop users receiving easy-read questionnaire | 20.7% | 7.2% | 0.0% | 47.0% |
| Prop users receiving no help with questionnaire | 21.8% | 6.6% | 9.6% | 54.1% |
| Prop users whose questionnaire was read by someone else | 46.6% | 5.3% | 26.7% | 60.3% |
| Prop users whose questionnaire was translated by someone else | 19.7% | 5.8% | 0.6% | 39.2% |
| Prop users whose questionnaire was only filled in by someone else | 39.1% | 5.4% | 22.6% | 50.9% |
| Prop users whose questionnaire was talked through with someone else | 28.1% | 3.9% | 6.3% | 36.8% |
| Prop users whose questionnaire was answered by someone else | 8.9% | 3.0% | 0.0% | 18.8% |
| Carer characteristics |   |   |   |   |
| Prop female carers | 67.1% | 4.2% | 44.3% | 76.3% |
| Prop carers aged 65 or older | 43.8% | 9.3% | 19.1% | 75.6% |
| Prop carers whose care recipient is 65 or older | 68.8% | 9.0% | 40.7% | 85.1% |
| Prop carers who are retired | 51.8% | 8.3% | 23.2% | 68.8% |
| Prop carers experiencing a clash between work and caring role | 4.8% | 1.6% | 1.2% | 9.2% |
| Prop carers receiving help with questionnaire | 89.4% | 5.7% | 46.4% | 99.7% |
| Prop carers in caring role between 6 months and 1 year | 2.9% | 1.5% | 0.3% | 11.1% |
| Prop carers in caring role for more than 1 year | 96.4% | 1.7% | 88.9% | 99.7% |
| Instruments |   |   |   |   |
| Distance from target index | 1.003 | 0.071 | 0.880 | 1.339 |
| Age-cost index | 0.977 | 0.132 | 0.632 | 1.249 |
| Market forces factor index | 1.006 | 0.069 | 0.927 | 1.160 |
| Council tax base per user | 7.9 | 4.3 | 1.7 | 29.1 |
| Business rates tax base per user | 0.0004 | 0.001 | 0.00003 | 0.013 |
| Area Cost Adjustment index | 1.043 | 0.064 | 1.000 | 1.361 |
| Observations | 146 |
| Std dev=standard deviation; Prop=proportion (expressed as percentage); ref=reference category. |

Table 3 – Mortality effects estimates and test for indirect mortality effects.

|  |  |  |
| --- | --- | --- |
| Independent variable | (1) | (2) |
| Ln of health care expenditure per capita | -0.257\*\*\* | -0.245\*\*\* |
| (0.081) | (0.075) |
| Ln of long-term care expenditure per user | -0.032\*\*\* | -0.032\*\*\* |
| (0.011) | (0.011) |
| ln of health care expenditure per capita × ln of long-term care expenditure per user |   | -0.304\*\* |
|   | (0.142) |
| LA population | Prop people who are blind or partially sighted | -0.016 | -0.027 |
| Prop people who are deaf or hard of hearing 2010 | 0.025\* | 0.030\*\* |
| Index of disability deprivation | 0.152\*\*\* | 0.146\*\*\* |
| Population density | -0.033 | -0.031 |
| Ln of index of multiple deprivation 2010 | -0.091\*\* | -0.070\* |
| Index of education deprivation | 0.002\*\* | 0.002 |
| Prop of people who are income deprived | 0.010\*\*\* | 0.010\*\*\* |
| Gross disposable household income per capita: quartile 2 | 0.016 | 0.017 |
| Gross disposable household income per capita: quartile 3 | -0.001 | -0.007 |
| Gross disposable household income per capita: quartile 4 (highest income) | -0.010 | -0.009 |
| LTC users | County LA | -0.007 | 0.008 |
| Metropolitan LA | -0.009 | -0.002 |
| Unitary Authority LA | 0.013 | 0.025 |
| Prop female users | -0.001\* | -0.001 |
| Prop users aged 65 or older | -0.001 | -0.001 |
| Prop users receiving easy-read questionnaire | 0.0003 | 0.0002 |
| Prop users receiving no help with questionnaire | -0.002 | -0.001 |
| Prop users whose questionnaire was read by someone else | 0.002 | 0.002 |
| Prop users whose questionnaire was translated by someone else | -0.002\*\* | -0.003\*\* |
| Prop users whose questionnaire was only filled in by someone else | -0.0001 | 0.0005 |
| Prop users whose questionnaire was talked through with someone else | -0.001 | -0.001 |
| Prop users whose questionnaire was answered by someone else | 0.0005 | 0.0004 |
| Prop female carers | -0.0001 | -0.0003 |
| Prop carers aged 65 or older | 0.001 | 0.0012\* |
| Prop carers whose care recipient is 65 or older | 0.0003 | 0.0003 |
| Prop carers in caring role between 6 months and 1 year | 0.002 | -0.004 |
| Prop carers in caring role for more than 1 year | 0.004 | -0.0002 |
| Prop carers who are retired | -0.003\*\* | -0.003\*\* |
| Prop carers experiencing a clash between work and caring role | 0.005 | 0.004 |
| Prop carers receiving help with questionnaire | 0.002 | 0.001 |
| Constant | 8.768\*\*\* | 7.052\*\*\* |
| Observations | 146 | 146 |
| Kleibergen-Paap rk Wald F statistic | 46.2 | 3.0 |
| Over-identification test's p-value | 0.741 | 0.609 |
| The dependent variable is the ln of age-standardised mortality rate. |
| All estimates are obtained from an over-identified instrumental variable specification. The instruments used to obtain the estimates in column 1 are ln of distance from target index, ln of age-cost index, ln of market forces factor index, and ln of council tax base per user. The instruments used to obtain the estimates in column 2 are ln of distance from target index, ln of council tax base per user, the product of these two instruments, ln of age-cost index, and ln of market forces factor index. |
| Robust standard errors in parentheses, \*\*\*=p-value<0.01, \*\*=p-value<0.05, \*=p-value<0.1 |

Table 4 – Results from the investigation of plausible channels for indirect mortality effects.

|  |  |  |  |
| --- | --- | --- | --- |
| Effect of long term-care expenditure per user on | Disease areas | Effect of health care expenditure per capita on  | All users |
| All | Largest two | Largest four |
| Health care expenditure | -0.007 |   |   | Long-term care expenditure | -0.607\*\* |
| Non-elective admission expenditure | -0.089\*\*\* | NR | NR | Nursing care expenditure | -1.198\* |
| Accident and emergency expenditure | -0.092\* | NR | NR | Residential care expenditure | -0.107 |
| Emergency transport expenditure | 0.013 | 0.004 | -0.008 | Community care expenditure | -1.098\*\*\* |
| Other emergency care expenditure | 0.087 | - | - | Social support expenditure | -4.512\*\* |
| Day case and elective care expenditure | -0.023 | 0.020 | -0.009 | Short-term care expenditure | -0.990 |
| Outpatient care expenditure | -0.028 | 0.156\*\* | 0.089\* | Equipment and adaptations expenditure | -3.457\* |
| Unbundled diagnostic imaging expenditure | -0.122 | -0.141 | -0.759\*\* | Information and early intervention expenditure | 0.522 |
| Unbundled critical care expenditure | -0.192\*\*\* | NR | NR | Social care activities expenditure | -0.370 |
| Unbundled drugs and devices expenditure | 0.048 | 0.278 | -0.121 | Commissioning and service delivery expenditure | 1.538 |
| Other secondary care expenditure | 0.115 | -0.202 | 0.089 |   |   |
| Primary care prescribing expenditure | -0.013 | -0.021 | 0.067 |   |   |
| Direct access diagnostic imaging expenditure | -0.313\*\* | - | - |   |   |
| Community and integrated care expenditure | 0.032 | 0.103 | 0.146 |   |   |
| End of life care expenditure | 0.320\*\* | NR | NR |   |   |
| Running costs | 0.112\*\*\* | NR | NR |   |   |
| NR=not reported because the estimate for expenditure on all diseases is at least weakly statistically significant at the 10% level, -=analysis not carried out because more than 15% of LAs in the sample have zero-expenditure. |
| All HC and LTC expenditure variables are per capita or per user, respectively. Estimates on the effect of ln of long-term care expenditure per user on ln of health care expenditure per capita variables are obtained from a just-identified instrumental variable specification, where the only instrument is ln of council tax base per user. Estimates on the effect of ln of health care expenditure per capita on ln of long-term care expenditure per user variables are obtained from an over-identified instrumental variable specification, where the instruments are ln of distance from target index, ln of age-cost index, ln of market forces factor index, and ln of council tax base per user. |
| \*\*\*=p-value<0.01, \*\*=p-value<0.05, \*=p-value<0.1 |

Table 5 – Estimates of the LTC direct mortality effect.

|  |  |
| --- | --- |
| Independent variable | (2) |
| Ln of decreasing portion of health care expenditure per capita | -0.030 |
| (0.100) |
| Ln of growing portion of health care expenditure per capita | -0.165\*\* |
| (0.081) |
| Ln of long-term care expenditure per user | -0.014 |
| (0.021) |
|  | Prop people who are blind or partially sighted | -0.028 |
| Prop people who are deaf or hard of hearing 2010 | 0.020 |
| Index of disability deprivation | 0.1475\*\*\* |
| Population density | -0.057 |
| Ln of index of multiple deprivation 2010 | -0.1680\*\*\* |
| Index of education deprivation | 0.0026\* |
| Prop of people who are income deprived | 0.0149\*\*\* |
| Gross disposable household income per capita: quartile 2 | 0.0337\*\* |
| Gross disposable household income per capita: quartile 3 | 0.018 |
| Gross disposable household income per capita: quartile 4 (highest income) | 0.001 |
| LTC users | County LA | -0.026 |
| Metropolitan LA | -0.034 |
| Unitary Authority LA | -0.007 |
| Prop female users | -0.0004 |
| Prop users aged 65 or older | -0.002\*\* |
| Prop users receiving easy-read questionnaire | -0.001 |
| Prop users receiving no help with questionnaire | -0.004 |
| Prop users whose questionnaire was read by someone else | 0.001 |
| Prop users whose questionnaire was translated by someone else | -0.003\*\* |
| Prop users whose questionnaire was only filled in by someone else | 0.000 |
| Prop users whose questionnaire was talked through with someone else | -0.003 |
| Prop users whose questionnaire was answered by someone else | -0.001 |
| Prop female carers | -0.0002 |
| Prop carers aged 65 or older | 0.001 |
| Prop carers whose care recipient is 65 or older | 0.0002 |
| Prop carers in caring role between 6 months and 1 year | 0.003 |
| Prop carers in caring role for more than 1 year | 0.005 |
| Prop carers who are retired | -0.003\* |
| Prop carers experiencing a clash between work and caring role | 0.004 |
| Prop carers receiving help with questionnaire | 0.001 |
| Constant | 7.998\*\*\* |
| Observations | 146 |
| Kleibergen-Paap rk Wald F statistic | 4.3 |
| Over-identification test's p-value | 0.131 |
| The dependent variable is the ln of age-standardised mortality rate. |
| All estimates are obtained from an over-identified instrumental variable specification. The instruments are distance from target index, ln of age-cost index, ln of market forces factor index, and ln of council tax base per user. |
| Robust standard errors in parentheses, \*\*\*=p-value<0.01, \*\*=p-value<0.05, \*=p-value<0.1 |

Table 6 – Summary of the key results.

|  |  |  |
| --- | --- | --- |
| Health care |   | Long-term care |
| Key summary statistics |
| Average population | 333,083 |   | Average users | 14,885 |
| Average expenditure per capita | 1,257 |   | Average expenditure per user | 8,633 |
| Key marginal effects on expenditure in the other sector |
| Long-term care expenditure | -0.607\*\* |   | Non-elective admission expenditure | -0.089\*\*\* |
| Nursing care expenditure | -1.198\* |   | Accident and emergency expenditure | -0.092\* |
| Community care expenditure | -1.098\*\*\* |   | Unbundled diagnostic imaging expenditure for largest 4 diseases | -0.759\*\* |
| Social support expenditure | -4.512\*\* |   | Unbundled critical care expenditure | -0.192\*\*\* |
| Equipment and adaptations expenditure | -3.457\* |   | Direct access diagnostic imaging expenditure | -0.313\*\* |
|   |   |   | Outpatient care expenditure for largest 4 diseases | 0.089\* |
|   |   |   | End of life care expenditure | 0.320\*\* |
|   |   |   | Running costs | 0.112\*\*\* |
| Marginal mortality effects |
| Direct mortality effect | -0.257\*\*\* |   | Direct mortality effect | None |
| Indirect mortality effect | None |   | Indirect mortality effect | -0.032\*\*\* |
| The average mortality rate is 1,010 deaths per million individuals. |
| \*\*\*=p-value<0.01, \*\*=p-value<0.05, \*=p-value<0.1 |

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# Appendix

#### Mediation analysis

The sequence of regressions discussed in Section 2.3.1 and 2.3.2 outlines a logic which is similar to the logic of mediation analysis (Robins and Greenland, 1992, Jun et al., 2016, Frölich and Huber, 2017). Briefly, mediation analysis can decompose the total effect of a treatment variable on an outcome into direct and indirect effects once the channels yielding the indirect effect, i.e. the mediators, are identified. The following IV mediation model aims to quantify the LTC indirect mortality effect:

 ,

 ,

 ,

 ,

 ,

To be noted that the mediation model - is to some extent similar to the first and second stage of regression . From -, the effects of interest are estimated as follows:

 ,

 ,

 .

The key parameters of interest *φ̂4*, *φ̂5* and *ψ̂5* are point-identified when using a dedicated instrument for the treatment variable, *expenditureiLTC*, and the mediator, *expenditurejHC*. In addition to the two common assumptions of relevance and exogeneity of the instruments, the IV mediation model requires the dedicated instruments to be not correlated. The following figure exemplifies the key aspects of the discussed IV mediation model:

Mediation analysis requires the structural assumption that the impact of the treatment variable (LTC expenditure per user) on the mediator (HC expenditure per capita for sub-sector *j*) *must* have indirect consequences on the outcome (mortality). This assumption, however, is unlikely to hold true within our context. As discussed in Section 1.2, a beneficial LTC indirect mortality effect may occur because, for example, better supply in the LTC sector reduces demand in the HC sector for services that are less effective than average. This implies that the needs of individuals no longer demanding HC services are fully met through the LTC sector. Therefore, in this case, unlike the structural assumption required in mediation analysis, lower expenditure in some HC services is expected not to have any impact on mortality. This scenario is made possible in the empirical strategy discussed in our main study and, therefore, we prefer it over mediation analysis.

Table A6 shows the results obtained through the mediation model -. Like our main findings, these results suggest that the total mortality effect is only composed of the indirect mortality effect.

#### LATE and monotonicity

Under the potential outcome model framework (Rubin, 1974, Rubin, 1978), the 2SLS estimates of the mortality effects have a local average treatment effect (LATE) interpretation. In the case of continuous endogenous treatment variables and continuous instruments, LATE estimates are weighted averages of the average treatment effect of the expenditure variables on mortality for those LAs that are compliers. These are LAs which are induced to increase, for example, health care expenditure per capita as a result of having a higher value of the DFT index. The identification of LATE requires the instruments to satisfy the monotonicity assumption. This means that LAs with higher levels of the instrument (e.g. higher DFT index) never spend less (e.g. on health care services per capita) than LAs with lower levels of the instrument. In our context this assumption is plausible because all the instruments are elements of the funding system which strongly determine spending power across LAs. The figures below show that, conditional on our covariates, there is no clear systematic violation of the monotonicity assumption. Therefore, this assumption, together with the assumption of exogeneity and relevance (discussed in Section 2.4), determines the validity of our LATE estimates. These may differ from the average treatment effect estimates if there exists heterogeneity in the treatment effect across LAs, i.e. if the treatment effect for LAs that are compliers differ from other LAs.






#### Descriptive statistics

Of the 152 LAs, six LAs were removed from the sample because of missing data on mortality or HC expenditure. Zero-expenditure tend to be observed more often across LAs for HC and LTC sub-sectors. In the analysis of sub-sector expenditure, as described in Section 2.3.1, to aid comparability across results by retaining the same sample, we mean-impute expenditure for those LAs with zero-expenditure. LAs with zero-expenditure would otherwise drop out of the sample because we take the logarithm of expenditure, as showed in regression and . When the proportion of LAs with zero-expenditure is greater than 15% we do not carry out the analysis because the sample is likely to be too small for comparability of results. Therefore, our sample includes 146 LAs.

Table 1 shows some descriptive statistics on HC and LTC expenditure for multiple sub-sectors. Emergency care expenditure accounts for 22% of HC expenditure with most of this expenditure being for non-elective admissions (15%). The four highest non-emergency care expenditure are expenditure for community and integrated care (35%), primary care prescribing (12%), day case and elective care (11%) and outpatient care (8%). Most of the LTC expenditure is for community (36%) and residential (29%) care. Other relevant sources of LTC expenditure are social care activities (10%), nursing care (9%), and commissioning and service delivery (7%).

Table 2 shows descriptive statistics for other variable involved in the analysis. On average, there are 1,010 age-standardised deaths per million individuals across LAs. LAs spend on average £412.4m to provide HC to a population of about 333 thousand people, and £107.5m to support about 15 thousand LTC users. This translates into HC spend of £1,257 per capita and LTC spend of £8,633 per user.

Across LAs, on average, 0.5% of people are blind or partially sighted and 0.4% deaf or hard of hearing. The average LA has a lower index of disability deprivation (0.097) than the median LA (0.126) suggesting most LAs are more deprived than average. There are almost 3 thousand people per square kilometre and the average LA has a higher index of multiple and education deprivation (23.4 and 21.9) than the median LA (23.3 and 20.5) indicating the most LAs are less deprived than average. In addition, on average, 15.7% of people are income deprived according to the income deprivation index, and the gross disposable household income per capita is almost £20 thousand. Among our 146 LAs there are 33 London boroughs, 22 county LAs, 36 metropolitan LAs and 55 unitary LAs. About LTC users, 60% are female, 60.9% are aged 65 or older, 20.7% received an easy-read questionnaire, and 21.8% received no help to fill the questionnaire while for most users (46.6%) the questionnaire was read by someone else. Data on informal unpaid carers suggest that 67.1% of carers are female, 43.8% are aged 65 or older and 68.8% care for someone aged 65 or older. Most carers are retired (51.8%) and 4.8% experience a clash between work and the caring role. The majority of carers received help with the questionnaire (89.4%) and spent more than 1 year in their caring role (96.4%).

The DFT index varies between 0.880 and 1.339 suggesting that budget allocation of some LAs in 2014/15 is 12% below and 33.9% above its target allocation, respectively. The age-cost index suggests that because of differences in the demographic profile of the local population LAs may have up to 36.8% lower and 24.9% higher HC expenditure than the average LA. The MFF index of the LAs with the least and most expensive input prices is 3.7% lower and 16% higher, respectively, than the average LA. In addition, there are on average 7.9 domestic properties per user and 4 non-domestic properties every 10,000 users. The ACA index is on average 1.043 indicating that labour costs are on average 4.3% greater than the LA with the lowest labour costs.

#### Formal test of instrument strength

We run a formal test of weak identification on our instruments following Andrews (2018). The author proposes a two-step procedure where, put simply, the first step tests the instrument strength and, depending on the first-step result, the second step allows the choice of either the standard Wald confidence intervals or confidence intervals that are robust to weak instruments. In the first step, a distortion coverage cut-off is empirically estimated and compared with the chosen coverage distortion level. The instrument is weak if the estimated distortion coverage cut-off is greater than the chosen coverage distortion level. In the second step, the weak-instrument-robust confidence intervals are estimated using a linear combination test. This two-step procedure is valid also under heteroscedasticity and autocorrelation. We implement it using the Stata command twostepweakiv (Sun, 2018). Following Yogo and Stock (2002), we assess the instrument strength by tolerating a coverage distortion cut-off no greater than 10%. For regression , we define a high-dimensional parameter grid of 246x32x305=2,400,650 points. We estimate a coverage distortion cut-off of 5% for all three endogenous variables, well below the 10% accepted limit. This suggests that the instruments are unlikely to be weak and, in turn, the standard Wald confidence intervals are valid. For regression , we define a high-dimensional parameter grid of 41x158x196=1,269,688 points. We estimate a coverage distortion cut-off of 6% for LTC expenditure per user and of 5% for the decreasing and increasing portion of HC expenditure per capita. Also in this case, this suggests that instruments are unlikely to be weak and, in turn, the standard Wald confidence intervals are valid.

Table A1 – Data sources.

| Variable | Original unit | Unit of analysis | Year | Source of data | Link | Date of last access |
| --- | --- | --- | --- | --- | --- | --- |
| Mortality indicator | Local authority | Local authority | 2015 | Office for National Statistics: Deaths registered by area of usual residence | <https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/deaths/datasets/deathsregisteredbyareaofusualresidenceenglandandwales> | 08/01/2021 |
| Public health care expenditure | CCG | Local authority | 2014/15 | NHS England | Requests for this dataset should be addressed to england.programmebudgeting@nhs.net | - |
| Number of people | LSOA | Local authority | 2014 | Office for National Statistics: Lower layer Super Output Area population estimates | <https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/lowersuperoutputareamidyearpopulationestimates> | 08/01/2021 |
| Public long-term care expenditure | Local authority | Local authority | 2014/15 | NHS Digital: Adult Social Care Activity and Finance Report | <https://digital.nhs.uk/data-and-information/publications/statistical/adult-social-care-activity-and-finance-report/personal-social-services-expenditure-and-unit-costs-england-2014-15-provisional-release> | 08/01/2021 |
| Long-term care activity volumes | Local authority | Local authority | 2014/15 | <https://digital.nhs.uk/data-and-information/publications/statistical/adult-social-care-activity-and-finance-report/community-care-statistics-social-services-activity-england-2014-15> | 08/01/2021 |
| Type of local authority | Local authority | Local authority | 2017/18 | <https://digital.nhs.uk/data-and-information/publications/statistical/adult-social-care-activity-and-finance-report/2017-18> | 08/01/2021 |
| Population characteristics including gender, ethnicity and single-person households | LSOA | Local authority | 2011 | Census | <https://census.ukdataservice.ac.uk/get-data/aggregate-data> | 08/01/2021 |
| Income deprivation, disability deprivation, education deprivation | LSOA | Local authority | 2015 | Ministry of Housing, Communities & Local Government website | <http://opendatacommunities.org/resource?uri=http%3A%2F%2Fopendatacommunities.org%2Fdata%2Fsocietal-wellbeing%2Fimd%2Findices> | 08/01/2021 |
| Disability support | Local authority | Local authority | 2014/15 | Office for National Statistics: nomis, official labour market statistics | <https://www.nomisweb.co.uk/query/construct/summary.asp?mode=construct&version=0&dataset=115> | 08/01/2021 |
| Gross disposable household income | Local authority | Local authority | 2014 | Office for National Statistics: Regional gross disposable household income by local authority | <https://www.ons.gov.uk/economy/regionalaccounts/grossdisposablehouseholdincome/datasets/regionalgrossdisposablehouseholdincomegdhibylocalauthorityintheuk> | 08/01/2021 |
| Long-term care user characteristics including cognitive status and reception of other forms of long-term care | Individual | Local authority | 2014/15 | NHS Digital: Personal Social Services Adult Social Care Survey | <https://digital.nhs.uk/data-and-information/publications/statistical/personal-social-services-adult-social-care-survey/personal-social-services-adult-social-care-survey-england-2014-15> | 08/01/2021 |
| Informal carer characteristics including time in caring role and caring task | Individual | Local authority | 2014/15 | NHS Digital: Personal Social Services Survey of Adult Carers in England | <https://digital.nhs.uk/data-and-information/publications/statistical/personal-social-services-survey-of-adult-carers/personal-social-services-survey-of-adult-carers-in-england-2014-15> | 08/01/2021 |
| Expenditure on non-long-term care services | Local authority | Local authority | 2014/15 | Government website: Local authority revenue expenditure and financing | https://www.gov.uk/government/statistical-data-sets/local-authority-revenue-expenditure-and-financing-england-2014-to-2015-individual-local-authority-data-outturn | 08/01/2021 |
| Distance from target index | Local authority | Local authority | 2014/15 | NHS England | <https://www.england.nhs.uk/allocations/allocations-2014-15-and-2015-16/> | 08/01/2021 |
| age-cost index |
| Market forces factor index |
| Council tax base | Local authority | Local authority | 2014/15 | Government website: Council Tax statistics | <https://www.gov.uk/government/statistics/council-tax-levels-set-by-local-authorities-in-england-2014-to-2015> | 08/01/2021 |
| Business rate tax base | Local authority | Local authority | 2014/15 | Government website: Non-domestic rating: stock of properties collection | <https://www.gov.uk/government/statistics/central-and-local-rating-lists-summary-england-and-wales> | 08/01/2021 |
| Area cost adjustment index | Local authority | Local authority | 2013/14 | National archive | [https://webarchive.nationalarchives.gov.uk/20140505105851/http:/www.local.communities.gov.uk/finance/1314/CalcFFs.pdf](https://webarchive.nationalarchives.gov.uk/20140505105851/http%3A/www.local.communities.gov.uk/finance/1314/CalcFFs.pdf) | 08/01/2021 |

Table A2 – First-stage results.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | Regression (2) |   | Regression (5) |   | Regression (6) | Regression (7) |   | Regression (8) |
| Ln of health care expenditure per capita | Ln of long-term care expenditure per user |   | Ln of health care expenditure per capita | Ln of long-term care expenditure per user | Interaction between expenditure variables |   | Ln of long-term care expenditure per user | Ln of health care expenditure per capita |   | Ln of decreasing portion of health care expenditure per capita | Ln of growing portion of health care expenditure per capita | Ln of long-term care expenditure per user |
| Instruments | Ln of Distance From Target index | 0.671\*\*\* | -0.586\*\* |   | 0.797\*\*\* | -0.030 | -1.472\*\*\* |   | -0.586\*\* | 0.643\*\*\* |   | 1.168\*\*\* | 0.097 | -0.586\*\* |
| Ln of age-sex index | 0.409\*\*\* | -0.221 |   | 0.409\*\*\* | -0.222 | 0.014 |   | -0.221 | 0.430\*\*\* |   | 0.080 | 0.770\*\*\* | -0.221 |
| Ln of Market Forces Factor index | 0.573\*\* | -1.711\*\*\* |   | 0.580\*\* | -1.680\*\*\* | -0.222 |   | -1.711\*\*\* | 0.699\*\*\* |   | 2.093\*\* | 2.548\*\*\* | -1.711\*\*\* |
| Ln of council tax base per user | -0.006 | 0.932\*\*\* |   | -0.005 | 0.936\*\*\* | -0.009 |   | 0.932\*\*\* | -0.036 |   | 0.108\*\*\* | -0.101\*\*\* | 0.932\*\*\* |
| Ln of business rates tax base per user |   |   |   |   |   |   |   |   | 0.029 |   |   |   |   |
| Ln of Area Cost Adjustment index |   |   |   |   |   |   |   |   | -0.105 |   |   |   |   |
| Ln of Distance From Target index × Ln of council tax base per user |   |   |   | -0.059 | -0.259 | 0.690\*\*\* |   |   |   |   |   |   |   |
| Sanderson-Windmeijer F statistics | 61.9 | 403.6 |   | 60.6 | 391.1 | 6.2 |   | 1,234.8 | 58.7 |   | 10.5 | 11.6 | 10.5 |
| The sample includes 146 LAs. Estimates for control variables and intercept are not reported. \*\*\*=p-value<0.01, \*\*=p-value<0.05, \*=p-value<0.1 |

Table A3 – Sensitivity analysis to controlling for other LA expenditures.

|  |  |
| --- | --- |
| Independent variable |   |
| Ln of health care expenditure per capita | -0.304\*\*\* |
| (0.115) |
| Ln of long-term care expenditure per user | -0.035\*\*\* |
| (0.012) |
| LA population | Prop people who are blind or partially sighted | -0.007 |
| Prop people who are deaf or hard of hearing 2010 | 0.032\*\* |
| Index of disability deprivation | 0.168\*\*\* |
| Population density | -0.001 |
| Ln of index of multiple deprivation 2010 | -0.104\*\* |
| Index of education deprivation | 0.002\* |
| Prop of people who are income deprived | 0.009\*\* |
| Gross disposable household income per capita: quartile 2 | 0.012 |
| Gross disposable household income per capita: quartile 3 | -0.001 |
| Gross disposable household income per capita: quartile 4 (highest income) | -0.004 |
| LTC users | County LA | 0.017 |
| Metropolitan LA | -0.012 |
| Unitary Authority LA | 0.024 |
| Prop female users | -0.001\*\* |
| Prop users aged 65 or older | 0.000 |
| Prop users receiving easy-read questionnaire | 0.0000 |
| Prop users receiving no help with questionnaire | -0.002 |
| Prop users whose questionnaire was read by someone else | 0.002 |
| Prop users whose questionnaire was translated by someone else | -0.002 |
| Prop users whose questionnaire was only filled in by someone else | -0.0010 |
| Prop users whose questionnaire was talked through with someone else | -0.002 |
| Prop users whose questionnaire was answered by someone else | 0.0010 |
| Prop female carers | 0.0000 |
| Prop carers aged 65 or older | 0.001\* |
| Prop carers whose care recipient is 65 or older | 0.0010 |
| Prop carers in caring role between 6 months and 1 year | 0.001 |
| Prop carers in caring role for more than 1 year | 0.007 |
| Prop carers who are retired | -0.002\*\* |
| Prop carers experiencing a clash between work and caring role | 0.004 |
| Prop carers receiving help with questionnaire | 0.001 |
| LA expenditures | Ln of expenditure per capita for education services | -0.015 |
| Ln of expenditure per capita for transport services | -0.044\*\*\* |
| Ln of expenditure per capita for housing services | 0.003 |
| Ln of expenditure per capita for cultural, environmental and planning services | 0.017 |
| Ln of expenditure per capita for police services | -0.002 |
| Ln of expenditure per capita for fire and rescue services | 0.048 |
| Constant | 8.868\*\*\* |
| Observations | 144 |
| Kleibergen-Paap rk Wald F statistic | 19.6 |
| Over-identification test's p-value | 0.564 |
| The dependent variable is the ln of age-standardised mortality rate. |
| All estimates are obtained from an over-identified instrumental variable specification. The instruments are ln of distance from target index, ln of age-cost index, ln of market forces factor index, and ln of council tax base per user. |
| Robust standard errors in parentheses, \*\*\*=p-value<0.01, \*\*=p-value<0.05, \*=p-value<0.1 |

Table A4 – Estimates of the effect of long-term care expenditure per user on health care expenditure per capita sub-sectors.

|  |  |
| --- | --- |
|   | *All disease areas* |
|  Variable | Ln of health care expenditure | Ln of non-elective admission expenditure per capita | Ln of accident and emergency expenditure per capita | Ln of emergency transport expenditure per capita | Ln of other unscheduled care expenditure per capita | Ln of day case and elective expenditure per capita | Ln of outpatient expenditure per capita | Ln of unbundled diagnostic imaging expenditure |
| Ln of long-term care expenditure per user | -0.007 | -0.089\*\*\* | -0.092\* | 0.013 | 0.087 | -0.023 | -0.028 | -0.122 |
| Over-identification test's p-value | 0.179 | 0.166 | 0.287 | <0.001\*\*\* | 0.769 | 0.100 | 0.012\*\* | 0.768 |
|   |   |   |   |   |   |   |   |   |
|  Variable | Ln of critical care expenditure | Ln of drugs and devices expenditure | Ln of other secondary care expenditure | Ln of primary care prescribing expenditure per capita | Ln of direct access diagnostic imaging expenditure | Ln of community and integrated care expenditure | Ln of end of life care expenditure | Ln of running costs |
| Ln of long-term care expenditure per user | -0.192\*\*\* | 0.048 | 0.115 | -0.013 | -0.313\*\* | 0.032 | 0.320\*\* | 0.112\*\*\* |
| Over-identification test's p-value | 0.077\* | 0.291 | 0.355 | 0.853 | 0.481 | 0.025\*\* | 0.403 | 0.235 |
|   | *Largest 2 disease areas (cancer and circulatory disease)* |
|  Variable | Ln of emergency transport expenditure per capita | Ln of day case and elective expenditure per capita | Ln of outpatient expenditure per capita | Ln of unbundled diagnostic imaging expenditure | Ln of unbundled drugs and devices expenditure | Ln of other secondary care expenditure | Ln of primary care prescribing expenditure per capita | Ln of community and integrated care expenditure |
| Ln of long-term care expenditure per user | 0.004 | 0.020 | 0.156\*\* | -0.141 | 0.278 | -0.202 | -0.021 | 0.103 |
| Over-identification test's p-value | <0.001\*\*\* | 0.646 | 0.421 | 0.106 | 0.076\* | 0.705 | 0.876 | 0.442 |
|   | *Largest 4 disease areas (cancer, circulatory, respiratory and gastro-intestinal disease)* |
|  Variable | Ln of emergency transport expenditure per capita | Ln of day case and elective expenditure per capita | Ln of outpatient expenditure per capita | Ln of unbundled diagnostic imaging expenditure | Ln of unbundled drugs and devices expenditure | Ln of other secondary care expenditure | Ln of primary care prescribing expenditure per capita | Ln of community and integrated care expenditure |
| Ln of long-term care expenditure per user | -0.008 | -0.009 | 0.089\* | -0.759\*\* | -0.121 | 0.089 | 0.067 | 0.146 |
| Over-identification test's p-value | <0.001\*\*\* | 0.176 | 0.685 | 0.488 | 0.129 | 0.135 | 0.760 | 0.732 |
| All estimates are obtained from a just-identified instrumental variable specification, where the only instrument is ln of council tax base per user. The number of observations is 146. The Kleibergen-Paap rk Wald F statistic is 1,234.8. The reported over-identification test is run using the Hansen J statistic and all available instruments for ln of long-term care expenditure per user. These include ln of council tax base, ln of business rate tax base and ln of area cost adjustment index. \*\*\*=p-value<0.01, \*\*=p-value<0.05, \*=p-value<0.1 |

Table A5 – Estimates of the effect of health care expenditure per capita on long-term care expenditure per user sub-sectors.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  Variable | Ln of long-term care expenditure per user | Ln of nursing care expenditure per user | Ln of residential care expenditure per user | Ln of community care expenditure per user | Ln of social support expenditure per user | Ln of short-term care expenditure per user | Ln of equipment and adaptations expenditure per user | Ln of information and early intervention expenditure per user | Ln of social care activities expenditure per user | Ln of commissioning and service delivery expenditure per user |
| Ln of health care expenditure per capita | -0.607\*\* | -1.198\* | -0.107 | -1.098\*\*\* | -4.512\*\* | -0.990 | -3.457\* | 0.522 | -0.370 | 1.538 |
| Over-identification test's p-value | 0.112 | 0.830 | 0.955 | 0.740 | 0.955 | 0.021\*\* | 0.544 | 0.201 | 0.885 | 0.359 |
| All estimates are obtained from an over-identified instrumental variable specification, where the instruments are ln of distance from target index, ln of age-cost index, and ln of market forces factor index. The number of observations is 146. The Kleibergen-Paap rk Wald F statistic is 41.7. The reported over-identification test is run using the Hansen J statistic. \*\*\*=p-value<0.01, \*\*=p-value<0.05, \*=p-value<0.1 |

Table A6 – Results of IV mediation analysis.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Variable | Ln of long-term care expenditure per user | Ln of decreasing portion of health care expenditure per capita | Ln of growing portion of health care expenditure per capita | Ln of age-standardised mortality rate |
| Ln of decreasing portion of health care expenditure per capita |   |   |   | 0.023 |
| Ln of growing portion of health care expenditure per capita |   |   |   | -0.312\*\*\* |
| Ln of long-term care expenditure per user |   | -0.116\*\*\* | 0.123\*\*\* | 0.010 |
| Instr | Ln of distance from target index |   | 0.011 | 0.859\*\*\* |   |
| Ln of age-sex index |   | 0.787\*\*\* | 0.267 |   |
| Ln of market forces factor index |   | 2.451\*\*\* | 1.228\* |   |
| Ln of council tax base per user | 0.919\*\*\* |   |   |   |
| LA population | Prop people who are blind or partially sighted | -0.004 | -0.007 | 0.040 | -0.005 |
| Prop people who are deaf or hard of hearing 2010 | -0.014 | -0.013 | -0.016 | 0.011\* |
| Index of disability deprivation | 0.145\*\*\* | 0.225\*\*\* | 0.163\*\* | 0.156\*\*\* |
| Population density | 0.016 | -0.008 | -0.002 | -0.003 |
| Ln of index of multiple deprivation 2010 | -0.085 | -0.110 | -0.422\*\*\* | -0.227\*\*\* |
| Index of education deprivation | 0.004 | -0.004 | -0.001 | 0.003\* |
| Prop of people who are income deprived | 0.024\*\*\* | 0.021\*\*\* | 0.031\*\* | 0.017\*\*\* |
| Gross disposable household income per capita: quartile 2 | -0.022 | -0.012 | 0.055 | 0.046\*\* |
| Gross disposable household income per capita: quartile 3 | -0.011 | 0.004 | 0.057 | 0.021 |
| Gross disposable household income per capita: quartile 4 (highest income) | 0.009 | -0.008 | 0.040 | 0.002 |
| LTC users | County LA | 0.059 | 0.031 | 0.010 | -0.024 |
| Metropolitan LA | -0.015 | 0.019 | -0.016 | -0.033 |
| Unitary Authority LA | 0.072 | 0.010 | -0.002 | -0.008 |
| Prop female users | 0.001 | -0.001 | 0.004 | 0.000 |
| Prop users aged 65 or older | -0.003 | 0.000 | -0.006\*\* | -0.003\*\* |
| Prop users receiving easy-read questionnaire | -0.003 | 0.005\* | -0.004 | -0.001 |
| Prop users receiving no help with questionnaire | 0.006 | -0.003 | -0.018\*\*\* | -0.006\* |
| Prop users whose questionnaire was read by someone else | 0.006\* | -0.005 | -0.012\*\* | 0.000 |
| Prop users whose questionnaire was translated by someone else | 0.003 | -0.006\*\* | -0.006 | -0.004\*\* |
| Prop users whose questionnaire was only filled in by someone else | 0.001 | -0.001 | 0.000 | 0.000 |
| Prop users whose questionnaire was talked through with someone else | 0.004 | 0.009\*\*\* | -0.004 | -0.004 |
| Prop users whose questionnaire was answered by someone else | 0.014\*\* | 0.001 | -0.017\*\* | -0.003 |
| Prop female carers | 0.002 | 0.000 | 0.003 | 0.000 |
| Prop carers aged 65 or older | 0.001 | 0.000 | -0.002 | 0.000 |
| Prop carers whose care recipient is 65 or older | 0.000 | 0.000 | 0.000 | 0.000 |
| Prop carers in caring role between 6 months and 1 year | 0.007 | 0.018 | 0.030 | 0.010 |
| Prop carers in caring role for more than 1 year | 0.014 | 0.009 | 0.019 | 0.010 |
| Prop carers who are retired | -0.003 | 0.001 | 0.003 | -0.002 |
| Prop carers experiencing a clash between work and caring role | 0.008 | 0.009 | 0.001 | 0.005 |
| Prop carers receiving help with questionnaire | 0.002 | -0.002 | 0.000 | 0.002 |
| Constant | 4.764\*\* | 5.863\*\*\* | 3.117 | 7.713\*\*\* |
| Observations | 146 | 146 | 146 | 146 |
| **LTC mortality effect** | -0.031\*\*\* |
| **LTC direct mortality effect** | 0.010 |
| **LTC indirect mortality effect** | -0.041 |
| ***LTC indirect mortality effect due to growing portion*** | -0.038\*\* |
| ***LTC indirect mortality effect due to decreasing portion*** | -0.003 |
| Robust standard errors in parentheses, \*\*\*=p-value<0.01, \*\*=p-value<0.05, \*=p-value<0.1 |

1. For simplicity, we ignore *ri* in the total differentiation. [↑](#footnote-ref-2)
2. Ideally, we would have used HC expenditure per patient rather than HC expenditure per capita. However, the latter is a reasonable measure of the former because HC in England is universal and free at the point of delivery. This implies that the whole population is covered by HC provision and most of the population is likely to access HC services. Moreover, the calculation of the exact number of all HC patients (including, for example, hospital patients, general practice patients, and patients of mental health institutions) might be carried out using data from multiple databases which require substantial research resources in terms of access and elaboration. On the other hand, the number of users accessing LTC services in England is known and available in the public domain. This is particularly important because LTC in England is means-tested and users of LTC services represent only a small proportion of the local population (on average, 5.7% across LAs in 2014/15). Therefore, calculating LTC expenditure per capita would severely underestimate the true LTC expenditure per user. [↑](#footnote-ref-3)
3. In addition, following Longo et al. (2021), we use business rates tax base per user and the ACA index as additional instruments to run over-identification tests in the case of equation . This regression estimates the effect of LTC expenditure per user on HC expenditure per capita using the council tax base per capita as the only instrument. [↑](#footnote-ref-4)
4. *β1* and *γ1* are assumed to reflect the long-run mortality effect of HC and LTC expenditure, respectively, i.e. they are assumed to capture both current and past mortality effects. This can be argued to be a plausible assumption for the English HC and LTC sector since public expenditure in these sectors tends to vary little over time and, therefore, current expenditure is likely to capture also the effects of past expenditure on current mortality. [↑](#footnote-ref-5)
5. The coefficients *β2* and *γ2* no longercapture the marginal effects of HC and LTC expenditure, respectively. The marginal effect of HC expenditure per capita is *β2*+*δ2*×ln(*expenditureiLTC*) while the marginal effect of LTC expenditure per user is *γ2*+*δ2*×ln(*expenditureiHC*). To aid intuition, we estimate and report the *average* marginal effect of HC and LTC expenditure, i.e. the marginal effect of HC and LTC *averaged* over the distribution of ln(*expenditureiLTC*) and ln(*expenditureiHC*), respectively. These average marginal effects, however, cannot be directly compared to the marginal effects *β1* and *γ1* since they have different definitions. [↑](#footnote-ref-6)
6. The structure of the proposed analysis follows the logic of mediation analysis (Robins and Greenland, 1992, Jun et al., 2016, Frölich and Huber, 2017). The plausible channels for indirect mortality effects discussed in Section 2.3.1 can be thought as mediators, and regressions and correspond to the outcome regression in mediation analysis. Therefore, mediation analysis is a plausible alternative empirical strategy. Section A1 of the Appendix discusses mediation analysis and contrasts it with the empirical strategy presented here. [↑](#footnote-ref-7)
7. In both these cases, regression estimates the HC direct mortality effect. In the first case, however, the HC indirect mortality effect will amount to the change in life saved due to the change in the level of LTC expenditure. In the second case, the HC indirect mortality effect will amount to the change in life saved due to the change in both level and composition of LTC expenditure. [↑](#footnote-ref-8)
8. In the first decade of the 2000s, a number of strategies were implemented to reduce health inequalities, including amendments to the way in which resources were allocated to deprived local areas outside of the usual formula. Any influence of this component is likely to be small given that a brand new formula was used for estimating the target allocation in 2014/15. Further, any residual endogeneity is negligible indeed once observable proxies for need are included as controls in our regressions. [↑](#footnote-ref-9)
9. Following Longo et al. (2021), we divide the council tax base by the number of users to replicate LAs’ funding approach as closely as possible. LAs in England are expected to allocate funding by prioritising services that must be guaranteed by law. ASC is one of these services and, therefore, LAs allocate to this sector most of the council tax revenues (Department for Communities and Local Government, 2017). The exact proportion of council tax revenues that LAs allocate to ASC is likely to be determined by the expected number of users rather than people. Moreover, as expectations on users are driven by local eligibility policy and level of need observable to LAs, once these have been accounted for, as we do, the number of users can be argued to be exogenous to LAs given the legal requirements. [↑](#footnote-ref-10)
10. The expenditure variables measured at the CCG level were recalculated to a LA geography using the proportion of the population (mid-2014 estimates) in each CCG that mapped into each LA. The majority of CCGs have a one-to-one correspondence with LAs in terms of their geographical boundaries. [↑](#footnote-ref-11)
11. On average, income from the NHS amounts to around 11% of the total gross LTC expenditure. [↑](#footnote-ref-12)
12. Adding functions of the exogenous variables, including interactions between them, to the instrument set is common practice (Wooldridge, 2010). Among the three HC instruments, we choose the DFT index to be interacted with council tax base per user because this instrument turns out to have the highest predictive power in the first stage. This is to be expected since the policy choices driving the DFT index are likely to determine greater variation in HC expenditure compared to relatively small differences in input prices and population characteristics across LAs. [↑](#footnote-ref-13)